ESSAYS ON THE IMPACT OF MICROCREDIT ON WOMEN'S EMPOWERMENT

A thesis submitted in partial fulfillment of the requirements for the degree

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Abstract

This thesis consists of four studies exploring whether microcredit alleviates poverty and enhances women's empowerment. The first three main chapters carefully replicate two influential studies in the field: Pitt and Khandker (1998) and Pitt, Khandker, and Cartwright (2006) and their respective replications, including Duvendack & Palmer-Jones (2012) and Roodman & Morduch (2014). These two studies have been controversial and have spawned several replications, which themselves have produced mixed results. My research attempts to reconcile the different findings from these studies. After conducting an in-depth replication of these studies, my last main chapter provides new evidence on the impact of microcredit on empowering women, using a nationally representative survey from Vietnam. The ultimate goal is to gain better understanding of the effect of microcredit on women's empowerment in developing countries.

Overall, I find weak evidence that microcredit improves families' well-being, especially women's well-being. In addition, microcredit has the potential to improve women's empowerment if loans are given to women, but the effects are small.

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Glossary

2SLS	Two-stage least squares
ATT	Average treated on the treated effect
BRAC	Bangladesh Rural Advancement Committee
BRDB	Bangladesh Rural Development Board
Chemin	Chemin (2008)
D&PJ	Duvendack & Palmer-Jones (2012)
DAGs	Directed Acyclic Graphs
FE	Fixed effects
GB	Grameen Bank
Gllamm	Generalized Linear Latent And Mixed Models
GSEM	General Structural Equation Model
ICC	Item Characteristic Curve
IRT	Item Response Theory
ITT	Intention-to-treat effects
IV	Instrument variable
LASSO/Lasso	Least absolute shrinkage and selection operator
MI	Multiple imputation
ML	Maximum likelihood
MOs	Mass Organizations
NGOs	Non-for-profit Non-government Organizations
OLS	Ordinary least squares
PCFs	People's Credit Funds
PK	Pitt and Khandker (1998)
PKC	Pitt, Khandker and Cartwright (2006)
PSM	Propensity score matching
RM	Roodman and Morduch (2014)
SEM	Structural equation modeling
SMD	The standardized mean difference
VARSH	Vietnam Access to Resources Household Survey
VBARD	Vietnam Bank for Agriculture and Rural Development
VBP/ VBSP	Vietnam Bank for the Poor/ Vietnam Bank for Social Policy

Chapter 1. Introduction

1.1 Background

Microcredit refers to small loans that are lent to low-income people to help them grow small businesses or become self-employed. It is based on the idea that credit is given as financial assistance to poor households, who lack collaterals to access money from traditional banking or monetary systems. It may help the poor pursue their self-employment projects that generate additional income, alleviate poverty, promote their well-being and improve women's empowerment. Microcredit has been described as a win-win program between microfinance institutions and recipients.

On the one hand, investors provide additional services for household activities and follow good banking practices. They operate in a sustainable manner and earn profits as they serve the poor. Government benefits through decreased social assistance costs and increased tax income. Newly created, small businesses create jobs that reduce unemployment, generate more income, improve human capital and economic growth. On the other hand, low-income families, armed with new knowledge, skills and experience provided by the microcredit institutions, can shift to new livelihood strategies.

Microfinance institutions tend to target women, based on the view that women account for the majority of the poor in the world and they lack financial independence, making them vulnerable members of society (Khan & Noreen, 2012). Compared to men, women have lower education on average, are more constrained in their access to the labor market, credit and other funding. These disadvantages lead to inequality in the sharing of power in domestic decision-making. Microcredit is considered to be a solution for this issue. Accessing microcredit, women are enabled to establish their own businesses and increase their income. In turn, women tend to spend more on household welfare, children's education and nutrition. As a result, they get more influentially involved in household activities and increase their role in domestic decision-making processes.

Microcredit impact assessment has drawn the attention of many scholars. Evidence from the empirical literature on microcredit impacts is mixed. On the one hand, there is a number of studies supporting the view that microcredit helps to reduce poverty and improve women's empowerment (Al-Shami, Majid, Mohamad, & Rashid, 2017; Amin & Becker, 1998; Asad, Hameed, Irfan, Jiang, & Naveed, 2020; Faraizi, Rahman, & McAllister, 2014; Khan & Noreen, 2012; Pitt, Khandker, & Cartwright, 2006; Swain & Wallentin, 2009). Women can obtain their own factors of production by accessing financial services. This empowers them and contributes to the economic success of their families.

In contrast, other studies find little convincing evidence of microcredit's substantial positive impacts (Angelucci, Karlan, & Zinman, 2015; Atmadja, Su, & Sharma, 2016; Banerjee, Duflo, Glennerster, & Kinnan, 2015). It is possible that loans given to women end up being controlled by men. This can have the unintended consequence of increasing conflict within the household (Haile, Bock, & Folmer, 2012). Furthermore, loans may shift the household debt burden onto women if they invest in non-productive activities. Thus, microfinance services may not necessarily empower women.

Researchers have long been investigating the impacts of microcredit in developing countries, especially Bangladesh. Bangladesh is known as a pioneer in implementing microcredit programs for poverty alleviation. Success stories have attracted the attention of researchers globally and there has been a desire to replicate this apparent success in other countries. Two prominent researchers in this field are Mark Pitt and Shahidur Khandker. They conducted a seminal study, Pitt and Khandker (1998), henceforth PK, about the effects of microcredit on poor households in Bangladesh.

PK analyzed a national survey collected in 1991-1992 and concluded that borrowing money reduces poverty by increasing household consumption expenditure, especially when the borrowers are women. A follow-up study by Pitt, Khandker and Cartwright (2006), henceforth PKC, analyzed the impact of microcredit on empowering women. It used data from a 1998-1999 survey, which followed the earlier 1991-92 survey. The later survey included a special component with a variety of women's empowerment indicators. PKC found that female credit had positive effects on women's empowerment while men's participation in microcredit programs generally negatively impacted women's empowerment. These two studies (PK and PKC) are the two most influential in the field. The former has received 2,313 Google Scholar citations, and the latter 696 citations, as of 12 November 2021.

Several studies have tried to replicate PK without success. An overview of studies related to PK is given in Table 1.1. Chemin (2008) modified PK's original analysis and used a different analytical method, Propensity Score Matching (PSM), to analyze PK's dataset. He generally confirmed PK's results, but found that the effects were smaller than reported by PK. Unfortunately, he did not explain whether the different results were because of the differences in the dataset construction or analytical methods.

Chemin (2008) also did not distinguish between female and male borrowers, a crucial factor in PK. Hence, to extend Chemin's analysis, Duvendack & Palmer-Jones (2012), henceforth D&PJ, replicated Chemin and then analyzed the effects by gender. However, D&PJ could not replicate Chemin's results. Further, their sensitivity analysis showed that the matches underlying Chemin's analysis were poor quality. In their extension, D&PJ failed to confirm PK's original findings that microcredit strongly increases female well-being. In another study, Roodman & Morduch (2014) conducted a very thorough replication of PK. They used the same data and methods as PK but subjected the analysis to a wide range of robustness checks. RM found much smaller impacts than the original study, adding to further pessimism about microcredit.

1.2 Motivation and research questions of my study

The above mixed findings raise questions about whether microcredit benefits women and women's empowerment in Bangladesh. Answering this question is important because Bangladesh has been portrayed as a "success story" in implementing microcredit. Other developing countries have tried to copy and apply microcredit as a poverty alleviation policy, and hope to improve women's empowerment simultaneously. Therefore, to contribute to this debate, I replicate and extend the two seminal studies, by PK and PKC, to get a better understanding of the impact of microcredit in Bangladesh, especially with respect to gender and women's empowerment.

Unfortunately, neither PK nor PKC provided me with complete sets of data and code that would allow me to replicate their findings. Therefore, I indirectly replicate PK by replicating D&PJ and RM, the two papers replicating PK using 1991-1992 data, for which I have data and code. D&PJ have kindly supplied their data and code directly to me while RM make their data and code publicly available online[1]. Replicating D&PJ using an alternative method helps to answer the question whether microcredit's estimated impacts vary across methods of analysis. In addition, in replicating RM paper, I use updated data from the later survey of 1998-1999 to investigate whether the impact of microcredit varies over time of estimation. After working on the 1991-1992 and 1998-1999 data sets, I independently replicate PKC using the 1998-1999

[1] https://web.archive.org/web/20131007073246/https:/www.cgdev.org/publication/impact-microcredit-poor-bangladesh-revisiting-evidence-working-paper-174-june-2013

data in a later chapter of the thesis. Taken together, the findings of my three replications provide an overview of the impact of microcredit on women and women's empowerment in Bangladesh and conclude that, overall, participation in microcredit has little effect on households' well-being regardless of the gender of borrowers. Female participation does have a positive impact on women's empowerment, but the effect is small (and smaller than estimated in PK and PKC).

Several other studies investigate the impact of microcredit on wellbeing of the poor in Bangladesh. First, Shahidur R Khandker (2005) used panel data in 1991-92 and 1998-99 to estimate how microcredit alleviates poverty and impacts poverty status. Khandker did not estimate the impact of microcredit on expanding other outcomes, including women's nonland assets, women's labor supply and girl education, while D&PJ and RM replicated PK and used many other outcomes to estimate the impact of microcredit on consumption, labor, assets and education. D&PJ and RM's studies provided more comprehensive outcomes. This thesis aims to estimate the impact of microcredit on women's empowerment and women's well-being. Hence, I replicate D&PJ and RM having a comprehensive picture of women's wellbeing rather than replicate Khandker (2005), which mainly focused on poverty and poverty status. Secondly, Shahidur R Khandker and Samad (2014) evaluated the dynamic impact of microcredit of short-term and long-term using the 1991-92, 1998-99 as well as the 3rd survey round collected in 2010-2011. However, the important contribution of my thesis is to replicate PKC (2006), an influent paper in microcredit and women's empowerment field. The PKC paper used the survey in 1998-99. Therefore, I use the data 1998-99 instead of the 2010-2011 survey to replicate the PKC in the subsequence chapter.

Finally, to examine whether the impact of microcredit varies across countries, I provide new evidence on empowering women through microcredit in Vietnam. In some respects, Vietnam has similar characteristics to Bangladesh. Specifically, Vietnam is a developing country with more than seventy percent of the population living in rural areas, and a large majority of the poor living rurally. Microcredit has been introduced in Vietnam as an important tool to support poor people and aims to enhance gender equality in rural areas. Most of the literature to date investigates how microcredit affects households' consumption, labor supply, children's education or social networks (H. A. Duong & Nghiem, 2014; P. B. Duong & Thanh, 2015; C. T. Phan, Sun, Zhou, & Beg, 2019, 2020). Research examining the effect of microcredit on women and women's empowerment in Vietnam is still limited. Hence, the last chapter of my thesis fills this gap.

1.3 Structure of the thesis

The rest of my thesis is organized as follows (see Figure 1.1):

Chapter Two replicates the work of Duvendack & Palmer-Jones (2012) titled "High Noon for Microcredit Impact Evaluations: Re-investigating the Evidence from Bangladesh", published in *The Journal of Development Studies*. The chapter begins by replicating key findings using the authors' data and code. I then perform a robustness check of D&PJ's results using a new method, entropy balancing, to analyze the impact of microcredit by gender of borrowers on household consumption expenditure. I also re-estimate the impact on alternative outcomes including labor supply by gender, non-land assets held by women, and girls' and boys' schooling enrolment. My re-analyzed results show weak evidence that microcredit increases participants' per capita expenditure. My research generally supports D&PJ's findings and adds to recent skepticism about the previously documented considerable benefits of microfinance programs. In so doing, I fail to support the original findings of PK that microcredit significantly and positively affects the poor in Bangladesh, especially if females borrow loans.

Chapter Three provides a replication of Roodman & Morduch's paper (2014) titled "The impact of Microcredit on the Poor in Bangladesh: Revisiting the Evidence", published in *The*

Journal of Development Studies. Using RM's data and code, I successfully replicate their results. In an extension, I employ updated data from the later survey in 1998-1999 to re-estimate the microcredit effect on household consumption expenditure. I also use entropy balancing to deal with the non-normality of data and invalidity of the eligibility criteria which are noted to bias the results using PK's method. My reproduction and extension again do not strongly suggest that microcredit significantly helps Bangladesh's low-income families and low-income women. Similar to RM, these findings fail to support PK's strong conclusion.

Chapter Four replicates the work of Pitt, Khandker and Cartwright in 2006 titled "Empowering women with micro finance: Evidence from Bangladesh", published in *Economic Development and Cultural Change*. This research focuses on re-investigating whether microcredit accessed by women (or men) increases women's empowerment. Because PKC were unable to provide data and code, I follow their reported estimation procedures and attempt to reproduce their results. By replicating D&PJ and RM, I learn a lot about data construction and variables' calculation using the 1991-1992 data. Then, I apply this knowledge to define and calculate variables in replicating PKC using the 1998-1999 data. I use an Item Response Theory model to estimate latent empowerment, and structural equation modeling with instrument variables and fixed effects to replicate PKC. My replication broadly matches their results and supports their claim that female access to microcredit enhances their empowerment. However, I once again find smaller impacts. Moreover, I cannot corroborate PKC conclusion that male access to microcredit reduces female empowerment. In an extension, I use the least absolute shrinkage and selection operator (Lasso) technique to select potential instrument and control variables to address the weak instrument issue. My extension results show weak evidence, qualitatively (but not quantitatively) supporting PKC's findings that microcredit borrowing increases women's empowerment when loans are given to female clients. Once again, loans to male clients do not seem to harm women.

Chapter Five investigates the effects of microcredit participation by gender on women's empowerment in rural Vietnam using data from the Vietnam Access to Resource Household Survey. Firstly, to address limitations of previous studies, I employ Directed Acyclic Graphs (DAGs) to select appropriate covariates for the empirical model. Secondly, I use Item Response Theory to estimate the latent empowerment variable. I then use fixed effects and instrumental variable methods to correct potential bias from unobserved household and province-level heterogeneity. I find some limited evidence that microcredit significantly affects female empowerment when women borrow. Male borrowing is again insignificant. My results are robust to using several alternative methods including Lasso instrumental variable fixed effects, treatment Lasso, and maximum likelihood procedures to address the problem of missing data.

Chapter Six sensitively analyzes key main results from the Chapter Two to Chapter Five to capture clustering standard errors of complex survey designs. Overall, main findings from clustering results in statistical significance are robust. Microcredit participations by men or women statistically insignificant impact women's wellbeing and women's empowerment. Also, the sizes of effects are small.

Chapter Seven provides an overall summary of the main findings and a conclusion of my research.

1.4 Contribution of the research

Conflicting results of research papers cause uncertainty for policy makers. PK and PKC are two influential studies which have drawn many controversies. One contribution of my study is hence to determine the reliability of PK and PKC's results. Replication that uses the same data set and models, independently examining the same question of interest, can make the findings from research studies more reliable. Using alternative econometric methods, extending time periods and updating empirical techniques can be used to provide robustness checks of the original results. The findings provide a more complete assessment of the effect of microcredit on poor women and women's empowerment.

Another contribution of my thesis is that it contributes to the practice of open data and code sharing in economics. PK and PKC are influential papers. However, the fact that their data construction and coding are not publicly available serves as a hindrance to other researchers who want to examine their results. I make all of my data and code available as part of my research. This allows other researchers to investigate PK and PKC's results and conduct further, related studies.

A final contribution of my thesis is that I provide new evidence on the impact of microcredit on women's empowerment. Little research on this subject is available for Vietnam, my home country. This study helps to fill this gap in the literature. The findings can be compared with the literature on Bangladesh. Ultimately, research on the effects of microcredit programs may enable the Vietnamese government, policy makers and microfinance institutions to improve the effectiveness of microcredit.

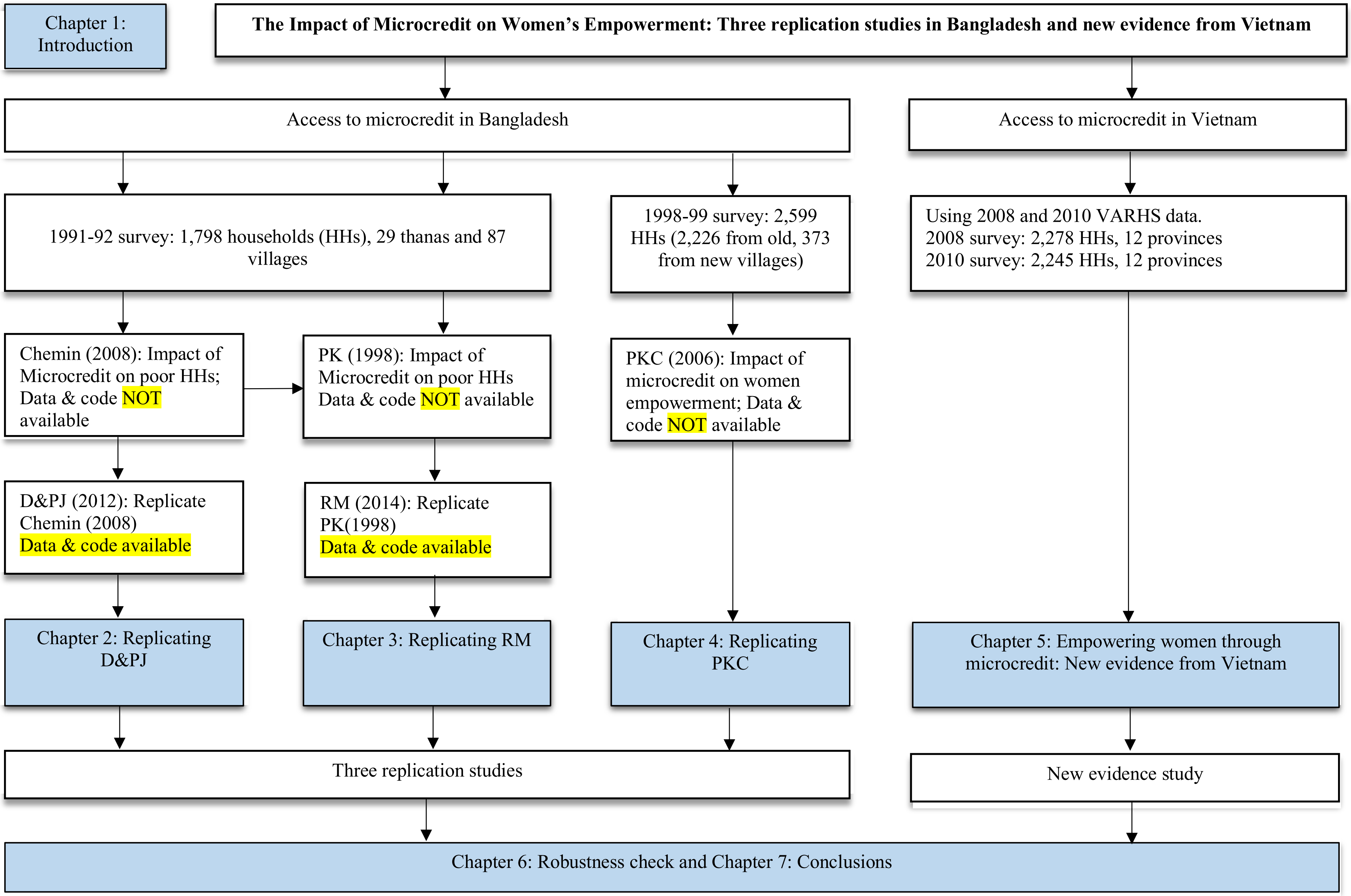

Figure 1.1 Research framework

Table 1.1 Overview of studies related to PK (1998)

	PK (1998)	*RM (2014) replicate PK*	*Chemin (2008)*	*D&PJ (2012) replicate Chemin*	*I replicate D&PJ*
Method	WESML-LIML-FE	cmp	PSM	PSM	Entropy Balancing
Data	1991-92	1991-92	1991-92	1991-92	1991-92
Outcome variables					
Log per capita expenditure (Taka)	Significant positive	Insignificant	Significant **positive** compared with non-participants in control villages, significant **negative** compared with non-participants in treatment villages	**Insignificant,** but significant **negative** for male borrowing	**Insignificant,** but significant **negative** for male borrowing
Log women non-landed assets (Taka)	Significant positive	**Insignificant** for male borrowing, Significant **positive** for female borrowing	Insignificant	Significant positive	Significant **positive** for female borrowing, significant **negative** for male borrowing
Female labor supply, aged 16-59 years, hours per month	Significant positive	Insignificant	Insignificant	Significant **positive** for female borrowing, significant **negative** for male borrowing	**Insignificant**, but significant **negative** for male borrowing
Male labor supply, aged 16-59 years, hours per month	Insignificant	**Insignificant** for male borrowing, Significant **negative** for female borrowing	Significant positive	**Insignificant,** but significant **positive** for male borrowing	Significant positive
Girl school enrolment, aged 5-17 years	Significant positive	Insignificant	Significant positive	Significant positive	Significant positive
Boy school enrolment, aged 5-17 years	Significant positive	Insignificant	Insignificant	**Insignificant** but significant **positive** for male borrowing	Significant positive
Variation of log per capita expenditure (Taka)	N/A	N/A	Insignificant	Significant negative	Significant negative

Note: WESML-LIML-FE: weighted exogenous sampling maximum likelihood – limited information maximum likelihood – fixed effects. PSM: propensity score matching. "cmp" (command) "is a flexible tool to estimate systems of equations with various link functions and with normally distributed and correlated error" (Bartus & Roodman, 2014, pp. 756-757).

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Chapter 2. A Replication of “High Noon for Microfinance Impact Evaluations: Re-investigating the Evidence from Bangladesh” (The Journal of Development Studies, 2012)

2.1 Introduction

Bangladesh is a pioneer in introducing and implementing the concept of microcredit. Two national surveys were conducted in 1991-92[2] and 1998-99[3] to examine the impacts of microcredit programs. As illustrated in Figure 1.1, Chemin (2008) and Pitt and Khandker (1998) use the same dataset (the Bangladesh survey 1991-92) to investigate how microcredit impacts and benefits the poor. However, they use different analytical methods.

PK (1998) use weighted exogenous sampling maximum likelihood–limited information maximum likelihood–fixed effects (WESML–LIML–FE) to evaluate the impact of three credit programs: Grameen Bank (GB), Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board (BRDB) on participants, by gender. They argue that the WESML–LIML–FE approach is robust to problems of self-selection and endogeneity. Only individuals in target villages and having landholdings less than 0.5 acres had the opportunity to participate in the microcredit programs. Participation in microcredit is measured by quantity of accumulated borrowing.

For outcome variables, PK focus on annual household consumption expenditure. They also examine other alternative outcome variables, such as total of assets, number of working hours supply and children's education. Impact is measured by comparing groups with and without the choice to participate. PK find that microcredit significantly influences many household outcomes and it is of more benefit if given to women.

Chemin applies another empirical approach, namely propensity score matching, to test PK's conclusion that microcredit is a benefit to borrowers, especially if they are women. He

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[2] https://datacatalog.worldbank.org/dataset/bangladesh-long-term-impact-microcredit-impacts-1991-1992
[3] https://datacatalog.worldbank.org/dataset/bangladesh-long-term-impact-microcredit-impacts-1998-1999

argues that PSM can solve self-selection bias and non-random program placement. Chemin assesses microcredit's impact on participants using two different control groups. The first control group are non-participants in program villages. The second control group are non-participants in non-program villages. Chemin focuses on per capita expenditure as the main outcome variable of interest. Further, he also examines other outcome variables such as the variation in log per capita expenditure, female non-land assets, women's and men's labor supply, and school enrolment by gender. Chemin's results show an overall positive impact of microcredit programs, but the effects are generally smaller than PK's findings.

Neither Chemin (2008) nor PK (1998) provide their data and code. Since Duvendack & Palmer-Jones (2012) directly replicate Chemin and provide their data and code, this became my starting point to investigate the effect of microcredit in Bangladesh. Replicating D&PJ helps me to investigate the influence of microcredit on the poor people in Bangladesh, with a focus on gender differences. Using the same data, I am able to determine to what extent different methods are responsible for different results. Further, I perform a robustness check of D&PJ's results using a new method, entropy balancing, to examine the impact of microcredit. This compares with D&PJ's use of PSM. Entropy balancing directly addresses issues of covariate imbalance, something that PSM does not (Hainmueller & Xu, 2013). The advantage of entropy balancing is that this method does not involve discarding of treatment units. Entropy balancing focuses on covariate balance directly and weights vary flexibly across observations and commonly retains more information than approaches that either math or discard each control unit in the pre-processed data. For example, the coarsened exact matching (CEM) method involves coarsening the variables to match units exactly on the coarsened scale. Treatment units that cannot be matched exactly control units are discarded. CEM often evolves dropping some treatment units and cause a loss of observations. The larger sample is the better, therefore, entropy balancing is used viz-a-viz other matching methods. A final benefit of working with D&PJ's data and code is that it helps me to better understand the structure of the data and survey. This sets me up to independently replicate PKC (2006) in subsequent chapters.

Using the dataset and Stata code that were kindly provided by Duvendack & Palmer-Jones, I successfully replicate their original results. However, in the robustness check using entropy balancing, instead of finding, like the original study, that male borrowing positively impacts on the value of female non-land assets, I find a negative impact. Moreover, Duvendack & Palmer-Jones (2012) state that female borrowing significantly and positively affects female labor supply and has no impact on male labor supply, while my findings show no impact on female working hours and a significant positive impact on male working hours.

Overall, I fail to find support for the original findings of PK (1998) that access to microcredit significantly benefits the poor. I also obtain several different findings about the role of the borrower's gender in comparison to Duvendack & Palmer-Jones (2012).

The remainder of this chapter is organized as follows: Section 2.2 replicates Duvendack & Palmer-Jones (2012), Section 2.3 conducts diagnostic balancing checks of the PSM method, Section 2.4 focuses on my robustness check, and Section 2.5 concludes.

2.2 Replication

2.2.1 Data

D&PJ's study used the 1991-92 dataset that was conducted by the Bangladesh Institute for Development Studies (BIDS) cooperating with the World Bank.[4] The household survey includes three rounds, and focuses on the effect of microcredit lending programs from three major banks in Bangladesh: GB, BRAC and BRDB. The total observations of 1,798 households (9,697 individuals) were randomly interviewed from 87 villages within 29 thanas in rural

[4] The raw data from the 1991 survey is available at https://microdata.worldbank.org/index.php/catalog/1317

Bangladesh. Any village with at least one operating microcredit program was designated a program village. Accordingly, the survey contains 72 program villages and other 15 villages do not have any program. With a focus on poor households, the financial programs set an eligibility criterion that relies on land ownership. A household that owned or cultivated land size of less than 0.5 acres was considered a target household. As a result, 1,538 target households are identified in the treatment and control villages. The control villages account for 255 target households and the treatment villages account for 1,283 target households. Among the target households, 59% (905 households) participated in microcredit programs.

2.2.2 Methodology

A criticism of microcredit programs is that they are not randomly assigned. They tend to be offered to residents of poorer villages. Comparing the impact of microcredit programs on individuals in program villages with those in control villages can introduce endogeneity bias. Secondly, target individuals self-select into the programs. This can cause self-selection bias. Program participants may have different entrepreneurial skills, education or other control characteristics that could account for differences in outcomes. Propensity score matching (PSM) is one solution designed to deal with these problems.

The idea of PSM is to artificially create a situation of random treatment assignment. The aim of PSM is pairing treatment recipients and non-treatment recipients that are similar in terms of their observable, pre-treatment characteristics. After accounting for these characteristics, treatment assignment is assumed to be random. If treatment is supposed to be randomly assigned, then differences in outcomes between participants and paired non-participants can be resulted of program participation, thus addressing self-selection bias.

D&PJ use PSM as the basis for forming a control group to match with those individuals who borrowed microcredit (treatment group). To calculate the propensity scores (i.e., the probabilities of receiving treatment), the authors employ a logit model of a participation dummy and a set of observation characteristics[5]. In the set of observation characteristics, age and sex are individual characteristics, while other variables refer to household characteristics. Arguably, the likelihood of being a borrower relies on both individual and family characteristics. For instance, age and gender of a person influence the chance to access microcredit programs. Some microcredit programs in Bangladesh prefer female and mature applicants. Furthermore, household characteristics, such as saving behavior or livestock assets, might significantly affect an individual's decision to take up a loan. An individual whose family has lower savings might face credit constraints. Therefore, s/he is more likely to borrow microcredit to fund his/her projects. PSM assumes that observed differences in treatment for individuals with the same probability of treatment are due to a random chance.

After calculating propensity scores for all the individuals in the sample, researchers must decide how to form a control group for those individuals that received microcredit. There are a variety of procedures to do this: nearest neighbor matching, caliper and radius matching, and stratification, along with different procedures for weighting observations in the matched control groups (e.g., kernel weighting).

Chemin and D&PJ used stratification and kernel matching algorithms. Stratification matching is also called interval and blocking matching. In this method, propensity scores are divided into intervals or blocks. Treated and control observations are grouped within similar propensity score strata. Treatment impact is estimated by the difference in outcomes between treated and non-treated individuals within a given stratum, with the total effect calculated by weighting the distribution of treated individuals across strata (Baser, 2006).

[5] Descriptive statistics of observed variables are reported in Table 2.2

In the case of D&PJ and Chemin's study, three different numbers of strata are used: 20, 10 and 5. In the matching literature, there is not clear about how many strata one should use. Propensity scores range between 0 and 100. Having a large number of smaller strata increases the common support but results in fewer observations within a given stratum (Chemin, 2008). The "common support assumption" means that individuals within a given stratum are assumed to be "close enough" to be viewed as practically identical with regard to their probability of receiving treatment.

Kernel weighting weights the control observations such that observations whose propensity scores differ the most from their matched treatment observations receive the lowest weight. If treated individuals have a close propensity score with a weighted average score of all control individuals, they are matched together. Chemin used three bandwidths including 0.05, 0.02 and 0.01 for the kernel matching technique. Similar to stratification, a smaller bandwidth will increase the common support but result in fewer control observations for the treated. For example, a bandwidth of 0.05 means propensity scores can differ from the matched treated observations by ±0.05. Both stratification and kernel techniques match each treated observation with one or more untreated observations.

The (weighted) difference in outcomes between participated and non-participated households is defined as the average treated on the treated effect, or ATT. The main outcome variable is the log of per capita expenditure. Other alternative outcomes include the variance of the log of per capita expenditure, the log of non-land assets held by women, labor supply and school enrolment by gender. Chemin's results show only modest impacts of microcredit programs on per capita expenditure and mixed effects on other outcome variables when comparing borrowers with non-borrowers.

This chapter reports the results of my replication of D&PJ. As D&PJ kindly provided me their dataset and Stata do files, an exact replication is straightforward. Table 2.1 reports the (logit) results of predicting the probability of being selected into microcredit borrowing[6]. The dependent variable is "microcredit participation." If the household participates in microcredit, this takes value of 1 and 0 otherwise. I report side-by-side results from Chemin, D&PJ, and my replication. I am able to exactly replicate D&PJ's findings[7].

Men are less likely to borrow because microcredit institutions tend to target women. Age positively impacts microcredit participation, which means that older people are more likely to access microcredit than younger people. However, the marginal effect of age in diminishing. Savings, livestock, non-agricultural wage and agricultural wage seem to have little impact on participating in microcredit, but are statistically insignificant. This suggests that microfinance institutions tend to focus on the poor who do not have loan collaterals. Individuals with lower education and belonging to smaller households are more likely to participate in microcredit. Finally, individuals with non-farm enterprises are more likely to access loan funds, perhaps because this reflects their ability to pay back their loans.

2.2.3 Replicating the main results

2.2.3.1 The impact of microcredit on the logarithm per capita expenditure

This section estimates the impact of microcredit on the log of household per capita expenditure, which is the primary outcome variable. Income and expenditure basically reflect household welfare, hence they are used as main outcomes to measure the impact of microcredit. Participate to microcredit could increase expenditure due to encouraging new businesses

[6] Chemin and D&PJ estimate alternative specifications, but as they emphasize Specification 3, I use Specification 3 as well.
[7] However, there are typos in D&PJ's results so my replication results differ from D&PJ's logit coefficients from Education to Age.

growth and end up increasing labor supply or self-employment. The effect of microcredit on log per capita expenditure is shown in Table 2.3.

To estimate the impact, Chemin and D&PJ use two approaches. The first approach compares expenditures between microcredit recipients and non-recipients within treatment villages. While this holds unobserved village characteristics constant, it allows externalities from the microcredit program to spill over into the outcomes of the control group. This would bias the estimates of the treatment effect downwards, assuming the externalities are positive.

The second approach compares expenditures of households that participate in microcredit programs in treated villages with non-participated households in non-program villages. This approach eliminates spillover effects of microcredit placement at the village level. However, it could be affected by non-random program placement across villages. Usually, microcredit programs are provided in poorer villages. This would bias the estimates of the treatment effect upwards. In principle, the two approaches allow one to bracket the true impact of microcredit.

Two matching techniques, stratification and kernel, are used to calculate ATTs. These are reported in two sets of three columns each (sets (1) and (2)). Chemin's results are reported in the top panel of Table 2.3. D&PJ and my replication results are reported in the bottom panel.

I first discuss results where the control group consists of non-participants in microcredit program villages. Chemin estimates that microcredit is associated with a significant, negative effect on household consumption expenditures. The estimates indicate that microcredit reduces expenditures by 3.5% to 4.6% relative to non-participants in the microcredit program villages. Chemin suggests this may be due to the presence of positive externalities resulting from microfinance. D&PJ's/my results range from -1.2% to +1.0%, but only the positive estimates are statistically significant. The positive estimates indicate that microcredit increases participants' per capita household expenditures relative to non-participants in program villages. However, the estimates are generally very small.

In contrast to the findings above, Chemin's results show that microcredit has a positive influence on household expenditures when the control group consists of non-participants in non-program villages. Treatment households spend on average 3% more than comparable households in a non-program village. DP&J's/my results are the opposite. Our estimations show that households are generally *worse off* compared to households in control villages. In particular, treatment households spend, on average, 0.4% to 6.5% less than control households.

These latter findings are surprising because it is expected that microcredit has positive impacts. It is difficult to come up with explanations for this result. Perhaps loan sizes are too small to fully fund productive activities. As a result, borrower families have to decrease their consumption in order to produce liquidity for production. Or perhaps the availability of loans induces recipient families to undertake unproductive projects. The associated losses may force these individuals to cut back their consumption expenditures (Seng, 2018).

2.2.3.2 The impact of microcredit on other alternative outcomes

Besides expenditure, Chemin and D&PJ also analyze microcredit's impact on other outcomes. Table 2.4 reports the impact of microcredit programs on these variables. These estimates again compare participants in microcredit program villages with non-participants in both microcredit program and non-program villages. The estimates are based on kernel matching. In the discussion below, I focus on D&PJ's/my replication results.

As before, my replication results exactly confirm D&PJ's results. These demonstrate that microcredit significantly (at the 10-percent level), negative impacts on the variation of log per capita consumption expenditures and insignificant, negative impacts on the level of log per capita expenditure. Microcredit has a significant, positive effect on non-landed assets owned by women. These are assets that women own other than land. The estimates indicate that microcredit participation increases women's non-land assets between 48.9% and 51.3%. After accessing the loans' funds, they were able to purchase livestock, appliances, joint loan-funded enterprises or productive activities. Before participating, these women would have had to rely on their husbands' salaries (Haile et al., 2012).

Microcredit is associated with an increase of 5.1% to 6.0% in girl school enrolment. On the other hand, the effect on boy school enrolment, while positive, is smaller and never significant at the 5-percent level. Likewise, the impact of microcredit on both male and female labor supply is positive but the statistic estimation is insignificant. As before, D&PJ/my replication results differ from Chemin's in a number of instances. Most noteworthy is the estimated effect on women's non-landed assets, where Chemin finds very small, and insignificant effects.

Table 2.5 explores the data further to investigate gender differences. In particular, it separates the impacts of borrowing by females and males on household outcome variables. Following D&PJ, the analysis is based on kernel matching with a bandwidth of 0.05. As my results are identical with D&PJ's, they are reported together.

While female borrowing seems to have relatively little effect on household consumption expenditure, expenditures *decrease* 6.6% if the borrower is a male. The value of women's non-landed assets appears to be more positively impacted when women borrow money. Microcredit is associated with increases of 131.4% and 80.5% for female borrowing and male borrowing, respectively. In addition, both female and male borrowing have a positive impact on girl school enrolment, increasing it by about 6.9% and 10.3%, respectively. Boy's enrolment also increases, but the effect is not significant for female borrowers. It seems that both men and women tend to invest more in their children's education when their access to funds increases (Haile et al., 2012).

Female borrowing has a positive effect on women's labor supply (increasing it by about 23.5 hours per month), while the effect on men's labor supply is bigger but statistically insignificant. Male borrowing positively impacts men's labor supply (increasing it by about 64 hours per month), while negatively impacting women's labor supply (by approximately 26 hours per month). It seems that people tend to work more after participating in microcredit.

Many of the effects are larger in absolute size for men's borrowing. This may be because men's amount of loans and size of projects tend to be bigger than those for women (Chemin, 2008). The main gender difference is that female labor supply decreases when males borrow, but increases when females borrow. In rural Bangladesh, men usually control their wives (Faraizi et al., 2014). Therefore, if their husband accesses more funds, women may be forced to limit their time working outside the home in order to take care of their families while the husband works more.

Up to this point, I have replicated what D&PJ did. I consistently reproduce the results that D&PJ reported in their paper. In the next section, I analyze their results more closely. In particular, I investigate whether PSM is the best approach to use. To do that, I apply diagnostic checking of covariate balance under the PSM method. I then employ another empirical procedure, entropy balancing, to see if D&PJ's results are robust.

2.3 Assessing the matching quality of PSM

The objective of matching methods is to create a control sample that is identical in every important respect to the treatment sample. PSM achieves matching based on the probability of receiving treatment. Individuals that have identical probabilities of receiving treatment are considered to be "identical" for comparison's sake. In other words, a control individual with the same probability of receiving treatment as a treatment individual is considered representative of the treatment individual if the treatment individual had not received treatment.

While PSM focuses on improving balance on propensity scores, there is no guarantee that it improves balance of the explanatory variables. In fact, it can even make balance on covariates worse (Blackwell, Iacus, King, & Porro, 2009; Sekhon, 2011). This is a problem if the variables associated with receiving treatment have an independent effect on the outcome. In other words, two matched observations with the same predicted probability of receiving treatment, but with very different covariate values, may have different expected outcomes due to differences in the explanatory variables, not the treatment.

Therefore, after using PSM to match treated and control individuals, it is necessary to assess how well the explanatory variables are balanced in the treatment and control samples. Substantial imbalances are indicative that the estimated treatment effects may not be reliable. There are several ways to assess whether the explanatory variables are balanced (Garrido et al., 2014). One of the most common is based on the standardized mean difference (SMD). The SMD is computed by taking both the means and variances of covariates into account (Faltermeier & Abdulai, 2009; Lee, 2013; Rosenbaum & Rubin, 1985). It is defined as “the difference in the mean of a variable between two groups divided by an estimate of the standard deviation of that variable” (Austin, 2009, p. 1229).

The associated formulae are as follows:

$$B_{before}(X) = (100)\frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{[V_T(X) + V_C(X)]}{2}}} \text{ ; and}$$

$$B_{after}(X) = (100)\frac{\bar{X}_{TM} - \bar{X}_{CM}}{\sqrt{\frac{[V_T(X) + V_C(X)]}{2}}},$$

where $\bar{X}_T$ and $\bar{X}_C$ are the means of explanatory variable X for the treatment and control groups before matching, $\bar{X}_{TM}$ and $\bar{X}_{CM}$ are the means of variable X for these groups after matching, and $V_T(X)$ and $V_C(X)$ stand for the variances of X in the original treatment and control samples. Both groups are considered to be "balanced" when SMD is close to zero.

There are two advantages of using SMD. First, unlike other statistical tests such as the t-test, the standardized mean difference is not impacted by sample size. Second, SMD allows one to compare balance in variables that have very different units of measurement, such as age (measured in years) and land size (measured in m^2) (Austin, 2009).

Assessing balance of propensity scores using stratification and kernel matching

In a matched sample, propensity scores should be similar in distribution for both groups (see the "common support assumption" discussed above). Figure 2.1 and Figure 2.2 show that before matching, the distribution of propensity score is different between the two groups. The overlap of propensity scores is limited. This means that it does not meet the requirement of the assumption of common support. Estimation of the impact of treatment on the treated will be suspect because the control group is not a representative of the treated group without treatment.

Not surprisingly, the distributions of propensity scores are very similar after matching, both for stratification and kernel matching. Non-participants are matched with participants rely on similarity in the likelihood scores. Aiding balance is the fact that the same control can be used for more than one treatment. Some controls will not be used at all because they do not match well with any treatment. Hence, after matching, the propensity scores of treated and control groups have similar distributions with high overlap (cf. Figure 2.1 and 2.2). The common support assumption can be considered to be satisfied.

The problem with PSM is that it focuses solely on propensity scores. Two individuals with very different values of explanatory variables could have identical propensity scores. As a result, it is now considered as a useful tool to check for balance of the individual covariates.

Assessing balance after stratification and kernel matching

Table 2.6 reports SMDs across explanatory variables after stratification matching. According to guidelines highlighted by Rosenbaum and Rubin (1985), if SMD is greater than twenty percent, it is considered large. For the matched sample in program villages, most of the SMDs are relatively close to zero. SMD is under 10% except for genders of household head, age of the head, and family size. However, for the matched control in non-program villages, many variables have SMDs greater than 20% or even 40%.

Similarly, after using kernel matching, SMDs across explanatory variables between treatment and control groups in program villages are close to zero (Table 2.7, column 3). However, many variables in the non-program villages matched sample have SMDs greater than 20%, with most of them greater than 10% (Table 2.7, column 6). These show a high imbalance across covariates in the matched data sets. Tables 2.7 and 2.8 indicate that stratification and kernel PSM leave substantial differences in the control variables, especially for matched samples using controls from non-program villages. As a result, in the next section, I explore an alternative matching procedure, entropy balancing, that is designed to produce better covariate balance between treatment and control groups.

2.4 Robustness check

PSM is a popular method of pre-processing data to estimate causal treatment effects. It is widely implemented across different fields of study such as economics, medicine, political science, etc. (Angelucci et al., 2015; M Caliendo & S Kopeinig, 2008). However, King and Nielsen (2016) recently argued that PSM has several disadvantages and should not be used for matching. Weaknesses of PSM are caused by its attempt to approximate a completely randomized experiment, while other matching approaches utilize a better technique, fully blocked randomized experiment.

A completely randomized experiment is a procedure in which pairs of control and treated groups are matched solely on propensity scores derived from the whole sample. A fully blocked randomized experiment is a procedure in which control and treated groups are blocked based on their observed covariates. Subjects are divided into blocks (strata) so that experimental units are similar to one another. Then subjects in treated and control groups within each block are matched based on propensity scores or some other criteria. The variation within a block is less than the variation between blocks. King & Nielson argue that PSM increases model dependence, inefficiency, bias, and imbalance.

The previous section demonstrated that, under PSM, the SMDs across explanatory variables were quite large in many cases. As a result, I now use an alternative method, entropy balancing. This method directly balances or equates the distribution of observed covariate variables in the treated and untreated groups. It achieves this by weighting the control group to make its explanatory variable distribution (up to several sample moments) similar to the explanatory variable distribution of the treatment group.

There are several advantages of using entropy balancing. Firstly, the weights are directly based on the known moments of sample, and hence this method always (at least weakly) improves on the distribution of explanatory variables balance achieved by conventional pre-processing methods. Secondly, the entropy balancing weights vary flexibly across observations and commonly retain more information than approaches that either match or discard each control unit in the pre-processed data. Entropy balancing is a relatively recent method and it is now considered good practice (Hainmueller, 2012; Hainmueller & Xu, 2013).

2.4.1 Balance diagnostics before and after entropy balancing

Table 2.8 and Table 2.9 report sample moments before and after weighting the control observations in the program and non-program villages, respectively. Comparing mean, variance and skewness across explanatory variables for both groups before entropy balancing reveals that the respective sample moments are very different.

For example, mean age for the treatment group is 34.57 compared to 20.57 for the control group (cf. "Treatment" and "Original Control" columns, Tables 2.8 and 2.9). After entropy balancing, the mean in the treatment and the mean in the reweighted control group are identical (cf. Tables 2.8 and 2.9, "Treatment" and "Weighted Control" columns). For example, mean age for the treated group *and* the "weighted" control group is 34.57.

Similarly, for the other variables, we can see that after adjustment, the mean, variance and skewness are almost identical for the two groups (treatment and weighted control, in program villages – Table 2.8, in non-program villages – Table 2.9). In comparison with PSM stratification and kernel matching, entropy balancing results in more balance in the distributions of the explanatory variables. Thus, one expects that entropy balancing will have less bias.

2.4.2 Comparison in standardized mean differences across explanatory variables among PSM (stratification and kernel matching) and entropy balancing

Table 2.10 compares SMDs across explanatory variables in stratification matching, kernel matching, and entropy balancing. A value of zero for SMD indicates identical means. The goal of pre-processing is to form well-balanced samples. PSM has a disadvantage of obtaining a joint balance for all covariates, especially with a large number of dimensions. Comparing to PSM, Entropy balancing yields better balance for such data.

This is evidenced in Table 2.10, where the weighted control group has the same means as the treated group on almost all covariates (the SMDs are zero or very close to zero for all covariates). In contrast, the two PSM matching methods (stratification and kernel) leave a number of covariates strongly unbalanced (cf. Table 2.10, columns (1), (2), (4), and (5)). Entropy balancing creates far better balance when matching borrowers and non-borrowers in both program and non-program villages (cf. columns (3) and (6)). Overall, entropy balancing is more efficient in improving covariate balance in the data.

2.4.3 Empirical robustness check results

Table 2.11 reports the results of estimating treatment effects with entropy balancing (cf. column 3), and compares them with results from PSM (cf. columns 1 and 2). The reported values are average treatment effects on the treated (ATTs) in per capita consumption expenditure. The results generally confirm D&PJ's kernel estimates. They show that households of treated individuals in treatment villages consume less than control households in treatment villages, though the difference is statistically insignificant.

The results are stronger when the control group consists of non-participants in non-program villages. Here, the entropy balancing results indicate that households with individuals that borrowed money under the microcredit program spent over 4 percent less on consumption than households that did not participate in microcredit. Further, this difference is statistically significant. These latter results may be explained by confounding because of differences between treatment and control villages if treatment villages were poorer than non-program villages.

Table 2.12 reports the impacts of microcredit on other outcomes. The entropy balancing estimates are consistent with D&PJ's PSM-kernel results, though the estimated effects are slightly different in absolute value. Participation in microcredit increases the value of non-landed assets held by women by 47.1%. School enrolment is 5.5% higher for girls and 4.8% higher for boys if their parents access microfinance credit, though the latter estimate is not significant at the 5 percent level. The estimated effects for both male and female labor supply are statistically insignificant and positive.

Table 2.13 reports the results of estimating separate effects based on the gender of the borrower. Again, most of my main results are similar to D&PJ's findings. While female borrowing has an insignificant influence on household consumption expenditure, male borrowing negatively and significantly affects per capita consumption expenditure. As noted above, this could be due to any number of causes. It might be that males are the actual main utilizers of female-borrowed money. Females may not use their loans themselves. Therefore, female borrowing would have no impact on family expenditure. Males may tend to use their borrowed money to invest in productive activities instead of spending on consumption. Unprofitable investments might lead to a need to substitute funds from other sources such as cutting consumption, reducing saving, and selling other utensils or assets (Kabeer, 2001). It may also reflect the fact that male borrowing is associated with a decrease in female labor supply (see below).

The results show that both male and female borrowing positively affect girl school enrolment, on average increasing it by 8.8% and 15.1% for borrowing by male and female parents, respectively. While D&PJ find that microcredit has an insignificant impact on boy school enrolment when women are borrowing, my results suggest that boy school enrolment increases by 9.5% if female members borrow and 6.4% if male members borrow, with both estimates being statistically significant. These results indicate that the parents invest in their children's education no matter the gender of their children. For labor supply, my results show that male borrowing increases their labor supply by 50-60 hours per month while reducing their wife's labor supply by 25-36 hours per month.

D&PJ's results show that if the borrowers are female, female labor supply increases by 23.4 hours per month while my findings show that female borrowing has a smaller and statistically insignificant impact on women's labor supply. If males are the actual main utilizers of borrowed money in the family, female loans may be appropriated by the husband or other male family members, thus having little to no impact on the woman's working hours.

Female non-landed assets increase by 73.9% if female members borrow and decrease by 27.5% if male members borrow. It might be the case that female borrowers tend to purchase non-landed assets such as livestock or appliances. However, male borrowers may tend to invest in large capital projects that exceed the loan's amount. Wives may then help their husbands by reducing their non-landed assets. This finding is in contrast to D&PJ's results that male and female borrowing both increase women's non-landed assets (by 131.4% and 80.5%, respectively). However, it should be noted that the entropy balancing estimate for male borrowing is not significant at the 5-percent level.

Overall, my entropy balancing estimates are not dramatically different from the PSM-kernel estimates of D&PJ.

2.5 Conclusion

An extensive literature on the effects of microcredit was spawned from seminal research by Pitt & Khandker (1998). Their research claimed a number of benefits from microcredit programs. In particular, they reported that microcredit reduced poverty and positively impacted household consumption. The impacts were more positive when loans were given to women. Follow-up research by Roodman & Morduch (2014) and Chemin (2008) found weaker evidence of the beneficial impacts of microcredit.

Contributing to this debate, Duvendack & Palmer-Jones (2012) identified several shortcomings in Chemin's data construction. Further, they criticized Chemin's lack of sensitivity analyses and failure to estimate separate impacts for male and female borrowers. Accordingly, D&PJ replicated and extended Chemin's work. They were unable to reproduce some of Chemin's main results, at the same time casting doubt on PK's original findings.

In this chapter, I contribute to this debate by replicating D&PJ's research. In addition to confirming their results using their data and code, I employ an alternative estimation method, namely entropy balancing. D&PJ's results rely on propensity score matching. While PSM is widely used, it has been criticized because it can match control observations that differ greatly from treatment observations (King & Nielsen, 2016). This issue is known as covariate imbalance. When individual characteristics of treatment and control observations differ substantially, the matched data are said to be unbalanced.

Indeed, I demonstrate that the matched data used by D&PJ are unbalanced. This motivates my use of entropy balancing, which constructs a synthetic control group that closely matches the treatment group. My re-analysis of their research using entropy balancing largely confirms their original results. However, I do find some differences. While D&PJ find that microcredit has a positive impact on the value of non-landed assets held by women, I find a positive impact when females borrow but a negative impact when males borrow. In addition, D&PJ report that female borrowing has a statistically significant and positive impact on female labor supply and a statistically insignificant impact on male labor supply. In contrast, my entropy balancing estimates find an insignificant impact on female labor supply and a positive impact on male labor supply when females borrow.

My research adds to recent skepticism about the previously documented large and far-reaching benefits of microfinance programs. My replication findings largely confirm the research of Duvendack & Palmer-Jones (2012). In doing so, they fail to support the original findings of Chemin, and by extension, PK, that microcredit significantly and positively affects the poor in Bangladesh, especially if female household members borrow.

The estimated impacts of microcredit programs may vary over time, across countries of interest, and be sensitive to the research methods used. This suggests that further studies with updated datasets or newer methods are warranted. Accordingly, my subsequent chapters will further explore this subject by updating the survey data with a more recent wave and using a different approach to estimate the microcredit impacts on the low-income people in Bangladesh.

2.6 References

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Table 2.1 Logit model to predict propensity scores: determinants of the probability of participation

Independent variables	*Chemin*	*D&PJ*	*Replication*
Sex (male=1)	-1.136***	-0.773***	-0.773***
	(0.128)	(0.000)	(0.000)
Age (years)	1.065***	0.559***	0.559***
	(0.159)	(0.000)	(0.000)
Age HH head (years)	-0.014**	-0.003	-0.003
	(0.006)	(0.454)	(0.454)
N. adult male in HH	0.823***	0.011	0.011
	(0.308)	(0.873)	(0.873)
Education	0.336***	0.000	-0.031**
	(0.113)	(0.196)	(0.012)
Savings	0.0002***	0.354***	0.000
	(0.00003)	(0.000)	(0.196)
Have non-farm enterprise (yes=1)	0.630***	-0.000	0.354***
	(0.111)	(0.129)	(0.000)
Livestock value	0.00005***	-0.122***	-0.000
	(0.00002)	(0.000)	(0.129)
HH size	-0.147***	-0.001	-0.122***
	(0.028)	(0.124)	(0.000)
Non-agricultural wage (in Taka)	-0.006*	-0.000	-0.001
	(0.003)	(0.992)	(0.124)
Agricultural wage (in Taka)	0.010**	-0.009***	-0.000
	(0.005)	(0.000)	(0.992)
Age squared	-0.028***	0.000***	-0.009***
	(0.006)	(0.000)	(0.000)
Age power of 4	-1.16E-6***	-0.773***	0.000***
	(0.0001)	(0.000)	(0.000)
Village dummies	Yes	Yes	Yes
N. of obs	5,037	9,397	9,397
Pseudo R-square	0.331	0.315	0.315

Note: This table reports the replication of column (6) of Table 1 in D&PJ (page 7). The data and Stata do files, which are kindly provided by D&PJ, are used for the replication. The numbers in parentheses below coefficients are p-values for D&PJ and the replication results, and t-statistics for Chemin's results. * significant at 10%, ** significant at 5% and *** significant at 1%. Source: Chemin (Table 1:471, column 4), D&PJ (Table 1:7, column 6) and author's replication. Chemin and D&PJ estimate some other specifications, but as they focus on their Specification 3, I also focus on Specification 3.

Table 2.2 Descriptive statistics

	Chemin		D&PJ		Replication	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*
Explanatory variables						
Age (years)*	n/a	22.372	9,397	22.22	9,397	22.22
		(17.422)		(17.424)		(17.424)
Sex (male=1)	n/a	0.513	9,679	0.5	9,679	0.5
		(0.499)		(0.5)		(0.5)
Age of HH head (years)*	n/a	42.313	9,679	42.97	9,679	42.97
		(12.383)		(12.413)		(12.413)
Highest grade by anyone in HH*	n/a	2.255	9,679	2.393	9,679	2.393
		(3.173)		(1.327)		(1.327)
Number of adult males in HH*	n/a	0.024	9,679	1.588	9,679	1.588
		(0.153)		(1.063)		(1.063)
Highest education by anyone in HH*	n/a	0.551	9,679	4.412	9,679	4.412
		(0.497)		(3.977)		(3.977)
Savings (Taka)*	n/a	1,128.9	9,679	1,354.392	9,679	1,354.392
		(4,201.37)		(5,738.28)		(5,738.28)
Non-farm enterprise (yes=1)*	n/a	0.468	9,679	0.474	9,679	0.474
		(0.499)		(0.499)		(0.499)
Livestock value (Taka)*	n/a	3,273.15	9,679	3,591.578	9,679	3,591.578
		(5,533.9)		(5,851.158)		(5,851.158)
HH size*	n/a	6.232	9,679	6.401	9,679	6.401
		(2.632)		(2.693)		(2.693)
Non-agricultural wage (Taka)*	n/a	4.023	9,679	71.156	9,679	71.156
		(16.303)		(128.291)		(128.291)
Agricultural wage (Taka)*	n/a	2.987	9,679	43.757	9,679	43.757
		(9.755)		(63.447)		(63.447)
Age squared	n/a	802	9,397	797.315	9,397	797.315
		(1,109.7)		(1,102.621)		(1,102.621)
Age power of 4	n/a	1,874,542	9,397	1,851,354	9,397	1,851,354
		(5,029,988)		(4,942,972)		(4,942,972)
Outcome variables						
Expenditure per capita (Taka)*					9,679	81.347
						(47.732)
Female non-land assets (Taka)*					9,679	2,480.9
						(8,514.806)
Female labor supply, aged 16-59 (hours per month)*					9,679	136.181
						(196.860)
Male labor supply, aged 16-59 (hours per month)*					9,679	901.513
						(586.920)

Girl school enrolment, aged 5-17 years (yes=1)*	6,394	0.620 (0.485)
Boy school enrolment, aged 5-17 years (yes=1)*	6,598	0.668 (0.471)

n/a: Not reported by Chemin

* Household characteristics.

Source: Chemin, Table 1, page 471, unweighted, based on averages data in three waves of the 1991–92 survey
D&PJ, Table A1, unweighted, based on averages across the three waves
Author's calculations, replicating D&PJ, unweighted, based on averages across three waves

Table 2.3 The overall impact estimation of ATT for log per capita expenditure (Taka)

Control groups	*Stratification number of strata (1)*			*Kernel matching bandwidth (2)*		
	20	10	5	0.05	0.02	0.01
Chemin's results						
Non-participants in treatment villages	-0.035*	-0.044**	-0.044*	-0.039*	-0.044*	-0.046*
Non-participants in control villages	0.028	0.028***	0.028*	0.028***	0.028***	0.028***
D&PJ's and replication results[a]						
Non-participants in treatment villages	-0.001***	-0.003***	-0.010***	-0.007	-0.011	-0.012
Non-participants in control villages	-0.004***	0.008***	-0.021***	-0.061***	-0.064***	-0.065***

Note: * significant at 10%, ** significant at 5%, *** significant at 1%. Data across three waves of the 1991-92 survey are used. All results are bootstrapped. Source: Chemin (2008, Table 2, page 476), D&PJs (2012, Table 2, page 9), and the authors' replication.

[a] Because data and Stata code are provided by D&PJ, I can directly reproduce their results. Their results and my identical replication results are reported in the same panel.

