ABSTRACT

Micro-Credit and Household Productivity: Evidence from Bangladesh

Emily W. Kerr, M.S.Eco.

Mentor: Pham Hoang Van, Ph.D.

This paper tests the effect of micro-credit on household productivity to determine whether micro-credit programs facilitate productivity gains through skills transfer and human capital formation in addition to the provision of credit. The data come from two rounds of household surveys in rural Bangladesh conducted by the World Bank and the Bangladesh Institute of Development Studies to analyze the impact of three micro-credit programs: the Rural Development-12 program of the Bangladesh Rural Development Board, the Bangladesh Rural Advancement Committee, and Grameen Bank. Controlling for macro events and household and village characteristics, I find that participating in a micro-credit program increases output per unit labor for household non-farm enterprises in a large and statistically significant way. These increases in productivity can provide the means for sustained improvements in standard of living and contribute to the economic growth of low-income countries.

Micro-Credit and Household Productivity: Evidence from Bangladesh

by

Emily W. Kerr, B.B.A.

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Approved by the Department of Economics

____
Steven L. Green, Ph.D., Chairperson

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Approved by the Thesis Committee

____
Pham Hoang Van, Ph.D., Chairperson

____
A. Scott Cunningham, Ph.D.

____
Amanda F.C. Sturgill, Ph.D.

Accepted by the Graduate School
May 2009

____
J. Larry Lyon, Ph.D., Dean

Page bearing signatures is kept on file in the Graduate School.

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LIST OF ABBREVIATIONS

BIDS	Bangladesh Institute of Development Studies
BRAC	Bangladesh Rural Advancement Committee
BRDB	Bangladesh Rural Development Board’s Rural Development-12 program
MCP	Micro-Credit Program
NFE	Non-Farm Enterprise

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CHAPTER ONE

Introduction

Micro-credit programs serve to meet the credit needs of the rural poor in an effort to help them become self-employed in some form of income-generating activity and lift themselves out of poverty. Their explicit objective is poverty reduction and their means of success is providing a small amount of credit that when combined with the existing skills of the poor and the opportunity in the market will result in economic advancement. Micro-credit serves to increase the productive capacity of the poor and allow borrowers to improve the welfare of their households. This paper adds to the growing literature on the impact of micro-credit impact by testing the effect of micro-credit on household productivity.

Overview of Micro-Credit

The concept of micro-credit is simple: small loans distributed by micro-credit programs allow the rural poor to become self-employed and generate the income necessary to improve their household's welfare. Developed by Nobel Peace Prize recipient Muhammad Yunus, this model for poverty alleviation stems from the notion that the financing of small enterprises can lead to economic advancement for the rural poor. In his home country of Bangladesh, Yunus created the pilot micro-credit program Grameen Bank in 1983.[1] Grameen Bank has been remarkably successful in improving the socio-economic status of its disadvantaged members and has cast great attention on micro-credit as an effective tool for reducing poverty. Its success caused such rapid growth that by 2006 Grameen Bank had opened over 2,000 branches in rural Bangladesh serving a total of 7 million active clients.

[1] Grameen means "rural" or "village" in Bangla language. Source: grameen-info.org.

Over 90 percent of Grameen Bank borrowers are women and the newfound role of women as income-earners is transforming the gender relations in Bangladesh and creating social respect and dignity for rural women (Kelkar, Nathan and Jahan 2004). The micro-credit model pioneered by Grameen Bank has been replicated by thousands of micro-credit programs across the world. In 2006, 3,316 of such programs submitted reports to the Microcredit Summit Campaign revealing that over 133 million clients were being reached by these micro-credit programs alone and that 70 percent of clients were among the poorest of the poor when they received their first loan (Daley-Harris 2007). [2]

The Micro-Credit Model

Although there is some variation in the way micro-credit programs operate, most follow a very similar model. Micro-credit programs typically target the rural landless poor, focus predominantly on women, follow a group-based lending model, and incorporate some level of non-financial services. These programs strive to generate self-employment as well as aid the productivity and welfare of participating households.

The rural landless poor are often the poorest subgroup of a low-income country's population and thus a primary focus for the targeted credit provided by micro-credit programs. These programs concentrate on generating non-farm self-employment for the rural landless poor to help move them away from the stagnant agricultural sector. In Bangladesh, a representative low-income country, 67 percent of the rural population lacking land ownership is poor, which is a much higher incidence of poverty than the 40 percent estimate for the total population (BBS 2006). Also, the rural landless poor have the most restricted access to formal credit with only 7 percent of households having access (Hossain 1988). An early

[2] The Microcredit Summit Campaign defines "poorest" as those living on less than US$1 a day.

study affirmed the validity of targeting of landless poor by showing that micro-credit's positive effect on income was greatest for landless households (Hossain 1988).

Micro-credit programs typically place a strong emphasis on providing credit to women. Relatively few rural women are gainfully employed and thus can benefit greatly from becoming self-employed at or near their home. The additional income earned by women and the increased labor force participation has positive economic effects. The income-generation serves to empower the women and increases their participation in household decisions, which allows them to take a more proactive role in taking good care of the family. Another reason for targeting women is the proven notion that female credit is more likely to influence the welfare of the family. Credit provided to women has twice the impact on household consumption than credit provided to men and has a significantly greater impact on household wellbeing, such as child nutrition and schooling (Pitt and Khandker 1998, Pitt *et al.* 2003).

The group-based lending model is what sets micro-credit apart from the traditional banking system. The exact policy varies between programs, but most follow a very similar credit delivery system. Borrowers form small groups, typically between five and ten people each, and group members share joint responsibility for the individual loans. If one member defaults on his or her loan, other group members become ineligible to receive further loans until the defaulting member pays what is owed. This unique system substitutes a form of peer pressure for physical collateral as security for the loan and minimizes information asymmetries. Initial loan amounts are quite low, typically less than US$150, and borrowers are eligible for subsequent loans of increasing amounts provided they maintain a successful repayment record. This model has proven to be very successful as the majority of micro-credit programs boast a loan recovery rate of well over 90 percent (Khandker 1998).

Loan periods are typically one-year with weekly or bi-weekly installments to keep repayment amounts very low. Micro-credit programs charge interest rates that are at or even above market rates in order to cover their high costs, and interest is usually paid at the end of the loan cycle. In Bangladesh, for example, micro-credit programs charge annual interest rates of 20 percent, which is 4 percent higher than the bank rate of 16 percent. However, the micro-credit borrowers typically do not have access to credit provided by traditional banks so the 20 percent interest rate is more sensibly compared to the 85 percent interest rate charged by their only alternative, informal moneylenders (Khandker 1998).

Non-financial aspects such as skills training and social development are typically included in the credit delivery process. Serving to promote productivity as well as household welfare, these aspects play an integral role in micro-credit's positive impact. Many programs provide organizational help, sector-specific training, and literacy and numeracy education to help facilitate the move to non-farm self-employment and increase productive capacity. Such skills development is widely regarded as a necessary instrument of a pro-poor strategy and Bennell (1999) asserts that skills training for the economically disadvantaged should serve to meet the specific work needs of the poor. In order to raise awareness for social issues and welfare-related topics, many micro-credit programs also educate members in areas such as children's health, the importance of education, family planning, and nutrition. These non-financial features are what make micro-credit a comprehensive tool for poverty reduction and economic growth.

Micro-Credit in Bangladesh

Bangladesh Country Profile

Bangladesh is among the poorest and most densely populated countries in the world and leads the growing set of low-income countries offering micro-credit. As in many poor countries, poverty in Bangladesh stems from unemployment, high population growth, and low productivity. A closer look at the economic struggles of Bangladesh will offer insight into low-income countries in general and will provide a background for how micro-credit can be an effective tool for poverty alleviation and economic growth around the world.

