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ECONOMETRIC EVALUATION OF THE SEWA BANK IN INDIA

APPLYING MATCHING TECHNIQUES BASED ON THE PROPENSITY SCORE

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ECONOMETRIC EVALUATION OF THE SEWA BANK IN INDIA

- APPLYING MATCHING TECHNIQUES BASED ON THE PROPENSITY SCORE -

ABSTRACT

This study assesses whether the microfinance institution SEWA Bank, India, is meeting its objective of raising its members' income. A cross-sectional analysis is undertaken to assess the overall income effect of being a member as well and the effect of being a first-time as compared to repeat borrower. Results suggest that while being a member has a positive and significant effect on income, taking a first loan does not. The latter finding is stressed in a longitudinal setting, applying Difference-in-Differences techniques. The effect of taking a first loan is estimated to be negative and highly insignificant. This confirms the hypothesis that positive effects of microfinance are not a matter of shortterm interventions.

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1. INTRODUCTION

This study assesses whether the microfinance institution SEWA Bank in Ahmedabad, India, a sister institution of the Self Employed Women's Association, is meeting one of its targeted ten point objectives: raising their members' income.[i] The data used in the analysis stems from surveys conducted in 1998 and 2000 by Harvard University researchers in close collaboration with a team of the Taleem Research Foundation, an Ahmedabad-based research firm. It provides a panel of 798 respondents, split up in members of SEWA Bank and non-members, the former ones again divided into savers and borrowers. This distinction permits both cross-section and longitudinal statistical tests of the effect of credit and savings programs of SEWA Bank. Non-parametric propensity score matching methods are applied; methods that control for endogeneity of the target population. There has been a long-standing debate as to whether evaluations of social programs that rely on techniques other than randomization can be relied upon. Several papers address this issue (see for example Heckman & Hotz, 1989, Heckman et al., 1997; 1998a; Smith & Todd, 2000; Diaz & Honda, 2004) and find that the estimator can perform extremely well in the evaluation of non-experimental programs given certain conditions. Given this context, this study puts emphasis on discussing the Ignorability of Treatment Assumption that one has to rely upon. Heckman and Hotz's (1998) indirect test is for example applied, different propensity score specifications used and several robustness checks on estimation results are performed. All results support the application of propensity score matching techniques.

To begin with, a simple cross-sectional analysis undertaken suggests positive and significant[ii] income effects for members in both survey rounds. Comparing estimated effects of both years reveal an increase in household level income and a decrease for respondents' income in the time period 1998 to 2000. Reasons for this observation are brought forward; the one dominating the rest of the analysis is the fact that fewer loans are taken by members previous to the second survey round than to the first one. Theory predicts that number of loans taken is positively correlated with the effect on outcome variables. The hypothesis to be tested is therefore whether the smaller treatment effect for members in the second survey round can be attributed to the fact that fewer loans have been taken.

To do so, the cross-sectional analysis from the previous section is undertaken with a restricted sample - only those women that took up their first loan in between the two survey rounds, are hence ‘new borrowers’, are looked at. Estimated effects are now smaller and mostly insignificant, confirming the hypothesis that repeat-borrowing has a greater effect for program participants.

The next step in the analysis is to make use of the available time dimension, which becomes possible due to the fact that in this setting, information on before and after having borrowed is available. This more advanced technique, named Difference-in-Differences, eliminates important time invariant sources of bias, such as local environment and systematic measurement error, and hence provides more reliable estimates. This is especially desirable in this setting, given that the restrained sample includes only 47 treated units.

Conclusions drawn from this longitudinal setting underline to an even greater extend the idea that the first loan taken does not have a significant effect on borrowers' income. The effects of taking a first loan on income variables are now estimated to even be negative and, more importantly, highly insignificant.

The results of the study hence suggest the dominance of repeat borrowing over a onetime credit. The policy implications that can be drawn from these findings in more general terms are to take a more holistic view by facilitating a shift from a minimalistic approach to a credit plus approach offering financial intermediation. Hence, while results in this study point to repeat-borrowing, also other services provided, such as saving possibilities and insurances, are believed to play a crucial role in enhancing members' welfare.

2. PREVIOUS RESEARCH

Over the last decades, microfinance turned out to be one of those ideas with enormous implications: It generated vast enthusiasm among aid donors and nongovernmental organizations as an instrument for reducing poverty. It is believed to have the potential to turn the Millennium Development Goal of cutting absolute poverty in half by 2015 into reality. This makes it even more surprising that the number of serious impact evaluations so far is negligible. A study by Subbaro et al (1999) found that only 5.4 percent of all projects sponsored by the World Bank in 1998 were designed such that a solid evaluation would be possible; including outcome indicators, baseline data and a suitable comparison group. Since then, the number of studies has been growing but is still small. This dearth of sound impact evaluations can be attributed to the fact that the self-selection bias, which will be elaborated on below, is particularly dominant in the context of microfinance.

Those studies that still attempt to estimate impact of microcredit find mixed results: some find moderate evidence supporting the elation over microfinance, others find that these positive impacts disappear when selection bias is accounted for. McKernan (2002) addresses the issue and finds that the effect of participating in a microfinancing-program can be overestimated by as much as 100 per cent when not controlling for such a bias.

Studies in India, Zimbabwe and Peru sponsored by USAID find that loan-takers had an average net-income gain only in India and Peru. Alexander (2001) takes a closer look at the Peru data and, when applying an instrumental variable approach to account for endogeneity, finds positive impacts to decrease and to become statistically insignificant. One of the probably most often cited impact assessment is of Grameen Bank, the founding microfinance institution in Bangladesh. The authors, Pitt and Khandker (1998), investigate program impact on poor households with a focus on female program participants. Besides a quasi-experimental survey design, their results rely on an instrumental variable approach to account for self-selection. One of their findings is a positive program impact that is greater for women than for men. Morduch (1998) criticizes the validity of the instrument used and refines the study, concluding that no evidence can be found for a higher consumption level or increase in school-enrolment but that variation in labour supply and consumption across seasons is much lower for program participants, male or female.

In another interesting study undertaken in Thailand, Coleman (1999; 2002) controls for endogenous self-selection as well as program placement by using data from a uniquely designed survey. He finds microfinance loans to positively affect many measures of household welfare, alas mainly for the wealthier members - the impact is largely insignificant for the very poor.

Unfortunately, seldom are studies this well-designed and non-experimental evaluation methods, where no randomized out comparison group exists, come into play. These typically impose non-testable assumptions. One particular type of non-experimental technique and also the one recent evaluation literature focuses on, is matching on the probability of participating in a program. Matching is a way of finding for each participating individual a comparable non-participant. The best-case scenario would be an individual that is identical regarding all relevant pre-program attributes except for not having obtained the treatment. This individual then serves in constructing a missing counterfactual outcome that can be used to calculate the effect of the program. The idea of this method originally stems from medical application, which is also the reason why program participation is equated with receiving treatment.

Most published literature applies this technique to employment and training programs. One exception is the study of Diaz and Handa (2004). They use a data set from a Mexican social experiment designed to evaluate that country's new poverty program PROGRESA, a conditional cash transfer program. Focus lies on estimation bias and they find that cross-sectional matching does well in replicating the benchmark for outcomes that are measured using similar survey instruments.

Within the evaluation of social programs one very influential study is of Dehejia and Wahba (1999; 2002). They use data from the National Supported Work (NSW) Demonstration, to evaluate the performance of nonparametric techniques, more explicitly propensity score matching methods. They find that the estimators succeed in closely replicating experimental results. These are far more positive conclusions about the quality of inferences based on observational data than previous ones for various model-based procedures: LaLonde (1986) for example concludes that social experiments are necessary to evaluate training programs.

Smith and Todd (2005) criticize, refine and extend findings of Dehejia and Whaba (1999; 2002) but also conclude that propensity score matching can be a useful econometric tool for program evaluation.

In what follows, these techniques will be applied to survey data from the microfinancing bank SEWA in Ahmedabad, India. This data set is particularly interesting as it includes information from two survey rounds as well as information on savers, borrowers and non-members. The SEWA Bank is one of the very few programs that concentrate on meeting the particular demands of poor women by offering saving as well as borrowing services.

4. THE PROGRAM UNDER CONSIDERATION

The services under consideration in this study are credit and savings programs of SEWA Bank, a sister institution of the trade union Self Employed Women's Association (SEWA) registered in 1972 and operating in Ahmedabad, the principal city of Gujarat state in western India.

Today, SEWA is dedicated to the struggle of poor women to gain recognition as well as income and food security in order to improve their own welfare and the one of their families.

It does so by providing a wide range of services such as savings, credits and insurance, tailored to the needs of its particular members. About half of the households led by these women live on less than one dollar a day and the others are not much above this poverty line. Not only this low income, but also their gender and the fact that most of the women belong to backward or scheduled castes or tribes makes them victims of discrimination in an environment of periodic civil unrest, slum eviction and environmental disasters such as flood, droughts and earthquakes.

Although any women above the age of 18 can join the SEWA Bank, most are SEWA members - working women from low-income households. SEWA is a membership-based organization, implying that besides these broad categories, no eligibility criteria exist. In order to become eligible to borrow, women must become shareholders of the bank. One share costs 10 Rupees (US$ 2.15). Additionally, she must have saved for at least half a year on a regular basis. The SEWA Bank provides secured and unsecured loans. They are given for specific purposes including housing, repayment of old debts, redemption of mortgaged assets, and social consumption purposes such as education, health, and weddings. It also provides loans for fixed and working capital for enterprises.

Most of the women take unsecured loans, since secured ones demand collateral in the form of either gold jewellery or fixed deposit savings, which only the better off members can afford. Unsecured loans, instead of physical collateral, require a ‘moral’ security, and - depending on the loan size - one or two guarantors. Hence, the regularity and volume of savings, a guarantor and the applicant's creditworthiness are decisive for whether a woman can take a loan or not. The creditworthiness is established by staff of the bank who keeps close contact with members.