Table 2.4 Impact assessment for alternative outcome variables, between participants and non-participants across program and non-program villages: Kernel matching

		Chemin			*D&PJ*			*Replication*		
Outcome variables	*Obs*	0.05	0.02	0.01	0.05	0.02	0.01	0.05	0.02	0.01
Variation of log per capita expenditure (Taka)	9,326	-0.008	-0.008	-0.008	-0.012*	-0.012*	-0.012*	-0.012*	-0.012*	-0.012
Log per capita expenditure (Taka)	9,397	n/a	n/a	n/a	-0.008	-0.011	-0.011	-0.008	-0.011	-0.011
Log women non landed assets (Taka)	9,397	0.037	0.037	0.038	0.513***	0.498***	0.489***	0.513***	0.498***	0.489***
Female labor supply, aged 16-59 years, hours per month	9,397	9.503	9.507	9.521	9.448	8.879	9.104	9.448	8.879	9.104
Male labor supply, aged 16-59 years, hours per month	9,397	17.001***	16.996***	16.974***	21.256	22.305	20.512	21.256	22.305	20.512
Girl school enrolment, aged 5-17 years	6,220	0.051***	0.051***	0.052***	0.051**	0.057**	0.060**	0.051**	0.057**	0.060**
Boy school enrolment, aged 5-17 years	6,449	0.035*	0.035	0.036	0.038	0.044*	0.047*	0.038	0.044*	0.047*

Note: * significant at 10%, ** significant at 5%, *** significant at 1%. Data and Stata do file are kindly provided by D&PJ. Results are bootstrapped. Source: Chemin (2008, Table 3; page 447), D&PJ (2012, Table 3; page 10) and author's replication.
Chemin and D&PJ use kernel matching and various bandwidths 0.05, 0.02 and 0.01, so I do as well.

Table 2.5 Impact assessment for alternative outcome variables by gender, between participants and non-participants across program and non-program villages

Outcome variables	*Bandwidth 0.05*	
	Female	*Male*
Variation of log per capita expenditure (Taka)	-0.019**	-0.026***
Log per capita expenditure (Taka)	-0.018	-0.066***
Log of women non-landed assets (Taka)	1.314***	0.805***
Female labor supply, aged 16-59 years, hours per month	23.440**	-25.592***
Male labor supply, aged 16-59 years, hours per month	40.860	63.909***
Girl school enrolment, aged 5-17 years	0.069**	0.103***
Boy school enrolment, aged 5-17 years	0.056*	0.068***

Note: * significant at 10%, ** significant at 5%, *** significant at 1%. Data and Stata do file are kindly provided by D&PJ. Results are bootstrapped. The result is the different estimation in the mean values between matched treatment and control groups.

D&PJ use kernel with bandwidth 0.05 to estimate this impact assessment, so I do as well. Note that D&PJ's results and my results are identical, so they are reported together.

Table 2.6 Covariate balance across treatment and control groups in villages with and without microcredit programs after weighting on the propensity score

	Stratification Matched Sample					
	Non-participants in program villages			*Non-participants in non-program villages*		
Variable	*Mean Treatment (n=60)*	*Mean Weighted Control (n=699)*	*Standardized Difference (%)*	*Mean Treatment (n=60)*	*Mean Weighted Control (n=699)*	*Standardized Difference (%)*
Sex of HH head (male=1)	0.52	0.43	16.6*	0.52	0.25	53*
Age (years)	31.67	32.52	-5.9	31.67	38.30	-45.4*
(max) Age of HH head (years)	36.68	38.47	-14.1*	36.68	33.31	27.5*
(max) Number of males in HH	1.57	1.52	4.3	1.57	1.17	30.8*
(max) Highest grade by anyone in HH	6.63	6.73	-2.6	6.63	7.12	-11.8*
(sum) Savings (Taka)	2,707.3	2,239.1	5.3	2,707.3	1,167.1	8.5
(max) Have non-farm enterprise (yes=1)	0.48	0.50	-3.3	0.48	0.30	38.1*
(mean) Livestock value (Taka)	4,176.9	3,871.9	3.1	4,176.9	2,127.8	32.1*
(max) HH size	4.98	4.45	18.5*	4.98	3.48	62.3*
Non-agricultural wage (Taka)	80.20	65.00	9.1	80.20	163.13	-52.9*
Agricultural wage (Taka)	3.35	4.43	-2.5	3.35	5.92	-7.8
Age squared	1,101.6	1,150	-4.8	1,101.6	1586.5	-44.5*
Age power of 4	1,700,000	1,800,000	-2.1	1,700,000	3,100,000	-25.5*

*Absolute value of MSDs above 10%

Using stratification with 10 strata because there is no consensus in the matching literature on how many strata should be used when matching.

Table 2.7 Covariate balance across treatment and control groups in villages with and without microcredit programs after weighting on the propensity score

	Kernel Matched Sample					
	Non-participants in program villages			*Non-participants in non-program villages*		
Variable	*Mean Treatment (n=920)*	*Mean Control (n=8,477)*	*Standardized Difference (%)*	*Mean Treatment (n=920)*	*Mean Control (n=920)*	*Standardized Difference (%)*
Sex of HH head (male=1)	0.39	0.41	-5.0	0.39	0.47	-17.1*
Age (years)	34.57	33.42	8.0	34.57	35.66	-7.6
(max) Age of HH head (years)	40.84	40.64	1.6	40.84	42.54	-14
(max) Number of males in HH	1.35	1.34	0.8	1.35	1.66	-32.4*
(max) Highest grade by anyone in HH	3.65	3.60	1.3	3.65	4.78	-30.4*
(sum) Savings (Taka)	1,219.2	1,400.7	-4.1	1,219.2	1,061.8	3.5
(max) Have non-farm enterprise (yes=1)	0.56	0.52	8.0	0.56	0.57	-2.2
(mean) Livestock value (Taka)	2,655.5	2,673.2	-0.3	2,655.5	3,430.1	-15.2*
(max) HH size	5.45	5.50	-1.9	5.45	6.16	-29.3*
Non-agricultural wage (Taka)	52.54	53.92	-1.2	52.54	66.71	-12.4*
Agricultural wage (Taka)	41.75	43.36	-2.6	41.75	36.34	8.7
Age squared	1,305.5	1,259.7	4.7	1,305.5	1,408.9	-10.5*
Age power of 4	2,400,000	2,300,000	1.7	2,400,000	3,000,000	-13.2*

*Absolute value of MSDs above 10%

The bandwidth used for kernel matching is 0.05

Table 2.8 Entropy balancing the matched sample in program villages

Variables	*Treatment*			*Original Control*			*Weighted Control*		
	mean	*variance*	*skewness*	*mean*	*variance*	*skewness*	*mean*	*variance*	*skewness*
Sex of HH head (male=1)	0.39	0.24	0.47	0.53	0.25	-0.11	0.39	0.24	0.47
Age (years)	34.57	110.60	0.79	20.57	306.00	1.11	34.57	111.00	0.70
(max) Age of HH head (years)	40.84	140.80	0.65	43.38	156.70	0.53	40.84	130.50	0.72
(max) Number of males in HH	1.35	0.63	2.10	1.63	1.17	1.91	1.35	0.63	2.16
(max) Highest grade by anyone in HH	3.65	11.75	0.82	4.63	16.51	0.55	3.65	14.61	0.84
(sum) Savings (Taka)	1,219	3,408,118	5.48	1,256	20,500,000	14.81	1,219	36,600,000	14.37
(max) Have non-farm enterprise (yes=1)	0.56	0.25	-0.22	0.48	0.25	0.09	0.56	0.25	-0.22
(mean) Livestock value (Taka)	2,656	15,300,000	2.00	3,888	39,400,000	3.61	2,656	20,100,000	3.43
(max) HH size	5.45	4.34	0.92	6.53	7.39	1.33	5.45	4.67	1.07
Non-agricultural wage (Taka)	52.54	8,641	2.94	71.54	16,616	3.23	52.54	9,160	3.30
Agricultural wage (Taka)	41.75	3,773	1.89	41.61	4,204	2.12	41.75	3,511	1.92
Age squared	1,305	682,560	1.45	729	1,252,906	2.44	1,306	688,789	2.33
Age power of 4	2,386,137	1.09E+13	3.01	17,84,402	2.68E+13	5.90	2,394,891	1.87E+13	10.62

Table 2.9 Entropy balancing the matched sample in non-program villages

Variables	*Treatment*			*Original Control*			*Weighted Control*		
	mean	*variance*	*skewness*	*mean*	*variance*	*skewness*	*mean*	*variance*	*skewness*
Age (years)	34.57	110.60	0.79	22.43	298.80	0.83	34.56	110.80	0.72
Sex of HH head (male=1)	0.39	0.24	0.47	0.52	0.25	-0.07	0.39	0.24	0.47
(max) Age of HH head (years)	40.84	140.80	0.65	41.28	142.30	0.56	40.84	131.60	0.75
(max) Number of males in HH	1.35	0.63	2.10	1.39	0.91	2.36	1.35	0.84	2.47
(max) Highest grade by anyone in HH	3.65	11.75	0.82	3.52	15.25	0.96	3.65	14.39	0.80
(sum) Savings (Taka)	1,219	3,408,118	5.48	1,808	82,000,000	7.39	1,219	37,700,000	9.62
Have non-farm enterprise (yes=1)	0.56	0.25	-0.22	0.40	0.24	0.43	0.56	0.25	-0.22
(mean) Livestock value (Taka)	2,656	15,300,000	2.00	3,173	28,000,000	2.49	2,656	21,500,000	2.67
(max) HH size	5.45	4.34	0.92	5.74	5.50	1.04	5.45	5.66	1.21
Non-agricultural wage (Taka)	52.54	8,641	2.94	63.02	20,051	4.67	52.55	14,143	4.88
Agricultural wage (Taka)	41.75	3,773	1.89	50.39	2,813	0.80	41.75	2,463	1.08
Age squared	1,305	682,560	1.45	802	1,169,793	2.12	1,305	683,364	1.84
Age power of 4	2,386,137	1.09E+13	3.01	1,811,108	2.13E+13	4.89	2,385,691	1.37E+13	5.60

Table 2.10 Test for standardized mean differences across explanatory variables among Stratification, kernel PSM and Entropy balancing

	Non-participants in program villages			*Non-participants in non-program villages*		
Variable	*Standardized difference after stratification matching*	*Standardized difference after kernel matching*	*Standardized difference after entropy balancing*	*Standardized difference after stratification matching*	*Standardized difference after kernel matching*	*Standardized difference after entropy balancing*
	(1)	(2)	(3)	(4)	(5)	(6)
Sex of HH head (male=1)	16.6*	-5.0	0.0	53*	-17.1*	0.1
Age (years)	-5.9	8.0	0.0	-45.4*	-7.6	0.0
(max) Age of HH head (years)	-14.1*	1.6	0.0	27.5*	-14	0.0
(max) Number of males in HH	4.3	0.8	0.0	30.8*	-32.4*	0.0
(max) Highest grade by anyone in HH	-2.6	1.3	0.0	-11.8*	-30.4*	0.0
(sum) Savings (Taka)	5.3	-4.1	0.0	8.5	3.5	0.0
(max) Have non-farm enterprise (yes=1)	-3.3	8.0	0.0	38.1*	-2.2	0.0
(mean) Livestock value (Taka)	3.1	-0.3	0.0	32.1*	-15.2*	0.0
(max) HH size	18.5*	-1.9	0.0	62.3*	-29.3*	0.0
Non-agricultural wage (Taka)	9.1	-1.2	0.0	-52.9*	-12.4*	0.0
Agricultural wage (Taka)	-2.5	-2.6	0.0	-7.8	8.7	0.0
Age squared	-4.8	4.7	-0.1	-44.5*	-10.5*	0.0
Age power of 4	-2.1	1.7	-0.2	-25.5*	-13.2*	0.0
Observations n	699 when weighted	920 when weighted	920 when weighted	699 when weighted	920 when weighted	920 when weighted

*Absolute value of MSDs above 10%
The bandwidth used for kernel matching is 0.05
The strata used for Stratification is 10

Table 2.11 Robustness check: the impact of microcredit participation on per capita expenditure using entropy balancing

	Stratification number of strata (1)			*Kernel matching bandwidth (2)*			*Entropy balancing (3)*
Control groups	20	10	5	0.05	0.02	0.01	Robustness check
Non-participants in treatment villages	-0.001***	-0.003***	-0.010***	-0.007	-0.011	-0.012	-0.007
Individuals in control villages	-0.004***	0.008***	-0.021***	-0.061***	-0.064***	-0.065***	-0.043**

Note: *, **, *** denote significance at 10%, 5%, and 1% levels. The results are bootstrapped.

Table 2.12 Robustness check: the impact of microcredit participation on alternative outcomes using entropy balancing

	Chemin			*D&PJ*			*Entropy balancing*
Outcome variables	0.05	0.02	0.01	0.05	0.02	0.01	
Variation of log per capita expenditure (Taka)	-0.008	-0.008	-0.008	-0.012*	-0.012*	-0.012*	-0.014*
Log per capita expenditure (Taka)	n/a	n/a	n/a	-0.008	-0.011	-0.011	-0.013
Log of female non landed assets (Taka)	0.037	0.037	0.038	0.513***	0.498***	0.489***	0.471***
Female labor supply, aged 16-59 years, hours per month	9.503	9.507	9.521	9.448	8.879	9.104	4.813
Male labor supply, aged 16-59 years, hours per month	17.001***	16.996***	16.974***	21.256	22.305	20.512	29.593
Girl school enrolment, aged 5-17 years	0.051***	0.051***	0.052***	0.051**	0.057**	0.060**	0.055**
Boy school enrolment, aged 5-17 years	0.035*	0.035	0.036	0.038	0.044*	0.047*	0.048*

Note: *, **, *** denote significance at 10%, 5%, and 1% levels. The results are bootstrapped.
Chemin and D&PJ use kernel with bandwidth 0.01, 0.02 and 0.05 to estimate their results

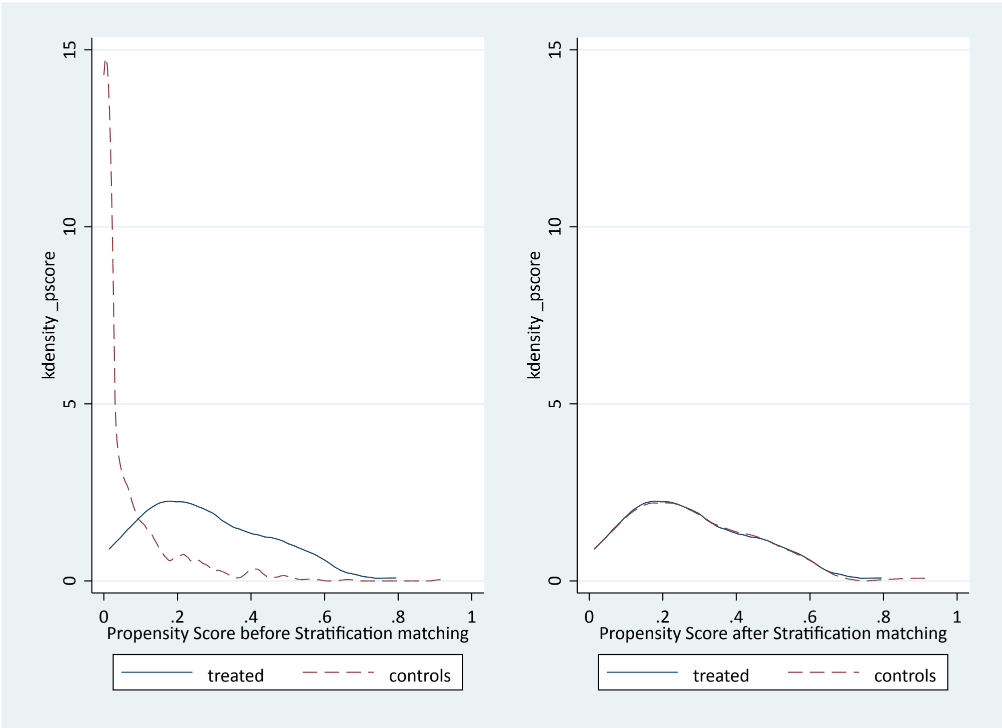
Table 2.13 Impact estimation for alternative outcome variables stratified by gender (entropy balancing)

Outcome variables	*Female (D&PJ)*	*Female (EB)*	*Male (D&PJ)*	*Male (EB)*
Variation of log per capita expenditure (Taka)	-0.019**	-0.023**	-0.026***	-0.050***
Log per capita expenditure (Taka)	-0.018	-0.016	-0.066***	-0.067***
Log of female non-landed assets (Taka)	1.314***	0.739***	0.805***	-0.275*
Female labor supply, aged 16-59 years, hours per month	23.440**	16.517	-25.592***	-36.302 ***
Male labor supply, aged 16-59 years, hours per month	40.860	49.463***	63.909***	53.004***
Girl school enrolment, aged 5-17 years	0.069**	0.088***	0.103***	0.151***
Boy school enrolment, aged 5-17 years	0.056	0.095***	0.068***	0.064***

Note: *, **, *** denote significance at 10%, 5%, and 1% levels. The results are bootstrapped
Using entropy balancing (EB) for robustness check.

Figure 2.1 Density plots of propensity score distribution of treatment and non-treatment groups in program villages (a) and in non-program villages (b) before and after matching, using Stratification technique strata 10

(a)



(b)

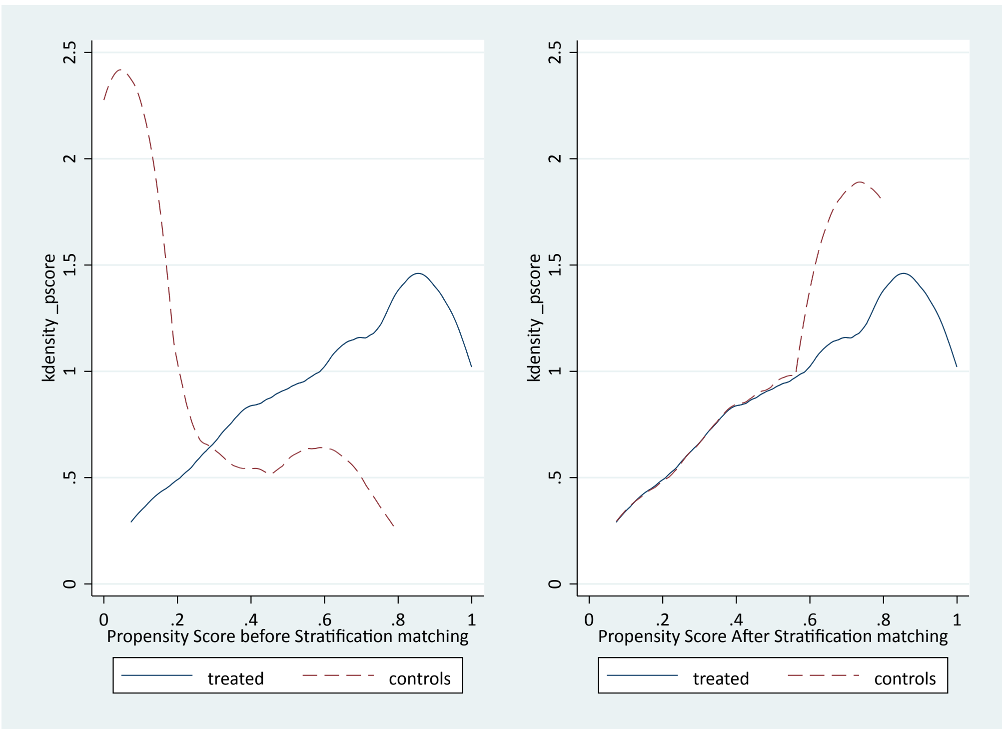
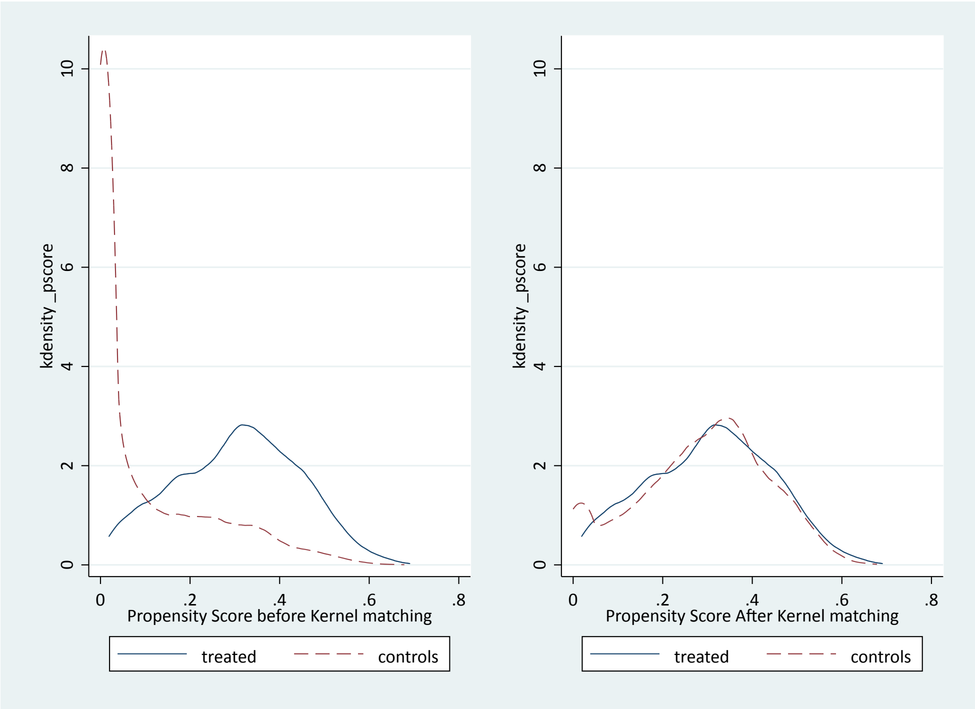
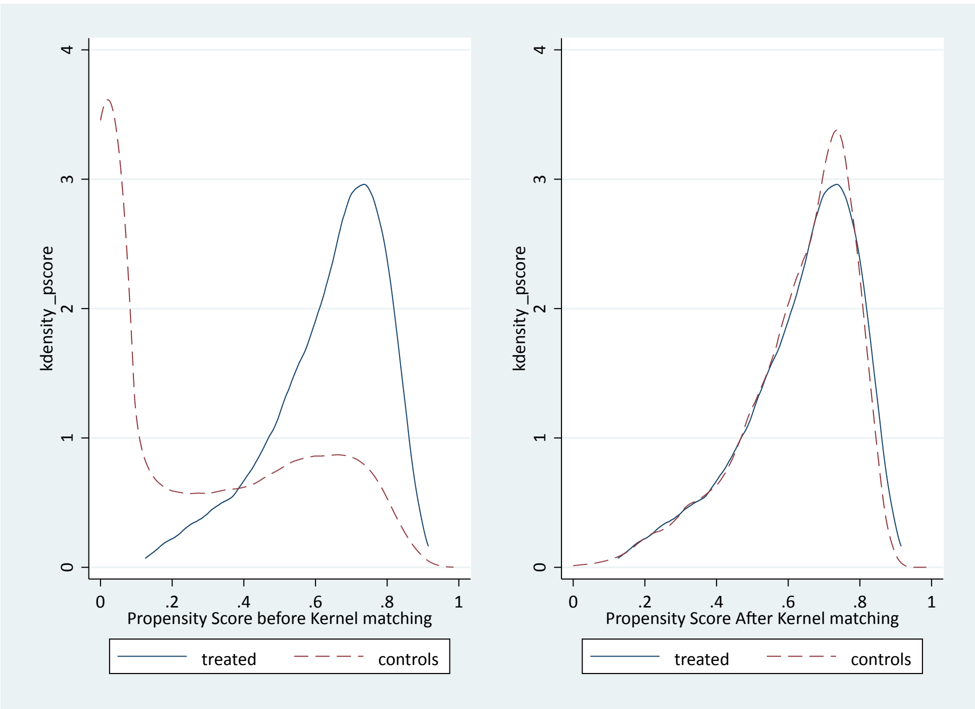


Figure 2.2 Density plots of the propensity score distribution of treatment and non-treatment groups in program villages (a) and in non-program villages (b) before and after matching, using kernel technique with bandwidth 0.05

(a)



(b)



2.7 Appendix: Programming code for Chapter 2

```
//Appendix for Chapter 2

clear matrix
drop _all
set mem 512m
set more off

// set paths to working data folders
global workingpath "C:\Users\dtv13\Dropbox\DIEM PhD Program\ Chapter 2_D&PJ\"

log close
log using "${workingpath}D&PJ_replication results", replace

// Open the data file PSM_Prep_all.DTA (Provided by D&PJ)
use  "${workingpath}PSM_Prep_all_Final.dta", clear


***************************************************************************
// TABLE 2.1, Column 3, Replication
***************************************************************************


// Data management/ D&PJ used
gen male = sex == 1
recode edslg (0=0) (1/5=1) (6/10=2) (11/12=3) (else=4), gen(hgrade)  //value from 0 to 16

gen agriincome1 = cropproductionincome
gen sharecropincome_net1 = sharcropincome - sharecropexpend
gen agriincome_net1 = agriincome1 - agricost
rename flcitpp agriincome
gen agriincome_net = agriincome - agricost
rename flciscrp sharecropincome
rename flciscpp sharecropexpenditure

label var agriincome "gross income from agriculture "
label var sharecropincome_net "net income from sharecropping"
label var agriincome_net "net income from agriculture "

gen sumnonagri = wagenonag
gen sumagri = wageag

* Create village dummies:
replace thanaid = floor(upzvill/10)
xi i.thanaid

// Set macro for control variables and villages dummy
global DPJSpec3 "male agey agehhhh no_of_adultmales maxed cssv nonfarm livestockvalue hhsize
sumnonagri sumagri agesq age4"
global treatvilldumm  "_Ithanaid_2  _Ithanaid_3 _Ithanaid_4 _Ithanaid_5 _Ithanaid_6
_Ithanaid_7 _Ithanaid_8 _Ithanaid_9 _Ithanaid_10 _Ithanaid_11 _Ithanaid_12 _Ithanaid_13
_Ithanaid_14 _Ithanaid_15 _Ithanaid_16 _Ithanaid_17 _Ithanaid_18 _Ithanaid_19 _Ithanaid_20
_Ithanaid_21 _Ithanaid_22 _Ithanaid_23 _Ithanaid_24"

// Table 2.1
logit elig_defacto_treatpp  $DPJSpec3 $treatvilldumm
gen sample_3 = e(sample)
predict ps3
estimates store Spec3


***************************************************************************
// TABLE 2.2
***************************************************************************


// Descriptive statistic, COLUMN 3 REPLICATION
global Sumstats "hgrade male agey agehhhh no_of_adultmales relhhh_1_trland relhhh_2_trland
relhhh_3_trland highedufat maxed cssv nonfarm livestockvalue hhsize sumnonagri sumagri agesq
age4 no_of_adultfemales agriincome agriincome_net maxedhhh other halaa injury agricost flopt
highedumat marital mliv fliv flopi equipment transport other dairy nfexpfv nferevw"

sum ${Sumstats}
```

```
*************************************************************************
//TABLE 2.3, row 3
*************************************************************************


// Non-participants in treatment villages
// Replication D&PJ Table 2, row 3
// Using stratification matching, log of expenditure per capita only

*** Prep for replicating D&PJ's table 2:
gen control1 = thanaid <= 24  // all treated vs non-part in treatvill
gen control2 = ~(elig_defacto_treatpp == 0 & thanaid <= 25) // treated vs all individuals in
control villages (excludes non-participants in treated villages)

*** Replicate results
mat results = J(3,3,.)
local i = 1
local rownames ""
foreach v in 5 10 20 {
	tempvar groupvars att g
	egen `groupvars' = cut(lnconsweekpc), group(`v')  // strata 5, 10 and 20
	tab `groupvars', sum(lnconsweekpc)
	gen `att' = .
	gen `g' = `groupvars'
	levels `g', local(gr)
	qui foreach j of local gr {
			psmatch2 elig_defacto_treatpp male agey agehhh no_of_adultmales maxed cssv
nonfarm livestockvalue hhsize sumnonagri sumagri agesq age4 _Ithanaid_2 _Ithanaid_3
_Ithanaid_4 _Ithanaid_5 _Ithanaid_6 _Ithanaid_7 _Ithanaid_8 _Ithanaid_9 _Ithanaid_10
_Ithanaid_11 _Ithanaid_12 _Ithanaid_13 _Ithanaid_14 _Ithanaid_15 _Ithanaid_16 _Ithanaid_17
_Ithanaid_18 _Ithanaid_19 _Ithanaid_20 _Ithanaid_21 _Ithanaid_22 _Ithanaid_23 _Ithanaid_24 if
control1 & `g' == `j', out(lnconsweekpc)
		replace `att' = r(att) if `g' == `j'
	}
	sum `att'
* to get significance level:
	reg `att' if elig_defacto_treatpp == 1 & control1   // tests if att is significantly
differnt from zero
	mat results[`i', 1] = `v'
	mat results[`i', 2] = _b[_cons]
	matrix a = vecdiag(e(V))
	matrix b = (e(b)\a)'
	local b = b[1,1]
	local se = b[1,2]
	local se = sqrt(`se')
	local t = `b'/`se'
	local no = e(N)
	local p = 2*ttail(`no',abs(`t'))
*	di "`t' `p' `b'"
	mat results[`i', 3] = `p'

*   reg att if elig_defactopp == 1 & ~control1      // tests if att is significantly differnt
from zero
	drop `att' `groupvars' `g'
	local ++i
}

***** Table 2.3 row 3:
mat colnames results = no_strata beta p_value
mat list results


*************************************************************************
//TABLE 2.3, row 4
*************************************************************************


// Non-participants in control villages
// Replication D&PJ Table 2, row 4
// Using Stratification matching, log of expenditure per capita only
mat results2 = J(3,3,.)
local i = 1
local rownames ""
foreach v in 5 10 20 {
```

```
        tempvar groupvars att2 g1
        egen `groupvars' = cut(lnconsweekpc), group(`v')  //strata 5, 10 and 20
        tab `groupvars', sum(lnconsweekpc)
        gen `att2' = .
        gen `g1' = `groupvars'
        levels `g1', local(gr)
        qui foreach j of local gr {
                psmatch2 elig_defacto_treatpp male agey agehhh no_of_adultmales maxed cssv
nonfarm livestockvalue hhsize sumnonagri sumagri ///
                agesq age4 if control2 & `g1'==`j', out(lnconsweekpc)
                replace `att2' = r(att) if  `g1'==`j'
        }
        sum `att2'
* to get significance level:
        reg `att2' if elig_defacto_treatpp == 1 & control2  // tests if att is significantly
differnt from zero
* reg att if participating_memberpp == 0 & elig & ~control2 // tests if att is significantly
differnt from zero
        mat results2[`i', 1] = `v'
        mat results2[`i', 2] = _b[_cons]
        matrix a = vecdiag(e(V))
        matrix b = (e(b)\a)'
        local b = b[1,1]
        local se = b[1,2]
        local se = sqrt(`se')
        local t = `b'/`se'
        local no = e(N)
        local p = 2*ttail(`no',abs(`t'))
* di "`t' `p' `b'"
        mat results2[`i', 3] = `p'
        drop `att2' `groupvars' `g1'
        local ++i
}

***** Table 2.3 row 4:
mat colnames results2 = no_strata beta p_value
mat list results2


**************************************************************************

* All treated, part vs non-part in treatvill:
logit elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control1
predict ps2
estimates store Ch2

* Compare part in treatvill with all indiv in control vill, excludes non-part in treatvill:
logit elig_defacto_treatpp $DPJSpec3 if control2 // $treatvilldumm
predict ps2b
estimates store Ch2b



**************************************************************************
// TABLE 2.3, row 3
**************************************************************************


// Non-participants in treatment villages
// Part vs non-part in treatvill
logit elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control1
predict ps2
estimates store Ch2

// Replication D&PJ Table 2, row 3
// Kernel matching, log of expenditure per capita only
// bandwith 0.01 0.02 0.05:
// lnconsweekpc only
mat results3 = J(3,5,.)
local i = 1
local rownames ""
foreach k in .01 .02 .05 {
        psmatch2 elig_defacto_treatpp, outcome(lnconsweekpc ) /// // sdlnconsweekpc
lnnonlandwomen labsupwomMD1 labsupmenMD1 fedec517_rpj medec517_rpj
                pscore(ps2) kernel k(normal) bwidth(`k')
        local diff = r(att)
```

```
        local semean = r(seatt)
* local i = 1
        mat results3[`i', 1] = `k'
        mat results3[`i', 2] = `diff'
        mat results3[`i', 3] = `semean'
        local sd = `semean' * sqrt(`diff')
        sum _treated
        local n = r(sum) - 1
        local pdiff = 2*ttail(`n', abs(`diff'/`semean'))
        local tdiff = `diff' / `semean'
        mat results3[`i', 4] = `pdiff'
        mat results3[`i', 5] = `tdiff'
        local rownames = "`rownames' `v'"
        local ++i
}

mat rownames results3 = `rownames'
mat colnames results3 = k diff semean pvalue tvalue
mat list results3



****************************************************************************
//TABLE 2.3, row 4
****************************************************************************


// Non-participants in control villages
// Compare part in treatvill with all indiv in control vill, excludes non-part in treatvill
logit elig_defacto_treatpp $DPJSpec3 if control2 // $treatvilldumm
predict ps2b
estimates store Ch2b

// Replication D&PJ Table 2, row 4
// Kernel matching, log of expenditure per capita only
// bandwith 0.01 0.02 0.05:
// lnconsweekpc only
mat results4 = J(3,5,.)
local i = 1
local rownames ""
foreach k in .01 .02 .05 {
        psmatch2 elig_defacto_treatpp, outcome(lnconsweekpc ) ///
                pscore(ps2b) kernel k(normal) bwidth(`k')
        local diff = r(att)
        local semean = r(seatt)
* local i = 1
        mat results4[`i', 1] = `k'
        mat results4[`i', 2] = `diff'
        mat results4[`i', 3] = `semean'
        local sd = `semean' * sqrt(`diff')
        sum _treated
        local n = r(sum) - 1
        local pdiff = 2*ttail(`n', abs(`diff'/`semean'))
        local tdiff = `diff' / `semean'
        mat results4[`i', 4] = `pdiff'
        mat results4[`i', 5] = `tdiff'
        local rownames = "`rownames' `v'"
        local ++i
}

mat rownames results4 = `rownames'
mat colnames results4 = k diff semean pvalue tvalue
mat list results4



****************************************************************************
// TABLE 2.4
****************************************************************************


// Replicate D&PJ's table 3
// Kernel matching, bandwith 0.05
// Run PSM for logit specification 3

mat results6 = J(21, 5, .)
```

```
local i = 1
local rownames ""
foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rpj {
        foreach k in .01 .02 .05 {
                psmatch2 elig_defacto_treatpp, outcome(`v') pscore(ps3) kernel k(normal)
bwidth(`k')
                local diff = r(att)
                local semean = r(seatt)
        * local i = 1
                mat results6[`i', 1] = `k'
                mat results6[`i', 2] = `diff'
                mat results6[`i', 3] = `semean'
                local sd = `semean' * sqrt(`diff')
                sum _treated
                local n = r(sum) - 1
                local pdiff = 2*ttail(`n', abs(`diff'/`semean'))
                local tdiff = `diff' / `semean'
                mat results6[`i', 4] = `pdiff'
                mat results6[`i', 5] = `tdiff'
                local k1 = string(`k')
                local k1 = subinstr("`k1'",".","_",1)
                local rownames "`rownames' `v'`k1'"
                local ++i
        }
}
mat rownames results6 = `rownames'
mat colnames results6 = k diff semean pvalue tvalue
mat list results6


****************************************************************************
// TABLE 2.5
****************************************************************************


// Devendack&Palmer-Jones' table 4
// Impacts segregated by gender:
// female and male MF borrowers:
*maleparthh and femaleparthh are indicators that a male or female borrower is in the
household
gen elig_female_in_male_borrower_hh =  elig_defacto_treat == 1 & maleparthh == 1 &
femaleparthh ~= 1 // no need for this variable to be "female" - can be eligble household with
male borrower


****************************************************************************
// TABLE 2.5, Column 1 (Female)
****************************************************************************


// Assess impact of women - all outcome variables
// kernel matching, 0.05
// female borrowers vs all females in households with no borrowers to assess the effect of
female borrowing:
mat results7 = J(7, 5, .)
local i = 1
local k = 0.05 //
local rownames ""
foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rp {
        psmatch2 elig_defacto_treatpp $DPJSpec3 if elig_defacto_treatpp == 1 & femaleparthh
///
                | ~ maleparthh, outcome(`v') kernel k(normal) bwidth(`k') logit // neighbor(1)
        local diff = r(att)     // extract att & seatt and store in resutls matrix
        local semean = r(seatt)
* local i = 1
        mat results7[`i', 1] = `k'
        mat results7[`i', 2] = `diff'
        mat results7[`i', 3] = `semean'
        local sd = `semean' * sqrt(`diff')
        sum _treated                    // extract  p- & t-values
        local n = r(sum) - 1
        local pdiff = 2*ttail(`n', abs(`diff'/`semean'))
        local tdiff = `diff' / `semean'
        mat results7[`i', 4] = `pdiff'
```

```
        mat results7[`i', 5] = `tdiff'
        local k1 = string(`k')
        local k1 = subinstr("`k1'",".","_",1)
        local rownames "`rownames' `v'`k1'"
        cap drop _treated_`v'
        cap drop _support_`v'
        cap drop _weight_`v'
        gen _treated_`v' = _treated
        gen _support_`v' = _support
        gen _weight_`v' = _weight
        local ++i
}
mat rownames results7 = `rownames'
mat colnames results7 = k diff semean pvalue tvalue
mat list results7


****************************************************************************
// TABLE 2.5, Column 2 (Male)
****************************************************************************


// Assess impact of Male borrowing  - all outcome variables (table 2.5, male)
// kernel matching, 0.05:
// compare outcomes for hh with male only borrowers and all other groups
mat results8 = J(7, 5, .)
local i = 1
local k = 0.05
local rownames ""
foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rpj {
        psmatch2 elig_female_in_male_borrower_hh $DPJSpec3 if femaleparthh ~= 1, ///
               outcome(`v') kernel k(normal) bwidth(`k') logit
        local diff = r(att)
        local semean = r(seatt)
* local i = 1
        mat results8[`i', 1] = `k'
        mat results8[`i', 2] = `diff'
        mat results8[`i', 3] = `semean'
        local sd = `semean' * sqrt(`diff')
        sum _treated
        local n = r(sum) - 1
        local pdiff = 2*ttail(`n', abs(`diff'/`semean'))
        local tdiff = `diff' / `semean'
        mat results8[`i', 4] = `pdiff'
        mat results8[`i', 5] = `tdiff'
        local k1 = string(`k')
        local k1 = subinstr("`k1'",".","_",1)
        local rownames "`rownames' `v'`k1'"
        cap drop _treated_`v'
        cap drop _support_`v'
        cap drop _weight_`v'
        gen _treated_`v' = _treated
        gen _support_`v' = _support
        gen _weight_`v' = _weight
        local ++i
}
di "estimated att for male borrowing
mat rownames results8 = `rownames'
mat colnames results8 = k diff semean pvalue tvalue
mat list results8


****************************************************************************
// TABLE 2.6
****************************************************************************


// pstest to check the balancing before and after matching (Using SMDs)
// After running Stratification matching with 10 strata
// 3 first columns Non-participants in program villages
pstest male agey agehhh no_of_adultmales maxed cssv nonfarm livestockvalue hhsize sumnonagri
sumagri agesq age4, both [ treated(_treated) mweight(_weight) support(_support) label]
// 3 last columns Non-participants in non-program villages
pstest male agey agehhh no_of_adultmales maxed cssv nonfarm livestockvalue hhsize sumnonagri
sumagri agesq age4, both [ treated(_treated) mweight(_weight) support(_support) label]
```

```
**************************************************************************
// FIGURE 2.1
**************************************************************************


// Figure 2.1a
// Graph before and after matching using stratification 10
// Non-participants in program villages
*before
twoway (kdensity _pscore if elig_defacto_treatpp, lw(thin)) ///
       (kdensity _pscore if !elig_defacto_treatpp, lw(thin) lp(dash)), ///
       legend(label(1 "treated") label(2 "controls")) ///
       xtitle("Propensity Score before Stratification matching") name(before, replace)
*after
twoway (kdensity _pscore if elig_defacto_treatpp [aw=_weight], lw(thin)) ///
       (kdensity _pscore if !elig_defacto_treatpp [aw=_weight], lw(thin) lp(dash)), ///
       legend(label(1 "treated") label(2 "controls")) ///
       xtitle("Propensity Score after Stratification matching") name(after, replace)
*combine//Figure 2.1a
graph combine before after, ycommon  note("Source:  Calculating by author") ///
title("The diagnostic graphs of the model-adjusted estimated density of covariates")

// Figure 2.1b
// Graph before and after matching using stratification 10
// Non-participants in non-program villages)
*graph before matching
       twoway (kdensity _pscore if elig_defacto_treatpp, lw(thin)) ///
       (kdensity _pscore if !elig_defacto_treatpp, lw(thin) lp(dash)), ///
       legend(label(1 "treated") label(2 "controls")) ///
       xtitle("Propensity Score before Stratification matching") name(before, replace)
*after
twoway (kdensity _pscore if elig_defacto_treatpp [aw=_weight], lw(thin)) ///
       (kdensity _pscore if !elig_defacto_treatpp [aw=_weight], lw(thin) lp(dash)), ///
       legend(label(1 "treated") label(2 "controls")) ///
       xtitle("Propensity Score After Stratification matching") name(after, replace)
*combine// Figure 2.1b
       graph combine before after, ycommon  note("Source:  Calculating by author") ///
       title("The diagnostic graphs of the model-adjusted estimated density and box plots of
covariates"


**************************************************************************
// TABLE 2.7
**************************************************************************


// After running kernel matching bandwidth 0.05
*3 first columns, Non-participants in program villages
pstest male agey agehhh no_of_adultmales maxed cssv nonfarm livestockvalue hhsize sumnonagri
sumagri agesq age4, both [ treated(_treated) mweight(_weight) support(_support) label]


*3 last columns Non-participants in non-program villages
pstest male agey agehhh no_of_adultmales maxed cssv nonfarm livestockvalue hhsize sumnonagri
sumagri agesq age4, both [ treated(_treated) mweight(_weight) support(_support) label]



**************************************************************************
//FIGURE 2.2
**************************************************************************



//FIGURE 2.2a
// After running kernel matching bandwidth 0.05
// Non-participants in program villages
*before
twoway (kdensity _pscore if elig_defacto_treatpp, lw(thin)) ///
       (kdensity _pscore if !elig_defacto_treatpp, lw(thin) lp(dash)), ///
       legend(label(1 "treated") label(2 "controls")) ///
       xtitle("Propensity Score before Kernel matching") name(before, replace)
*after
twoway (kdensity _pscore if elig_defacto_treatpp [aw=_weight], lw(thin)) ///
```

```
        (kdensity _pscore if !elig_defacto_treatpp [aw=_weight], lw(thin) lp(dash)), ///
        legend(label(1 "treated") label(2 "controls")) ///
        xtitle("Propensity Score After Kernel matching") name(after, replace)

*combine//Figure 2.2a
graph combine before after, ycommon   ///
title("The diagnostic graphs of the model-adjusted estimated density of covariates") ///
note("Source:  Calculating by author")

// Figure 2.2b
// Kernel matching bandwidth 0.05
// Non-participants in non-program villages
 *before
twoway (kdensity _pscore if elig_defacto_treatpp, lw(thin)) ///
        (kdensity _pscore if !elig_defacto_treatpp, lw(thin) lp(dash)), ///
        legend(label(1 "treated") label(2 "controls")) ///
        xtitle("Propensity Score before Kernel matching") name(kernelbf, replace)
*after
twoway (kdensity _pscore if elig_defacto_treatpp [aw=_weight], lw(thin)) ///
        (kdensity _pscore if !elig_defacto_treatpp [aw=_weight], lw(thin) lp(dash)), ///
        legend(label(1 "treated") label(2 "controls")) ///
        xtitle("Propensity Score After Kernel matching") name(kernelaf, replace)
*comebine, Figure 2.2b
graph combine kernelbf kernelaf, ycommon ///
title("The diagnostic graphs of the model-adjusted estimated density of covariates") ///
note("Source:  Calculating by author")



****************************************************************************
// TABLE 2.8, 2.9 and 2.10
// Using regression results of Table 2.11 and are calculated by Excel
****************************************************************************


****************************************************************************
// TABLE 2.11, ROBUSTNESS CHECK USING ENTROPY BALANCING
****************************************************************************


// using entropy balancing for ROBUSTNESS CHECK DUVENDACK et al,.(2012)
// Table 2 (D&PJ), OUR TABLE 2.11
use "${workingpath1}\Chemin_Logit_Prep3.0.DTA", clear

******
// before matching: sort data randomly
set seed 1000
cap drop x
generate x=uniform()
sort x
set more off

* Table 2.11, row 1, control1 //  all treated vs elig non-part treatvill - eligpbility
calculated on total land owned - D&PJ used this variable
* Regression results are also calculated and reported in Table 2.8 (treatment-control in
program villages)

ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control1, gen(e_weight)
regress lnconsweekpc elig_defacto_treatpp [pw=e_weight]
drop e_weight


******* BOOTSTRAPPING EBALANCE
cap program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control1, gen(_webal)
reg lnconsweekpc elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end

bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal


* Table 2.11, row 2 control2 // treated vs all individuals in control villages (excludes non-
participants in treated villages)
```

```
* Regression results are also reported in Table 2.9 (treated-control in non-program villages)

ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control2, gen(e_weight)

regress lnconsweekpc elig_defacto_treatpp [pw=e_weight]
drop e_weight

******** BOOTSTRAPPING EBALANCE
cap program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control2, gen(_webal)
reg lnconsweekpc elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end

bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal


***************************************************************************
// TABLE 2.12
***************************************************************************


* Robust check Table 3 D&PJ using EBELANCE, using chemin's Specification 3
* treated vs all individuals in control villages (excludes non-participants in treated
villages)
set seed 1000
set more off

foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rp {
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm, gen(e_weight)
regress `v' elig_defacto_treatpp [pw=e_weight]
drop e_weight

}

* ALTENATIVE OUTCOMES BOOTSTRAPPING EBALANCE(TABLE 2.12)


***************************************************************************
// TABLE 2.13
***************************************************************************


*ROBUST CHECK TABLE 4 (D&PJ), Robustness check using Ebalance, different in gender borrow

* Female borrow (Table 2.13, column 2)/ 7 alternative outcomes

*1/ Log per capita expenditure
cap program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg lnconsweekpc elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*2/ Variation of log per capita expenditure
program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg sdlnconsweekpc elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*3/ Log of female non-landed assets
program drop bootebal
program define bootebal, rclass
```

```
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg lnnonlandwomen elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*4/ Female labor supply
program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg labsupwomMD1 elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*5/ Male labor supply
program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg labsupmenMD1 elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*6/ Girl school enrolment
program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg fedec517_rpj elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*7/ Boy school enrolment
program drop bootebal
program define bootebal, rclass
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(_webal)
reg medec517_rp elig_defacto_treatpp [pw=_webal]
return scalar att = _b[elig_defacto_treatpp]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal


* male borrow (Table 2.13, column 4)/ 7 alternative outcomes

*1/ Log per capita expenditure
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg lnconsweekpc elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*2/ Variation of log per capita expenditure
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg sdlnconsweekpc elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal
```

```
*3/ Log of female non-landed assets
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg lnnonlandwomen elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*4/ Female labor supply
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg labsupwomMD1 elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*5/ Male labor supply
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg labsupmenMD1 elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*6/ Girl school enrolment
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg fedec517_rpj elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal

*7/ Boy school enrolment
program drop bootebal
program define bootebal, rclass
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(_webal)
reg medec517_rp elig_female_in_male_borrower_hh [pw=_webal]
return scalar att = _b[elig_female_in_male_borrower_hh]
drop _webal
end
bootstrap att = r(att), reps(500) saving(etreats, replace): bootebal
```

Chapter 3. A Replication of “The Impact of Microcredit on the Poor in Bangladesh: Revisiting the Evidence” (The Journal of Development Studies, 2014)

3.1 Introduction

Pitt and Khandker's (1998) seminal study "The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter?" stimulated a flood of research on the impact of microcredit on the poor. It also opened up a cottage industry on replications of their research. Chemin (2008), Duvendack and Palmer-Jones (2012), and Roodman and Morduch (2014) have all undertaken re-analyses of PK's study. The main conclusion of these studies is that the economically and statistically significant findings of PK are generally not robust to modifications in estimation procedures and data.

This chapter continues my effort to reproduce and replicate these previous studies. Chapter 2 focused on Duvendack and Palmer-Jones (2012). This chapter will focus on Roodman and Morduch (2014), henceforth RM. The broad goal of this research effort is to put all of these studies within a common research framework where the respective arguments by the replicators, and responses by PK, can be carefully evaluated.

As RM provide their data and code, it is straightforward for me to reproduce their findings. RM's main criticisms center around data irregularities and PK's estimation procedure. With respect to data irregularities, they point out that the eligibility criteria for the microcredit program are frequently violated in the data. Specifically, almost a quarter of the recipients received loans despite having landholdings in excess of the eligibility limits. This raises issues about the appropriate assignment of observations to treatment and controls. RM also note that the normality assumptions underlying their maximum likelihood estimation are not supported by the data.

While RM provide a detailed re-analysis of PK's data, there are several important areas they do not examine. First, their approach closely follows the Tobit-based, multi-equation, maximum likelihood method employed by PK, even while identifying numerous deficiencies of this approach. In contrast, I replicate their analysis using a weighted, linear model based on entropy balancing (Hainmueller, 2012). This has the advantage of weighting the control observations to achieve balance in the covariates.

The second major way I expand on RM's analysis is that I extend their analysis to include a later survey. PK's analysis, and RM's replication of PK, relied on data from a 1991/92 survey. However, a later survey was conducted in 1998/99 that addressed the same issues of micro-credit and poverty reduction. I replicate PK's study using these updated data. Throughout, I take into consideration the data irregularities (such as outliers) pointed out by RM, and the subsequent replies and counter-arguments by PK. Construction of the updated data is my important contribution in this chapter and the next chapter (Chapter 4).

The end result of my extensive reproduction and replication of RM's research is that I confirm that the data do not support PK's conclusions. In general, the estimated effects of microcredit are statistically insignificant. Even ignoring the issue of significance (see Dahal and Fiala, "What do we know about the impact of microfinance? The problems of statistical power and precision", World Development 2020), the sizes of the estimated effects are small and economically unimportant.

This chapter is organized as follows: Section 3.2 discusses the original papers. Section 3.3 presents the model, and Section 3.4 summarizes the statistics. Section 3.5 replicates RM, which investigates the linkages between microcredit and per capita expenditures and other outcomes by replicating PK. Section 3.6 performs the robustness check, and Section 3.7 concludes.

3.2 Discussion of the original papers

3.2.1 Pitt and Khandker (1998)

PK provide an empirical analysis of the impacts of microcredit participation in three group-based programs (Grameen Bank (GB), the Bangladesh Rural Development Board (BRDB) and the Bangladesh Rural Advancement Committee (BRAC)) on poverty alleviation and other outcomes by gender. Their outcomes of interest include labor supply, children's school enrolment, and female nonland assets.

Microcredit programs in Bangladesh provide small-scale credit to the poor in rural areas, especially to poor women. The assignment to credit programs is non-random. Participants self-select into loan programs. Participants may have different education, ability or other characteristics that generate different outcomes. PK use a weighted, limited information maximum likelihood-fixed effects (LIML-FE) estimator applied to a quasi-experimental survey design to control for the potential bias that arises from unobserved characteristics of individuals, households and villages. This method is a form of regression discontinuity design.

The programs studied by PK made (de jure) eligibility a function of (i) having less than 0.5 acres of cultivated land, and (ii) residence in designated program villages. PK measured the effect of the microcredit programs based on the difference between those who borrowed money and those who did not; i.e., they measured ATT.

PK report positive results of microcredit programs in terms of poverty reduction, mainly among female borrowers. They find that, on average, consumption increases 18 percent if females borrow, and 11 percent if males borrow. Their findings also indicate that there are significant effects of microcredit on other outcomes.

Particularly, credit accessed by women is more likely to influence their wellbeing than credit accessed by men. There is a positive effect on the value of women’s nonland asset holdings if loans are given to women; male participation does not generate such impact.

PK estimate a statistically significant positive impact of female participation in credit on women's weekly hours working. However, the elasticity is small, only 0.104. It is possible that credit increases women's productivity rather than the number of hours they supply in the labor market. In contrast, participation in microcredit does not increase male labor supply.

In terms of children's school enrolment, while microcredit significantly positive affects on the probability of boys' school enrolment, female borrowing has an insignificant effect on her daughters' schooling. This potentially reflects the close substitution of women in the household goods' production (i.e., daughters help out at home when their mother is working while boys do not). Overall, PK conclude that microcredit significantly influences household wellbeing and it is of more benefit if the financial resource is given to women.

3.2.2 Roodman and Morduch (2014)

Subsequent studies (Chemin, 2008; Duvendack & Palmer-Jones, 2012; Roodman & Morduch, 2014) raised questions about the robustness of PK's findings. RM (2014) replicate PK (1998) using both the original and alternative methods to figure out whether the different impacts of microcredit are due to different methodologies.

Mark Pitt provided RM a subset of their data, which was sufficient for replicating PK (1998)'s main regression results. RM subsequently supplemented those data with additional data from the World Bank in an effort to reproduce PK's full, original dataset. RM use LIML-FE to examine the influence of microcredit on household consumption expenditure by gender and lenders. They successfully replicate PK's results, generally showing positive effects of credit borrowing on per week capita household consumption. The impact is smaller and statistically insignificant if males are borrowing. RM also attempt to replicate and reproduce PK's findings for other outcomes. Although none of their results are exactly the same as PK, all replicated findings closely match in sign, significance, and magnitude.

However, RM express several concerns with PK's estimation specifications. First, the important condition of quasi-experimental identification, that is the discontinuity in credit design (below vs. above 0.5 acres of land), is not supported by the data. In the treatment group, many borrowers (24% of borrowing households) owned more than 0.5 acres of cultivated land. These households are coded in PK as eligible, leading to potential endogeneity in this 'intention to treat' variable. This violates the quasi-experimental condition.

Second, the long right tail in household per capita expenditure violates the normality assumption and generates bimodal behavior in the corresponding likelihood functions. In a key estimation equation, the likelihood function yields two local maxima, with the higher and the lower maxima producing positive and negative results, respectively. This causes PK's results to be unstable. When RM drop the 16 rightmost outliers, the estimated coefficients collapse to zero and the estimated beneficial effects of microcredit participation disappear.

RM conclude that the relationship between microcredit and poverty alleviation cannot be answered using the original data. In other words, they do not refute PK. They just point out that there are enough data and estimation problems that one cannot regard their results as reliable. In the next several sections, I present RM's replication of PK, along with my replication of RM. However, as my replication generally produces results that are identical to RM, I combine the results in one column. This allows the reader to focus on the differences between PK's original results and RM's/my replication.

3.3 The model

Before presenting the empirical results, I review the estimation model that PK, and then RM, estimate. To understand the model, it is important to take into consideration the institutional features of the credit program. The presence of credit programs across villages was non-random. Often, programs were put in place in areas where the percentage of poverty was high, and/or in villages that requested to be included in the program (Pitt & Khandker, 1998).

As a result, simply comparing the incidence of poverty in villages with credit programs vs. villages without programs may lead to biased conclusions that microcredit has increased poverty (Shahidur R Khandker, 2005). In other words, a positive effect of microcredit may reflect pre-existing systematic differences between control and treatment villages. To address this, PK use village fixed effects to capture differences in unobservable characteristics.

Fixed effects may remove spurious correlation between program placement and outcome variables. However, without further controlling for variation in program availability, observed village characteristics also affect outcomes, such as economic policies, infrastructure of communities, prices, etc., are not identifiable between villages. This is not an insurmountable problem if exogenous rules of eligibility within villages are set up. The exogenous rule that PK use is the restriction borrowers place on land ownership. Specifically, households that have landholdings less than 0.5 acres are eligible to borrow loans. This approach assumes that land ownership is exogenous in this population (turnover of land market is low in South Asia).

Another problem is that participants may self-select into microcredit programs. Participants may have differences in unobserved traits such as ability, skill, experience or other characteristics that could account for differences in outcomes. Fixed effects estimation may eliminate the endogeneity caused by unobserved village attributes including non-random program placement. Nevertheless, the endogeneity problem cannot be removed if unobservable household-specific characteristics affecting demand for credit and household outcomes are not controlled. Because of the lack of identifying instrumental variables, PK construct their sample through a quasi-experimental design.

Specifically, they use limited information maximum likelihood-fixed effects (LIML-FE) to address the above problems. The resulting model (disaggregated by gender) can be written as follows:

$$y_{ij} = C_{fm}\delta + X'\beta_0 + Village\ FE + \epsilon_0$$

$$C_f^* = X'\beta_f + Village\ FE + \epsilon_f\ if\ credit\ available\ and\ female\ eligible = 1$$

$$C_m^* = X'\beta_m + Village\ FE + \epsilon_m\ if\ credit\ available\ and\ male\ eligible = 1$$

$$C_f = \begin{cases} C_f^* & if\ C_f^* \geq C_t \\ C_v & otherwise \end{cases}$$

$$C_m = \begin{cases} C_m^* & if\ C_m^* \geq C_t \\ C_v & otherwise \end{cases}$$

$$\epsilon \equiv (\epsilon_0, \epsilon_f, \epsilon_m)$$

$$\epsilon | X \sim iid\ N(0, \Sigma) \quad (3.1)$$

where y_{ij} are outcomes of interest of household *i* in village *j*. Outcomes are log per capita household consumption, log female nonland assets, log female and male labor supply, girls' and boys' school enrolment. A household/household member is deemed eligible if they have no more than 0.5 acres of land.

