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Working Paper

Microfinance and the Millennium Development Goals in Pakistan: Impact assessment using propensity score matching

ADBI Discussion Paper, No. 104

Provided in Cooperation with:

Asian Development Bank Institute (ADBI), Tokyo

Suggested Citation: Setboonsarng, Sununtar; Parpiev, Ziyodullo (2008) : Microfinance and the Millennium Development Goals in Pakistan: Impact assessment using propensity score matching, ADBI Discussion Paper, No. 104, Asian Development Bank Institute (ADBI), Tokyo

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**Microfinance and the Millennium Development Goals in Pakistan:
Impact Assessment Using Propensity Score Matching**

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March 2008

ADB Institute Discussion Paper No. 104

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Suggested citation:

Setboonsarng, Sununtar, and Ziyodullo Parpiev. 2008. Microfinance and the Millennium Development Goals in Pakistan: Impact Assessment Using Propensity Score Matching. ADBI Discussion Paper 104. Tokyo: Asian Development Bank Institute. Available: <http://www.adbi.org/discussion-paper/2008/04/18/2526.microfinance.millennium.dev.goals.pakistan/>

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Abstract

Microfinance is recognized as contributing both directly and indirectly to the Millennium Development Goals (MDGs). Using data from a survey of clients of a microfinance bank, Khushhali Bank, in 2005, the study revisited the survey data and found that despite the Bank's strict poverty-targeting program used in client selection and despite the survey's design to address the selectivity bias, the selectivity bias indeed still existed in the sampled households. Using the Propensity Score-Matching Methods (PSM) to address the selectivity bias, this study found that the lending program contributed significantly to income generation activities such as agricultural production and, in particular, animal raising (MDG 1). However, the impacts on other MDGs—education, health, female empowerment, and so forth—were of limited significance. This is due partly to the fact that 70% of the Bank's clients in the survey went through only one loan cycle, so the impacts on other MDGs are yet to be realized. Comparing the results to previous impact estimates done by Montgomery on the same dataset using OLS and Logit estimation, the PSM method yielded slightly different results. Although both studies recorded similar microfinance impacts on poverty, the degree of impact was less pronounced when the selectivity bias was addressed.

JEL Classification: I32, C43, D23

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I. INTRODUCTION

The member states of the United Nations have committed to achieving the Millennium Development Goals (MDGs), including the goal of halving extreme poverty by 2015. Microfinance is recognized as an effective development intervention for poverty reduction. The Consultative Group to Assist the Poor (CGAP) estimates that of the nearly three billion poor/low income people who could benefit from formal financial services, only 500 million have access. In rural areas, such access is needed most for agricultural activities. In urban areas, possible microfinance clients are mostly vendors, small traders, cottage industry workers, and low-wage earners.

While microfinance is recognized for its ability to reduce poverty, to what extent and how to implement it is unknown, due in part to common methodological problems of all impact studies.

This study aims to assess the impact of Khushhali Bank (KB), the leading microfinance bank in Pakistan, on specific targets consistent with MDGs. This study is the second study using the same set of data, but it adopted a different research methodology. The first study, conducted by Montgomery in 2005, assumed no self-selection bias occurred, whereas this study adopted econometric methods to address that issue. This study aims to facilitate Khushhali Bank's adjustments to maximize Pakistani poverty reduction.

Following the Introduction, Section II reviews literature on the impacts of microfinance on MDGs and research methodologies used in impact studies. Section III describes the case study, the Khushhali Bank, the survey, and a summary of client characteristics. Section IV discusses the issue of selectivity bias and the use of Propensity Score Matching. Sections V-VII estimate and discuss the impact of Khushhali Bank's lending program on key welfare indicators. Section VIII presents the conclusions.

II. LITERATURE REVIEW AND MOTIVATION

A. Review on the Effects of Microfinance on MDGs

The contribution of microfinance toward the achievement of MDGs goes beyond simply financial services for businesses investing in health and education, managing household emergencies, and meeting the wide variety of other cash needs encountered. The following reviews highlight the role of microfinance in the areas of eradicating poverty, promoting children's education, improving health outcomes for women and children, empowering women, and environmental sustainability.

Eradicate Poverty and Hunger (MDG 1)

Target 1: Reduce by half the proportion of people living on less than a dollar a day.

Microfinance services contribute directly to reducing extreme poverty by improving the income of poor people. In a study conducted in Lombok, Indonesia, Panjaitan-Drioadisuryo et al. (1999) find Bank Rakyat Indonesia (BRI) clients' incomes increased by 112%. Moreover, this increase was enough to move 90% of these families above the poverty line. Only 12 out of 121 respondents reported that their income did not increase, because their husbands used the money for other purposes. Simanowitz (2003), with the use of Poverty Assessment Tool (PAT), found out that, in India, three-fourths of the Microfinance Institution (MFI) clients saw significant economic improvements and half the clients got out of poverty. The World Bank found, in 1998, that the poorest 48% of Bangladeshi families with access to

microcredit from Grameen Bank rose above the poverty line. In People's Republic of China (PRC), microfinance programs have helped lift 150 million people out of poverty since 1990 (UNHDR, 2005). Moreover, in Ghana, MKNelly and Dunford (1998) found that clients increased their income by \$36, compared with \$18 for nonclients. Clients of microfinance generally shifted from irregular, low-paid daily jobs to more secured employment in India (Simanowitz, 2003) and Bangladesh (Zaman, 2000). Filipino households increased income, consumption, and capital (Chowdhury, 2004).

Target 2: Reduce by half the proportion of people who suffer from hunger.

Microfinance allows poor people to diversify and increase income sources, the essential path out of hunger. Diversification makes people more resilient to external shocks. The study in Lombok, Indonesia, reported that 93% of microfinance members ate three meals a day, compared with 51% of nonmembers (Panjaitan-Drioadisuryo et al., 1999). A survey by UNICEF in Viet Nam showed that 73 of the nonborrowers faced food shortages of three months or more compared with 12% of borrowing households (UNICEF, 1996). In Bangladesh, a study on MFI clients found that fewer members suffered from severe malnutrition (relative to the control group), and, more importantly, the extent of severe malnutrition declined as the length of membership increased (Chowdhury and Bhuiya, 2001).

Universal Primary Education (MDG 2)

Target 3: Ensure that all boys and girls complete a full course of primary schooling.

Studies show that children of MFI clients are likelier to attend and stay in school longer. Student drop-out rates are also much lower in MFI client households. A study in Bangladesh found that basic competency in reading, writing, and arithmetic among 11- to 14-year-olds in member households increased from 12 to 27% between 1992 and 1995. In nonmember households, only 14% of children could pass the education competency tests in 1995 (Chowdhury and Bhuiya, 2001).

There has been significant improvement in school attendance of children as well. In UNICEF's Viet Nam microfinance program, 97% of borrowers' daughters attended school compared with 73% of nonborrowers' daughters (UNICEF, 1996). Children (ages 6–21) of Zimbabwe repeat borrowers were likelier to stay in school than those of non-clients (Barnes et al., 2001).

Gender Equality and Women's Empowerment (MDG 3)

Target 4: Eliminate gender disparity in primary and secondary education.

A majority of microfinance programs generally target women—often more financially responsible at repaying than men—as clients, providing them with direct control over resources. A survey in Bangladesh showed that credit-program clients' empowerment increased with duration of membership, suggesting strong program influence (Hashemi et al., 1996).

The Women's Empowerment Program of a Nepalese MFI found that 68% of its female members made household decisions like selling property, the children's education, and budgeting—all traditionally male duties (Cheston and Kuhn, 2002). For one MFI, female household-fund managers increased from 33 to 51% (Cheston and Kuhn, 2002). Also, in the Lao PDR, women who ran family-owned economic activities significantly increased household asset value (Sengsourivong, 2006).

Female clients of MFIs in the Philippines, Nepal, Bolivia, and Bangladesh have become elected officials. In Russia, female MFI clients organized a campaign for democracy in the Russian elections. Clients of MFIs in India have organized rallies for better wages, female worker rights, and legal changes. (Littlefield et al, 2003).

Children's Health, Maternal Health, and Diseases (MDGs 4, 5, & 6)

Target 5: Reduce by two-thirds the mortality rate among children under five.

MFI client households appear to have better nutrition, living conditions, and preventive healthcare than comparable nonclient households. UNICEF, in 1995, noted that infant mortality rates in Nepal were lower in areas with a combined credit and basic social services approach than in areas where credit was extended without social services and in those where no credit was provided. Severe malnutrition declined with the increase in length of MFI membership in Bangladesh (Chowdhury and Bhuiya, 2001). Indonesian MFI members ate three meals a day (93%) (Panjaitan-Drioadisuryo et al., 1999).