The Survey[iii]

The data used in this study stems from a study undertaken by AIMS project (Assessing the Impact of Microenterprise Services), funded by the Office of Microenterprise Development of the US Agency for International Development (USAID).

Data collection for this survey was conducted by Harvard University researchers in close collaboration with a team of the Taleem Research Foundation, an Ahmedabad-based research firm. Preliminary research on fieldwork basis was carried out in order to achieve the most-suitable questionnaire design.

The samples were determined in a three-step process: First the geographical area was chosen, followed by the two client samples and the non-client group. The surveyed clients were randomly drawn from a list of those members living within the pre-specified geographical area.

For the non-client selection, a "preliminary pre-survey was carried out in the neighbourhood of each of the 300 sample borrowers to identify households in which there were economically active women over age 18 who were not SEWA members. […] within these 15,000 households, all economically active women over age 18 were listed. Third, a random sample of 300 women was drawn from this list." (Chen and Snodgrass, 2001, p. 53)

In early 1998 the first round (R1) of interviews took place, interviewing 300 borrowers, 300 savers and 300 non-members, followed by the second survey round (R2) with a slightly refined questionnaire in early 2000. In this second survey round, it proved possible to re-interview a total of 786 women of which 264 were borrowers, 260 savers, and 262 non-members. Tests of similarities or differences between those that dropped out of the survey and those that were interviewed in the second round could not be undertaken as data on drop-outs were not available. The study needs to rely on the analysis by Chen and Snodgrass (2001), indicating that drop-outs turned out to be quite similar in their personal and household characteristics to the sample as a whole.

Characteristics of Survey Respondents and their Households

Resulting from the survey design, members of SEWA Bank as well as non-members (subsequently also referred to as controls), share the characteristics of being female, over eighteen years of age and of having been economically active at the time of the first survey round.

		Borrower		Saver		Control	
		R1	**R2**	**R1**	**R2**	**R1**	**R2**
Respondent's Characteristics							
Mean Age		38	40	35	37	35	38
Marital Status, %[1]	Married	88	88	78	86	85	79
	Never Married	3	2	5	4	6	6
	Other	9	10	7	10	9	15

Religion, %	Hindu	72	73	77	77	77	77
	Muslim	27	26	23	23	23	22
	Other	0.3	1	0	0	0	0.3
Caste, %	Upper Caste	15	14	16	16	23	24
	Backward Caste	45	47	41	44	39	40
	Scheduled Caste	30	32	35	36	30	32
	Scheduled Tribe	10	7	8	4	8	4
Mean Highest Grade completed		3.9	3.9	4.3	4.3	4.2	4.2
Household (hh) Characteristics							
Mean Size		6	6.1	5.6	5.7	5.8	5.7
Composition, %[1]	Single Person	5	2	2	2	1	2
	Nuclear Family	48	45	53	51	55	49
	Joint/Complex Family	42	49	37	40	37	41
Head, %	Respondent	17	18	12	17	16	21
	Husband	71	70	72	67	62	60
Mean Nr. of Children	0<age<5	1.3	1.1	1.4	1	1.4	1
	5<=age<10	1	0.8	0.9	0.8	1.1	0.8
	10<=age<=15	0.8	0.8	0.8	0.8	0.8	0.8
Mean Age of oldest hh member		44	48	41	46	42	48
Mean Age of youngest hh member		5	6	4	6	5	6
House Ownership, %	(De Facto) Own	62	78	68	74	62	70
	Rented	33	20	30	20	34	27
	Other	5	2	2	6	3	3
Highest level of education of any hh member		8.7	9	9.1	8	8.4	9

[1] Note: *Numbers presented for Marital Status, Religion and Caste are percentages of the respective group (borrower, saver, control). R1 and R2 stand for surey round 1 (1998) and survey round 2 (2000) respectively.*

Figure 1a: Key Characteristics of Respondents and their Households

They can be broadly classified into three occupational categories: Hawkers and vendors, home-based producers and manual labourers or service providers. As some of these women work as casual labourers or sub-contractors, not all can be classified as micro-entrepreneurs per se. The biggest portion are self-employed women though (~ 40%), closely followed by piece-rate workers (=home-based producers).

The key characteristics of these same women and their corresponding households are displayed in Figure 1a. Information is given for each of the three surveyed groups, borrowers, savers and non-members separately in both survey rounds, R1 and R2.

		SEWA vs Control		**Borrower vs Saver**		**Borrower vs Control**		**Saver vs Control**	
		R1	**R2**	**R1**	**R2**	**R1**	**R2**	**R1**	**R2**
Respondent's Characteristics									
Age		0.264	0.155	0.000	0.000	0.005	0.002	0.366	0.496
Marital Status, %[1]	Married	0.011	0.009	0.742	0.561	0.021	0.012	0.048	0.055
	Never Married	0.145	0.070	0.228	0.296	0.065	0.043	0.517	0.316
	Other	0.048	0.082	0.533	0.922	0.176	0.155	0.050	0.131
Religion, %	Hindu	0.414	0.411	0.273	0.270	0.211	0.208	0.880	0.880
	Muslim	0.379	0.409	0.317	0.363	0.208	0.243	0.799	0.798

	Other	0.617	1.000	0.322	0.160	0.996	0.568	0.320	0.320
Caste, %	Upper Caste	0.013	0.003	0.753	0.661	0.024	0.007	0.052	0.023
	Backward Caste	0.371	0.187	0.280	0.474	0.155	0.133	0.735	0.434
	Scheduled Caste	0.417	0.630	0.183	0.340	0.969	0.953	0.172	0.372
	Scheduled Tribe	0.927	0.297	0.348	0.362	0.660	0.174	0.762	0.651
Highest Grade completed		0.729	0.254	0.241	0.000	0.381	0.004	0.777	0.339
Household (hh) Characteristics									
Household Size		0.896	0.307	0.046	0.050	0.273	0.064	0.357	0.910
Composition, %[1]	Single Person	0.312	1.000	0.001	0.508	0.028	0.729	0.181	0.751
	Nuclear Family	0.801	0.801	0.096	0.193	0.296	0.386	0.535	0.662
	Joint/Complex	0.221	0.028	0.047	0.066	0.043	0.005	0.969	0.323
Head, %	Respondent	0.623	0.175	0.126	0.791	0.755	0.303	0.224	0.197
	Husband	0.533	0.067	0.314	0.198	0.964	0.028	0.294	0.358
Nr. of Children	0<age<5	0.668	0.785	0.354	0.077	0.403	0.288	0.912	0.498
	5<=age<10	0.069	0.598	0.325	0.858	0.288	0.584	0.036	0.715
	10<=age<=15	0.579	0.312	0.748	0.779	0.524	0.466	0.749	0.311
Age of oldest hh member		0.936	0.346	0.055	0.633	0.331	0.308	0.323	0.562
Age of youngest hh member		0.896	0.441	0.020	0.150	0.222	0.971	0.303	0.178
House Ownership, %	(De Facto) Own	0.463	0.049	0.129	0.924	0.912	0.083	0.161	0.103
	Rented	0.154	0.046	0.912	0.984	0.200	0.910	0.243	0.089
	Other	1.000	0.220	0.105	0.572	0.484	0.159	0.320	0.316
Highest level of educ. any hh member		0.105	0.430	0.277	0.062	0.363	0.972	0.063	0.200

Figure 1b: T-statistics of equivalence of means

Respondents are on average around 38 years of age, with borrowers being on average about 2.5 years older than savers and controls. This difference is confirmed when formally testing for it. Table 1b displays t-statistics for the equivalence of difference in means between different groups. One can see that at the same time significantly more borrowers are married. This is in line with borrowers being older – excluding the youngest 8 per cent of respondents leaves one unable to reject the null hypothesis of a difference in mean. It is the great majority of women, about 87 per cent, that is married; of the remaining ones, only a small fraction never took the vows, most are widowed. They are either Hindu or Muslim, with around 77 per cent of the women of all groups being Hindi and a little more than 20 per cent Muslim. A similar consistency in distribution across groups is found for the caste the women belong to. This stems from the fact borrowers, savers and controls were drawn from the same neighbourhood, living in a country where residential neighbourhoods tend to be segregated by both caste and religion. The majority of the women belong to the backward caste (~40%) and the scheduled caste (~32%), the remaining percentages are split between the upper caste and schedule tribes with around 15% and 7% respectively. A slight tendency of less women belonging to the scheduled tribes, the lowest caste, can be observed in the second round.

Literacy among respondents is in general quite low. On average, women completed the fourth grade only. This number is downward biased though given that about forty percent had never attended school at all. Nevertheless, while these numbers might seem low by European standards, they are above average compared to the whole of India with an illiteracy rate of 61 per cent at that time and Gujarat state itself of 52 per cent.

A typical sample household, be it for a saver, borrower or non-member, consists of a nuclear, joint or complex family with an average of six members, led by the husband of the respondent. Not much more than twenty percent of all households are led by the respondents themselves or another female. Most households own their own place, having a legal title, affidavit or de facto ownership.

The dependent variable

As SEWA Bank offers a broad range of financial services to its members - main ones being savings, loans and insurance - impact will be very widespread among different aspects of women's lives.

Loans have the common goal of capitalizing or re-capitalizing members but are given for specified purposes only. These range from housing improvements to debt reduction but also social services such as weddings. Unsecured and secured loans are both made for three-year terms, have a 25,000 rupee ($538) ceiling, incur interest at 17 per cent per annum on the outstanding balance, and require monthly repayments. One further focus is income smoothing, for which also savings are an important means to the end; it is actually titled as SEWA's core financial service and has the goal of enabling women to accumulate assets and to promote financial discipline. In the end, women will have to save to repay loans taken. The frequency of deposits are up to the client although SEWA Bank stresses the importance of regular savings, Interest rates range from 6-13 per cent depending on the term of the deposit.

As it is out of the scope of this study to do an extensive analysis of all variables possibly influenced by these services, decision was taken to concentrate on income variables.