$C_f^*(C_m^*)$ stands for the total amount that females (males) in a given household would like to borrow. It represents six (=2×3) variables which are defined by two genders and three credit suppliers. The desired amounts are unobserved. PK assume that there is some minimum amount a program participant can borrow. Below this amount they choose not to borrow, perhaps because there are fixed costs associated with borrowing. PK identify this minimum threshold as C_t and set its value equal to log(1000) (the currency is taka), which is smaller than the minimum observed amount of borrowing.

PK further assume that if an individual chooses not to borrow, total household borrowing equals C_v. Note that this generates a problem when the household does not borrow, because the log of zero is undefined. As a result, PK set the amount borrowed in the absence of borrowing to 1, so that $C_v = 0$, because log(1) = 0. Finally, X represents a vector of household characteristics, and $\epsilon \equiv (\epsilon_0, \epsilon_f, \epsilon_m)$ are unobserved errors.

In this chapter, I first use PK's method, weighted LIML-FE, to replicate RM's results. Then, to fix the econometric problems discussed by RM, I use an alternative method (and updated 1998-1999 survey data) to examine whether the estimated impact of microcredit is robust (and stable over time). The alternative method I employ is a multivariate reweighting method -- entropy balancing -- that reweights the covariate distribution of the control group so as to make it similar to that of the treatment group. The resulting balanced sample can address issues such as the failure of the quasi-experimental condition of discontinuity, non-normal distribution with outliers in LIML estimation, and, in my extension, an unavailable weighted sampling variable in the 1998-1999 survey.

3.4 Summary statistics

To evaluate the impact of microcredit on household consumption expenditure and other outcomes, RM supplemented the data they received from PK with a 1991-1992 survey that was collected by the BIDS in cooperation with the World Bank[8]. The purpose of collecting these data was to investigate the effect of microcredit on poverty alleviation, gender equality, household well-being and other outcomes in rural Bangladesh.

Table 3.1 and Table 3.2 compare PK's summary statistics with those generated by RM and my replication. As I am able to exactly reproduce RM's results, I combine RM's and my

[8] More detail about the 1991-92 survey data is descripted in Section 2.3.1, Chapter 2

replication results in one column. RM conclude, and I agree, that they are generally able to match PK's original data.

3.5 Replication

This section replicates the main findings from RM using their data and code. RM study the impacts of microcredit on six outcomes. For each outcome, they separate estimations by credit supplier and gender, leading to six coefficients of interest.

3.5.1 The impact of microcredit on per capita expenditure

Table 3.3 presents the estimation of log per capita household consumption regressed on the log of total microcredit borrowing, the model of primary interest in PK and RM. PK's results are reported in the first column. RM and my replication results are reported in the second column. As noted above, I am (almost always) able to precisely replicate RM because I use the data and code they supplied. As a result, I will focus on noteworthy differences between RM/my replication and PK.

While the estimates for PK and RM/Replication are not exactly the same, they are very close. For example, the elasticity for the log of cumulative female borrowing from BRAC is estimated by PK to be 0.0394, compared to 0.0389 by RM/me. This indicates that a 1 percent increase in female cumulative borrowing is associated with a 0.04 percent increase in household consumption. To state the obvious, the economic magnitude of this effect is very small. Further, the difference between PK's and RM's/my estimates is negligible. While most of the other differences are larger than this, the overall estimates continue to be very small, and the differences are generally economically negligible.

The estimated elasticities in Table 3.3 are generally positive, but a few of the estimates for male borrowing are negative. This is not entirely unexpected. Borrowers, especially male borrowers, may decide to invest the entire amount into their business. If they are facing a minimum investment requirement, they may need to reduce consumption or accumulate savings in the short run as the loan amount may be insufficient to cover the required capital (Augsburg, De Haas, Harmgart, & Meghir, 2015). As a result, there may be only a minor effect of microcredit on family consumption expenditure if borrowers first need to utilize investment opportunities such as purchasing livestock, agricultural equipment/machines or a new business (Augsburg et al., 2015).

3.5.2 The impact of microcredit on other outcomes

PK and RM also analyze the effects of borrowing microcredit on other outcomes, including female non-land assets and total assets (Table 3.4), female and male labor supply (Table 3.5), and school enrolment for girls and boys (Table 3.6). Noting the significant differences in the results for female-owned non-land assets between RM and PK in Table 3.4, RM focus on the impact of microcredit on total female assets where they obtain a better match with the original study.

Table 3.4 presents the impacts of microcredit on female non-land assets and female total assets. Since female assets, like household consumption, are expressed in natural logarithms, the estimated parameters are elasticities. Based on the RM/Replication estimates, a 1 percent increase in female borrowing is associated with a 0.10 to 0.17 percent increase in their non-land assets, and a 0.08 percent to 0.14 percent increase in their total assets. With the exception of borrowing from Grameen Bank, the impacts of microcredit on female non-land assets and female total assets are generally positive but small and statistically insignificant. In contrast, microcredit borrowed by male is estimated to have a generally negative effect on both female non-land and total assets, though almost all of the estimates are insignificant.

Both male and female borrowing generally have small and negative effects on female labor supply (measured in work hours/month), with the exception of borrowing from Grameen

Bank. Again focusing on the RM/Replication estimates, a one percent increase in female borrowing from Grameen Bank increases female labor supply by 0.025 percent. Borrowing from the other banks decreases female labor supply by -0.002 to -0.026 percent. However, all these results are statistically insignificant. In contrast, female borrowing has a significantly negative impact on male working hour supply. Specifically, a 1 percent increase in female borrowing is associated with a decrease of 0.21 percent to 0.27 percent in male labor supply. I shall return to these estimates below.

While PK show that male borrowing positively impacts both girls' and boys' school enrolment, the results from RM/Replication show little evidence that borrowing by either parent affects either girls' or boys' school enrolment. The estimates waffle between positive and negative values, and they are always small in magnitude, and almost always statistically insignificant.

To summarize, the estimated effects of microcredit on female nonland assets, female total assets, labor supply and children's school enrolment are generally small with most estimates being statistically insignificant. RM note that the only consistent set of significant estimates come from household consumption and male labor supply. This causes them to explore the nature of the estimation procedure more closely When they do, they find evidence of bi-modality in the likelihood function for these two variables.

Table 3.7 illustrates. The dependent variable is household consumption and the estimates represent the associated effect of borrowing by gender and lender. The values in the first column represent the estimates associated with the higher peak (as represented by the larger likelihood value). The values in the second column represent the estimates associated with the lower peak. Note that there is substantial instability in the estimates. In particular, the estimates for female borrowing switch signs and lose significance in the second column. While the estimates in the first column are arguably preferable, and the ones that PK reported, the fact that they are relatively fragile casts doubt on how much weight one should attach to them. This is further illustrated by a bootstrapping exercise that RM do in which they generate two peaks of estimates, one peak centered around a positive value, and one centered around a negative value. This underscores that the strongest results in terms of statistical significance in PK, the ones for household consumption expenditure and weekly working hours supplied by male, are also the least robust.

RM further note that PK's maximum likelihood estimates rest on the validity of the assumption of error normality. The twin-peakedness of the likelihood function, along with other data irregularities they discover, cause RM to doubt the appropriateness of using maximum likelihood estimation.

In the next section, I present my own robustness analysis. I take on board RM's concerns about the eligibility criteria and the appropriateness of maximum likelihood estimation. Hence, instead of using LIML-FE, I my analysis uses a reweighting method to create a balanced sample of controls. To the extent that self-selection is a function of observables, this balanced design between treatment and controls allows me to control for biases caused by non-random participation and non-random program placement. I also follow PK and RM in using village fixed effects to control for unobservable, time-invariant village attributes.

3.6 Robustness analysis

3.6.1 Updated data

Survey data on Bangladesh's microcredit programs are available for 1991-92 and 1998-99. The later survey addresses the same issues of micro-credit and poverty reduction. PK and RM use the data from the 1991-92 wave. My robustness analysis uses data from the 1998-99 wave to examine whether the impacts of microcredit changed over time.

The first survey wave included 1,798 households randomly interviewed from 87 villages in 29 thanas, in which 24 thanas had one (or more) of the three credit programs (Grameen Bank, the Bangladesh Rural Development Board and the Bangladesh Rural Advancement Committee). Five thanas did not have any microcredit programs. In each thana that had microcredit programs been operating for three years or more, three villages were randomly drawn. Any village with at least one operating microcredit program was labeled as a "program village". In total, there were 72 (=24×3) program villages and 15 (=5×3) non-program villages.

The survey covered both "target" households and non-target households in program and non-program villages. Target households were households holding less than or equal 0.5 acres of cultivated land. By this definition, out of the 1,798 surveyed families, 1,538 were target families and 260 were non-target families. 59% of target families participated in microcredit programs.

Approximately eight years later, these households were revisited in 1998-99. By that time, 131 households had left the survey (7.4% attrition rate). Since the 1991-92 survey, one or more microcredit programs had expanded to some of the non-credit (control) villages by 1998-99, making them program villages. Three new thanas and some new households from original villages, new villages from original thanas were added. Altogether, there were 104 villages from 32 thanas included in the second survey, raising the sample size to 2,599 families - 2,226 from original villages and 373 from new villages.

In addition, several new microcredit programs were added, including the Association for Social Advancement (ASA), Proshika, Youth Development Program, Gano Shahajyo Sangstha (GSS), and some small local NGOs. Grameen Bank, BRAC, and DRDB continued to offer microcredit. Overall, there were 1,282 household program participants in 1998-99, which accounts for 52.7 percent of sample size. The remainders were eligible non-participants (20.1

percent) and non-target households (27.3 percent). The updated data also evidenced some major changes in program participation. 47 percent of eligible non-participants in 1991-92 became participants in 1998-99, and 28 percent of non-target households in 1991-92 became participants in 1998-99.

While RM did not use 1998-99 survey data in their analysis, it is included in the dataset they provided. I used their data to independently construct a dataset for 1998-99 from the raw data. In this respect, I was advantaged by having access to RM's code. This allowed me to follow the commands they used in generating variables from the 1991-92 raw data. That way, I could use similar commands to create matching variables for the 1998-99 data. The latter data comprise a rich household-level and individual-level dataset, covering more than 45 sections and 600 questions for more than 2,500 households and 13,500 individuals. Table 3.8 and Table 3.9 report the summary statistics for the 1998-99 wave in comparison with the 1991-92 wave.

3.6.2 Some characteristics of the updated data

A missing discontinuity

A quasi-experimental method of analysis is useful when there is an intervention, such as the microcredit program in Bangladesh, which uses criteria other than random assignment (S. Y. Kim & Lee, 2019). In particular, this approach can be used when there are specific criteria that must be met by individuals/households before they can participate in the intervention being evaluated (White & Sabarwal, 2014). PK use the eligibility cut-off for land ownership as a point of discontinuity. Only families which own half an acre or less, could *officially* borrow. However, data on *actual* borrowing are missing this discontinuity point. RM point out that this is an issue with the 1991-92 data employed by PK.

A similar problem arises in the 1998-99 wave. Figure 3.1 uses the 1998-99 data and plots household borrowing in thousands of Taka against the household landholdings before borrowing.

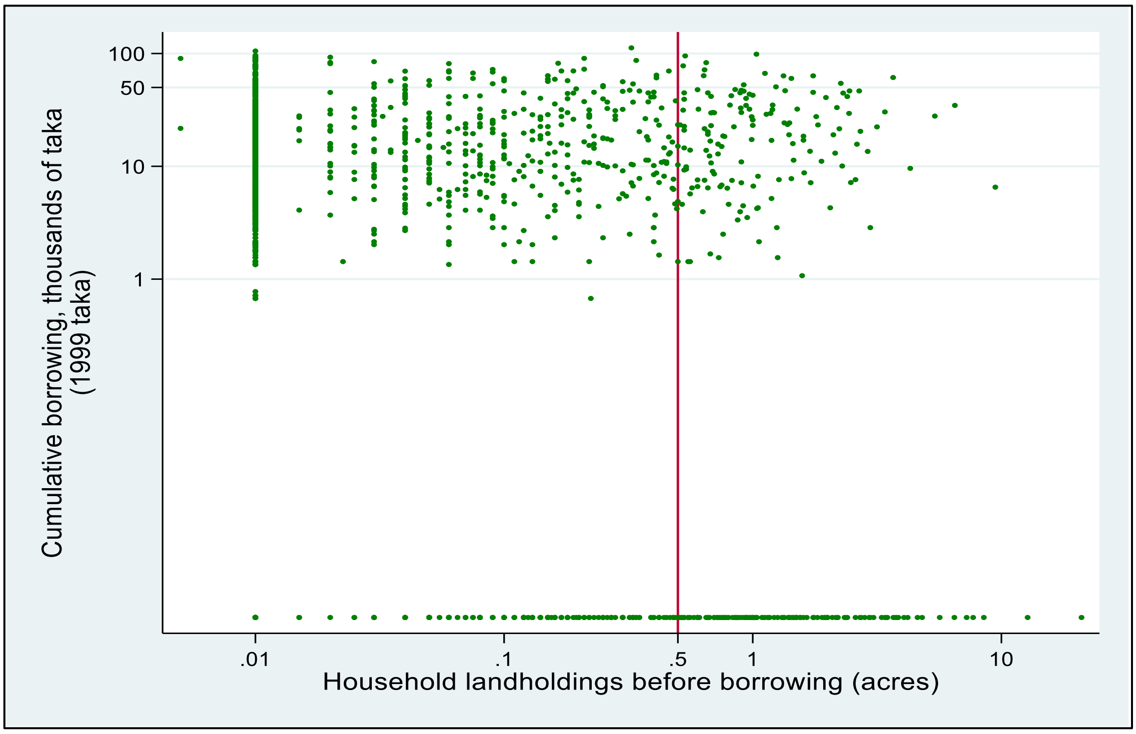


Figure 3.1 Amount of borrowing vs. household landholdings before borrowing in program villages (1998-1999 data)

PK define households as eligible in they own less than or equal to 0.5 acres of land. However, participants among non-target families, who have landholding more than 0.5 acres, account for nearly 30 percent of all participants. This blurs the eligibility discontinuity and vitiates the quasi-experimental design.

Figure 3.1 makes clear that the de jure eligibility rule of land ownership was not strictly followed in practice. Households that owned more than 0.5 acres of cultivated land oftentimes borrowed. Grameen Bank's policy since 1983 has been that a household is eligible to access loans if it holds less than 0.5 acres of cultivated land or owns assets worth no more than or equal to 1.0 acre of medium-quality land (Hossain, 1988, p. 25). Some of the discrepancies may therefore arise from classification/reclassification of land as cultivated vs. medium-quality. Pitt (1999) himself argued that land quality matters in the definition of eligibility. The eligibility rule of these credit programs is typically in terms of cultivable land while what constitutes “cultivable” land for the purposes of program eligibility is ambiguous. For example, many households own uncultivable or less cultivable land by a river, poorly quality of erosion land, or land in seasonal flood areas. How much land gets classified may vary.

It is also possible that some credit officers were either not aware of the eligibility rule of owing half-acre land or were pragmatically “bending it” to extend microcredit to households that were likely reliable and families were low-income by global standards, after all. (Roodman & Morduch, 2014).

To the extent that the eligibility rule used in quasi-experimental analysis is violated, PK’s method could lead to biased results. Therefore, instead of using PK/RM’s quasi-experimental method with the 1998-99 survey data, I use a multivariate reweighting method that does not rely on eligibility discontinuity. Moreover, by creating a balanced sample it can account for the endogeneity problem where households are eligible and choose to participate in the microcredit programs systematically differ from families that cannot or do not participate in programs (White & Sabarwal, 2014).

Outliers and non-normality

Another data issue identified by RM in PK’s 1991-92 data relates to outliers and the violation of the normality assumption. A similar issue arises in the 1998-99 data. Figure 3.2 illustrates the density distribution of weekly household consumption in the updated data. The distribution of household consumption, the primary interest variable, shows a long right tail.

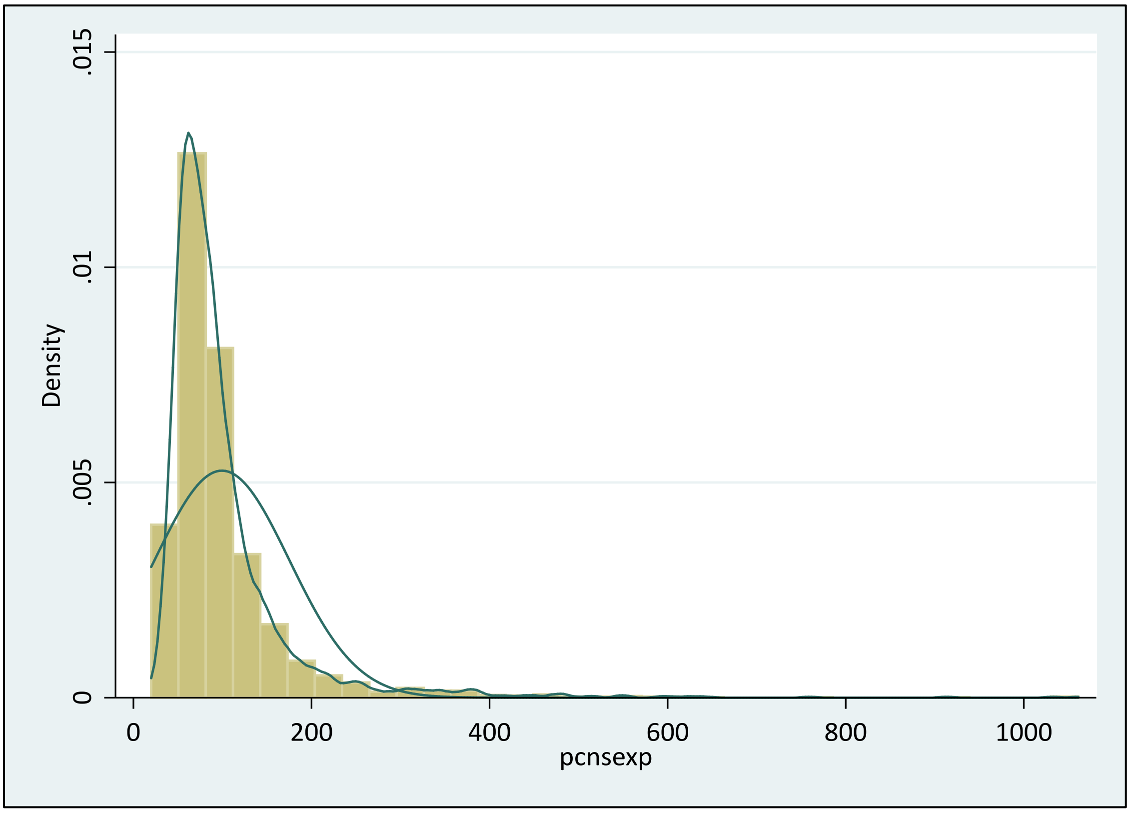


Figure 3.2 Density distribution of household consumption

Table 3.10 reports the results of applying Shapiro-Francia's W test of normality to the per capita consumption data, *Pcnsexp* (Shapiro & Wilk, 1965). The null hypothesis is that per capita consumption is normally distributed. This hypothesis is rejected with a p-value well below 1 percent. As the rejection of normality violates the assumption of normality underlying the LIML estimator used by PK, I instead opt for a weighted, fixed effects, linear regression approach that balances the observed characteristics of the treatment and control observations.

3.6.3 An alternative approach -- Entropy balancing

Four important issues in estimating the impact of microcredit are (1) non-random program placement across villages, (2), self-selection associated with meeting the eligibility requirement, (3) self-selection associated with choosing to participate in the microcredit program, and (4) the difference between de jure and de facto eligibility.

Credit programs are designed to target poor villages or vulnerable areas. Households in program villages thus tend to be poorer than households in non-program villages. Hence, unless pre-treatment conditions are comprehensively controlled for, a comparison of treatment households in program villages with households in non-program villages will likely produce a downwardly biased estimate of the impact of microcredit.

An alternative is to estimate the impact of microcredit by comparing treatment and control households within program villages. However, this likely also introduces a bias. Households that meet the eligibility requirement of having less than 0.5 acres of cultivated land likely differ in important ways with households that have more than 0.5 acres of cultivated land. If those differences are associated with outcomes, a bias will be introduced. On the other hand, if one limits control households to households in program villages that have less 0.5 acres of cultivated land, but chose not to participate in microcredit, that also likely introduces a self-selection bias.

The last issue, mentioned several times above, is that a substantial number of households that should not have been eligible, specifically, households in program villages with more than 0.5 acres of land, were allowed to participate in the microcredit program. This introduces yet additional self-selection issues.

For all of the above reasons, I choose to estimate the impact of the microcredit program using an alternative method based on matching/sample balancing. One benefit of a matching method is that the use of eligibility criteria based on land ownership in order to identify the impact of treatment, unlike in PK is not required (Pitt, 2012). When there is no clear criterion to explain participation of households in microcredit, sample balancing is preferred (Chemin, 2008).

For this reason, I use a multivariate reweighting method, entropy balancing, to create a control group that is “balanced” in pre-treatment observables relative to the treatment group (Hainmueller, 2012). Based on a maximum entropy balancing scheme, this method reweights and adjusts the covariate distributions in the untreated groups to produce exact balance up to several moments of the respective variable distributions (mean, variance, and skewness).

Entropy balancing uses a pre-processing design where variable balance is directly created into the weight function that is employed to adjust the controls. A balanced sample can control for potential endogeneity of self-selection and non-random presence of credit. Then, the difference in results between treatment and reweighted un-treatment groups can be referred to program participation (Hainmueller, 2012; Hainmueller & Xu, 2013).

Because microcredit programs are specifically targeted at households with low income, the estimate coefficient is the average treatment effect on the treated (ATT) (Marco Caliendo & Sabine Kopeinig, 2008). After creating a balanced sample, the difference in outcomes between control and treatment households gives us the ATT. Specifically, to analyze the effect of microcredit participation (treatment T) on per capita expenditure (outcome Y), we calculate the following:

$$\alpha = E(Y_i^1|T_i = 1) - E(Y_i^0|T_i = 1) = [\mathrm{E}(Y_i^1 - Y_i^0|T_i = 1)] \tag{3.2}$$

where α represents a measure of the ATT. $\mathrm{E}(Y_i^1|\, T_i = 1)$ is the expected value of the outcome of a treatment household i if it receives the treatment. $\mathrm{E}(Y_i^0|\, T_i = 1)$ is the expected value of the outcome of the same household in the (unobserved) counterfactual case of not receiving the loan.

As the counterfactual, $\mathrm{E}(Y_i^0|T_i = 1)$, is not observed, entropy balancing creates a counterfactual group from households that did not receive treatment. As explained above, the problem with simply comparing microcredit participants to non-participants is that they may be systematically different. After subtracting and adding the term $E(Y_i^0|\, T_i = 0)$ in Equation (3.2), I obtain:

$$\left[\mathrm{E}(Y_i^1 - Y_i^0 \middle| T_i = 1)\right] = \left[E(Y_i^1 \middle| T_i = 1) - E(Y_i^0 \middle| T_i = 0)\right] - \left[E(Y_i^0 \middle| T_i = 1) - E(Y_i^0 \middle| T_i = 0)\right]. \tag{3.3}$$

Note that the second term, $E(Y_i^0|T_i = 1) \ + \ E(Y_i^0|T_i = 0)$ represents selection bias associated with differences between those receiving intervention and those not receiving intervention. If a matching algorithm produces a control group such that this term is zero, then the first term, $\left[E(Y_i^1 \middle| T_i = 1) - E(Y_i^0 \middle| T_i = 0)\right]$, yields an unbiased estimate of the ATT.

If selection is based on observable pre-treatment characteristics of the individual/household, then entropy balancing provides an attractive method for minimizing this bias (Dehejia & Wahba, 2002). Entropy balancing weights the observations in the control group such that the moments of the distributions of pre-treatment variables for the control group match those of the treatment group (Hainmueller, 2012; Hainmueller & Xu, 2013). Entropy balancing always improves covariate balance because the weights are directly adjusted to the sample moments of the treatment group's variables.

Definition of treatment and control groups

I assess microcredit's impact on participants using two different treatment groups in comparison with three other control groups, creating a total of six different comparisons. The first treatment group includes households who are actual participants, so-called de facto participants. The second group contains households who are actual participants and have cultivated land less than or equal to 0.5 acres, so-called de jure participants. In the de jure group, actual participants who have more than 0.5 acres of land should arguably be excluded from the estimation (Morduch, 1998).

Figure 3.1 above allows a comparison of borrowing between de facto and de jure participants. It shows cumulative borrowing (vertical axis) graphed against household landownership (horizontal axis). De jure participants are the subset of participants with cultivated land less than or equal to 0.5 acres. The graph does not find demonstrable differences between the two groups in terms of borrowing. Thus, it suggests that it may be okay to include households with more than 0.5 acres in the treatment group. As this allows for a larger sample, I estimate the impact of microcredit using both treatment groups.

I use three different groups for control households. The first control group is all non-participants. It would arguably be better to use non-participants in non-program villages only. However, in the eight years since 1991-92, many microcredit programs expanded to original control villages. In addition, many new microfinance institutes started providing credit. As a result, the 1998-1999 survey includes only 40 non-participant households in non-program villages. This is too small a sample for reliable estimation. For this reason, I decided to combine all non-participants into one control group.

The second control group is a subset of the first control group that only includes non-participants in treatment villages. The third control group organizes non-participants by gender -- those with no female borrowing in villages with female-only microcredit programs, and those with no male borrowing in villages with male-only programs. The most important challenge in this particular context is to identify a group of households that are like microcredit borrowers in all relevant attributes apart from not having received loans. Entropy balancing helps one to do that.

Handling Outliers

Outliers are defined as values or points that significantly differ from other observations in the data. They can mask relationships that characterize the true data generating process. I use the outlier identification method known as interquartile range (IQR). Define $q_{0.25}$ and $q_{0.75}$ as the values associated with the first (25%) and third (75%) quartile values of the distribution of residuals. Define IQR as $q_{0.75}$ - $q_{0.25}$. The IQR method sets a lower and upper bound of "acceptable" values, where the lower bound equals $q_{0.25}$ – (1.5×IQR) and the upper bound equals $q_{0.75}$ + (1.5×IQR). 1.5 represents a threshold parameter and is widely accepted (Hernandez et al., 2017; Walfish, 2006). Values outside these bounds are defined as outliers and dropped from the analysis (Dawson, 2011; Jeong et al., 2017).

3.6.4 Robustness analysis with updated data and alternative methodology

Diagnostic balanced sample after weights using entropy balancing

Substantial imbalances are indicative that the estimated treatment effects may not be reliable. Thus it is important to demonstrate how entropy balancing is able to balance the explanatory variables in the treatment and control groups. Table 3.11 reports sample moments (mean, variances and skewness) and standardized mean differences (SMD) across explanatory variables for treatment and non-treatment groups before and after entropy balancing (Pre and Post)[9]. Comparing SMDs across explanatory variables before and after weighting the control observations, the weighted control group has identical means with the treatment group on almost all variables and the SMDs are very close to zero or zero for all covariates. I conclude that entropy balancing has produced a high level of balance between treatment and controls.

The impact of microcredit on per capita expenditure

My earlier estimates indicated that were no substantial differences across the estimated effects of borrowing from the three original credit programs. According to Table 3.3, a 1 percent increase in female borrowing from BRAC, BRDB and Grameen was associated with

[9] More details how SMD used to assess balanced samples are described in Section 2.3, Chapter 2

increases in household consumption of 0.039, 0.041 and 0.042 percent, respectively (cf. Column 2). Hence, in this section, I focus on borrowing from any bank instead of analyzing the different programs separately.

Table 3.12 presents the results of estimating treatment impacts for per capita consumption for de facto and de jure participants. Estimates are based on comparisons with three alternative control groups: (i) all non-participants (C1), non-participants in program villages (C2), and non-participants in female/male program villages (C3). The top panel includes all observations, the bottom panel reports results after dropping outliers.

The results fail to support PK's findings. None of the estimated impacts in the table is statistically significant at the 5 percent level. Further, many of the estimated effects of microcredit on consumption are negative. This is consistent with D&PJ's findings based on the 1991-1992 survey data. Dropping outliers cause the signs of a number of estimates to change. However, the estimates remain insignificant.

Table 3.13 expands the reporting of results for the full set of six outcome variables. Having learned from Table 3.12 that the differences across alternative control groups were negligible, I only report estimates for C1, the control group consisting of all non-participants. Other than the effect of female borrowing on female labor supply, all the estimates remain small in size and statistically insignificant.

3.7 Conclusion

The crucial question whether microcredit plays a role in lifting the poor out of poverty still challenges researchers today. There is still no consensus among economists in regards to the impact of microcredit on the poor. In their prominent study, PK (1998) argue that microcredit provides a number of benefits to the poor, and helps them end the poverty cycle. They conclude that the effects are even greater if loans are given to women.

Building on this research, Morduch (1998), Chemin (2008), D&PJ (2012) and RM (2014) report, at best, weak evidence, and at worst, no evidence, to support PK's findings of the beneficial impacts of microcredit. This generated a research backlash from Pitt who produced strong rebuttals to their criticisms (Pitt, 1999; Pitt, 2012, 2014).

In the context of this controversy, this chapter makes two significant contributions. First, it makes a data contribution. Although I was unable to obtain the data and code originally used by PK in their study (nobody has been able to obtain their full dataset), I was able to indirectly reproduce key findings of PK by following the replication work of RM. Further, I extended RM's data by transforming their raw data for 1998/99 and creating a dataset that allows one to replicate PK's 1991/92 study using these later data. As part of this thesis, I will make all my data and code available to other researchers who wish to further analyze these data.

Second, I add further research findings on the effects of microcredit. I took note of the weaknesses of PK's analysis as pointed out by RM, and used a new research methodology to address these weaknesses. In particular, the LIML-FE approach adopted by PK, and replicated by RM, depends crucially on the validity of the eligibility criteria and the normality of the data. RM convincingly show that both of these aspects are not well-supported by the data.

As a result, I turned to a newer methodology, entropy balancing that does not require these conditions. Applying this methodology to a later set of survey data allowed me to revisit PK's analysis afresh. In doing so, I was unable to confirm PK's original conclusions. In almost all cases, the associated estimates were statistically insignificant, in contrast to PK, and sometimes wrong-signed. Further, even if one ignores the issue of significance (Dahal & Fiala, 2020), the sizes of the estimated effects are small and economically unimportant.

Although this study finds little impact of microcredit on per capita household consumption, microcredit may benefit the poor in other areas. Microcredit may have effects on human or social capital such as women’s empowerment or gender equality, and women’s legal and political awareness. Subsequent chapters of this thesis pursue this line of inquiry by investigating the impact of microcredit on women’s empowerment.

3.8 References

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Table 3.1 Weighted means and standard deviations of individual- and household-level independent variables (PK, RM, Replication)

	Mean		Standard deviation	
	PK	RM/Replication	PK	RM/Replication
Age of all individuals*	23.0	23.0	18.000	18.000
Schooling of individual 5 or above[1, *]	1.377	1.386	2.773	2.780
Parents of household head own land?	0.256	0.250	0.564	0.559
# of brothers of household head owning land	0.815	0.796	1.308	1.298
# of sisters of household head owning land	0.755	0.737	1.208	1.197
Parents of household head's spouse own land?	0.529	0.521	0.784	0.780
# of brothers of household head's spouse owning land	0.919	0.905	1.427	1.421
# of sisters of household head's spouse owning land	0.753	0.74	1.202	1.195
Household land (in decimals)	76.142	75.883	108.54	107.980
Highest grade completed by household head[1]	2.486	2.479	3.501	3.500
Sex of household head (1 = male)	0.948	0.947	0.223	0.223
Age of household head (years)	40.821	40.803	12.795	12.790
Highest grade completed by any female household member[1]	1.606	1.601	2.853	2.851
Highest grade completed by any male household member[1]	3.082	3.069	3.081	3.770
Adult female not present in household?	0.017	0.017	0.129	0.130
Adult male not present in household?	0.035	0.036	0.185	0.185
Spouse not present in household?	0.126	0.126	0.332	0.332
Amount borrowed by female from BRAC (taka)	350.345	350.369	1,573.65	1,573.630
Amount borrowed by male from BRAC (taka)	171.993	171.973	1,565	1,565.000
Amount borrowed by female from BRDB (taka)	114.348	114.119	747.301	746.722
Amount borrowed by male from BRDB (taka)	203.25	202.79	1,572.66	1,571.620
Amount borrowed by female from Grameen Bank (taka)	956.159	953.581	4,293.36	4,287.960
Amount borrowed by male from Grameen Bank (taka)	374.383	373.94	2,922.79	2,921.460
Non-target household	0.295	0.293	0.456	0.455

Note: PK, RM, Replication: N=1,757 using the first survey round 1991, weighted
[1] Treats current students as having no years of schooling.
*Individual-level
Amount borrowed is the cumulative amount of credit borrowed since December 1986 from any of these credit programs adjusted to 1992 prices.
Source: PK table A1, page 993; RM table 1, page 587. Author's calculations, replicating RM, weighted. Data and coding are provided by RM, I exactly replicated their statistic description.

Table 3.2 Weighted means and standard deviations of endogenous variables as reported in PK, RM and in replication

	Program villages									
	Participants		Nonparticipants		Total		Nonprogram villages		All villages	
	PK	RM/Replication	PK	RM/Replication	PK	RM/Replication	PK	RM/Replication	PK	RM/Replication
Cumulative female	5498.85	5,554.04			2,604.45	2,617.61			2,604.45	2,617.61
borrowing, first survey	[7,229.35]	[7,580.10]			[5,682.40]	[5,896.01]			[5,682.40]	[5,896.01]
round (1992 taka)	N = 779	N = 779	N = 326	N = 326	N = 1,105	N = 1,105			N = 1,105	N = 1,105
Cumulative male	3691.99	3,757.37			1,729.63	1,748.91			1,729.63	1,748.91
borrowing, first survey round	[7081.58]	[7,409.36]			[5,184.67]	[5,390.53]			[5,184.67]	[5,390.53]
(1992 taka)	N = 631	N = 631	N = 263	N = 263	N = 894	N = 894			N = 895	N = 894
Per-capita household	77.014	77.014	85.886	85.886	82.959	82.959	89.661	89.661	84.072	84.072
spending, all three survey	[41.496]	[41.496]	[64.82]	[64.82]	[58.309]	[58.308]	[66.823]	[66.825]	[59.851]	[59.851]
rounds (taka/week)	N = 2,696	N = 2,696	N = 1,650	N = 1,650	N = 4,346	N = 4,346	N = 872	N = 872	N = 5,218	N = 5,218
School enrolment of	0.535	0.535	0.528	0.527	0.531	0 .530	0.552	0.552	0.534	0.534
girls aged 5–17,	[0.499]	[0.499]	[0.500]	[0.500]	[0.499]	[0.499]	[0.498]	[0.498]	[0.499]	[0.499]
first survey round (yes = 1)	N = 802	N = 802	N = 434	N = 434	N = 1,236	N = 1,236	N = 225	N = 225	N = 1,461	N = 1,461
School enrolment of	0.566	0.566	0.555	0.556	0.558	0.559	0.55	0.553	0.559	0.558
boys aged 5–17,	[0.496]	[0.496]	[0.498]	[0.497]	[0.497]	[0.497]	[0.497]	[0.498]	[0.497]	[0.497]
first survey round (yes = 1)	N = 856	N = 856	N = 468	N = 468	N = 1,324	N = 1,324	N = 265	N = 267	N = 1,589	N = 1,591
Women's labor supply, all	40.328	40.389	37.68	32.467	38.905	35.087	43.934	31.269	39.54	34.467
survey rounds(hours/month,	[70.478]	[70.558]	[71.325]	[64.297]	[70.934]	[66.529]	[74.681]	[60.214]	[71.432]	[65.556]
aged 16–59)	N = 3,420	N = 3,420	N = 2,108	N = 2,108	N = 5,528	N = 5,528	N = 1,074	N = 1,074	N = 6,602	N = 6,602
Men's labor supply,	202.758	202.749	185.858	185.758	191.31	191.239	180.94	180.528	189.477	189.346
all survey rounds	[10.527]	[100.820]	[104.723]	[104.904]	[103.678]	[103.897]	[98.805]	[99.405]	[102.902]	[103.19]
(hours/month, aged 16–59)	N = 3,534	N = 3,534	N = 2,254	N = 2,254	N = 5,788	N = 5,788	N = 1,126	N = 1,126	N = 6,914	N = 6,914
Female nonland assets, first	7,399.23	2,366.09	4,716.42	1,724.55	5,608.03	1,937.76	1,801.84	831.84	4,970.67	1,752.57
survey round (taka)	[293.02]	[6,693.24]	[19,901]	[5,033.62]	[23,509.1]	[5,645.45]	[6,287.49]	[2,207.09]	[21,649.4]	[5,245.48]
Female assets, first		7,512.51		4,793.83		5,697.37		1,975.24		5,074.08
survey round (taka)1		[31,572.9]		[19,922]		[24,443.4]		[6,428.01]		[22,498.9]
		N = 899		N = 542		N = 1,441		N = 292		N = 1,733

Note: Standard deviations are in parentheses.
Cumulative female and male borrowing, school enrolment of girls and boys aged 5-17, and female non- and female assets are calculated in the first survey round in 1991-1992. Other variables are calculated in all survey rounds in 1991-1992. Source: PK table A2, page 994; RM table 2, page 588. Author's calculations, replicating RM, weighted. Data and coding are provided by RM, I exactly replicated their statistic description.

Table 3.3 Replication and robustness tests of PK's LIML-FE household consumption regression

	PK	RM/Replication
Log of cumulative female borrowing, BRAC	0.0394	0.0389
	[4.237]***	[3.987]***
Log of cumulative female borrowing, BRDB	0.0402	0.0407
	[3.813]***	[3.643]***
Log of cumulative female borrowing, Grameen	0.0432	0.0425
	[4.249]***	[4.032]***
Log of cumulative male borrowing, BRAC	0.0192	0.0156
	[1.593]	[0.911]
Log of cumulative male borrowing, BRDB	0.0233	0.0182
	[1.936]*	[1.024]
Log of cumulative male borrowing, Grameen	0.0179	0.0132
	[1.431]	[0.755]
p female	−0.4809	−0.4739
	[4.657]***	[4.340]***
p male	−0.2060	−0.1314
	[1.432]	[0.607]
2nd stage errors		
Skew		0.71***
Kurtosis		5.12***
Instruments included linearly (F test p value)		
Log likelihood	−6,634	−6,541
Observations	5,218	5,218

Note: z statistics clustered by household in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%
Source: PK Table 2, column 4, page 981; RM Table 3, column 2, page 590. I exactly replicate RM's results.
The survey was conducted three times during 1991-92 (3 rounds/waves). Therefore, there were three times of observations in the same households. So, it makes the observations to be 5218 from original 1757 households.

Table 3.4 LIML-FE estimations of the impact of microcredit on female nonland assets and female total assets

	log female non-land assets		log female assets	
	PK	RM/Replication	RM	Replication
Log of cumulative female borrowing, BRAC	0.0318	0.1058	0.0832	0.0832
	[0.356]	[1.488]	[0.965]	[0.965]
Log of cumulative female borrowing, BRDB	0.1257	0.1565	0.0988	0.0988
	[1.043]	[1.717]*	[1.145]	[0.906]
Log of cumulative female borrowing, Grameen	0.1 131	0.1683	0.1435	0.1435
	[1.317]	[2.349]**	[1.665]*	[1.678]*
Log of cumulative male borrowing, BRAC	0.1005	0.0137	−0.0210	-0.0210
	[0.468]	[0.130]	[0.243]	[-0.154]
Log of cumulative male borrowing, BRDB	0.0334	−0.0940	−0.1476	-0.1476
	[0.141]	[0.879]	[1.712]*	[-1.120]
Log of cumulative male borrowing, Grameen	−0.0457	−0.1039	−0.1798	-0.1798
	[0.200]	[0.952]	[2.086]**	[-1.314]
p female	0.1136	0.0718	0.0914	0.0914
	[1.325]	[0.657]	[0.757]	[0.757]
p male	−0.0148	0.1527	0.2256	0.2256
	[0.053]	[0.881]	[1.126]	[1.126]
Observations	1,757	1,757	1,757	1,757
Log Pseudolikehood		−4,048	−4,195	-4195.4

Note: Source: PK table 2, column 10, page 981; RM table 6, page 600. Author's calculations, replicating RM, weighted. Data and coding are provided by RM, I exactly replicated RM's results in coefficients, but there are some differences in z-statistics, hence the separate columns for RM and Replication for log female assets. *significant at 10%, **significant at 5%, ***significant at 1%

Table 3.5 LIML-FE estimation of the impact of microcredit on alternative outcomes: labor supply

	Log female labor hours/month		Log male labor hours/month		
	PK	RM/Replication	PK	RM/Replication	RM/Replication
Log of cumulative female borrowing, BRAC	−0.0117	−0.0017	−0.1813	−0.2165	−0.2277
	[0.128]	[0.017]	[5.884]***	[8.254]***	[9.409]**
Log of cumulative female borrowing, BRDB	−0.0139	−0.0260	−0.2308	−0.2654	−0.2723
	[0.139]	[0.228]	[7.066]***	[9.290]***	[10.499]***
Log of cumulative female borrowing, Grameen	0.0152	0.0250	−0.2189	−0.2124	−0.2183
	[0.162]	[0.274]	[6.734]***	[9.127]***	[10.104]***
Log of cumulative male borrowing, BRAC	−0.0448	−0.1052	−0.1369	−0.1634	0.0186
	[0.520]	[1.085]	[2.155]**	[3.918]***	[0.509]
Log of cumulative male borrowing, BRDB	−0.0144	−0.0857	−0.1440	−0.1713	0.0154
	[0.181]	[0.916]	[2.129]**	[4.018]***	[0.409]
Log of cumulative male borrowing, Grameen	−0.0570	−0.1044	−0.1592	−0.1584	−0.0076
	[0.677]	[1.241]	[2.524]**	[4.354]***	[0.229]
p female	0.1255	0.1192	0.6564	0.6942	0.7358
	[1.062]	[0.975]	[7.461]***	[10.615]***	[14.315]***
p male	0.0560	0.1298	0.4929	0.5091	−0.0265
	[0.592]	[1.228]	[2.512]**	[4.070]***	[0.258]
Observations	6,602	6,602	6,914	6,914	6,914
Log Pseudolikehood		−17,552		−20,865	−20,875

Note: Source: PK table 3, column 6 and 10, page 983; RM table 6, page 600. Author's calculations, replicating RM, weighted. Data and coding are provided by RM, I exactly replicated RM's results. *significant at 10%, **significant at 5%, ***significant at 1%

Table 3.6 LIML-FE estimations of the impact of microcredit on alternative outcomes: children schooling

	School enrolment girls, 5-17		School enrolment of boys, 5-17	
	PK	RM/Replication	PK	RM/Replication
Log of cumulative female borrowing, BRAC	−0.0203	−0.0567	0.0394	−0.005
	[0.552]	[1.200]	[0.917]	[0.085]
Log of cumulative female borrowing, BRDB	−0.0099	−0.0541	0.1210	0.074
	[0.220]	[0.988]	[2.573]**	[1.149]
Log of cumulative female borrowing, Grameen	0.0128	−0.0301	0.1025	0.063
	[0.334]	[0.721]	[2.364]**	[1.319]
Log of cumulative male borrowing, BRAC	0.0495	0.0019	−0.0040	−0.000
	[1.152]	[0.027]	[0.107]	[0.008]
Log of cumulative male borrowing, BRDB	0.0321	−0.0162	0.0361	0.052
	[0.665]	[0.240]	[0.934]	[0.957]
Log of cumulative male borrowing, Grameen	0.0582	−0.0004	0.0736	0.095
	[1.298]	[0.007]	[1.688]*	[2.025]**
p female	0.1648	0.3042	0.2192	0.0184
	[1.029]	[1.573]	[1.054]	[0.075]
p male	−0.1360	0.0922	−0.0284	−0.1648
	[0.720]	[0.304]	[0.177]	[0.762]
Observations	2,885	1,443	2,940	1,587
Log Pseudolikehood		−2,446		−2,737

Note: Source: PK table 4, columns 6 and 11, page 993; RM table 6, page 600. Author's calculations, replicating RM, weighted. Data and coding are provided by RM, I exactly replicated RM's results. *significant at 10%, **significant at 5%, ***significant at 1%

Table 3.7 Testing related to bimodality

	RM/replication	RM/Replication
Log of cumulative female borrowing, BRAC	0.0389	−0.0191
	[3.987]**	[1.287]
Log of cumulative female borrowing, BRDB	0.0407	−0.0219
	[3.643]**	[1.334]
Log of cumulative female borrowing, Grameen	0.0425	−0.0183
	[4.032]***	[1.200]
Log of cumulative male borrowing, BRAC	0.0156	0.0221
	[0.911]	[1.460]
Log of cumulative male borrowing, BRDB	0.0182	0.0232
	[1.024]	[1.463]
Log of cumulative male borrowing, Grameen	0.0132	0.0214
	[0.755]	[1.385]
p female	−0.4739	0.3160
	[4.340]***	[1.716]*
p male	−0.1314	−0.2397
	[0.607]	[1.274]
2nd stage errors		
Skew	0.714***	0.752**
Kurtosis	5.121***	5.370**
Log likelihood	−6,541	−6,548
Observations	5,218	5,218

Note: Source: RM Table 4, columns 1 and 2, author's calculation exactly replicates RM's results due to data and code is provided. *significant at 10%, **significant at 5%, ***significant at 1%

Table 3.8 Summary statistics for RM's 1991/92 data and my 1998/99 data

	Mean		Standard deviation	
	RM Data 1991/92	Updated data 1998/99	RM Data 1991/92	Updated data 1998/99
Age of all individuals *	23.0	25.0	18.000	18.826
Schooling of individual 5 or above[1*]	1.386	1.740	2.780	3.143
Parents of household head own land?	0.250	0.164	0.559	0.447
# of brothers of household head owning land	0.796	0.612	1.298	1.137
# of sisters of household head owning land	0.737	0.497	1.197	1.027
Parents of household head's spouse own land?	0.521	0.383	0.780	0.657
# of brothers of household head's spouse owning land	0.905	0.730	1.421	1.337
# of sisters of household head's spouse owning land	0.74	0.523	1.195	1.077
Household land (in decimals)	75.883	67.281	107.980	135.514
Highest grade completed by household head[1]	2.479	2.884	3.500	2.966
Sex of household head (1 = male)	0.947	0.896	0.223	0.306
Age of household head (years)	40.803	45.009	12.790	13.548
Highest grade completed by any female household member[1]	1.601	3.045	2.851	6.598
Highest grade completed by any male household member[1]	3.069	4.745	3.770	4.645
Adult female not present in household?	0.017	0.007	0.130	0.081
Adult male not present in household?	0.036	0.031	0.185	0.174
Spouse not present in household?	0.126	0.951	0.332	0.215
Amount borrowed by female from BRAC (taka)	350.369	1,147.580	1,573.630	4,385.900
Amount borrowed by male from BRAC (taka)	171.973	97.264	1,565.000	1,571.240
Amount borrowed by female from BRDB (taka)	114.119	303.566	746.722	2,227.430
Amount borrowed by male from BRDB (taka)	202.79	261.880	1,571.620	2,184.520
Amount borrowed by female from Grameen Bank (taka)	953.581	6,075.520	4,287.960	15,836.200
Amount borrowed by male from Grameen Bank (taka)	373.94	1,253.770	2,921.460	7,007.360
Nontarget household	0.293	0.055	0.455	0.228

Note: RM: N=1,757 using the first survey round 1991, 1998: N=2,373, using the fourth survey round 1998.
[1] Treats current students as having no years of schooling.
*Individual-level
RM's data: Amount borrowed is the cumulative amount of credit borrowed since December 1986 from any of these credit program adjusted to 1992 prices.
Updated data (1998-99): Amount borrowed is the cumulative amount of credit borrowed since January 1991 from any of these credit program adjusted to 1992 prices.

Table 3.9 Summary statistics: Endogenous variables in RM's 1991/92 data and my 1998/99 data

	Program villages									
	Participants		Nonparticipants		Total		Nonprogram villages		All villages	
	RM	Updated data 1998	RM	Updated data 1998	RM	Updated data 1998	RM	Updated data 1998	RM	Updated data 1998
Cumulative female borrowing, (Taka)	5,554.04 [7,580.10] N = 779	14,389.2 [19,727.6] N = 1,248	N = 326	N = 1,001	2,617.61 [5,896.01] N = 1,105	8,426.12 [16,277.80] N = 2,249			2,617.61 [5,896.01] N = 1,105	8,426.12 [16,277.80] N = 2,249
Cumulative male borrowing, (Taka)	3,757.37 [7,409.36] N = 631	3,868.46 [10,991.2] N = 879	N = 263	N = 653	1,748.91 [5,390.53] N = 894	2,285.01 [8,551.24] N = 1,532			1,748.91 [5,390.53] N = 894	2,285.01 [8,551.24] N = 1,532
Per-capita household spending (Taka/week)	77.014 [41.496] N = 2,696	96.134 [69.593] N = 1,395	85.886 [64.82] N = 1,650	104.245 [82.733] N = 1,149	82.959 [58.308] N = 4,346	99.797 [75.902] N = 2,544	89.661 [66.825] N = 872	75.305 [51.119] N = 40	84.072 [59.851] N = 5,218	99.4183 [75.634] N = 2,584
School enrolment of girls aged 5–17, (yes=1)	0.535 [0.499] N = 802	0.695 [0.461] N = 1,259	0.527 [0.500] N = 434	0.694 [0.461] N = 864	0 .530 [0.499] N = 1,236	0.695 [0.461] N = 2,123	0.552 [0.498] N = 225	0.444 [0.506] N = 27	0.534 [0.499] N =1,461	0.692 [0.462] N = 2,150
School enrolment of boys aged 5–17, (yes=1)	0.566 [0.496] N = 856	0.639 [0.481] N = 1,356	0.556 [0.497] N = 468	0.662 [0.474] N = 904	0.559 [0.497] N = 1,324	0.648 [0.478] N = 2,260	0.553 [0.498] N = 267	0.577 [0.504] N = 26	0.558 [0.497] N =1,591	0.647 [0.478] N = 2,286
Women's labor supply, (hours/month, aged 16-59)	40.389 [70.558] N = 3,420	23.131 [55.091] N = 1,839	32.467 [64.297] N = 2,108	14.694 [44.681] N = 1,502	35.087 [66.529] N = 5,528	19.338 [50.843] N = 3,341	31.269 [60.214] N=1,074	10.667 [54.267] N = 48	34.467 [65.556] N=6,602	19.215 [50.985] N = 3,398
Men's labor supply, (hours/month, aged 16–59)	202.749 [100.82] N = 3,534	160.103 [119.255] N = 1,986	185.758 [104.904] N = 2,254	136.6 [120.558] N = 1,682	191.239 [103.897] N = 5,788	149.516 [120.396] N = 3,614	180.528 [99.405] N =1,126	147.489 [117.525] N = 45	189.346 [103.191] N = 6,914	149.491 [120.346] N = 3,659
Female nonland assets, (Taka)	2,366.09 [6,693.24]	5,401.39 [20,076.9]	1,724.55 [5,033.62]	7,720.21 [57,658.5]	1,937.76 [5,645.45]	6,441.97 [41,407.9]	831.84 [2,207.09]	1,100.75 [2,608.34]	1,752.57 [5,245.48]	6358.74 [41,090.5]
Female assets, first survey round (Taka)	7,512.51 [31,572.9] N = 899	19,535.3 [159,644] N = 1,393	4,793.83 [19,922.0] N = 542	17,653 [148,413] N = 1,134	5,697.37 [24,443.4] N = 1,441	18,690.6 [154,677.0] N = 2,527	1,975.24 [6,428.01] N = 292	1,100.75 [2,608.34] N = 40	5,074.08 [22,498.9] N =1,733	18,416.5 [153,483.0] N = 2,567

Note: Cumulative female and male borrowing, school enrolment of girls and boys aged 5-17, and female non- and female assets are calculated in the first survey round in 1991-1992. Other variables are calculated in all survey rounds in 1991-1992. For data in 1998 - 1999, all variables are calculated in the fourth round.