Upon gaining its independence from Pakistan in 1971, Bangladesh was an overpopulated country with almost three-quarters of the population living below the poverty line (Hossain and Sen 1992). Over the past few decades, however, Bangladesh has made astounding progress. Poverty rates declined to 40 percent by 2005, with nearly one-quarter of the decline occurring since 2000 (BBS 2006). Figure 1 shows regional poverty rates for Bangladesh from 1991/92 to 2005. During the 1990s Bangladesh was able to bring the annual population growth rate down to 1.5 percent which is half its 1971 level. Since 1971, Bangladeshi life expectancy has risen 14 years, infant mortality has declined by 70 percent, literacy has doubled, and the gender disparity in primary and secondary education has disappeared (World Bank 2007).

The development gains of Bangladesh, especially those realized in the last decade and a half, can be largely attributed to income growth. Bangladesh's per-capita inflation-adjusted Gross Domestic Product (GDP) is now more than double what it was in 1975. Productive reforms, deregulation, and political democratization in the 1990s gave the GDP annual growth rate a boost from its previous 1.2 percent level to an impressive 3.3 percent which is three times as high as the median low-income country. The per-capita Gross National Income

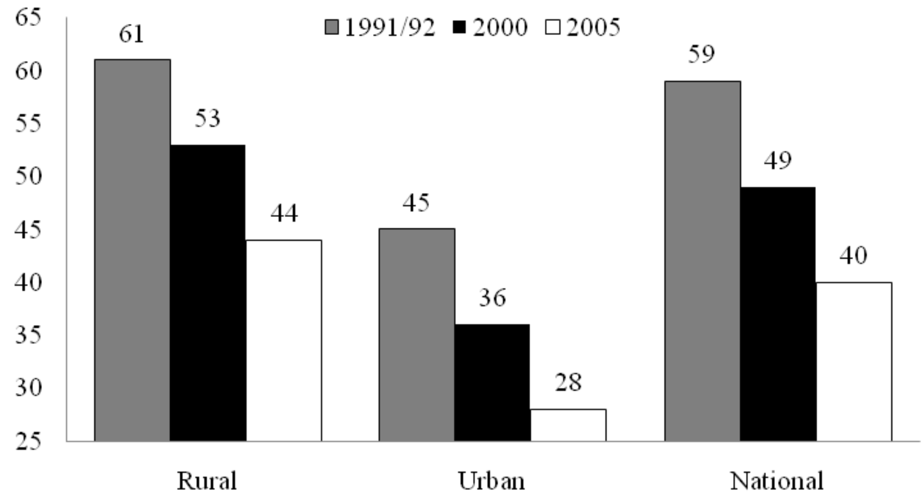

Figure 1. Headcount of Poverty (%) in Bangladesh, by Residence, 1991/92 to 2005
Source: Household Income and Expenditure Surveys, Bangladesh Bureau of Statistics.

(GNI) of Bangladesh reached US$470 in 2005 and if the economy continues to sustain such high levels of growth, Bangladesh's per-capita GNI could reach that of a middle-income country within fifteen years (World Bank 2007).

Although the advancement is notable, there is still much progress to be made in Bangladesh. Income inequality persists, fertility rates remain high, nearly half of the population is considered illiterate, absolute poverty numbers continue to be high and unchanged, and malnutrition pervades as the level of underweight children remains among the highest in the world (World Bank 2002).

Also of great concern is the high proportion of Bangladeshis that live in the countryside. In the year 2005, over 75 percent of the population and over 92 percent of the poor live in rural areas where agriculture is the predominant activity (BBS 2006). The cultivatable land in Bangladesh faces high pressure as the population continues to grow and as agricultural land is diverted for urban use. The shrinking land base and lack of agricultural diversification are major constraints on economic growth for the rural sector. The generation of non-farm employment in the rural areas of Bangladesh is a necessary strategy for continued economic development and poverty reduction (World Bank 2007, 2002).

Setting the Stage for Micro-Credit

The lack of productive employment, especially for the rural poor, is a major issue in most low-income economies as it hinders both growth and poverty alleviation. Promoting gainful employment opportunities particularly in the non-farm sector is essential for economic expansion. This is especially true in Bangladesh. According to the World Bank (2002), "The non-farm rural economy – composed of trade, transport, manufacturing, processing, retail sales and services and the like – holds significant potential for further, strong growth. Accordingly, poverty-reduction policies will need to capitalize on that growth potential." Much of the activity in this sector is in the form of small or medium-sized household enterprises. These enterprises, which already employ over 1.7 million people in rural Bangladesh, have a direct impact on poverty and hold significant growth potential (World Bank 2002).

The promotion of non-farm enterprises for the rural poor has its difficulties. Poor entrepreneurs have only their inheritance or household savings to use as capital, which is often insufficient. Credit is crucial for the establishment or expansion of even a small enterprise, but the poor rarely have access to traditional financial services because of their lack of physical collateral. Two-thirds of enterprise-operating households claim that inadequate access to credit is their biggest constraint (World Bank 2002). Increasing access to credit for the rural poor should be at the forefront of a pro-poor economic growth strategy.

As in many low-income countries that lack natural resources, Bangladesh's chief asset is labor. Because the agricultural sector is saturated and the urban sector remains too small to provide much additional employment, creating non-farm self-employment opportunities is the most effective strategy for utilizing the abundant labor supply. The female labor force is markedly underutilized and thus Bangladeshi micro-credit programs focus predominantly on women. The labor participation rate of women in Bangladesh is quite low, often due to cultural restrictions that keep women from seeking wage employment. In 2005, over 70 percent of rural women were unpaid family workers (BBS 2008). Figure 2 shows labor force participation for women in rural Bangladesh in 2005. The provision of credit allows these women to become gainfully self-employed and bring additional income into the household.

Figure 2. Distribution of Female Labor Force in Rural Bangladesh (%), by Employment Status, 2005. Source: 2005-2006 Labour Force Survey, Bangladesh Bureau of Statistics.

Scope and Impact

Bangladesh is at the forefront of widespread micro-credit opportunity. In 2004, 582 micro-credit programs operated in Bangladesh serving 14.3 million active borrowers. The outstanding loan portfolio for these programs totaled over US$1.3 billion. This large micro-credit sector reaches 37 percent of Bangladeshi households, which is among the highest coverage in the world (World Bank 2005). The wide scope of micro-credit in Bangladesh has allowed rural entrepreneurs to acquire the capital necessary to start or expand their non-farm enterprises, as one-quarter of such enterprises reported having access to credit (World Bank 2007).

The gainful non-farm employment generated by the access to credit has far-reaching benefits. In low-income countries where agriculture dominates the employment industry, it is vital to shift the rural population away from agricultural labor which is typically the least productive sector in the economy and usually has the highest incidence of poverty. Figure 3 shows the difference in poverty rates among various occupations for households in Bangladesh, illustrating the disparity between agricultural laborers and self-employed entrepreneurs. Because traditional urbanization efforts are typically slow-moving, providing the means for rural residents to generate non-farm self-employment allows this section of the population to actively participate in economic growth. Also, the generation of new rural enterprises and the expansion of existing ones bring employment benefits in the form of income for the entrepreneur as well as wages for any hired workers. The participation in non-farm enterprises helps households diversify their income which reduces their reliance on seasonal agricultural employment and smoothes their consumption (World Bank 2002).