Income being quite comprehensive, it is believed the best choice among variables to capture a broad array of impacts. It should be noted, that income is self-reported and hence issues of quality arise. Nevertheless, as stated by Chen and Snodgrass (2001, p.72), ‘in both rounds of the survey, conscientious efforts were made to measure household income in the preceding week, month, and year. […] Average incomes for the previous month and week were generally consistent with these annual figures.’ Furthermore, income sources that can be hypothesized to be least affected by program participation also do not contribute significantly to overall income (see Figure 2): Such other income generating activities include pensions, remittances, rental income and gifts – most of which typically add greatly to complications that arise when measuring income in monetary terms.

Keeping the issues of measurement in mind, income is taken as a general indicator for measuring the impact being a SEWA member.

Income, as defined in the survey, comprises numerous sources. Respondents' primary economic activity is listed in Figure 2.[iv]

main economic activity	Borrower				Saver				Control			
	R1		R2		R1		R2		R1		R2	
	#	%	#	%	#	%	#	%	#	%	#	%
self employed	22,004	43	26,820	45	15,422	38	17,079	36	13,397	37	10,831	28
production	4,990	10	4,493	8	3,288	8	2,392	5	4,521	13	2,021	5
trade	8,932	17	11,216	19	6,057	15	7,664	16	4,906	14	4,069	11
service	8,082	16	11,111	19	6,098	15	7,023	15	3,970	11	4,741	12
piece rate work	4,245	8	3,685	6	5,561	14	4,224	9	2,938	8	3,083	8
labour	10,128	20	10,121	17	7,010	17	8,722	18	9,112	25	10,282	27
semi-permanent empl.	8,511	17	10,393	17	6,919	17	9,043	19	6,870	19	8,402	22
salaried work	6,434	13	8,302	14	5,297	13	7,998	17	2,906	8	4,552	12
other source	63	0	382	1	171	0	322	1	580	2	1,094	3
total	**51,385**	**100**	**59,703**	**100**	**40,401**	**100**	**47,388**	**100**	**35,803**	**100**	**38,244**	**100**

Figure 2: Respondents' Income Sources

It can be seen that borrowers' households in the panel reported the highest average annual income in both survey rounds with 51,385 rupees (equivalent to US$ 1,408) and 59,703 rupees (US$ 1,442) in round one and two respectively.[v] Savers have the second highest average income, followed by the control group. In one-fourth of all sampled cases, the primary income source of the woman respondent corresponds to the primary income source of the household. Most frequently, in 50 per cent of all cases, a salary or wage earned by another household member contributes as the main income source. Ten other percent are made up of an own-account venture controlled by someone other than the respondent.

Women's micro-enterprises, including production, service and trade, play an important part in income acquisition with about 39.3 per cent in 1997 and 36.3 per cent in 1999 (the years precedent to each survey round). The second most important source was casual labour (21.6%) followed by semi-permanent employment (18.5%) and salaries (12.8%). Not surprisingly, borrowers earned a larger share of their income from self-employment than savers and non-members. Otherwise, patterns across groups are comparable.

In the analysis to follow, the program's impact on three measures of income on household as well as individual level is estimated. These measures are:

(a) total household income the year before the survey round,

(b) variable (a) divided by number of household members, and

(c) total annual income of the respondent.

3. Methodology

To analyze the effect that being a member of the SEWA-Bank has on women's income, matching techniques are applied. These are among the leading techniques in program evaluation, when no randomized-out control group exists and given that certain conditions are met: That the data set is rich in variables, that respondents are exposed to the same economic conditions and that outcomes of members as well as non-members are measured using identical survey instruments.

The Evaluation Problem

The *potential outcome approach to causality* is what lies at the heart of the standard treatment effect literature. One starts from a counterfactual as assessing any intervention requires making an inference about the outcomes that would have been observed for program participants had they not participated.

The main building blocks for the notation are:

- *treatment*: Participating in the program under consideration or not - the assignment indicator is labelled with ω and indicates receivement of treatment (ω=1) or not (ω=0)[vi]
- *units*: Here individuals *i* that either receive treatment and hence participate (are members of SEWA Bank) or do not receive treatment, are non-participants and hence serve as control units,
- potential *outcomes y*, also called *responses*. And finally
- *covariates* are those variables (characteristics of individual *i*) *X* that are unaffected by treatment.

Let y_1 and y_0 denote *potential* outcomes for one individual, where y_1 is the outcome with and y_0 the outcome without treatment. Interest lies in the difference between the two outcomes, $y_1 - y_0$. Ignoring for now that one only observes one outcome and is hence confronted with a missing-data problem, the most obvious evaluation parameter is the *average treatment effect* (ATE), defined as:

$$ATE = E(y_1 - y_0)$$

It estimates the average impact of the program.

Depending on which questions are attempted to be answered, studies consider alternative estimators. Most often, as is the case in this study, interest lies in the average impact of the program among those participating in it - the *average effect of treatment on the treated* (ATT), defined as:

$$ATE = E(y_1 - y_0 \mid \omega = 1)$$

Finding the best counter-factual match

As mentioned, one faces the problem of missing data, namely that for each individual only one outcome is observed. Therefore, to calculate the difference $y_1 - y_0$, matches need to be found for program participants. For each i, other individuals whose characteristics are similar but who were not exposed to the treatment are used to calculate the counter-factual. This is the idea that lies at the heart of matching.

The matching estimator is given by:

$$\hat{\alpha}_M = \sum_{i \in T} \left(y_i - \sum_{j \in C} W_{ij} y_j \right) \xi_i \tag{1}$$

where y_i is defined as the potential outcome for individual i, T and C are treatment and control group respectively, W_{ij} is the weight placed on control observation j for individual i and ξ_i accounts for the re-weighting that reconstructs the outcome distribution for the treated sample. A typical choice for ξ_i is $\omega_i = n_T^{-1}$, where n_T is the number of treated units. These weights will be use in the discussion that follows. Matching estimators are based on the two assumptions already mentioned, namely:

<u>Assumptions</u>:

(1) Ignorability of Treatment: $(y_1, y_0) \perp \omega \mid Z$, where Z is a sub- or a superset of X

(2) $0 < \Pr(\omega = 1 \mid Z) < 1$

The first part is a rigorous definition of the restriction that choosing to participate in a program is purely random for similar individuals. The intuition of the second part is quite innate: If all individuals with given observables chose for a treatment, then there would be no observations on similar individuals who chose not to participate. The assumption hence assures that a match can be found for each individual with ω=1. A violation of it occurs, meaning that not for every individual a match can be found, if there are regions where the support of *Z* does not overlap for treatment and control groups. This problem is resolved by performing the matching over the *common support* region.

When both assumptions hold in this setting, one can define treatment as 'strongly ignorable'.

Reducing the Dimensionality

Various matching estimators have been proposed in the literature, of which the first generation paired observations based on either a single variable or weighting several variables. (See for example Bassi (1984), Cochran and Rubin (1973), Rosenbaum (1995), Rubin (1974; 1979))

As matching can be difficult when the set of conditioning variables is large, recent evaluation literature focuses on Rosenbaum and Rubin's (1983) approach and matches on the propensity score, leading to a simple non-parametric estimator. This method uses the propensity score - the probability of receiving treatment – to select from the control group the most comparable sample counterpart in order to construct the counterfactual information on the treated outcomes had they not been treated. By doing so it corrects for selection bias that stems from - for the econometrician

observable - differences between the two groups.

The propensity score matching method combines pairs or groups with different values of *X*, but the same or close values of Pr(ω=1|*X*).

The estimator, resulting from matching based on the propensity score is a version of equation (1), where $\sum_{j\in C} W_{ij} y_i$ becomes $\hat{E}(y_{0i} \mid \omega_i = 1, p_i)$ and the weights ξ_i become $\omega_i = n_T^{-1}$ so that the estimator thus looks as follows:

$$\hat{\alpha}_M = \frac{1}{n_T} \sum_{i\in T} \left(Y_i - \hat{E}(y_{0i} \mid \omega_i = 1, p_i) \right) \qquad (2)$$

where p_i is the estimated probability of receiving treatment for individual *i*.

Heckman, Ichimura and Todd (1998b), Hahn (1998) and Angrist and Hahn (1999) analyse efficiency of matching estimators based on $p(X)$ and X directly. Only if the treatment effect is constant, they find it more efficient to condition on the propensity score. Else, neither of the two methods was found to be superior.

Matching Estimators

When implementing matching, basically three issues arise: (1) whether or not to match with replacement, (2) how many control units to match to each treated unit, and (3) which matching method to choose.

For this study, the decision was taken to match with replacement as it minimizes the propensity score distance between the matched control units and the treatment unit: each treatment unit can be matched to the nearest comparison unit, implying that a comparison unit might be matched more than once, which results in a qualitatively better match. Furthermore, two different matching methods are applied: The first one is the *Nearest Neighbour Matching* method. It uses a single match and hence ensures the smallest propensity-score distance between the two units.

The second method applied is *Kernel Matching*. This is a recently developed non-parametric matching estimator where all treated units are matched with a weighted average of all controls. Weights used are inversely proportional to the distances between the propensity scores of treated and comparisons.

Including a Time Dimension

As two rounds of data are available, effects can be analyzed by including a time-dimension. Doing so eliminates all bias due to omitted variables that are time-invariant and leaves one with a more robust and more reliable estimate of the impact of treatment. This is achieved when combining matching with the Difference-in-Difference (DID) approach.

The resulting estimator is:

$$\hat{\alpha}^{L}_{MDID} = \sum_{i \in T} \left(\left[Y_{it_1} - Y_{it_0} \right] - \sum_{i \in C} W_{ij} \left[Y_{jt_1} - Y_{jt_0} \right] \right) \xi_i, \tag{3}$$

where t_0 and t_1 stand for before and after the program and the rest of the notation is as before.