Many MFIs also provide target clients with useful health information and with healthcare education to improve nutrition and to make them more aware of contagious diseases and preventive care. A growing number of MFIs have forged partnerships with insurance providers to offer health insurance to clients. An impact study showed that clients had better breast-feeding practices, were likelier to give rehydration therapy to children with diarrhea, and had higher rates of diphtheria, tetanus, and poliomyelitis (DPT) immunizations for their children (MkNelly and Dunford, 1999).

Target 6: Reduce by three-quarters the maternal mortality rate.

Target 7: Halt and begin to reverse the spread of HIV/AIDS.

Target 8: Halt and begin to reverse the incidence of malaria and other major diseases.

The awareness of family-planning activities among clients of the MFI appears higher than that of nonclients. A survey in Bangladesh indicated that rates of contraceptive use were significantly higher for Grameen clients (59%) than for nonclients (43%) (Schuler et al., 1994). This is generally due to both greater awareness of contraceptive programs gained by attending group meetings and from increased mobility that allows women to seek out such services. Of Ugandan MFI female clients, 32% tried at least one AIDS prevention technique versus only 16% of nonclients (Barnes et al., 2001).

Environmental Sustainability (MDG 7)

Target 9: Integrate the principles of sustainable development into country policies and programs; reverse loss of environmental resources.

Target 10: Reduce by half the proportion of people without sustainable access to safe drinking water.

Target 11: Achieve a significant improvement in the lives of at least 100 million slim dwellers.

A number of MFIs are currently integrating sustainable development concerns into their credit services. The MFIs' role is especially important since developing countries often lack environmental awareness and management.

There is evidence that increased earnings—stemming from access to financial services—lead to investments for improved housing, water, and sanitation, thus leading to improved health. Nepalese households with latrines were twice as high in areas where credit and basic social services were linked (UNICEF, 1995). Many MFI programs provide loans specifically for tube-wells and toilets. In India, the MFI provides loans to upgrade community infrastructure (including tap water, toilets, drainage, and paved roads). In one notable development, one Thai MFI recognizes organic agriculture certification and contracts with buyers of organic products as loan collateral. Organic agriculture is environmentally friendly and is most often practiced by poor households in marginal areas. For example, 70% of organic tea in the E.U. market is grown by poor households in mountainous areas in Wuyuan County of the PRC. MFI efforts to finance activities such as organic agriculture should add positive notes on environmental sustainability. At the same time these could foster global partnerships between consumers in developed countries and the poor in developing countries.

Develop a Global Partnership for Development (MDG 8)

Target 12: Develop further an open, rule-based, predictable, non-discriminatory trading and financial system.

The providing of financial services by MFIs to the poor is an MDG goal. Since MFIs are the key to development of microenterprise operated by the poor, they allow the poor to produce products for the market. Very often, these products are sold in export markets; thus, it could be said that microfinance enhances global partnership for development.

B. Review on Impact Assessment of Microfinance Institutions

MFIs are mandated to serve the poor. To target the poor, one of the common strategies among MFIs is to limit loan size. Some MFIs also use a poverty checklist to screen prospective borrowers. Since offering loans regardless of the amount requires the same transaction costs, MFIs tend to drift away from serving the poor. The better-off poor tend to self-select themselves into MFIs' programs, making impact assessments challenging.

In one study, Thai borrowers, prior to borrowing, were much wealthier than nonborrowers (Coleman, 2006). He attributes the difference to either a selection bias or a program-placement bias. A proper impact analysis should control for the initial wealth differences between borrowers and nonborrowers.

Coleman (1999) addresses this problem by collecting data on 445 households in 14 villages. Of these, eight had village banks operating at the start of 1995. The remaining six hadn't started operations, but village banks were set up already, allowing the households to self-select according to the village banks' procedures. Since the selected households were forced to wait one year before getting their first loans, it was possible to use this group of households as a control group. This "quasi-natural" experiment controlled for self-selection bias. Coleman finds that controlling for selection makes an important difference: The average program impact is not significantly different from zero after controlling for endogenous member selection and program placement.

In studying the impact of the Khushhali Bank on a range of outcome variables, Montgomery (2005) basically followed the methodology of Coleman (1999) with one crucial difference. Since it was not possible to identify a control group in the sense of Coleman's study, Montgomery followed USAID's AIMS project methodology, which compares "old borrowers" to "new borrowers" within the same area. Montgomery (2005) distinguishes three distinct groups: KB borrowers (Treatment Group), soon-would-be borrowers (Control Group 1), and nonborrowers (Control Group 2). Since borrowers self-select into the microfinance program,

the Treatment Group and Control Group 1 should have similar characteristics. The only difference between them is that the Treatment Group is already participating, while Control Group 1 is yet to participate. If the two groups share similar characteristics (e.g., initial wealth level), then Control Group 1 can serve as a controlled variable in impact estimations, effectively allowing estimation of the impact of borrowing from Khushhali Bank on numerous outcome variables, such as consumption, income, education, health, and empowerment.

To apply their methodology to the microfinance impact study, Coleman and Montgomery made a crucial assumption: The characteristics of early- and late-entering clients are the same. As Armendariz and Morduch (2005) note, this assumption might be unrealistic. Why did the new borrowers not sign up earlier? Why were the older borrowers first in line? If their timing of entry was due to unobservable attributes like ability, motivation, and entrepreneurship, the comparisons may do little to address selection biases and could, in fact, exacerbate bias.

Karlan (2001) and Alexander-Tedeschi and Karlan (2002) point out additional problems due to MFI program drop-outs and graduates that can be especially severe in cross-section studies, which rely on comparing old borrowers to new ones. Sometimes borrowers graduate MFI programs because they are doing so well that they no longer need assistance. More often, it is the borrowers in trouble that leave. The result of drop-outs is that only successful borrowers remain in the program, resulting in overestimation of program impact. Hulme (1999) reports that dropout rates are 25 to 60% per year in East Africa. Gonzalez-Vega et al. (1997) report that just half of the clients who ever borrowed from BancoSol were still active at the time of analysis. In rural areas, however, the fraction of active borrowers numbered two-thirds of all borrowers, possibly reflecting the fact that there are fewer alternative lending sources in the countryside.

It is likely that these “older borrowers” (i.e., those who remain active) have the positive qualities of survivors, while “new borrowers” have yet to be tested. If borrowers who had difficulties paying the loan are likelier to drop out, comparing old to new borrowers will overestimate impacts. We suspect that the Khushhali Bank survey also suffers from these problems and distinguishing “old” borrowers from “new” ones will not solve them. If this is the case, the findings of Montgomery (2005) likely exaggerate the impact of microfinance.

To cope with program placement and self-selection biases, we need to identify a control group that is identical to the “treatment” population. In this study, we use the Propensity Score Matching (PSM) method, extensively employed in medical studies and sociology, to assess the impact of Khushhali Bank borrowing on a host of outcome variables.

III. A BRIEF DESCRIPTION OF THE KHUSHHALI BANK SURVEY

In Pakistan, it is estimated that of 6.5 million poor people who need microfinance services, only about 5% are being served by microfinance institutions. To expand microfinance services to the poor, the Khushhali Bank (KB) was established in August 2000 by 14 private and 2 state-owned commercial banks as a flagship microfinance bank. It became an integral part of the Islamic Republic of Pakistan’s Poverty Reduction Strategy and its Microfinance Sector Development Program (MSDP), developed with the assistance of the Asian Development Bank (ADB). Khushhali Bank’s primary objective is to provide sustainable microfinance services to the poor in order to reduce poverty and promote economic development through community building and social mobilization.

Through consolidation of several NGOs’ microfinance operations, Khushhali Bank shortly became one of the largest microfinance institutes in the country with 31 branches covering 33 districts and US\$12 million in disbursements. But real expansion occurred after the government of Pakistan signed a loan agreement of US\$150 million with the Asian

Development Bank in 2002 to support the operations of Khushhali Bank and to promote the microfinance sector in Pakistan. Khushhali Bank obtained a US\$70 million component of this loan for microloans to the poor—particularly to women of the country's rural and urban areas—and a US\$10 million component allocated toward institutional capacity building. Another US\$70 million component has been allocated to support policy reforms of the microfinance sector in Pakistan.