Micro-credit has its share of shortcomings, however. Khandker (1998) enumerates several such limitations. The benefits of micro-credit may only be experienced by the segments of the poor that are able to use the small loans in a productive way. The poor who lack human capital may not be able to successfully assume the risks associated with self-employment and tend not to participate in or benefit from micro- credit programs. For these people, programs supporting wage employment such as those that focus on and invest in labor-intensive industries might be more suitable. Also, many micro-credit programs rely on

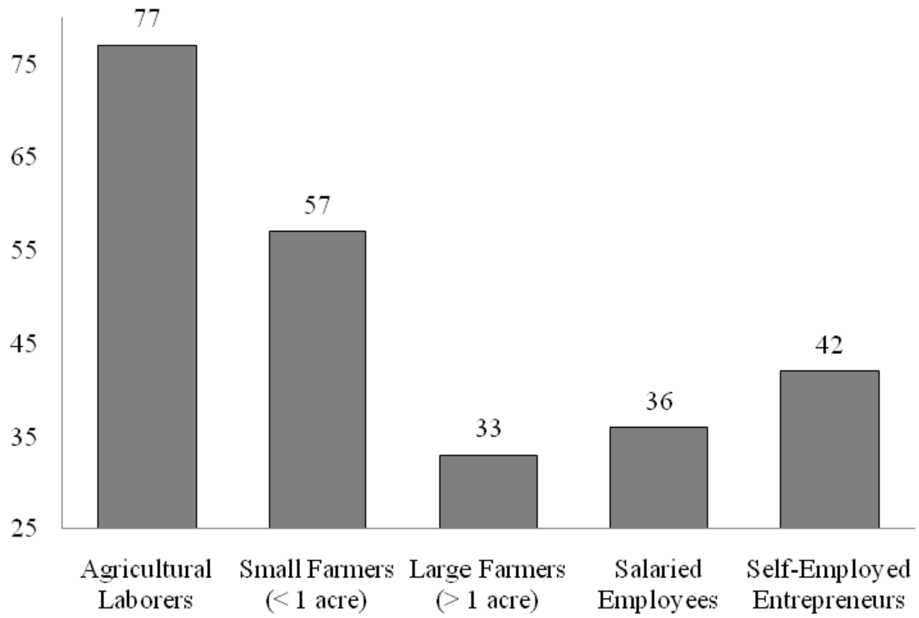

Figure 3. Headcount of Poverty (%) in Bangladesh, by Occupation of Household, 2000
Source: World Bank Report No. 31846-BD, World Bank.

subsidies to cover the high costs associated with lending to the poor. Thus, the benefits of micro-credit must be weighed against its costs to determine if it is cost-effective in its mission to reduce poverty. In some cases, it may be that other poverty-alleviation programs are better suited to efficiently serve the needs of the poor (Khandker 1998).

Organization of Paper

Chapter Two reviews the previous literature that has empirically studied the impact of micro-credit, focusing on the research studies that are at the forefront of micro-credit analysis. I discuss the statistical methods used in these studies and the methodological issues associated with each analysis, in addition to describing the results. I then describe how the focus on household welfare outcomes has resulted in the exclusion of the analysis of one important micro-credit outcome: household productivity. I use the explicit objectives of micro-credit programs and the emphasis placed on human capital formation to motivate my current research, which examines the impact of micro-credit on household productivity.

Chapter Three describes the data I use in my empirical analysis, discusses my estimation strategy, and details my results. In this section I review the issues associated with micro-credit program evaluation and describe how I treat such problems. I also explain how I measure household productivity and how I proxy for micro-credit participation, as well as enumerate the data I use as control variables. I use several specifications to test the effect micro-credit has on household productivity and I motivate the use of each one as well as describe their results.

Chapter Four discusses the findings of this study and draws conclusions regarding the impact of micro-credit on household productivity. In this chapter I also make suggestions for further research.

CHAPTER TWO

Literature Review

Previous Research

Numerous studies have been conducted to measure the overall success and impact of micro-credit programs, but few have addressed the selection and endogeneity issues associated with determining the true effect of program participation. The availability of pertinent data constrains the statistical analysis of micro-credit impact. However, a set of household surveys conducted by the World Bank and the Bangladesh Institute of Development Studies (BIDS) during the 1990s in Bangladesh has provided the first comprehensive dataset to be used to measure the impact of three major micro-credit programs, including Grameen Bank.

Pitt and Khandker (1998) were among the first to use the initial World Bank-BIDS survey data from Bangladesh, collected in 1991/92, to empirically test the impact of micro-credit on various measures of poverty such as household consumption expenditure and children's schooling. A village-level fixed-effects model was used to correct for endogeneity issues associated with the non-random nature of micro-credit program placement and the unmeasured village characteristics affecting outcomes. Endogeneity issues associated with unobserved household-level characteristics (such as innate ability or attitudes) persisted, however, and may have affected both program participation and household outcomes. A weighted exogenous sampling maximum likelihood – limited information maximum likelihood – fixed effect (WESM-LIML-FE) was used to determine the effects of program participation, which was measured as the quantity of credit borrowed from the micro-credit programs under analysis. Pivotal to the study was instrumentation using the land-based eligibility requirement for micro-credit programs. The authors found that an additional 1 taka borrowed by women increases annual household consumption expenditure by 0.18 taka at the mean.[1] The increase in expenditure is 0.11 taka for the same increase in borrowing by men. A 1 percent increase in women's borrowing from Grameen Bank increased the likelihood of girls' and boys' school enrollment by 1.9 and 2.4 percent, respectively. Credit provided to men had no statistically significant impact on girl's school enrollment but increased boys' school enrollment by 0.4 percentage points more than credit provided to women. Overall, Pitt and Khandker (1998) determined that micro-credit has a significant impact on household outcomes and that women's borrowing is more likely to positively affect these outcomes than borrowing by men.

Pitt and Khandker (2002) used the same data and econometric methods as their 1998 study to examine the effect of micro-credit on consumption smoothing, utilizing the 1991/92 survey data that was collected from households during each of the three cropping seasons in Bangladesh. They found that credit's largest effects on consumption expenditure were during the leanest cropping season, asserting that micro-credit allows households to smooth consumption by diversifying their income sources away from agriculture.

Pitt *et al.* (2003) applied a maximum likelihood estimation to the 1991/92 Bangladesh survey data to determine the effect micro-credit has on children's health status. They utilized anthropometric data collected on all children under the age of 15 in the villages under survey and found that a 10 percent increase in female credit increases daughter's arm circumference by 6 percent and increases height-for-age of both daughters and sons by over 1 percent. This

[1] The taka is the currency of Bangladesh. 2008 Exchange Rate: $1 US = 68 taka. Source: US Department of the Treasury.

suggests the incidence of child malnutrition is lower among participating households. Male credit effects were not statistically significant for any measure of children's health.

Khandker and Chowdhury (1996) used the 1991/92 World Bank/BIDS survey data from Bangladesh to test the impact of micro-credit on poverty levels. They found that the poverty rate of Grameen Bank participants who had taken one loan or less was 76 percent, whereas only 57 percent of participants who had taken at least five loans were below the poverty line. This indicates that there was a 4 percent per year reduction in poverty among participants of Grameen Bank.

Morduch (1998) took issue with the econometric model used in the aforementioned studies citing serious issues with their control framework and how they handled the survey data from Bangladesh. The previous studies implemented a regression discontinuity design using the maximum landholding eligibility requirement for micro-credit program participation. This approach would allow clean impact results of micro-credit on households clustered just above or below the landholding cut-off only if household landholding is exogenous and the maximum landholding requirement is strictly enforced. Morduch argued that neither condition is met in the sample data and therefore the results using this technique are biased. The previous studies using the 1991/92 Bangladesh dataset asserted that land sales are low in South Asia as land was acquired mainly by inheritance, thus landholding was exogenously determined. Morduch, however, found substantial land purchases occurring in the households under study, indicating that landholding may not be exogenous. Morduch also found that 20 to 30 percent of micro-credit participants have landholding in excess of the half-acre maximum set by all three programs under study. This poses a comparison problem as the landholding restriction was imposed strictly on the survey households that had no access to micro-credit programs. Therefore, asymmetry issues exist between the treatment and control groups and the richer households (with landholding in excess of half an acre) that participate in micro-credit programs may bias the impact results upwards.