One can think of DID matching as the difference of two cross-sectional matching estimates. The first estimate, from the 'before' period, estimates purely the difference in the average fixed effect between the treated and untreated units. The cross-sectional matching estimate from the 'after' period on the other hand gives one the average difference in the average fixed effect plus the average treatment effect on the treated. Subtracting the 'before' estimate from the 'after' estimate leaves one then with nothing else but the average treatment effect on the treated.

Testing the Assumption

Before coming to the presentation of results, a few words about the *Ignorability of Treatment Assumption* that matching techniques rely upon are apposite. This assumption is basically a restriction that choosing to participate in a program is purely random for similar individuals. Like OLS, propensity score matching requires that selection is based on observables only. One therefore relies on a high quality control group. The Ignorability-Assumption is not directly testable but several arguments can be brought forward in favour of it to hold in this study:

(1) Matching reduces bias itself by imposing common support condition. The number of observations that fall outside the common support of the propensity score from the cross sectional analysis for both survey rounds is very small: 1.15 per cent in the first and 0.25 per cent in the second survey round. The density of the propensities for participants and non-participants are plotted in Appendix A-C. Given the very small percentage the support problem for the cross-sectional analysis is negligible. Nevertheless, the percentage of observations outside the common support increases to 16 per cent when considering the score for first-time borrowers. Most of these observations outside the common support are those with very high propensity scores. Since matching ‘unmatchable’ observations can result in a substantial bias of the matching estimator (Heckman, Ichimura and Todd, 1997), observations outside the common support were excluded from the estimation. This restriction implies a redefinition of the estimated effect, namely to the effect on observations for which a comparable counterpart exists.[1]

[1] Observations outside the common support were no different from those within the common support in terms of their caste (upper caste, backward caste, scheduled caste, scheduled tribes), the type of wok (selfemployed, piece rate work, salary work), the highest education within the household and the type of family (joint, nuclear single). They differed with respect to their religion (outside the common support were more hindus and less muslims),

(2) An indirect test of the assumption (suggested by Heckman and Hotz (1987)) was performed additionally. In this test, one estimates the causal effect of the treatment on a variable not affected by the treatment. A significant effect would imply a failure of the assumption; an insignificant one is no guarantee for the assumption to hold but good news anyway. In this study, a subset of those women that became member only right in the beginning of the first survey-round was defined. Income in the year before the first survey round was then chosen as the variable not affected by treatment. Estimating the effect of treatment on this variable results in all treatment effects to be insignificant - again good news for the reliability of the assumption.[vii]

(3) Heckman, Ichimura, Smith and Todd (1998) find that the assumption can be relied upon if the data set fulfils three conditions: A rich set of control variables, treated and control units stemming from the same local labour market, and the dependent variable to be measured in the same way. While one should keep in mind that the authors did not look at the evaluation of microfinance programs - all these three conditions are basically fulfilled by the data set in hand.

In addition to these points, two further diagnostic checks for the quality of the control group were undertaken in the course of this study:

(4) A different, less parsimonious, propensity score was estimated and the treatment analysis repeated. This issue is stressed by Dehejia (2005) and suggested as an important diagnostic tool to check the sensitivity of results. When doing so, estimated effects are found to be quite similar and hence not sensitive to the score specification. This implies the control group to be well chosen.[viii] [ix]

(5) Furthermore, in addition to the commonly applied estimation of treatment effects where non-members are matched to members, also the reverse was conducted - meaning that non-members are defined as the treated group and hence one needs to find matches to each non-member from the group of members. This was done due to the fact that matching to each member corresponding/close non-members results in a relatively small pool of control units - namely 252 in comparison to 534 treated units. In general, estimated effects in this "reversed" setting are found to be somewhat

their age (slightly older), the respondents marital status (less married and more widowed and never married) and the age of their children (more kids younger than five and less older than five).

smaller in magnitude. Effects are smallest when Nearest Neighbour Matching is used and rise with Kernel method. Results can be obtained from the author on request.

5. RESULTS

Impact of Being a SEWA-Bank Member

The first step to be undertaken in the analysis to follow is the estimation of the propensity score. In order to minimize selection bias in estimation, one needs to include all variables that affect treatment selection and potential outcome. Given the rich set of control variables in the survey, the propensity score specification can be assumed to capture the most important factors. Included is information of the respondent (such as age, religion, education, economic activity...), the household (head, size, composition, children...), expenditures, assets and information indicating the role the respondent plays in the household and the community. The results of the different propensity scores can be found in Appendix A-C. A logit model was used and all scores satisfy the balancing property.

Figure 3 presents the results from the analysis for both survey rounds. As conclusions for both survey rounds, 1999 as well as 2000 are comparable, only the more recent results will be discussed here, followed by a comparison of the two rounds.

			Obs	Mean	ATT (i)	Std.Err. (ii)	t-stat (iii)	bias-corr. CI (iv)
(A) Household yearly Income								
Nearest Neighbour	**R1**	T	522	46030	**9417**	4361	2.182	*(64;15797)*
		C	166	36613				
	R2	T	530	53587	**5162**	5760	0.896	*(-2192;19248)*
		C	169	48424				
Kernel	**R1**	T	522	46030	**8049**	3240	2.484	*(1615;13990)*
		C	262	37982				
	R2	T	530	53587	**11084**	3130	3.542	*(4685;17087)*
		C	247	42503				
(B) Household yearly Income per hh member								
Nearest Neighbour	**R1**	T	522	8517	**1550**	797	1.944	*(32;3128)*
		C	166	7918				
	R2	T	530	9662	**1644**	703	2.34	*(492;3204)*
		C	169	8017				

Kernel	**R1**	T	522	8517	**1578**	592	2.666	*-6,913,463*
		C	262	6939				
	R2	T	530	9662	**2077**	454	4.571	*(1030;2912)*
		C	247	7585				
(c) Tot. Income of Respondent last year								
Nearest Neighbour	**R1**	T	522	16896	**6833**	1670	4.092	(3867;9747)
		C	166	10064				
	R2	T	530	16189	**6723**	2264	2.969	*(4423;8995)*
		C	169	9467				
Kernel	**R1**	T	522	16896	**4737**	1588	2.984	*(1560;7400)*
		C	262	12159				
	R2	T	530	16190	**4264**	1494	2.855	*(1253;6969)*
		C	247	11925				

Note: Each block ((A)-(C)) gives results for one of the outcome variables in Survey Round 1 (R1) and 2 (R2). Column (i) gives the estimated Average Treatment Effect, Column (ii) its (bootstrapped) standard errors, Column (iii) the corresponding t-statistic and the last column (iv) displays the bias-corrected confidence interval.

Figure 3: Results of the Cross-Section Analysis, R1 and R2

Conclusions from the estimation can be generalized for all three outcome variables:[x]

With one exception, the estimated treatment effect is found to be significantly positive in all cases. Only when applying Nearest Neighbour Matching effect on household income is estimated to be insignificant. Nevertheless, given that Nearest Neighbour Matching displays the strongest variation which is partly to blame on the fact that only one observation is being chosen as a control for each treated individual, one can conclude from the results that being a SEWA Bank member raises the income of members on an individual as well as on a household basis.

Chen and Snodgrass (2001), conducting an ANCOVA analysis, find the effect on household yearly income to be 9,907 Rupees (~ US$ 230) when comparing members to non-members and 1,668 Rupees (~ US$ 39) for household yearly income per capita. For both variables, these numbers lie closely within the range of the effects estimated in this study. The third outcome variable, total income of the respondent in the past year, was not investigated in their study.

Figure 4 below present the estimated treatment effects on investigated variables for both survey rounds.

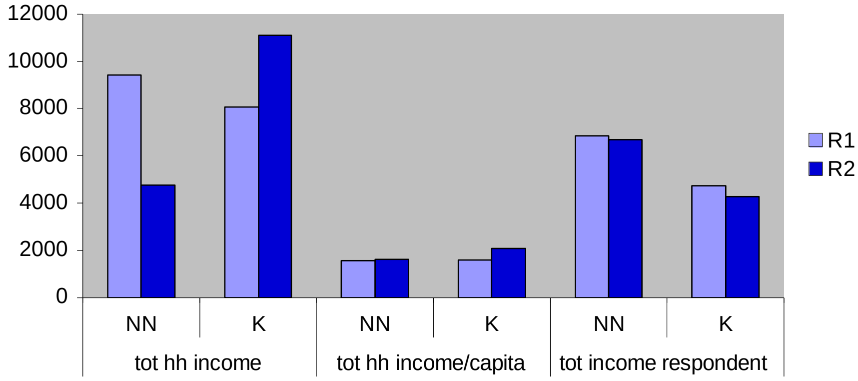


Figure 4: Estimated Treatment Effects for R1 andR2

It becomes very obvious from these graphs that being a SEWA member has a positive impact on outcome variables in both rounds, no matter what method is being applied. Somewhat surprising is the finding that on the household level, significant impacts increase from one round to the next, whereas respondents themselves experience a smaller effect in their income in the year previous to the second round.

This tendency is reflected in income figures as shown in Figure 5: Only savers experience a slight increase in their personal income in R2 as compared to R1, borrower's and control's income decreases whereas for all groups the total household income increased.

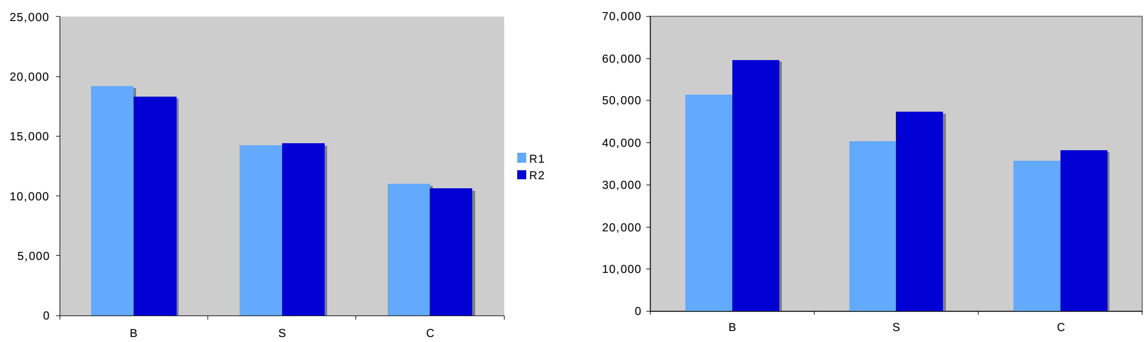


Figure 5: Yearly Incomes of Respondent and total hh

This could be explained by different pieces of evidence. The first one is observed by Chen and Snodgrass (2001) who state that the largest contributor to rising household income were salaries and semi-permanent employment. These sectors are both dominated by male workers. Many of the respondents work on the other hand in self-employed activities and piece-rate-work, of which some even experienced a decreasing income flow.