Table 3.10 Shapiro-Francia W test of normality

Variable	*Obs*	*W*	*z*	*Prob>z*
Pcnsexp	2,584	0.61654	15.596	0.00001

Table 3.11 Covariate balance pre and post reweighted for treated and controls

Variables	Means			Variances			Skewness			SMD	
	Treated	Controls		Treated	Controls		Treated	Controls			
		Pre	Post		Pre	Post		Pre	Post	Pre	Post
HH head's spouse absent (yes=1)	0.960	0.940	0.960	0.038	0.056	0.038	-4.707	-3.722	-4.708	9.1	0
Highest grade completed by any female HH member (max)	2.632	3.535	2.632	43.65	46.69	24.54	5.889	4.662	3.688	-13.4	0
Highest grade completed by any female HH member (max)	3.448	4.803	3.448	28.76	37.74	21.16	3.181	2.245	1.887	-23.5	0
Adult female not present in HH (yes=1)	0.001	0.012	0.001	0.001	0.012	0.001	32.82	9.06	32.77	-13.7	-0.01
Adult male not present in HH (yes=1)	0.023	0.038	0.023	0.023	0.037	0.023	6.342	4.804	6.343	-8.8	0.01
Sex of HH head (male=1)	0.901	0.890	0.901	0.089	0.098	0.089	-2.684	-2.498	-2.684	3.5	-0.03
Age of HH head (years)	44.93	44.72	44.93	143.3	203.7	214.3	0.619	0.503	0.525	1.6	0
Log HH land at time of survey	1.219	0.828	1.219	2.709	2.708	3.613	1.083	1.831	1.256	23.8	0
Highest grade completed by HH head (max)	2.183	3.298	2.183	22.23	28.31	13.77	4.495	3.116	3.05	-22.2	0
Sister of HH head's spouse own land (yes=1)	0.425	0.564	0.425	0.981	1.231	0.935	2.876	2.383	2.734	-13.2	0
Brother of HH head's spouse own land (yes=1)	0.609	0.779	0.609	1.564	1.921	1.599	2.541	1.985	2.34	-12.9	0.01
Parents of HH head's spouse own land (yes=1)	0.338	0.392	0.338	0.387	0.447	0.396	1.671	1.446	1.663	-8.3	0.02
Sister of HH head own land (yes=1)	0.362	0.556	0.362	0.789	1.162	0.721	3.321	2.255	2.892	-19.7	-0.01
Brother of HH head own land (yes=1)	0.466	0.680	0.466	0.953	1.446	0.918	2.558	2.042	2.508	-19.5	0
Parents of HH head own land (yes=1)	0.129	0.170	0.129	0.162	0.201	0.163	3.277	2.842	3.479	-9.7	0
Household member (person)	5.273	5.165	5.273	4.015	6.005	7.253	1.113	1.386	1.652	4.8	0

Table 3.12 Impact estimates for log weekly per capita expenditures (Taka)

Treatment	*De facto participants*			*De jure participants*		
	C1	**C2**	**C3**	**C1**	**C2**	**C3**
All observations						
Dummy female borrowing	-0.0423*	-0.0424*	-0.0424*	-0.0313	-0.0316	-0.0316
	[0.023]	[0.025]	[0.023]	[0.024]	[0.022]	[0.022]
Dummy male borrowing	-0.0260	-0.0261	-0.0298	-0.0303	-0.0303	-0.0358
	[0.044]	[0.048]	[0.050]	[0.049]	[0.053]	[0.048]
Drop outliers						
Dummy female borrowing	-0.0019	-0.0020	-0.0020	0.0005	0.0004	0.0004
	[0.018]	[0.020]	[0.018]	[0.020]	[0.020]	[0.015]
Dummy male borrowing	0.0239	0.0239	0.0218	0.0151	0.0151	0.0127
	[0.040]	[0.038]	[0.037]	[0.042]	[0.042]	[0.041]

Note: standard error in parenthesis, *significant at 10%, **significant at 5%, ***significant at 1%
C1: control group = all non-participants
C2: control group = non-participants in program villages
C3: control group = non-participants in female/male program villages
De jure participants: drop HHs who participated in credit programs but had land of more than 0.5 acres

Table 3.13 Impact assessment for alternative outcome variables, between participants and non-participants across program and non-program villages, by gender

	Female borrowing		Male borrowing	
Outcome variables	De facto	De jure	De facto	De jure
Log per capita expenditure (Taka)	-0.0423*	-0.0313	-0.0260	-0.0303
	[0.028]	[0.028]	[0.051]	[0.053]
Log women non landed assets (Taka)	0.1597	0.1363	-0.1350	-0.3114
	[0.186]	[0.188]	[0.348]	[0.348]
Log women assets (Taka)	0.2553	0.2181	0.0086	-0.1932
	[0.193]	[0.193]	[0.353]	[0.351]
Log female labor supply, aged 16-59 years, hours per month	0.0789***	0.0896***	0.0134	0.0147
	[0.022]	[0.024]	[0.034]	[0.039]
Log male labor supply, aged 16-59 years, hours per month	0.0566	0.0502	0.1430	0.1213
	[0.051]	[0.053]	[0.087]	[0.096]
Girl school enrolment, aged 5-17 years	0.1018	0.0507	0.1228	0.1941
	[0.080]	[0.084]	[0.137]	[0.153]
Boy school enrolment, aged 5-17 years	0.0576	0.0408	0.0870	0.1255
	[0.076]	[0.079]	[0.140]	[0.148]

Note: control group = all non-participants, treatment is one if female/male borrowing by gender
De jure participants: drop HHs who participated in credit programs but had land of more than 0.5 acres
*significant at 10%, **significant at 5%, ***significant at 1%

3.9 Appendix: Programming code for Chapter 3

```
// Appendix for Chapter 3
// REPLICATION RM RESULTS

// This part sets global, define and prepare data

* Global set and define
cap program drop ResetGlobals
program define ResetGlobals
	global depvar lpcnsexppk
	global  covsy scoheadpk  afedhighpk  amedhighpk  afadultdpk  amadultdpk  sexheadpk
ageheadpk  llandbefpk  edheadpk  spsislnddpk  spbrolnddpk  spparlnddpk  hdsislnddpk
hdbrolnddpk  hdparlnddpk  _Iwave*
	global  covsf scoheadpk1 afedhighpk1 amedhighpk1             amadultdpk1 sexheadpk1
ageheadpk1 llandbefpk1 edheadpk1 spsislnddpk1 spbrolnddpk1 spparlnddpk1 hdsislnddpk1
hdbrolnddpk1 hdparlnddpk1 _Ivill*
	global  covsm scoheadpk1 afedhighpk1 amedhighpk1 afadultdpk1             sexheadpk1
ageheadpk1 llandbefpk1 edheadpk1 spsislnddpk1 spbrolnddpk1 spparlnddpk1 hdsislnddpk1
hdbrolnddpk1 hdparlnddpk1 _Ivill*
	global covsfm scoheadpk1 afedhighpk1 amedhighpk1 afadultdpk1 amadultdpk1 sexheadpk1
ageheadpk1 llandbefpk1 edheadpk1 spsislnddpk1 spbrolnddpk1 spparlnddpk1 hdsislnddpk1
hdbrolnddpk1 hdparlnddpk1 _Ivill*
	global creditvars lfbraclvpk1 lfbrdblvpk1 lfgramlvpk1 lmbraclvpk1 lmbrdblvpk1
lmgramlvpk1
	global creditw lfproglvpk1
	global creditm lmproglvpk1
	global credit  lproglvpk1
	global nontarvar nontarpk
	global extracovsy
	global insts zf* zm* choicefpk1 choicempk1
end

*Define indicators
cap program drop DefineIndicators
program define DefineIndicators
	cap drop indf indm indfm
	gen byte indf = cond($creditw<=ln(1000)+.001, $cmp_left, $cmp_cont)
	gen byte indm = cond($creditm<=ln(1000)+.001, $cmp_left, $cmp_cont)
	cap gen byte indfm = cond($credit<=ln(1000)+.001, $cmp_left, $cmp_cont)
end

* load and prepare household-level data set
cap program drop PrepHHData
program define PrepHHData
	qui {
	 use "Roodman & Morduch HH 2.dta", clear
		keep if wave<4 & pksample
		sort nh wave
		ren pksamplempk choicempk
		ren pksamplefpk choicefpk
		gen byte choicepk = choicefpk | choicempk
		gen byte progidpk = mod(int((villagepk-10)/80)+1, 4) // 1 = BRAC village, 2 =
BRDB, 3 = Grameen, 0 = none

		xi i.wave i.villagepk
		gen double fasset = fnlasset + flandvalb

		foreach var in fproglvpk mproglvpk {
			gen double l`var' = ln(`var')
			recode l`var' (. = `=cond(inlist("`var'", "fproglvpk", "mproglvpk"),
`=C_t', `=C_v')' )
		}
		replace llandbefpk = log(123) if nh==321111 & wave==3 // fix data error. log
land=log(10123) in wave 3 and log(123) in waves 1-2
		gen double landbefpk = exp(llandbefpk)
		gen double pcnsexppk = exp(lpcnsexppk)

		bysort villagepk: egen byte fprogvillpk = max(choicefpk) // dummy for villages
with female credit groups
		by     villagepk: egen byte mprogvillpk = max(choicempk) // ditto for male
		gen byte progvillpk = fprogvillpk | mprogvillpk

* For first-stage eqs, make variables based on first-wave data only
```

```
		sort nh wave
		foreach var in choicepk choicefpk choicempk lfproglvpk lmproglvpk lfbraclvpk
lfbrdblvpk lfgramlvpk lmbraclvpk lmbrdblvpk lmgramlvpk scoheadpk afedhighpk amedhighpk
afedhighnspk amedhighnspk afadultdpk amadultdpk sexheadpk ageheadpk llandbefpk edheadpk
edheadnspk hdbrolnddpk hdsislnddpk hdparlnddpk spbrolnddpk spsislnddpk spparlnddpk monlypk
fonlypk partpk {
			cap by nh: gen double `var'1 = `var'[1]
		}
		foreach prog in brac brdb gram {		// credit variables aggregated
accross gender
			bysort nh (wave): gen double l`prog'lvpk1 = ln(`prog'lvpk[1])
			recode l`prog'lvpk1 (. = 0)
		}
		bysort nh: gen double lproglvpk1 = ln(proglvpk[1])
		recode lproglvpk1 (. = `=ln(1000)')

		recode lfproglvpk lmproglvpk (0 = `=ln(1000)')	// First-stage LHS variables
take censoring *threshold* (not censoring *value*)
		bysort nh (wave): gen double lfproglvpk1ln1 = log(fproglvpk[1])
		bysort nh (wave): gen double lmproglvpk1ln1 = log(mproglvpk[1])
		bysort nh (wave): gen double lproglvpk1ln1 = log(proglvpk[1])
		recode l*proglvpk1ln1 (. = 0)

		bysort nh (wave): gen byte nontrgth_dejure = landbefpk[1] >= 50.01

		ResetGlobals
		DefineIndicators

* interact controls with choice dummies to make instruments
		foreach var of varlist $covsf {
			gen double zf`var' = `var' * choicefpk
		}
		foreach var of varlist $covsm {
			gen double zm`var' = `var' * choicempk
		}
		foreach var of varlist $covsf afadultdpk1 _Ivill* {
			cap gen double zb`var' = `var' * choicepk
		}
	}
end


***************************************************************************
// TABLE 3.1
***************************************************************************


// Descriptive statistics
// Using data 1991-1992

clear
cap log close
cap estimates drop *

set more off
set matsize 800
cmp setup
global indy $cmp_cont
scalar C_t = ln(1000)
scalar C_v = ln(1)

global path "C:\Users\dtv13\Dropbox\DIEM PhD Program\Chapter 3_DM\Robust_1998_99_data\"
cd "$path"

PrepHHData

tempfile TempOutregFile
// Table 3.1: weighted means and sds of RHS vars in first wave. sd's are displayed as "Root
MSE"
foreach var in fbraclvpk mbraclvpk fbrdblvpk mbrdblvpk fgramlvpk mgramlvpk scoheadpk
afedhighpk amedhighpk afadultdpk amadultdpk sexheadpk ageheadpk landbefpk edheadpk spsislnddpk
spbrolnddpk spparlnddpk hdsislnddpk hdbrolnddpk hdparlnddpk nontarpk {
	cap reg `var' if wave==1 [aw=weightpk]
	if !_rc {
		reg
```

```
		qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("`var'-wave 1")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
	}
}
copy "`TempOutregFile'" "Table 3.1(1991-92).txt", replace


****************************************************************************
// TABLE 3.2
****************************************************************************


// Table 3.2: means and sds of dep vars. sd's are displayed as "Root MSE".
forvalues varn = 1/9 {
	if `varn'==6 {
		preserve
		use "$path/Roodman & Morduch ind 2.dta", clear
		keep if wave<4 & pksample
		ren pksamplempk choicempk
		ren pksamplefpk choicefpk
		bysort villagepk: egen byte fprogvillpk = max(choicefpk)
		by     villagepk: egen byte mprogvillpk = max(choicempk)
		gen byte progvillpk = fprogvillpk | mprogvillpk

		reg age if wave==1 [aw=weightpk]
		qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("age-wave 1")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
		reg ed if wave==1 & age>=5 [aw=weightpk]
		qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("ed-wave 1")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
		reg edns if wave==1 & age>=5 [aw=weightpk] // education of non-students,
students=0, needed to match PK
		qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("edns-wave 1")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
	}
	local var : word `varn' of fproglvpk mproglvpk pcnsexppk fasset fnlasset fwork mwork
fedec517 medec517
	local varsample : word `varn' of "choicefpk & wave==1" "choicempk & wave==1" 1
"!afadultdpk & wave==1" "!afadultdpk & wave==1" "sex==0 & age>=16 & age<60" "sex==1 & age>=16
& age<60" "wave==1 & sex==0 & age>=5 & age<18" "wave==1 & sex==1 & age>=5 & age<18"

	forvalues samplen = 1/5 {
		local sample : word `samplen' of progid<4 "progid>=4 & progvillpk"
progvillpk !progvillpk 1
		local samplename : word `samplen' of part non-part prog-vill non-prog-vill all
		cap reg `var' if `varsample' & `sample' [aw=weightpk]
		if !_rc {
			reg
			qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("`var'-
`samplename'") dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
		}
	}
}
restore
copy "`TempOutregFile'" "Table 3.2(1991-92).txt", replace
tempfile TempOutregFile
global TempOutregFile `TempOutregFile'


****************************************************************************
// TABLE 3.3
****************************************************************************


// Table 3.3 column 2
* REPLICATION Roodman & Morduch Table 3, col 2
use "$path/Roodman & Morduch HH 2.dta", clear
ResetGlobals
DefineIndicators
* Perform PK-type estimate, then "flip" estimates and rerun search starting from that point.
Save both results.
cap program drop EstimatePKFlip
program define EstimatePKFlip
	syntax [if], runname(string) [maleonly femaleonly pooled nolendersplit noOUTREG *]
	EstimatePK`pooled' `if', `options' `maleonly' `femaleonly'
	SaveEstimates, runname(`runname') addstat(`"`addstat'"') `outreg'
```

```
        tempname b
        mat `b' = e(b)
        if "`lendersplit'" == "" mat `b' = -`b'[1,1..6], `b'[1,7...]
                else mat `b' = -`b'[1,1..2], `b'[1,3...]
        if "`maleonly'`femaleonly'" == "" {
                mat `b'[1, colsof(`b') - 2] = -`b'[1, colsof(`b') - 2]
                mat `b'[1, colsof(`b') - 1] = -`b'[1, colsof(`b') - 1]
        }
        else {
                mat `b'[1, colsof(`b')] = -`b'[1, colsof(`b')]
        }
        EstimatePK`pooled' `if', init(`b') `options' `maleonly' `femaleonly'
        SaveEstimates, runname(`runname'_flip) addstat(`"`addstat'"') `outreg'
end

* core PK nonlinear LIML estimator
cap program drop EstimatePK
program define EstimatePK
        syntax [if], [bs femaleonly maleonly TECHnique(string) *]
        if "`technique'"=="" local technique dfp nr
        cmp  ($depvar = $creditvars $nontarvar $covsy $extracovsy _Ivill*) ///
             `=cond("`maleonly'"==""  , "($creditw = $covsf)", "")' ///
                `=cond("`femaleonly'"=="", "($creditm = $covsm)", "")' ///
                [pw=weightpk] `if', tech(`technique') `=cond("`bs'"=="", "cluster(nh)", "")'
///
                ind("$indy" `=cond("`maleonly'"=="","choicefpk*indf","")'
`=cond("`femaleonly'"=="","choicempk*indm", "")') `options' ghkdraws(101, anti) nolr
end

// Estimation
EstimatePKFlip, runname(replication) // Roodman & Morduch Table 3, col 2


****************************************************************************
// TABLE 3.4
****************************************************************************


// LIML-FE estimations of the impact of microcredit on female nonland assets and female total
assets
use "$path/Roodman & Morduch HH 2.dta", clear
* outcome: log female (non-land) assets
scalar Y_0 = ln(10)      // female non-land asset censoring threshold? (2 is lowest observed
value, in wave 2, 10 lowest in wave 1.)
gen double lfnlasset = ln(fnlasset)
gen double lfasset = ln(fasset)
replace lfnlasset = Y_0 if lfnlasset<Y_0 | lfnlasset==.
replace lfasset = Y_0 if lfasset<Y_0 | lfasset==.
// Table 3.4, column 2
global depvar lfnlasset
global indy "cond($depvar<=Y_0, $cmp_left, $cmp_cont)"
EstimatePKFlip if wave==1, runname($depvar) // RM Table 6, col 2
// Table 3.4, column 4
global depvar lfasset
global indy "cond($depvar<=Y_0, $cmp_left, $cmp_cont)"
EstimatePKFlip if wave==1, runname($depvar) // RM Table 6, col 3


****************************************************************************
// TABLE 3.5
****************************************************************************


// LIML-FE estimation of the impact of microcredit on alternative outcomes: labor supply
// Table 3.5, replicate RM table 6, col 5, 7 and 8

use "$path/Roodman & Morduch ind 2.dta", clear
keep if wave<4 & pksample
ren pksamplempk choicempk
ren pksamplefpk choicefpk
xi i.wave i.village
foreach var in fproglv mproglv {
        gen double l`var'pk = ln(`var'pk)
        recode l`var'pk (. = `=C_v')
}
gen age2 = age^2
```

```
* For first-stage eqs, make variables based on first-wave data only
sort nh pid wave
foreach var in choicepk choicefpk choicempk fprogvillpk mprogvillpk lfproglvpk lmproglvpk
lfbraclvpk lfbrdblvpk lfgramlvpk lmbraclvpk lmbrdblvpk lmgramlvpk scoheadpk afedhighpk
amedhighpk afedhighnspk amedhighnspk afadultdpk amadultdpk sexheadpk ageheadpk llandbefpk
edheadpk edheadnspk hdbrolnddpk hdsislnddpk hdparlnddpk spbrolnddpk spsislnddpk spparlnddpk
monlypk fonlypk partpk {
        cap by nh pid: gen double `var'1 = `var'[1]
}
DefineIndicators

* outcome: female and male hours worked
// Table 3.5, column 2
scalar Y_0 = ln(1)      // labor supply censoring level? (1 is lowest observed value, occuring
in fwork.)
gen double lfwork = ln(fwork)
gen double lmwork = ln(mwork)
recode lmwork lfwork (. = `=Y_0')
global extracovsy age age2 ed
global depvar lfwork
global indy cond($depvar<=Y_0, $cmp_left, $cmp_cont)

EstimatePKFlip if !afadultdpk & age>=16 & age<60 & sex==0, runname($depvar) // RM Table 6, col
5

// Table 3.5 column 4 and 5
global depvar lmwork
global indy cond($depvar<=Y_0, $cmp_left, $cmp_cont)
gen byte d = mwork==0
sum d [aw=weightpk] if !afadultdpk & age>=16 & age<60 & sex==1, mean
di "share of male labor supply obs that are censored:" r(mean)
EstimatePKFlip if !amadultdpk & age>=16 & age<60 & sex==1, runname($depvar) // RM Table 6,
cols 7-8


**************************************************************************
// TABLE 3.6
**************************************************************************


// Continue the code run by Table 3.5
* outcome: school enrollment
global extracovsy age age2
global indy $cmp_probit
// Table 3.6, column 2
global depvar fedec517
EstimatePKFlip if wave==1 & sex==0 & age>=5 & age<18, runname($depvar) tech(dfp) // RM Table
6, cols 10
// Table 3.6, column 4
global depvar medec517
EstimatePKFlip if wave==1 & sex==1 & age>=5 & age<18, runname($depvar) // RM Table 6, cols 12


**************************************************************************
// TABLE 3.7
**************************************************************************



use "$path/Roodman & Morduch HH 2.dta", clear

* REPLICATION: reported in Roodman & Morduch, JDS: give 1st-stage & credit vars wave-1 values
throughout; include nontar; drop crcensored; censor with log 1
ResetGlobals
DefineIndicators
EstimatePKFlip, runname(replication) // Roodman & Morduch Table 4, cols 1-2


**************************************************************************
// ROBUSTNESS RESUTLS USING THE 1998/99 DATA
// TABLE 3.8
**************************************************************************


// Summary statistics 1998/99 data
// set paths to working data folders
```

```
global path "C:\Users\dtv13\Dropbox\DIEM PhD Program\Chapter 3_DM\Robust_1998_99_data\"
cd "$path"
// access HH and individual data
global hhname "003_Diem_HH"
global indname "003-Diem-ind"

// Set globals

cap program drop SetGlobals
program define SetGlobals
global hhconvar scohead afedhigh amedhigh afadultd amadultd sexhead agehead ///
               llandbef  edhead spsislndd spbrolndd spparlndd hdsislndd hdbrolndd hdparlndd
hhnmembers
global indconvar age ed scohead afedhigh amedhigh afadultd amadultd sexhead agehead ///
               llandbef  edhead spsislndd spbrolndd spparlndd hdsislndd hdbrolndd hdparlndd
hhnmembers
global vill _Ivill*
global creditvar lfproglv1 lmproglv1 //female and male borrowing, credit zero will be replace
as log(1)
end


clear
set more off
use "$path/$hhname", clear
keep if wave==4  // Data 1998/99 = wave 4

* Descriptive statistics

global resultsfile Diemresults.txt
global meansfile Diemstatistics.txt
cap log close
log using "$path/Robustlog_1998_Diem", replace
cap estimates drop *

cap erase $resultsfile

set more off
set matsize 800
tempfile TempOutregFile

* Table 3.8: means and sds of RHS vars in wave = 4 . sd's are displayed as "Root MSE" (No
weight)
foreach var in fbraclv mbraclv fbrdblv mbrdblv fgramlv mgramlv scohead afedhigh amedhigh
afadultd amadultd sexhead agehead landbef landaft edhead spsislndd spbrolndd spparlndd
hdsislndd hdbrolndd hdparlndd nontar {
       cap reg `var' if wave==4
       if !_rc {
              reg
              qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("`var'-wave 4")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
       }
}

copy "`TempOutregFile'" "Table 3.8(1998).txt", replace

tempfile TempOutregFile


************************************************************************
// TABLE 3.9
************************************************************************


* Table 3.9: means and sds of dep vars. sd's are displayed as "Root MSE".
forvalues varn = 1/9 {
       if `varn'==6 {
       //individual, table 3.8, variable 6 forward in individuals
              preserve
              use "$path/$indname", clear

              keep if wave==4
              reg age if wave==4
              qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("age-wave 4")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
              reg ed if wave==4 & age>=5
```

```
                qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("ed-wave 4")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
                reg edns if wave==4 & age>=5  // education of non-students, students=0
                qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("edns-wave 4")
dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
        }
        local var : word `varn' of fproglv mproglv pcnsexp fasset fnlasset fwork mwork
fedec517 medec517
        local varsample : word `varn' of "choicef & wave==4" "choicem & wave==4" ///
                                       //var la bien, varsample la loc
                                          1 "!afadultd & wave==4" "!afadultd & wave==4" ///
                                          "sex==0 & age>=16 & age<60" "sex==1 & age>=16 &
age<60" ///
                                          "wave==4 & sex==0 & age>=5 & age<18" "wave==4 &
sex==1 & age>=5 & age<18"

        forvalues samplen = 1/5 {
                local sample : word `samplen' of progid<4 "progid>=4 & progvill"
progvill !progvill 1
                local samplename : word `samplen' of part non-part prog-vill non-prog-vill all
                cap reg `var' if `varsample' & `sample'
                if !_rc {
                        reg
                        qui outreg2 using "`TempOutregFile'", noparen noaster ctitle("`var'-
`samplename'") dec(10) adec(10) addstat("S.d.", `=string(e(rmse), "%12.4f")')
                }
        }
}
restore
copy "`TempOutregFile'" "Table 3.9(1998).txt", replace
tempfile TempOutregFile
global TempOutregFile `TempOutregFile'


****************************************************************************
// TABLE 3.10
****************************************************************************


//Test for nornal distribution
clear
set more off
use "$path/$hhname", clear
sfrancia pcnsexp if wave==4


****************************************************************************
// TABLE 3.11
// Using Excel to calculate Covariate balance pre and post reweighted for treated and controls
****************************************************************************


****************************************************************************
// TABLE 3.12
****************************************************************************


// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Facto, top panel

use "$path/$hhname", clear
keep if wave==4

preserve
set more off
set matsize 800
set seed 1234

SetGlobals
global depen lpcnsexp

*treatment C1, control group = all non-participants
*female borrowing
cap drop treatf
gen treatf = 1 if fproglv>0
```

```
replace treatf = 0 if proglv==0
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(50) saving(etreats, replace): bootebalRM

*male borrowing
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C2, control group = non-participants in program villages
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
```

```
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C3, control group = non-participants in female/male program villages
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(50) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Jure, borrowing and landownership <=50, top panel

*treatment C1
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
```

```
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
*reg $depen lfproglv1 $hhconvar $vill [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
*reg $depen lmproglv1 $hhconvar $vill [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C2
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
```

```
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C3
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

***************************************************************************
// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Facto, bottom panel

*drop outliers
*De Facto
*C1
preserve
```

```
set more off
set matsize 800
set seed 12345
histogram pcnsexp, normal kdensity

local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)            //subtract the first quartile from the third
quartile
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr      //interquartile Range
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr       // rule of thums is 1.5
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
cap drop treatm
set seed 12345
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C2
*De Facto,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
```

```
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C3
*De Facto,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity

local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
```

```
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

****************************************************************************
// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Jure, bottom panel

*drop outliers
*treatment C1
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
```

```
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C2
*De Jure,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp

/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
```

```
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore

*treatment C3
*De Jure,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight]
return scalar att = _b[treatf]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]

cap program drop bootebalRM
program define bootebalRM, rclass
```

```
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight]
return scalar att = _b[treatm]
drop E_weight
end

bootstrap att = r(att), reps(100) saving(etreats, replace): bootebalRM

restore


***************************************************************************
// TABLE 3.13
***************************************************************************


// Other outcomes between participants and non-participants across program and non-program
villages, by gender

// Log female nonland / fnlasset
// De facto
* female borrow
clear
set more off
use "$path/$hhname", clear
sfrancia pcnsexp if wave==4
preserve
set more off
set seed 12345

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0
gen lfnlasset =ln(fnlasset) //female non-land asset
               recode lfnlasset (. = `=ln(1)')  //ln(1) = 0, no non-land asset
gen lfasset =ln(fasset) //female asset
               recode lfasset (. = `=ln(1)')  //ln(1) = 0, no asset

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)

foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatf [pw=E_weight]
}
drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)

foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatm [pw=E_weight]
}
drop E_weight

restore

*De Jure
*female borrow
preserve
set more off
set seed 12345

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

gen lfnlasset =ln(fnlasset) //female non-land asset
               recode lfnlasset (. = `=ln(1)')  //ln(1) = 0, no non-land asset
```

```
gen lfasset =ln(fasset) //female asset
                recode lfasset (. = `=ln(1)')  //ln(1) = 0, no asset

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)

foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatf [pw=E_weight]
}

drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)

foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatm [pw=E_weight]
}

drop E_weight

restore


//USING INDIVIDUAL DATA/ Log female &male labor: mwork & fwork /School enrolment: feduc517,
meduc517/
clear
set more off
use "$path/$indname", clear

// PREPAREDATA
keep if wave<=4
                sort nh wave

                ren rfem choicef
                ren rmale choicem
                gen byte choice = choicef | choicem
                gen byte progid4 = progid // 1 = BRAC village, 2 = BRDB, 3 = Grameen, 0 = none
                recode progid4 (4 5 = 0)  //eligible but not borrow, 5 ineligible
                xi i.village
                gen double fasset = fnlasset + flandvalb
                gen lfproglv = ln(fproglv)
                replace lfproglv = 0 if missing(lfproglv)
                gen lmproglv = ln(mproglv)
                replace lmproglv = 0 if missing(lmproglv)
                gen llandbef =ln(landbef)
                recode llandbef (. = `=ln(1)')  //ln(1) = 0, no land
                gen lpcnsexp= ln(pcnsexp)
                gen nontar = 1 - eligible // non-target = 1 - eligible
                sort nh wave
                bysort nh: gen double lproglv = ln(proglv)
                recode lproglv (. = `=ln(1)')
                recode lfproglv lmproglv (0 = `=ln(1)')     // First-stage LHS variables take
censoring *threshold* (not censoring *value*)
                bysort nh (wave): gen byte nontrgth_dejure = landbef >= 50.01
                gen crcensored=1 if choice==1 & proglv==0
                recode crcensored (. =0)


SetGlobals

// female borrowing

preserve
set more off
keep if wave==4
set seed 12345
SetGlobals
```

```
gen lfwork =ln(fwork) //labor supply, including self-employment (hours/month), if female
               recode lfwork (. = `=ln(1)')  //ln(1) = 0, no labor supply
gen lmwork =ln(mwork) //labor supply, including self-employment (hours/month), if male
               recode lmwork (. = `=ln(1)')  //ln(1) = 0, no labor supply

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $indconvar $vill, gen(E_weight)

// Impact on female and male labor supply
foreach v in lfwork lmwork {
regress `v' treatf [pw=E_weight]
}
// Impact on girl and boy school enrolment
foreach v in fedec517 medec517{
probit `v' treatf [pw=E_weight]
}

drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $indconvar $vill, gen(E_weight)
// Impact on female and male labor supply
foreach v in lfwork lmwork {
regress `v' treatm [pw=E_weight]
}
// Impact on girl and boy school enrolment
foreach v in fedec517 medec517 {
probit `v' treatm [pw=E_weight]
}
drop E_weight

restore

*De Jure

preserve
set more off
keep if wave==4
set seed 12345
SetGlobals

gen lfwork =ln(fwork) //labor supply, including self-employment (hours/month), if female
               recode lfwork (. = `=ln(1)')  //ln(1) = 0, no labor supply
gen lmwork =ln(mwork) //labor supply, including self-employment (hours/month), if male
               recode lmwork (. = `=ln(1)')  //ln(1) = 0, no labor supply

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $indconvar $vill, gen(E_weight)
// Impact on female and male labor supply
foreach v in lfwork lmwork {
regress `v' treatf [pw=E_weight]
}
// Impact on girl and boy school enrolment
foreach v in fedec517 medec517{
probit `v' treatf [pw=E_weight]
}
drop E_weight

*male borrowing
set seed 12345
cap drop treatm
```

```
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $indconvar $vill, gen(E_weight)
// Impact on female and male labor supply
foreach v in lfwork lmwork {
regress `v' treatm [pw=E_weight]
}
// Impact on girl and boy school enrolment
foreach v in fedec517 medec517 {
probit `v' treatm [pw=E_weight]
}
drop E_weight

restore


***************************************************************************
// FIGURE 3.1
***************************************************************************


use "C:\Users\dtv13\Dropbox\DIEM PhD Program\003_Diem_HH.dta", clear

// graph of distribution of landownership and actual borrowing

replace landbef=1 if landbef==0
replace proglv=1 if proglv==0
gen landbef100 = landbef/100
gen proglv1000 = proglv/1000
replace landbef100=1 if landbef100==0
replace proglv1000=1 if proglv1000==0

scatter proglv1000 landbef100 if progvill==1& wave==4, xsc(log) ysc(log) mcolor(green)
msize(tiny..) xline(0.5) ///
       ytitle("Cumulative borrowing, thousands of taka" "(1999 taka)") ///
       ylabel(1 10 50 100, labsize(small)angle(horizontal))  ///
       xtitle("Household landholdings before borrowing (acres)") /// // keep last two lines
for ppt
       xlabel(0.01 0.1 0.5 1 10, labsize(small))


***************************************************************************
// FIGURE 3.2
***************************************************************************


use "C:\Users\dtv13\Dropbox\DIEM PhD Program\003_Diem_HH.dta", clear
keep if wave==4
histogram pcnsexp, normal kdensity
```

Chapter 4. A replication of "Empowering Women with Micro Finance: Evidence from Bangladesh" (Economic Development and Cultural Change, 2006)

4.1 Introduction

The primary goals of microcredit are lifting the poor out of poverty and promoting women's empowerment (Norwood, 2005). However, the question of whether microcredit really helps the poor, especially female clients, and promotes women's empowerment is still the subject of intense debate within the scientific community.

In the literature, two studies have been particularly influential, namely Pitt and Khandker (1998), henceforth PK, and Pitt et al. (2006), henceforth PKC. PK and PKC analyze the impact of microcredit in rural Bangladesh on household per capita consumption expenditure by gender, and on women's empowerment, respectively. These two studies have been very controversial and have spawned several replications, which themselves have produced mixed results. Because of the importance of these studies and the controversy they have generated, my thesis undertakes a careful replication of both PK and PKC.

In Chapter 2 and Chapter 3, I replicated two PK's replications which had been conducted by Duvendack & Palmer-Jones (2012) and Roodman and Morduch (2014). My replication results do not support PK's findings, which stated that microcredit significantly improves female participants' per capita income. My findings do not confidently suggest that microcredit really helped poor households, especially poor women, in Bangladesh. This is also consistent with the conclusions of Duvendack & Palmer-Jones (2012) and Roodman and Morduch (2014).

This chapter replicates Pitt, Khandker, and Cartwright (2006), "Empowering Women with Micro Finance: Evidence from Bangladesh", published in the journal *Economic Development and Cultural Change*. PKC is one of the most influential papers in the field. It has received 696 Google Scholar citations, as of 12 November 2021. My study is the first replication of PKC and aims to find out whether microcredit significantly empowers women, which it turn contributes to gender equality as one of the original microcredit goals.

Using a rural community survey in Bangladesh in 1998-99, PKC investigated the impact of participation in microcredit programs on empowerment of women. Empowerment is modeled as a latent variable, which can be measured indirectly from observed behaviors. PKC used Item Response Theory (IRT) to estimate the empowerment variables. They then related these latent variables to a series of observable behaviors by using structural equation modeling (SEM). Instrument variables (IVs) and village fixed effects are employed to control for potential endogeneity. The authors reported that the presence of microcredit programs in a village as well as giving women an opportunity to participate in microcredit helped increase female empowerment. In contrast, male involvement in microcredit had adverse effects on women's empowerment.

Unfortunately, PKC were unable to provide their data and code to me. I have therefore collected data myself from various sources, including a dataset from the World Bank and a dataset from Roodman and Morduch (2014). In writing the programming code, I have been in contact with Mark Pitt and appreciated guidance over matters not covered or not covered clearly in PKC. I use an IRT model and a SEM model to estimate women empowerment indicators, by gender of microcredit participants. IRT and factor analysis (FA) are two common methods to estimate latent variables. FA is often used to estimate latent covariates with a set of observed continuous variables. When applied to discrete data, FA is always misspecified in some context while IRT models should fit the discrete and ordinal data better than FA models in applications. Because empowerment responses in Bangladesh data are binary, IRT model is used to estimate women's empowerment indicators (Maydeu-Olivares, Cai, & Hernández, 2011). Although my replication does not precisely match PKC's result, my findings generally support PKC's claim that female microcredit participation enhances women's empowerment. In contrast, the impact is smaller and statistically insignificant if borrowers are male.

However, PKC did not test the validity of their instrumental variables. My study conducts IV tests and cannot reject the hypothesis that the IVs are weak and insufficiently relevant. This failed rejection raises questions about the reliability of PKC's findings. To address this concern, I use the least absolute shrinkage and selection operator (Lasso) technique (Belloni, Chen, Chernozhukov, & Hansen, 2012) to find the optimal number of IVs for the first stage. This approach selects potential IVs in the first stage estimation and then uses the selected IVs to run the second stage estimation. Lasso improves the predictive relationship between endogenous regressors and the instrumental variables in the first stage of the two-stage least square method (2SLS), while adjusting for the sampling error introduced through the IV selection process (J. S. Kim, Jiang, Li, & Yang, 2019). Moreover, Lasso can also be used to pick control variables in the second step of 2SLS estimation. The automated procedure of selecting IVs and control variables addresses a concern about "cherry-picking" variables to produce specific results.

My extended replication of PKC's research generally supports PKC's findings. PKC find that the results of average treatment effects on the treated (ATTs) in women's empowerment are positive if microcredit programs are targeted at women and negative if microcredit programs are targeted at men. My findings also show that women who participate in microcredit improve their empowerment; however, the effects are smaller than in PKC. In contrast, my re-analyses do not find evidence that male participation in microcredit has a significant negative impact on female empowerment. Furthermore, PKC analyze the intention-to-treat effect of microcredit on female empowerment and find considerable evidence that the presence of microcredit in a village (intend to treat effects) positively influences women's empowerment. My findings show smaller effects.

My study significantly contributes to the literature by making data and code available, which allows other researchers to investigate PKC's results and conduct further, related studies.

This chapter is organized as follows: Section 4.2 discusses the methodology and Section 4.3 presents my data and variables. Section 4.4 replicates PKC (2006), Sections 4.5, 4.6 and 4.7 include my robustness check, and Section 4.8 concludes.

4.2 Methodology

Before presenting the empirical results, I review the estimation of women's empowerment and specification models in PKC.

4.2.1 Women's empowerment estimation

Women's empowerment is a process in which women can take control and expand their choices and improve their lives (Kabeer, 1999). Taking control of life has two main aspects; control over resources such as physical, financial, and economic assets; and control over ideology such as attitudes, opinions or beliefs (Cornwall, 2016). Therefore, women's empowerment cannot directly be observed as other economic behaviors. It is modeled as a latent variable that can be measured indirectly from observed behaviors. Many papers refer women's empowerment as an indicator that reflects the sharing power of a female relative to a male in household decision-making and household allocation of resources. According to Pitt et al. (2006), self-reporting of decision-making does not imply that women actually have more power. An empirical indicator therefore instead relies on accumulated evidence. This evidence comes from a variety of dimensions, including freedom of movement outside the household without being controlled by male members of the family, ability to develop networks with relatives and communities, independence in financial and asset ownership, accessing funds, joining in family planning and child-rearing, awareness of laws and governmental politics, and so on. The literature reveals that there are broadly five types of empowerment: political, legal, social, cultural, and economic (Kapila, Singla, & Gupta, 2016). Consequently, PKC measure latent women's empowerment as encompassing nine groups of observed indicators[10]. These indicators are proxies for the ability of women to involve in household and social decision-making, women's autonomy, women's freedom in developing social networks and mobility, knowledge and awareness of laws and politics, and involved sharing in family planning and taking care of children.

Each type of empowerment is called an empowerment factor. One empowerment factor is measured by a set of observed indicators. For instance, the empowerment factor of 'purchasing' decision making is measured by indicators such as: what percentage of common household items, clothes, furniture, land and assets are women in households able to purchase without their husband's permission. Factor analysis (FA) is a common method that is used to estimate latent covariates with a set of continuous indicators. However, the FA approach is inappropriate in the case where variables are binary or categorical as presented in the Bangladesh survey. Instead, the Item Response Theory (IRT) model is used to estimate women's latent empowerment. In comparison to the FA model, IRT is more appropriate when the key variables are binary indicators (Maydeu-Olivares et al., 2011; Pitt et al., 2006).

The IRT with one-parameter logistic (IRT-1PL) model is one of the most broadly used IRT models in diverse applications. It is also known as the Rasch model (Rasch, 1960). The IRT-1PL is used to estimate the latent empowerment in this study as follow:

$$R_{qi} = T_q + y_i \qquad \text{(Equation 4.1)}$$

Where R_{qi} is the response of household (HH) i to question q (binary response, yes = 1, no = 0); T_q represents a question-specific threshold for a positive response to question $q;$ and y_i is a latent measure of women's empowerment of HH i.

[10] Purchasing, resources, finance, transaction management, mobility and networks, activism, household attitudes, husband's behaviour, fertility and parenting.

As demonstrated above, the IRT-1PL method fundamentally measures a random-effects binary response model such as a random-effects logit model. Accordingly, the conditional density of the response of household i to question q, given the latent empowerment, y_i, depends on the given binary response of household i, R_{qi}.

The question-specific threshold for a positive response (T_q) expresses how "difficult" it is to obtain a "1" (="yes") response. It is measured as the natural log of the ratio of the proportion of "no" responses to the proportion of "yes" responses per question q. If a question has a higher "no/yes" ratio, it is more difficult or has a higher threshold for a positive response. The second component (y_i) of Equation 4.1 is unique to the individual. This is an additive component that is basically a number added to the different q equations, like a fixed effect or a constant effect. This number represents how the empowerment status of the woman from the household i affects her response to question q.

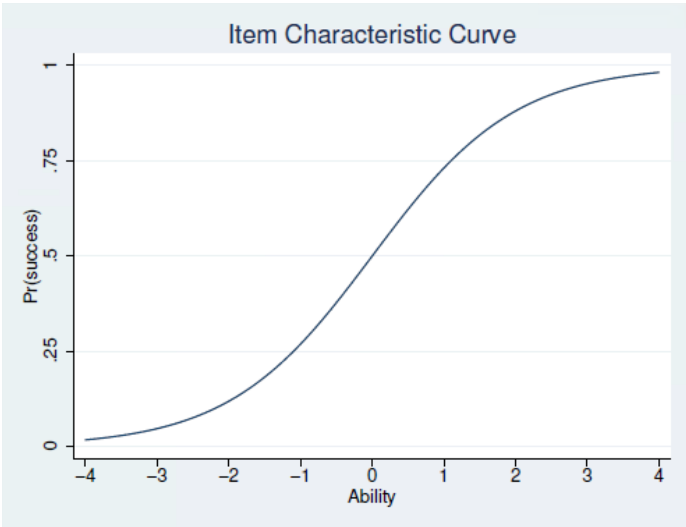

Figure 4.1 The Item Characteristic Curve (ICC)

It can be seen that the probability of a "yes" response ($R_{ij} = 1$) of a woman in household i to question q is determined by the threshold of question q for a positive response and the woman's ability to be involved in household decision-making. Graphically, the "Item Characteristic Curve" (ICC) shows the relationship among the three variables: (1) the probability of a "yes" response; (2) the threshold of question q for a positive response; and (3) the woman's "ability" – or, in my application, her empowerment level (Figure 4.1). The horizontal axis shows the "ability"/ empowerment level, which is assumed to have a normal distribution with average values of zero. The vertical axis shows the probability of giving a "yes" response.

The IRT-1PL model assumes that different questions have the same discrimination, which means that the slope of ICCs is the same for every question. However, item questions might differ in their specific threshold for a positive response. For example, the likelihood of women participating in decisions to purchase candy for children is relatively higher than that indecisions to purchase an expensive asset.

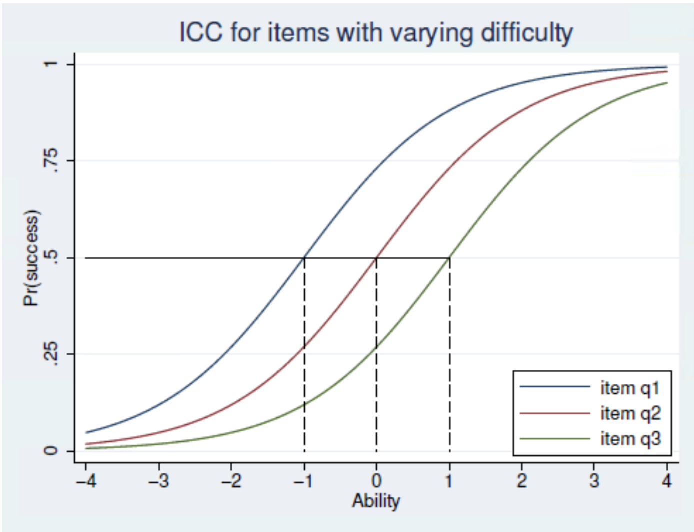

Figure 4.2 ICC for questions with varying question-specific thresholds for a positive response

Figure 4.2 shows an example of the ICCs for three questions, Question 1 has the highest likelihood for answering "yes" while Question 3 has the lowest likelihood of a "yes" response at a given ability level. Accordingly, the figure shows that it takes a lower empowerment value ("ability") to generate a positive response for Question 1 compared to Question 3 -- where a positive response occurs when the likelihood rises above 0.5 (An & Yung, 2014).

Equation 4.1 is used to estimate the nine latent women's empowerment factors, given the binary responses R_{qi}. Assuming normally distributed errors, the random effects y_i produce essentially a random effect logit model. PKC use the *gllamm6* package of Rabe-Hesketh, Skrondal, and Pickles (2004) to carry out this estimation of nine factors of women's empowerment. IRT is used to estimate the nine women's latent empowerment factors because of their binary nature. In addition, PKC estimate an aggregate "all" factor that encompasses the nine individual factors above. Because the factor "all" is continuous over the nine individual factors, it is estimated using the FA model. The estimated results of empowerment factors are reported in Table 4.2.

In this chapter, I first use PKC's method, IRT-1PL model with the updated *gllamm* package to estimate women's empowerment. Then, I use IRT-1PL with General Structural Equation Model (GSEM) updated technique as an alternative way to construct women's empowerment variables.

4.2.2 Women's latent empowerment through microcredit

After using IRT and FA models to estimate 10 factors of empowerment (including 9 individual factors and an aggregate "all" factor), the equation below is employed to estimate the effect of microcredit choice on improving women's empowerment:

$$y_{ij} = C_{ij}^{f}\alpha_f + C_{ij}^{m}\alpha_m + X_{ij}\beta + Z_j\delta + \mu_j + \varepsilon_{ij} \qquad \text{(Equation 4.2)}$$

Where y_{ij} is a measure of women's empowerment in HH i in village j; C_{ij}^{f} and C_{ij}^{m} are participation option ("choice") dummy variables for HH i in village j, by gender (female and male, respectively). X_{ij} is a vector of HH characteristics and Z_j is a set of village characteristics[11]. μ_j are village j fixed effects and ε_{ij} is an unobserved error that varies across households.

A woman (man) has the option to participate in a credit program (C_{ij} = 1) if that woman (man) lives in village j where a credit program is available to them and their household has cultivable land ownership of no more than 0.5 acres. The coefficient α_f (α_m) represents the average effect of microcredit presence of eligible women (men) on women's empowerment y_{ij}. This measures the intention-to-treat effects (ITT) of microcredit on women's empowerment.

The 1998-99 data includes households in both program villages and non-program villages. Thus, the village fixed effect estimation technique is employed to remove potential bias from the estimation of non-random program placement and unobserved fixed village characteristics.

4.2.2.1 Structural equation model

PKC use a SEM multiple regression analysis to evaluate the effect of microcredit on women's empowerment. The SEM combines the IRT model of women's empowerment (Equation 4.1) and impact factors of women's empowerment model (Equation 4.2). The former is a measurement model which is used to estimate unobserved latent empowerment of women using a set of observed indicators; the latter is known as a structural model and is used to estimate the relationship of the predicted latent variables from the measurement model with a set of observable covariates. PKC first use maximum likelihood to estimate the IRT model and predict latent empowerment factors from Equation 4.1. Then, they use these predicted latent variables as the dependent variables in Equation 4.2. In the latter step, PKC employ OLS/fixed

[11] Ordinary least square regressions included a set of village-level variables to control for systematic difference across villages.

effects/and fixed effects with IVs to analyze the impact of microcredit variables and control variables on empowerment.

4.2.2.2 Estimating the impact of cumulative borrowing from a female or male credit program on the empowerment of landless women

PKC's study also attempts to estimate the effects of accumulated microcredit borrowings on women's empowerment. As this estimates the effect of actually participating in the program as opposed to merely being eligible to participate in the program, it measures the average treatment effects on the treated (ATTs). The estimation aims to evaluate whether women's empowerment is enhanced if women/men are more involved in microcredit. The impact of the level of microcredit borrowings on women's empowerment outcome y_{ij} is measured by:

$$y_{ij} = C_{ij}^{f}\alpha_f + C_{ij}^{m}\alpha_m + X_{ij}\beta_y + \mu_j^{y} + \varepsilon_{ij}^{y} \qquad \text{(Equation 4.3)}$$

$$C_{ij}^{f/m} = X_{ij}\beta_c + \mu_j^{c} + \varepsilon_{ij}^{c} \; if \frac{female}{male} choice = 1, \qquad \text{(Equation 4.4)}$$

$$C_{ij}^{f/m} = 0, \text{otherwise}$$

Where y_{ij} is again a measure of women's empowerment in HH i in village *j*; C_{ij}^{f} and C_{ij}^{m} are the credit amounts of HH i in village *j,* borrowed by a female and a male, respectively. X_{ij} is a vector of characteristics of HH *i* in village *j;* μ_j^{y} *and* μ_j^{c} are village fixed effects, as an unmeasured determinant of y_{ij} and C_{ij}, respectively. ε_{ij}^{y} and ε_{ij}^{c} are non-systematic errors which reflect unmeasured determinants that vary across households. In Equation 4.4, $female/male\ choice = 1$ if the household is based in a village that has a female/male microcredit program available and they are eligible to access loans. A woman or a man is eligible to borrow loans if their household owns cultivable landholdings no more than 0.5 acres and resides in a microcredit village.

4.2.2.3 Potential econometric problems

Participating in microcredit may cause endogeneity due to non-random placement of microcredit programs, as well as unobserved household and village features that impact both the demand for microcredit and women's empowerment. These concerns come from the potential correlation of μ_j^y with μ_j^c and ε_{ij}^y with ε_{ij}^c in Equations 4.3 and 4.4.

The terms μ_j^y and μ_j^c represent unmeasured (unobservable), fixed village factors that influence women's empowerment and microcredit participation such as infrastructure, socio-economic status of villages, prices, village attitudes and the nature of the environment. The correlation of μ_j^y and μ_j^c arises when these unmeasured village characteristics impact both the demand for borrowing credit, $C_{ij}^{f/m}$, and the outcome interests of household, y_{ij}. For instance, better infrastructure in a village would bring more business opportunities for its residents. As a result, the village households may be more likely to borrow credit for their small projects. At the same time, better infrastructure, such as roads which facilitate mobility, would also increase household accessibility to information, potentially including information about gender equity, which is expected to boost women's empowerment in the village.

Similarly, the estimation strategy should also take into account the correlation of unmeasured household attributes. Both ε_{ij}^y and ε_{ij}^c are non-systematic errors that vary across households, such as endowments of innate health, fecundity, household attitudes and preferences. These unobserved household factors might affect both the credit demand and women's empowerment. For example, a household with a positive attitude towards equal treatment of its men and women is more likely to give female members an opportunity to access microcredit in comparison to their counterparts in a less egalitarian household. Also, a more egalitarian household tends to be aware of the issue of gender equity, and may hence encourage its female members to access more opportunities and to participate in household decision-making. Moreover, a woman with higher empowerment is more likely to borrow money than her counterpart with lower empowerment, leading to an issue of reverse causality. If these correlations are not taken into account, they may lead to a biased estimation of relationship between microcredit and women's empowerment.

By using fixed-effect estimation technique, the correlation between μ_j^y and μ_j^c can be controlled (Pitt et al., 2006). Village fixed effects estimation removes the endogeneity caused by unobserved village characteristics and non-random microcredit arrangement. However, this technique cannot control for the correlation between ε_{ij}^y and ε_{ij}^c. Therefore, PKC use 2SLS to deal with the possible correlation between ε_{ij}^y and ε_{ij}^c.

PKC assume that land ownership is exogenous because the land market in South Asia is stable. Land ownership turnover is low and there is not an active land market. Therefore, PKC assume that land ownership is not correlated with unobserved household characteristics that affect the likelihood of increasing women's empowerment of that household. PKC use a designed survey that includes both those who are eligible borrowers and those who are ineligible to borrow. The people who are ineligible to borrow own more than 0.5 acres of cultivable land or live in non-program villages. PKC use a dummy variable that represents the eligibility criteria for participation as a valid IV. Due to the fact that the eligibility variable is assumedly correlated with program participation but uncorrelated with women's empowerment (outcomes), it is a promising candidate for an IV.

For the subset of women or men who have program choice, the first stage of 2SLS is specified by Equation 4.4. For women/men who are ineligible to participate in credit programs, i.e., who own more than 0.5 acres of cultivable land or do not live in a program village, their program participation C_{ij} is zero. Equation 4.4 can be rewritten to combine the "choice" and "nonchoice" subsets as follows:

$$C_{ij} = X_{ij}\beta_c + (d_{ij}-1)X_{ij}\beta_c + \mu_j^c + \left(d_{ij}-1\right)\mu_j^c + \varepsilon_{ij}^c + (d_{ij}-1)\varepsilon_{ij}^c, \text{ Equation 4.5}$$

Where the dummy variable d_{ij} is equal to 1 if household i in village j has “choice”/ is ”eligible” and is equal to 0 if that HH has “no choice”/is ”ineligible”. Then, the elements of the vector $(d_{ij}-1)X_{ij},$ the interactions of “choice” and the exogenous variables $X_{ij},$ plus the variables $\left(d_{ij}-1\right)\mu_j^c$, the interactions of “choice” and the village fixed effects, are used as valid IV in the second stage estimation of Equation 4.3. The program choice is assumed to impact microcredit participation decision while it is assumed not to be directly related to women’s empowerment.

4.3 Data and variables

4.3.1 Data

Household surveys on Bangladesh’s microcredit programs were conducted in 1991-92 and 1998-99. The survey in 1998-99 was a follow up to the 1991-92 survey. Both surveys were conducted under cooperation of the Bangladesh Institute for Development Studies (BIDS) and the World Bank[12].

The main purpose of the surveys was to provide data for analyzing the impact of microcredit on poverty alleviation and only the 1998-99 survey includes a special section with women’s empowerment questions. PKC used the later survey and women’s empowerment data to estimate how microcredit empowers women. Unfortunately, PKC were not able to provide the data and code to me to replicate their findings of microcredit impact on empowering women. Hence, I have collected and combined data from various sources, including an archive of online

[12] More details are presented in Section 2.2.1 and Section 3.6.1 of this thesis.

data sources at the World Bank[13] and online data from RM's study, which is available online[14]. In writing the programming code, I have been in contact with Mark Pitt to obtain guidance over matters not covered or not covered clearly in PKC's article.

A total of 2,074 households with married couples were asked questions related to women's empowerment. The module on women's empowerment includes roughly 80 questions across nine thematic categories: 1. sharing in household purchasing decision-making, 2. accessing resources, 3. finance, 4. who is managing transactions, 5. women's freedom in mobility and networks, 6. women's freedom in activism, 7. awareness and attitudes, 8. the behavior of the husband, and 9. women's role in fertility planning and parenting. Each category contains similar types of information. Most of the responses are binary. One response can be used once or several times in estimating different factors. Table 4.1 reports the mean of responses to empowerment questions and is aggregated by the type of respondent (husband or wife). Roughly 20% of questions are designed for husbands, and 80% are designed for wives. In order to estimate the impact of microcredit on women's empowerment, PKC employ nine different factors to proxy for women's empowerment. These factors are discussed in the next section.

4.3.2 Latent variables

Although the original PKC data are not available, my statistics of observed indicators (Table 4.1) closely match those reported in PKC (Table A1, p.819) – though not exactly.

PKC employed an outcome-based method to evaluate how microcredit empowers women in rural Bangladesh. As discussed above, this method constructs women's

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[13] https://datacatalog.worldbank.org/dataset/bangladesh-long-term-impact-microcredit-impacts-1998-1999

[14] RM make their data and code available online at: https://web.archive.org/web/20131007073246/https:/www.cgdev.org/publication/impact-microcredit-poor-bangladesh-revisiting-evidence-working-paper-174-june-2013

empowerment indicators based on behaviors reported directly by the wife or husband. The nine empowerment dimensions mentioned earlier have the following characteristics:

Group 1-purchasing: This group includes questions related to the ability to spend money independently, which shows whether women can purchase household items without their husband's permission. It is expected that women's independence in purchasing leads to an increase in their empowerment. Generally, statistics from Table 4.1 show that women are more likely to purchase small items such as children's candy or household utensils. However, they rarely buy expensive items such as assets, furniture, land, even food or clothes without husband's permission. Specifically, while more than 60% of women answer that they can purchase children's candy and household utensils on their own, only 5% of them buy furniture by themselves. Fewer than 20% of women can buy food or clothing without husband's control. Similarly, when husbands were interviewed about their attitude towards wives' purchases, 87% reported that their wives were not able to purchase assets without their permission. Fewer than 2% of women were able to purchase land/equipment independently.

Group 2-resource: This group includes questions that reflect general economic power. About 22% of female respondents had their own income. However, roughly 60% of them could not independently spend their own income without their husband's permission. Similarly, around 40% of surveyed women had their independent savings, but 85% of them did not control the use of their own savings. In emergency cases, if women need to access money, under 4% can sell their own assets or borrow from other people. This shows that men in rural Bangladesh significantly controlled women's spending in the late 1990s.

Group 3-finance: This group reflects power of the wife and husband in a household related to the ability to borrow money from formal and informal sources. Most of the decisions regarding loans again require the husband's approval and only under 3% of women reported having autonomous control of loans. In emergency cases, about 20% of women can get money from their husbands, husbands' relatives or their own relatives while fewer than 2% of them can borrow from moneylenders.

Group 4-transaction management: This group includes questions related to buying, repairing, or building a house; purchasing and selling livestock; mortgage of land; and purchases of transport means, household equipment, land and assets. Fewer than 2% of women reported that they decided on these issues and spent money on these items independently.

Group 5-mobility and networks: Mobility is low in rural Bangladesh. When asked about wives' mobility, approximately 85% of husbands answered that their wives have never traveled alone to markets, a bank, a health center and so on. Approximately 87% of them said that because of rules, traditions and family restrictions, women were not allowed to go out alone. Another problem is that safety issues often prevent women from traveling alone. Women also reported that 55% of them are accompanied by their husbands or sons, and 22% of them are accompanied by other women when they go out. Close to 11% of women said that they had not left the area at all. In terms of networks, 82% of women reported that they needed their husbands' permission if they wanted to visit their parents or other relatives.

Group 6-activism: This group includes questions related to awareness of the law and politics, and related autonomous actions. Although about 85% of female respondents voted in the last election, up to 75% of them did not independently vote. They reported that their husbands had influenced their vote. Over 90% of female respondents were aware of inheritance laws which specify that a widow has a legal claim over her dead husband's property. Over 96% of female respondents could not stop their husbands from remarrying. Fewer than 25% of women reported ever protesting against incidents of wife-beating. Remarkably, nearly 92% and 65% of women reported that they did not think inheritance laws and the social structure, respectively, were obstacles to women's empowerment. Roughly 50% of female respondents viewed religion as an obstacle to women's empowerment.

Group 7-household attitudes: This group includes attitudes and opinions of wives and husbands regarding societal gender issues. Overall, both men and women thought that men were superior to women in both education and aptitudes. Approximately 68% of men thought that they were more intelligent than their wives, about 80% of them answered that they did not believe their wives would be able to make decisions about purchasing or selling expensive items or important household assets. Attitudes of men towards women's empowerment varied widely. When asked to describe what kind of effect of women's empowerment would have on society. Approximately 43% of men responded that empowering women leads to a better society and 79% of them believed that women raising kids would be good for their families. Women's empowerment would be beneficial for the family's economy. However, 72% of husbands believed that women's empowerment causes loss of family peace.

Group 8-household behavior: Female respondents reported that 77% of husbands had compelled them to give them money/assets when the wives did not want to. Roughly 59% of married men forced their wives not to work outside home even when the wives wanted to. When women were asked about spousal argument and abuse, the most common topics of an argument were: children, finances and household work. When an argument occurred, around 20% of women said they experienced verbal abuse and 16% faced physical abuse.

Group 9-fertility and parenting: This final factor assesses women's power in family planning and parenting. The answers show that birth control tends to be used by wives rather than husbands. Over 72% of women had initiated discussion of birth control method and use with their husbands, but 90% of female respondents replied that they had never succeeded in convincing their husbands to use male birth control. Most male respondents (93%) reported not using birth control.

Overall, the statistical picture of rural Bangladesh in the late 1990s is that social structures, people's attitudes, lack of independent income and savings, lack of safety, as well as religious restrictions lead to gender inequality.

4.3.3 Summary statistics

I use the same survey dataset as PKC for my replication study. Table 4.2 presents PKC's summary statistics and my summary statistics based on the data I had compiled. The summary statistics table reports 10 latent women's empowerment factors (the 9 factors discussed above plus an overall index of female empowerment), 13 household characteristics, and the 'treatment variables' of interest including: eligibility of female/male to participate in microcredit ('female/male choice'), actual female/male participation in microcredit, and the logarithm of the amount of actual borrowing. The summary statistics reported using my calculation in general closely match PKC's results but there are a few exceptions, discussed below.

The average age of household members calculated by PKC is higher than my calculation by 10 years: 34.95 vs. 24.76 years, respectively. Average household land assets reported by PKC are 86.75 decimals while my statistic is 63.23 decimals. In addition, while PKC statistics show that the proportion of 'male choice' households and 'female choice' households are similar (61.5% male choice and 68.5% female choice), my statistics show that the percentage of 'female choice' households is higher than that of 'male choice' households (78.0% vs. 51.7%, respectively). This is perhaps because in 1998-99, most microcredit programs in Bangladesh were designed for female borrowers. In terms of actual program participation, my calculations show that the percentage of both female and male participants in microcredit is higher than in PKC. While PKC reported 44.3% of females and 10.6% of males participating in microcredit programs, my work shows 52% of females and 21.3% of males participating in microcredit programs. PKC did not provide either the data set they used or the code to construct these variables; thus, the differences cannot be explained.

Generally, in the sample, the education level of respondents is low, 1.85 out of 14 levels, on average. While PKC show that the highest education of males in the household is *lower* than the highest education of females, my statistics show the opposite pattern. Overall, land owned by males is higher than land owned by females in the household. Taken together, these statistics show that women tend to be lower educated and own less land than men. This is likely because in Bangladesh, especially in rural areas, the societal structure and religion give men more rights than women.

According to PKC, due to the sampling design, they use appropriate weights in all regressions (PKC, 2006, p. 795. However, I do not find any evidence of how the authors obtain/calculate the sample weights. When I compile data available online (including from RM), sample weights are available for the 1991-92 survey but not available for the 1998-99 survey. I therefore use the 1998-99 data without sampling weights to replicate, and test the robustness of PKC's results.

4.4 Replication of main results

This section replicates the main findings from PKC without their data and code. PKC examine the impact of microcredit presence (ITTs) and microcredit amount of borrowing (ATTs) by gender on women's empowerment.

4.4.1 Determinants of women's latent empowerment (ITT effects)

This section focuses on how microcredit presence in a village affects women's empowerment, which is the PKC primary outcome variable. The presence of a microcredit program could empower women by encouraging project start-ups and raising labor supply.

These allow women to generate their income and increase their power share relative to men in their households. Creative start-up projects or training programs might also have a spillover impact on other women who have not accessed microcredit but live in the same village. They can learn from the success stories of their neighbors. This leads to an increase in their knowledge and empowers sharing decisions in their household.

Table 4.3 presents results from a model of nine specific women's empowerment factors and one overall empowerment factor "factor all" regressed on the presence of female and male credit programs using OLS and village FE. PKC's results are reported in columns (1) and (4) for OLS and village FE estimation, respectively. My replication results using Gllamm package and IRT updated package are reported in columns (2), (3), (5) and (6), respectively. As shown in Table 4.3, my results using the Gllamm package that PKC used and results using IRT package are similar in sign, magnitude, and statistical significance. I therefore mainly focus my discussion on the results using Gllamm.