Using the land data provided by the 1991/92 Bangladesh household survey, Morduch (1998) examined the same household outcomes as the Pitt and Khandker studies but applied strict eligibility definitions and excludes households that are micro-credit participants but exceed landholding eligibility requirements. Implementing a difference-in-difference strategy, Morduch found no statistically significant evidence that micro-credit programs increase consumption or children's school enrollment relative to control villages. He did, however, find evidence that access to micro-credit programs diversified labor supply and income across agricultural seasons which led to consumption smoothing for households. The treatment framework used in this study is not without its own faults, as issues arise in how to measure landholdings for micro-credit participants who accumulated land subsequent to joining the program. If measured using current landholdings, a household that joins a micro-credit program and successfully increases its income and chooses to increase its landholding will be removed from the treatment group, biasing micro-credit impacts downwards. Measuring landholding using data from when the household initially joined the program would provide more favorable outcomes to micro-credit but such estimates might be biased upward. Pitt wrote a response to Morduch (1998) arguing Morduch misunderstood and misinterpreted the methodology used in Pitt and Khandker (1998) and used erroneous methods to obtain his results.[2]

When a second household survey was conducted by the World Bank and BIDS in 1998/99 revisiting the same Bangladeshi households surveyed in 1991/92, Khandker was able to improve on the initial studies. Using the newly available panel data, Khandker (2005)

[2] Pitt's response paper is available online at www.pstc.brown.edu/~mp.

more accurately tested the impact of micro-credit without relying on land-based eligibility as an instrument. Since the data include more than one observation for each household, a household-level fixed-effects model was used which Khandker argued corrects for both household-level and village-level endogeneity issues, assuming the unobserved household and village characteristics remained fixed over time. The results showed that cumulative female borrowing increased per capita household consumption by more than 20 percent on average. Extreme poverty rates among eligible program participants decreased 20 percent from 1992 to 1999, which was 5.6 percent more of a decline than for eligible non-participants in the same villages during the same period. The yearly reduction in poverty rates among program participants was 3 percent and more than half of that decline was found to be attributable solely to micro-credit. Spillover effects of micro-credit reached non-participants in program villages and poverty was reduced by 1 percent per year at an aggregate level, signifying that 30 to 40 percent of the overall reduction in poverty in these rural Bangladeshi villages could be attributed to micro-credit. The study followed Morduch (1998) and excluded borrowing households that exceeded the landholding eligibility requirement as a robustness test and found that results were not sensitive to whether those households were included or excluded.

Motivation for Research on Productivity

Most previous research has focused predominately on welfare outcomes for households that participate in micro-credit programs. Such analyses show how the additional, diversified income generated by the non-farm self-employment opportunities facilitated by micro-credit can be used to better the lives of the participating poor. However, one outcome yet to be examined is the effect of micro-credit participation on household productivity. Are participating households able to be more lucrative with the time they dedicate to their self-employment activities as a result of their micro-credit involvement? To examine the impact of micro-credit on productivity is to examine the potential that participating households have for sustained improvements in their livelihoods and lasting impacts on their welfare.

Micro-credit programs incorporate skills-based training which fosters human capital formation among participants. Also, the group-based nature of the lending format facilitates interaction between members which allows them to benefit from one another's experience and knowledge. Both of these facets of the micro-credit model exist to promote the productive capacity of the poor, which is essential to their own economic advancement. It is important to test if these non-financial aspects of micro-credit are providing productivity gains that go above and beyond the productivity gains achieved by using credit to increase inputs. This would show that micro-credit increases the total factor productivity of a household, which has revenue benefits that transcend the credit itself.

Some researchers have studied the effect of micro-credit involvement on household income, production, and profits but have yet to focus exclusively on household productivity. Also, none have utilized panel data to control for the endogeneity of program participation. Hossain (1988) used 1985 field survey data collected from Grameen Bank households and non-participating households and found that household income for micro-credit participants was 28 percent higher than the incomes of non-participating eligible households located in the same villages. Khandker (1998) used the 1991/92 World Bank/BIDS survey data from Bangladesh and found that households located in villages where a micro-credit program was in operation had an increase in average production of over 50 percent. McKernan (2002) used the 1991/92 World Bank-BIDS data to study self-employment profits and reported that participation in micro-credit programs increased monthly profits by 2,944 taka (US$43) on average.[3] The McKernan (2002) study examined returns to productivity but did not benefit

[3] 2008 Exchange Rate: $1 US = 68 taka. Source: US Department of the Treasury.

from the use of panel data and may not have adequately controlled for selection bias and other endogeneity issues associated with measuring micro-credit program impact.

The findings of the three aforementioned studies support the notion that the small enterprise creation or expansion afforded by the access to micro-credit generates output and monetary gains for participating households. However, the determination of self-employment output impacts on a per-unit-input basis would provide an interesting evaluation of whether participating households are making more efficient use of their resources. If such productivity gains exist, they can provide the means for sustained improvements in household wellbeing.

CHAPTER THREE

Empirical Analysis

Data

The panel data used in this study come from household surveys carried out in Bangladesh to provide information for the analysis of micro-credit impact. Conducted by the World Bank and the Bangladesh Institute of Rural Development Studies (BIDS), the surveys focused on collecting data to measure the impact of three major micro-credit programs in Bangladesh: Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and the Bangladesh Rural Development Board's Rural Development-12 program (BRDB). The survey covered 1,798 households from 87 villages located in 29 rural thanas in Bangladesh.[1] Twenty-four of the thanas chosen were program thanas; that is, thanas reached by one of the three micro-credit programs, with eight program thanas selected for each micro-credit pogram. The remaining five thanas were non-program thanas where there was no program that offered credit services. From each of the program thanas, three villages were selected where the respective micro-credit program had been operating for more than three years. Three villages were selected from the non-program thanas as well and approximately 20 households to be surveyed were randomly chosen from each of the 87 total villages.

The 1,798 households were surveyed three times in 1991/92, once during each of Bangladesh's three cropping seasons, and the same households were revisited and surveyed once in 1998/99. A number of the original households were not available for re-survey, leaving 1,638 households with survey data from both time periods.

[1] A thana is an administrative unit that is smaller than a district and consists of a number of villages. Source: World Bank.

The three micro-credit programs of interest for the impact analysis fit the traditional model as they each lend exclusively to the rural landless poor, practice group-based lending, focus on lending to women, and offer non-financial services. All three programs stipulate that for program eligibility the household must own no more than half an acre of cultivatable land. Group sizes are similar across the programs: Grameen Bank requires 5 members per group, BRAC requires 5 to 7, and BRDB requires 4 to 5. All of these programs call for the groups to meet on a weekly basis. Collateral is not required by any program but all use group liability to secure the loans. These three programs follow a similar credit delivery system with loans being paid back in 50 weekly installments and interest due at the end of the loan cycle. Interest rates are set at 20 percent for Grameen Bank and BRAC and 16 percent for BRDB. Loan recovery rates are high, well over 90 percent, for all three programs. Three-quarters of program participants for Grameen Bank and BRAC are women while just under half of BRDB's participants are women. All three programs integrate social- and health-related education into their provision of credit and each program has its own code of conduct that guides borrowers to make wise lifestyle decisions (Khandker 1998).

The primary variation between these three micro-credit programs pertains to the incorporation of skills training. Grameen Bank believes that only credit is necessary for the poor to productively gain from self-employment activities and thus minimal skills-based training is offered. It requires 15 to 30 days of training prior to receiving a loan and much of this training is familiarization with bank policies. Grameen Bank asserts that the poor are already knowledgeable in the activity associated with their enterprise and therefore no additional skills training is necessary. BRAC places a very strong emphasis on the provision of skills training and organizational development to borrowers, believing credit can be used much more productively if such training is provided. For this reason, six months of skills development training is required before BRAC members may receive a loan. Like BRAC, BRDB views skills training as an integral part of a successful credit delivery process. BRDB requires 3 to 6 months of training prior to initial loan disbursement and the training is sector-specific, providing borrowers with skills that are directly associated with their enterprise activity (Khandker 1998).

I utilize the household-level survey data pertaining to micro-credit program involvement and the non-farm enterprises (NFEs) operated by households to test the impact of micro-credit on household productivity. I focus specifically on the productivity of household NFEs as these enterprises are the non-farm self-employment activities directly supported by the credit and skills training provided by micro-credit programs. I also use household- and village-level characteristics from the dataset as control variables and I implement a household- and village-level fixed-effects method to control for program placement and participation endogeneity.

Estimation Strategy

I use a difference-in-difference estimation exploiting the panel data from Bangladesh to determine the effect micro-credit participation has on household productivity. I limit the dataset to include only households who are eligible for a Bangladeshi micro-credit program (MCP), indicating that they own less than half an acre of cultivatable land and therefore qualify as rural landless poor, which is the segment of the poor targeted by micro-credit. 87 percent of the households surveyed meet this eligibility requirement. I use households that are eligible for a MCP but do not participate in one as the control group and I use eligible households that actually participate in a MCP as the treatment group. This method estimates program effects on household productivity by comparing outcomes of the control and treatment group.