By the end of 2005, KB had 63 branches and employed 1,576 people. KB reported that in 2003, it provided loans to 100,000 households. It aimed to reach 700,000 households by 2007. The bank's line of products includes short-tenure microloans, up to US\$500 for working capital and asset purchase, as well as training and consulting. It does not offer deposit services. Its lending is based on the Grameen model, i.e., it loans to community groups without collateral. To ensure that the loan reaches the target segment (e.g., the poor), KB has limited the loan size to about US\$150, an equivalent of 36% of the per capita GDP, an amount in which wealthy people would not have interest. In practice, however, different members of the same household often borrow in tandem, rendering the small loan limit an ineffective deterrent. Khushhali Bank also uses another method of targeting: ranking poor prospective borrowers by tracking the economic status of their beneficiaries. This approach, however, is not adopted rigorously and suffers from subjectivity since participating households generally self-select themselves as poor. Moreover, the very aims of the Khushhali Bank—obtaining group guarantees for repayment and maintaining a close scrutiny of monthly cash flows to determine the repayment capacity of potential clients—can potentially exclude the poor, a priori.

A Khushhali Bank survey was conducted by the Asian Development Bank Institute in May–June 2005. The survey covered 2,881 households, of which 1,416 are KB borrowers and 1,465 nonborrowers. Additional data on loan characteristics such as purpose, duration, installments, and interest rate were provided by Khushhali Bank. When matching survey data and KB data on borrowers, 18 observations were lost due to unknown reasons and thus data from 1,398 client households were used in the final analysis. The survey covered KB borrowers from 11 regions: 8 rural and 3 urban. Table 1 shows that out of 2,881 households, 2,126 (74%) were rural households and 726 (26%) were urban households.

This sampling of rural versus urban households is consistent with Khushhali Bank's portfolio, in which around 75% of Khushhali Bank's lending goes to the rural population. To be representative, the survey design covers the same distribution with 74% of rural households.

Table 1: Survey Participants by Region

Region	Urban	Rural	Total
DG Khan		363	363
DI Khan		248	248
Jacobabad		312	312
Karachi	392		392
Kohat		242	242
Lahore	208		208
Loralai		208	208
Muzaffarabad		260	260
Nawabshah		262	262
Quetta	132		132
RY Khan		254	254
Total	732	2,149	2,881

Table 2: Distribution of KB Borrowers and Nonborrowers by Region

	Urban	Rural	Total
Non-borrower	436	1,241	1,677
KB borrower	296	908	1,204
Total	732	2,149	2,881

In Pakistan, due to cultural reasons, extended families are very common. Graph 1 depicts the distribution of household size among survey participants.¹ While households with 6 family members are most common, 16% of all households have 10 or more members. The average number of household members in the sample is 6.5 people.

Graph 1: Distribution of Household Size Among Survey Participants

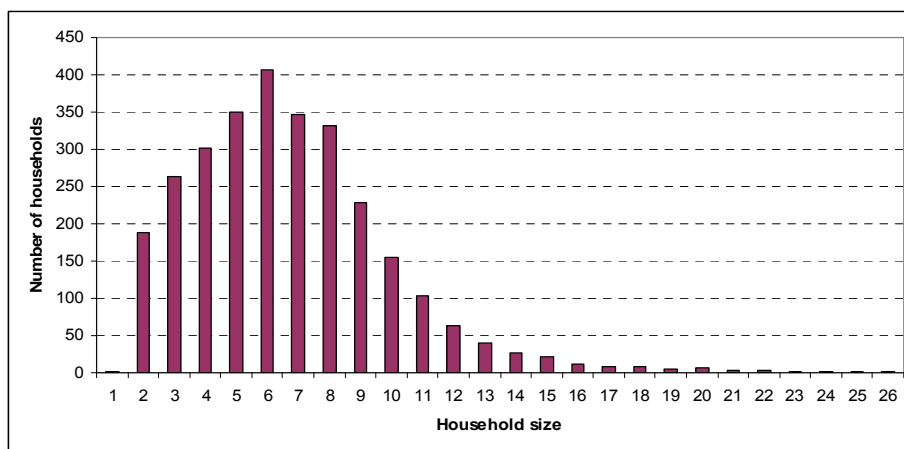


Table 3 shows that female borrowers consist of 44% of all borrowers in the survey, which is significantly higher than the 30% of women in the overall pool of KB borrowers. This fact is mainly explained by the survey design to give greater weight to women so as to infer the program’s impact on gender empowerment. For comparison, the labor force participation rate of Pakistani women in 2005 was only 11%, compared with 49% of men.

Table 3: Gender Distribution of Khushhali Bank Borrowers

Female dummy	Freq.	Percent	Cum.
0	792	55.6	55.6
1	633	44.4	100.0
Total	1,425	100.0	

From the time of its establishment in 2000 until the survey in 2005, the average loan repayment rate was more than 97%. High repayment rates occur either by good portfolio management or by rapid expansion into new areas. In the latter case, high repayment rates among the first-time borrowers bolsters the average. Indeed, the Khushhali Bank has been expanding very fast. This growth is illustrated by the number of first-time borrowers. Table 4 shows the number of loan cycles broken down by gender. In particular, the survey shows that around 70% of KB borrowers have borrowed only once or are first-time borrowers.

¹ The definition of household is quite broad, including all people residing in the same house and those members who reside in other cities but regularly send money back or receive financial assistance.

Table 4: Number of Loan Cycles

		Number of Loan Cycles								
		1	2	3	4	5	6	7	8	Total
Male		551	151	46	20	10	6	8	1	793
Female		438	130	36	17	5	5	1	1	633
Total		989	281	82	37	15	11	9	2	1426

The standard loan size of Khushhali Bank is 10,000 rupees or less. To discern whether multiple family members borrow from the Khushhali Bank at the same time, we turn to the distribution of currently active loans. Table 5 shows that 11% of the households appear to have outstanding loan amounts exceeding 10,000 rupees, indicating that some households can effectively circumvent KB's loan size restriction and borrow more at the same time. Table 6 shows the cumulative loan size by sample households since the establishment of Khushhali Bank in 2000. By mid-2005, 60 households (more than 4% of all surveyed households) have borrowed more than 41,000 rupees.

Table 5: Current Loan Size by Households

Loan amount	Freq.	Percent	Cum.
≥5000	22	5.2	5.2
6000-9600	27	6.3	11.5
10000	329	77.2	88.7
11000-28400	48	11.3	100.0
Total	426	100.0	

Table 6: Cumulative Loan Size by Households

Loan amount	Freq.	Percent	Cum.
2000-9975	187	13.2	13.2
10000	729	51.5	64.7
11000-19800	160	11.3	76.0
20000-21500	64	4.5	80.6
22000	113	8.0	88.6
22400-40000	102	7.2	95.8
41000-150600	60	4.2	100.0
Total	1,415	100.0	

To investigate if KB achieved its goal of targeting the poor, Table 7 shows that 62% of sample households can be classified as poor using the criterion of the national poverty line in 2005, less than 878.6 rupees of consumption per capita, which is necessary to provide 2,350 calories per day. This ratio of the poor among KB clients is slightly lower than the comparable ratio of the poor among nonborrowers in the sample (64%).

Table 7: Distribution of the Poor Between KB Borrowers and Non-Borrowers

	Non-poor	Poor	Total
Non-borrower	608	1069	1677
KB borrower	455	749	1204
Total	1063	1818	2881

To further investigate if KB reaches the core poor, defined as people spending less than 500 rupees on consumption, which is a little bit more than half of the national poverty line, Table

8 shows that around 21% of all borrowers can be classified as the core poor. This ratio is consistent with the ratio of the core poor in the whole sample. Thus, it could be concluded that KB was effective in reaching the poor.

Table 8. Distribution of the Core Poor Between KB Borrowers and Nonborrowers

	Non-core poor	Core poor	Total
Non-borrower	1314	363	1677
KB borrower	946	258	1204
Total	2260	621	2881

IV. DESCRIPTION OF BORROWERS AND NONBORROWERS: ISSUE OF SELF-SELECTION BIAS

One of the most difficult issues a researcher has to address in an impact study is to sort out whether wealth is created due to the program participation or participants were already relatively wealthy when they joined the program, known as selection bias. When people decide to join the program, they first self-select into it and are selected by their peers in the group-lending scheme. This double selection can create a bias in several instances. First, the wealthy or people with more entrepreneurship abilities are likelier to self-select into the program. Second, even if the poor want to join the program, they may not be selected into it by the wealthier peers.

To prevent the wealthy from joining, microfinance programs usually have some built-in mechanisms such as small loan amounts, risk of stigmatization by being in a club for the poor, and, in some cases, explicit participation criteria. In this respect, KB programs do not sufficiently discourage self-selection bias. It is pointed out in the previous section that although one household is limited to one loan of 10,000 rupees, the wealthy households can effectively circumvent the loan size restrictions by including several household members into microfinance programs. Since the interest rate of the KB lending program is relatively low, it attracts non-poor households to join the program. Although KB has criteria that borrowers must have income less than the minimum taxable limit, it is not clear if this stipulation is strictly enforced.