A further observation concerns the number of loans taken. Theory predicts and studies confirm that loans have in general a positive impact on income. Not for nothing is microfinance believed to have the potential of turning the Millennium Development Goal of cutting absolute poverty in half by 2015. As displayed in Figure 6, the data at hand shows, that surveyed SEWA members took significantly less loans in the years preceding the second survey round, than they did in the years before round one - a possible reason for the smaller treatment effect found for respondents in the second round.

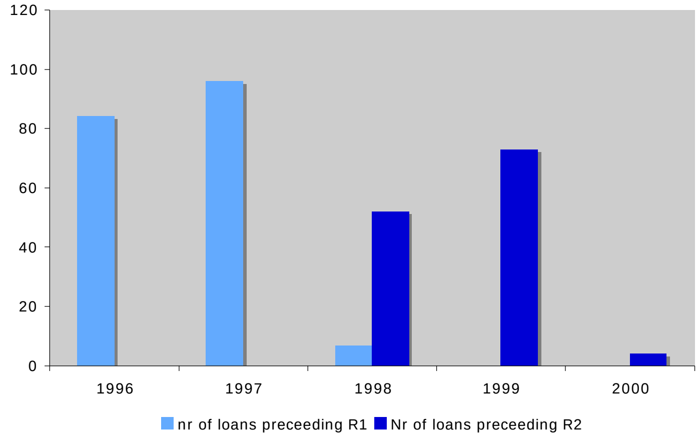


Figure 6: Number of Loans taken per year

Impact of Being a Onetime Borrower

Given the results from the previous section, the hypothesis to be tested is whether the smaller treatment effect for members in the second survey round can be attributed to the fact that fewer loans have been taken.

To do so, the cross-sectional analysis from the previous section is undertaken with a constrained sample - only those women that took up their first loan in between the two survey rounds and are hence ‘new borrowers’, are looked at. The construction of this subset of the data results 47 women making up the group of treated units, where treatment is borrowing (at least once) from SEWA Bank. Two of these 47 women even went from being nonclients to taking a first loan with SEWA Bank, implying that they were part of the control sample in the first survey round.

Besides the sample size for this analysis being very small, which can result in noisy estimates, another shortcoming of the data might be exacerbated in this setting; namely the fact that members are likely to be self selected (as well as selected by their group members) on a set of unobservable variables, which can result in biased estimates. An example of such a variable that is often cited as a source of bias is entrepreneurial spirit. One would expect people with more entrepreneurial spirit to be also more likely to join a microfinance program. Borrowers might be more ambitious than nonclients and more risk-taking than savers. Especially the two observations that went from being nonclients to taking a loan are candidates for such inherited characteristics.

The next section will account for such bias stemming from time invariant variables. For now, we rely on the assumption participation is random given the observable variables included in the model and hence the choice of the control group is again crucial. To minimize the selection bias, the control group was chosen to be those women that were and stayed non-member plus savers. The decision was taken to include both these groups as the treated group also includes members that graduated from being a nonclient as well as from being a saver.

The signs of estimated coefficients deliver mixed evidence on the effect of taking a first loan on the household level, especially when looking at results from Nearest Neighbour matching. While all Kernel estimates are positive, the signs of the Nearest Neighbour estimates differ depending on the chosen control group, being negative when the control group consists of savers only and positive when nonclients are included. These irregular results are most likely to results from the small sample size. Not only is the group of treated units very small but the matched controls are made up of even less observations; 47 and 35 respectively. The latter number decreases to 31 women when nonclients are excluded from the control group.

Nevertheless, the estimated effects are consistently insignificant, independent on the control group and estimation technique chosen, suggesting that the first loan does not have a noteworthy impact on customers.

(A) Household yearly Income						
			ATT **(i)**	**Std.Err.** **(ii)**	**t-stat** **(iii)**	**bias-corr. CI** **(iv)**
NN	new-borrowers (47)	vs non-members + savers (35)	**10979**	7327	1.5	*(-3173;24656)*
		vs savers (31)	**-3349**	9239	-0.36	*(-23549;14820)*
Kernel	new-borrowers	vs non-members + savers (391)	**8186**	5334	1.54	*(-1511;15552)*

		vs	savers (183)	**2108**	7051	0.3	*(-10376;17575)*
(B) Household yearly Income per hh member							
NN	new-borrowers (47)	vs	non-members + savers (35)	**2435**	1485	1.64	*(-149;5356)*
		vs	savers (31)	**-256**	1964	-0.13	*(-3738;2841)*
Kernel	new-borrowers (47)	vs	non-members + savers (391)	**1588**	907	1.75	*(-39;3573)*
		vs	savers (183)	**698**	1190	0.59	*(-1126;3617)*
(C) Tot. Income of Respondent last year							
NN	new-borrowers (47)	vs	non-members + savers (35)	**257**	4505	0.06	*(-9189;8268)*
		vs	savers (31)	**-5264**	4718	-1.12	*(-16136;2480)*
Kernel	new-borrowers (47)	vs	non-members + savers (391)	**-1835**	2102	-0.87	*(-5658;3139)*
		vs	savers (183)	**-5285**	3617	-1.46	*(-12866;3071)*

Note: Each block ((A)-(C)) gives results for one of the outcome variables.Two cases are considered: In the first, new-borrowers are matched to non-members and in the second, to non-members and savers. Column (i) gives the estimated Average Treatment Effect, Column (ii) its (bootstrapped) standard errors, Column (iii) the corresponding t-statistic and the last column (iv) displays the bias-corrected confidence interval.

Figure 7: Estimation Results: R2, treated are the 47 new-borrowers

The interpretation for the outcome variable 'yearly income of the respondent' is more straightforward. Interestingly, no matter which matching method has been applied, estimated effects decrease vastly and also become insignificant across-the-board. Except for the case of nearest neighbour matching with nonclients and savers as the control group, results suggest a negative effect on respondents' income. A possible explanation for this is an observation made by Chen and Snodgrass (2001): 'Long-term participation in SEWA Bank through repeated borrowing has several positive impacts. Compared to onetime borrowers, repeat borrowers enjoy greater increases in income, spend more on household improvements and consumer durables, are more likely to have girls enrolled in primary school, and have higher expenditures on food.'

Hence, while results are mixed on the household level, on the individual level they suggest that new borrowers do not experience noteworthy increases in their incomes.

Results of these two analyzes are displayed in Figure 7.

Longitudinal Setting:

Given the definition of the treatment group in this setting, it is possible to estimate the treatment effect by including a time-dimension. Doing so eliminates all bias due to omitted variables that are time-invariant and leaves one with a more robust and more reliable estimate of the impact of treatment.

As mentioned above, certain unobservable variables can be cause of bias in estimates, some of which particularly stringent in the context of microfinance. Entrepreneurial sprit was one such variable; others that can be brought forward are characteristics such as how people interact in groups or how well they are integrated in their community. These are important as members have to form groups and are jointly liable for the credit of their group-members. Of course members will then think twice whom they decide to join a group with.

Nevertheless, one can assume a number of these variables to be relatively constant over time, especially when not considering a period no longer than a few years, in which case they will be eliminated as a source of bias combining matching with the Difference-in-Difference (DID) approach. This is especially desirable given the small number of treated individuals that the sample needs to be constrained to in this section.

Two caveats are at hand: First, estimating a differenced equation can worsen attenuation bias due to measurement error, resulting in coefficients shrinking towards zero. Second, time-varying unobservables are not addressed. As described, there are many factors that play a role in becoming a member of a microfinance institution, some important ones being unobservable and at the same time time-varying. We can therefore not expect to be totally free of bias in the presented results and need to kkep this in mind in the interpretation.

In fact, this and the fact that the method makes it impossible to analyze the roles of time-invariant variables such as gender and enterprise sector made Chen and Snodgrass (2001) decide not to opt for this procedure when analyzing the impact of SEWA Bank. Nevertheless, to put it in Morduch's (2003, p.) words: 'It turns out that the omitted observables […] do make a large difference, and not addressing them undermines the credibility of the AIMS impact studies'.

This statement is based on findings of Alexander (2001) who works with the AIMS Peru data and estimates a differenced equation. She tests for the endogeneity of her treatment variable and in doing so finds impacts on enterprise profits to be much smaller and no longer significant.

In order to apply this estimator, one needs data from before and after program participation. In line with the previous analysis, looking at first-time borrowing fulfils this 'before' and 'after' criterion so that equation (3) can be estimated with this sample of first time borrowers as treated and savers and nonclients (only savers as well as both groups combined) as control units.[xi]

The estimated effects are consistent whether applying nearest neighbour or kernel. On a household level the sign suggests that first-time borrowers are on average better off in terms of their income than non-SEWA borrowers. On the other hand, in comparison to only savers, first-time borrowers seem to be worse off. Without any exception, household impacts are now found to be insignificant though, most even highly so.

Also for respondents' income, all results are again consistent. In this longitudinal setting, impact is suggested to be negative for all methods applied, indicating that first-time borrowers experienced a greater decline in their income from one survey round to the next. One of the four ATTs is significant (applying kernel and looking at savers only for the control group), all others are not.

These results, displayed in Figure 8, confirm previous ones and support to an even greater extent the hypothesis that the first loan taken does not have a significant effect on borrowers' income.