Several endogeneity issues arise when attempting to obtain an unbiased measurement of program impact, mainly pertaining to micro-credit program placement and participation. The placement of MCPs is non-random because programs are often placed in areas with a high incidence of poverty. Thus, treating program placement as random and comparing households in program and non-program areas would lead to a downward bias in outcomes and even erroneously conclude that micro-credit increases poverty. MCP placement may also be non-random because programs may choose locations based on the attitudes of village residents, choosing to locate in areas where villagers are enthusiastic about the prospect of micro-credit. This may lead to an upward bias in outcomes if program placement were treated as random. Program impact may also be affected by unobservable village-level attributes such as infrastructure, climate and environment, or location. A village-level fixed-effect method can resolve these issues as it eliminates the endogeneity associated with non-random program placement and unobservable village characteristics that remain fixed over time.

Unobservable household-level characteristics also create measurement problems because they may cause program participation to be endogenous. Attributes such as innate health, attitude towards assuming risk, and inherent ability are unobserved but are likely to influence whether a household participates in a MCP. Without controlling for such endogeneity, it is impossible to determine whether outcomes for participating households are a result of micro-credit or if they are simply a result of characteristics that independently cause a household to be more or less productive. In measuring productivity outcomes, a potentially strong upward bias would result from treating MCP participation as exogenous because only households that feel they have the ability to use the loan productively enough to pay it back with interest will self-select into MCPs. This will likely show MCP participants to have higher productivity than non-participants but some of that difference is attributable to factors unconnected to micro-credit. A household-level fixed-effects method resolves this endogeneity issue. Implementing a household-level fixed-effect method utilizing panel data to treat household-level endogeneity has advantages over cross-sectional analyses which are quite sensitive to the various identification techniques used, especially those basing their identification on landholding restrictions which are not strictly enforced by the MCPs.

The household-level fixed-effects method resolves any time-invariant endogeneity related to MCP participation. If unobserved household characteristics that influence a household's decision to participate in a MCP do not change with time, the household-level fixed-effects method produces unbiased results. There is reason to believe this is the case, as the household attributes of innate health, attitude towards assuming risk, and inherent ability are likely to have remained fixed over the survey period. However, the household-level fixed-effects method may not yield consistent and unbiased results if there are unobserved characteristics that affect MCP participation and productivity outcomes that do vary with time. The use of instrumental variables would be the best technique to deal with the endogeneity issues associated with this study. Unfortunately, the quasi-experimental design of the World Bank-BIDS survey makes it difficult to find a valid instrument within the dataset. I attempted to find a suitable instrument for micro-credit participation but was unable to find one that met the validity requirements. Thus, a household-level fixed-effects model is used to treat endogeneity.

Implementing a household-level fixed-effects model that utilizes the panel data from the World Bank-BIDS surveys in Bangladesh, I can address the endogeneity issues of micro-credit participation and effectively control for selection bias. Therefore, I can generate outcomes that do not suffer from the same bias as many of the previous studies that used cross-sectional analyses.

Explanation of Variables

To study the productivity of households participating in the non-farm sector, I make use of all of the information collected from households regarding their NFEs. 46 percent of eligible households covered by the surveys have full information regarding their NFEs in operation. For the purpose of this study, I define household productivity as *revenue* per unit *labor* for a household's NFE. *Revenue* is measured as the value of goods or services produced by the NFE per month that are either sold for profits or consumed by the household. *Labor* is measured as hours of family labor contributed to the NFE per month. Measuring productivity in this manner indicates how productive a household is with the time dedicated to the NFE. This makes more intuitive sense than measuring productivity in terms of revenue per unit land or capital, as would be typical for determining the productivity of agriculture or industry, because family labor is the main input for most small-scale NFEs.

Other important variables related to the operation of NFEs and included in this analysis are *capital* and *operating_expenses*. *Capital* is calculated as the value of assets specifically used for the NFE including land, buildings, equipment, and other assets. *Operating_expenses* are calculated by summing the amount of money spent on behalf of the NFE per month on the following items: raw materials, fuel, transportation, storage, wages for hired labor, rent for land or buildings, electricity, maintenance, and other related expenses. Incorporating measures of capital and operating expenses makes it possible to determine what productivity outcomes result from using micro-credit to increase inputs. For example, a seamstress may use her loan to purchase a sewing machine which makes her much more efficient than sewing by hand, or a provisions trader may use his loan to increase the scale of his enterprise and benefit from increased profit margins that stem from buying in bulk. After controlling for changes in inputs, it can be determined that the residual productivity outcomes are attributable to the skills training and knowledge transfer associated with micro-credit. This is the key productivity measure under examination in this study and is similar in theory to measures of total factor productivity.

I construct two variables to proxy for micro-credit participation and I separately test the impact they have on household productivity. I use a binary variable, *mcploan*, to indicate whether a household took one or more loans from a MCP. This is a simple measure of micro-credit participation and reveals that the household joined a MCP and met the requirements necessary to receive at least one loan. In the sample, approximately 55 percent of eligible households that operate a NFE took a loan from a MCP. I use a continuous variable, *mcploan_amt,* to indicate the cumulative amount of credit received by a household from a MCP. This is a more detailed measure of micro-credit participation. The median loan size in the sample is 9,000 taka (US$132) and a larger value for this variable suggests that the household has taken numerous successive loans and therefore has had extended exposure to the financial and non-financial benefits of micro-credit.[2] The receipt of a loan and the quantity of credit are only two measures of the flow of services and benefits provided by MCPs but they are observable and well measured, thus making them good proxies for micro-credit participation.

In one regression specification, I differentiate between NFEs based on the sector in which they operate, as this may be an important factor in how micro-credit can affect productivity. For this reason, I created variables that signify if the household NFE is involved in trade (*nfe_trade*), industry (*nfe_industry*), business (*nfe_business*), or services

[2] All U.S. Dollar calculations are based on 2008 Exchange Rate: $1 US = 68 taka.

(*nfe_service*). Over half of the NFEs are involved in trade while 17 percent are involved in industry, 14 percent are involved in business, and 11 percent are involved in the service sector.

In another set of regression specifications, I independently test the impact of each of the three Bangladeshi MCPs under study: Grameen Bank, BRAC, and BRDB. As mentioned previously, these programs are quite similar in most respects but vary considerably in their attitude towards the provision of skills training. Since this study focuses on the impact of the human capital formation facilitated by MCP involvement, it is important to determine if some programs are more successful than others in this respect. It may be of interest to examine if the disparity between outcomes matches the supposition that BRAC and BRDB will have a greater positive impact on household productivity than Grameen Bank because of their greater emphasis on skills training and organizational development. The program variables are *mcploan_grameen*, *mcploan_brac*, and *mcploan_brdb*.

I include several household control variables such as family size (*fam_size*), which represents the total number of family members residing in the household, and family education (*fam_edu*), which represents the maximum level of education achieved by any household member. For households that participate in a MCP, I include the gender, age, and education (*male, age, edu*) of the participating household member as control variables. Approximately 70 percent of MCP participants in the sample are women, the average age is 35, and over 60 percent of participants have had no formal education. Also, I include two MCP control variables, *groupsize* and *centersize* that represent the number of people belonging to a participating household's specific loan group and MCP center. Table 1 shows descriptive statistics for each of the variables.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum	No. Obs
mcploan	0.55	0.50	0	1	1020
mcploan_amt	16027	16028	1000	91355	562
revenue	20562	37406	0	471639	947
labor	264	167	0	1312	938
capital	6844	37094	0	915474	948
operating_expenses	16512	33915	1.13	435890	947
fam_size	6.14	2.41	1	20	948
fam_edu	4.29	3.52	0	15	948
male	0.31	0.46	0	1	696
age	34.72	10.84	11	70	643
edu	1.43	2.31	0	12	645
groupsize	4.25	2.45	0	20	541
centersize	32.80	14.73	5	112	536
grameen	0.29	0.45	0	1	1020
brac	0.15	0.36	0	1	1020
brdb	0.15	0.36	0	1	1020
nfe_industry	0.17	0.38	0	1	878
nfe_business	0.14	0.35	0	1	878
nfe_service	0.11	0.31	0	1	878
nfe_trade	0.58	0.49	0	1	878