We turn to a simple t-test to assess if self-selection bias is pronounced among KB borrowers. Table 9 shows the results of testing the mean difference between borrowers and nonborrowers on a host of variables. To assess if borrowers and nonborrowers have similar initial wealth status, we paid particular attention to ownership of large assets, which are not likely to change due to microfinance. The results show that KB borrowers own significantly more land, operate larger cultivation areas, and own more production and household assets. Although the significant difference in variable values (e.g., sales or profit from non-agriculture enterprise) could be attributed to participating in KB's lending program, it is questionable if the initial conditions of KB members are far better than nonmember households. Based on the findings presented in Table 9, it could be concluded that selectivity bias is pronounced among KB clients.

Table 9. Tests for Difference Between KB Borrowers and Nonborrowers

Variable	KB member, mean	Nonmember, mean	Difference
Amount of land owned, acres	18.53	11.72	6.81***
Operated amount of land (area self-cultivated + area leased in), acres	20.79	14.45	6.33***
Agricultural sales to third parties, rupees	31991.08	19041.94	12949.13***
Value of farm equipment owned, rupees	16606.3	6537.228	10069.07***
Consumer durable assets, rupees	207931.1	184461.6	23469.48**
Value of livestock	45309.37	34910.87	10398.49***
Total sales of non-agricultural enterprises, rupees	46736.95	30761.24	15975.71***
Profits from non-agricultural enterprises, rupees	16130.79	11680.71	4450.08***
Monthly consumption expenditures per capita, rupees	1916.616	1810.916	105.69*
Monthly non-food consumption expenditures per capita, rupees	825.28	735.37	89.90*

Note: ***, **, and * denote 1, 5, and 10% significance levels, respectively.

As KB borrowers in the sample appear to be initially wealthier than the control group, the nonborrowers, if we run a naïve regression and estimate impact of borrowing from the KB on different wealth indicators, we are very likely to overestimate the impact of microfinance.

In the case of the previous KB study, Montgomery (2005) drew causal linkages in part based on the assumption that the survey design would minimize the selection bias. In this study we use the PSM method to address the selectivity bias and reassess the impacts on key parameters of household well-being.

V. ESTIMATION STRATEGY

The PSM method has been specifically designed to assist researchers in drawing causal inferences in observational studies. The propensity score is a conditional probability that an individual is assigned to the treatment group (Rosenbaum and Rubin, 1983). Generally, it is estimated by using probit (or logit) regression with the covariates collected from the participants as X and participant's status on the treatment variable as Y (Rosenbaum, 1987). The covariates in the probit model are non-treatment variables such as the participant's background characteristics. The estimated propensity score abstracts the information of these covariates. Using such estimated propensity scores, a researcher can match a participant from the treatment group with a participant from the control group to facilitate causal inference.

The use of PSM methods in economics is relatively new. Previous papers include Heckman et al. (1998), Friedlander, et al. (1997), and Dehejia and Wahba (2002). As Dehejia and Wahba (2002) point out, PSM can be invaluable for cross-sectional survey data. In such a setting, resurveying thousands of units at a later date might be costly, making data on the outcome variable for a comparison group difficult to obtain. An important feature of this method is that, after units are matched, the unmatched comparison units are discarded and not directly used in estimating the treatment impact.

Using the propensity score, a researcher can match participants from the treatment group with participants from the control group, so that the treatment group and control group can

be balanced. This approach can significantly reduce bias in observational study (Rosenbaum, 1987, 2004; Rosenbaum and Rubin, 1985; Rubin and Thomas, 1992).

Ideally, the households representing one matched pair are identical to each other except for their borrowing from Khushhali Bank. As a consequence, this approach isolates the impact idiosyncratic factors have on outcome variables by reducing observed heterogeneity between KB borrowers and nonborrowers.

Since the true propensity score is unknown, a model-based estimation procedure has been developed (Rosenbaum and Rubin, 1984, 1985). The broadly used probit model for the propensity score is a multi-step approach: (1) selecting the powerful covariates that distinguished the treatment and control groups the most; (2) including the selected covariates and their interaction in a one-equation probit model to estimate the propensity score, using the maximum likelihood method; and (3) using the estimated propensity scores to match treatment and control groups or stratify these two groups into equivalent subclasses. This procedure may include the stepwise model selection, with repeating step (1) to step (3) until the closest treatment and treatment groups are achieved.

After the propensity score is estimated, different algorithms can be employed in order to identify matching partners (Rubin, 1974). The Nearest-Neighbor Algorithm is the most applied algorithm, so we used this algorithm in our estimations.

In this paper, the PSM is based on comparing borrowers to nonborrowers within the same area. A key assumption is that the characteristics of people that enter programs are unchanged over time, and the method should control for the fact that borrowers are not a random group of people.

After identifying the matching partners, the channel effect and the self-selection effect can be determined. As was mentioned earlier, the purpose of the matching approach is to estimate the counterfactual outcome and therefore to correct for the selection biases created by non-random sampling of the microfinance program participants (Dehejia and Wahba, 2002). As a consequence, the counterfactual outcome represents the indicators of KB borrowers' well-being after accounting for selection biases. This is explained by the fact that matching KB borrowers and nonborrowers based on those variables that influence their participation corrects for the non-random sampling of the borrowers. Thus, the average well-being of KB borrowers before matching still includes self-selection, whereas the average profitability after matching does not.

In this paper we concentrate on estimating the average effect of treatment on the treated (ATT). This parameter estimates the average impact among Khushhali Bank borrowers and is defined as:

$$\hat{\Delta}^{ATT} = E[Y^1 | D = 1] - E[Y^0 | D = 1] \quad (1)$$

where

$\hat{\Delta}^{ATT}$: Estimated Average Treatment-on-Treated effect,

Y^1 : Program participation

Y^0 : Program non-participation

$D=1$: KB borrower

$D=0$: Nonborrower

$E[Y^1 | D = 1]$: Expected outcome after borrowing from KB

$E[Y^0 | D = 1]$: Hypothetical outcome without borrowing from KB for those who borrowed from KB

Since the counterfactual outcome for those being treated - $E[Y^0 | D = 1]$ - is not observed, a researcher has to choose a proper substitute in order to estimate ATT. If the condition $E[Y^0 | D = 1] = E[Y^0 | D = 0]$ holds, we can use the nonborrowers as a control group. However, due to the self-selection bias, the above condition will not hold; therefore, we use propensity score distribution of participants to estimate the unobservable component.

VI. RESULTS AND DISCUSSIONS

A. Propensity Score Estimations

The first stage in the propensity score matching is to model the probability of being a KB borrower. With that purpose, we include variables that influence the likelihood of borrowing from Khushhali Bank. The rationale behind this is that, if a variable influences participation but not the outcome, there is no need to control for differences with respect to this variable in the treatment versus the control groups. Likewise, if the variable influences the outcome but not the treatment likelihood, there is no need to control for that variable since the outcome will not significantly differ in the treatment versus the control groups. Variables that affect neither treatment nor the outcome are also clearly unimportant. Therefore, only those variables that influence both the treatment and the outcome are needed for the matching and are included in the probit model from which we derive the propensity score.

Table 10 shows the propensity score estimations by probit regression method. In general, the model is well specified with high Likelihood Ratio Chi-squared and Pseudo R-squared coefficients.

The probit estimations show the relatively good fit of the model, expressed by Chi-squared and Pseudo R-squared statistics. Among the covariates, holding some office in the neighborhood, having a literate adult in the household, owning land, and living in remote villages positively affect the probability of borrowing from Khushhali Bank. More importantly, being female and having an experience of borrowing from sources other than Khushhali

Bank greatly increases the odds of borrowing from Khushhali Bank. In contrast, other variables, such as age of household head, dummy for being rural households, adult numeracy, and dummy for being poor do not strongly explain the participation in the Khushhali Bank lending program.

Table 10: Probit Model
 Dependent variable – Dummy for KB borrower

Probit regression		Number of obs. =		2881		
		LR chi2(10) =		1491.58		
		Prob > chi2 =		0		
Log likelihood = -1212.1627		Pseudo R2 =		0.3809		
Dependent variable - KB borrower dummy						
	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Constant	-1.147	0.132	-8.680	0.000	-1.406	-0.888
Age of household head	0.001	0.002	0.430	0.667	-0.003	0.005
Dummy for holding office	0.270	0.082	3.300	0.001	0.109	0.430
Dummy for rural	-0.074	0.081	-0.910	0.361	-0.231	0.084
Dummy for adult literacy	0.354	0.097	3.640	0.000	0.163	0.545
Dummy for adult numeracy	-0.099	0.119	-0.830	0.408	-0.333	0.135
Dummy for poor	-0.066	0.061	-1.080	0.281	-0.186	0.054
Dummy for land ownership	0.202	0.070	2.910	0.004	0.066	0.338
Distance to nearest town	0.005	0.002	2.040	0.041	0.000	0.009
Dummy for non-KB-borrowing	2.317	0.113	20.530	0.000	2.096	2.538
Dummy for female	1.720	0.078	22.060	0.000	1.567	1.873
Note: The common support option has been selected. The region of common support is [0.09819986, 0.99993056].						