The OLS and village FE estimates are similar both qualitatively and quantitatively. Therefore, PKC focus their discussion on the village FE estimation. Overall, PKC's results show that a female microcredit presence in a village positively affects women's empowerment. The results show significant effects on eight out of ten empowerment factors. The remaining two positive but insignificant effects are on factor 7, household's attitude, and factor 8, husband opinion and behaviors related to women's status in the household. Although my replication does not exactly match PKC's results, the replication does generally support PKC's findings. The presence of female microcredit programs (ITTs) seems to empower women. However, my results and somewhat weaker than PKC's: only fourth out of ten factors see a statistically significant increase in women's empowerment at the 10% level, and the sizes of effects are smaller compared to PKC's findings.

To meaningfully interpret coefficient magnitudes, it is important to appreciate that the IRT model (Equation 4.1) is first used to estimate and predict empowerment factors. These factors are then used as dependent variables in Equation 4.2 to estimate the ITT effects of microcredit programs on women's empowerment. The estimated empowerment factors have a normal distribution and have been scaled to have unit variance (standard deviations).

As shown in PKC's results of village FE (column 4), overall, the coefficient on female microcredit eligibility in explaining "factor all" is 0.473. This means that if a female microcredit program is present in a village, female empowerment of women in that village on average increases by 0.473 standard deviations. Assuming the "factor all" variable has a normal distribution, female microcredit program presence increases empowerment of a median woman in the village from the 50th percentile to the 68th percentile. Similarly, my replication shows that a median woman on average enhances her empowerment from the 50th percentile to the 63th percentile. Microcredit enables its borrowers access to small and self-employed activities that can increase their earning abilities and economic conditions. These small businesses may create new jobs for other women in the village even if they do not directly borrow loans. Earning an independent income and contributing more financially to the household may help women join household decision-making, raise their self-esteem and gain more power. Furthermore, accessing microcredit encourages women to participate more in social activities in the community. These then possibly affect their knowledge, attitudes and make them more self-confident, which positively affects their power within their household and community.

In contrast, according to PKC, male microcredit programs have negative and statistically significant impacts on four out of the nine female empowerment factors and never have a statistically significant positive effect. In terms of magnitude, PKC report that male microcredit programs present in a village on average reduce female empowerment from the 50th percentile to the 43rd percentile. When loans are allocated to men, it may give them more self-perceived right to control money and decision-making. The more relative power men have, the less relative power women have as they become more depend on their husbands, especially in the patriarchal society. However, my replication results show that the presence of microcredit programs for males reduces only reduces their wives' empowerment from the 50th percentile to the 49.5th percentile and the effect is statistically insignificant. Hence, my replications result deviate here from PKC in that they show that the impact of having male microcredit programs on women's empowerment is negligible.

PKC find that the availability of microcredit for female in a village causes the largest gain in women's empowerment in terms of access to resources, mobility and networks. There are about 19 percentage point (an average of 0.509 standard deviations), and 17 percentage point (about 0.433 standard deviations) increases in women's empowerment in accessing resources and in improved mobility and networks, respectively. My replication results do not find significant effects in these areas. Instead, the largest percentage gains in my results relate to transaction management and fertility planning/parenting, which increase roughly by 12 percentage points (an average of 0.299 standard deviations) and 5.3 percentage points (an average of 0.134 standard deviations). These effects are statistically significant only at the 10 percent level. In my results, the impacts of a female microcredit presence in a village on other empowerment factors are around 0 to 2.8 percentage points but they are statistically insignificant. This weakly suggests that access to small loans improves women's economic conditions and their contribution in the household. They play a larger role in participating in discussions about child-rearing and spending on important items such as repairing the house, buying or selling livestock or land. However, they still do not independently spend their money and depend on their husbands' permissions.

In terms of the presence of male programs, PKC reported that the largest decline in women's empowerment comes in the form of reduced mobility, reduced role in fertility planning and parenting, and in regards to finance and resource factors. Male programs reportedly reduce women's mobility and networks by roughly 11 percentage points (an average of -0.275 standard deviations). In contrast to PKC's findings, my replication results show that for all factors, male microcredit presence in a village causes statistically insignificant and small effects on women's empowerment. One reason for the absence of an effect may be that a small amount of loan does not dramatically change men's labor market attachment and income and hence their relative standing, or the situation of their household as a whole.

Overall, my replication results confirm PKC's main finding that female microcredit eligibility (ITTs) increases empowerment of landless women, but my results show smaller effects than PKC. My replication could not find enough evidence to support PKC's finding that male microcredit eligibility has a negative impact on women's empowerment.

4.4.2 The impact of actual participation in microcredit by gender on women's empowerment (ATT effects)

This section extends the analysis of the impact of microcredit participation by studying the effect of the amount of borrowing on empowerment (ATTs). Results for the impact of microcredit borrowing by gender on women's empowerment estimated by OLS, FE and FE-IV are reported in Table 4.4. PKC results are reported in columns (1), (4) and (7). My replication results using Gllamm and IRT packages are reported in columns (2), (3), (5), (6), (8), and (9). The estimation results using Gllamm and IRT packages are again not qualitatively or quantitatively different; hence, I mainly focus on discussing estimation results using the Gllamm package, which is used by PKC.

My replication results generally support PKC's findings. As shown in Table 4.4, the impact of loan borrowing amounts on women's empowerment does not vary importantly by analysis method. If microcredit tends to be allocated to villages where eligible women already tend to be more empowered, the OLS estimate of women's empowerment should be larger (biased upward) than results with village FE. As shown in columns (2) and (5), four out of nine factors using FE estimates are smaller than OLS estimates but the difference between OLS estimates and FE estimates is very small in every case. For example, a 10% increase in female credit borrowing leads to 0.0034 and 0.0032 units of standard deviation increase in women's empowerment represented by purchasing, using OLS and FE, respectively.

Furthermore, if a woman who has more power already tends to participate in microcredit, the village FE model would be expected to overestimate the treatment effects compared to FE-IV estimates. As shown in columns (5) and (8), this is true in four out of nine instances. Overall, female microcredit participation has a positive effect on women's empowerment, in seven out of nine factors a statistically significant one (the exceptions are factor 5: mobility and networks and factor 8: husband's behavior). The results using FE and FE-IV are not importantly different. Overall, similar to PKC's findings, my replication results show that if a woman increases her loan amount by 10%, her empowerment is expected to increase between 0.001 to 0.008 units of standard deviation, depending on the specific empowerment factor.

PKC stated that a woman who borrows money at the mean level of female participants has a 22-percentile increase in her empowerment. My result shows that a 10% increase in female borrowing leads to an increase of 0.011 standard deviations (approximately a 0.44-percentile increase) in women's empowerment. My replication hence supports PKC's finding qualitatively but it shows a much smaller effect size compared to PKC's result.

Male credit participation is generally not statistically significant, regardless of what the estimation method is. Even ignoring the issue of statistical significance, the sizes of the estimated effects are small and economically unimportant.

Up to this point, my study has replicated the main PKC's estimation; the ITT and ATT effects of microcredit programs on women's empowerment. In support of PKC's findings, my results show positive (even if smaller) ITT and ATT effects of microcredit on women empowerment if borrowers are female. However, while PKC find a negative impact on women's empowerment if men borrow loans, my results are insignificant and have very small effect sizes. In the following sections, I investigate whether the baseline findings are robust. To do that, I conduct diagnostic testing of the instrumental variables. Then, I use alternative methods including GSEM and Lasso as robustness checks.

4.5 Robustness analysis using GSEM

4.5.1 Using an updated technique to estimate the ITTs on women's empowerment

General Structural Equation Modelling (GSEM) is an updated technique replacing GLLAMM. Table 4.5 reports robustness results of the effect of microcredit for eligible females and males on female empowerment, using GSEM. Column (1) presents PKC findings using village FE, and column (2) presents robustness results using GSEM village FE.

PKC results show that nine empowerment factors improve if a female program is present in a village. Seven out of these nine factors have a statistically significant effect. My robustness results using GSEM show that female programs generally have a positive effect on women's empowerment. However, the effects are again much smaller than PKC findings. Most of my results are statistically insignificant, except for the resource factor and "factor all", which are only significant at the 10% level. Moreover, all of my estimated effects are small. For example, six of the nine estimates imply that the presence of the programs increases female empowerment by less than 0.2 standard deviations. PKC estimates are substantially larger than mine and statistically significant. My robustness results show that the ITTs of male microcredit are small, of mixed sign, and statistically insignificant, whereas PKC find that they negatively affect female empowerment. This discrepancy occurs throughout my analysis.

4.5.2 Using an updated technique to estimate the ATTs on women's empowerment

This section uses the updated technique of GSEM as a further robustness check of PKC results on the ATT impact of microcredit by gender on the nine empowerment factors. PKC results are reported in column (1) of Table 4.6. The robustness results are reported in column (2) for OLS and in column (3) for village FE estimation.

PKC show that female borrowing has a significantly positive effect on nine women's empowerment factors. In contrast, male borrowing has a negative effect on nine empowerment factors, with only factor 5 (mobility and networks) having a statistically significant effect at the five percent level. Other factors are statistically insignificant if borrowers are male.

My ATT results for female borrowing are similar to PKC findings. Specifically, I find that the amount that females borrow positively impacts seven out of nine empowerment factors. Two factors, including factor 3 (finance) and factor 8 (husband's behavior), show a minimal effect and are statistically insignificant. The level of microcredit borrowing otherwise plays an important role in enhancing women's empowerment if it is targeted to female clients. On average, my robustness check using GSEM-FE shows that a 10% increase in female borrowing leads to an increase of approximately 0.0073, 0.0079 and 0.0091 units of standard deviation in empowerment representing purchasing, economic resources, and transaction management, respectively. Once again however, microcredit amount borrowed by males is unimportant in both economic and statistical terms.

4.6 Diagnostics IV testing

The instrumental variable approach is common to tackle endogeneity issues. However, in practice, it is not easy to find optimal instruments. The IV must satisfy two essential criteria.

A suitable IV must be correlated with the variable suspected of being endogenous. Also, it must be uncorrelated with the estimated outcome directly. The former condition is known as the relevance condition, and the latter is referred to the exclusion condition. PKC used a quasi-experimental survey design to construct their instruments. Specifically, they used interactions of male/female choice with control variables and interactions of male/female choice with village dummy variables as their IVs. PKC hence assumed that the male/female choice is associated with the amount of money that microcredit participants would borrow, while it is not directly related to female empowerment. However, PKC did not test for the validity of these instrumental variables. In this section, I conduct diagnostic testing of IVs to check the reliability of PKC's results.

Table 4.7, column (1) reports p-value statistics of the Durbin-Wu-Hausman test, which checks whether variables are endogenous. At the 95% confidence level, the results fail to reject the null hypothesis that the specified endogenous variables (amount of borrowing) can be treated as exogenous. This suggests that the amount of borrowing may actually be treated as exogenous.

The F-statistic, developed by Stock and Yogo (2005), is a common metric used to test the strength of the relationship between a set of IVs and an endogenous variable. This technique tests the null hypothesis that the instrument is "weak". My results in column (3) cannot reject the null hypothesis that the instrumental variables do not correlate strongly with the endogenous variables. This signals a problem of weak instruments and raises questions about the reliability of IV estimation results.

Finally, the J-test, which is developed by Sargan (1958) and Hansen (1982), is used to assess the overidentified restrictions. A complexity in my case is that this involves multiple tests of ten empowerment equations. In the first stage of the 2SLS, the relevance condition between IVs (the interaction terms of choice variables with village dummy and control variables) and the amount of microcredit borrowing does not vary over ten estimation equations. However, the second stage of 2SLS tests the exclusion condition of IV and ten empowerment factors, involving simultaneous testing of more than one hypothesis. In multiple testing, the familywise/experiment wise error rates increase across a collection of statistical analyses on the same sample of data. If an individual hypothesis is evaluated based on an unadjusted marginal p-value, Type I error probability will increase. This leads to an increase in the probability of rejecting some of the true hypotheses. In testing PKC's IVs, the chance of erroneously rejecting at least one true hypothesis amongst the family of ten analyses is equal to $1-(1-0.05)^{10} = 0.4013$ (40.13%). A classical method to solve the familywise error is the Bonferroni correction. This method compensates for the increase of familywise error by using a significance level of α/m for testing each individual hypothesis; where α is the desired overall alpha level, and m is the number of hypotheses.

Testing PKC's IVs of nine empowerment factors where m=9 with the desired α=0.05, the Bonferroni adjusted p-value to test each hypothesis is given by 0.05/9=0.006. Any observed p-value less than the corrected p-value (0.006) is declared to be statistically significant. Table 4.7, column (4) shows that all of the p-values of over-identification tests (in the range of 0.028 to 0.487) are greater than the Bonferroni correction p-value of 0.006. Hence, the results technically satisfy the overidentifying restrictions in 2SLS estimation.

However, the Bonferroni correction does not come without cost. When the number of statistical analyses increases, the Bonferroni adjusted p-values decrease. In my case, this ends up with no statistically significant results. But decreasing the likelihood of Type I error increases the probability of making Type II errors (Perneger, 1998). Given this concern, whether researchers should use Bonferroni correction depends on the circumstances of the study (Streiner & Norman, 2011). If the "universal null hypothesis" (H_0) requires all the tests to be insignificant, the use of Bonferroni corrections is appropriate (Armstrong, 2014).

To sum up, my results of the IV validity tests show that: the amount of borrowing may actually be treated as exogenous but if a cautious approach towards endogeneity is selected and PKC's IVs are used, they seem to be "valid" but rather weak (relevance condition) instruments. To address the concern of weak instruments undermining 2SLS results, I turn to another strand of literature that focuses on selecting appropriate instrumental variables from a set of potential valid instruments. This method is known as "the least absolute shrinkage and selection operator" (Lasso) and post-Lasso estimation (Windmeijer, Farbmacher, Davies, & Davey Smith, 2019).

4.7 Robustness check using an alternative method to deal with endogeneity (Lasso)

Two-stage least squares is a common approach to dealing with endogeneity. However, it is not always straightforward to find valid IVs. This approach can result in imprecise and inconsistent estimates if IVs do not satisfy the relevance and exclusion conditions. Section 4.6 showed that the IV tests failed to reject the null hypothesis that PKC's IVs are insufficiently relevant. Using many instruments or trying to approximate optimal instruments can enhance the performance of IV estimation. Adding more IVs may decrease the standard error of the 2SLS estimation, but it may come at a cost. Among other concerns, adding more IVs risks increasing the likelihood that the instruments are themselves endogenous, which would increase bias. In fact, 2SLS is well known to have large biases when many instruments are used (Hausman, Newey, Woutersen, Chao, & Swanson, 2012).

Another solution is to improve the first-stage correlation without an increase in the number of IVs. One of the common approaches for selecting an optimal IV is to use Lasso (Belloni et al., 2012). The Lasso technique improves the correlation between an IV and an endogenous variable (J. S. Kim et al., 2019) and the method is described in detail in the following sections.

4.7.1 Lasso

I am ultimately interested in estimating the impact of microcredit borrowing (*Ci*) on women's empowerment (*yi*), controlling for household characteristics (*Xi*) so that:

$$y_{ij} = C_{ij}\,\alpha \;+\; X_{ij}\beta_y + \;\mu_j^y \;+\; \varepsilon_{ij}^y$$

Where *Cij* is the credit amount of household *i* in village *j* and *Xi* is a vector of household characteristics; the average values of error terms ε_{ij}^y are expected to equal zero. However, when using rich information from a household survey, it is not obvious what subset of available control variables should be included (Belloni, Chernozhukov, & Hansen, 2014).

To address this concern – and, by extension, an appropriate selection of IVs, Lasso is employed to select variables by selecting the covariates with nonzero estimated parameters (Belloni et al., 2012). Lasso works by using a shrinking procedure to estimate coefficients, in which regression coefficients are estimated by minimizing the sum of the usual least-squares function and the sum of absolute values of the coefficients (Belloni et al., 2012). To demonstrate on a generic example, consider a usual regression model of *y* on *x*; $y_i = f(x_i)$; where *y* is a dependent variable and *f(x)* includes a set of controls for the *i* observation. OLS coefficients are obtained simply by minimizing the square of residuals. However, the estimation results can be improved with Lasso by shrinking to zero otherwise "small" coefficients. This process leads to reducing the predicted value's variance, improving prediction accuracy. This procedure contrasts with a common practice of researchers whereby they "manually" choose the subset of control variables that have significant effects. Lasso shrinks some minor coefficient effects and sets others to zero using a well-specified algorithm (Tibshirani, 1996). Lasso estimates $\beta_{\_hat}$ as follows:

$$\beta\_hat = \arg\min \frac{1}{N}\sum_{i=1}^{N}(y_i - \beta_j x_{ij})^2 + \frac{\lambda}{n}\sum_{j} |\beta_j|$$

The second term, $\lambda \sum_j |\beta_j|$, is a penalty for the absolute sum of the coefficients. In the next section, as a robustness check of PKC's results, I use Lasso to determine the optimal set of IVs in the first step of 2SLS, and then again to select the control variables in the second step of 2SLS.

4.7.2 Robustness check results using Lasso

In this section, Lasso is employed to select instruments from a set of potential instruments. This method eliminates the problem of "cherry-picking", which may cause weak instruments or irrelevant instruments or control variables to be included in the model. I use the same control variables and IVs that PKC use. Recall that the IVs are the interactions between male/female choice and control covariates and between male/female choice and village fixed effects. However, for control variables, I enter them as linear, quadratic and possible interaction terms. This is often called Taylor-series expansion.

Table 4.8 reports the microcredit treatment effect on women's empowerment by gender of participants (ATTs). PKC results are reported in column (1) and column (3) for FE and FE-IV estimations, respectively. My robustness results using Lasso are reported in columns (2) and (4). The differences between the FE and FE-IV estimates are minor. Thus, only the FE-IV results are discussed in this section.

My robustness results for female borrowing broadly support PKC findings. However, once again, my results show smaller effects on female empowerment, with only three out of nine coefficients statistically significant if females participate in a microcredit program. There is little evidence that male borrowing has a substantive impact on female empowerment.

Empowerment variables are measured by unit variance. The interpretation of the coefficient on the logarithm of credit is that an increase by 1% of loan amount leads to a change in women's empowerment by Beta/100 units of a standard deviation. The magnitude of effects can hence be evaluated using Lasso FE-IV as follows:

Resources: Accessing microcredit enhances women's empowerment in terms of female access to and control of economic resources in the household. My results are similar to PKC findings. If the amount of female microcredit increases by 10%, the standard deviation of latent empowerment factor representing the economic resource power of a median woman is expected to increase by 0.0062 and 0.0056 units of a standard deviation in PKC and my result, respectively. Accessing credit may help women generate self-employment activities which are in turn increasing their independent income and savings. This results in an improvement in controlling her assets, income, and the ability to sell assets in emergency cases. In contrast, a husband accessing microcredit does not seem to yield such benefits.

Transaction management: This factor represents the power of conducting major household economic transactions such as who decides about spending on repairs/construction of the house, selling/purchasing livestock/land/transport/household equipment and who decides to borrow money or household loans. PKC results and my robustness results are similar. The participation of women in microcredit significantly increases their empowerment which is represented by major household economic transactions. According to PKC and my results, a 10 percent increase in the amount of loans results in 0.0024 and 0.0023 units of a standard deviation increase in transaction management power, respectively. PKC result is significant at 1% (t=4.75) while my result is significant at 10% (t=1.84). Male participation in microcredit programs potentially very weakly negatively affects female power in implementing household repair, livestock purchasing, and land and equipment transactions. However, both PKC and my results show extremely small effects (-0.0004 and -0.0013, respectively) and are statistically insignificant. Hence, we once again cannot reject a null impact of male borrowing on female empowerment.

Household attitudes and husband's behavior: Household attitudes represent what wife and husband in a household think about wife's ability, intelligence, and empowerment. My results show that female participation in microcredit in general positively impacts household attitudes. An increase of 10% in the amount of loan causes an increase of 0.0031 units of a standard deviation in empowerment represented by household attitudes. Microcredit participation helps women participate in regular meetings. When women are able to obtain knowledge, this allows them to become more confident, increases their self-esteem and understanding of their rights. They can strengthen their bargaining positions in the households. In contrast, there is some evidence in my Lasso FE-IV results that male access to loans negatively affects household attitudes towards women. The estimated coefficient is large but needs to be treated with caution given its sensitivity to the estimation method.

It is expected that accessing microcredit helps increase women's economic contributions in their households, changing male attitudes towards women. It is worth noting however that female as well as male borrowing have an insignificant influence on husband's observed behavior.

Fertility and parenting: This factor represents how women are involved in children's education, children's nurturing and family birth control planning. Estimated results show that this factor of female empowerment increases by 0.0038 and 0.0034 units of a standard deviation in PKC and my results, respectively, if female borrowing increases by 10%. Previous research suggests that when women have independent income or access to money, their priority is to invest in their family welfare and their children (Ganle, Afriyie, & Segbefia, 2015).

Purchasing: PKC find that a 10% increase in female borrowing leads to an increase of 0.0031 units of a standard deviation in the empowerment factor representing women's autonomy with purchasing. Amount of loans borrowed by females significantly enhance women's involvement in purchasing and making spending decisions in households, such as increasing the ability to buy household utensils and daily items with her husband or by herself. However, my finding shows the effect of female microcredit on her purchasing ability is just about 0.0011 units of a standard deviation and is statistically insignificant. It may be that a woman can access microcredit, but she lets her husband manage the money. This may result in still depending on husband's permission rather than increasing the likelihood that the wife can buy assets with her husband or by herself. Secondly, even if a husband does not control his wife's credit, his attitudes toward his wife may not change and hence her degree of autonomy may not change. Thirdly, women may be using their loans to invest in small businesses or spend on expensive assets rather than buying small items such as clothes or utensils.

Male borrowing does not seem to impact women's empowerment in purchasing.

Finance: This factor represents the ability to access money in emergency cases. The emergency money might come from other people or banks, or other financial organizations. Female participation in microcredit does not seem to have an effect on her financial empowerment. Restrictions on mobility and networks may perhaps be hindering women's ability to access banks and expand social groups that may help them borrow money in emergency situations.

Mobility and networks: Mobility is expected to empower women by increasing their freedom to access markets, education and information. However, my robustness results do not show any statistically significant effect of microcredit borrowing on this empowerment dimension. Women in Bangladesh are often subject to religious and societal norms which do not allow them to travel independently inside and outside their villages. Therefore, accessing microcredit may not mitigate this constraint (Li, Gan, & Hu, 2011). Another possible reason is that women still prefer to accompany their husbands, sons, fathers, or brothers for safety reasons or otherwise. It is also possible that women who transfer their loans to the family's male members do not experience a significant change in societal attitudes (Qazi, Isran, Isran, & Syed, 2013). Finally, some previous studies have also suggested that disagreement over loan use within the household may even worsen women's standing (Ganle et al., 2015; Rahman, 1999) so an impact on her social autonomy is not straightforward.

PKC only interpret the coefficient on "factor all" in their discussion of results. Specifically, they stated that: "the regression results predict that a woman who has median overall empowerment and has never participated in a microcredit program would be in the 72nd empowerment percentile (a 22 percentile increase) if she had borrowed at the mean (log) level of woman participation" (p. 812f.) However, this result is difficult to corroborate. The "factor all" coefficient is not reported in PKC (i.e., it is missing from Table 5, p. 813). In my robustness analysis using GSEM and Lasso, the coefficients on "factor all" are 0.036 and 0.091 respectively. This means that if a woman participates in a female microcredit program and borrows at the mean (log) level of female borrowing amounts, her empowerment on average increases by 1.44 percentage (percentile) points and 3.63 percentage (percentile) points, respectively. [15] These numbers are significantly smaller than PKC result.

[15] I assume that "empowerment factors" have a normal distribution and I scale the estimated coefficients to have unit variance (standard deviation). Like PKC, I assume that a median Woman in the sample has her empowerment at the 50th percentile (zero standard deviation) if she has never participated in any microcredit program. If this woman then participates in a female microcredit program and borrows at the mean amount of female borrowing, her empowerment will increase by about 0.091 standard deviations according to my Lasso estimate. The 0.091 standard deviations move her to the 53.63th percentile in the empowerment distribution. Therefore, on average, microcredit participation increases her empowerment from the 50th percentile to the 53.63th percentile (a 3.63 percentile increase). The same procedure can be applied to convert any coefficients in Table 4.8 to percentile changes.

Otherwise, PKC discuss the estimation results of nine individual empowerment factors based on the positive sign and statistical significance alone. They do not discuss the magnitude of these coefficients. It is worth noting that the sizes of these coefficients are small. For example, the impact of female microcredit on female empowerment represented by access to resources is 0.062. This means that if a median woman in the sample increases her borrowing by 10%, it is expected to increase her empowerment by roughly 0.0062 units of a standard deviation (i.e., her empowerment would end up approximately in the 50.025th percentile in the empowerment distribution, a 0.025 percentile increase). Although this number is statistically significant, it is not economically important.

4.8 Conclusion

PKC (2006) argue that women's participation in microcredit helps to empower them. They use the 1998-99 survey conducted in Bangladesh to estimate the impact of microcredit participation by gender on many aspects of women's empowerment. PKC conclude that accessing microcredit helps women expand their social networks, increase their mobility, have greater access to finance and economic resources, and increases equality in household decision-making. They also conclude that male involvement in a village's microcredit program negatively impacts on empowering women. However, the literature still debates the evidence of the positive impact of microcredit participation on empowering women (Banerjee et al., 2015; Crépon, Devoto, Duflo, & Parienté, 2011; Debnath, Rahman, Acharjee, Latif, & Wang, 2019). Conflicting results of research papers in policy and economics cause uncertainty for policymakers. Therefore, my study replicates PKC to determine its reliability. Replication of PKC is a challenge because they use a complex statistical analysis but have an unclear research design, their data are not very transparently documented, and they do not provide their programming code.

My replication of PKC makes two significant contributions to the literature. Firstly, I make my data and programming code available. These will help researchers who want to replicate PKC's or my study or conduct further research in microcredit. Reconstructing household data is challenging and potentially fraught with errors. My data and code will save much time and effort for researchers who desire to explore further the data underlying PKC.

Secondly, my study provides a more robust research design than PKC, producing more reliable results. I use IRT-1PL and SEM to replicate PKC results. Then I use an updated GSEM technique to investigate robustness. I also undertake diagnostic testing on the instrumental variables that PKC use. The tests cannot reject the hypothesis that the IVs are weak, raising concerns about PKC findings' reliability. In response, I use the least absolute shrinkage and selection operator (Lasso) technique to find optimal IV and control variables. This technique is based on removing irrelevant variables in the model. It improves first stage estimation of the relationship between the endogenous variable and the instruments while adjusting the standard errors to incorporate the effects of model uncertainty.

My replication and extension results using GSEM and Lasso techniques are summarized in Table 4.9. With respect to the estimated ITT effects on female empowerment, my findings generally support PKC (see top panel of Table 4.9), albeit I find smaller effects. PKC report that the presence of a female program in a village increases female empowerment by 0.473 standard deviations, which is significant at the 1 percent level. My replication and robustness results suggest that the availability of microcredit programs for females increases female empowerment between 0.107 and 0.335 standard deviations. However, my estimates are only significant at the 10 percent level. In addition, 18 out of 27 individual factor estimates are statistically insignificant at the 10-percent level in terms of individual factor results. 21 out of 27 estimates imply that the program's presence increases female empowerment by less than

0.2 standard deviations. These results are reported in columns (5) and (6) of Table 4.3 and column (2) of Table 4.5 (but excluded from Table 4.9 for brevity).

With respect to the other findings by PKC, my results are generally not supportive. PKC report that male credit presence in a village has a negative impact on women's empowerment. They estimate that the presence of a male credit program lowers female empowerment by 0.167 standard deviations. In contrast, I estimate much smaller effects. I find that the availability of a microcredit program for males reduces female empowerment by between 0.013 and 0.005 standard deviations. Further, neither of my estimates are significant at even the 10 percent level.

Turning next to their ATT estimates, PKC state their results imply that: "a woman who has median overall empowerment and has never participated in a microcredit program would be in the 72nd empowerment percentile (a 22 percentile increase) if she had borrowed at the mean (log) level of woman participants" (page 812f.). However, they do not report the corresponding regression estimate in their tables. In contrast, my replication and robustness estimates indicate that a 10% increase in female borrowing increases empowerment between 0.004 and 0.011 standard deviations. While my estimates are significant at the 1 percent level, the effect sizes are negligibly small in terms of economic significance.

Finally, while PKC do not report the effects of male borrowing on "overall female empowerment", my estimates indicate the effect is virtually nil. I estimate that a 10% increase in male borrowing is associated with either a negligibly small positive impact (0.000), or negative effects of -0.000 and -0.014 standard deviations, with only the latter estimate significant, and that only at the 10 percent level.

In summary, my replication of PKC finds only weak evidence to support their conclusion that microcredit programs increase female empowerment. While there is some evidence that the presence of a program is associated with moderate increases in female empowerment, actual borrowing has very little impact. Perhaps it is not the actual act of borrowing that impacts female empowerment, but a change in an environment associated with the presence of the program. Perhaps the availability of these programs expands the “production possibilities frontier” of what women can do, and this feeds into local standards that influence household behavior.

That being said, the impact of microcredit on women’s empowerment may differ between regions and countries because of traditional attitudes, social norms and constructs, as well as religious restrictions. Thus, further estimating the impact of microcredit on women’s empowerment in other countries is warranted. Accordingly, my next chapter will focus on the impact of microcredit on women’s empowerment in Vietnam.

4.9 References

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Table 4.1 Survey measurement of female empowerment

	Name of variable	Full text from questionnaires	Coding*	Asked of:	Proportion		Thematic group	Number of observations
					PKC	Replication		
1	Food purchase	Do you buy the family's daily consumable food items?	Yes=1, No=0	Wife	0 = .839 1 = .161	0 = .821 1 = .179	1	2,074
2	Cosmetics purchase	Do you buy toiletries and cosmetics for your own use?	Yes=1, No=0	Wife	0 = .709 1 = .291	0 = .684 1 = .316	1	2,073
3	Candy purchase	Do you buy ice creams, candies, or cookies for your children?	Yes=1, No=0	Wife	0 = .386 1 = .614	0 = .374 1 =.626	1,9	2,029
4	Utensils purchase	Do you buy utensils, pots, and pans for the HH?	Yes=1, No=0	Wife	0 = .362 1 = .638	0 = .355 1 = .645	1	2,070
5	Furniture purchase	Do you buy HH furniture?	Yes=1, No=0	Wife	0 = .960 1 = .040	0 = .956 1 = .044	1	2,061
6	Children's clothing purchase	Do you buy clothing for your children?	Yes=1, No=0	Wife	0 = .837 1 = .163	0 = .834 1 = .166	1,9	2,047
7	Own clothing purchase	Do you buy clothing for yourself?	Yes=1, No=0	Wife	0 = .806 1 = .194	0 = .805 1 = .195	1	2,061
8	Wife initiates discussion (birth control methods)	Do you initiate discussion of birth control methods?	Yes=1, No=0	Wife	0 = .287 1 = .713	0 = .272 1 = .728	9	2,024
9	Wife initiates discussion (birth control use)	Do you initiate discussion of birth control use?	Yes=1, No=0	Wife	0 = .270 1= .730	0 = .253 1 = .747	9	2,032
10	Wife initiates discussion (children's education)	Do you initiate discussion of children's education?	Yes=1, No=0	Wife	0 = .172 1 = .828	0 = .158 1 = .842	9	1,977
11	Wife initiates discussion (birth timing)	Do you initiate discussion of birth timing?	Yes=1, No=0	Wife	0 = .300 1 = .700	0 = .305 1 = .695	9	2,064
12	Husband initiates discussion (birth timing)	Does your husband initiate discussion of birth timing?	Yes=1, No=0	Wife	0 = .368 1 = .632	0 = .369 1 = .631	9	2,064
13	Wife initiates discussion (birth numbers)	Do you initiate discussion of birth numbers?	Yes=1, No=0	Wife	0 = .272 1 = .728	0 = .267 1 = .733	9	2,068
14	House repair decision	Who decides issues of repair/construction of the house?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .231 1 = .753 2 = .016	0 = .210 1 = .771 2 = .019	4	2,068
15	House repair implementation	Who implements issues of repair/construction of the house?	Husband alone=0 Husband and wife=1	Wife	0 = .227 1 = .769	0 = .217 1 = .777	4	2,068

			Wife alone=2		2 = .004	2 = .006		
16	House repair spending	Do you spend on repair/construction of the house?	Yes=1, No=0	Wife	0 = .990 1 = .010	0 = .987 1 = .013	1,4	1,946
17	Livestock purchase decision	Who decides issues of sale/purchase of livestock?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .240 1 = .747 2 = .013	0 = .207 1 = .774 2 = .019	4	2,004
18	Livestock purchase implementation	Who implements issues of sale/purchase of livestock?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .383 1 = .611 2 = .006	0 = .374 1 = .618 2 = .008	4	2,004
19	Livestock spending	Do you spend on sale/purchase of livestock?	Yes=1, No=0	Wife	0 = .985 1 = .015	0 = .981 1 = .019	1,4	1,817
20	Household loans decision	Who decides issues of borrowing money?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .278 1 = .702 2 = .020	0 = .251 1 = .722 2 = .027	3,4	2,062
21	Household loans implementation	Who implements issues of borrowing money?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .376 1 = .613 2 = .011	0 = .360 1 = .627 2 = .013	3,4	2,062
22	Household loans spending	Do you spend on issues of borrowing money?	Yes=1, No=0	Wife	0 = .973 1 = .027	0 = .966 1 = .034	1,3,4	1,906
23	Land/ equipment decision	Who decides issues of sale/purchase/mortgage of land/transport or HH equipment/irrigation equipment?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .308 1 = .678 2 = .014	0 = .271 1 = .710 2 = .019	4	2,051
24	Land/ equipment implementation	Who implements issues of sale/purchase/mortgage of land/transport or HH equipment/irrigation equipment?	Husband alone=0 Husband and wife=1 Wife alone=2	Wife	0 = .466 1 = . 529 2 = .005	0 = .446 1 = .547 2 = .007	4	2,051
25	Land/ equipment spending	Do you spend on issues of sale/purchase/mortgage of land/transport or HH equipment/irrigation equipment?	Yes=1, No=0	Wife	0 = .989 1 = .011	0 = .985 1 = .015	1,4	1,844
26	Husband says wife intelligent	Do you think that your wife is as intelligent as you are?	Less=0 Same=1 More=2	Husband	0 = .688 1 = .241 2 = .071	0 = .680 1 = .242 2 = .079	7,8	2,025
27	Wife can by an asset	Do you think your wife can take decisions in selling/buying of major HH assets?	Yes=1, No=0	Husband	0 = .807 1 = .193	0 = .794 1 = .206	1,7	2,025
28	Wife can buy an asset without husband's permission	Can your wife buy any asset on her own without your permission?	Yes=1, No=0	Husband	0 = .880 1 = .120	0 = .872 1 = .128	1	2,025
29	Wife has own income	Does your wife have her own income?	Yes=1, No=0	Husband	0 = .641 1 = .359	0 = .620 1 = .380	2	2,025

30	Husband says wife travels alone	Does your wife go to market/bank/doctor's chambers and so on alone? If not…	Yes=1, No=0	Husband	0 = .842 1 = .158	0 = .828 1 = .172	5	2,025
31	Reason: women not allowed outside	…Why? Because women are not allow to go outside?	Yes=0, No=1	Husband	0 = .867 1 = .133	0 = .873 1 = .127	5	1,677
32	Reason: lack of safety	…Why? Because lack of safety?	Yes=1, No=0	Husband	0 = .884 1 = .116	0 = .890 1 = .110	5	1,677
33	Reason: wife goes with husband/ son	…Why? Because she goes with husband or son?	Yes=1, No=0	Husband	0 = .430 1 = .571	0 = .447 1 = .553	5	1,677
34	Reason: wife goes with neighbor	…Why? Because she goes with a neighbor or relative?	Yes=1, No=0	Husband	0 = .845 1 = .155	0 = .818 1 = .182	5	1,677
35	Wife has independent income	Do you have own income, which you can spend without your husband's permission?	Yes=1, No=0	Wife	0 = .787 1 = .213	0 = .780 1 = .220	2	2,074
36	Wife has independent saving	Do you have your own saving?	Yes=1, No=0	Wife	0 = .645 1 = .355	0 = .580 1 = .420	2	2,074
37	Wife has independent savings which she herself controls	Do you have your own saving which you can decide how to utilize?	Yes=1, No=0	Wife	0 = .822 1 = .178	0 = .853 1 = .147	2	871
38	Emergency fund access	If you need 500 taka in an emergency, could you get it? (from any source)?	Yes=1, No=0	Wife	0 = .342 1 = .658	0 = .338 1 = .662	2	2,074
39	Emergency funds access (asset sale)	If you need 500 taka in an emergency, could you get it by selling own assets)?	Yes=1, No=0	Wife	0 = .977 1 = .023	0 = .961 1 = .039	2	1,373
40	Emergency funds access (from husband)	If you need 500 taka in an emergency, could you get it from your husband?	Yes=1, No=0	Wife	0 = .798 1 = .202	0 = .712 1 = .288	8	1,373
41	Emergency fund access (husband's relatives)	If you need 500 taka in an emergency, could you get it from your husband's relatives?	Yes=1, No=0	Wife	0 = .830 1 = .171	0 = .721 1 = .279	3,5	1,373
42	Emergency fund access (own relatives)	If you need 500 taka in an emergency, could you get it from your own relatives?	Yes=1, No=0	Wife	0 = .788 1 = . 212	0 = .680 1 = .320	3,5	1,373
43	Emergency fund access (moneylenders)	If you need 500 taka in an emergency, could you get it by borrowing from moneylenders?	Yes=1, No=0	Wife	0 = .984 1 = .016	0 = .977 1 = .023	3	1,373
44	Emergency fund access (other people)	If you need 500 taka in an emergency, could you get it by borrowing from other people?	Yes=1, No=0	Wife	0 = . 966 1 = .034	0 = .951 1 = .049	3,5	1,373
45	Remittance	Have you received money from parents/brothers/sisters or other relatives outside the HH in the last 12 months?	Yes=1, No=0	Wife	0 = .841 1 = .159	0 = .849 1 = .151	2,5	2,072
46	Wife can decide how to use remittance	Can you decide yourself how to use that remittance?	No=0 Partially = 1 Yes = 2	Wife	0 = .182 1 = .634 2 = .184	0 = .209 1 = .626 2 = .165	2	297
47	Money seizure by husband		Yes=0, No=1	Wife	0 = .777	0 = .777	2,8	2,074

		Has your husband ever compelled you give him money/assets if you don't want to?			1 = .223	1 = .223		
48	Freedom to remit	Can you give away your money/assets at will to some body?	Yes=1, No=0	Wife	0 = .805 1 = .195	0 = .809 1 = .191	2	2,074
49	Husband forbids work outside home	Has your husband forced you not to work outside home even if you wanted to?	Yes=0, No=1	Wife	0 = .539 1 = .461	0 = .592 1 = .408	8	2,074
50	Visits relatives (without husband's permission)	Have you ever visited your parents or other relatives without your husband's permission?	Yes=1, No=0	Wife	0 = .819 1 = .181	0 = .815 1 = .185	5	2,074
51	Marriage has kabinnama	Does your marriage has kabinnama (prenuptial bride price agreement?	Yes=1, No=0	Wife	0 = .294 1 = .706	0 = .291 1 = .709	6	2,074
52	Awareness of kabinnama	Can Kabinnama help a woman in the events of a divorce?	Yes=1, No=0	Wife	0 = .056 1 = .944	0 = .054 1 = .946	6	2,074
53	Awareness of inheritance laws	Can a window establish her legal claim over her dead husband's property?	Yes=1, No=0	Wife	0 = .071 1 = .929	0 = .054 1 = .946	6	2,074
54	Has prevented husband remarrying	Have you ever been successful in stopping your husband from remarrying?	Yes=1, No=0	Wife	0 = .965 1 =. 035	0 = .965 1 = .035	6	1,887
55	Vote (al all)	Did you vote in the last election?	Yes=1, No=0	Wife	0 = .153 1 = .845	0 = .139 1 = .861	6	2,074
56	Voted independently	Did you vote in the last election without your husband telling you who to vote for?	Yes=1, No=0	Wife	0 = .785 1 = .215	0 = .741 1 = .259	6	1,785
57	Protest against domestic abuse	Did you ever protest against any incidents if wife beating?	Yes=1, No=0	Wife	0 = .761 1 = .239	0 = .758 1 = .242	6	2,074
58	Thinks dowry is good	Do you think dowry is good?	Yes=0, No=1	Wife	0 = .193 1 = .807	0 = .198 1 = .802	6,7	2,074
59	Protested against corruption	Did you ever protest against any favoritism by a chairman or a member who distributes government relief?	Yes=1, No=0	Wife	0 = .972 1 = .028	0=.966 1=.0338	6	2,074
60	Confidant within bari	With anybody outside your immediate family/HH, but within bari, are you close enough to share your feelings?	Yes=1, No=0	Wife	0 = .151 1 = .849	0 = .153 1 = .847	5	2,074
61	Confidant outside bari	With anybody outside your bari, are you close enough to share your feelings?	Yes=1, No=0	Wife	0 = .293 1 = .708	0 = .270 1 = .730	5	2,074
62	Severity of spouse arguments	When you and your husband argue, how bad does the argument get?	Physical abuse=0 Verbal abuse=1 Loud arguments=2 Mild argument=3	Wife	0 = .144 1 = .197 2 = .268 3 = .391	0 = .158 1 = .197 2 = .268 3 = .377	8	2,042
63	Own relatives in same village	Do your parents or any sibling live in the same village as you do with your husband?	Yes=1, No=0	Wife	0 = .825 1 = .175	0 = .812 1 = .188	5	2,074

64	Wife thinks husband is superior	Is your husband superior to you in qualities and education?	Yes=0, No=1	Wife	0 = .946 1 = .054	0 = .937 1 = .063	7	2,074
65	Husband uses male birth control	Do you yourself use any male birth control method?	Yes=1, No=0	Husband	0 = .933 1 = .067	0 = .942 1 = .058	9	2,074
66	Husband says women's empowerment leads to better society	Does women's empowerment lead to a better society?	Yes=1, No=0	Husband	0 = .571 1 = .429	0 = .564 1 = .436	7	2,025
67	Husband says women's empowerment leads to chaos in society	Does women's empowerment lead to chaos in society?	Yes=0, No=1	Husband	0 = .456 1 = .544	0 = .441 1 = .559	7	2,025
68	Husband says women's empowerment leads to problems with kids	Does women's empowerment lead to problems bringing up the children?	Yes=0, No=1	Husband	0 = .208 1 = .792	0 = .208 1 = .792	7	2,025
69	Husband says women's empowerment leads to loss of peace	Does women's empowerment lead to loss of family peace?	Yes=0, No=1	Husband	0 = .275 1 = .725	0 = .276 1 = .724	7	2,025
70	Husband says women's empowerment leads to the family being better off economically	Does women's empowerment lead to the family being better off economically?	Yes=1, No=0	Husband	0 = .678 1 = .323	0 = .673 1 = .327	7	2,074
71	Husband cites positive impact of women's empowerment	Does women's empowerment have a good impact?	Yes=1, No=0	Husband	0 = .507 1 = .493	0 = .515 1 = .485	8	2,005
72	Husband cites negative impact of women's empowerment	Does women's empowerment have a bad impact?	Yes=0, No=1	Husband	0 = .586 1 = .413	0 = .481 1 = .519	8	2,025
73	Wife has made husband use birth control	Have you ever succeeded in making your husband adopt a male birth control method?	Yes=1, No=0	Wife	0 = .903 1 = .097	0 = .916 1 = .084	9	1,997
74	Wife has income - generating activity	Do you have any income-generating activity?	Yes=1, No=0	Wife	0 = .696 1 = .304	0 = .760 1 = .240	2	2,074
75	Degree of mobility	How do you go to banks, markets, health centers, or places outside the village (except for your parents' place)?	Doesn't go at all=0 Goes with husband or son=1 Goes with women=2 Goes alone =3	Wife	0 = .111 1 = .549 2 = .217 3 = .123	0 = .087 1 = .528 2 = .218 3 = .131	5	2,074
76	Prevent remarriage (local government)	How can a wife prevent her husband from remarrying...By pressing charges in the local administration?	Yes=1, No=0	Wife	0 = .692 1 = .308	0 = .688 1 = .312	6	2,074
77	Prevent remarriage (parishad)	How can a wife prevent her husband from remarrying...By pressing charges in the Union Parishad?	Yes=1, No=0	Wife	0 = .791 1 = .209	0 = .794 1 = .206	6	2,074

78	Wife views social structure as obstacle	Is the social structure an obstacle to women's empowerment?	Yes=1, No=0	Wife	0 = .639 1 = .361	0 = .654 1 = .346	6	2,074
79	Wife views laws as obstacle	Is inheritance law an obstacle to women's empowerment?	Yes=1, No=0	Wife	0 = .919 1 = .081	0 = .917 1 = .083	6	2,074
80	Wife views religion as obstacle	Is religion an obstacle to women's empowerment?	Yes=1, No=0	Wife	0 = .508 1 = .492	0 = .516 1 = .484	6	2,074

Note: Coding yes=1, no=0,
In categories coding (shading): if female involving =1, otherwise=0

Table 4.2 Summary statistics

	Mean		Standard deviation	
	PKC	Replication	PKC	Replication
Age of household member (years)	34.95	24.67	10.59	8.42
Education of the member (years)	1.85	1.85	3.07	2.15
If parents of household head own land	0.161	0.145	0.367	0.353
If brothers of household head own land	0.349	0.300	0.477	0.458
If sisters of household head own land	0.287	0.257	0.453	0.437
If parents of household head's spouse own land	0.331	0.326	0.471	0.469
If brothers of household head's spouse own land	0.338	0.315	0.473	0.465
If sisters of household head's spouse own land	0.284	0.264	0.451	0.441
Household land asset (decimals)	86.750	63.227	167.230	128.49
Age of household head (years)	43.690	43.363	12.140	11.916
Education of household head (years) [1]	2.820	2.493	3.790	3.561
Highest male education in household (years) [2]	2.830	4.243	3.770	4.019
Highest female education in household (years) [3]	4.200	3.195	4.490	3.445
Household has male choice (yes=1)	0.615	0.517	0.487	0.500
Household has female choice (yes=1)	0.685	0.780	0.465	0.414
F1: Purchasing	0.0088	0.00074	1.035	0.879
F2: Recourses	0.00006	0.00002	0.500	0.771
F3: Finance	–0.00008	0.000000006	0.175	0.417
F4: Transaction management	–0.0015	0.0061	1.409	0.899
F5: Mobility networks	0.0002	–0.000000004	0.178	0.194
F6: Activism	0.00005	–0.00000002	0.192	0.502
F7: Household attitudes	–0.00075	0.00000089	0.542	0.802
F8: Husband's behavior	–0.00097	0.000000	0.188	0.178
F9: Fertility and parenting	0.000077	0.000035	0.686	0.859
Factor : All factors	–0.000	0.000	0.910	1.663
Female borrowing: log(female program loans +1)	4.127	4.303	4.707	4.905
Male borrowing: log(male program loans +1)	0.948	0.985	2.845	2.960
Female participation (yes=1)	0.443	0.520	0.497	0.500
Male participation (yes=1)	0.106	0.213	0.307	0.410
Number of observations	2,064	2,069		

Note: In my calculation: [1] 2,041 observations, [2] 2,063 observations, [3] 2,056 observations, other variables include 2069 observations.
Source: PKC Table 3, page 805; replication: authors' calculation. Latent factors are calculated by using IRT-1PL

Table 4.3 Effect of credit program eligibility on the empowerment of women (ITT effects)

		OLS (clustered)			Village FE		
		(1)	(2)	(3)	(4)	(5)	(6)
Factors		PKC	Replication GLLAMM	Replication IRT-Rasch	PKC	Replication GLLAMM	Replication IRT-Rasch
F1: Purchasing	Female choice	0.199**	0.266**	0.237**	0.224***	0.039	0.029
		(2.16)	(2.14)	(2.15)	(3.10)	(0.37)	(0.31)
	Male choice	0.035	-0.079	-0.073	-0.018	0.125	0.120
		(0.34)	(-0.71)	(-0.74)	(-0.28)	(1.14)	(1.24)
F2: Resources	Female choice	0.438***	0.134**	0.219**	0.509***	0.071*	0.106
		(4.86)	(2.19)	(2.20)	(6.84)	(1.64)	(1.52)
	Male choice	-0.601	-0.063	-0.107	-0.148***	-0.062	-0.093
		(-0.66)	(-1.07)	(-1.12)	(-2.08)	(-1.31)	(-1.22)
F3: Finance	Female choice	0.411***	0.003	-0.003	0.366****	0.029	0.078*
		(4.69)	(0.14)	(-0.06)	(4.67)	(1.29)	(1.70)
	Male choice	-0.160	0.001	0.029	-0.171***	-0.011	-0.017
		(-1.88)	(0.03)	(0.55)	(-2.35)	(-0.49)	(-0.35)
F4: Transaction management	Female choice	0.471***	0.171	0.102	0.302***	0.299*	0.194*
		(4.85)	(0.91)	(0.83)	(3.89)	(1.81)	(1.83)
	Male choice	-0.121	0.004	0.011	-0.089	-0.107	-0.072
		(-1.36)	(0.02)	(0.10)	(-1.25)	(-0.64)	(-0.67)
F5: Mobility and networks	Female choice	0.376***	0.000	0.024	0.433***	0.000	0.021
		(3.80)	(1.13)	(1.26)	(5.12)	(1.16)	(1.04)
	Male choice	-0.230***	0.000	0.023	-0.275***	0.000	0.021
		(-2.58)	(0.76)	(1.28)	(-3.54)	(0.24)	(0.92)
F6: Activism	Female choice	0.109	0.018	0.041	0.188***	-0.002	-0.015
		(1.12)	(0.94)	(0.67)	(2.2)	(-0.16)	(-0.33)
	Male choice	0.052	-0.003	0.016	-0.068	0.016	0.057
		(0.62)	(-0.15)	(0.25)	(-0.9)	(1.16)	(1.17)
F7: Household attitudes	Female choice	0.181**	0.109*	0.172*	0.114	0.031	0.029
		(2.01)	[1.68]	(1.70)	(1.4)	(0.63)	(0.38)
	Male choice	-0.013	-0.066	-0.113	0.03	0.003	0.042
		(-0.15)	(-1.10)	(-1.23)	(0.36)	(0.06)	(0.52)
F8: Husband's behavior	Female choice	0.144	0.000	0.008	0.122	0.000*	0.044**
		(1.53)	(-0.28)	(0.39)	(1.47)	(-1.7)	(2.28)
	Male choice	-0.080	-0.002	0.021	-0.043	0.000	-0.020
		(-0.94)	(-1.16)	(0.96)	(-0.53)	(-0.44)	(-0.97)
F9: Fertility and parenting	Female choice	0.310***	0.082	0.111	0.341***	0.134*	0.185***
		(3.49)	(0.97)	(1.09)	(4.28)	(1.71)	(2.04)
	Male choice	-0.057	0.080	0.097	-0.185***	0.011	-0.008
		(-0.73)	(1.06)	(1.06)	(-2.52)	(0.14)	(-0.09)
F10: All variables[1]	Female choice	0.512***	0.420**	0.410*	0.473***	0.335*	0.380**
		(6.08)	(2.02)	(1.96)	(6.4)	(1.88)	(2.12)
	Male choice	-0.134	-0.042	0.012	-0.167***	-0.013	0.015
		(-1.57)	(-0.20)	(0.06)	(-2.39)	(-0.07)	(0.08)

Note: OLS estimation includes a set of 9 village characteristics: village average male wage, village average female wage, village price of wheat flour, village price of potato, village price of rice, village price of mustard oil, village price of hen egg, village price of milk, villages have any primary school. PKC did not make clear the set of village characteristics that they used to estimate their OLS results.
[1] Factor all F10 is estimated from continuous FA over the nine continuous groups of latent empowerment factors.
Replication GLLAMM: using generalized linear latent and mixed models.
Replication IRT-Rasch: using Item Response Theory one-parameter logistic model.
*, **, *** denote significance at 10%, 5%, and 1% levels.

Table 4.4 Effect of credit program borrowing on the empowerment of women in participating households (ATT effects)

		OLS (cluster)			Village FE			Village FE-IV		
		PKC	Replication		PKC	Replication		PKC	Replication	
		(1)	(2) Gllamm	(3) IRT	(4)	(5) Gllamm	(6) IRT	(7)	(8) Gllamm	(9) IRT
Factor 1:	Female credit	0.032***	0.034***	0.029***	0.034***	0.032***	0.027***	0.031***	0.034***	0.030***
Purchasing		(5.77)	(5.90)	(5.73)	(7.15)	(7.38)	(7.19)	(4.10)	(2.45)	(2.49)
	Male credit	0.001	0.020*	0.018**	-0.009	-0.002	-0.001	-0.004	0.014	0.014
		(0.10)	(1.82)	(1.88)	(-1.04)	(-0.29)	(-0.22)	(-0.25)	(0.60)	(0.73)
Factor 2:	Female credit	0.066***	0.031***	0.050***	0.070***	0.028***	0.045***	0.062***	0.019***	0.031***
resources		(12.1)	(11.81)	(11.80)	(14.63)	(14.01)	(13.97)	(8.00)	(2.80)	(2.85)
	Male credit	0.01	0.007	0.012*	0.00	-0.001	-0.002	-0.022	-0.012	-0.016
		(0.82)	(1.62)	(1.67)	(0.02)	(-0.4)	(-0.35)	(-1.35)	(-1.05)	(-0.88)
Factor 3: finance	Female credit	0.046***	0.009***	0.015***	0.046***	0.009***	0.013***	0.051***	0.012***	0.026***
		(7.84)	(7.48)	(5.62)	(8.49)	(9.41)	(7.49)	(5.73)	(3.70)	(3.93)
	Male credit	-0.006	-0.002	-0.004	0.001	-0.002	-0.004	-0.002	0.000	-0.002
		(-0.46)	(-0.82)	(-0.94)	(0.05)	(-1.46)	(-1.32)	(-0.13)	(0.06)	(-0.22)
Factor 4:	Female credit	0.045***	0.055***	0.035***	0.038***	0.041***	0.026***	0.043***	0.083***	0.054***
transaction		(7.77)	(6.84)	(6.74)	(7.56)	(7.09)	(6.93)	(4.75)	(4.07)	(4.09)
management	Male credit	-0.0004	0.000	0.000	0.008	-0.009	-0.006	0.011	0.002	0.002
		(-0.04)	(0.01)	(0.04)	(0.82)	(-0.95)	(-0.95)	(0.61)	(0.05)	(0.09)
Factor 5: mobility	Female credit	0.045***	0.000***	0.005***	0.045***	0.000***	0.004***	0.051***	0.000**	0.007***
and networks		(6.84)	(3.83)	(3.50)	(7.51)	(5.57)	(4.47)	(4.86)	(1.99)	(2.14)
	Male credit	-0.011	0.000	0.000	-0.022***	-0.000***	-0.003***	-0.03***	-0.000	-0.001
		(-0.84)	(-0.51)	(-0.25)	(-2.43)	(-2.70)	(2.26)	(-2.07)	(-0.02)	(-0.24)
Factor 6: activism	Female credit	0.021***	0.002***	0.006**	0.026***	0.003***	0.010***	0.021***	0.001	0.005
		(3.35)	(1.44)	(1.90)	(4.47)	(5.01)	(4.99)	(2.56)	(0.46)	(0.83)
	Male credit	0.005	0.001	0.009	-0.001	0.000	0.003	-0.010	0.003	0.009
		(0.6)	(0.54)	(1.56)	(-0.16)	(-0.08)	(0.99)	(-0.76)	(0.93)	(0.85)
Factor 7:	Female credit	0.031***	0.014***	0.022***	0.03***	0.014***	0.022***	0.018***	0.013*	0.022*
household		(5.67)	(4.19)	(4.09)	(5.65)	(5.84)	(6.04)	(2.07)	(1.72)	(1.86)
attitudes	Male credit	0.006	0.002	0.001	0.009	0.001	0.000	0.018	0.001	-0.004

		(0.49)	(0.37)	(0.12)	(1.02)	(0.2)	(-0.07)	(1.21)	(0.09)	(-0.18)
Factor 8: husband's behavior	Female credit	0.016***	0.000	0.001	0.021***	-0.000	0.001*	0.016*	-0.000*	0.005*
		(2.86)	(-0.36)	(1.32)	(3.66)	(-0.73)	(1.92)	(1.77)	(-1.74)	(1.95)
	Male credit	0.005	0.000	-0.001	0.011	0.000	-0.001	0.011	-0.000	-0.003
		(0.70)	(0.63)	(-0.42)	(1.01)	(0.80)	(-0.77)	(0.83)	(0.73)	(-0.62)
Factor 9: fertility and parenting	Female credit	0.032***	0.025***	0.029***	0.036***	0.023***	0.026***	0.038***	0.018*	0.023*
		(5.87)	(5.65)	(5.36)	(6.79)	(7.45)	(7.18)	(4.28)	(1.61)	(1.72)
	Male credit	-0.003	0.012*	0.015**	-0.016*	-0.002	-0.002	-0.200	-0.002	-0.008
		(-0.31)	(1.82)	(1.93)	(-1.66)	(-0.36)	(-0.37)	(-1.27)	(-0.11)	(-0.43)
Factor all: all variables[1]	Female credit	----	0.102***	0.096***	----	0.094***	0.087***	----	0.108***	0.114***
			(10.27)	(9.59)		(13.14)	(12.20)		(4.57)	(4.89)
	Male credit	----	0.015	0.017	----	-0.018	-0.015	----	0.000	-0.007
			(1.09)	(1.10)		(-1.44)	(-1.23)		(0.01)	(-0.18)

Note: OLS estimation includes a set of 9 village characteristics: village average male wage, village average female wage, village price of wheat flour, village price of potato, village price of rice, village price of mustard oil, village price of hen egg, village price of milk, villages have any primary school. PKC did not make clear the set of village characteristics that they used to estimate their OLS results.