Results

Using panel data from the 1991/92 and 1998/99 World Bank-BIDS household surveys in Bangladesh, I first examine the effect of *mcploan* on the log of *revenue* per unit *labor* to see what effect, if any, micro-credit participation has on household NFE productivity. I estimate productivity outcomes using a village-level fixed effects model that takes the form,

$$P_{ht} = \alpha_0 + \beta_1 \cdot mcploan_{ht} + \beta_2 \cdot (capital \text{ per unit } labor)_{ht} + \beta_3 \cdot (operating\_expenses \text{ per unit } labor)_{ht} + \delta \cdot X_h + \lambda \cdot Y_h + \sum \alpha_{1V} \cdot Village_V + \alpha_2 \cdot year + \varepsilon_{ht}$$

where P_{ht} is household productivity, measured as *revenue* per unit *labor*, for household *h* in survey period *t*. The coefficients β_1, β_2, and β_3 are of primary interest to be estimated by the regression, X is a vector of household-level controls (such as family size), Y is a vector of household MCP controls (such as loan group size), and δ and λ are unknown parameters. The term $\sum\alpha_{1V}\cdot\text{Village}_V$ represents village-level fixed-effects where v is a dummy variable for the village in which the household resides, and the term $\alpha_2\cdot year$ represents year fixed-effects that control for environmental or macro-level changes that took place between the 1991/92 and 1998/99 survey periods that may have affected productivity. ε_{ht} is an error term assumed to be independently, identically distributed normal.

A household-level fixed-effects method resolves village-level endogeneity as well as household-level endogeneity. Therefore, I also estimate productivity outcomes using a household-level fixed effects model that takes the form,

$$P_{ht} = \alpha_0 + \beta_1\cdot mcploan_{ht} + \beta_2\cdot(capital\text{ per unit }labor)_{ht} + \beta_3\cdot(operating\_expenses\text{ per unit }labor)_{ht} + \delta\cdot X_h + \lambda\cdot Y_h + \sum\alpha_{1h}\cdot\text{Household}_h + \alpha_2\cdot year + \varepsilon_{ht}$$

where $\sum\alpha_{1h}\cdot\text{Household}_h$ represents household-level fixed-effects. The household-level fixed-effects model is the main specification used to empirically determine productivity outcomes, as it is the best treatment for the endogeneity issues associated with measuring MCP impact.

In all the regression specifications, I use logarithms for some terms which compress the data and allows for the interpretation of results in percentage terms. I report robust standard errors for each regression, but tables reporting standard errors clustered at the village level can be found in the Appendices. I report both village- and household-level fixed-effects specifications, but I focus on the results from the latter.

The results of the regressions using *mcploan* as a proxy for micro-credit participation are shown in Table 2. The household-level fixed-effects specification shows *mcploan* to have a positive effect on productivity but the results are not statistically significant. There are several reasons why this set of regressions may not have yielded strong productivity outcomes. The binary variable, *mcploan*, is an imperfect measure of micro-credit participation as it does not distinguish between households that are new to the MCP and households that have actively been participating in micro-credit for an extended period of time. The households new to a MCP may not be immediately reaping the productivity gains afforded by micro-credit while the veteran households may be experiencing significant increases in their productive capacity. Also, one-third of participating households have only received one or two loans and it is possible that this portion of households may be detracting from productivity results. These initial loans are typically quite small in value and may not always be put to productive use but may instead be used for consumption purposes. Therefore, it may be necessary to use a more precise measure of micro-credit participation to obtain a true measure of the impact of micro-credit on household productivity.

Table 2. Micro-Credit Participation (*mcploan*) and Household Productivity

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
mcploan	- 0.045	- 0.037	0.018	0.176	0.203	0.103
	(0.096)	(0.104)	(0.038)	(0.133)	(0.158)	(0.077)
log of *capital*		0.143***	0.062***		0.150***	0.091***
		(0.031)	(0.013)		(0.038)	(0.020)
log of *operating_expenses*			0.641***			0.585***
			(0.027)			(0.054)
fam_size	0.066***	0.084***	0.010	0.023	0.042	0.007
fam_edu	0.050***	0.032**	0.007	0.037*	0.008	0.005
constant	5.489***	5.001***	0.994	4.082**	3.048	0.484
Number of Observations	856	677	677	933	727	727
Adjusted R^2	0.282	0.335	0.875	0.573	0.636	0.86
Year Fixed Effects						

Notes: Numbers in parentheses are robust standard errors.
Logs of *capital* and *operating_expenses* are per unit *labor* .
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

To get a more precise measure of impact, I use the more detailed *mcploan_amt* variable to proxy for micro-credit participation. I estimate the effect of cumulative micro-credit borrowing on household NFE productivity using village- and household-level fixed effect models, which take the same form as the previous regressions but substitute *mcploan_amt* for *mcploan*. The results from these regressions are shown in Table 3.

The results show strong evidence that micro-credit participation increases household productivity. The household-level fixed-effects specification reveals that a 1 percent increase in *mcploan_amt* increases household productivity by 0.303 percent. Therefore, the doubling of *mcploan_amt* increases household productivity by 30.3 percent. This gain in productivity brings an additional $45 of monthly revenue to households on average, based on the median values for *labor* and *revenue* per unit *labor*. A $45 increase in monthly revenue is quite substantial, as average household NFE revenue is $136. This outcome is both statistically and economically significant.

Much of this productivity increase is a result of using the MCP loan to invest in capital and purchase additional inputs for the NFE, which allow the household to be much more efficient with the time it dedicates to the enterprise. After controlling for increases in NFE inputs, the residual productivity gains can be interpreted as increases in total factor productivity, attributable to the human capital formation facilitated by micro-credit participation. The results from Table 3 show that a 1 percent increase in *mcploan_amt* increases household productivity by 0.116 percent after controlling for increases in *capital* and *operating_expenses*. Therefore, the doubling of *mcploan_amt* increases the total factor productivity of a household by 11.6 percent. This gain in productivity is responsible for a $19 increase in monthly revenue on average and reveals that nearly half of the $45 total increase in monthly revenue is due to increases in productivity stemming from the non-financial benefits of micro-credit. This outcome is also significant, both statistically and economically.

Table 3. Micro-Credit Participation (*mcploan_amt*) and Household Productivity

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
log of *mcploan_amt*	0.351***	0.258***	0.133***	0.303***	0.236**	0.116*
	(0.064)	(0.076)	(0.033)	(0.080)	(0.102)	(0.062)
log of *capital*		0.079	0.067***		0.044	0.077*
		(0.053)	(0.021)		(0.070)	(0.040)
log of *operating_expenses*			0.585***			0.448***
			(0.043)			(0.099)
fam_size	0.055*	0.087**	- 0.001	- 0.015	- 0.028	- 0.051
fam_edu	0.015	0.003	- 0.006	0.053	0.027	- 0.003
age	- 0.001	0.002	- 0.003	- 0.001	0.001	0.002
edu	0.017	0.025	- 0.006	0.021	- 0.052	- 0.003
male	0.404**	0.280	0.089	- 0.215	- 0.137	- 0.153
groupsize	- 0.002	- 0.045	- 0.012	- 0.021	- 0.050	- 0.048
centersize	0.008	0.009	0.004*	0.003	0.006	0.006
constant	5.194***	5.981**	0.722	5.494**	6.064**	0.599
Number of Observations	479	373	373	479	373	373
Adjusted R^2	0.385	0.386	0.859	0.656	0.692	0.864
Year Fixed Effects						

Notes: Numbers in parentheses are robust standard errors.
Logs of *mcploan_amt*, *capital*, and *operating_expenses* are per unit *labor*.
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

Adding variables to control for the sector in which the household's NFE belongs reveals an interesting result. Table 4 shows the results of these regressions. It appears the omitted variable, *nfe_trade*, is associated with greater returns to productivity than any of the non-trade sector variables. The disparity exists mainly in productivity gains resulting from increases in *operating_expenses*. This indicates that the household NFEs that participate in trade activities can benefit substantially by simply using micro-credit to increase the scale of their trade enterprise.