Remote villages have the greater probability of having a KB program, indicating that Khushhali Bank is doing well in reaching the remote areas. On the other hand, dummy for being poor is insignificant, indicating that Khushhali Bank’s lending toward the poor is neutral.

After deriving the propensity score, we need to ensure that there is enough common support. This is done by discarding treated individuals with a propensity score lying outside the range of propensity scores for individuals in the control group.

Table 11: Description of the Estimated Propensity Score in Region of Common Support

Estimated propensity score					
Percentiles		Smallest			
1%	0.101	0.098			
5%	0.113	0.098			
10%	0.131	0.098	Obs	2856	
25%	0.176	0.098	Sum of Wgt.	2856	
50%	0.220		Mean	0.420	
			Std. Dev.	0.331	
75%	0.794	1.000			
90%	0.944	1.000	Variance	0.110	
95%	0.999	1.000	Skewness	0.753	
99%	1.000	1.000	Kurtosis	1.750	

The final number of blocks is 11. This number of blocks ensures that the mean propensity score is not different for treated and controls in each block. The balancing property is

satisfied. The table below shows the inferior-bound, the number of treated, and the number of controls for each block.

**Table 12: Distribution of KB Borrowers and Nonborrowers
Based on the Propensity Score**

Inferior of block of pscore	Khushhali bank borrower		Total
	0	1	
0.091	786	130	916
0.182	626	182	808
0.273	130	51	181
0.364	13	7	20
0.636	14	33	47
0.727	53	195	248
0.818	12	186	198
0.909	18	420	438
Total	1,652	1,204	2,856

Note: the common support option has been selected

From Table 12 one can see that the distribution of KB borrowers and nonborrowers along the propensity score is not similar. To the extent that there are substantial differences between treatment group and comparison group, there should be little overlap. There is some overlap between KB borrowers and nonborrowers when the propensity score is between 0.09 and 0.18, implying that the two groups share the same characteristics in these brackets, but there is little overlap over the higher propensity score brackets. As mentioned earlier, a higher propensity score basically means a higher probability of borrowing from Khushhali Bank.

B. Matching and Impact Estimations

Once the common support requirement is fulfilled, we can carry out the matching for all pairwise combinations. Various propensity score matching methods have been proposed in the literature as a means to identify a comparison group. Each of these methods implies a trade-off between quality and quantity of the matches. The most intuitive matching method is the Nearest-Neighbor (or one-to-one) matching, which matches each treated observation to a control observation with the closest propensity score. In the case of the Nearest-Neighbor method, all treated units find a match. However, it is obvious that some of these matches are fairly poor, because for some treated units the Nearest-Neighbor may have a very different propensity score. The Radius Matching and Kernel Matching methods offer a solution to this problem. With Radius Matching, each treated unit is matched only with the control units whose propensity score falls in a predefined neighborhood of the propensity score of the treated unit. If the dimension of the neighborhood (i.e., the radius) is set to be very small, it is possible that some treated units are not matched because the neighborhood does not contain control units.

Another matching method, stratification, consists of dividing the range of variation of the propensity score in intervals such that, within each interval, treated and control units have on average the same propensity score. For practical purposes, the same blocks identified by the algorithm that estimates the propensity score can be used. Then, within each interval in which both treated and control units are present, the difference between the average outcomes of the treated and the controls is computed. The ATT of interest is finally obtained as an average of the ATT of each block with weights given by the distribution of treated units across blocks.

Once each treated observation is matched to a control group observation, the difference between the outcomes for the treated versus the control observations is computed. This procedure is usually implemented with replacement; that is, each treated individual has one match, but a control group individual may be matched to more than one treated individual. Once each treated unit is matched with a control unit, the difference between the outcome of the treated units and the outcome of the matched control units is computed. The ATT is then obtained by averaging these differences. Dehejia and Wahba (1998) found that matching with replacement improves the performance of the match and is less demanding with regard to the common support requirement.

Table 13 presents the results of the comparison of Khushhali Bank borrowers with nonborrowers, matched by the Nearest-Neighbor Matching method. The first two columns of the table show the number of treated (KB borrowers) and matched nontreated (non-KB borrowers). The ATT is displayed for different outcome variables classified by type of functions. The last two columns provide standard errors and corresponding t-statistics of the ATT estimations. In all, 1,204 households that borrowed from the Khushhali Bank were matched with 663 non-KB borrowers. Those nonborrowers who did not match with corresponding borrowers are eliminated.

The results in Table 13 show that with regard to household production and consumption or income poverty—MDG 1—Khushhali Bank has had positive impact on agricultural production and, in particular, animal-raising activities. On crop production, KB clients use more pesticides and possess more farm equipment. The point estimate of pesticide use shows that KB borrowers on average are 24% likelier to use pesticides than nonborrowers. The implications, however, of the higher use of pesticides should be interpreted with care.

While pesticides enhance agricultural outputs, they are toxic substances that the poor often are not trained to use properly. The inappropriate use of pesticides could lead to negative outcomes on other MDGs, e.g., farmer's health (MDGs 4-6) and the environment (MDG 7), which will be discussed in a later section.

On ownership of farm equipment, KB borrowers possess higher-value farm equipment, valued in Pakistan Rupees (PRs), 12,814² higher on average than nonborrowers. Also, rental income from farm equipment is PRs 882.5 higher.

KB membership has the strongest impact on animal raising. The value of livestock, sales, and profits were all highly positive and statistically significant for animal raising. The value of livestock owned by KB clients is on average PRs 17,705 higher than that of nonborrowers. Also, KB borrowers have PRs 6,494.2 higher profit on livestock than that of nonborrowers. This shows the strong positive effect of KB borrowing on a farmer's poverty situation.

² US\$1 = PRs 62.40 as of the 2008/01 average.

Table 13: The Effect of Khushhali Bank Membership on Household Well-Being and the MDGs. Average Treatment Effect on the Treated (ATT). Nearest-Neighbor Matching Method.

	No. of treated	No. of control	ATT	Standard errors	t-statistics
			<i>Household consumption</i>		
Monthly consumption expenditure, total	1204	663	-1021.4	968.1	-1.06
Monthly consumption expenditure per capita	1204	663	23.4	146.9	0.16
Monthly expenditure per capita - Food	1204	658	-33.0	78.7	-0.42
Monthly expenditure per capita - Non-food	1204	658	63.1	104.7	0.60
			<i>Agricultural production</i>		
Agricultural sales to third parties	1204	663	5755.8	8321.5	0.69
Inputs- amount of pesticide use	1204	663	0.2	0.1	2.19
Value of farm equipment	1204	663	12814.0	4812.9	2.66
Rental income from farm equipment	1204	663	882.5	434.8	2.03
			<i>Animal raising</i>		
Value of livestock	1204	663	17705.5	7995.4	2.21
Sales of livestock and products	1204	663	67399.3	24596.9	2.74
Annual inputs	1204	663	2451.1	2760.0	0.88
Profits	1204	663	6494.2	2438.3	2.66
			<i>Income transfers from outside</i>		
Household's 'outside' income	1204	663	-2014.7	3866.1	-0.52
			<i>Household durable assets</i>		
Quantity of consumer durables	1204	663	-0.1	0.8	-0.12
Value of household consumer durables	1204	663	-1262.0	58975.5	-0.02
			<i>Non-agricultural enterprise</i>		
Gross of capital assets	1204	663	7652.9	10714.4	0.71
Net capital assets	1204	663	7328.8	10782.2	0.68
Monthly inputs	1204	663	15683.8	26215.7	0.59
Sales	1204	663	3115.6	13841.8	0.23
Profits (reported)	1204	663	4779.9	6075.3	0.78
			<i>Savings and credit</i>		
Household savings	1204	663	-39.4	5080.9	-0.01
			<i>Education</i>		
Monthly expense per child	1204	658	-0.7	5.1	-0.13
School expenses per child	1204	663	-11.3	107.0	-0.11
School expenses per girl	1204	663	-14.9	44.6	-0.33
School expenses per boy	1204	663	15.0	97.7	0.15
			<i>Healthcare</i>		
Monthly healthcare expenditure per capita	1204	658	-2.0	26.0	-0.07
When ill, seek medical treatment	1204	663	0.1	0.1	2.00
Have funds to pay for medical treatment	1204	663	0.1	0.1	2.11
When ill with diarrhea, children given ORS	1204	663	0.0	0.0	0.17
Whether children under 5 vaccinated	1204	663	0.0	0.1	0.08
			<i>Empowerment</i>		
Women have a say in schooling matters	1204	663	-0.1	0.1	-0.98
Women have a say in health care	1204	663	-0.1	0.1	-1.23
Women's use of contraception	1204	663	-0.1	0.1	-1.78
Incidence of domestic violence	1204	663	0.0	0.0	1.49
			<i>Labor and child labor</i>		
Adult working hours on farm crop	1204	663	30.62	24.75	1.24
Adult working hours on animal raising	1204	663	24.91	19.56	1.27
Adult working hours on non-agricultural business	1204	663	-34.00	22.64	-1.50
Adult total working hours	1204	663	21.5	42.7	0.51
Child working hours on farm crop	1204	663	6.02	4.40	1.37
Child working hours on animal raising	1204	663	14.11	5.21	2.71
Child working hours on non-agricultural business	1204	663	-5.98	3.02	-1.98
Child total working hours	1204	663	14.14	8.28	1.71