Furthermore, the comparison between only savers and savers plus nonmembers as the control group support the idea that providing microcredit need not be the main answer to credit market problems, such as credit constraints. Some argue that 'promoting microsavings is another (albeit slower) route to the same end' (Morduch, 2003). And one might (not at last based on the results of this study) add that it is also a much less risky approach – given that saving facilities are available.

<table>
<tr><th colspan="10">(A) First Difference of Household yearly Income</th></tr>
<tr><th></th><th></th><th></th><th></th><th>Obs</th><th>Mean</th><th>ATT (i)</th><th>Std.Err. (ii)</th><th>t-stat (iii)</th><th>bias-corr. CI (iv)</th></tr>
<tr><td rowspan="4">Nearest Neighbour</td><td rowspan="4">new-borrowers</td><td rowspan="2">vs</td><td rowspan="2">non-members + savers</td><td>47</td><td>8650</td><td rowspan="2">19363</td><td rowspan="2">14031</td><td rowspan="2">1.38</td><td rowspan="2">(-3320;51421)</td></tr>
<tr><td>35</td><td>-10713</td></tr>
<tr><td rowspan="2">vs</td><td rowspan="2">savers</td><td>45</td><td>7811</td><td rowspan="2">-10500</td><td rowspan="2">10152</td><td rowspan="2">-1.035</td><td rowspan="2">(-36134;6687)</td></tr>
<tr><td>26</td><td>18317</td></tr>
<tr><td rowspan="4">Kernel</td><td rowspan="4">new-borrowers</td><td rowspan="2">vs</td><td rowspan="2">non-members + savers</td><td>47</td><td>8650</td><td rowspan="2">4712</td><td rowspan="2">5210</td><td rowspan="2">0.9</td><td rowspan="2">(-5671;14439)</td></tr>
<tr><td>401</td><td>3938</td></tr>
<tr><td rowspan="2">vs</td><td rowspan="2">savers</td><td>45</td><td>7811</td><td rowspan="2">-688</td><td rowspan="2">6167</td><td rowspan="2">-0.122</td><td rowspan="2">(-13097;10042)</td></tr>
<tr><td>187</td><td>8499</td></tr>
<tr><th colspan="10">(B) First Difference of Household yearly Income Per HH member</th></tr>
</table>

				N	Mean	(i)	(ii)	(iii)	(iv)
Nearest Neighbour	new-borrowers	vs	non-members + savers	47 35	1395 -1088	**2483**	2032	1.223	*(-1022;7447)*
		vs	savers	45 26	5563 2810	**-1496**	1679	-0.891	*(-5517;1039)*
Kernel	new-borrowers	vs	non-members + savers	47 401	1395 768	**628**	907	0.692	*(-1007;2743)*
		vs	savers	45 187	1314 1373	**-59**	1125	-0.053	*(-2138;2145)*
(C) First Difference of tot. Income of respondent									
Nearest Neighbour	new-borrowers	vs	non-members + savers	47 35	-643 3593	**-4236**	3960	-1.07	*(-12539;2479)*
		vs	savers	45 26	-734 11356	**-12100**	5181	-2.34	*(-25000;-6673)*
Kernel	new-borrowers	vs	non-members + savers	47 401	-643 2000	**-2644**	3039	-0.87	*(-8477;3160)*
		vs	savers	45 187	-733 3578	**-4412**	3572	-1.235	*(-11614;1878)*

Note: Each block ((A)-(C)) gives results for one of the outcome variables.Two cases are considered: In the first, new-borrowers are matched to non-members and in the second, to non-members and savers. Column (i) gives the estimated Average Treatment Effect, Column (ii) its (bootstrapped) standard errors, Column (iii) the corresponding t-statistic and the last column (iv) displays the bias-corrected confidence interval.

Figure 8: Results of DID

6. CONCLUSION

The purpose of this study was to assess whether the microfinance institution SEWA Bank is meeting one of its targeted Ten-Point objectives: raising their members' income. The institution's hypothesis is that microfinance makes households wealthier, yielding an income effect that pushes up consumption levels and, holding all else the same, increases the demand for issues such as health and children's education. More explicitly, added income for female members raises the respect and hence the influence of female household participants, pushing toward greater spending in areas of particular concern to women.

To analyze the effect that being a member of the SEWA Bank has on women's and their household’s income, Nearest Neighbour and Kernel matching techniques, all based on the propensity score, were applied. Several indirect tests of the underlying assumptions of this technique were undertaken and supported their use. Also in sync with this line of thought are results of analyzing how sensitive estimated effects are to the specification of the propensity score: The surveyed non-members seem to serve as a useful comparison group given that estimated income effects do not deviate greatly.

Results of the simple cross-sectional analysis performed on the whole sample suggest positive and significant income effects for members in both survey rounds. This holds for the setting where matches are found for members as well as for the reverted setting, meaning were not being a member was defined as ‘treatment’.

Findings for estimated effects change, when constraining the treatment group to women that took up only one loan and are hence so-called ‘new borrowers’. The treatment effect of borrowing for the first time turns out to be smaller in magnitude than the overall effect of being a member and is insignificant. This confirms the hypothesis that repeat-borrowing has a greater effect for program participants.

Among the matching methods chosen, Nearest Neighbour, using only a single match, can be seen as leading to the most credible inference with the least bias. However, Abadie and Imbens (2002) show that for the case when only one continuous covariate, such as the propensity score, is used to match, one can gain efficiency due to a smaller asymptotic variance by allowing for a greater number of matches, as is the case for Kernel Matching.

Smith and Todd's (2005) findings also suggest that such details of the matching procedure do not have a strong effect on estimated impacts. The choice between cross-sectional matching and Difference-in-Differences on the other hand influences results to a great extent. DID matching, being a variant of the method extended to a longitudinal setup, is seen as superior to simple cross-sectional matching techniques given that it eliminates important time invariant sources of bias such as local environment and systematic measurement error.

Applying this technique to the data results in effects on income becoming statistically insignificant, which suggests that the simple cross-sectional analysis undertaken before is biased due to omitted time-invariant variables. The results reinforce previous findings by authors such as Coleman (1999; 2002) and Pitt and Khandker who determine that estimates ignoring selection bias will overstate the impact of credit.

It needs to be stressed though that also the DID results are likely to still inherit some degree of bias due to variables that were impossible to account for. As elaborated on before, the particular approach of microfinance has potential for many unobservables, which we cannot assume to be all time-invariant and hence to be eliminated when applying DID.

Nevertheless, evidence is given that microfinance, and especially microcredit, is not an overnight cure and requires time. Chen and Snodgrass (2001) are among those who show that repeat-borrowers experience greater increases in income as compared to one-time borrowers. Results of the previous analysis support this finding and provide evidence that becoming a first-time borrower actually drives down income as compared to remaining a saver. This study hence confirms that the degree to which clients participate in the various components of a program are of high significance, and the pure access to financial services is not the driving and sole determinant of impacts.

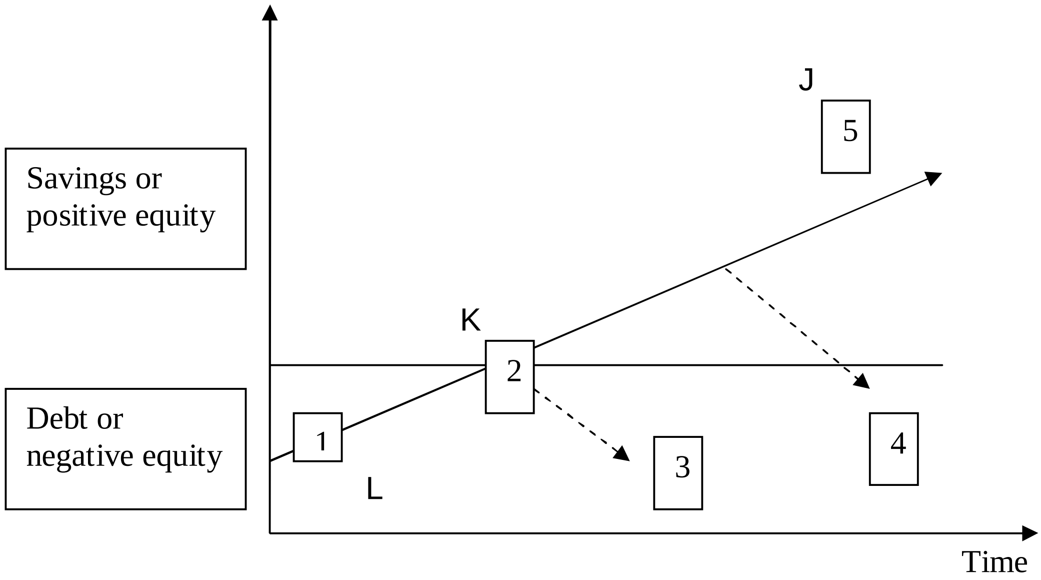
Moreover, solely considering income neglects the broader picture: A program not increasing income on average may still offer members and their households' ways to reduce vulnerability. For example Shah and Mandava (2005) in their study on written and unwritten rules and regulations of street-hawking in India find that:

> "The NASVI study found that harassment and bribery is less prevalent for female hawkers who are members of SEWA. As per their study, 75 street vendors were members of SEWA abd they did not pay bribes. The police constable were wary of taking bribes from these vendors. At the same time, the remaining 225 street vendors in their sample who were not unionised complained that they faced regular harassment and had to pay bribes regularly to the municipal authorities and the local police to ward off harassment." (p.66)

A reduction of vulnerability can furthermore result from a diversification of income sources. In the USAID study of Zimbabwe for example, clients were shown to do exactly this - diversifying their income sources, more so than others - resulting in a potentially important means of risk diversification.

This goes in hand with the fact that the demand for savings services, not at last as a mean of risk-diversification, by poor households and microenterprises is as strong as or stronger than the demand for credit. Expansion of the outreach of savings services can have a potentially significant impact on both institutional sustainability and poverty reduction.