Table 4. Household Productivity Outcomes by NFE Sector

	log of *revenue* per unit *labor*		
	1	2	3
log of *mcploan_amt*	0.352***	0.272***	0.130***
	(0.062)	(0.073)	(0.033)
log of *capital*		0.107**	0.072***
		(0.049)	(0.022)
log of *operating_expenses*			0.584***
			(0.044)
nfe_trade	--	--	--
nfe_service	- 1.029***	- 1.240***	- 0.042
	(0.185)	(0.190)	(0.114)
nfe_industry	- 0.424**	- 0.438**	- 0.042
	(0.191)	(0.211)	(0.095)
nfe_business	- 0.295*	- 0.357**	- 0.163*
	(0.156)	(0.170)	(0.085)
constant	6.237***	6.121**	0.525
Number of Observations	479	373	373
Adjusted R^2	0.428	0.456	0.859
Village Fixed Effects			
Year Fixed Effects			

Notes: Numbers in parentheses are robust standard errors.
Logs of *mcploan_amt*, *capital*, and *operating_expenses* are per unit labor.
Regressions also include the following control variables: *fam_size, fam_edu, age, edu, male, groupsize, centersize.*
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

Next, I examine the effects of household participation in each specific MCP on productivity. I use *mcploan* to proxy for micro-credit participation and I distinguish between the three MCPs in the regressions using the variables *mcploan_grameen*, *mcploan_brac*, and *mcploan_brdb*. The results from this analysis are shown in Table 5. Although all three programs have a positive effect on productivity, only BRDB has a statistically significant impact. Grameen Bank has the least impact on household productivity, in both the village- and household-level fixed-effects models. This is in line with the hypothesis that BRAC and BRDB will have greater returns to productivity than Grameen Bank because of their emphasis on skills training and organizational development.

Table 5. Household Productivity Outcomes by MCP

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
mcploan_grameen	- 0.128	- 0.036	0.033	0.129	0.016	0.058
	(0.137)	(0.144)	(0.056)	(0.163)	(0.204)	(0.114)
mcploan_brac	- 0.080	- 0.080	0.051	0.218	0.135	0.132
	(0.138)	(0.146)	(0.087)	(0.148)	(0.160)	(0.174)
mcploan_brdb	0.043	0.011	0.072	0.143	0.370	0.229**
	(0.155)	(0.173)	(0.064)	(0.207)	(0.239)	(0.108)
log of *capital*		0.143***	0.062***		0.152***	0.091***
		(0.032)	(0.013)		(0.039)	(0.021)
log of *operating_expenses*			0.641***			0.584***
			(0.026)			(0.052)
fam_size	0.065***	0.083***	0.010	0.022	0.040	0.008
fam_edu	0.049***	0.032**	0.008	0.037*	0.008	0.005
constant	5.229***	4.869***	0.957	4.334***	2.864*	0.411
Number of Observations	856	677	677	922	727	727
Adjusted R^2	0.281	0.333	0.875	0.572	0.636	0.884
Year Fixed Effects						

Notes: Numbers in parentheses are robust standard errors.
Logs of *capital* and *operating_expenses* are per unit *labor*.
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

To better investigate how the three MCPs measure up to one another in terms of productivity outcomes, I limit the sample to include only households that participate in a MCP. Table 6 shows the results of these regressions which use Grameen Bank as the omitted MCP. The results from the household-level fixed-effects specification reveal that BRAC and BRDB are more successful at facilitating productivity gains for their members than Grameen Bank. Also, the total factor productivity outcome for BRDB is notably greater than that of Grameen Bank and the difference is statistically significant. This may be a result of the sector-specific training offered by BRDB.

Table 6. Household Productivity Outcomes by MCP, Limited Sample

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
mcploan_grameen	--	--	--	--	--	--
mcploan_brac	- 0.149	- 0.140	0.281	0.003	0.047	0.433
	(0.240)	(0.267)	(0.238)	(0.198)	(0.249)	(0.292)
mcploan_brdb	0.232	0.176	0.434**	0.534	0.736	0.691**
	(0.386)	(0.418)	(0.189)	(0.373)	(0.567)	(0.340)
log of *capital*		0.116**	0.075***		0.090	0.087**
		(0.048)	(0.020)		(0.063)	(0.035)
log of *operating_expenses*			0.604***			0.485***
			(0.037)			(0.079)
fam_size	0.047*	0.083**	0.001	- 0.036	- 0.029	- 0.023
fam_edu	0.039**	0.018	0.003	0.043	0.002	- 0.003
constant	4.652**	4.274**	0.031	3.871*	3.018	0.164
Number of Observations	510	399	399	553	425	425
Adjusted R^2	0.329	0.358	0.860	0.615	0.674	0.874
Year Fixed Effects						

Notes: Numbers in parentheses are robust standard errors.
Logs of *capital* and *operating_expenses* are per unit *labor* .
These results are not sensitive to the inclusion of NFE sector control variables. Refer to Appendix E.
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

CHAPTER FOUR

Conclusion

Micro-credit serves to reduce poverty by promoting self-employment and improving the productive capacity of the poor. Numerous impact assessments have been conducted to examine the poverty impacts of micro-credit, yet none focused on its effect on productivity and very few utilized panel data.

This study uses panel data from rural Bangladesh to determine the impact of micro-credit on household productivity, implementing a household-level fixed-effects model to resolve endogeneity. I find that micro-credit participation has a statistically and economically significant positive impact on the productivity of non-farm enterprises run by borrowing households. Micro-credit increases the productivity of these household enterprises by allowing borrowers to purchase additional inputs as well as develop human capital.

I use cumulative borrowing to proxy for micro-credit participation and find that a 1 percent increase in borrowing increases household productivity by 0.3 percent. This means that on average, a 100 percent increase in borrowing increases household productivity enough to generate an additional $45 in monthly revenue for the household's non-farm enterprise. As the median revenue for these non-farm enterprises is $136 per month, a $45 increase is quite significant. After controlling for inputs such as capital and operating expenses, I find that nearly half of the gains in productivity are attributable to increases in total factor productivity. This suggests that the non-financial services offered by micro-credit programs, such as skills training and organizational development, as well as knowledge spillover resulting from the group-based nature, indeed serve to increase the productive capacity of borrowers.

I find that household enterprises involved in the trade sector have the highest returns to productivity. Access to micro-credit allows households to increase the size of their trade activity which provides revenue benefits through scale economies. Thus, micro-credit can immediately increase profit margins for trade enterprises. This is an important conclusion, as over half of the non-farm enterprises are involved in trade activities.

I also test productivity outcomes between micro-credit programs. The three Bangladeshi programs of focus for this study differ explicitly in their attitudes towards the incorporation of skills-based training into the lending model. Grameen Bank believes such training is not essential, whereas BRAC and BRDB feel it is an indispensable component. BRDB even offers training that is specific to the sector in which the household's enterprise belongs. As the purpose of skills-based training is to develop human capital and promote total factor productivity, it is important to determine if the programs that emphasize this type of training foster greater productivity gains for borrowers. I find that BRBD has the greatest productivity gains and in terms of total factor productivity, the difference is statistically significant. BRAC follows BRBD in positive productivity outcomes and Grameen Bank has the lowest return to productivity, although the difference is not statistically significant. This result suggests that the skills-based training plays an important role in increasing the productivity of borrowing households and should not be neglected by micro-credit programs.

Suggestions for Further Research

There are several potential research possibilities pertaining to this study that could be explored in further research. First, the use of a valid instrument for micro-credit participation would better deal with endogeneity issues associated with program analysis. Although cumulative borrowing may be a good proxy for micro-credit participation, outcomes may suffer from selection bias as only the more productive households will continue to access loans of increasing value. The household-level fixed-effects method resolves some of this bias but may not completely resolve the issue. Finding a valid instrument to proxy for micro-credit participation may require additional data collection. Second, this study has not explored the variation in productivity outcomes between male and female borrowing. The outcomes of this study show no statistical difference between genders but this result is not necessarily conclusive as this study was not specifically set up to test for such differences. Finally, it may be of interest to examine any spillover effects of the household productivity gains, whether they be at a village level or even at a household level. It is possible that productivity gains of micro-credit participants may incite productivity gains for non-participants in program villages. It is also possible that the increase in total factor productivity for participating households may be transferable to a household's other activities, such as agriculture.