Regarding consumption expenditures, KB members appear to spend less than nonborrowers—particularly on food—although the difference is not statistically significant. This may point to the fact that agriculture loans have led to increased on-farm food production, leading to borrowers spending less on food and more on non-food items than nonborrowers.

Borrowing from Khushhali Bank is not associated with higher durable assets and higher transfers from outside, which is consistent with the fact that the loans are largely for home enterprises, agriculture, and non-agriculture. With regard to non-agricultural enterprise activities, KB clients reported higher values of associated variables (e.g., value of assets, sales, and profit), none of which are significantly higher than nonborrowers. Contrary to most MFIs, since 74% of KB clients in the survey are agricultural households, many in remote areas, this finding simply reflects the low level of nonfarm activities in the communities.

The findings show that clients' households, both rural and urban, invested immediately in animal raising, which requires minimal skills and land. Contrary to lending programs of other MFIs where microenterprise financing is the main use of funds, the impacts of KB's program on microenterprise is yet to be significant, given the limited cycle of the loans and the predominantly agricultural households in the client profiles.

The results show that KB clients do not have significantly longer working hours in crop production and animal raising. The results suggest that there was a shift in labor use from non-agricultural activities to agricultural-related activities.

Since child labor is widespread in Pakistan, we were interested in assessing the impact of the microfinance program on child labor. The evidence in this respect is inconclusive. Similar to the pattern of adult labor use, there is an increase in working hours of children in animal raising along with a decline in child working hours in non-agricultural activities.

The impact of KB borrowing on the education of children (MDG 2) is not significant on any of the education indicators. Impacts on the empowerment of women (MDG 3) also are not significantly visible. Apart from the significantly higher possibility (10%) of KB-client household women using more contraception, other indicators are not significantly different. Women having a say in schooling matters, women having a say in healthcare, and the incidence of domestic violence are, in fact, better in nonborrowing households, although not significantly. The limited cycle of loans may explain these results.

With regard to healthcare (MDGs 4–6), KB membership has a positive impact on the possibility of households seeking medical treatment. The results also showed that the possibility of KB members having funds to pay for medical treatment is significantly higher than that of nonmembers.

With regard to the environment (MDG 7), the significantly higher amount of pesticide use among KB borrowers should be approached with caution. Among poor farmers, particularly illiterate farmers, inappropriate use of pesticides often leads to negative health outcomes and environmental consequences. The public sector, together with the Khushhali Bank may need to explore providing information or training programs such as the Integrated Pest Management Program to ensure that the loan does not lead to worsening health outcomes and negative environmental consequences.

In summary, we found that the microfinance program positively impacted some income-generating activities, such as agriculture and animal raising. We mostly failed to confirm the beneficial impact of Khushhali Bank on other outcome variables such as household durables, consumption, savings, education, and healthcare expenditures. These findings can be interpreted in two different ways. On the one hand, they might indicate that the impact of

Khushhali Bank lending on households' well-being (i.e., consumption, education, healthcare, and labor) is quite modest. On the other hand, it is possible that most of the KB borrowers are going through an initial phase of capital accumulation, when their increased income-generating capacities have not translated into increased consumption, education, and healthcare expenditures.

C. Impact of the Lending Program on Poor Households

To assess the impact of Khushhali Bank on the poor, we carried out the same analysis on a subset of poor households in the sample. (To distinguish the poor from the non-poor, we used the national poverty threshold of 878.6 PRs, deemed necessary to provide 2,350 calories per day). The results are shown in Table 14.

In total, 749 poor households who borrowed from Khushhali Bank were matched with 439 non-poor, non-KB borrowers. Table 14 shows that impacts of the KB lending program on poor households are essentially similar to the impacts on clients in general. The Khushhali Bank membership positively affects animal raising and agricultural activities. While the level of significance is similar for animal raising, the level of significance was less in agricultural production. With regard to non-agricultural enterprise, durable assets, consumption, education, healthcare, and empowerment, the impacts were not significant. Borrowing from KB led, notably, to a significant increase in the time spent on raising animals and a reduction in the time spent on non-agricultural enterprise for both adult and children.

**Table 14: The Impact of Khushhali Bank Lending on the Well-Being of the Poor.
Average Treatment Effect on the Treated (ATT). Nearest-Neighbor Matching Method.**

	No. of treated	No. of control	ATT	Standard errors	t-statistics
			<i>Household consumption</i>		
Monthly consumption expenditure, total	749	439	275.9	1029.5	0.27
Monthly consumption expenditure per capita	749	439	49.0	109.1	0.45
Monthly expenditure per capita - Food	749	439	15.8	28.9	0.55
Monthly expenditure per capita - Non-food	749	439	9.1	86.0	0.11
			<i>Agricultural production</i>		
Agricultural sales to third parties	749	439	12628.5	11304.7	1.12
Inputs- amount of pesticide use	749	439	0.2	0.2	1.45
Value of farm equipment	749	439	10913.3	5411.1	2.02
Rental income from farm equipment	749	439	833.1	482.0	1.73
			<i>Animal raising</i>		
Value of livestock	749	439	23371.7	10361.1	2.26
Sales of livestock and products	749	439	91883.1	33406.6	2.75
Annual inputs	749	439	3554.2	4189.6	0.85
Profits	749	439	8832.9	3332.2	2.65
			<i>Income transfers from outside</i>		
Household's 'outside' income	749	439	-3962.0	16466.4	-0.241
			<i>Household durable assets</i>		
Quantity of consumer durables	749	439	-0.3	1.1	-0.23
Value of household consumer durables	749	439	13025.4	62530.5	0.21
			<i>Non-agricultural enterprise</i>		
Gross of capital assets	749	439	4948.6	10573.2	0.47
Net capital assets	749	439	4668.9	10571.8	0.44
Monthly inputs	749	439	-4438.6	25772.4	-0.17
Sales	749	439	-4379.7	16754.8	-0.26
Profits (reported)	749	439	4350.7	4937.5	0.88
			<i>Savings and credit</i>		
Household savings	749	439	-1495.9	8030.6	-0.19
			<i>Education</i>		
Monthly expense per child	749	439	1.0	5.6	0.17
School expenses per child	749	439	48.4	131.6	0.37
School expenses per girl	749	439	2.2	57.0	0.04
School expenses per boy	749	439	54.3	113.1	0.48
			<i>Healthcare</i>		
Monthly healthcare expenditure per capita	749	439	24.0	33.1	0.73
When ill, seek medical treatment	749	439	0.1	0.1	0.82
Have funds to pay for medical treatment	749	439	0.1	0.1	1.46
When ill with diarrhea, children given ORS	749	439	0.1	0.0	1.23
Whether children under 5 vaccinated	749	439	0.1	0.1	1.37
			<i>Empowerment</i>		
Women have a say in schooling matters	749	439	0.0	0.1	0.27
Women have a say in health care	749	439	0.0	0.1	-0.56
Women's use of contraception	749	439	0.0	0.1	-0.55
Incidence of domestic violence	749	439	0.0	0.0	0.72
			<i>Labor and child labor</i>		
Adult working hours on farm crop	749	439	66.66	34.80	1.92
Adult working hours on animal raising	749	439	71.89	27.37	2.63
Adult working hours on non-agricultural business	749	439	-26.9	30.7	-0.88
Adult total working hours	749	439	111.6	57.9	1.93
Child working hours on farm crop	749	439	8.57	18.62	0.46
Child working hours on animal raising	749	439	15.41	7.51	2.05
Child working hours on non-agricultural business	749	439	-8.78	4.38	-2.01
Child total working hours	749	439	15.21	22.72	0.67

D. Robustness of Results

The Nearest-Neighbor Matching method, which we have used so far, is not the only method of assessing the average treatment effect on the treated. Other methods such as Radius Matching, Kernel Matching, and Stratification Matching have advantages and disadvantages; therefore, their joint consideration offers a way to assess the robustness of the results.