As stated in Fischer & Sriram (2002) about SEWA (p.64): "[…] the impact has been more on reducing vulnerability and enhancing security, and less on lifting clients out of poverty. This is in line with SEWA Bank's emphasis on savings and insurance but suggests fewer moving are moving to the higher levels […]". They give a graphic representation that summarized SEWA Bank's perspectives, into which the findings of this paper fit very nicely:



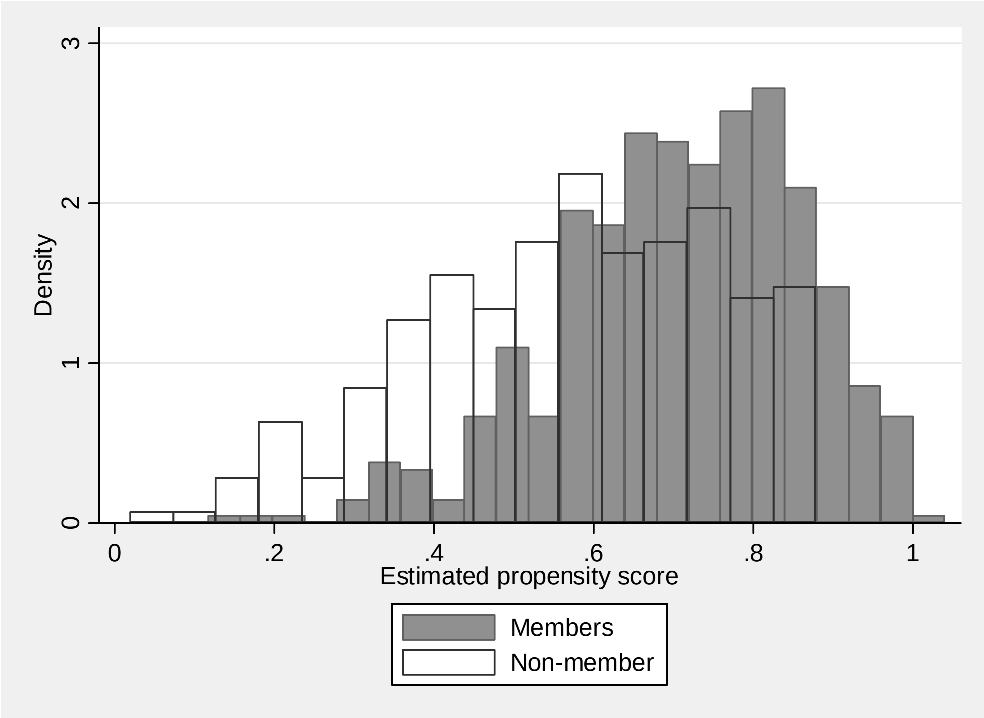
A women starts with negative equity (point 1), savings help her to move to wards positive equity (point 2 and results of the cross-sectional analysis), her vulnerability can easily make her fall back to negative equity (point 3 and the argument for need of safety nets such as insurance). Further savings and credit enable women to built up equity and to move towards point 5 (results from the cross-sectional analysis), nevertheless the risk to fall back to point 4 remains and calls for the continued need of insurance products, accumulated savings and the like. Results from the DID analysis show that the first loan seems to be one of those factors that bear the risk of pushing customers towards point four, which calls for particular guidance during this period.

Appendix A - Probability of being a SEWA Bank member - R1

variable	coef	std.err	P>|z|
age	0.117	0.055	0.034
age^2	-0.001	0.001	0.039
married	0.262	0.330	0.427
muslim	0.488	0.239	0.041
ucaste	-0.855	0.242	0.000
secondary school	-0.256	0.266	0.335
piece-rate work	-0.665	0.200	0.001
wage work	-0.553	0.226	0.015
hh head husband	0.379	0.237	0.110
nuclear hh	-0.475	0.233	0.041
subnuclear hh	-0.503	0.408	0.218
highest education respondent	0.031	0.025	0.208
agemax hh	-0.006	0.008	0.470
children 0-5	-0.078	0.106	0.464
children 5-10	-0.135	0.116	0.242
children 10-15	-0.069	0.122	0.571
hh size	-0.091	0.085	0.283
house rented	-0.036	0.190	0.850
expenditure on food outside the house	0.048	0.018	0.009
tot expenditure on food	0.005	0.004	0.225
have item - other 2	-0.004	1.192	0.997
have item - other 1	0.301	0.454	0.507
have item - poultry	0.283	1.322	0.831
have item - goat	0.192	0.451	0.670
have item - sheep/goat	-2.238	1.286	0.082
have item - sewing machine	0.293	0.232	0.207
have item - scooter	0.425	0.331	0.199
have item - moped	-0.165	0.183	0.367
have item - bycicle	0.007	0.655	0.991
have item - ivory jewelry	0.300	0.219	0.169
have item - silver jewelry	0.382	0.229	0.096
have item - gold jewelry	0.086	0.202	0.669
have item - watches	-0.053	0.161	0.744
have item - clock	-0.049	0.219	0.824
have item - tv b&w	-0.214	0.347	0.538
have item - tv colour	-0.179	0.193	0.355
have item - tap recorder	0.161	0.220	0.465
have item - radio	-0.716	0.539	0.185
have item - hot water hitting coil	0.334	0.247	0.177
have item - mixer or blender	0.562	0.247	0.023
have item - pressure cooker	-0.388	0.300	0.196
have item - fan	0.066	0.204	0.748
have item - stove kerosene	-0.293	0.346	0.397
have item - utensils	0.295	0.200	0.139
grade completed respondent	-0.030	0.030	0.316
grade enrolled	0.104	0.133	0.435
enrolled yes/no	-0.116	0.216	0.591
amount non-sewa savings	0.000	0.000	0.082
respect for contribution in hh	0.246	0.332	0.459
respect for contribution in community	-0.345	0.199	0.084
constant	-1.060	1.291	0.412

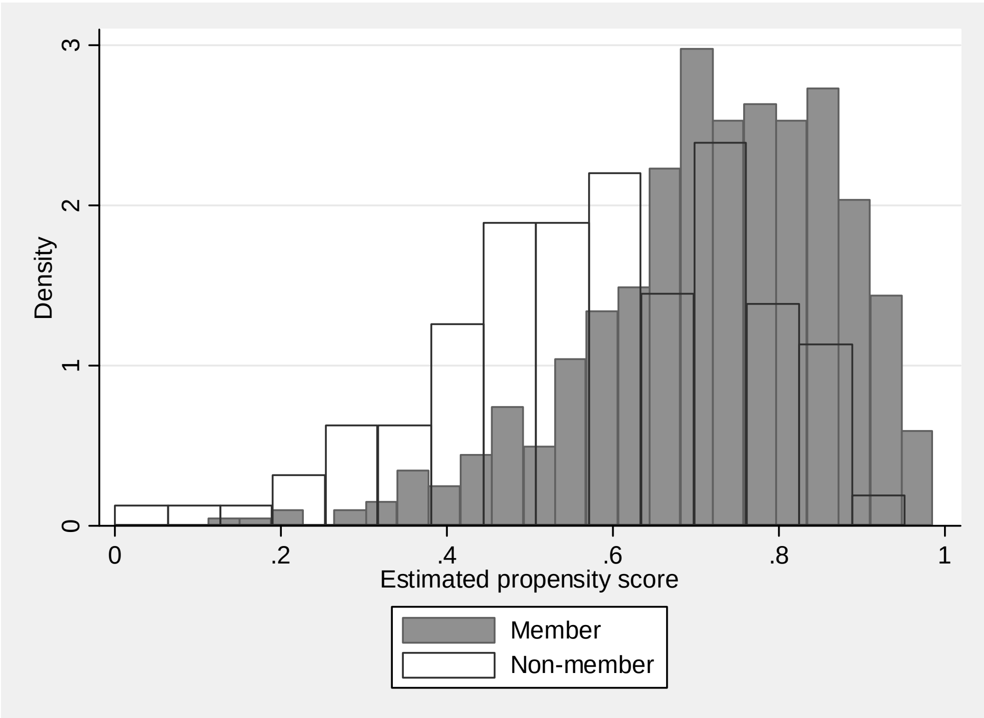
Common support was chosen and yielded the following region:[0.118, 0.999], percentage on common support: 98.85; Model Indications: LR Chi²(50)=116.73, Pseudo R^2=0.12.

Distribution of the estimated propensity score, R1



Appendix B - Probability of being a SEWA Bank member – R2

Distribution of the estimated propensity score, R2



variable	coef	std.err	P>|z|
age	0.104	0.049	0.035
age^2	-0.001	0.001	0.074
married	0.568	0.340	0.095
muslim	0.605	0.250	0.015
ucaste	-0.776	0.243	0.001
secondary school	-0.075	0.341	0.826
piece-rate work	-0.742	0.213	0.000
wage work	-0.348	0.218	0.111
hh head husband	0.219	0.232	0.347
nuclear hh	-0.351	0.251	0.161
subnuclear hh	-0.043	0.456	0.925
highest education respondent	-0.067	0.030	0.025
agemin hh	0.002	0.013	0.855
agemax hh	-0.019	0.009	0.030
children 0-5	-0.182	0.119	0.127
children 10-15	-0.266	0.112	0.018
hh size	0.089	0.068	0.193
house rented	-0.139	0.207	0.502
expenditure on food outside the house	0.017	0.012	0.144
tot expenditure on food	0.004	0.004	0.336
have item - other 2	0.012	0.015	0.435
have item - other 1	0.002	0.021	0.905
have item - poultry	-0.059	0.075	0.433
have item - goat	0.097	0.414	0.814
have item - sewing machine	0.451	0.224	0.044
have item - moped	1.033	0.589	0.079
have item - bycicle	0.365	0.184	0.047
have item - ivory jewelry	0.184	0.622	0.768
have item - silver jewelry	0.103	0.108	0.341
have item - gold jewelry	-0.411	0.245	0.094
have item - watches	-0.137	0.204	0.501
have item - clock	0.138	0.383	0.720
have item - tv b&w	-0.249	0.226	0.272
have item - tv colour	-0.059	0.289	0.838
have item - tap recorder	0.065	0.189	0.730
have item - radio	-0.202	0.248	0.415
have item - hot water hitting coil	-0.569	0.483	0.239
have item - mixer or blender	0.376	0.228	0.099
have item - pressure cooker	0.382	0.290	0.188
have item - fan	0.303	0.344	0.377
have item - stove kerosene	-0.311	0.355	0.381
have item - utensils	0.248	0.219	0.258
grade completed respondent	0.023	0.043	0.597
enrolled r1	0.381	0.384	0.322
enrolled r2	-0.098	0.657	0.881
amount non-sewa savings	0.000	0.000	0.618
respect for contribution in hh	0.160	0.420	0.703
respect for contribution in community	0.448	0.224	0.045
constant	-2.316	1.855	0.212