Discussion

Overall, this study adds to the relatively small group of empirical micro-credit impact analyses that provide an accurate examination of participation outcomes. The key finding of this study is that micro-credit increases the productive capacity of its poor borrowers. The financial dimension of micro-credit programs generates productivity gains for households by allowing them to increase physical capital. Households can purchase equipment that improves the efficiency of their non-farm enterprise and can expand their businesses to reap benefits from economies of scale. The non-financial dimensions of micro-credit programs generate productivity gains for households by facilitating an increase in human capital. Participants receive skills training that is applicable to the operation of their enterprises and benefit from knowledge-sharing between group members. Both the financial and the non-financial aspects of micro-credit have positive impacts on household productivity that are both statistically and economically important. Thus, micro-credit is indeed successful at improving the productive capacity of the poor, which is vital to overall poverty reduction and economic advancement.

APPENDICES

APPENDIX A

Table A2. Micro-Credit Participation (*mcploan*) and Household Productivity

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
mcploan	- 0.045	- 0.037	0.018	0.153	0.176	0.079
	(0.123)	(0.137)	(0.044)	(0.207)	(0.235)	(0.087)
log of *capital*		0.143***	0.062***		0.139**	0.085**
		(0.038)	(0.015)		(0.061)	(0.034)
log of *operating_expenses*			0.641***			0.572***
			(0.039)			(0.092)
fam_size	0.066**	0.084***	0.010	0.047	0.075	0.026
fam_edu	0.050**	0.032**	0.007	0.033	0.005	0.003
constant	5.489***	5.001**	0.994	4.354*	3.545	0.778
Number of Observations	856	677	677	856	677	677
Adjusted R^2	0.282	0.335	0.875	0.572	0.650	0.886
Year Fixed Effects						

Notes: Numbers in parentheses are standard errors clustered at the village level.
Logs of *capital* and *operating_expenses* are per unit *labor* .
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

APPENDIX B

Table A3. Micro-Credit Participation (*mcploan_amt*) and Household Productivity

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
log of *mcploan_amt*	0.351***	0.258**	0.133***	0.303**	0.236*	0.116
	(0.082)	(0.086)	(0.040)	(0.120)	(0.141)	(0.082)
log of *capital*		0.079	0.067**		0.042	0.077
		(0.063)	(0.026)		(0.104)	(0.068)
log of *operating_expenses*			0.585***			0.448**
			(0.063)			(0.164)
fam_size	0.055	0.087**	- 0.001	- 0.018	- 0.039	- 0.058
fam_edu	0.015	0.003	- 0.006	0.053	0.028	- 0.003
age	- 0.001	0.002	- 0.003	- 0.001	0.001	0.001
edu	0.017	0.025	- 0.005	0.021	- 0.054	- 0.004
male	0.404*	0.280	0.089	- 0.207	- 0.137	- 0.135
groupsize	- 0.002	- 0.045	- 0.012	- 0.022	- 0.053	- 0.050
centersize	0.008	0.009	0.004*	0.003	0.007	0.006
constant	5.194**	5.981**	0.722	5.460	5.958	0.532
Number of Observations	479	373	373	479	373	373
Adjusted R^2	0.385	0.386	0.859	0.656	0.692	0.864
Year Fixed Effects						

Notes: Numbers in parentheses are standard errors clustered at the village level.
Logs of *mcploan_amt*, *capital*, and *operating_expenses* are per unit *labor*.
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

APPENDIX C

Table A5. Household Productivity Outcomes by MCP

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
mcploan_grameen	- 0.128	- 0.036	0.033	0.150	0.033	0.054
	(0.163)	(0.179)	(0.061)	(0.213)	(0.277)	(0.150)
mcploan_brac	- 0.080	- 0.080	0.051	0.220	0.152	0.143
	(0.180)	(0.202)	(0.130)	(0.221)	(0.268)	(0.313)
mcploan_brdb	0.043	0.011	0.072	0.078	0.298	0.183
	(0.206)	(0.235)	(0.062)	(0.375)	(0.398)	(0.163)
log of *capital*		0.143***	0.062***		0.141**	0.086**
		(0.038)	(0.016)		(0.063)	(0.034)
log of *operating_expenses*			0.641***			0.571***
			(0.038)			(0.089)
fam_size	0.065**	0.083***	0.010	0.050	0.074	0.028
fam_edu	0.049**	0.032*	0.008	0.034	0.004	0.003
constant	5.229***	4.869**	0.957	4.699**	3.464	0.747
Number of Observations	856	677	677	856	677	677
Adjusted R^2	0.281	0.333	0.875	0.571	0.649	0.887
Year Fixed Effects						

Notes: Numbers in parentheses are standard errors clustered at the village level.
Logs of *capital* and *operating_expenses* are per unit *labor*.
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

APPENDIX D

Table A6. Household Productivity Outcomes by MCP, Limited Sample

	Village Fixed Effects			Household Fixed Effects		
	log of *revenue* per unit *labor*			log of *revenue* per unit *labor*		
	1	2	3	1	2	3
mcploan_grameen	--	--	--	--	--	--
mcploan_brac	- 0.149	- 0.140	0.281	- 0.022	0.031	0.465
	(0.241)	(0.300)	(0.372)	(0.260)	(0.399)	(0.596)
mcploan_brdb	0.232	0.176	0.434**	0.522	0.728	0.706
	(0.479)	(0.544)	(0.203)	(0.539)	(0.797)	(0.506)
log of *capital*		0.116**	0.075**		0.090	0.088
		(0.054)	(0.023)		(0.094)	(0.056)
log of *operating_expenses*			0.604***			0.486***
			(0.052)			(0.123)
fam_size	0.047	0.083**	0.001	- 0.042	- 0.033	- 0.015
fam_edu	0.039**	0.018	0.003	0.043	0.003	- 0.004
constant	4.652**	4.274*	0.031	3.872	3.049	0.196
Number of Observations	510	399	399	510	399	399
Adjusted R^2	0.329	0.358	0.860	0.613	0.676	0.875
Year Fixed Effects						

Notes: Numbers in parentheses are standard errors clustered at the village level.
Logs of *capital* and *operating_expenses* are per unit ***labor.***
*Coefficient is significant at the 10 percent level or better.
**Coefficient is significant at the 5 percent level or better.
***Coefficient is significant at the 1 percent level or better.

APPENDIX E

Table B6. Household Productivity Outcomes by MCP, Limited Sample

	log of *revenue* per unit *labor*		
	1	2	3
mcploan_grameen	--	--	--
mcploan_brac	- 0.127	- 0.112	0.276
	(0.232)	(0.254)	(0.234)
mcploan_brdb	0.375	0.415	0.415**
	(0.373)	(0.386)	(0.190)
log of *capital*		0.147**	0.079***
		(0.045)	(0.021)
log of *operating_expenses*			0.604***
			(0.037)
nfe_trade	--	--	--
nfe_service	- 1.053***	- 1.282***	- 0.013
	(0.193)	(0.196)	(0.116)
nfe_industry	- 0.517**	- 0.482**	- 0.006
	(0.186)	(0.200)	(0.093)
nfe_business	- 0.340**	- 0.437**	- 0.167**
	(0.154)	(0.163)	(0.081)
fam_size	0.033	0.061**	- 0.002
fam_edu	0.054**	0.026	- 0.002
constant	5.511**	4.242**	- 0.064
Number of Observations	510	399	399
Adjusted R^2	0.377	0.431	0.861
Village Fixed Effects			
Year Fixed Effects			

Notes: Numbers in parentheses are robust standard errors.

Logs of *capital* and *operating_expenses* are per unit *labor*.

**Coefficient is significant at the 5 percent level or better.

***Coefficient is significant at the 1 percent level or better.

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