On the other hand, the smaller the neighborhood, the better the quality of the matches. With Kernel Matching, all treated are matched with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity scores of treated and controls. Table A.2 in the Appendix shows the results for the whole dataset obtained by the Kernel Matching method. Standard errors are obtained by bootstrapping, using 50 replications. The 1,204 borrower households are matched with 1,652 nonborrower households.

Compared to Nearest-Neighbor Matching, the results of the Kernel Matching method show the stronger impact of Khushhali Bank on the borrowers. The basic impacts in general remain unchanged; as before, there is strong impact on animal raising and agricultural production. In addition, there is a statistically significant positive impact of the microfinance program on the value of household durable assets, sales, and profits from non-agricultural family business. The other results remain essentially unchanged; thus, the findings are robust.

Results of Stratification Matching, presented in Table A.3 in the Appendix, show that borrowing from Khushhali Bank had a positive impact mainly on income-generating activities—agriculture, animal production, non-agricultural business, and healthcare. We find no significant impact of the lending program on household consumption, assets, savings, education, and female empowerment. The evidence on the other outcome variables such as adult and child labor is mixed.

E. Comparison of Results to an Earlier Study

As our study used the same dataset as, but adopted a different research methodology from, a previous study to assess the impacts of the KB program, in this section we compare the results of the two studies. In the previous study conducted by Montgomery (2005), it was assumed that the selectivity bias was addressed through the survey design and a series of OLS, and Logit Regression was run to assess impacts of different variables. In this study, we employed propensity score matching to correct for self-selection bias and estimate the impact of the Khushhali Bank lending program. The results on selected comparable variables are reported in Table 15.

The comparison of the results presented in Table 15 shows that while there are some common findings on some variables' impacts, the degree of significance differs. At the same time, the findings on certain variables' impacts are directly opposite. The Montgomery study found, for instance, that impacts on agricultural sales to a third party, sales and profit from microenterprise, health expenditure per capita, and amount of pesticide use are positive and significant at the 1% level while the P-Score estimates show the impacts in the same direction but at the lower significant level of 5%. The regression estimate showed positive but not significant impacts on sales and profit of livestock, while the PSM showed a significant impact at the 1% level. On the other hand, OLS estimates showed a significantly positive impact at the 5% level on "women have say in healthcare" and "health expenditure per capita" while PSM showed opposite but not significant results.

Montgomery (2005) reported that both access to and participation in the program had strong positive impacts on all variables tested for income generation. She showed that as the number of loan cycles increased, assets in terms of amount of land cultivated, value of farm equipment, and hours of tractor use increased significantly. There are two reasons, however, which suggest that those results were overestimated. Firstly, the loan size offered by KB is generally limited to 10,000 PRs. Given the small size of loan, even with repeated borrowing, it is questionable if it would have generated large amounts of income to purchase additional land and heavy farm equipment. Secondly, since 70% of the KB clients in the survey were first-time borrowers or borrowed only once, the larger size of cultivated land and the higher

value of farm equipment are most likely not the results of the borrowing from KB but reflections of the higher level of wealth among repeat KB clients.

**Table 15: Comparison of Impacts on Selected Variables
Two Methods of Impact Assessment**

<i>Variables</i>	OLS and Logit³		PSM	
	<i>Effect</i>	<i>Significance</i>	<i>Effect</i>	<i>Significance</i>
MDG 1				
Agricultural sales to third party	+	***	+	no
Amount of pesticide use	+	***	+	**
Value of farm equipment	+	***	+	***
Value of livestock	+	***	+	**
Sales of livestock and products	+	no	+	***
Profit from livestock	+	no	+	***
Sales from microenterprise	+	***	+	no
Profit from microenterprise	+	***	+	no
MDG 2				
School expense per child	-	no	-	no
MDG 3				
Women have say in children's schooling	+	***	-	no
Women have say in healthcare	+	**	-	no
Incidence of domestic violence			+	no
MDG 4-6				
Seek medical treatment when sick	+	**	+	**
Have funds to pay for medical treatment	+	**	+	**
Children vaccinated	+	no	+	no
Health expenditure per capita	+	**	-	no
MDG 7				
Amount of pesticide use	+	***	+	**
Notes:	"OLS and Logit" results of "Sales from microenterprise" and "Profit from microenterprise" are for urban sample.			
	** and *** indicate significance level of 5 and 1% respectively.			

Overall, the results of the PSM estimate showed a lower degree of impacts of KB's lending programs on the households. Given the fact that a selectivity bias does exist as shown in Table 9 in the earlier section, the comparison of the results confirm that running OLS and Logit Regression on the survey sample without correcting for selectivity bias led to overestimating of the impacts of KB's program on the households.

VII. CONCLUSION

Our review of microfinance contributions to the MDGs concludes that microfinance institutions have been effective in contributing, directly and indirectly, to all the eight MDGs. Microfinance contributes to improving income and reducing hunger (MDG 1), providing children school education and training (MDG 2), and paying for health services (MDG 4 – 6). The main beneficiaries of microfinance services are women, so MFIs contribute to women's empowerment and gender equality (MDG 3). As for the environment (MDG 7), MFIs are increasingly combining environmental programs with their financial services, although the contribution may be indirect. For MDG 8, since Target 12 calls for the development of open, rule-based, non-discriminatory financial systems, the expansion of microfinance programs

³ OLS and Logit results are taken from Montgomery (2005).

themselves is the achievement of MDG 8. The extent of microfinance impacts on each MDG, however, is context specific.

Our impact study on Khushhali Bank further provides concrete evidence of the pathways and degree of MFI impacts on the MDGs. The study confirms that KB has been effective, overall, in reaching out to the poor and has rapidly expanded its outreach to remote rural areas of Pakistan, consistent with the government's poverty alleviation program. Differing from most MFIs, which lend mainly to microenterprises and small traders, KB's lending is predominantly geared to agricultural households with limited microenterprise activities.

Using the PSM to address the selectivity bias generally existent in surveys of this nature, we found that Khushhali Bank's lending program contributes significantly to income generation activities such as agricultural production and, in particular, animal raising (MDG 1).

The impact of the program appears to have limited significance on other MDGs—education, health, female empowerment, and so forth. This is due in part to the fact that two-thirds of KB clients are from agricultural households in poor communities with limited nonfarm activities. In addition, since 70% of KB clients in the survey were first-time borrowers and went through only one loan cycle, it is not surprising that the impacts on other MDGs are yet to be realized.

Highly significant is the borrowing households' increased use of pesticides. While pesticides lead to improved productivity and income, inappropriate use may lead to negative outcomes on health and the environment. With globalization's increased requirements for food safety standards in the export market, it is recommended that Khushhali Bank collaborate with extension agencies to make available to their clients integrated pest management (IPM) and training and information on the appropriate use of pesticides.

It could be said that an impact study of this nature on Khushhali Bank in 2005 may have been premature as a majority of the clients went through only one cycle of borrowing. At the same time, it is remarkable to note that only with a loan of 10,000 PRs (US\$150), these households could improve their agricultural income significantly. The income generated will, no doubt, eventually lead to the development of nonfarm enterprise and overall development of the rural communities.

In the aspect of methodology, this study points to several lessons for future impact studies. Despite KB's strict poverty-targeting program used in client selection and despite the survey's design to address the selectivity bias, our study found that selectivity bias indeed still existed in the sampled households. The fact that MFIs tend to lend to clients of better-off households is not surprising since achieving financial sustainability is an important aspect of microfinance operations. When it comes to reviewing results of impact studies, one must first interpret impact studies that do not take into consideration program-placement bias and self-selection bias. It is noteworthy that the PSM technique resulted in different outcomes when compared to that of OLS or Logit estimation used by Montgomery. The difference is especially noticeable in the case of income generation, education, and female empowerment. In addition, impact studies that use cross-sectional data might be prone to incorrect inference. Since the impacts of microfinance programs are spread over a period of time, the element of time should be included to reflect the true impact of microfinance.