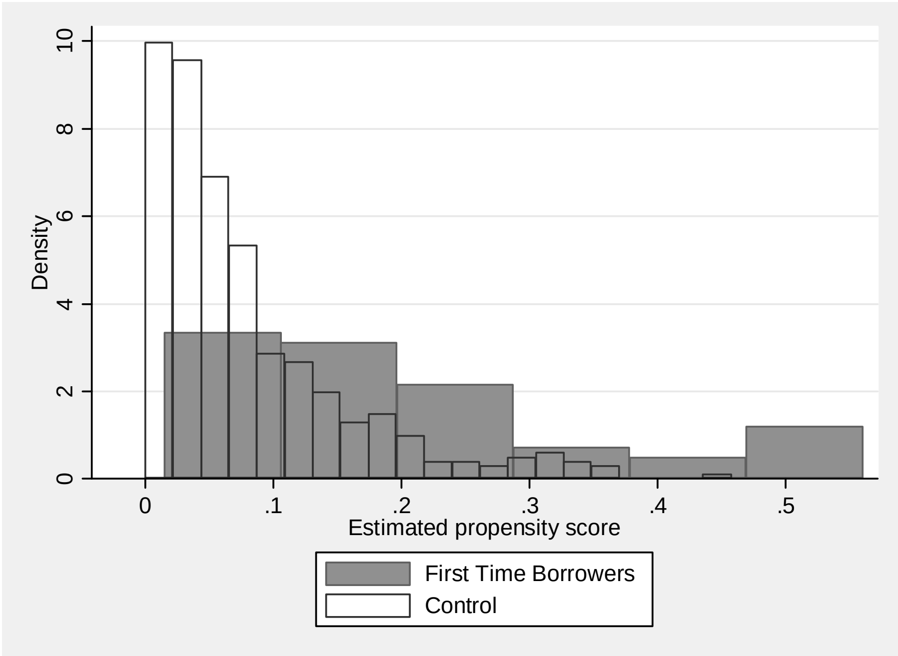
Common support was chosen and yielded the following region: [0.113, .987], percentage on common support: 99.75; Model Indications: LR $Chi^2(48)=111.35$*, Pseudo* $R^2=0.11$.

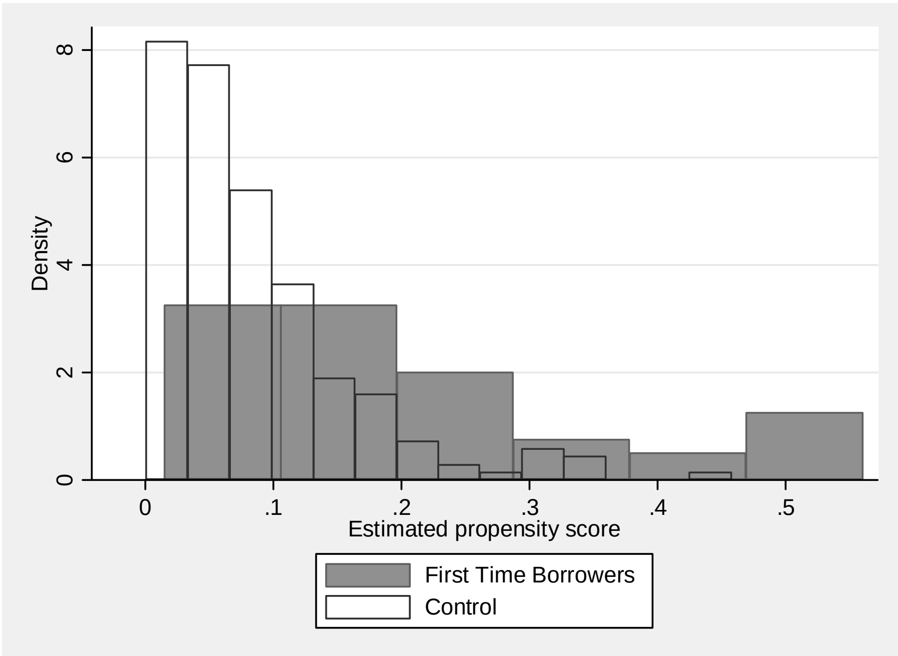
Appendix C - Probability of Being a First-time Borrower with the SEWA Bank

variable	coef	std.err	P>|z|
age	-0.078	0.065	0.226
age^2	0.000	0.001	0.594
married	0.913	0.957	0.340
muslim	-0.250	0.509	0.624
ucaste	-0.134	0.509	0.792
secondary school	0.139	0.687	0.839
piece-rate work	0.236	0.427	0.580
wage work	-0.148	0.480	0.758
hh head husband	1.339	0.551	0.015
nuclear hh	0.464	0.518	0.370
subnuclear hh	1.965	1.143	0.086
highest education respondent	-0.076	0.067	0.252
agemin hh	0.003	0.034	0.923
agemax hh	0.039	0.018	0.032
children 0-5	-0.376	0.262	0.152
children 10-15	-0.212	0.232	0.360
hh size	0.241	0.141	0.087
house rented	-0.639	0.483	0.186
expenditure on food outside the house	0.026	0.011	0.016
tot expenditure on food	-0.008	0.008	0.324
have item - other 2	0.000	0.032	0.991
have item - other 1	-0.030	0.046	0.508
have item - sewing machine	0.474	0.386	0.219
have item - moped	0.546	0.767	0.477
have item - bycicle	-0.398	0.365	0.276
have item - ivory jewelry	0.359	1.140	0.753
have item - silver jewelry	-0.231	0.434	0.595
have item - gold jewelry	0.193	0.548	0.725
have item - watches	0.281	0.445	0.527
have item - clock	-1.326	0.742	0.074
have item - tv b&w	-0.057	0.483	0.907
have item - tv colour	-0.044	0.583	0.940
have item - tape recorder	0.255	0.372	0.493
have item - radio	-0.506	0.556	0.362
have item - hot water hitting coil	0.426	0.841	0.612
have item - mixer or blender	0.287	0.419	0.493
have item - pressure cooker	1.098	0.838	0.190
have item - fan	1.458	1.183	0.218
have item - stove gas	-0.238	0.425	0.575
have item - stove kerosene	-0.150	0.669	0.822
have item - utensils	-0.210	0.482	0.664
grade completed respondent	0.015	0.090	0.871
enrolled r1	1.397	1.017	0.169
enrolled r2	-1.308	0.670	0.051
amount non-sewa savings	0.000	0.000	0.235
amount sewa savings	0.000	0.000	0.000
respect for contribution in hh	-0.325	0.864	0.707
respect for contribution in community	-0.155	0.469	0.742
constant	-5.488	3.104	0.077

Common support was chosen and yielded the following region: [.0052, .9142] percentage on common support: 84; Model Indications: LR Chi²(48)=69.65, Pseudo R²=0.20.

Distribution of the estimated propensity score, First time borrowers





[i] The remaining nine objectives are to increase income security, improve nutrition and housing plus water and sanitation facilities, increase access to health services and to childcare, increase household assets, self-reliance, access to education, built strong women's organizations and women leaders and to improve sources of energy.

[ii] This study works with the conventional significance level of 5%.

[iii] For a detailed description of the methodologies used to collect data, please refer to Chen and Snodgrass (2001).

[iv] "Rupee figures in this report are converted to dollars using appropriate market exchange rates obtained from OANDA.com and the International Monetary Fund. Rates used to deflate annual figures are averages for the last day of each month in the year. For the most relevant years, these were 1996: 35.4 rupees to the dollar; 1997: 36.5; 1998: 41.4; and 1999: 43.2." Chen and Snodgrass (2001)

[v] Income figures for Round 2 were deflated to January 1998 prices by dividing by 1.156. This was the value of the Ahmedabad consumer price index for labourers in January 2000, expressed on a base of January 1998. (Chen and Snodgrass, 2001, p.75)

[vi] This is the switching regression model of Quandt (1972), the Roy model of income distribution (Roy, 1951; Heckman and HonorÈ, 1990) and also the Neyman-Fisher-Cox-Rubin model of potential outcomes.

[vii] All results from all these analyses can be obtained from the author on request.

[viii] This is also reflected in the sample averages in outcome variables analysed: For all different samples, no matter which matching technique used, the matched samples are closer in average outcome than the unmatched ones.

[ix] Please note that results reported includes dummies on asset ownership. Including these variables assumes they cannot be influenced through attendance in the microfinance program. This might be a questionable assumption given that the program might have a strong influence on female labour supply and hence the resources available to the household. Interpretations of reported results do not change though, when using a propensity score without the asset-dummy variables.

[x] As mentioned in Section 3.6 two different scenarios were estimated. Results in the table are those where to each member corresponding/close non-members are matched. As a robustness check the same estimation was repeated defining non-members as the treatment group given the relatively small pool of control units in the common setting. Please note though, that reversing the setting in order to have a bigger pool of controls than treated units, does not necessarily lead to better matches as the densities of the propensity score of the first round shows for example that for non-members with a low propensity score, it is difficult to find close matches.

[xi] The corresponding propensity score specification is displayed in Appendix C.

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