[1] Factor all is estimated from continuous FA over the nine continuous groups of latent empowerment factors

*, **, *** denote significance at 10%, 5%, and 1% levels

Table 4.5 Robustness check: Effect of credit program eligibility on the empowerment of women (ITT) estimated with GSEM

		PKC	Robustness
		(1)	(2)
Method		SEM	GSEM
		Village FE	
Factor 1: Purchasing	Female choice	0.224***	-0.031
		(3.10)	(-0.13)
	Male choice	-0.018	0.307
		(-0.28)	(1.22)
Factor 2: Resources	Female choice	0.509***	0.205*
		(6.84)	(1.73)
	Male choice	-0.148***	-0.161
		(-2.08)	(-1.23)
Factor 3: Finance	Female choice	0.366****	0.182
		(4.67)	(1.28)
	Male choice	-0.171***	-0.074
		(-2.35)	(-0.50)
Factor 4: Transaction management	Female choice	0.302***	0.478
		(3.89)	(1.44)
	Male choice	-0.089	-0.237
		(-1.25)	(-0.70)
Factor 5: Mobility and networks	Female choice	0.433***	0.019
		(5.12)	(0.22)
	Male choice	-0.275***	0.022
		(-3.54)	(0.25)
Factor 6: Activism	Female choice	0.188***	-0.009
		(2.20)	(-0.10)
	Male choice	-0.068	0.024
		(-0.9)	(0.26)
Factor 7: Household attitudes	Female choice	0.114	0.063
		(1.40)	(0.47)
	Male choice	0.03	0.073
		(0.36)	(0.50)
Factor 8: Husband's behavior	Female choice	0.122	-0.002
		(1.47)	(-0.02)
	Male choice	-0.043	-0.006
		(-0.53)	(-0.07)
Factor 9: Fertility and parenting	Female choice	0.341***	0.282
		(4.28)	(1.55)
	Male choice	-0.185***	-0.080
		(-2.52)	(-0.42)
Factor 10: All variables	Female choice	0.473***	0.107*
		(6.40)	(1.67)
	Male choice	-0.167***	-0.005
		(-2.39)	(-0.08)

Note: SEM: Structural equation modeling, GSEM: Generalized structural equation modeling
Factor all is estimated from all of the binary indicator responses (encompassing nine individual factors) using IRT-1PL
*, **, *** denote significance at 10%, 5%, and 1% levels

Table 4.6 Robustness check: Effect of credit program borrowing on the empowerment of women in participating households (ATT) estimated with GSEM

		PKC	Robustness (Using GSEM)	
		(1)	(2)	(3)
		Village FE	OLS	Village FE
Factor 1: Purchasing	Female credit	0.034***	0.080***	0.073***
		(7.15)	(5.65)	(6.91)
	Male credit	-0.009	0.038*	-0.010
		(-1.04)	(1.79)	(-0.60)
Factor 2: resources	Female credit	0.07***	0.090***	0.079***
		(14.63)	(10.74)	(13.77)
	Male credit	0.00	0.022*	-0.001
		(0.02)	(1.75)	(-0.13)
Factor 3: finance	Female credit	0.046***	0.046***	0.010
		(8.49)	(5.39)	(0.42)
	Male credit	0.001	-0.014	-0.005
		(0.05)	(-1.04)	(-0.48)
Factor 4: transaction management	Female credit	0.038***	0.126***	0.091***
		(7.56)	(6.53)	(6.80)
	Male credit	0.008	-0.008	-0.029
		(0.82)	(-0.27)	(-1.30)
Factor 5: mobility and networks	Female credit	0.045***	0.026***	0.023***
		(7.51)	(5.34)	(6.63)
	Male credit	-0.022***	-0.004	-0.013**
		(-2.43)	(-0.60)	(-2.16)
Factor 6: activism	Female credit	0.026***	0.011**	0.017***
		(4.47)	(2.01)	(5.08)
	Male credit	-0.001	0.020**	0.007
		(-0.16)	(2.06)	(1.15)
Factor 7: household attitudes	Female credit	0.03***	0.040***	0.040***
		(5.65)	(4.04)	(6.21)
	Male credit	0.009	-0.001	-0.001
		(1.02)	(-0.07)	(-0.07)
Factor 8: husband's behavior	Female credit	0.021***	-0.005	-0.003
		(3.66)	(-1.31)	(-0.93)
	Male credit	0.011	0.002	0.003
		(1.01)	(0.22)	(0.54)
Factor 9: fertility and parenting	Female credit	0.036***	0.062***	0.051***
		(6.79)	(5.21)	(6.76)
	Male credit	-0.016*	0.028	-0.010
		(-1.66)	(1.60)	(-0.78)
Factor 10: All factors	Female credit	----	0.041***	0.036***
			(10.57)	(13.55)
	Male credit	----	0.011*	-0.003
			(1.91)	(-0.67)

Note: OLS estimation includes a set of 9 village characteristics: village average male wage, village average female wage, village price of wheat flour, village price of potato, village price of rice, village price of mustard oil, village price of hen egg, village price of milk, villages have any primary school.
Factor all is estimated by using IRT-1PL
*, **, *** denote significance at 10%, 5%, and 1% levels

Table 4.7 Diagnostics IV testing

Model	(1) Endogeneity test[1]	(2) Under-identification test[2]	(3) Weak identification test[3]	(4) Over-identification test[4]
Factor 1	0.937	129.516 (0.202)	1.119/2.269	129.397 (0.186)
Factor 2	0.116	129.516 (0.202)	1.119/2.269	118.091 (0.429)
Factor 3	0.500	129.516 (0.202)	1.119/2.269	138.314 (0.077)
Factor 4	0.216	129.516 (0.202)	1.119/2.269	128.335 (0.204)
Factor 5	0.854	129.516 (0.202)	1.119/2.269	143.004 (0.045)
Factor 6	0.687	129.516 (0.202)	1.119/2.269	123.909 (0.291)
Factor 7	0.991	129.516 (0.202)	1.119/2.269	115.849 (0.487)
Factor 8	0.586	129.516 (0.202)	1.119/2.269	117.85 (0.4346)
Factor 9	0.344	129.516 (0.202)	1.119/2.269	146.930 (0.028)
Factor 10	0.744	129.516 (0.202)	1.119/2.269	137.060 (0.089)

Note: [1]Reports the Durbin-Wu-Hausman chi-sq test; [2]Reports the Kleibergen–Paap rk LM statistic; [3]Reports the Cragg–Donald Wald F statistic; [4]Reports the Hansen J statistic.

[2,3]Test relevant condition between IV and endogenous covariates. Because IV and endogenous covariates are unchanged in the first stage of 2SLS, the results are the same for ten equations. However, in the second stage of 2SLS, [4]Test exclusion condition between IV and ten outcomes of empowerment factors. The ten of empowerments are not identical, so the results of the over-identification test are different.

Table 4.8 Robustness check: Effect of credit program borrowing on the empowerment of women in participating households (ATT) estimated with LASSO

		Village FE		Village FE-IV	
		(1)	(2)	(3)	(4)
		PKC Original	Lasso	PKC Original	Lasso
Factor 1: Purchasing	Female credit	0.034***	0.025***	0.031***	0.011
		(7.15)	(6.80)	(4.10)	(0.91)
	Male credit	-0.009	-0.001	-0.004	-0.029
		(-1.04)	(-0.15)	(-0.25)	(-0.83)
Factor 2: resources	Female credit	0.07***	0.044***	0.062***	0.056***
		(14.63)	(14.22)	(8.00)	(5.66)
	Male credit	0.00	-0.003	-0.022	0.014
		(0.02)	(-0.50)	(-1.35)	(0.44)
Factor 3: finance	Female credit	0.046***	0.012***	0.051***	0.008
		(8.49)	(6.92)	(5.73)	(1.35)
	Male credit	0.001	-0.004	-0.002	0.011
		(0.05)	(-1.43)	(-0.13)	(0.60)
Factor 4: transaction management	Female credit	0.038***	0.024***	0.043***	0.023*
		(7.56)	(6.50)	(4.75)	(1.84)
	Male credit	0.008	-0.004	0.011	-0.013
		(0.82)	(-0.65)	(0.61)	(-0.38)
Factor 5: mobility and networks	Female credit	0.045***	0.004***	0.051***	0.002
		(7.51)	(4.44)	(4.86)	(0.50)
	Male credit	-0.022***	-0.003**	-0.03***	-0.019
		(-2.43)	(-1.99)	(-2.07)	(-1.59)
Factor 6: activism	Female credit	0.026***	0.010***	0.021***	0.009
		(4.47)	(5.18)	(2.56)	(1.45)
	Male credit	-0.001	0.003	-0.010	-0.008
		(-0.16)	(0.97)	(-0.76)	(-0.35)
Factor 7: household attitudes	Female credit	0.03***	0.020***	0.018***	0.031***
		(5.65)	(5.87)	(2.07)	(2.25)
	Male credit	0.009	0.000	0.018	-0.155***
		(1.02)	(0.01)	(1.21)	(-3.07)
Factor 8: husband's behavior	Female credit	0.021***	0.001	0.016*	0.000
		(3.66)	(1.93)	(1.77)	(0.14)
	Male credit	0.011	-0.001	0.011	-0.001
		(1.01)	(-0.72)	(0.83)	(-0.10)
Factor 9: fertility and parenting	Female credit	0.036***	0.024***	0.038***	0.034***
		(6.79)	(6.91)	(4.28)	(3.04)
	Male credit	-0.016*	-0.001	-0.200	-0.003
		(-1.66)	(-0.12)	(-1.27)	(-0.09)
Factor 10: all variables	Female credit	----	0.080***	----	0.096***
			(11.75)		(3.74)
	Male credit	----	-0.013	----	-0.126
			(-0.98)		(-1.75)

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

Table 4.9 Summary of results

Table/Column	Dependent variable	Treatment variable	Size of the effect	Interpretation of size of the effect
		ITT: Microcredit Program for Females		
PKC's estimate:				
Table 4.3, column 4	Factor all	Female choice	0.473***	The presence of a microcredit program for females in a village increases female empowerment by 0.473 standard deviations.
My replications and robustness results:				
Table 4.3, column 5	Factor all	Female choice	0.335*	The presence of a microcredit program for females in a village increases female empowerment by 0.335 standard deviations.
Table 4.5, column 2	Factor all	Female choice	0.107*	The presence of a microcredit program for females in a village increases female empowerment by 0.107 standard deviations.
		ITT: Microcredit Program for Males		
PKC's estimate:				
Table 4.3, column 4	Factor all	Male choice	-0.167***	The presence of a microcredit program for males in a village reduces female empowerment by 0.167 standard deviations.
My replications and robustness results:				
Table 4.3, column 5	Factor all	Male choice	-0.013	The presence of a microcredit program for males in a village reduces female empowerment by 0.013 standard deviations
Table 4.5, column 2	Factor all	Male choice	-0.005	The presence of a microcredit program for males in a village reduces female empowerment by 0.005 standard deviations.

ATT: Female Borrowing

PKC's estimate:

PKC state that "a woman who has median overall empowerment and has never participated in a microcredit program would be in the 72nd empowerment percentile (a 22 percentile increase) if she had borrowed at the mean (log) level of woman participants" (page 812f.).

My replications and robustness results:

Table 4.4, column 8	Factor all	Log of female borrowing	0.108***	A 10% increase in female borrowing leads to an increase of 0.011 standard deviations in women's empowerment.
Table 4.6, column 3	Factor all	Log of female borrowing	0.036***	A 10% increase in female borrowing leads to an increase of 0.004 standard deviations in women's empowerment.
Table 4.8, column 4	Factor all	Log of female borrowing	0.096***	A 10% increase in female borrowing leads to an increase of 0.009 standard deviations in women's empowerment.

ATT: Male Borrowing

PKC's estimate:

The impact of male borrowing on women's empowerment representing by "factor all" is not reported in PKC paper.

My replications and robustness results:

Table 4.4, column 8	Factor all	Log of male borrowing	0.000	A 10% increase in male borrowing has virtually no measurable effect on women's empowerment.
Table 4.6, column 3	Factor all	Log of male borrowing	-0.003	A 10% increase in male borrowing has virtually no measurable effect on women's empowerment.
Table 4.8, column 4	Factor all	Log of male borrowing	-0.126*	A 10% increase in male borrowing reduces female empowerment by 0.013 standard deviations.

4.10 Appendix: Programming code for Chapter 4

```
// Appendix for Chapter 4


// set paths to working data folders
global path "C:\Users\dtv13\Dropbox\DIEM PhD Program\2020.Chapter4_PKC\Data\"

etime, start
cap log close
log using "$path/T04_RepIRT",replace
clear
cap estimates drop *
set more off
use "$path/HHobservation002.dta", replace


****************************************************************************
// TABLE 4.2: Descriptive statistics (replicate Table 3, PKC, p.805)
****************************************************************************


sum agemem edumem parentheadland broheadland sistheadland parentspouseland brospouseland
sistspouseland land agehead eduhead higedumale higedufemale malechoice femalechoice
logfmaleloans logmaleloans mpart fpart theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8
theta9 factorall


****************************************************************************
// TABLE 4.3, column 3 (IRT, OLS)
****************************************************************************


// Replication Table 4, column 1, PKC, p.806
// Using OLS clusterd villages and 9 villages characteristics
// Using IRT to estimate latent empowerement

set more off
sum wagem wagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed // other village
characteristics are missing in data

// Set macro path for control variable list and village characteristics
global xvar agemem edumem parentheadland broheadland ///
sistheadland parentspouseland brospouseland sistspouseland land agehead eduhead higedumale
higedufemale
global vvar wagem wagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed

// OLS regression the impact of female/male choice to microcredit program on 10 women's
empowerment indexs

foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall theta10
{
reg `v' femalechoice malechoice $xvar $vvar, cluster(vilid) nocons
}


****************************************************************************
// TABLE 4.3, column 6 (IRT, FE)
****************************************************************************


// Replication Table 4, column 2, PKC, p.806
// Using village Fixed effects estimates
// Using IRT to estimate latent empowerment

set more off
global xvar agemem edumem parentheadland broheadland ///
sistheadland parentspouseland brospouseland sistspouseland land agehead eduhead higedumale
higedufemale

foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall theta10
{
xi: reg `v' femalechoice malechoice $xvar i.vilid, vce(robust) nocons
}
```

```
 etime
log close


*****************************************************************************
// TABLE 4.3, column 2, (Gllamm, OLS)
*****************************************************************************


// set paths to working data folders
global path "C:\Users\dtv13\Dropbox\DIEM PhD Program\2020.Chapter4_PKC\Data\"
etime, start
// Merge latent variables from GLLAMM estimates to the main dataset
clear
use "$path/latentgllamm.dta", replace
global varkeep scorem1 scorem2 scorem3 scorem4 scorem5 scorem6 scorem7 scorem8 scorem9
scoreall

clear
use "$path/HHobservation002.dta", replace
merge 1:m hhcode using "$path/latentgllamm.dta", keepusing($varkeep)
keep if _merge==3
drop if _merge==2
cap drop _merge

// Replication Table 4, column 1, PKC, p.806
// Using OLS clusterd villages and 9 villages characteristics
// Using GLLAMM to estimate latent empowerement

set more off
global xvar agemem edumem parentheadland broheadland sistheadland ///
parentspouseland brospouseland sistspouseland land agehead eduhead higedumale higedufemale
global vvar wagem wagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed

foreach v in scorem1 scorem2 scorem3 scorem4 scorem5 scorem6 scorem7 scorem8 scorem9 scoreall
{
reg `v' femalechoice malechoice $xvar $vvar, cluster(vilid) nocons
}


*****************************************************************************
// TABLE 4.3, column 5 (Gllamm, FE)
*****************************************************************************


// Replication Table 4, column 2, PKC, p.806
// Using village Fixed effects estimates
// Using GLLAMM to estimate latent empowerment

set more off
foreach v in scorem1 scorem2 scorem3 scorem4 scorem5 scorem6 scorem7 scorem8 scorem9 scoreall
{
xi: reg `v' femalechoice malechoice $xvar i.vilid, vce(robust) nocons
}

  etime
log close


*****************************************************************************
// TABLE 4.4
*****************************************************************************


global path "C:\Local\dtv13\Dropbox\Diem Canterbury PhD\2020.Chapter3_PKC\Data\"
etime, start

clear
cap log close
log using "$path/T05_IRT_GLLAMM (Rep)",replace
use "$path/HHobservation002.dta", replace

//1. Creating Instrument variables (IVs): interact female/male choice variables with control
variables
set more off
```

```
global xvar agemem edumem parentheadland broheadland ///
sistheadland parentspouseland brospouseland sistspouseland land agehead eduhead higedumale
higedufemale

global vvar wagem wagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed
// Interact female choice with control variables
macro drop ivfxvar
foreach var of global xvar {
cap drop ivf`var'
gen ivf`var' = (femalechoice-1)*`var'
global ivfxvar $ivfxvar ivf`var'
}
// Interact male choice with control variables
macro drop ivmxvar
foreach var of global xvar {
cap drop ivm`var'
gen ivm`var' = (malechoice-1)*`var'
global ivmxvar $ivmxvar ivm`var'
}

// 2. Create IV by interact dummy villages with control variables

egen vilid = group(Thanaid Villid)
tab vilid, gen(ivvil)
global vilvar ivvil2 ivvil3 ivvil4 ivvil5 ivvil6 ivvil7 ivvil8 ivvil9 ivvil10 ivvil11 ivvil12
ivvil13 ivvil14 ivvil15 ivvil16 ivvil17 ivvil18 ivvil19 ivvil20 ivvil21 ivvil22 ivvil23
ivvil24 ivvil25 ivvil26 ivvil27 ivvil28 ivvil29 ivvil30 ivvil31 ivvil32 ivvil33 ivvil34
ivvil35 ivvil36 ivvil37 ivvil38 ivvil39 ivvil40 ivvil41 ivvil42 ivvil43 ivvil44 ivvil45
ivvil46 ivvil47 ivvil48 ivvil49 ivvil50 ivvil51 ivvil52 ivvil53 ivvil54 ivvil55 ivvil56
ivvil57 ivvil58 ivvil59 ivvil60 ivvil61 ivvil62 ivvil63 ivvil64 ivvil65 ivvil66 ivvil67
ivvil68 ivvil69 ivvil70 ivvil71 ivvil72 ivvil73 ivvil74 ivvil75 ivvil76 ivvil77 ivvil78
ivvil79 ivvil80 ivvil81 ivvil82 ivvil83 ivvil84 ivvil85 ivvil86 ivvil87 ivvil88 ivvil89
ivvil90 ivvil91 ivvil92 ivvil93 ivvil94 ivvil95 ivvil96 ivvil97 ivvil98 ivvil99 ivvil100
ivvil101 ivvil102 ivvil103 ivvil104
// Interact female choice with dummy villages
macro drop ivfvill
foreach var of global vilvar {
cap drop ivf`var'
gen ivf`var' = (femalechoice-1)*`var'
global ivfvill $ivfvill ivf`var'
}
// Interact male choice with dummy villages
macro drop ivmvill
foreach var of global vilvar {
cap drop ivm`var'
gen ivm`var' = (malechoice-1)*`var'
global ivmvill $ivmvill ivm`var'
}


****************************************************************************
// TABLE 4.4 column 3 (IRT, OLS)
****************************************************************************


// Replication PKC Table 5, column 1
// Using OLS villages clustered and IRT to estimate latent variables

set more off
foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall {

reg `v' logfmaleloans logmaleloans $xvar $vvar, cluster(vilid) nocons

}


****************************************************************************
// TABLE 4.4 column 6 (IRT, FE)
****************************************************************************


// Replication PKC Table 5, column 2
// Using village fixed effects and IRT to estimate latent variables

set more off
foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall {
```

```
xi:reg `v' logfmaleloans logmaleloans $xvar i.vilid, vce(robust) nocons

}


****************************************************************************
// TABLE 4.4 column 9 (IRT, FE-IV)
****************************************************************************


// Replication PKC Table 5, column 3
// Village fixed effects, instrumental variables (IV) and using IRT
set more off
foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall {

xi: ivreg2 `v' $xvar (logfmaleloans logmaleloans= ivf* ivm*) i.vilid, robust nocons
endog(logfmaleloans logmaleloans)

}


****************************************************************************
// TABLE 4.4 column 2 (Gllamm, OLS)
****************************************************************************


// Replication PKC Table 5, column 1
// Using OLS villages clustered and Gllamm to estimate latent variables
set more off

foreach v in scorem1 scorem2 scorem3 scorem4 scorem5 scorem6 scorem7 scorem8 scorem9 scoreall
{
reg `v' logfmaleloans logmaleloans $xvar $vvar, cluster(vilid) nocons
}


****************************************************************************
// TABLE 4.4 column 5 (Gllamm, FE)
****************************************************************************


// Replication PKC Table 5, column 2
// Using village fixed effects and Gllamm to estimate latent variables

set more off

foreach v in scorem1 scorem2 scorem3 scorem4 scorem5 scorem6 scorem7 scorem8 scorem9 scoreall
{
xi:reg `v' logfmaleloans logmaleloans $xvar i.vilid, vce(robust) nocons
}


****************************************************************************
// TABLE 4.4 column 8 (Gllamm, FE-IV)
****************************************************************************


// Replication PKC Table 5, column 3
// Village fixed effects, instrumental variables (IV) and using Gllamm
set more off
foreach v in scorem1 scorem2 scorem3 scorem4 scorem5 scorem6 scorem7 scorem8 scorem9 scoreall
{

xi: ivreg2 `v' $xvar (logfmaleloans logmaleloans= ivf* ivm*) i.vilid, robust nocons
endog(logfmaleloans logmaleloans)

}



****************************************************************************
// TABLE 4.5 column 2 (GSEM, FE)
****************************************************************************

cap log close
```

```
log using "$path/T045_GSEM",replace
cap estimates drop *

clear
set more off
use "$path/HHobservation002.dta", replace

// Group indicators according to PKC described in table A1, page 819
// These groups are used to estimate latent empowerment using IRT
* In this research: latent variable is women empowerment related to 9 factors:
* Purchasing; Resource; Finance; Transaction management; Mobility and networks; Activism; HH
attitudes; Husband's behavior; Fertility and Parenting


// Purchasing
global factor1 y1foodpurchase y2cosmeticpurchase y3candypurchase y4utensilspurchase
y5furniturepurchase y6kidclothe y7ownclothpurchase y16hrepairspending y19livestockspend
y22borrowspend y25landequimentspend y27wifecanbuyassset y28wbuywithoutperm
// Resource
global factor2 y29whasincoem y35whasinincome y36whasinsaving y37windesavingcontrol y38emerfund
y39emerassetsale y45remittance y46wdeciuseremit y47seizurebyhus y48freeremit y74wiincomesource
// Finance
global factor3 y20borrowdecision y21borrowimplement y22borrowspend y41emerfundfhusre
y42emerfundfownre y43emerfundlender y44emerfundother
// Transaction management
global factor4 y14hrepairdecision y15hrepairimplement y16hrepairspending y17livestockpur
y18livestockimple y19livestockspend y20borrowdecision y21borrowimplement y22borrowspend
y23landequimentdeci y24landequimentimplement y25landequimentspend
** avoil highly correlation
/*gen emerfun = 1 if y41emerfundfhusre==1 | y42emerfundfownre==1 | y44emerfundother==1
replace emerfun=0 if y41emerfundfhusre==0 & y42emerfundfownre==0 & y44emerfundother==0
gen reason = 1 if y33reasongowhus == 1 | y34reasongownei == 1
replace reason=0 if y33reasongowhus == 0 & y34reasongownei == 0
*/
//Mobility and networks
global factor5 y30wtravelalone y31reasonnotalone y32reasonnotsafe y33reasongowhus
y41emerfundfhusre y42emerfundfownre y44emerfundother y45remittance y50visitwoutpermi
y60confidantbari y61confidentoutside y63ownrelativessame y75mobility //y33reasongowhus
y34reasongownei y41emerfundfhusre y42emerfundfownre y44emerfundother
// Activism
global factor6 y51marriagehaska y52awareofkabi y53awareofinheri y54preremarri y55vote
y56voteinde y57proabuse y58dowrygood y59againstcorru y76preremarlocal y77preremarunion
y78wsocialobstacle y79wlarobstacle y80religionobstacle
//HH attitudes
global factor7 y26hussaywifeintel y27wifecanbuyassset y58dowrygood y64husbandsuperior
y66hussayempbett y67hussaychao y68problemkid y69losspeace y70familybetter
// Husband's behavior
global factor8 y26hussaywifeintel y40emerfundfhus y47seizurebyhus y49husforbidw
y62severityspouse y72husnegativeimpact y71posimpact
// Fertility and Parenting
global factor9 y3candypurchase y6kidclothe y8wbirthctmethod y9wbirthctuse y10childedu
y11wbirthtimming y12hubirthtimming y13wbirthnumber y65Hususebirthct y73wmakehuscontr


cap drop fscore1 fscore2 fscore3 fscore4 fscore5 fscore6 fscore7 fscore8 fscore9

// Estimate results
global xvar agemem edumem parentheadland broheadland sistheadland parentspouseland ///
sistspouseland brospouseland land agehead eduhead higedumale higedufemale
global vvar wagem wagef nowagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed

gsem (femalechoice malechoice  $xvar i.vilid -> PURCHASING, vce(robust) nocons) (PURCHASING ->
($factor1)@1, logit)
 predict fscore1, latent(PURCHASING)
 estimates store mimic1

gsem (femalechoice malechoice $xvar  i.vilid -> RESOURCES, vce(robust) nocons) (RESOURCES ->
($factor2)@1, logit)
 predict fscore2, latent(RESOURCES)
 estimates store mimic2

gsem (femalechoice malechoice $xvar  i.vilid -> FINANCE, vce(robust) nocons) (FINANCE ->
($factor3)@1, logit)
 predict fscore3, latent(FINANCE)
 estimates store mimic3
```

```
gsem (femalechoice malechoice $xvar  i.vilid -> TRANSACTION, vce(robust) nocons) (TRANSACTION
-> ($factor4)@1, logit) , nonrtolerance
/* Options control how results are obtained, from starting values,
//to numerical intergration, to how variance estinates are obtained
//vce(robust ot cluster clustvar)
//set tolerance() for determining convergence for the adaptive parameters; defaut is
tolerance(1e-8)
// convergence is declared when the relative change in the log likelihood is less than or
equal to the tolerance
*/ nonrtolerance to avoid not concave, this is one option to solve convergence problem
  predict fscore4, latent(TRANSACTION)
  estimates store mimic4

gsem  (femalechoice malechoice $xvar  i.vilid -> MIBILITY, vce(robust) nocons) (MIBILITY ->
($factor5)@1, logit), nonrtolerance
 predict fscore5, latent(MIBILITY)
 estimates store mimic5

gsem (femalechoice malechoice $xvar  i.vilid -> ACTIVISM, vce(robust) nocons) (ACTIVISM ->
($factor6)@1, logit),  nonrtolerance
 predict fscore6, latent(ACTIVISM)
 estimates store mimic6

gsem (femalechoice malechoice $xvar i.vilid -> ATTITUDE, vce(robust) nocons) (ATTITUDE ->
($factor7)@1, logit)
 predict fscore7, latent(ATTITUDE)
 estimates store mimic7

gsem (femalechoice malechoice $xvar i.vilid -> HUSBANDBH, vce(robust) nocons) (HUSBANDBH ->
($factor8)@1, logit) ,  nonrtolerance
 predict fscore8, latent(HUSBANDBH)
 estimates store mimic8

gsem (femalechoice malechoice $xvar  i.vilid -> FERPARENT, vce(robust) nocons) (FERPARENT ->
($factor9)@1, logit)
 predict fscore9, latent(FERPARENT)
 estimates store mimic9

 //factor10 (factorall)
gsem (femalechoice malechoice $xvar i.vilid -> FACTORALL, vce(robust) nocons) (FACTORALL ->
(y*)@1, logit)
 predict fscore10, latent(FACTORALL)
 estimates store mimic10

global fsrall fscore1 fscore2 fscore3 fscore4 fscore5 fscore6 fscore7 fscore8 fscore9

qui pca $fsrall
cap drop fsrall
predict fsrall, score
label variable fsrall "Factor all"

gsem (fsrall <- femalechoice malechoice $xvar i.vilid, vce(robust) nocons)

  etime
log close


**************************************************************************
// TABLE 4.6 column 2 (GSEM, OLS)
**************************************************************************


global xvar agemem edumem parentheadland broheadland ///
sistheadland parentspouseland brospouseland sistspouseland land agehead eduhead higedumale
higedufemale
global vvar wagem wagef nowagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed

set more off
gsem (logfmaleloans logmaleloans $xvar $vvar -> PURCHASING, vce(cluster vilid) nocons)
(PURCHASING -> ($factor1)@1, logit)
 predict fscore1, latent(PURCHASING)

gsem (logfmaleloans logmaleloans $xvar $vvar -> RESOURCES, vce(cluster vilid) nocons)
(RESOURCES -> ($factor2)@1, logit)
 predict fscore2, latent(RESOURCES)
```

```
gsem (logfmaleloans logmaleloans $xvar $vvar -> FINANCE, vce(cluster vilid) nocons) (FINANCE
-> ($factor3)@1, logit)
 predict fscore3, latent(FINANCE)

gsem (logfmaleloans logmaleloans $xvar $vvar -> TRANSACTION, vce(cluster vilid) nocons)
(TRANSACTION -> ($factor4)@1, logit)
  predict fscore4, latent(TRANSACTION)

gsem  (logfmaleloans logmaleloans $xvar $vvar -> MIBILITY, vce(cluster vilid) nocons)
(MIBILITY -> ($factor5)@1, logit)
 predict fscore5, latent(MIBILITY)

gsem (logfmaleloans logmaleloans $xvar $vvar -> ACTIVISM, vce(cluster vilid) nocons) (ACTIVISM
-> ($factor6)@1, logit)
 predict fscore6, latent(ACTIVISM)

gsem (logfmaleloans logmaleloans $xvar $vvar -> ATTITUDE, vce(cluster vilid) nocons) (ATTITUDE
-> ($factor7)@1, logit)
 predict fscore7, latent(ATTITUDE)

gsem (logfmaleloans logmaleloans $xvar $vvar -> HUSBANDBH, vce(cluster vilid) nocons)
(HUSBANDBH -> ($factor8)@1, logit)
 predict fscore8, latent(HUSBANDBH)

gsem (logfmaleloans logmaleloans $xvar $vvar -> FERPARENT, vce(cluster vilid) nocons)
(FERPARENT -> ($factor9)@1, logit)
 predict fscore9, latent(FERPARENT)

gsem (logfmaleloans logmaleloans $xvar $vvar -> FACTORALL, vce(cluster vilid) nocons)
(FACTORALL -> (y*)@1, logit)
 predict fscore10, latent(FACTORALL)


****************************************************************************
 // TABLE 4.6 column 3 (GSEM, FE)
****************************************************************************


set more off
gsem (logfmaleloans logmaleloans $xvar i.vilid -> PURCHASING, vce(robust) nocons) (PURCHASING
-> ($factor1)@1, logit)
 predict fscore1, latent(PURCHASING)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> RESOURCES, vce(robust) nocons) (RESOURCES ->
($factor2)@1, logit)
 predict fscore2, latent(RESOURCES)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> FINANCE, vce(robust) nocons) (FINANCE ->
($factor3)@1, logit),  nonrtolerance
 predict fscore3, latent(FINANCE)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> TRANSACTION, vce(robust) nocons)
(TRANSACTION -> ($factor4)@1, logit)
  predict fscore4, latent(TRANSACTION)

gsem  (logfmaleloans logmaleloans $xvar i.vilid -> MIBILITY, vce(robust) nocons) (MIBILITY ->
($factor5)@1, logit)
 predict fscore5, latent(MIBILITY)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> ACTIVISM, vce(robust) nocons) (ACTIVISM ->
($factor6)@1, logit)
 predict fscore6, latent(ACTIVISM)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> ATTITUDE, vce(robust) nocons) (ATTITUDE ->
($factor7)@1, logit)
 predict fscore7, latent(ATTITUDE)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> HUSBANDBH, vce(robust) nocons) (HUSBANDBH ->
($factor8)@1, logit)
 predict fscore8, latent(HUSBANDBH)

gsem (logfmaleloans logmaleloans $xvar i.vilid -> FERPARENT, vce(robust) nocons) (FERPARENT ->
($factor9)@1, logit)
 predict fscore9, latent(FERPARENT)
```

```
gsem (logfmaleloans logmaleloans $xvar i.vilid -> FACTORALL, vce(robust) nocons) (FACTORALL ->
(y*)@1, logit)
 predict fscore10, latent(FACTORALL)


**************************************************************************
// TABLE 4.7
**************************************************************************

*Test endogeneity and validity of IVs
// replication Table 4.4 column 9
// Fixed effect with Instrument variables (IV)

set more off
foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall {

xi: ivreg2 `v' $xvar (logfmaleloans logmaleloans= ivf* ivm*) i.vilid, robust nocons
endog(logfmaleloans logmaleloans)

}

foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall {

xi: ivreg2 `v' $xvar (logfmaleloans logmaleloans= ivf* ivm*) i.vilid, nocons
ivendog
ivendog logfmaleloans
ivendog logmaleloans
}


**************************************************************************
// TABLE 4.8 (LASSO)
**************************************************************************


clear
global path "C:\Users\dtv13\Dropbox\DIEM PhD Program\2020.Chapter3_PKC\Data\"
etime, start
cap log close
log using "$path/Robutness",replace
set more off
use "$path\HHobservation002.dta"

// Keep using variables
keep theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 theta10 factorall vilid
agemem edumem parentheadland broheadland sistheadland parentspouseland brospouseland
sistspouseland land agehead eduhead higedumale higedufemale malechoice femalechoice
logfmaleloans logmaleloans mpart fpart

// Dummy villages
tab vilid, gen(ivvil)
global vilvar ivvil2 ivvil3 ivvil4 ivvil5 ivvil6 ivvil7 ivvil8 ivvil9 ivvil10 ivvil11 ivvil12
ivvil13 ivvil14 ivvil15 ivvil16 ivvil17 ivvil18 ivvil19 ivvil20 ivvil21 ivvil22 ivvil23
ivvil24 ivvil25 ivvil26 ivvil27 ivvil28 ivvil29 ivvil30 ivvil31 ivvil32 ivvil33 ivvil34
ivvil35 ivvil36 ivvil37 ivvil38 ivvil39 ivvil40 ivvil41 ivvil42 ivvil43 ivvil44 ivvil45
ivvil46 ivvil47 ivvil48 ivvil49 ivvil50 ivvil51 ivvil52 ivvil53 ivvil54 ivvil55 ivvil56
ivvil57 ivvil58 ivvil59 ivvil60 ivvil61 ivvil62 ivvil6 ivvil64 ivvil65 ivvil66 ivvil67 ivvil68
ivvil69 ivvil70 ivvil71 ivvil72 ivvil73 ivvil74 ivvil75 ivvil76 ivvil77 ivvil78 ivvil7 ivvil80
ivvil81 ivvil82 ivvil83 ivvil84 ivvil85 ivvil86 ivvil87 ivvil88 ivvil89 ivvil90 ivvil91
ivvil92 ivvil93 ivvil94 ivvil9 ivvil96 ivvil97 ivvil98 ivvil99 ivvil100 ivvil101 ivvil102
ivvil103 ivvil104

// Lasso procedure
vl set
vl list vluncertain
vl move (edumem agehead eduhead higedumale higedufemale) vlcontinuous
macro list vlcategorical
macro list vlcontinuous
vl create ccbase = vlcontinuous - (theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8
theta9 theta10 factorall logfmaleloans logmaleloans vilid iv*)
vl create fcbase = vlcategorical - (malechoice femalechoice mpart fpart ivvil*)
macro list ccbase
macro list fcbase
vl create choice = (malechoice femalechoice)
vl create finstbase = ($vilvar parentheadland broheadland sistheadland parentspouseland
brospouseland sistspouseland)
```

```
vl create cinstbase = (agemem edumem land agehead eduhead higedumale higedufemale)
macro list finstbase
macro list cinstbase
macro list choice

// control variables and instrument variables (interact between choice and control variables)
vl substitute contvars = c.ccbase##c.ccbase c.ccbase##i.fcbase i.fcbase##i.fcbase
vl substitute inst =  i.choice#c.cinstbase   i.choice#i.finstbase
macro list contvars
macro list inst

set emptycells drop


// TABLE 4.8 column 2 (LASSO, FE)
// Lasso FE regression
foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall theta10
{
xporegress `v' logfmaleloans logmaleloans i.vilid, controls($contvars) rseed(12345)
vce(robust)
lassoinfo
}


// TABLE 4.8 column 3 (LASSO, FE-IV)
// Lasso FE-IV regression

foreach v in theta1 theta2 theta3 theta4 theta5 theta6 theta7 theta8 theta9 factorall theta10
{
xpoivregress `v' (logfmaleloans logmaleloans = $inst) i.vilid, controls($contvars)
rseed(12345) vce(robust)
dis "Inst_select: " e(inst_sel)
dis "Inst_select: " e(controls_sel)
lassoinfo
}

etime
log close
```

Chapter 5. The impact of microcredit on women’s empowerment: Evidence from Vietnam

5.1 Introduction

Microcredit is widely touted as a useful tool to improve women's empowerment (Gan, Nartea, & Xia, 2017; Sondhi & Bala, 2019). The influence of microcredit on female empowerment has received considerable research attention, and produced a wide range of estimates. Different results among studies may be due to differences in the definition of women's empowerment, and differences in methodologies, countries, and time of estimations.

In the previous chapter, using Bangladesh data, I replicate PKC paper which states that microcredit improves female empowerment if females borrow loans while it negatively impacts female empowerment if males borrow loans. My replication and robustness results support female empowerment enhancement through microcredit, but the effects are smaller. However, my findings suggest little evidence if male microcredit has an impact on female empowerment. This study aims to expand on the previous study's results in which the estimation of microcredit on empowerment of women is explored by using a dataset in Vietnam.

Vietnam is a developing country located in South East Asia and represents an appropriate field for the study in several aspects. First, the country has similar characteristics to Bangladesh. Vietnam has more than seventy percent of the population living in rural areas, and most of the poor live rurally. Second, the Vietnamese government has implicated microcredit policy as an important tool to support poor people and target enhancing gender equality in rural areas. Most studies focus on whether microcredit significantly improves household income, consumption, social networks and successfully alleviates poverty (H. A. Duong & Nghiem, 2014; C. T. Phan et al., 2019). However, few writers have investigated the effect of microcredit on women and women's empowerment using Vietnamese data. Hence, this chapter examines empowering women through microcredit, new evidence from Vietnam.

This study applies a mixed methodological approach. Microcredit impact is estimated by two forms; microcredit participation and microcredit amount of borrowing by gender. Empowerment is a latent variable that is reflected in responses to a set of survey questions. This study employs Item Response Theory (IRT) to measure the latent empowerment variable. Similar to Bangladesh data, empowerment responses in Vietnamese data are binary. Therefore, IRT model is used to estimate women's empowerment indicators (Maydeu-Olivares et al., 2011). Although factor analysis (FA) is a common method to estimate latent variables, this method often fits a set of observed continuous variables. When applied to discrete data, FA is always misspecified in some context while IRT models should fit the discrete and ordinal data better than FA models in applications. This empowerment variable is then used as the dependent variable in an empirical model that estimates the impact of microcredit participation and borrowing.

To address limitations in selecting the specification model in previous studies, I employ Directed Acyclic Graphs (DAGs) to create a causal diagram to minimize bias in empirical practice. DAGs enable one to select appropriate covariates for the practical model. Showing in graphs, DAGs help researchers think clearly about the interrelations between variables to avoid variables that would block the direct effects of microcredit on women's empowerment. In addition, I use the fixed-effects and instrument variables method to correct bias from unobserved household and province-level heterogeneity.

Using a Vietnamese dataset of rural households surveyed over the period of 2008-2010, I find weak evidence that microcredit participation and microcredit amount of borrowing positively impact female empowerment if accessing microcredit is done by females in the household, but only on certain dimensions of female empowerment, and the sizes of the effects are small. In contrast, there is no evidence that microcredit participation or borrowing by males show affects female empowerment.

I use a wide variety of estimation procedures to estimate the effects of microcredit. These include fixed effects linear regression, instrumental variables, Lasso (for variable selection), propensity score matching and augmented inverse propensity score weighting, and full information maximum likelihood to accommodate missing values in the data. There are some approaches to deal with missing data. The conditional approach is 'listwise deletion'. This method may cause a loss of statistical power. The other common methods are multiple imputations (MI) and maximum likelihood (ML). MI involves substituting missing values with predicted values multiple times, using observed data. MI includes separate steps of imputation and analysis. To be effective, the imputation model, used to predict the missing observations, has to be "congenial" with the main equation being estimate. That is not an issue with ML because everything is done with a single model. ML could produce similar MI's results but ML is simpler.

The chapter proceeds as follows: Section 5.2 briefly reviews related literature. Section 5.3 discusses the methodology and empirical framework. Section 5.4 presents data and variables. Section 5.5 analyzes empirical results. Section 5.6 conducts robustness results, and Section 5.7 concludes.

5.2 Literature review

5.2.1 Microcredit in Vietnam

In the last decades, microcredit has been seen as one of the efficient developing policies.[16] It aims to provide small capital to impoverished people, especially targeting poor women for income generating by self-employment activities (Nawai & Shariff, 2010). Due to a lack of

[16] The terms of microcredit and microfinance are often used interchangeably in the literature; however, these concepts differ. Microcredit refers to small loans, whereas microfinance includes microcredit and other financial services such as money transfers, payment, savings, insurance, and among others. Microcredit is one component of microfinance. This study focuses on microcredit content as small loans provided to low-income households.

physical collateral, low-income families often fail to get approved for loans in the formal financial sector. In order to obtain money to fund their essential production and consumption, poor households seek credit from informal sources but often with higher interest rates and shorter lending periods. Accessing loans with high-interest rates has been considered a burden on low-income families because it erodes their income and leads poor borrowers into a "credit trap," a cycle of debt and poverty. Governments in developing countries have introduced microcredit programs to help low-income households.

In Vietnam, after the *"Doi moi"* reform in 1986, microcredit was introduced through several channels via international organizations, non-organizations, and bilateral development programs. The main aims of these programs were poverty alleviation and income parity. In the early 1990s, the Vietnamese government established a national poverty alleviation program, where microcredit was included as one of the critical tools. The government provided credit through national banks and subsidized policy lending institutions. Prominent among these was the Vietnam Bank for Agriculture, established in 1988 for financial support to the poor, which mainly focused on agricultural sector. It was later named as Vietnam Bank for Agriculture and Rural Development (VBARD).

To meet an increasing credit demand in the growing economy, People's Credit Funds (PCFs) were introduced in 1993. PCFs are rural microcredit institutions that provide loans and financial services to local farmers at commune levels. PCFs aim to form groups of donors to increase their capital, and then the PCFs offer saving and credit services to the poor. PCFs also promote assistance among its members and self-help groups.

Most of the funds of microcredit institutions comes from the Vietnamese government and donors. Several foreign donors that significantly contribute to the development of microcredit in Vietnam are the World Bank, the Asian Development Bank, International

Monetary Fund and other aid programs. Although the public financial system has tried to offer convenient services to rural people and has dominated the credit market, formal credit is still insufficient to meet microcredit demand. Therefore, semi-formal and informal sectors exist to fill the demand gap. Currently, microcredit is provided by three main categories in Vietnam: formal, semi-formal and informal sectors.

5.2.1.1 Formal sector

The two state-owned banks, namely VBARD and the Vietnam Bank for Social Policy (VBSP), are the main microcredit providers in Vietnam. In 1995, target customers of the VBARD were mainly in agricultural sectors and rural areas. Since then, its customer base has increased rapidly. The VBARD served 3.5 million households in 1996. This number increased to 13.5 million by 2019 (VBARD, 2019). The VBARD targets clients who meet the requirement of collateral for their loans. Although the poor are not direct VBARD's target customers, approximately 47% of its clients are poor.

In 1995, the government started to provide microcredit to the poor via the Fund for the Poor, which was replaced by a Vietnam Bank for the Poor (VBP). The VBP was managed by VBARD. The VBP aims to provide low-interest rate credit to low-income families that require less or no collateral and flexible payment requirement. Households that are classified as "poor" by the local commune's People Committee and the Ministry of Labor, Invalids, and Social Affairs of Vietnam (MOLISA), or are sponsored by the Women's Union or Farmer's Union, are eligible to access low-interest loans.

In 2003, the VBP was reorganized to become the VBSP that was independent of the VBARD. It takes over the small-scale microcredit and the poverty-alleviation programs managed by VBARD. The VBSP is the leading microcredit provider to low-income households and has become a primary channel to deliver many government lending programs to the poor in rural areas (Lensink & Pham, 2012). According to the Vietnam Access to Resources Household Survey (VARSH) in 2016, VBSP provides credit to 58.3% of the surveyed rural poor households, followed by the VBARD with 23.8%. The PCFs share 3% of the rural credit market.

5.2.1.2 Semi-formal sector

The semi-formal sector includes microcredit institutions that are registered as banks with particular characteristics. Generally, the semi-formal lenders are the non-government institutions operated by non-for-profit Non-government Organizations (NGOs). They provide loans that are paid in small, frequent and manageable installments. Mass Organizations[17] (MOs) and NGOs are leading semi-formal microcredit providers in Vietnam. The MOs play a role as social mediation to facilitate the lending processes. They establish networks from the central government to commune levels. These social groups assist microcredit programs in seeking customers, scanning potential clients, performing transactions and monitoring loan used and repayment.

The semi-formal groups connect with VBARD, VBSP and government programs to help look for and assess customers. The government programs involving MOs are directed towards poverty alleviation. NGOs provide finance targets for the poor and offer non-financial activities such as training or/and education. The semi-formal sector is relatively minor and accounts for 5-10% of the overall rural credit market. This number is insignificant when compared to the number of borrowers served by the formal sector. However, the semi-formal tends to serve the remote areas in Vietnam where the formal sector is unable or unwilling to go (C. T. Phan, 2020).

[17] Key MOs in Vietnam are social unions, the Women's Union, the Farmer's Union, the Youth Union, Veterans Association, and Elderly Association.

5.2.1.3 Informal sector

The informal sector providers include moneylenders, relatives, friends, and other provide financial groups. The informal sector is also a common microcredit provider to rural families. Usually, VBARD and VBSP offer credit for investment purposes. The remaining customers, who need loans for consumption, especially before harvests, depend on informal moneylenders. These loans are often small scale as well as short-term (Le & Tran, 2005). The interest rates charged by these types of providers vary. Loans that come from relatives and friends are primarily free of charge. While moneylenders offer a wide range of services, including loans for consumption with a simple procedure to meet urgent demand, they charge high interest rates to compensate for their risks. According to the VARSH 2016, the informal sector accounts for 27% of the rural credit market.

5.2.2 Gender equality status in Vietnam

Gender inequality still exists in Vietnamese society. Women have many responsibilities in their families, including taking care of children and older people, doing household works and participating in labor market to generate income for families. However, in Vietnamese culture and attitude, men are the core people and main decision-makers in their families. In Asian culture, men are likely to have more rights and more important roles in families than women (Dineen & Le, 2015).

The unequal status of women is reflected in domestic violence, which is often unreported. Among the reasons that have been given for why women do not report domestic violence is that they consider it normal, have weak attitudes about gender equality, or wish to avoid the social stigma associated with reporting domestic violence (Bulte & Lensink, 2019). Approximately 31% of women who were asked about domestic violence answered that they had experienced physical abuse (Krause, Gordon-Roberts, VanderEnde, Schuler, & Yount, 2016). These created unbalanced gender situations in Vietnamese society, especially in rural areas. It lacks strong foundations concerning women's rights. The gender inequality problem is far more severe in families where women do not have an independent income.

In past decades, the government has made a strong effort to enhance gender equality and has gained considerable results. First, the status of Vietnamese women has greatly improved. According to the Gender Equity Index (GEI) (World Economic Forum) 2021, Vietnam ranked 6^{th} below the Philippines, Laos, Singapore, Timor-Leste, and Thailand, in South East Asia.

Second, many national policies on women have been implemented, including the Law on Gender Equality in 2006 and the Law on Domestic Violence in 2007. The former provides further regulations for gender equality and addressing gender disparities. It also calls for equity gender in public administration. The latter provides rules which help protect women against domestic violence. Moreover, the Women's Union plays a role in implementing women's supporting programs such as education, health care, awareness of domestic violence, and development projects such as microcredit and microenterprise.

Although gender gap has had an impressive reduction in the last decades, globally, Vietnam is at 87^{th} over the report ranks 156 countries in 2021. In addition, gender disparity is still observed in education, job opportunities and politics between males and females in Vietnam. Almost 80% of Vietnamese women participate in the workforce, compared to 86.4% of men. The schooling years for females are on average 8.0 years, compared to 8.6 years for males. The estimated gross national income per capita is higher for males, 6644$ compared to 8224$. In terms of The Economic Participation and Opportunity index, the gap is 0.765 females participating in economic activities compared to one male. Education attainment is 0.982/1 ratio female/male. The area where gender gaps remain the widest is Political Empowerment, 0.113/1 for female/male. (Source World Economic Forum report 2021).

5.2.3 Microcredit and women's empowerment

Women's empowerment has been considered a substantial component of development. However, gender inequality is more serious in many developing countries in terms of women's unequal access to economic resources, labor market, and social and political activities. Women are more credit-constrained, unequal share of power in household decision-making, higher unemployment rates than men. In this context, microcredit is often considered a simple approach to improve financial services accessing of women.

Given more power in controlling finances and resources, women tend to participate in the labor market, develop community projects, and spend more on education, health, and nutrition. These reduce unemployment, generate more income, and improve human capital and economic growth (Duflo, 2012). In addition to financial benefits, an increase in women's roles in the household economy results in enhancing their empowerment (Alhassan & Akudugu, 2012; Garikipati, 2008). Higher women's empowerment also contributes to more balanced sex ratios at births (L. Phan, 2016).

In the 1990s, microcredit programs targeting poor women in developing countries became important policies of development organizations. Within the microcredit literature, many studies pay attention to the empowerment of women topics (Al-shami, Razali, & Rashid, 2018; Debnath et al., 2019; Kulb, Hennink, Kiiti, & Mutinda, 2016; Li et al., 2011). However, there is no consensus from research findings on microcredit and female empowerment. This is partly due to methodological inconsistencies in the definition and measurement of empowerment and different approaches to solving endogeneity issues.

On the one hand, recent evidence suggests that the provision of microcredit does not empower women. Crépon, Devoto, Duflo, and Parienté (2015) used a 2008-2010 household survey from rural areas of Morocco to estimate household lending programs on female empowerment. They constructed a summary index of women's involvement in making decisions, their mobility inside and outside the village as a women’s empowerment index. By utilizing a randomized control survey, the authors found no evidence of microcredit effect on any empowerment index. Banerjee et al. (2015) analyzed the intent to treat impact of group-lending microcredit programs in Hyderabad, India, over the 2005-2010 period. They used women’s decision-making as a measure of women’s bargaining power (empowerment proxy). They compared results between treatment and control groups and found no significant changes in women’s empowerment. Atmadja et al. (2016) evaluated the impact of microfinance on women-owned microenterprises using a sample of 136 women-owned enterprises in Surabaya, Indonesia in 2010. They estimated that microfinance negatively affects women's microenterprises, decreasing women’s income and in turn leading to a decrease in women-empowerment.

On the other hand, many studies report that microcredit positively influences female empowerment. Pitt et al. (2006) evaluated the effects of microfinance on women’s empowerment in Bangladesh from 1998-1999. Control and treatment groups were formed to estimate the average treatment effects. They used nine categories of decision-making to measure women’s empowerment: purchasing decision-making; resources; finance; transaction management; mobility and networks; activism; household attitudes; husband’s behavior; and fertility and parenting. Using instrument variables, fixed effects, and structural equation models, they estimated a positive impact on female empowerment when females borrowed loans and a negative effect if males borrowed money.

A recent study by Asad et al. (2020) evaluated the role of microfinance services on female empowerment in Pakistan. They found that microcredit, micro-saving, and micro-insurance significantly increase women-empowerment. They defined women's empowerment based on four indicators: freedom of mobility, economic security, family decision-making, and household economic power. Mtamakaya, Jeremia, Msuya, and Stray-Pedersen (2018) employed logistic regression to examine the credit participation impact on 18 indicators of female empowerment. They found that microcredit empowers women in Tanzania.

In summary, previous research shows that participation in microcredit programs has mixed outcomes for women's empowerment status. Contributing to the strand of literature, this chapter investigates whether microcredit impacts women's empowerment in rural Vietnam. Vietnam offers interesting evidence because the country has been considered one of the successful samples of promoting gender equity and applying microcredit. A better understanding of the contribution of microcredit to the improvement of female empowerment and its implications are important and helpful for policymakers in Vietnam and other countries.

Moreover, there is not much literature on this topic for Vietnam. There are a few studies that investigate the microcredit impact on female empowerment using data from specific provinces in Vietnam. Dineen and Le (2015), using a sample of 50 microcredit borrowers in Quang Tri province in 2008 and 2012, analyzed the enhancement of women's empowerment through an integrated microcredit program. Empowerment was calculated by the mean of 12-interview questions that related to women's empowerment and used Likert type 5-point scales. They used Ordinary Least Squares to estimate the change in income and training on women's empowerment after women accessed microcredit. The results supported microcredit leading to higher income and greater gender equality.

Nguyen (2018) employed data from the Impact Assessment Survey conducted by the TYM Fund in 2007, which is one of three regulated microfinance institutions in Vietnam and a part of the Vietnamese Women's Union. The sample included 544 clients collected from Northern Vietnam. The author estimated the influence of microcredit participation on economic and social aspects representing female empowerment. He measured empowerment based on three achievement dimensions: change in economic power, change in major household decision-making, and change in community activities. The empowerment index is the sum of the three dimensions. Logistic regression results support the hypothesis that a woman participating in microcredit programs enhances her empowerment in decision-making and community involvement.

Together, it can be seen that little attention is devoted to investigating the effect of microcredit on female empowerment in Vietnam. Most previous studies use primary data from a specific province sample or have been carried out in an area that leads to the results not being nationally representative. This study uses a national panel dataset that covers data from 12 provinces from the North, Central, and South of Vietnam to fill this gap. As such, it provides a more comprehensive assessment of the impact of microcredit on female empowerment of rural Vietnamese households. In addition, this study employs various methodologies to deal with endogeneity issues and bias estimations that have not been dealt with in the previous studies.

5.3 Methodology and empirical framework

5.3.1 Measuring women's empowerment

Different papers measure women's empowerment differently. According to Sharaunga, Mudhara, and Bogale (2019), a sense of agency and capacity to control resources are the appropriate proxies of female empowerment. Empowerment of women is a process in which women can take control of their choices, actions, and lives (Kabeer, 1999; Petesch, Smulovitz, & Walton, 2005). Similarly, the World Bank states that empowerment is freedom of choice and action to decide how one lives (Narayan-Parker, 2002). Schuler and Hashemi (1994) define another view of empowerment as a function of economic, social, and political power, freedom in physical mobility, and freedom from domestic domination and violence. Empowerment can be financial, social, or political (Kapila et al., 2016). Although definitions of empowerment are not identical in the literature, they generally conceptualize empowerment as a process or outcome in which women can control their choices and lives.

It is argued that women in developing and underdeveloped countries are limited in terms of asset ownership, the ability to spend money independently, and freedom of movement. This study focuses on four related dimensions of women's empowerment: (1) involvement in household decision-making, (2) mobility, (3) financial transaction management, and (4) input in family planning and decisions about bearing children. I also measure general women's empowerment, *'factor all,'* by encompassing all four of the above factors.

Table 5.2 lists all of the observed indicators, grouped by the respective empowerment factors. Because most of the answers are binary, I employ the IRT one-parameter logistic model (IRT–1PL) [18] to estimate each of the five empowerment factors:

$$R_{qit} = T_{qt} + \lambda_{it} \text{ (Equation 5.1)}$$

where R_{qit} is Response of household (HH) i to question q at time t; T_{qt} represents a question-specific threshold for a positive response to question q at time t; and λ_{it} is a latent measure of women's empowerment of HH i at time t.

These empowerment factors are then used as dependent variables in empirical models that estimate the impact of microcredit participation/borrowing and a series of observable behaviors on women's empowerment.

5.3.2 Using DAGs to build up an empirical model

Establishing causal relationships is challenging. Traditionally, studies include as many control variables as possible to address omitted variable bias. The choice of control variables

[18] More details are presented in Section 4.2.1 this thesis.

is based on model assumptions and availability of data. The inclusion of more controls is often seen as resulting in improved ability to establish causal relationships (Spector & Brannick, 2011). However, there are sometimes good reasons to omit relevant variables from regressions (Westfall & Yarkoni, 2016). According to Elwert and Winship (2014), researchers should not include "colliders"[19] and "mediators"[20] if their interest is in estimating the total effect of the treatment variable on the outcome variable. Colliders, which are related to sample selection, induce spurious correlations between the treatment variable and the outcome variable. Mediators block the indirect effect of the treatment variable on the outcome variable (Rohrer, 2018). Previous research has generally ignored these issues in their effort to include "the kitchen sink" as control variables.

To clarify the nature of the causal relationship between microcredit and empowerment, this research employs Directed Acyclic Graphs (DAGs). DAGs provide a graphical representation of the key concepts of relevance, including exposure, outcome, causation, confounding and bias. They help researchers think clearly about the interrelations between variables, and guide selection of the appropriate covariates for research models (Williams, Bach, Matthiesen, Henriksen, & Gagliardi, 2018). DAGs also provide principled procedures for considering removing covariates that cause bias estimation through adjustment (Textor, van der Zander, Gilthorpe, Liśkiewicz, & Ellison, 2016).