References

- Alexander-Tedeschi, G., and D. Karlan, 2002. *Microfinance Impact: Bias from Dropouts*. Connecticut: Yale University.
- Armendariz, B., and J. Morduch. 2005. *The Economics of Microfinance*. Cambridge: MIT Press.
- Barnes, C., and G. Gaile, et al. 2001. *The Impact of Three Microfinance Programs in Uganda: USAID/Uganda*. Washington, D.C.: AIMS.
- Chen, M. A., and D. Snodgrass. 2001. *Managing Resources, Activities, and Risk in Urban India: The Impact of SEWA Bank*. Washington, D.C.: AIMS.
- Cheston, S., and L. Kuhn. 2002. *Empowering Women Through Microfinance*. New York: UNIFEM.
- Chowdhury, A.M.R., and A. Bhuiya. 2001. *Do Poverty Alleviation Programmes Reduce Inequity in Health: Lessons from Bangladesh*. Quoted in *Poverty Inequity and Health*, eds. D. Leon and G. Walt. Oxford: Oxford University Press.
- Chowdhury, M.J.A. 2004. *Poverty and Microfinance in the Philippines*. Bangladesh: University of Dhaka.
- Coleman, B. E. 1999. *The impact of group lending in Northeast Thailand*, *Journal of Development Economics*, Vol. 60, Issue 1, Pages 105-141
- . 2006. *Microfinance in Northeast Thailand: Who benefits and how much?*, *World Development*, Vol. 34, Issue 9, Pages 1612-1638
- Dehejia, R.H., and S. Wahba. 2002. Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics* 84 (1): 151–161.
- Friedlander, D., D.H. Greenberg and P.K. Robins. 1997. *Evaluating Government Training Programs for the Economically Disadvantaged*, *Journal of Economic Literature*, American Economic Association, Vol. 35(4), Pages 1809-1855.
- Gonzalez-Vega, C., M. Schreiner, R.L. Meyer, J. Rodriguez-Meza, and S. Navajas. 1997. BancoSol: The Challenge of Growth for Microfinance Organizations. pp. 129–170 in Hartmut Schneider (ed.), *Microfinance for the Poor?*, Paris: OECD
- Hashemi, S., S. Schuler, et al. 1996. Rural Credit Programs and Women's Empowerment in Bangladesh. *World Development* 24 (4): 635–53.
- Heckman, J., H. Ichimura, and P. Todd. 1998. Matching as an Econometric Evaluation Estimator. *Review of Economic Studies* 65 (223): 261–294.
- Hulme, D. 1999. Client Drop-outs from East African Microfinance Institutions. *MicroSave*.
- Karlan, Dean. 2001. Microfinance Impact Assessments: The Perils of Using New Members as a Control Group. *Journal of Microfinance* 3 (2): 75-85.
- Littlefield, E., J. Morduch, and S. Hashemi. 2003. *Is Microfinance an Effective Strategy to Reach the Millennium Development Goals?* Washington, D.C.: CGAP.

- MkNelly, B. and C. Dunford. 1998. "Impact of Credit with Education on Mothers and Their Young Children's Nutrition (Ghana)."
- . 1999. "Impact of Credit with Education on Mothers and Their Young Children's Nutrition (Bolivia)."
- Montgomery, H. 2005. *Meeting the Double Bottom Line – The Impact of Khushhali Bank's Microfinance Program in Pakistan*. Tokyo: ADBI.
- Panjaitan-Drioadisuryo, R. D. M., and K. Cloud. 1999. Gender, Self-Employment and Microcredit Programs: An Indonesian Case Study. *The Quarterly Review of Economics and Finance* 39: 769–79.
- Rosenbaum, P. R. 2004. *Matching in Observational Studies*. Quoted in *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*, eds, A. Gelman and X-L Meng (pp. 15-23). Hoboken: Wiley.
- , and D.B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70 (1): 41-55.
- . 1984. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70 (1): 41-55.
- . 1985. Constructing a Control Group using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *The American Statistician* 39 (1): 33-38.
- Rubin, D.B. 1974. Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology* 66: 688-701.
- Schuler, S. R., and S. M. Hashemi. 1994. Credit Programs, Women's Empowerment, and Contraceptive Use in Rural Bangladesh. *Studies in Family Planning* 25 (2).
- Sengsourivong, K. 2006. *The Impact of Microfinance on Household Welfare: Case Study of a Savings Group in Lao PDR*. Kobe: Graduate School of International Cooperation Studies, Kobe University.
- Simanowitz, A. 2003. *Appraising the Poverty Outreach of Microfinance: A Review of the CGAP Poverty Assessment Tool (PAT)*. Occasional Paper 1. Imp-Act, Institute of Development Studies.
- UNICEF. 1995. *Evaluation Study of the Small Farmer Development Programme, UNICEF Nepal*. Available: <http://www.unicef.org/credit>.
- UNICEF. 1996. *An Evaluation of Credit Mechanisms and Impact, UNICEF Viet Nam*. Available: <http://www.unicef.org/credit>.
- Zaman, H. 2000. *Assessing the Poverty and Vulnerability Impact of Micro-Credit in Bangladesh: A Case Study of BRAC*. Washington, D.C.: The World Bank.

Appendix 1

Table A.1: Descriptive Statistics for Variables

Variable	Obs.	Mean	Std.Dev.	Min.	Max.
Age of household head	2881	44.81	14.47	0	135
Dummy for holding office	2881	0.16	0.37	0	1
Dummy for rural	2881	0.75	0.44	0	1
Dummy for adult literacy	2881	0.74	0.44	0	1
Dummy for adult numeracy	2881	0.84	0.37	0	1
Dummy for poor	2881	0.63	0.48	0	1
Dummy for land ownership	2884	0.32	0.47	0	1
Distance to nearest town	2884	9.16	13.84	0	97
Dummy for non-KB borrowing	2884	0.18	0.38	0	1
Dummy for female	2881	0.22	0.41	0	1
Monthly consumption expenditure, total	2881	9559.2	8998.4	1532	246470
Monthly consumption expenditure per capita	2881	1720.3	1551.8	0	44812.7
Monthly expenditure per capita - Food	2859	863.8	555.7	0	8990.46
Monthly expenditure per capita - Non-food	2859	772.9	1316.2	38.1	41969.7
Agricultural sales to third parties	2881	24453.5	76306.6	0	1300000
Inputs- amount of pesticide use	2881	0.29	0.46	0	1
Value of farm equipment	2881	10745.2	63604.0	0	939200
Rental income from farm equipment	2881	635.9	8948.4	0	200000
Value of livestock	2881	39256.5	73610.5	0	1200000
Sales of livestock and products	2881	88328.6	712289.0	0	27000000
Annual inputs	2881	6443.8	17555.8	0	513000
Profits	2881	81884.8	710166.0	-51300	2700000
Household's 'outside' income	2881	8915.3	47955.2	0	2000000
Quantity of consumer durables	2881	6.6	6.4	0	75
Value of household consumer durables	2881	194270.0	414494.0	0	9000000
Gross of capital assets	2881	17180.9	78757.9	0	1200000
Net capital assets	2881	16766.2	77827.8	-281000	1000000
Monthly inputs	2881	51840.1	328586.0	0	14000000
Sales	2881	37437.7	109191.0	0	1000000
Profits (reported)	2881	13540.4	45040.2	0	700000
Household savings	2881	2439.5	26046.3	0	900000
Monthly educational expense per child	2859	24.6	38.8	0	511.167
School expenses per child	2881	630.7	897.6	0	11900
School expenses per girl	2881	172.6	377.6	0	7933.33
School expenses per boy	2881	464.6	773.2	0	9910
Monthly healthcare expenditure per capita	2859	96.9	274.6	0	8333.33
When ill, seek medical treatment	2881	0.60	0.49	0	1
Have funds to pay for medical treatment	2881	0.52	0.49	0	1
When ill with diarrhea, children given ORS	2881	0.11	0.30	0	1
Whether children under 5 vaccinated	2881	0.45	0.47	0	1
Women have a say in schooling matters	2881	0.59	0.49	0	1
Women have a say in health care	2881	0.65	0.48	0	1
Women's use of contraception	2881	0.22	0.42	0	1
Incidence of domestic violence	2881	0.07	0.25	0	1
Adult working hours on farm crop	2881	120.2	245.8	0	3330
Adult working hours on animal raising	2881	121.1	214.0	0	3810
Adult working hours on non-agricultural business	2881	70.4	183.6	0	4800
Adult total working hours	2881	311.6	415.3	0	6720
Child working hours on farm crop	2881	11.9	67.1	0	1980
Child working hours on animal raising	2881	14.4	86.9	0	3600
Child working hours on non-agricultural business	2881	1.4	17.8	0	416
Child total working hours	2881	27.7	119.8	0	3600