This chapter looks at the relationship between microcredit participation/borrowing by gender and women's empowerment. The hypothesis is that females participating in microcredit or a continuous variable that measures how much of the loans the person received (the exposure) leads to increase her empowerment (the outcome) (Figure 5.1). I can observe that a household

---

[19] A collider is converted of two paths; A→C←B; representing selection bias.
[20] A mediator is a variable in the middle of a chain; A →C→B; The conditional association between A and B given C does not identify the causal effect of A and B.

with female participation in microcredit has an average of empowerment at x, whereas those who did not participate in microcredit have a level of empowerment at y. However, I cannot compare x and y to conclude whether participation in microcredit enhances female empowerment without considering the effects of other variables.

Figure 5.1 A simple DAG predicting a causal relationship in which microcredit has an impact on female empowerment

Individuals who receive loans likely differ in other characteristics such as education, gender, age and other variables. These variables may affect female empowerment. These covariates could potentially fully account for differences in women's empowerment between treatment and control groups. In addition, these variables may also affect microcredit participation/borrowing. Therefore, *"common cause"* factors that affect both microcredit and female empowerment but are not directly in the causal pathway need to be controlled in the model.

"*Common cause"* variables include household head's characteristics (HH head's age, HH head's education and HH head's gender), female characteristics (age of female spouse, number of male/female children) and household characteristics (HH size, number of dependent members, ethnicity, highest male diploma and female diploma in HH, loans in a previous year). These variables are defined as potential confounders, which affect more than one variable in DAGs model. If confounders are not controlled, this could lead to biased results and incorrect conclusions about the true relationship between microcredit (the exposure) and women's empowerment (the outcome) (Williams et al., 2018). The DAGs encode these causal assumptions in Figure 5.2.

DAGs are a powerful method that can guide the specification of estimation models. An attractive feature of DAGs is that they can be used to identify confounding bias. Firstly, all variables that affect microcredit but have no causal impact on other variables in DAGs do not need to be included in the model (such as interest rate, microcredit providers and so on) (Elwert, 2013). These variables do not help in explaining the causal effect between microcredit and empowerment. Secondly, variables that are considered as colliders or mediators should not be controlled in the model. They may add more or remove away the actual value of the causal effect (Rohrer, 2018).

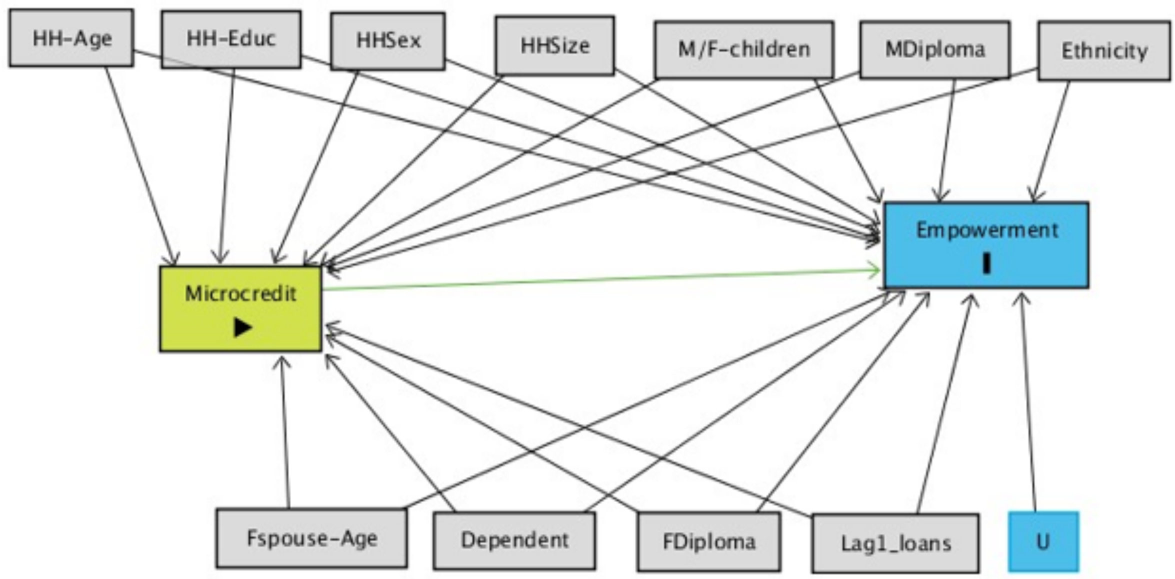

Figure 5.2 An extension of Figure 5.1. Characteristics of HH head, female characteristics and HH characteristics affect both microcredit and female empowerment (adjusted variables), and microcredit has an effect on empowerment.

For example, Figure 5.2 can extend to Figure 5.3 by adding assets/or income into the model. Assets/income variables are mediators of the effect of microcredit and women's empowerment. Microcredit would affect assets/income, which would, in turn, affect empowerment variable. Controlling for mediators would block the indirect causal pathway between microcredit and female empowerment. This causes an incomplete estimate of the impact of accessing microcredit. Hence, this study uses an analysis model without controlling these variables, as presented in Figure 5.2. Unfortunately, confounders are unlikely to completely control all of the causal effects due to residual confounding. This is represented by "U" in the DAG below. Our assumption is that the effect of this confounder is negligible.

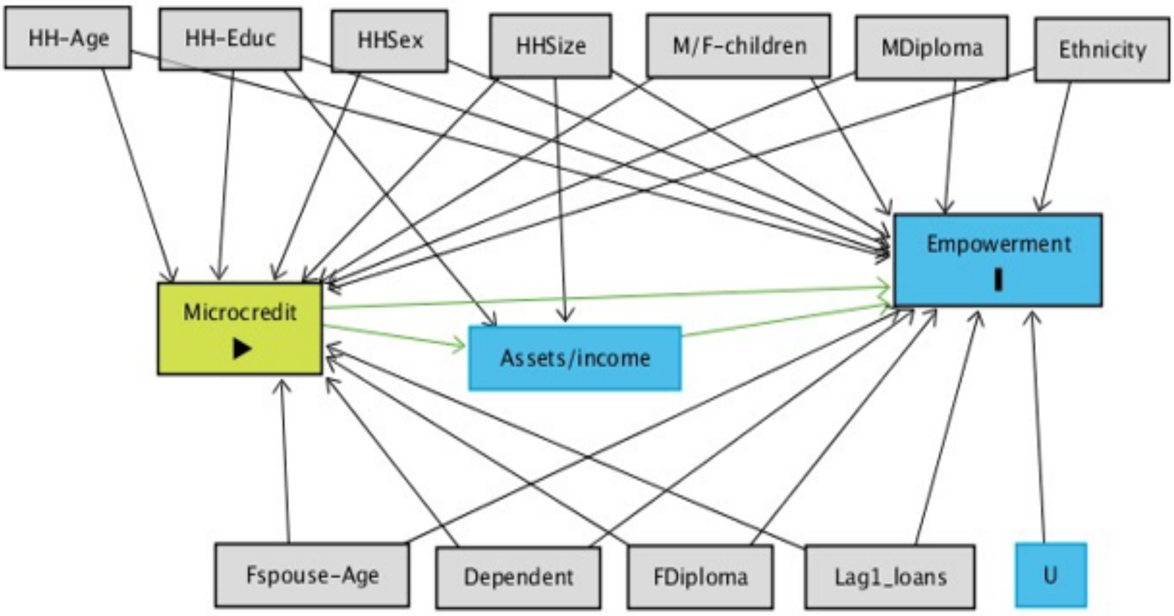

Figure 5.3 A DAGs expending Figure 5.2 by adding "Assets/income" into the model. In this model, other variables (excepting assets/income) confound the association between microcredit and female empowerment, but simultaneously assets/income is a mediator of the effect of microcredit on empowerment.

DAGs are non-parametric nature. Researchers employ DAGs to determine which variables should be included and which need to be removed from the empirical model. After using DAGs to draw model specifications, regression analysis for analyzing the model is needed. The following subsection presents parametric methods that are used to estimate the quantitative impact of microcredit on female empowerment, based on the DAG above.

5.3.3 Estimating the impact of microcredit participation and amount of microcredit borrowing on women's empowerment

It is expected that after accessing microcredit, female borrowers can run small businesses and generate self-employment activities. These help them increase their income, which increases their ability to spend money independently, be involved in household decision-making, and have input in family planning decisions. Participating in microcredit may also help them expand social networks via the Women's Union or Famers' Union, and improve freedom of movement. Meeting with other people and participating in miniature training courses provided by microfinance institutions can lead to an increase in women's awareness of politics and law. These activities might enhance their empowerment.

Using Equation 5.2 and Equation 5.3, I test whether women's participation in microcredit is positively associated with empowerment via the five empowerment factors described above[21]. I use two formulations of the treatment variable: a microcredit participation dummy (D) and a variable measuring amount of microcredit borrowing (C). In addition, I evaluate the effect of microcredit on female empowerment when the loans are given to men.

$$\lambda_{it} = D_{it}^{m}\delta_m + D_{it}^{f}\delta_f + X_{it}\beta + \mu_i + \varepsilon_{it} \qquad (5.2),$$

$$\lambda_{it} = C_{it}^{m}\rho_m + C_{it}^{f}\rho_f + X_{it}\beta + \mu_i + \varepsilon_{it} \qquad (5.3)$$

where λ_{it} is a measure of women's empowerment factor for household (HH) *i* at time *t*; D_{it}^{m} and D_{it}^{f} are program participation dummies for males and females in HH i at time *t*, respectively; C_{it}^{m} and C_{it}^{f} are credit amounts that males and females of HH i borrow, respectively, at time *t*; X_{it} is vector of characteristics (e.g., age of HH head, HH head education,

[21] (1) Household decision-making; (2) Mobility; (3) Financial transaction management; (4) Family planning and childbearing; and (5) Factor all, encompass all of factors.

HH size,…) of HH i at time t; μ_i is unobserved, time–invariant fixed effect for HH i; ε_{it} is an unobserved error that varies across households; and δ_m, δ_f, ρ_m and ρ_f are the treatment effects, which are the parameters of interest.

The coefficient δ_f (δ_m) represents the average effect of female (male) microcredit participation on women's empowerment factor λ_i at time t. Similarly, the coefficient ρ_f (ρ_m) represents the average effect of the amount borrowed by females (males) on women's empowerment factor λ_i at time t. The treatment groups are households where women/men participate/borrow in credit programs. Control groups consist of non–participants in microcredit programs by gender. These estimates measure the average treatment effects on the treated (ATT).

To estimate Equation 5.2 and Equation 5.3, I employ various methods including structural equation modeling (SEM), Lasso, instrumental variables, propensity score matching, augmented inverse propensity score matching, and maximum likelihood procedures to address missing data.

5.4 Data and variables

5.4.1 The Vietnam Access to Resources Household Survey

This chapter uses a two-year panel household survey data from Vietnam Access to Resources Household Survey (VARHS)[22] in 2008 and 2010. The VARHS is a panel dataset constructed biannually by Vietnam's government institutions[23] in collaboration with the

[22] The dataset can be downloaded from the United Nations University (UNI-WIDER) website https://www.wider.unu.edu/database/viet-nam-data

[23] The Vietnamese government's institutions include the Central Institute for Economic Management (CIEM), the Ministry of Planning and Investment (MPI), the Centre for Agricultural Policy, the Institute of Labor Science and Social Affairs of Vietnam, and the Development Economics Research Group Vietnam.

University of Copenhagen, Denmark. VARHS is a large-scale survey. The surveys are conducted in the rural areas of 12 selected provinces, ranging from the North to the South of the country[24]. Communes, which are local jurisdictions, are randomly chosen from the 12 provinces. Then, households are randomly selected from each selected commune.

The survey is designed to be nationally representative of rural households in Vietnam. It targets the population of poor rural families and women in remote areas. It provides a wide range of detailed information on household demographics, education, health, agriculture, non-agriculture, agricultural production, household consumption, savings, assets, employment, housework, land law, and credit. Survey data are available from 2008-2016. However, only the 2008 and 2010 surveys include questions on women's empowerment. Therefore, I use the data from these years to test the effects of microcredit participation on female empowerment.

There are 2,278 and 2,245 households in the 2008 and 2010 surveys, respectively. After dropping outliers[25], 4,499 observations remain; 2,265 from 2008 and 2,234 from 2010. Of these, 2,117 households participated in microcredit (nearly a half of the sample).

5.4.2 Latent measures of women's empowerment

Table 5.1 reports information about the 19 questions used to measure women's empowerment. Highlighted variables are coded in three categories ("Wife alone=2", "Wife jointly with husband or someone=1", "Husband or someone alone=0"). Other variables are binary. The questions span four thematic categories: 1. Sharing in household decision-making,

[24] These provinces include Ha Tay, Lao Cai, Phu Tho, Lai Chau, Dien Bien, Nghe An, Quang Nam, Khanh Hoa, Daklak, Dak Nong, Lam Dong, and Long An.

[25] The outliers include observations with "negative value" of amount of borrowing or income, households' heads less than 18 years old, and unusual distance from households to commune center or people's committees. A commune is "a type of third-tier subdivision" of Vietnam. It includes some small towns and usually is on average 29.67 km squares. Therefore, if a reported distance from a household to its commune's center or people's committee is large such as over 500km to 1000km, it is treated as outliers.

2. Women's freedom in mobility, 3. Financial transaction management, 4. Women's role in childrearing and parenting. These are described below:

Group 1-decision making: this group includes questions about how much women are involved in general household decision-making on household purchases, children's schooling and health care, having/having more children or using contraception. The assumption is that involvement in decision-making reflects empowerment in these areas. The statistics show that women are actively involved in the decision to purchase daily needs for their households while rarely have discretion to buy large and expensive items. 70.4% of households report that the women decide to buy daily needs alone (E2), while only 11.2% can purchase costly items without their husbands' permission (E3). When it comes to their own health care (E5), having children (E6), children's schooling (E7), children healthcare (E8), and deicing whether to another child (E9), over 90% of women either make the decision themselves or jointly with their husbands or someone else.

Group 2-mobility: this group includes questions that reflect whether women decide or involve in decide to visit their family/friends/relatives, whether they can get shelter for a couple of nights their birth family, whether they receive financial support from their birth family if necessary, and aware of the new Land Law which benefits them. Women report that 45.5% of them can decide to visit family/friends/relatives by themselves, and 52.1% are involved in discussing this issue with their husbands (E1). More than 90% of those interviewed indicate that they could shelter some nights at someone from their family (E10) and get financial support when needed (E11). However, only about 22.7% of female respondents are aware of the new Land Law (E19), which allows them to share land ownership. Generally, women are not restricted in mobility in Vietnam.

Group 3-financial transaction management: this group includes questions related to selling or/and disposing of land, Jewelry, livestock, bike/motorbike, and other assets without husband's permission. Approximately 82.6%-85.8% of women answer that they could not sell or/and dispose of land, motorbike and other assets without their husband's consent (E12, E15 and E16). About 64.5% and 71.6% of women report that they could not independently sell or purchase livestock (E14) and Jewelry (E13) without their husbands' permission, respectively. These statistics show that men mainly manage financial transactions for rural households.

Group 4-childbearing and family planning: this factor assesses women's power in family planning and children bearing. Over 96% of women are involved in discussing with husbands about having children (E6), but only 8.4% can decide on their own whether to have an(other) child (E9). In addition, the report shows that wives are more likely to use birth control than husbands (E18). However, as noted above, women tend to be actively involved in deciding on health care and education for their children. More than 90% of female respondents either decide on their own or join with their husbands to determine their children's health care (E8) and schooling (E7). Over 54% of women make decisions about their own health care without discussing it with husbands (E5).

Overall, the statistical picture of rural areas in Vietnam in the late 20th century is that women's mobility is high and women are actively involved in most household decision-making either by themselves or with their husbands. However, the proportion of women involved and managing household financial transactions, and having an awareness of the Land Law, is relatively low. Economic empowerment is vital in gender equality. This provides evidence that gender inequality still exists in Vietnamese society, especially in rural areas.

5.4.3 Summary statistics

Table 5.2 reports information about the 2,117 households who participated in microcredit (nearly half the sample). It provides a summary of household borrowing from credit providers by gender and year. Households can borrow loans from more than one institution, which is why the total in the table (2,898) is greater than the number of borrowing households (2,117). The table shows that microcredit in rural areas is mainly provided by the formal sectors, which account for 60% of the total microcredit market. VBSP ("Social Policy Bank") and VBARD ("Bank for Agriculture and Rural Development") are the two leading providers. Nevertheless, the informal and semi-formal sectors are also important.

Table 5.3 reports summary statistics for the key variables in my analysis. The statistics show that the percentage of male participants in microcredit is higher than that of female participants. 32.1% of households in the sample have males that borrow loans, while only 16.3% of households have females that participate in microcredit.

The total amount of loans borrowed is measured by summing all current loans. To account for endogenous selection, microcredit borrowing is treated as an endogenous variable and instrumented with three variables: the proportion of borrowers at the district, the number of banks located in the commune, and distance from people's committee. According to the survey, around 47% of the population accessed at least one loan. A typical commune has at least one bank present. The distance is approximately 2.1km to people's committee.

Age, education and gender of household head are the primary household head characteristics. Average household heads' age is 53. On average, the household head's highest completed grade is 6.5 out of 12. Notably, fewer than 22% of household heads are female. Females tend to have more male children than female. In Asian culture, sons are preferred to daughters. Women who have more male children are likely to have more power. For household characteristics, the proportion of members who have not obtained a diploma is high. 88.2% of males and 91.4% females do not finish diploma. Tertiary education is relatively low, 1.2% and 1.3% of males and females, respectively. The highest diploma obtained by male members is more elevated than female members. Although there are moderate differences in education between males and females, males take over important roles in households, such as accessing microcredit or being household heads.

In the empirical estimation, some variables, which contain "zero value" and are used in logarithm transformation, are added "one" before transforming to logarithm form. This approach is commonly used in literature (Pitt & Khandker, 1998; Roodman & Morduch, 2014). Monetary values are reported in Vietnam Dong (VND) and nominal money values are converted to the real values using the producer price index with the base year 2010.

5.5 Empirical results

SEM is employed to estimate the baseline results of Equations 5.2 and 5.3. SEM can be viewed as a parametric form of DAGs that encodes linear functions instead of arbitrary non-linear functions. DAGs explicitly identify the assumptions that allow one to attach causal interpretation to estimated results. Firstly, DAGs assume that causality occurs in time order. Secondly, DAGs allow for a variable to affect more than one variable at the same time. Third, DAGs do not allow for true simultaneity, where microcredit participation/borrowing affects female empowerment while female empowerment does not affect microcredit. These assumptions imply no simultaneous link that causes potential endogeneity. Hence, this section uses SEM to estimate microcredit impact on women's empowerment under assumptions of DAGs.

An important advantage of SEM is that, under certain conditions, it is possible to include *"latent"* empowerment variables in the causal model. SEM combines the IRT model of women's empowerment (Equation 5.1) and the impact of the empowerment model factors

(Equation 5.2 and 5.3). The former is a measurement model that uses maximum likelihood to estimate the IRT model and predict latent empowerment factors. The latter is known as the structural model and is used to assess the impact of microcredit participation on the predicted empowerment factors.

5.5.1 The impact of microcredit participation on female empowerment using SEM

Table 5.4 presents the estimated effects of microcredit participation by gender (cf. Equation 5.2) on the four estimated empowerment factors and one overall empowerment factor, *"factor all"*. Estimation outputs without province fixed effects are shown in columns (1) and (2). Estimation outputs using province fixed effects are reported in columns (3) and (4). The sign and statistical significance of the two sets of estimates are consistent. Consequently, I focus discussion on the province fixed effects estimates. I only report the estimates for the treatment variable. Estimates for the respective control variables are not reported so I can focus on the most important results.

The findings provide weak evidence that microcredit improves female empowerment if clients are females, and no evidence if males are borrowers. The "Factor all" estimates indicate that, on average, women participate who participate in at least one microcredit program experience an increase in overall female empowerment of 0.159 standard deviations (cf. Table 5.4, column 3); however, the estimate is only significant at the 10% level. Likewise, the estimate for "Childbearing and family planning" indicates that participating in a microcredit program increases women's empowerment on this factor by 0.318 standard deviations; but it again is only significant at the 10% level. The only estimate that is significant at the 5% level is for the factor "Financial management", with participation associated with an increase of 0.344 standard deviations.

The results for "Financial management" are consistent with what I would expect. Accessing loans opens job opportunities for poor women by self-employment, which generates stable income. This leads to an increase in their contribution to the household economy, asset building, and more financial independence. They have more right to sell or buy assets which increase financial transaction management. Such economic empowerment provides women with new skills and information that help them involve household expenditures and family planning such as children's education, family welfare, and social activities. Being involved more in household and social activities helps women increase their status and self-esteem. In addition, by joining microcredit programs, women are organized into groups or open social networks to share diverse information to learn more about the outside world. This helps them become more conscious about their quality of life and family welfare.

The explanation for why participation in microcredit has a relatively smaller impact on "Decision-making" and "Mobility" can be attributed to the fact that women in rural households in Vietnam are already involved in most domestic household decision-making and freedom to travel or ask for help from their family or relative. According to the VARSH, 90% of women are involved in household decision-making in almost all household activates.

For the male participants, the estimates are smaller in absolute size and all are statistically insignificant at the 5% level (cf. Table 5.4, column 4). It is possible that loan borrowing or a small loan does not significantly change male job opportunities, income, and related environment. Hence, there is little "spillover" effect on female standing.

5.5.2 The impact of microcredit borrowing on female empowerment using SEM

In this section, I repeat the analysis, but this time estimating Equation (5.3), where the treatment variable is the amount of borrowing as opposed to mere participation in the program. These results are reported in Table 5.5. I supplement this analysis by estimating the effect of borrowing on the individual empowerment variables introduced in Table 5.1. To do that, I convert all the empowerment variables to binary variables. Where the outcomes are 2 =“Wife alone”, 1 = “Wife jointly with husband or someone”, 0 = ”Husband or someone alone”, I combine categories 1 and 2 and use probit to estimate the model. The associated estimates are reported in Table 5.6 and are marginal effects. All the regressions in Tables 5.5 and 5.6 include the same control variables.

Table 5.5 reports the regression outputs for the male/female amount of borrowing impact on women’s empowerment with province fixed effects and clustered standard errors. The estimated effects of microcredit amount of borrowing do not vary significantly by regression method. So, only the FE estimation (columns 3 and 4) is discussed in this section. The coefficient of credit borrowing is, technically, the effect of a 100% increase in borrowing on empowerment, measured in units of standard deviations. However, nonlinearity makes that a bad approximation. To get the impact of a 10% increase in borrowing, one should multiply the respective coefficients by 0.1. I first discuss the estimated impacts of female borrowing (cf. Table 5.5, column 3) and only discuss the most noteworthy results.

Financial transaction management (Group 3 in Table 5.1; F3 in Table 5.5, column 3; E2, E3, E11 to E15 in Table 5.6, “Female credit coefficient” column). This factor represents the power of conducting major household economic transactions such as who decides about selling or purchasing land, jewelry, livestock, bike/motorbike, other assets, large household purchases and daily items. The estimates indicate a 10% increase in loans results in a 0.0038 standard deviation increase in the empowerment factor “Financial management”. While the size of the estimated effect is very small, it is statistically significant at the 5% level. In terms of individual empowerment questions, I estimate positive and significant effects on the proportion of females involved in purchasing, selling and disposing land (E12), jewelry (E13), livestock (E14), and other assets (E16).

I also estimate a significant effect of borrowing on "Factor all". However, the size of this effect is very small. A 10% increase in borrowing is associated with an increase in female empowerment of 0.0018 standard deviations. Based on the results in Tables 5.5 and 5.6, most of this effect appears to be coming from the impact of borrowing on the "Financial management" factor. Overall, my results provide some evidence that microcredit helps empower women, particularly in the areas of financial management, but the estimated impact is small.

Turning now to the effect of male borrowing on female empowerment, I find that male borrowing is significantly associated with a number of the individual empowerment variables in Table 5.6, with many of the estimates being negative. Nevertheless, there is no evidence that these effects are large enough significantly impact the cumulative factors in Table 5.5.

5.6 Robustness results

The baseline results provide evidence that microcredit participation and microcredit borrowing by females has a positive impact on the "Financial management" component of female empowerment. On the other hand, there is no evidence that participation or borrowing by males has any effect on female empowerment. To check for the robustness of my findings, I use various methods, including Lasso with fixed effects and instrumental variables, treatment effects and Lasso, propensity score matching, and maximum likelihood procedures to deal with missing data.

5.6.1 Using Lasso to select control variables and instrumental variables

5.6.1.1 Potential endogeneity and instrumental variables

The previous analysis assumed endogeneity was eliminated through the inclusion of confounding variables. However, it did not address endogeneity due to simultaneity. In practice, participating in microcredit may be endogenous due to non-random placement and non-random self-selection into microcredit. There is also the possibility of endogeneity arising from household and village characteristics that are not properly controlled.[26] In the analysis below, I address these issues through a variety of procedures.

5.6.1.2 The ATE and ATT of microcredit on female empowerment using Te-lasso

My first approach addresses endogeneity from incomplete control of confounding variables by using a combination of inverse probability weighting and Lasso selection of control variables. The procedure I employ is the Stata command "telasso" which stands for "Treatment-effects estimation using Lasso". It uses Lasso inference methods to select control variables. To address possible nonlinearities, I take the full set of control variables and, in addition to the linear terms, I include quadratic terms and linear interactions of all control variables. I then let Lasso select the control variables from this large set. Simultaneously, telasso uses augmented inverse probability matching whereby the samples of treatments and controls are weighted to make the two samples "look like" each other. Subsequent analysis adds control variables back in so that the final estimate is "doubly robust." The telasso procedure produces estimates of both an average treatment effect (ATE) and an average treatment effect on the treated (ATT).

Note that unlike the SEM estimates presented earlier, this is a two-step procedure. In the first step I use IRT to estimate the individual factors. I then save the predicted values from this analysis and treat them as observed variables when using telasso. While this would, by itself, result in underestimation of standard errors, I compensate by using a cluster robust procedure to estimate standard errors.

Table 5.7 reports the results from using this procedure. As the differences between the ATE and ATT estimates are minor, I only discuss the ATT results. The results differ somewhat from the earlier estimates. Of the four individual empowerment factors, this time only the

[26] More details of potential econometric problems are presented in Section 4.2.2.3 this thesis.

“Childbearing and family planning” factor is significantly associated with female participation in a microcredit program. I estimate that participation increases this factor by 0.095 standard deviations. My estimate for the “Financial management” factor indicates a positive effect of 0.061 standard deviations, but this estimate is not significant at the 5% level. In both cases, the sizes of the estimates effects are small, even smaller than the SEM estimates in Table 5.4. As before I find no evidence that male participation in a microcredit program affects female empowerment on any dimension.

5.6.1.3 The impact of the amount of microcredit borrowing on female empowerment using Lasso to select both control and instrumental variables

In this section, I further address endogeneity by instrumenting the treatment variable. In addition, I expand my use of Lasso to select both instruments and controls.

As instruments I use three variables: borrower networks, the number of banks in a commune, and distance from households to people’s committees. Borrower networks in a commune are measured by the proportion of borrowers who have accessed microcredit. This instrumental variable measures households’ ability to access information connecting households in the commune, thus facilitating credit uptake. The more borrowers in a commune, the better information a credit seeker can access. By providing information about credit sources or credit borrowing procedures through friends, relatives, and neighbors, borrower networks lower the cost of searching and increase the accessibility of credit sources for new borrowers. Thus, a network enables increased microcredit borrowing.

The second instrument I use is the number of banks in a commune. This variable measures the availability of credit in the commune. The more banks are located in the commune, the more options for credit its residents can access, which facilitates increased borrowing. A third instrument is the distance from households to people’s committees also encourages microcredit borrowing. In rural areas, people's committees play a vital role in connecting state-owned banks and government programs to customers. Poor people without physical collateral who want to borrow money from the formal sector need to be officially classified as "poor" by the local commune's people's committee. People's committees also sponsor poor households' access to microcredit. The shorter the distance from households to people's committees, the more households can access information, sponsorship and support to access microcredit.

Two-stage least squares is a common approach to dealing with endogeneity. However, it is not always straightforward to select valid IVs. Rather than a priori selecting instruments, I use Lasso to select them. To get maximum use of lasso's instrument selection procedure, I fit a more flexible model by including higher-order terms and interactions. As before, I use Lasso to select the control variables for the model. Again as before, I include linear, quadratic and interaction terms and allow Lasso to select control variables from this set.

Table 5.8 reports the results of estimating microcredit borrowing on female empowerment using fixed effects OLS (columns 1 and 2), and fixed effects IV (columns 3) and 4). As in the previous section, I use a two-stage process. In the first stage I use SEM to obtain predicted values for the individual factors. In the second stage, the predicted values become the dependent variable and I estimate the respective models using Lasso. I focus on the FE-IV estimates. These are similar to what I found in the previous section. The only factor showing a significant effect of microcredit borrowing is "Childbearing and family planning". The estimated impact is significant at the 1 percent level and indicates that a 10% increase in borrowing is associated with an increase in this factor of 0.0098 standard deviations; again, a positive, but very small effect. The "Financial management" factor, which was significantly associated with microcredit borrowing in the SEM estimation of Table 5.5, shows an estimated treatment effect slightly larger than what was estimated there, though still very small, and is only significant at the 10 percent level. As I have consistently found in my previous analyses, there is no evidence to indicate that male borrowing affects female empowerment.

5.6.2 Using Maximum likelihood procedures to address missing data

5.6.2.1 Maximum likelihood procedures

The last issue I want to address is missing data. As is evident in Tables 5.1 and 5.3, many of the variables I use in my analysis have missing data on both the dependent and independent variables. The conventional approach to dealing with such data is to omit the respective observations from the analysis. This is known as "listwise deletion" or "complete case analysis". Depending on why the data are missing, this can cause bias, or at the very least a loss of statistical power (Newsom, 2018). In recent years, there has been much progress on approaches to estimating models with missing data (Enders, 2010).

Two major approaches are used to handle missing values, namely multiple imputation (MI) and maximum likelihood (ML). The required conditions of both methods are that data are "missing at random". In words, this means that the probability that an observation is missing for a given variable is the same for all observations once one controls for the other variables in the model.

MI involves substituting missing values with predicted values multiple times, using observed data. Predicted values are supplemented with random errors to accommodate the fact that the predictions are generated by a regression model with errors. MI creates multiple datasets. Estimates are produced for each dataset and the multiple estimated parameters are combined into one. Unlike MI, ML does not impute missing values. Instead, ML adjusts the likelihood function to accommodate that some values of the variable are not observed, estimating a conditional likelihood function by integrating out the marginal distribution of the missing variable (Dong & Peng, 2013). The estimated parameter using ML is the parameter's value most likely to produce the observed dataset.

MI and ML are increasingly popular methods for handling missing data. However, ML is usually better than MI for several important reasons. Firstly, MI includes separate steps of imputation and analysis. To be effective, the imputation model, used to predict the missing observations, has to be "congenial" with the main equation being estimated. That is not an issue with ML because everything is done with a single model. Secondly, ML analysis produces a deterministic set of results for a given dataset. In contrast, the results from MI are stochastic because random draws are a crucial part of the MI procedure (Jakobsen, Gluud, Wetterslev, & Winkel, 2017). Variability can be reduced if by imputing more data sets, but there is no generally agreed approach for determining how many data sets are "enough". Thirdly, ML is more efficient (Von Hippel, 2016). Given the advantages of ML, I will use this technique in the subsequent analysis.

5.6.2.2 Results from re-estimation of models in Table 5.4 and 5.5 using maximum likelihood to accommodate missing data

Tables 5.9 and 5.10 report the results from repeating the analyses of Tables 5.4 and 5.5, but this time using maximum likelihood to include observations with missing data. As before, I focus on the FE estimates.

In terms of size of estimated effects, the estimates in Tables 5.9 and 5.10 are similar to those in Tables 5.4 and 5.5, respectively. In terms of statistical significance, they closely match the results from the preceding robustness analyses. As in those preceding analyses, the only factor significantly associated with microcredit is "Childbearing and family planning". From Table 5.9, participation in the microcredit program is associated with a 0.385 standard deviation increase in the female empowerment on the dimension of "Childbearing and family planning”. From Table 5.10, an increase of 10% in female borrowing is associated with a 0.0039 standard deviation increase in this factor. The results for male borrowing are similar to previous results in generally finding no relationship between male borrowing and female empowerment with one exception: In Table 5.10, a 10% increase in male borrowing is associated with a 0.0020 standard deviation increase in “Childbearing and family planning” empowerment for women.

5.7 Conclusion

Women’s empowerment is considered a significant component of development and economic growth. However, women are likely to have limited access to labor market, education, economic resources and unequal share of power in a domestic household as well as in community. If given more power in controlling finance and resources, women tend to participate in the labor market, which leads to increased income and spending more on education and health care for a family. These lead to sharing more roles and being involved more in decision-making in her family. In this context, microcredit has been seen as a potentially useful method to increase female accessing financial services and then lead to enhance social and economic empowerment of women. However, the relationship between microcredit and women’s empowerment is still debated among researchers.

This chapter explores the effects of microcredit participation and microcredit borrowing on female empowerment using data from 2008-2010 in rural Vietnam. I use a wide variety of estimation approaches to estimate the microcredit effect on female empowerment. I look at two types of treatment: participation in microcredit, and amount of borrowing. Further, I estimate separate impacts on women’s empowerment when women access microcredit, and when men access microcredit.

To measure women's empowerment, I use structural equation modeling and item response theory to estimate Rasch models relating responses to individual questions about women's decision-making in the household to four latent factors: "Decision-making", "Mobility", "Financial management", and "Childbearing and family planning". I also aggregate all the questions together to form a single factor, "Factor all". These latent variables are then used as dependent variables in a variety of linear regressions to estimate the effect of microcredit on the respective factors.

My overall conclusion is that there is weak evidence to support the hypothesis that microcredit increases empowerment of women when they participate in microcredit programs, and no evidence that male borrowing affects women's empowerment. However, the sizes of the estimated effects are small, and mostly concentrated on two factors, "Financial management" and "Childbearing and family planning". There are too many results to discuss everything, but Table 5.11 provides a selected summary of my main findings. The table only reports the estimated effects of microcredit on the aggregated factor, "Factor all". Panels A and C give the results for female participation in microcredit. Most, but not all, of the estimates are significant. However, the sizes of the estimated effects are fractions of a standard deviation in the latent women's empowerment variable. All the estimates for male participation in microcredit programs are statistically insignificant and even smaller in size.

I conclude from my analysis that microcredit programs have the potential to improve women's empowerment in rural areas when women are given the opportunity to borrow funds. However, my results should temper expectations about the results from those programs. The small effects I find suggest that microcredit is not a "silver bullet." However, policy makers may find that the aggregate benefits from these programs, when benefits to female empowerment are combined with other benefits on economic and social outcomes, are sufficient to justify their costs.

5.8 References

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Table 5.1 Individual empowerment variables

	Content of variables	Coding*	Proportion	Thematic group	Number of observations
E1	Decide/involve to visit to family/friends/relatives	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.455 1=.521 0=.024	1,2	3,612
E2	Decide/involve household purchases for daily need	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.704 1=.285 0=.011	1,3	3,612
E3	Decide/involve large household purchases	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.112 1=.834 0=.054	1,3	3,612
E4	Decide/involve whether to use contraception	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone = 0	2=.141 1=.725 0=.027	1,4	2,953
E5	Decide/involve to have own health care	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.545 1=.443 0=.012	1,4	3,612
E6	Decide/involve to have children	yes = 1, no = 0	1=.966 0=.034	1,4	3,612
E7	Decide/involve schooling for children	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.178 1=.729 0=.024	1,4	3,363
E8	Decide/involve health care for children	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.258 1=.667 0=.011	1,4	3,379
E9	Decide/involve whether to have an(other) child	Wife alone = 2 or Wife jointly with husband or someone=1, husband or someone alone = 0	2=.084 1=.767 0=.024	1	3,158

E10	Get shelter for a couple of nights at someone from your birth family if necessary	yes = 1, no = 0	1=.903 0=.097	2	3,612
E11	Get financial support from someone from your birth family if necessary	yes = 1, no = 0	1=.933 0=.067	2	3,612
E12	Sell/dispose of land without permission from husband	yes = 1, no = 0	1=.120 0=.858	3	3,530
E13	Sell/dispose of Jewelry without permission from husband	yes = 1, no = 0	1=.259 0=.716	3	3,520
E14	Sell/dispose of livestock without permission from husband	yes = 1, no = 0	1=.339 0=.645	3	3,550
E15	Sell/dispose of bike/motorbike without permission from husband	yes = 1, no = 0	1=.138 0=.834	3	3,508
E16	Sell/dispose of other assets without permission from husband	yes = 1, no = 0	1=.149 0=.826	3	3,518
E17	Aware of the use of contraception	yes = 1, no = 0	1=.723 0=.253	4	3,228
E18	Using men or women birth control	men = 1, women = 0	1=.163 0=.578	4	2,372
E19	Aware of the new Land Law from 2003	yes = 1, no = 0	1=.227 0=.773	2	3,295

Note: Group 1 decision-making, 2 mobility, 3 financial management, 4 family planning and childbearing
Coding yes=1, no=0,
In categories coding (shading): if female alone/involving =1, otherwise=0

Table 5.2 Microcredit provider sectors by gender and year

	2008		2010		Total	
Financial sectors	Male	Female	Male	Female	Borrowers	%
Formal sectors						
Social Policy Bank	187	92	400	173	852	*29.40*
Bank for Agriculture and Rural Development	295	84	233	87	699	*24.12*
Other State-owned commercial Bank	19	13	33	6	71	*2.45*
People's Credit Funds	23	17	21	9	70	*2.42*
Local Authorities	2	2	3	0	7	*0.24*
Private Bank	11	1	12	6	30	*1.04*
	537	**209**	**702**	**281**		
	(61.30%)	*(45.73%)*	*(67.05%)*	*(54.25%)*	**1,729**	***59.66***
Semi-formal sector						
Farmers Union	27	11	10	2	50	*1.73*
Veterans Union	18	6	8	2	34	*1.17*
Women's Union	26	62	9	32	129	*4.45*
Other credit associations	16	6	3	2	27	*0.93*
	87	**85**	**30**	**38**		
	(9.93%)	*(18.60%)*	*(2.87%)*	*(7.34%)*	**240**	***8.28***
Informal sectors						
Private Trader	68	67	80	33	248	*8.56*
Private Money Lender	45	28	47	25	145	*5.00*
Friends/Relatives	115	59	151	113	438	*15.11*
Informal credit scheme (including Roscas)	4	3	7	1	15	*0.52*
	232	**157**	**285**	**172**		
	(26.48%)	*(34.35%)*	*(27.22%)*	*(33.20%)*	**846**	***29.19***
	20	**6**	**30**	**27**		
Others	*(2.28%)*	*(1.31%)*	*(2.87%)*	*(5.21%)*	**83**	***2.86***
Total	**876**	**457**	**1047**	**518**	**2,898**	***100.00***

Note: One household can borrow loans from one or more institutions

Table 5.3 Descriptive statistics

Description of variables	Obs (HH)	Mean	SD	Min	Max
Treatment variables					
Male participation (yes=1)	4,499	0.321	0.467	0	1
Female participation (yes=1)	4,499	0.163	0.369	0	1
Male borrowing: Log(amount male borrowing +1)	4,499	3.108	4.568	0	14.662
Female borrowing: Log(amount female borrowing +1)	4,499	1.505	3.450	0	13.305
Amount of male borrowing (000VND)	4,499	11,422.34	55,369	0	2,330,866
Amount of female borrowing (000VND)	4,499	3,688.55	20,631	0	599,999
HH head's characteristics					
Highest grade completed by HH head (year)	4,499	6.479	3.626	0	12
Age of household head (year)	4,499	52.507	13.625	20	96
Gender of HH head (male=1)	4,499	0.782	0.413	0	1
Women's characteristic in HH (spouse/head)					
Age of female spouse/head (years)	4,336	49.997	13.415	19	96
Number of male children	4,499	1.124	0.924	0	6
Number of female children	4,499	1.000	0.968	0	6
Household characteristics					
HH NET annual income (VND)	4,499	67,928.37	111,325.00	1	2,711,160
HH assets (VND)	4,499	26,798.43	503,117.00	1	32,600,000
HH size (person)	4,499	4.426	1.774	1	13
Number of dependent members in the HH (person)	4,499	1.356	1.230	0	9
HH ethnicity (Kinh=1, other=0)	4,499	0.793	0.405	0	1
Highest diploma obtained by any male HH member:					
0=no diploma	4,499	0.882	0.323	0	1
1=short/long training	4,499	0.062	0.241	0	1
2=high school/college diploma	4,499	0.044	0.205	0	1
3=bachelor/master/PhD	4,499	0.012	0.110	0	1
Highest diploma obtained by any female HH member:					
0=no diploma	3,601	0.914	0.280	0	1
1=short/long training	3,601	0.034	0.180	0	1
2=high school/college diploma	3,601	0.039	0.194	0	1
3=bachelor/master/PhD	3,601	0.013	0.112	0	1
Lag_1 HH borrowing: log(amount of borrowing last year + 1)	4,499	5.232	4.872	0	14.662
Province dummy	4,499			12	12
Year dummy	4,499			2008	2010

Potential instrument variables					
The proportion of borrowers at the district (percent)	4,499	0.470	0.087	0	0.9
Number of banks located in the commune	4,370	1.062	0.857	0	5
Distance from people's committee (km)	4,499	2.112	2.650	0	100
Dependent variables (Empowerment factors)					
F1: HH decision-making	4,499	0.010498	0.492	-3.050	0.217
F2: Mobility	4,499	0.000432	0.576	-2.413	0.965
F3: Financial management	4,499	-0.004388	0.765	-2.400	1.886
F4: Childbearing and family planning	4,499	0.000004	0.554	-2.942	1.134
F5: All of factors	4,499	0.000014	0.755	-3.725	2.349

Note: SD for standard deviation; HH for household

Table 5.4 The impact of microcredit participation by gender on female empowerment using SEM: Results from estimating Equation (5.2)

	OLS		FE	
	Female	Male	Female	Male
Factor	(1)	(2)	(3)	(4)
	0.301	0.060	0.293	0.079
F1: Decision-making	(0.72)	(0.29)	(0.76)	(0.38)
	-0.193	-0.085	-0.173	0.014
F2: Mobility	(-0.90)	(-0.63)	(-0.85)	(0.14)
	0.357**	-0.001	0.344**	-0.030
F3: Financial management	(2.19)	(-0.01)	(2.24)	(-0.30)
	0.348**	0.064	0.318*	0.115
F4: Childbearing and family planning	(2.00)	(0.59)	(1.89)	(1.09)
	0.168*	-0.007	0.159*	0.019
F5: Factor all	(1.89)	(-0.15)	(1.87)	(0.46)

Note: z statistics clustered by province in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%

Table 5.5 The impact of microcredit borrowing by gender on female empowerment using SEM: Results from estimating Equation (5.3)

	OLS		FE	
	Female	Male	Female	Male
Factor	(1)	(2)	(3)	(4)
	0.032	0.011	0.031	0.012
F1: Decision-making	(0.67)	(0.54)	(0.72)	(0.61)
	-0.014	-0.006	-0.012	0.006
F2: Mobility	(-0.75)	(-0.46)	(-0.64)	(0.62)
	0.039**	0.004	0.038**	0.001
F3: Financial management	(2.19)	(0.37)	(2.23)	(0.09)
	0.034**	0.010	0.032*	0.016
F4: Childbearing and family planning	(2.03)	(0.97)	(1.90)	(1.55)
	0.019**	0.002	0.018**	0.005
F5: Factor all	(2.07)	(0.40)	(2.07)	(1.17)

Note: z statistics clustered by province in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%

Table 5.6 Credit effects on individual empowerment questions (province fixed effects estimates)

Variable	Name of variable	Female credit coefficient (S.D)		Male credit coefficient (S.D)	
E1	Decide/involve to visit to family/friends/relatives	-0.00583	(0.328)	-0.00514	(0.182)
E2	Decide/involve household purchases for daily need	0.248***	(0.032)	-0.114***	(0.038)
E3	Decide/involve large household purchases	0.184***	(0.061)	-0.119***	(0.030)
E4	Decide/involve whether to use contraception	-0.226***	(0.042)	0.0850	(0.069)
E5	Decide/involve to have own health care	0.200***	(0.053)	-0.145***	(0.026)
E6	Decide/involve to have children	0.178	(0.190)	0.0222	(0.164)
E7	Decide/involve schooling for children	0.169	(0.159)	-0.0726	(0.120)
E8	Decide/involve health care for children	-0.177***	(0.068)	0.126***	(0.032)
E9	Decide/involve whether to have an(other) child	-0.179***	(0.065)	0.142***	(0.024)
E10	Get shelter for a couple of nights at someone from your birth family if necessary	0.212***	(0.030)	-0.132***	(0.020)
E11	Get financial support from someone from your birth family if necessary	0.211***	(0.033)	-0.123***	(0.023)
E12	Sell/dispose of land without permission from husband	0.221***	(0.048)	-0.0810	(0.050)
E13	Sell/dispose of Jewelry without permission from husband	0.162**	(0.076)	-0.0899*	(0.046)
E14	Sell/dispose of livestock without permission from husband	0.249***	(0.029)	-0.0634	(0.049)
E15	Sell/dispose of bike/motorbike without permission from husband	0.170	(0.116)	-0.0233	(0.095)
E16	Sell/dispose of other assets without permission from husband	0.243***	(0.029)	-0.0806*	(0.043)
E17	Aware of the use of contraception	0.0456	(0.176)	0.118	(0.076)
E18	Using men or women birth control	0.177	(0.149)	-0.0110	(0.097)
E19	Aware of the new Land Law from 2003	0.0814	(0.150)	-0.0551	(0.096)

Note: Robust standard errors in parentheses, cluster by household; *significant at 10%, **significant at 5%, ***significant at 1%

Table 5.7 Using Treatment Effects Lasso to estimate the ATE and ATT of microcredit by genders on female empowerment: Results from estimating Equation (5.2)

	ATE		ATT	
	Female	Male	Female	Male
Factor	(1)	(2)	(3)	(4)
	0.042	0.007	0.042	0.005
F1: Decision-making	(1.38)	(0.33)	(1.26)	(0.28)
	-0.045	-0.012	-0.046	-0.001
F2: Mobility	(-1.38)	(-0.52)	(-1.32)	(-0.06)
	0.064*	-0.029*	0.061*	-0.032*
F3: Financial management	(1.66)	(-1.74)	(1.92)	(-1.83)
	0.100***	0.018	0.095***	0.006
F4: Childbearing and family planning	(2.67)	(0.78)	(2.68)	(0.29)
	0.090***	-0.023	0.077**	-0.021
F5: Factor all	(2.57)	(-1.40)	(2.40)	(-1.10)

Note: z statistics clustered by province in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%
(1), (3) Treated: HH has female borrow, control: otherwise (HH no borrow or HH has only male borrow)
(2), (4) Treated: HH has male borrow, control: otherwise (HH no borrow or HH has only female borrow)

Table 5.8 Using Lasso to estimate the impact of the amount of microcredit borrowing on female empowerment: Results from estimating Equation (5.3)

	FE		FE-IV	
	Female	Male	Female	Male
Factor	(1)	(2)	(3)	(4)
	0.005*	0.003	0.037	-0.012
F1: Decision-making	(1.72)	(1.35)	(1.47)	(-0.78)
	-0.003	0.000	0.026	-0.034
F2: Mobility	(-1.03)	(0.21)	(0.95)	(-2.19)
	0.005	-0.003	0.057*	0.016
F3: Financial management	(1.20)	(-1.38)	(1.73)	(0.83)
	0.010***	0.005***	0.098***	0.014
F4: Childbearing and family planning	(3.72)	(3.47)	(3.29)	(0.86)
	0.008***	0.000	0.093***	0.004
F5: Factor all	(2.01)	(-0.16)	(2.76)	(0.18)

Note: z statistics clustered by province in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%

Table 5.9 The impact of microcredit participation by gender on female empowerment using SEM/ML: Results from estimating Equation (5.2)

	OLS (cluster)		FE	
	Female	Male	Female	Male
Factor	(1)	(2)	(3)	(4)
	0.387	0.082	0.373	0.099
F1: Decision-making	(1.23)	(0.43)	(1.22)	(0.51)
	-0.101	-0.057	-0.059	0.040
F2: Mobility	(-0.47)	(-0.43)	(-0.30)	(0.39)
	0.186	-0.106	0.158	-0.150
F3: Financial management	(1.19)	(-1.03)	(1.01)	(-1.51)
	0.412**	0.121	0.385**	0.167
F4: Childbearing and family planning	(2.48)	(1.15)	(2.46)	(1.64)
	0.110	-0.030	0.105	-0.013
F5: Factor all	(1.43)	(-0.63)	(1.34)	(-0.32)

Note: z statistics clustered by province in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%

Table 5.10 The impact of microcredit participation by gender on female empowerment using SEM/ML: Results from estimating Equation (5.3)

	OLS (cluster province)		FE	
	Female	Male	Female	Male
Factor	(1)	(2)	(3)	(4)
	0.041	0.012	0.038	0.014
F1: Decision-making	(1.15)	(0.65)	(1.09)	(0.74)
	-0.006	-0.003	-0.001	0.009
F2: Mobility	(-0.29)	(-0.23)	(-0.06)	(0.89)
	0.014	-0.006	0.011	-0.010
F3: Financial management	(0.78)	(-0.55)	(0.61)	(-1.00)
	0.040**	0.016	0.039**	0.020**
F4: Childbearing and family planning	(2.43)	(1.55)	(2.41)	(2.16)
	0.009	-0.001	0.009	0.001
F5: Factor all	(1.05)	(-0.13)	(1.00)	(0.32)

Note: z statistics clustered by province in parentheses, *significant at 10%, **significant at 5%, ***significant at 1%

Table 5.11 Summary of results

Table/Column	Dependent variable	Treatment variable	Size of the effect	Interpretation of size of the effect
		Panel A: <u>Microcredit participation by females</u>		
<u>Baseline results:</u>				
Table 5.4, column 3	Factor all	Female participation	0.159*	A woman participating in microcredit increases her empowerment by 0.159 standard deviations.
<u>Robustness results:</u>				
Table 5.7, column 3	Factor all	Female participation	0.077**	A woman participating in microcredit increases her empowerment by 0.077 standard deviations.
Table 5.9, column 3	Factor all	Female participation	0.105	A woman participating in microcredit increases her empowerment by 0.105 standard deviations.
		Panel B: <u>Microcredit participation by males</u>		
<u>Baseline results:</u>				
Table 5.4, column 4	Factor all	Male participation	0.019	Male participation in microcredit increases female empowerment by 0.019 standard deviations.
<u>Robustness results:</u>				
Table 5.7, column 4	Factor all	Male participation	-0.021	Male participation in microcredit decreases female empowerment by 0.021 standard deviations
Table 5.9, column 4	Factor all	Male participation	-0.013	Male participation in microcredit decreases female empowerment by 0.013 standard deviations

		Panel C: Amount of female borrowing		
Baseline results:				
Table 5.5, column 3	Factor all	Female borrowing	0.018**	A 10% increase in female borrowing leads to an increase of 0.0018 standard deviations in women's empowerment.
Robustness results:				
Table 5.8, column 3	Factor all	Female borrowing	0.093***	A 10% increase in female borrowing leads to an increase of 0.0093 standard deviations in women's empowerment.
Table 5.10, column 3	Factor all	Female borrowing	0.009	A 10% increase in female borrowing leads to an increase of 0.0009 standard deviations in women's empowerment.
		Panel D: Amount of male borrowing		
Baseline results:				
Table 5.5, column 4	Factor all	Male borrowing	0.005	A 10% increase in male borrowing leads to an increase of 0.0005 standard deviations in women's empowerment.
Robustness results:				
Table 5.8, column 4	Factor all	Male borrowing	0.004	A 10% increase in male borrowing leads to an increase of 0.0004 standard deviations in women's empowerment.
Table 5.10, column 4	Factor all	Male borrowing	0.001	A 10% increase in male borrowing leads to an increase of 0.0001 standard deviations in women's empowerment.

5.9 Appendix: Programming code for Chapter 5

```
//Appendix: Programming code for Chapter 5

global path "C:\Users\dtv13\Dropbox\DIEM PhD Program\(20201118)_VARHS-2008-16Clean\"


*****************************************************************************
// TABLE 5.3
*****************************************************************************


use "$path/DatasetHH.dta", clear
set more off
sum creditm creditf logcreditmale logcreditfemale creditmale creditfemale highestheadedu
agehead genderhead fagenummchild numfchild allincome assetvalue nummem denummem ethinicity
i.mdiploma i.fdiploma llag_loans province year borrowernet bank dispeoplecom decision
mobility financial childfam factorall


*****************************************************************************
// TABLE 5.4
*****************************************************************************


// Using structural equation model (SEM), latent variables include 5 groups: EMPOWERMENT
(factor all), DECISION, MOBILITY, FINANCE, CHILDFAM
// Using OLS and Fixed effects
// Dummy participation; male and female credit
cap log close
log using "$path/Table5.4",replace
use "$path/DatasetHH.dta", clear

set more off
set matsize 5000
xtset hhidentifier t

//control variables
global xvar highestheadedu agehead genderhead fage nummchild numfchild nummem denummem
ethinicity llag_loans i.fdiploma i.mdiploma

set more off

// OLS, column 1 and 2
gsem (creditf creditm $xvar -> EMPOWERMENT, vce(cluster provinifer) nocons) (EMPOWERMENT ->
(em1-em19)@1, logit)
gsem (creditf creditm $xvar -> DECISION, vce(cluster provinifer) nocons) (DECISION -> (em1-
em9)@1, logit)
gsem (creditf creditm $xvar -> MOBILITY, vce(cluster provinifer) nocons) (MOBILITY -> (em1
em10 em11 em19)@1, logit)
gsem (creditf creditm $xvar -> FINANCE, vce(cluster provinifer) nocons) (FINANCE -> (em12
em13 em14 em15 em16 em2 em3)@1, logit)
gsem (creditf creditm $xvar -> CHILDFAM, vce(cluster provinifer) nocons) (CHILDFAM -> (em4
em5 em6 em7 em8 em17 em18)@1, logit)


// Fixed effects, column 3 and 4

gsem (creditf creditm $xvar i.provinifer -> EMPOWERMENT, vce(cluster provinifer) nocons)
(EMPOWERMENT -> (em1-em19)@1, logit)
gsem (creditf creditm $xvar i.provinifer -> DECISION, vce(cluster provinifer) nocons)
(DECISION -> (em1-em9)@1, logit)
gsem (creditf creditm $xvar i.provinifer -> MOBILITY, vce(cluster provinifer) nocons)
(MOBILITY -> (em1 em10 em11 em19)@1, logit)
gsem (creditf creditm $xvar i.provinifer -> FINANCE, vce(cluster provinifer) nocons) (FINANCE
-> (em12 em13 em14 em15 em16 em2 em3)@1, logit)
gsem (creditf creditm $xvar i.provinifer -> CHILDFAM, vce(cluster provinifer) nocons)
(CHILDFAM -> (em4 em5 em6 em7 em8 em17 em18)@1, logit)



*****************************************************************************
// TABLE 5.5
*****************************************************************************
```

```
// Using structural equation model (SEM), latent variables include 5 groups: EMPOWERMENT
(factor all), DECISION, MOBILITY, FINANCE, CHILDFAM
// Using OLS and Fixed effects
// microcredit amount of borrowing, by gender

cap log close
log using "$path/Table5.5",replace
use "$path/DatasetHH.dta", clear

set more off
set matsize 5000
xtset hhidentifier t

// OLS
set more off
gsem (logcreditfemale logcreditmale $xvar -> EMPOWERMENT, vce(cluster provinifer) nocons)
(EMPOWERMENT -> (em1-em19)@1, logit)

gsem (logcreditfemale logcreditmale $xvar -> DECISION, vce(cluster provinifer) nocons)
(DECISION -> (em1 em4 em5 em7 em8 em9)@1, logit)

gsem (logcreditfemale logcreditmale $xvar -> MOBILITY, vce(cluster provinifer) nocons)
(MOBILITY -> (em10 em11 em19)@1, logit)

gsem (logcreditfemale logcreditmale $xvar -> FINANCE, vce(cluster provinifer) nocons)
(FINANCE -> (em12 em13 em14 em15 em16 em2 em3)@1, logit)

gsem (logcreditfemale logcreditmale $xvar -> CHILDFAM, vce(cluster provinifer) nocons)
(CHILDFAM -> (em4 em6 em17 em18)@1, logit)

// Fixed effects

gsem (logcreditfemale logcreditmale $xvar i.provinifer -> EMPOWERMENT, vce(cluster
provinifer) nocons) (EMPOWERMENT -> (em1-em19)@1, logit)

gsem (logcreditfemale logcreditmale $xvar i.provinifer -> DECISION, vce(cluster provinifer)
nocons) (DECISION -> (em1 em4 em5 em7 em8 em9)@1, logit)

gsem (logcreditfemale logcreditmale $xvar i.provinifer -> MOBILITY, vce(cluster provinifer)
nocons) (MOBILITY -> (em10 em11 em19)@1, logit)

gsem (logcreditfemale logcreditmale $xvar i.provinifer -> FINANCE, vce(cluster provinifer)
nocons) (FINANCE -> (em12 em13 em14 em15 em16 em2 em3)@1, logit)

gsem (logcreditfemale logcreditmale $xvar i.provinifer -> CHILDFAM, vce(cluster provinifer)
nocons) (CHILDFAM -> (em4 em6 em17 em18)@1, logit)


*************************************************************************
// TABLE 5.6
*************************************************************************


use "$path/DatasetHH.dta", clear
// Using probit model
set more off
global ivv bank borrowernet

ivprobit em1 $xvar llag_loans (logcreditfemale logcreditmale = $ivv) i.provinifer, first
vce(cluster hhidentifier)
outreg2 using probitmodel.xls, replace

foreach v in em2 em3 em4 em5 em6 em7 em8 em9 em10 em11 em12 em13 em14 em15 em16 em17 em18
em19 {

 ivprobit `v' $xvar  llag_loans (logcreditfemale logcreditmale= $ivv) i.provinifer, first
vce(cluster hhidentifier)
outreg2 using probitmodel.xls, append
}
foreach v in em1 em2 em3 em4 em5 em6 em7 em8 em9 em10 em11 em12 em13 em14 em15 em16 em17 em18
em19 {
```

```
 probit `v' $xvar llag_loans logcreditfemale logcreditmale i.provinifer, vce(cluster
hhidentifier)
outreg2 using probitmodel.xls, append
}


***************************************************************************
// TABLE 5.7 and TABLE 5.8
***************************************************************************


// Prepare data
cap log close
log using "$path/Lasso",replace
clear
set more off
set matsize 5000

// Keep using variables
keep hhidentifier t em1-em21 decision mobility financial childfam factorall logcreditfemale
logcreditmale llag_loans highestheadedu agehead genderhead fage nummchild numfchild nummem
denummem ethinicity highestfedu highestmedu year borrowernet bank dispeoplecom disallwearoad
disasters provinifer fdiploma mdiploma

// Dummy categories
tab fdiploma, gen(dipf)
tab mdiploma, gen(dipm)
global diplomam dipm2 dipm3 dipm4
global diplomaf dipf2 dipf3 dipf4

vl set
vl list vluncertain
vl move (agehead nummem highestheadedu fage highestfedu highestmedu provinifer) vlcontinuous
macro list vlcategorical
vl move (denummem nummchild numfchild disasters bank) vlcontinuous
macro list vlcontinuous
vl create ccbase = vlcontinuous - (hhidentifier provinifer dispeoplecom disallwearoad
borrowernet logcreditmale logcreditfemale llag_loans decision mobility financial childfam
factorall highestfedu highestmedu disasters bank)
vl create fcbase = vlcategorical - (year em1-em21 t dipm1 dipf1 fdiploma mdiploma)

macro list ccbase
macro list fcbase
vl create cinstbase = (bank borrowernet dispeoplecom)
vl substitute contvars = c.ccbase c.ccbase##i.fcbase i.fcbase
vl substitute inst = c.cinstbase##c.cinstbase c.cinstbase
set emptycells drop


***************************************************************************
// TABLE 5.7
***************************************************************************


// Using Treatment Effect Lasso -- Te-Lasso FE ate
// Table 5.7 column 1, 2
foreach v in decision mobility financial childfam factorall {
telasso (`v' $contvars i.provinifer) (creditm $contvars i.provinifer), rseed(12345)
vce(cluster provinifer)
}
foreach v in decision mobility financial childfam factorall {
telasso (`v' $contvars i.provinifer) (creditf $contvars i.provinifer), rseed(12345)
vce(cluster provinifer)
}
// Te-lasso FE atet
// Table 5.7 column 3, 4
foreach v in decision mobility financial childfam factorall {
telasso (`v' $contvars i.provinifer) (creditm $contvars i.provinifer), rseed(12345)
vce(cluster provinifer) atet
}
foreach v in decision mobility financial childfam factorall {
telasso (`v' $contvars i.provinifer) (creditf $contvars i.provinifer), rseed(12345)
vce(cluster provinifer) atet
}
```

```
***************************************************************************
// TABLE 5.8
***************************************************************************


// Lasso FE regression, table 5.8 column 1, 2
foreach v in decision mobility financial childfam factorall {
xporegress `v' logcreditmale logcreditfemale i.provinifer, controls($contvars) rseed(12345)
vce(cluster provinifer)
lassoinfo
}

// Lasso FE-IV regression, table 5.8 column 3, 4
foreach v in decision mobility financial childfam factorall {
xpoivregress `v' (logcreditmale logcreditfemale = $inst) i.provinifer, controls($contvars)
rseed(12345) vce(robust)
dis "Inst_select: " e(inst_sel)
dis "Inst_select: " e(controls_sel)
lassoinfo
}

log close


***************************************************************************
// TABLE 5.9 using Mplus
***************************************************************************


// Table 5.9, OLS, column 1

Mplus VERSION 8.5
MUTHEN & MUTHEN
Data:
File is DiemData.dat ;

// decision making
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm em1 em2 em3 em4 em5 em6 em7 em8 em9 fdip2
fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em9;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
DECISION BY em1-em9@1;
DECISION*;
DECISION ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// monility
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm em1 em10 em11 em19 fdip2 fdip3 fdip4
mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
MOBILITY BY em1-em19@1;
MOBILITY*;
MOBILITY ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
```

```
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// financial management
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm em2 em3 em12 em13 em14 em15 em16 fdip2
fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em2-em16;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
FINANCE BY em2-em16@1;
FINANCE*;
FINANCE ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// childbearing and family planning
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm em4 em5 em6 em7 em8 em17 em18 fdip2 fdip3
fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em4-em18;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
CHILDFAM BY em4-em18@1;
CHILDFAM*;
CHILDFAM ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// all factorall
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm em1-em19 fdip2 fdip3 fdip4 mdip2 mdip3
mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
EMPOWERMENT BY em1-em19@1;
EMPOWERMENT*;
EMPOWERMENT ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;


// Table 5.9, Fixed effects, column 2

// decision making
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm prov2-prov12 em1 em2 em3 em4 em5 em6 em7
em8 em9 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em9;
```

```
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
DECISION BY em1-em9@1;
DECISION*;
DECISION ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// monility
Data:
File is DiemData.dat ;
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm prov2-prov12 em1 em10 em11 em19 fdip2
fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
MOBILITY BY em1-em19@1;
MOBILITY*;
MOBILITY ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// financial management
INPUT INSTRUCTIONS
TITLE: LogF
Data:
File is DiemData.dat ;
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm prov2-prov12 em2 em3 em12 em13 em14 em15
em16 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em2-em16;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
FINANCE BY em2-em16@1;
FINANCE*;
FINANCE ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// childbearing and family planning
Data:
File is DiemData.dat ;
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm em4 em5 em6 em7 em8 em17 em18 fdip2 fdip3
fdip4 mdip2 mdip3 mdip4 prov2-prov12;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em4-em18;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
```

```
MITERATIONS = 2000;
MODEL:
CHILDFAM BY em4-em18@1;
CHILDFAM*;
CHILDFAM ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// all factorall
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans creditf creditm prov2-prov12 em1-em19 fdip2 fdip3 fdip4
mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
EMPOWERMENT BY em1-em19@1;
EMPOWERMENT*;
EMPOWERMENT ON creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
creditf creditm agehead genderhead nummem denummem ethinicity highestheadedu nummchild
numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;


*****************************************************************************
// TABLE 5.10 using Mplus
*****************************************************************************


// Table 5.10, OLS, column 1

Mplus VERSION 8.5
MUTHEN & MUTHEN
Data:
File is DiemData.dat ;

// decision making
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em1 em2 em3 em4 em5 em6 em7
em8 em9 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em9;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
DECISION BY em1-em9@1;
DECISION*;
DECISION ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// monility
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em1 em10 em11 em19 fdip2
fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
```

```
MITERATIONS = 2000;
MODEL:
MOBILITY BY em1-em19@1;
MOBILITY*;
MOBILITY ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// financial management
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em2 em3 em12 em13 em14 em15
em16 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em2-em16;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
FINANCE BY em2-em16@1;
FINANCE*;
FINANCE ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// childbearing and family planning
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em4 em5 em6 em7 em8 em17
em18 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em4-em18;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
CHILDFAM BY em4-em18@1;
CHILDFAM*;
CHILDFAM ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;

// all factorall
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditfemale logcreditmale em1-em19 fdip2 fdip3 fdip4
mdip2 mdip3 mdip4;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
EMPOWERMENT BY em1-em19@1;
EMPOWERMENT*;
EMPOWERMENT ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheaded
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4;
```

// **Table 5.10, Fixed effects, column 2**

```
// decision making
```

```
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em1 em2 em3 em4 em5 em6 em7
em8 em9 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4
prov2-prov12;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em9;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
DECISION BY em1-em9@1;
DECISION*;
DECISION ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-
prov12;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// monility
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em1 em10 em11 em19 fdip2
fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
MOBILITY BY em1-em19@1;
MOBILITY*;
MOBILITY ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-
prov12;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// financial management
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em2 em3 em12 em13 em14 em15
em16 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4
prov2-prov12;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em2-em16;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
FINANCE BY em2-em16@1;
FINANCE*;
FINANCE ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-
prov12;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// childbearing and family planning
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em4 em5 em6 em7 em8 em17
em18 fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em4-em18;
Missing are all (-9999) ;
```

```
Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
CHILDFAM BY em4-em18@1;
CHILDFAM*;
CHILDFAM ON logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity
highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-
prov12;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;

// all factorall
USEVARIABLES = province agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans logcreditmale logcreditfemale em1-em19 fdip2 fdip3 fdip4
mdip2 mdip3 mdip4 prov2-prov12;
Missing are all (-9999) ;
CLUSTER = province;
CATEGORICAL = em1-em19;
Missing are all (-9999) ;

Analysis:
ESTIMATOR = MLR;
TYPE = COMPLEX;
MITERATIONS = 2000;
MODEL:
EMPOWERMENT BY em1-em19@1;
EMPOWERMENT*;
EMPOWERMENT ON logcreditfemale logcreditmale agehead genderhead nummem denummem
ethinicity highestheadedu nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3
mdip4 prov2-prov12;
logcreditfemale logcreditmale agehead genderhead nummem denummem ethinicity highestheadedu
nummchild numfchild fage llag_loans fdip2 fdip3 fdip4 mdip2 mdip3 mdip4 prov2-prov12;
```

Chapter 6. Robustness check key estimated results using clustered standard errors

6.1 Introduction

The key findings from the previous replication chapters show that microcredit does not really help poor households, especially poor women in Bangladesh. If the issue of significance is ignored, the sizes of the estimated effects are small and economically unimportant. In addition, the impact of microcredit participation by gender on women's empowerment is evaluated in Chapter 4 and Chapter 5. The findings generally support the claim that microcredit participation by females has a positive impact on women's empowerment. The effect is small and statistically insignificant if male accesses loans. However, these results may be sensitive to complex sample designs. Hence, this chapter takes account of clustering standard errors within villages and provinces to analyze the sensitivity of the key results.

6.2 Complex sample design issues

Data that are collected from complex sampling have key features. First, there is an issue of variances and within-cluster spatial autocorrelation. In an effort to save costs, a survey is generally conducted by clusters of population, which are either geographic areas or establishments. Interviewers can collect information in limited geographical regions. The disadvantage of clustering samples is that the standard errors are increased if the variance of an interesting variable within clusters is smaller than the variance between clusters. Second, social survey data are often collected by giving unequal selection probability. For example, not all households have the same chance to survey. This gives rise to the need to use weights when computing finite population estimates and reducing the systematic difference. Hence, complex survey designs require special methods for variance estimation and inference analysis.

Both Bangladesh and Vietnamese data are complex sample designed surveys. The 1991-92 Bangladesh survey consists of 29 thanas randomly drawn from 391 rural thanas, of which 24 had one or more of the three credit programs, and five thanas had none of them. Three villages in each program were randomly selected from a list of program villages. Three villages in each non-program thana were randomly selected from the village census of the Government of Bangladesh. There were three villages per thana and an average of 21 households per village. It is likely that the number of thanas (29 thanas) is a small subset and the number of households is a small sample fraction. These make the sample not representative of the population. The 1998-99 survey followed the 1991-92 survey. Hence, they are both complex survey designs.

The same issues are in the Vietnamese data survey. VARHS surveyed rural households living in 12 different provinces out of 65 provinces in Vietnam. There are 2161 households from 464 communes in the 12 provinces across seven regions. The sample may not give the same probability for all households and did not collect data from all rural provinces in Vietnam. Three enumeration areas are selected per commune, and each enumeration area has an average of 100 households. It also appears that the VARHS sample is based on the Vietnam Household Living Standards Survey, which is based on a multi-stage sample. Therefore, this departure from simple random assumptions required to take account of variance estimation issues.

Clustering frequently occurs in cross-section and panel data applications. Observations on households drawn from the same village (cluster) may correlate highly, while observations on households across villages do not (Baum, Schaffer, & Stillman, 2003). Due to unobserved village effects, there is a correlation in the covariates across households within the same village or province (Cameron & Trivedi, 2005). This leads to complicated estimation and inference at the village level. For example, I estimate how microcredit participation impacts per capita expenditure and other outcomes, including women's non-land assets, labor supply and children's enrolment. These variables are likely to have a very strong degree of spatial correlation. The children in the same village probably all go to the same school. So if there is a shock such as teacher leaves, gets sick, or school gets damaged, there will be a high within-village correlation in enrolments. The labor supply is likely to be in the same labor market, creating spillovers. The non-land assets are probably purchased in the same "thin" markets, creating spillovers. It is the nature of life in rural villages of developing countries that there are high within-village correlations. The correlation among households within a village leads to the usual law of large numbers of observations and the central limit theorem not being able to apply. The correlations among error terms within groups result in IV-FE estimation still consistently but the standard errors and hypothesis testing are not efficient. Therefore, this chapter applies clustering standard errors by village/province level to take account of the complex sample designs, valid inference and diagnostic testing possible (Wooldridge, 2010).

6.3 The sensitivity analyses of key findings

Two common methods are used to control complex sample designs: weighted sample and clustered standard errors. Due to the sample weights are not available for the 1998-99 Bangladesh and Vietnamese data, I use clustered villages and provinces for estimation and to check how sensitive in inference. Three key findings from Chapter 2 to Chapter 5 are re-estimated using clustered standard errors for complex designs. First, the impact of microcredit participation by gender on household well-being and other alternative outcomes using the 1991-92 Bangladesh data is reported in Table 6.1, Table 6.2 and Table 6.3. Second, Table 6.4 and Table 6.5 report the impact of microcredit participation by gender on per capita expenditure and other factors accounting for clustered standard errors and considering outliners, using the 1998-99 Bangladesh data. The third key finding, the impact of microcredit on women's empowerment, is reported in Table 6.6 using the 1998-99 Bangladesh and Vietnamese panel data.

Table 6.7 provides a selected summary of my main results when clustered standard errors are used. Most of the re-estimated findings using cluster errors remain as significant/insignificant as results without clustered standard errors. Only the coefficient of girl school enrolment becomes insignificant and the coefficient of boy school enrolment becomes insignificant when clustered standard errors are used (cf. table 6.7, top panel). Overall, the sensitivity analyses (particularly hypothesis tests) show that after taking account of complex sample designs (clustered standard errors), all findings are robust. The clustering findings are consistent with the main outcomes without clustered standard errors. My results show weak evidence to support the idea that microcredit significantly enhances families' well-being, especially women's well-being, regardless of gender of borrowers. Although microcredit has the potential to improve women's empowerment if loans are given to women, the effects are small. In contrast, male participation in microcredit has little impact on women's empowerment and the findings are statistically insignificant.

6.4 References

Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal, 3*(1), 1-31.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*: Cambridge University Press.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*: MIT Press.

Table 6.1 The impact of microcredit participation on per capita expenditure using entropy balancing - clustered villages

Control groups	*Entropy balancing* *(1)*	*Entropy balancing* *Clustered villages* *(2)*
Non-participants in treatment villages	-0.007	-0.007
	[-0.66]	[-0.52]
Individuals in control villages	-0.043**	-0.043
	[-2.41]	[-0.86]

Note: t-statistics in parentheses *, **, *** denote significance at 10%, 5%, and 1% levels. The results are bootstrapped.

Table 6.2 The impact of microcredit participation on alternative outcomes using entropy balancing – clustered villages

Outcome variables	*Entropy balancing* *(1)*	*Entropy balancing* *Clustered villages* *(2)*
Variation of log per capita expenditure (Taka)	-0.014*	-0.014
	[-1.89]	[-1.55]
Log per capita expenditure (Taka)	-0.013	-0.013
	[-0.94]	[-0.95]
Log of female non-landed assets (Taka)	0.471***	0.471**
	[2.65]	[1.99]
Female labor supply, aged 16-59 years, hours per month	4.813	4.813
	[0.60]	[0.55]
Male labor supply, aged 16-59 years, hours per month	29.593	29.593
	[1.57]	[1.61]
Girl school enrolment, aged 5-17 years	0.055**	0.055*
	[2.16]	[1.92]
Boy school enrolment, aged 5-17 years	0.048*	0.048**
	[1.95]	[2.26]

Note: t-statistics in parentheses *, **, *** denote significance at 10%, 5%, and 1% levels. The results are bootstrapped.
Chemin and D&PJ use kernel with bandwidth 0.01, 0.02 and 0.05 to estimate their results

Table 6.3 Impact estimation for alternative outcome variables stratified by gender

Outcome variables	*Female (EB) (1)*	*Female EB, clustered villages (2)*	*Male (EB) (3)*	*Male EB, clustered villages (4)*
Variation of log per capita expenditure (Taka)	-0.023**	-0.023*	-0.050***	-0.050**
	[-2.49]	[-1.86]	[-6.74]	[2.50]
Log per capita expenditure (Taka)	-0.016	-0.016	-0.067***	-0.067*
	[-1.06]	[-0.83]	[-6.67]	[-1.89]
Log of female non-landed assets (Taka)	0.739***	0.739**	-0.275*	-0.275
	[3.45]	[2.01]	[-1.88]	[-0.53]
Female labor supply, aged 16-59 years, hours per month	16.517	16.517	-36.302 ***	-36.302***
	[1.59]	[1.19]	[-7.28]	[-2.75]
Male labor supply, aged 16-59 years, hours per month	49.463***	49.463*	53.004***	53.004
	[2.98]	[1.90]	[4.57]	[0.88]
Girl school enrolment, aged 5-17 years	0.088***	0.088**	0.151***	0.151***
	[2.78]	[1.99]	[7.75]	[2.98]
Boy school enrolment, aged 5-17 years	0.095***	0.095***	0.064***	0.064
	[3.04]	[2.92]	[3.27]	[1.66]

Note: t-statistics in parentheses, *, **, *** denote significance at 10%, 5%, and 1% levels. The results are bootstrapped
Using entropy balancing (EB) for robustness check. Columns (1) and (3) without clustered villages and columns (2) and (4) taking account of clustered villages

Table 6.4 Impact estimates for log weekly per capita expenditures (Taka)

Treatment	*De facto participants*			*De jure participants*			*De facto participants Clustered villages*			*De jure participants Clustered villages*		
	C1	**C2**	**C3**	**C1**	**C2**	**C3**	**C1**	**C2**	**C3**	**C1**	**C2**	**C3**
All observations												
Dummy female	-0.0423*	-0.0424*	-0.0424*	-0.0313	-0.0316	-0.0316	-0.0423*	-0.0424*	-0.0424*	-0.0313	-0.0316	-0.0316
borrowing	[0.023]	[0.025]	[0.023]	[0.024]	[0.022]	[0.022]	[0.025]	[0.025]	[0.025]	[0.023]	[0.023]	[0.023]
Dummy male	-0.0260	-0.0261	-0.0298	-0.0303	-0.0303	-0.0358	-0.0260	-0.0261	-0.0298	-0.0303	-0.0303	-0.0358
borrowing	[0.044]	[0.048]	[0.050]	[0.049]	[0.053]	[0.048]	[0.048]	[0.048]	[0.048]	[0.049]	[0.049]	[0.048]
Drop outliers												
Dummy female	-0.0019	-0.0020	-0.0020	0.0005	0.0004	0.0004	-0.0019	-0.0020	-0.0020	0.0005	0.0004	0.0004
borrowing	[0.018]	[0.020]	[0.018]	[0.020]	[0.020]	[0.015]	[0.019]	[0.019]	[0.019]	[0.018]	[0.018]	[0.018]
Dummy male	0.0239	0.0239	0.0218	0.0151	0.0151	0.0127	0.0239	0.0239	0.0218	0.0151	0.0151	0.0127
borrowing	[0.040]	[0.038]	[0.037]	[0.042]	[0.042]	[0.041]	[0.035]	[0.035]	[0.035]	[0.033]	[0.033]	[0.033]

Note: standard error in parenthesis, *significant at 10%, **significant at 5%, ***significant at 1%

C1: control group = all non-participants

C2: control group = non-participants in program villages

C3: control group = non-participants in female/male program villages

De jure participants: drop HHs who participated in credit programs but had land of more than 0.5 acres

Table 6.5 Impact assessment for alternative outcome variables, between participants and non-participants across program and non-program villages, by gender

	Female borrowing				Male borrowing			
Outcome variables	De facto	De factor Clustered	De jure	De jure clustered	De facto	De facto Clustered	De jure	De jure Clustered
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log per capita expenditure (Taka)	-0.0423*	-0.0423*	-0.0313	0.0313	-0.0260	-0.0260	-0.0303	-0.0303
	[0.028]	[0.025]	[0.028]	[0.023]	[0.051]	[0.048]	[0.053]	[0.049]
Log women non-landed assets	0.1597	0.1597	0.1363	0.1363	-0.1350	-0.1350	-0.3114	-0.3114
(Taka)	[0.186]	[0.177]	[0.188]	[0.181]	[0.348]	[0.350]	[0.348]	[0.356]
Log women assets (Taka)	0.2553	0.2553	0.2181	0.2181	0.0086	0.0086	-0.1932	-0.1932
	[0.193]	[0.163]	[0.193]	[0.170]	[0.353]	[0.325]	[0.351]	[0.322]
Log female labor supply, aged 16-	0.0789***	0.0789***	0.0896***	0.0896***	0.0134	0.0134	0.0147	0.0147
59 years, hours per month	[0.022]	[0.021]	[0.024]	[0.024]	[0.034]	[0.022]	[0.039]	[0.029]
Log male labor supply, aged 16-59	0.0566	0.0566*	0.0502	0.0502	0.1430	0.1430	0.1213	0.1213
years, hours per month	[0.051]	[0.034]	[0.053]	[0.038]	[0.087]	[0.047]	[0.096]	[0.046]
Girl school enrolment, aged 5-17	0.1018	0.1018	0.0507	0.0507	0.1228	0.1228	0.1941	0.1941
years	[0.080]	[0.085]	[0.084]	[0.089]	[0.137]	[0.119]	[0.153]	[0.145]
Boy school enrolment, aged 5-17	0.0576	0.0576	0.0408	0.0408	0.0870	0.0870	0.1255	0.1255
years	[0.076]	[0.081]	[0.079]	[0.078]	[0.140]	[0.124]	[0.148]	[0.149]

Note: control group = all non-participants, treatment is one if female/male borrowing by gender
De jure participants: drop HHs who participated in credit programs but had land of more than 0.5 acres
*significant at 10%, **significant at 5%, ***significant at 1%
Columns (2), (4), (6) and (8) taking account of clustered villages

Table 6.6 The impact of microcredit participation by gender on female empowerment using Bangladesh data 1998-99 and Vietnamese data 2008-2010, clustered villages/provinces

Using Bangladesh data 1998-99				
Methods	Female participation	Female participation Clustered village	Male participation	Male participation Clustered village
	(1)	(2)	(3)	(4)
GSEM FE	0.036***	0.036***	-0.003	-0.003
	[13.55]	[11.31]	[-0.67]	[-1.12]
LASSO FE	0.080***	0.080***	-0.013	-0.013
	[11.75]	[12.48]	[-0.98]	[-0.35]
LASSO FE-IV	0.091***	0.096**	-0.126	-0.126
	[3.74]	[2.34]	[-1.75]	[-1.42]]
Using Vietnamese data 2008-2010				
Methods		Female participation Clustered province		Male participation Clustered province
		(1)		(2)
GSEM FE		0.018**		0.005
		[2.07]		[1.17]
LASSO FE		0.008***		0.000
		[2.01]		[-0.16]

Note: t-statistics in parentheses clustered villages for Bangladesh data and clustered provinces for Vietnamese data *, **, *** denote significance at 10%, 5%, and 1% levels

Table 6.7 Summary of results

Table/Column	Dependent variable	The results of using cluster-robust standard errors
Table 6.2, column 2:	Variation of log per capita expenditure (Taka)	Coefficient remains insignificant when clustered standard errors are used
	Log per capita expenditure (Taka)	Coefficient remains insignificant when clustered standard errors are used
	Log of female non-landed assets (Taka)	Coefficient remains significant when clustered standard errors are used
	Female labor supply, aged 16-59 years, hours per month	Coefficient remains insignificant when clustered standard errors are used
	Male labor supply, aged 16-59 years, hours per month	Coefficient remains insignificant when clustered standard errors are used
	Girl school enrolment, aged 5-17 years	Coefficient **becomes insignificant** when clustered standard errors are used
	Boy school enrolment, aged 5-17 years	Coefficient **becomes significant** when clustered standard errors are used
Table 6.5, column 2, 4, 6, 8:	Variation of log per capita expenditure (Taka)	Coefficient remains insignificant when clustered standard errors are used
	Log per capita expenditure (Taka)	Coefficient remains insignificant when clustered standard errors are used
	Log of female non-landed assets (Taka)	Coefficient remains insignificant when clustered standard errors are used
	Female labor supply, aged 16-59 years, hours per month	Coefficient remains significant when clustered standard errors are used if female borrowing Coefficient remains insignificant when clustered standard errors are used if male borrowing
	Male labor supply, aged 16-59 years, hours per month	Coefficient remains insignificant when clustered standard errors are used
	Girl school enrolment, aged 5-17 years	Coefficient remains insignificant when clustered standard errors are used
	Boy school enrolment, aged 5-17 years	Coefficient remains insignificant when clustered standard errors are used
Table 6.6, column 2, 4, top panel:	Factor all of women's empowerment (using GSEM FE)	Coefficient remains significant when clustered standard errors are used if female borrowing Coefficient remains insignificant when clustered standard errors are used if male borrowing
	Factor all of women's empowerment (using LASSO FE)	Coefficient remains significant when clustered standard errors are used if female borrowing Coefficient remains insignificant when clustered standard errors are used if male borrowing
	Factor all of women's empowerment (using LASSO FE-IV)	Coefficient remains significant when clustered standard errors are used if female borrowing Coefficient remains insignificant when clustered standard errors are used if male borrowing
Table 6.6, column 1, 2, bottom panel:	Factor all of women's empowerment (using GSEM FE)	Coefficient remains significant when clustered standard errors are used if female borrowing Coefficient remains insignificant when clustered standard errors are used if male borrowing
	Factor all of women's empowerment (using LASSO FE)	Coefficient remains significant when clustered standard errors are used if female borrowing Coefficient remains insignificant when clustered standard errors are used if male borrowing

6.5 Appendix: Programming code for Chapter 6

```
// Appendix Programming code for Chapter 6
clear matrix
drop _all
set mem 512m
set more off

// set paths to working data folders

global workingpath1  "/Volumes/Data/Dropbox/DIEM PhD Program/Diem Canterbury PhD/2020_PhD
Thesis/2020.Outline&Writing/Overall thesis/Final Data_Code/"

// working data files for round 1-3cap

cap log close
log using "${workingpath1}revisethesis", replace

use "${workingpath1}Chapter 2_D&PJ/Chemin_Logit_Prep3.0.dta", clear

******
/*before matching: sort data randomly*/
set seed 1000
cap drop x
generate x=uniform()
sort x
set more off

// Set macro for control variables and villages dummy
global DPJSpec3 "male agey agehhhh no_of_adultmales maxed cssv nonfarm livestockvalue hhsize
sumnonagri sumagri agesq age4"
global treatvilldumm  "_Ithanaid_2  _Ithanaid_3 _Ithanaid_4 _Ithanaid_5 _Ithanaid_6
_Ithanaid_7 _Ithanaid_8 _Ithanaid_9 _Ithanaid_10 _Ithanaid_11 _Ithanaid_12 _Ithanaid_13
_Ithanaid_14 _Ithanaid_15 _Ithanaid_16 _Ithanaid_17 _Ithanaid_18 _Ithanaid_19 _Ithanaid_20
_Ithanaid_21 _Ithanaid_22 _Ithanaid_23 _Ithanaid_24"


*************************************************************************************
// Table 2.11 --> Table 6.1
*************************************************************************************


* (Table 2.11, row 1) control1 //  all treated vs elig non-part treatvill - eligpbility
calculated on total land owned - D&PJ used this variable
* Regression results are also reported in Table 2.8 (treatment-control in program villages)

ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control1, gen(e_weight)

******* EBALANCE, BOOTTEST
regress lnconsweekpc elig_defacto_treatpp [pw=e_weight], cluster(upzvill)
boottest elig_defacto_treatpp
drop e_weight

* Table 2.11, row 2 control2 // treated vs all individuals in control villages (excludes non-
participants in treated villages)
* Regression results are also reported in Table 2.9 (treated-control in non-program villages)

ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if control2, gen(e_weight)
regress lnconsweekpc elig_defacto_treatpp [pw=e_weight], cluster(upzvill)
boottest elig_defacto_treatpp
drop e_weight


***********************************************************************************
// Table 2.12 --> Table 6.2
***********************************************************************************


* Robust check Table 3 D&PJ using EBELANCE, using chemin's Specification 3
* treated vs all individuals in control villages (excludes non-participants in treated
villages)

set seed 1000
set more off
```

```
foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rp {
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm, gen(e_weight)
regress `v' elig_defacto_treatpp [pw=e_weight], cluster(upzvill)
boottest elig_defacto_treatpp
drop e_weight

}


*********************************************************************************
// Table 2.13 --> Table 6.3
*********************************************************************************


*ROBUST CHECK TABLE 4 (D&PJ), Robustness check using Ebalance, different in gender borrow

* Female borrow (Table 2.13, column 2)/ 7 alternative outcomes
set seed 1000
set more off

foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rp {
ebalance elig_defacto_treatpp $DPJSpec3 $treatvilldumm if elig_defacto_treatpp == 1 &
femaleparthh | ~ maleparthh, gen(e_weight)
regress `v' elig_defacto_treatpp [pw=e_weight], cluster(upzvill)
boottest elig_defacto_treatpp
drop e_weight

}
* male borrow (Table 2.13, column 4)/ 7 alternative outcomes

* Devendack&Palmer-Jones' table 4
* Impacts segregated by gender:
* female and male MF borrowers:
*maleparthh and femaleparthh are indicators that a male or female borrower is in the
household
gen elig_female_in_male_borrower_hh =  elig_defacto_treat == 1 & maleparthh == 1 &
femaleparthh ~= 1 // no need for this variable to be "female" - can be eligble household with
male borrower

set seed 1000
set more off

foreach v in lnconsweekpc sdlnconsweekpc lnnonlandwomen labsupwomMD1 labsupmenMD1
fedec517_rpj medec517_rp {
ebalance elig_female_in_male_borrower_hh $DPJSpec3 $treatvilldumm if femaleparthh ~= 1,
gen(e_weight)
regress `v' elig_female_in_male_borrower_hh [pw=e_weight], cluster(upzvill)
boottest elig_female_in_male_borrower_hh
drop e_weight

}

*********************************************************************************
// TABLE 3.12 → Table 6.4
*********************************************************************************

// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Facto, top panel

global path "/Volumes/Data/Dropbox/DIEM PhD Program/Diem Canterbury PhD/2020_PhD
Thesis/2020.Outline&Writing/Overall thesis/Final Data_Code/Chapter 3_RM/Robust_1998_99_data"

//cd "$path"
*do "$path/DiemProg.do"

global hhname "003_Diem_HH"
global indname "003-Diem-ind"

// Set globals

cap program drop SetGlobals
program define SetGlobals
```

```
global hhconvar scohead afedhigh amedhigh afadultd amadultd sexhead agehead ///
               llandbef  edhead spsislndd spbrolndd spparlndd hdsislndd hdbrolndd hdparlndd
hhnmembers
global indconvar age ed scohead afedhigh amedhigh afadultd amadultd sexhead agehead ///
               llandbef  edhead spsislndd spbrolndd spparlndd hdsislndd hdbrolndd hdparlndd
hhnmembers
global vill _Ivill*
*global bank allobs bracvill brdbvill gramvill //bracvill: =1 if in brac village, othervise =
0, similar for other banks
*global nontarvar nontar
*global insts zf* zm* choicef choicem //interraction between control variables (X)
                                                                                    // and villages fixed
effects with choice
global creditvar lfproglv1 lmproglv1 //female and male borrowing, credit zero will be replace
as log(1)
*global covsf scohead afedhigh amedhigh             amadultd sexhead agehead llandbef edhead
spsislndd spbrolndd spparlndd hdsislndd hdbrolndd hdparlndd hhnmembers crcensored1 _Ivill*
*global covsm scohead afedhigh amedhigh afadultd            sexhead agehead llandbef edhead
spsislndd spbrolndd spparlndd hdsislndd hdbrolndd hdparlndd hhnmembers crcensored1 _Ivill*

end

clear
set more off
use "$path/$hhname", clear
keep if wave==4

SetGlobals
global depen lpcnsexp

gen lfproglv1 = ln(fproglv)
replace lfproglv1=ln(1) if missing(lfproglv1)
gen lmproglv1 = ln(mproglv)
replace lmproglv1=ln(1) if missing(lmproglv1)
gen crcensored1 = 1 if progid==4 //eligibility but non-credit member
replace crcensored1=0 if missing(crcensored1)
tab crcensored1 wave



preserve
set more off
set matsize 800
set seed 1234

SetGlobals
global depen lpcnsexp

*treatment C1, control group = all non-participants
*female borrowing
cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0
cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)
boottest treatf

*male borrowing
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)
boottest treatm

restore


*treatment C2, control group = non-participants in program villages
*female borrowing
preserve
set more off
set matsize 800
```

```
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore

*treatment C3, control group = non-participants in female/male program villages
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore
// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Jure, borrowing and landownership <=50, top panel

*treatment C1
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
```

```
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore

*treatment C2
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore


*treatment C3
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp
cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore

// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Facto, bottom panel

*drop outliers
*De Facto
*C1
```

```
clear
set more off
use "$path/$hhname", clear
keep if wave==4

preserve
set more off
set matsize 800
set seed 12345
histogram pcnsexp, normal kdensity

local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)            //subtract the first quartile from the
third quartile
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr      //interquartile Range
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr       // rule of thums is 1.5
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
cap drop treatm
set seed 12345
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)


restore

*treatment C2
*De Facto,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
```

```
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore

*treatment C3
*De Facto,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity

local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore

**********************************************************************************
// Impact estimates for log weekly per capita expenditures
// Table 3.12
// De Jure, bottom panel

*drop outliers
*treatment C1
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
```

```
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)


restore

*treatment C2
*De Jure,
*female borrowing
preserve
set more off
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp

/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore

*treatment C3
*De Jure,
*female borrowing
preserve
set more off
```

```
set matsize 800
set seed 12345

SetGlobals
global depen lpcnsexp

histogram pcnsexp, normal kdensity
local X pcnsexp
/***/dis "Dropping outlier for `X'"
/***/sum `X', detail
/***/gen outlier_iqr = r(p75) - r(p25)
/***/gen outlier_lower = r(p25) - 1.5*outlier_iqr
/***/gen outlier_upper = r(p75) + 1.5*outlier_iqr
/***/gen outlier_`X'_dummy = 1 if `X' < outlier_lower | `X' > outlier_upper
/***/drop if outlier_`X'_dummy == 1
/***/drop outlier_*
histogram pcnsexp, normal kdensity

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0 & progvill==1 & fprogvill==1

cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
reg $depen treatf [pw=E_weight], cluster(village)

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0 & progvill==1 & mprogvill==1
cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
reg $depen treatm [pw=E_weight], cluster(village)

restore



*************************************************************************************
// TABLE 3.13 → Table 6.5
*************************************************************************************


// Other outcomes between participants and non-participants across program and non-program
villages, by gender

// Log female nonland / fnlasset
// De facto
* female borrow
clear
set more off
use "$path/$hhname", clear

preserve
set more off
keep if wave==4
set seed 12345

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0

gen lfnlasset =ln(fnlasset) //female non-land asset
               recode lfnlasset (. = `=ln(1)')  //ln(1) = 0, no non-land asset
gen lfasset =ln(fasset) //female asset
               recode lfasset (. = `=ln(1)')  //ln(1) = 0, no asset


cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)
foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatf [pw=E_weight], cluster(village)
}
```

```
drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)
foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatm [pw=E_weight], cluster(village)
}

drop E_weight

restore

*De Jure

* female borrow
preserve
set more off
keep if wave==4
set seed 12345

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

gen lfnlasset =ln(fnlasset) //female non-land asset
               recode lfnlasset (. = `=ln(1)')  //ln(1) = 0, no non-land asset
gen lfasset =ln(fasset) //female asset
               recode lfasset (. = `=ln(1)')  //ln(1) = 0, no asset


cap drop E_weight
ebalance treatf $hhconvar $vill, gen(E_weight)

foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatf [pw=E_weight], cluster(village)
}

drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $hhconvar $vill, gen(E_weight)

foreach v in lpcnsexp lfnlasset lfasset {
regress `v' treatm [pw=E_weight], cluster(village)
}

drop E_weight

restore


//INDIVIDUALS/ Log female &male labor: mwork & fwork /School enrolment: feduc517, meduc517/
clear
set more off
use "$path/$indname", clear


// PREPAREDATA
keep if wave<=4
               sort nh wave
```

```
		ren rfem choicef
		ren rmale choicem
		gen byte choice = choicef | choicem
		gen byte progid4 = progid // 1 = BRAC village, 2 = BRDB, 3 = Grameen, 0 = none
		recode progid4 (4 5 = 0)  //eligible but not borrow, 5 ineligible
		xi i.village
		gen double fasset = fnlasset + flandvalb

		gen lfproglv = ln(fproglv)
		replace lfproglv = 0 if missing(lfproglv)
		gen lmproglv = ln(mproglv)
		replace lmproglv = 0 if missing(lmproglv)

		gen llandbef =ln(landbef)

		recode llandbef (. = `=ln(1)')  //ln(1) = 0, no land

		gen lpcnsexp= ln(pcnsexp)
		gen nontar = 1 - eligible // non-target = 1 - eligible

		sort nh wave

		bysort nh: gen double lproglv = ln(proglv)
		recode lproglv (. = `=ln(1)')

		recode lfproglv lmproglv (0 = `=ln(1)')     // First-stage LHS variables take
censoring *threshold* (not censoring *value*)
		//bysort nh (wave): gen double lfproglvln = log(fproglv)
		//bysort nh (wave): gen double lmproglvln = log(mproglv)
		//bysort nh (wave): gen double lproglvln = log(proglv)
		//recode l*proglvln (. = 0)

		bysort nh (wave): gen byte nontrgth_dejure = landbef >= 50.01

		gen crcensored=1 if choice==1 & proglv==0
		recode crcensored (. =0)
SetGlobals
/*
* interact controls with choice dummies to make instruments
		foreach var of varlist $covsf {
			gen double zf`var' = `var' * choicef
		}
		foreach var of varlist $covsm {
			gen double zm`var' = `var' * choicem
		}
		foreach var of varlist $covsf afadultd _Ivill* {
			cap gen double zb`var' = `var' * choice
		}

	*/
//female borrowing

preserve
set more off
keep if wave==4
set seed 12345
SetGlobals

gen lfwork =ln(fwork) //labor supply, including self-employment (hours/month), if female
		recode lfwork (. = `=ln(1)')  //ln(1) = 0, no labor supply
gen lmwork =ln(mwork) //labor supply, including self-employment (hours/month), if male
		recode lmwork (. = `=ln(1)')  //ln(1) = 0, no labor supply

cap drop treatf
gen treatf = 1 if fproglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $indconvar $vill, gen(E_weight)

foreach v in lfwork lmwork {
regress `v' treatf [pw=E_weight], cluster(village)
}
foreach v in fedec517 medec517{
probit `v' treatf [pw=E_weight], cluster(village)
}
```

```
drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $indconvar $vill, gen(E_weight)
foreach v in lfwork lmwork {
regress `v' treatm [pw=E_weight], cluster(village)
}

foreach v in fedec517 medec517 {
probit `v' treatm [pw=E_weight], cluster(village)
}
drop E_weight

restore

*De Jure

preserve
set more off
keep if wave==4
set seed 12345
SetGlobals

gen lfwork =ln(fwork) //labor supply, including self-employment (hours/month), if female
               recode lfwork (. = `=ln(1)')  //ln(1) = 0, no labor supply
gen lmwork =ln(mwork) //labor supply, including self-employment (hours/month), if male
               recode lmwork (. = `=ln(1)')  //ln(1) = 0, no labor supply

cap drop treatf
gen treatf = 1 if fproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatf = 0 if proglv==0

cap drop E_weight
ebalance treatf $indconvar $vill, gen(E_weight)
foreach v in lfwork lmwork {
regress `v' treatf [pw=E_weight], cluster(village)
}
foreach v in fedec517 medec517{
probit `v' treatf [pw=E_weight], cluster(village)
}
drop E_weight

*male borrowing
set seed 12345
cap drop treatm
gen treatm = 1 if mproglv>0 & landbef <= 50
drop if landbef>50 & proglv>0
replace treatm = 0 if proglv==0

cap drop E_weight
ebalance treatm $indconvar $vill, gen(E_weight)

foreach v in lfwork lmwork {
regress `v' treatm [pw=E_weight], cluster(village)
}
foreach v in fedec517 medec517 {
probit `v' treatm [pw=E_weight], cluster(village)
}
drop E_weight

restore

 //Test for nornal distribution
sfrancia pcnsexp if wave==4

//After drop outliers, test for the normal distribition again
```

```
*******************************************************************************
// CHAPTER 4 → Table 6.6, top panel
*******************************************************************************


clear
global path "/Volumes/Data/Dropbox/DIEM PhD Program/Diem Canterbury PhD/2020_PhD
Thesis/Thesis revise_Exam/"

cap log close
log using "$path/chapter6_revise",replace

global path "/Volumes/Data/Dropbox/DIEM PhD Program/Diem Canterbury PhD/2020_PhD
Thesis/2020.Chapter3_PKC/Data/"
use "$path/HHobservation002.dta", clear

//Lasso

set more off

// IV

global xvar agemem edumem parentheadland broheadland ///
sistheadland parentspouseland brospouseland sistspouseland land agehead eduhead higedumale
higedufemale
global vvar wagem wagef nowagef pzwflour pzpotato pzrice pzmoil pzhegg pzmilk primcoed


macro drop ivfxvar
foreach var of global xvar {
cap drop ivf`var'
gen ivf`var' = (femalechoice-1)*`var'
global ivfxvar $ivfxvar ivf`var' // vi trong vong lap co nhieu bien, ket hop ten bien cu va
ivf*, tao luon global
}                                  // ton tai tat ta cac bien IV, chu khong phai 1 bien IV

macro drop ivmxvar
foreach var of global xvar {
cap drop ivm`var'
gen ivm`var' = (malechoice-1)*`var'
global ivmxvar $ivmxvar ivm`var'
}

// Tao bien IV, tao ra 103 bien Dummy, tao ra 1 global chua 103 bien do
//egen vilid = group(Thanaid Villid)
tab vilid, gen(ivvil)
global vilvar ivvil2 ivvil3 ivvil4 ivvil5 ivvil6 ivvil7 ivvil8 ivvil9 ivvil10 ivvil11 ivvil12
ivvil13 ivvil14 ivvil15 ivvil16 ivvil17 ivvil18 ivvil19 ivvil20 ivvil21 ivvil22 ivvil23
ivvil24 ivvil25 ivvil26 ivvil27 ivvil28 ivvil29 ivvil30 ivvil31 ivvil32 ivvil33 ivvil34
ivvil35 ivvil36 ivvil37 ivvil38 ivvil39 ivvil40 ivvil41 ivvil42 ivvil43 ivvil44 ivvil45
ivvil46 ivvil47 ivvil48 ivvil49 ivvil50 ivvil51 ivvil52 ivvil53 ivvil54 ivvil55 ivvil56
ivvil57 ivvil58 ivvil59 ivvil60 ivvil61 ivvil62 ivvil63 ivvil64 ivvil65 ivvil66 ivvil67
ivvil68 ivvil69 ivvil70 ivvil71 ivvil72 ivvil73 ivvil74 ivvil75 ivvil76 ivvil77 ivvil78
ivvil79 ivvil80 ivvil81 ivvil82 ivvil83 ivvil84 ivvil85 ivvil86 ivvil87 ivvil88 ivvil89
ivvil90 ivvil91 ivvil92 ivvil93 ivvil94 ivvil95 ivvil96 ivvil97 ivvil98 ivvil99 ivvil100
ivvil101 ivvil102 ivvil103 ivvil104

macro drop ivfvill
foreach var of global vilvar {
cap drop ivf`var'
gen ivf`var' = (femalechoice-1)*`var'
global ivfvill $ivfvill ivf`var'
}

macro drop ivmvill
foreach var of global vilvar {
cap drop ivm`var'
gen ivm`var' = (malechoice-1)*`var'
global ivmvill $ivmvill ivm`var'
}

// GSEM -- FE, factor all
 gsem (logfmaleloans logmaleloans $xvar i.vilid -> FACTORALL, vce(cluster vilid) nocons)
(FACTORALL -> (y*)@1, logit)
 predict fscore10, latent(FACTORALL)
```

```
 estimates store mimic10

 // LASSO -- FE, factor all

 // keep using variables
keep theta10 factorall vilid agemem edumem parentheadland broheadland sistheadland
parentspouseland brospouseland sistspouseland land agehead eduhead higedumale higedufemale
malechoice femalechoice logfmaleloans logmaleloans mpart fpart

// iv
tab vilid, gen(ivvil)
global vilvar ivvil2 ivvil3 ivvil4 ivvil5 ivvil6 ivvil7 ivvil8 ivvil9 ivvil10 ivvil11 ivvil12
ivvil13 ivvil14 ivvil15 ivvil16 ivvil17 ivvil18 ivvil19 ivvil20 ivvil21 ivvil22 ivvil23
ivvil24 ivvil25 ivvil26 ivvil27 ivvil28 ivvil29 ivvil30 ivvil31 ivvil32 ivvil33 ivvil34
ivvil35 ivvil36 ivvil37 ivvil38 ivvil39 ivvil40 ivvil41 ivvil42 ivvil43 ivvil44 ivvil45
ivvil46 ivvil47 ivvil48 ivvil49 ivvil50 ivvil51 ivvil52 ivvil53 ivvil54 ivvil55 ivvil56
ivvil57 ivvil58 ivvil59 ivvil60 ivvil61 ivvil62 ivvil63 ivvil64 ivvil65 ivvil66 ivvil67
ivvil68 ivvil69 ivvil70 ivvil71 ivvil72 ivvil73 ivvil74 ivvil75 ivvil76 ivvil77 ivvil78
ivvil79 ivvil80 ivvil81 ivvil82 ivvil83 ivvil84 ivvil85 ivvil86 ivvil87 ivvil88 ivvil89
ivvil90 ivvil91 ivvil92 ivvil93 ivvil94 ivvil95 ivvil96 ivvil97 ivvil98 ivvil99 ivvil100
ivvil101 ivvil102 ivvil103 ivvil104

// Lasso procedure
vl set
vl list vluncertain
vl move (edumem agehead eduhead higedumale higedufemale) vlcontinuous
macro list vlcategorical
macro list vlcontinuous
vl create ccbase = vlcontinuous - (theta10 factorall logfmaleloans logmaleloans vilid iv*)
vl create fcbase = vlcategorical - (malechoice femalechoice mpart fpart ivvil*)
macro list ccbase
macro list fcbase
vl create choice = (malechoice femalechoice)
vl create finstbase = ($vilvar parentheadland broheadland sistheadland parentspouseland
brospouseland sistspouseland)
vl create cinstbase = (agemem edumem land agehead eduhead higedumale higedufemale)
macro list finstbase
macro list cinstbase
macro list choice

vl substitute contvars = c.ccbase##c.ccbase c.ccbase##i.fcbase i.fcbase##i.fcbase
vl substitute inst =  i.choice#c.cinstbase   i.choice#i.finstbase
macro list contvars
macro list inst

set emptycells drop

// Lasso FE regression
foreach v in factorall theta10 {
xporegress `v' logfmaleloans logmaleloans i.vilid, controls($contvars) rseed(12345)
vce(cluster vilid)

lassoinfo
}

// Lasso FE-IV regression

foreach v in factorall theta10 {
xpoivregress `v' (logfmaleloans logmaleloans = $inst) i.vilid, controls($contvars)
rseed(12345) vce(cluster vilid)

dis "Inst_select: " e(inst_sel)
dis "Inst_select: " e(controls_sel)
lassoinfo

}

log close


*********************************************************************************
// CHAPTER 5 → Table 6.6, bottom panel
*********************************************************************************
```

```
clear
global path "/Volumes/Data/Dropbox/DIEM PhD Program/Diem Canterbury PhD/2020_PhD
Thesis/Thesis revise_Exam/"

cap log close
log using "$path/keyfindings_chapter5",replace

global path "/Volumes/Data/Dropbox/DIEM PhD Program/Diem Canterbury PhD/2020_PhD
Thesis/2020.Outline&Writing/Overall thesis/Final Data_Code/Chapter 5_Vietnam/"

use "$path/DatasetHH.dta", clear

etime, start

set more off
set matsize 5000
cap drop t
gen t = 0 if year==2008
replace t=1 if year==2010

xtset hhidentifier t

global xvar highestheadedu agehead genderhead fage nummchild numfchild nummem denummem
ethinicity llag_loans i.fdiploma i.mdiploma

// Using SEM, latent variables: EMPOWERMENT (factor all)
set more off
 gsem (logcreditfemale logcreditmale $xvar -> EMPOWERMENT, vce(cluster provinifer) nocons)
(EMPOWERMENT -> (em1-em19)@1, logit)
 gsem (logcreditfemale logcreditmale $xvar i.provinifer -> EMPOWERMENT, vce(cluster
provinifer) nocons) (EMPOWERMENT -> (em1-em19)@1, logit)

use "$path/DatasetHH.dta", clear

set matsize 5000
cap drop t
gen t = 0 if year==2008
replace t=1 if year==2010
xtset hhidentifier t

 // keep using variables
keep hhidentifier t em1-em21 decision mobility financial childfam factorall logcreditfemale
logcreditmale llag_loans highestheadedu agehead genderhead fage nummchild numfchild nummem
denummem ethinicity highestfedu highestmedu year borrowernet bank dispeoplecom disallwearoad
disasters provinifer fdiploma mdiploma

//Dummy categories
tab fdiploma, gen(dipf)
tab mdiploma, gen(dipm)
global diplomam dipm2 dipm3 dipm4
global diplomaf dipf2 dipf3 dipf4

vl set
vl list vluncertain
vl move (agehead nummem highestheadedu fage highestfedu highestmedu provinifer) vlcontinuous
macro list vlcategorical
vl move (denummem nummchild numfchild disasters bank) vlcontinuous
macro list vlcontinuous

vl create ccbase = vlcontinuous - (hhidentifier provinifer dispeoplecom disallwearoad
borrowernet logcreditmale logcreditfemale llag_loans decision mobility financial childfam
factorall highestfedu highestmedu disasters bank)
vl create fcbase = vlcategorical - (year em1-em21 t dipm1 dipf1 fdiploma mdiploma)
//vl create ccbase = vlcontinuous - (hhidentifier provinifer dispeoplecom disallwearoad
borrowernet logcreditmale logcreditfemale decision mobility financial childfam factorall
disasters bank)
//vl create fcbase = vlcategorical - (year em1-em21 t fdiploma mdiploma)
macro list ccbase
macro list fcbase

//vl create finstbase = (disasters bank borrowernet  disallwearoad disasters)
vl create cinstbase = (bank borrowernet dispeoplecom)

vl substitute contvars = c.ccbase c.ccbase#i.fcbase i.fcbase
```

```
//vl substitute inst =  c.cinstbase##i.finstbase i.finstbase##i.finstbase
c.cinstbase##c.cinstbase
vl substitute inst = c.cinstbase#c.cinstbase c.cinstbase
set emptycells drop
macro list inst
set more off

// Lasso FE regression
foreach v in factorall {
xporegress `v' logcreditmale logcreditfemale i.provinifer, controls($contvars) rseed(12345)
vce(cluster provinifer)

lassoinfo
}

// Lasso FE-IV regression

foreach v in factorall {
xpoivregress `v' (logcreditmale logcreditfemale = $inst) i.provinifer, controls($contvars)
rseed(12345) vce(cluster provinifer)

dis "Inst_select: " e(inst_sel)
dis "Inst_select: " e(controls_sel)
lassoinfo

}


etime
log close
```

Chapter 7. Conclusion

My thesis is mainly structured around my attempts to understand the impact of microcredit on women's empowerment. The first part of my thesis includes three chapters, which re-examine whether microcredit lifts families out of poverty and empowers women and whether the impacts vary by gender of participants, using data from Bangladesh. Bangladesh is known as a pioneer and a "success story" in introducing and implementing the concept of microcredit to help the poor, especially women. However, studies in this field, especially the most influential studies conducted by PK (1998) and PKC (2006), have attracted several replications and remain controversial. Both policy-makers and researchers are interested in knowing whether microcredit benefits the poor and empowers women when loans are given to women. In investigating these issues, replication is an important procedure to confirm original studies' reliability and avoid errors in data construction and complex analysis. Thus, to provide a clear picture of microcredit in Bangladesh, the first part of my thesis carefully replicates PK and PKC.

Neither PK nor PKC provide their data and code. I therefore replicate them indirectly by replicating D&PJ (Chapter Two) and RM (Chapter Three). Since D&PJ and RM replicated PK and kindly provided their data and code, this becomes my starting point to investigate the effect of microcredit in Bangladesh. After carefully working on D&PJ and RM, I understand data construction and variable definition and independently replicate PKC (Chapter Four).

In Chapter Two, my replication results confirm D&PJ using their data and code. However, in the assessment of matching balancing using PSM, I demonstrate that matched data used by D&PJ are unbalanced. This motivates me to employ entropy balancing, which constructs a synthetic control group that closely matches the treatment group. My re-analysis of their research using entropy balancing mainly confirms D&PJ's results. Similar to D&PJ, I find weak evidence to support the causal relationships between microcredit and poverty alleviation. However, I find a significant impact on female labor supply, female non-land assets, and girls' schooling enrolment when women have an opportunity to borrow loans. Overall, my research adds more skepticism about the previously documented large and broad benefits of microcredit programs found in PK.

In Chapter Three, I continue my effort to reproduce and replicate PK by replicating RM. By using their data and code, I find it straightforward to replicate their results. Second, I take note of the weaknesses of PK's analysis pointed out by RM. Specifically, that the LIML-FE approach adopted by PK, and replicated by RM, depends crucially on the validity of the eligibility criteria and the normality of the data. I conducted a check on these issues, and neither of these aspects is well-supported by the data. Hence, I use a new method, entropy balancing that does not require these conditions. Third, I expand on RM's analysis by using updated data from the 1998-1999 survey. My replication and extension do not find evidence that microcredit really helped poor households, especially poor women, in Bangladesh. In general, the estimated impacts of microcredit are small and statistically insignificant. These findings are consistent with the conclusion of RM and fail to support PK's conclusion.

My next step focuses on whether microcredit participation enhances women's empowerment by replicating PKC (Chapter Four). My study is the first replication of PKC, one of the most influential papers in this field. Although my replication does not precisely match PKC's result, my findings generally confirm PKC's claim that female participation enhances women's empowerment. However, when I test the validity of PKC's instrumental variables (which PKC did not do), my results fail to reject the null hypothesis of weak instruments. I therefore employ the least absolute shrinkage and selection operator (Lasso) technique to address this concern. My Lasso robustness check shows weak evidence to support PKC's conclusion that microcredit programs increase female empowerment. While I find some evidence to support their findings that the presence of a program is associated with an increase in female empowerment, actual borrowing shows very little impact.

Finally, I conduct a novel study and investigate the effect of microcredit by gender of borrowers on female empowerment using Vietnamese data (Chapter Five). I look at two types of treatments - participation in microcredit, and amount of borrowing - and I employ a mixed-method to evaluate the main model. DAGs are employed to create a causal diagram for minimizing bias in empirical practice. Then, I use structural equation modeling and item response theory to estimate latent variable and microcredit impact. I use several methods for robustness checks of my findings, including Lasso instrumental variable fixed effects, treatment effect Lasso, and maximum likelihood procedures to deal with missing values. Overall, my results show weak evidence that microcredit enhances female empowerment when women participate in microcredit programs and no evidence that male borrowing affects women's empowerment. While there is some evidence that microcredit participation improves female empowerment as represented by financial management and childbearing and family planning, the sizes of estimated effects are small.

In conclusion, this research provides insights into the microcredit impact by gender of participants on poor women and women's empowerment. I find weak evidence that microcredit improves families' well-being, especially women's well-being. In addition, microcredit has the potential to improve women's empowerment if loans are given to women, but the effects are small. The presence of microcredit in villages is associated with moderate increases in female empowerment. Furthermore, in all chapters of my thesis, I estimate separate impacts on women's empowerment when men access microcredit. The results are consistently insignificant, and the sizes of the estimated effects are negligible.

I close with some final thoughts about replication. The impact of microcredit on reducing poverty and improving women's empowerment has received much attention in the empirical literature. The question of why recent findings contradict the findings of the most influential papers by PK is difficult to answer. One way to resolve discrepancies is to replicate the respective studies and check them for robustness. Maybe the reason they contradict each other is because of different empirical procedures, data, or time periods. In principle, replication and robustness checking allow one to determine how fragile or solid the findings are.

While my replications, along with Chemin, D&PJ, and RM, provide a body of work that challenges PK's findings, they unfortunately cannot identify the reason(s) why this work produces different results than PK. Pitt, in responding to PK's critics, also does not provide a way to reconcile the differences (Pitt, 2011a, 2011b). The reason is that PK's data and code are not available to compare. This highlights one of the shortcomings of replication. It is hard to make a comparison if the original studies' data constructions and code are omitted. Replication can only lead to reconciliation of conflicting results when the relevant data and code are available to investigate and compare.

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