The Long and The Short of It: Revisiting the Effects of Microfinance-Oriented Banks on Household Welfare in the Philippines

Cherry Wyle G. Layaoen[*]
Kazushi Takahashi[§]

Abstract

This study addresses the issue by evaluating a household-level panel data and a unique event in the Philippines when the microfinance industry was mainstreamed and commercialized in the banking sector with microfinance-oriented banks (MOBs) opening in 2004. We find that when MOBs offer households longer access to microfinance, the positive effects on entrepreneurial income and activities diminish or even regress over time. Moreover, no significant impacts are noted on real expenditures. Heterogeneity analysis further reveals that real expenditures of poor families also did not improve and the immediate positive effect on entrepreneurial income and activities did not accrue indefinitely. Lastly, no benefits are realized by non-poor families from access to microfinance. Consistent with the literature, MOB presence is therefore not transformative enough to lift the poor out of poverty. We, however, argue that MOB presence may reduce vulnerability as it affords households options to be entrepreneurs.

JEL Classification: G21, G23, G28

Keywords: microfinance; sample selection bias; household welfare; difference-in-differences; inverse probability weighting; Philippines

* Supervisory Policy and Research Department, Bangko Sentral ng Pilipinas; Email: *LayaoenCG@bsp.gov.ph*
§ Graduate School of Policy Studies, National Graduate Institute for Policy Studies; Email: *kaz-takahashi@grips.ac.jp*

1. Introduction

Microfinance has been positioned as an important financial instrument for poverty alleviation and socioeconomic development. Its proliferation is fueled by the belief that simply "lending to the poor" will indeed improve their economic (e.g., wealth and income) and social (e.g., education and health status) welfare (Buera, Kaboski, & Shin, 2012; Coleman, 2006). Many empirical studies have been conducted to understand these impacts of microfinance on income, employment, consumption, asset accumulation, and profits (Angelucci, Karlan, & Zinman, 2015; Attanasio, Augsburg, De Haas, Fitzsimons, & Harmgart, 2015; Augsburg, De Haas, Harmgart, & Meghir, 2012; Kaboski & Townsend, 2012; Karlan & Zinman, 2011; Morduch, 1998; Pitt & Khandker, 1998). However, they are mostly concerned with the short-term effects, and very few studies evaluate medium- and long-term effects, perhaps due to the difficulty of obtaining data with longer time interval between pre- and post-intervention surveys—approximately three years or longer.

To the best of our knowledge, only two studies exist that explicitly investigate the differential impacts of microcredit in terms of duration, and the results are mixed. Using data from Bangladesh, Islam (2011) finds that gains from microcredit programs vary with the length of participation and the benefits are larger for those participating in the program longer. He also finds that benefits may continue even after the participant leaves the program, but their magnitude diminishes. On the other hand, Banerjee, Duflo, Glennester, and Kinnan (2015), in their study on a group lending microcredit program in Hyderabad, India, find no significant short- or long-term impact on non-durable consumption, education, or health after the introduction of microfinance.

Our study aims to complement the limited literature by evaluating whether—and to what extent—the impact of microfinance varies with the length of exposure. We expand the scope of the existing studies in two important respects. First, as will be explained in more detail below, we will not only quantify the impact of *long-term* access to microfinance but also differentiate said impact to *immediate*, *incremental*, and *total* (or *net*) effects. It is important to understand these dynamics because a household that has access to microfinance for more than a year may see positive *immediate* effects but will have negative *incremental* effects several years after the access. Second, the study further investigates heterogeneous effects with respect to socio-economic classes, that is, whether the impact of microfinance differs by poverty level. The study's approach is closest to that of Islam (2011), but his study does not differentiate the effects in terms of poverty level.

We rely on a case from the Philippines where the microfinance industry has been growing on a commercial (i.e., for-profit lenders and extending individual liability credit) basis. The Bangko Sentral ng Pilipinas (BSP), or Central Bank of the Philippines, partially lifted the moratorium on the establishment of new banks in 2001, as long as the new bank is to be microfinance oriented. We scrutinize this event as a quasi-experiment with nationally representative panel data from 2003, 2006, and 2009 taken from the Family Income and Expenditure Survey (FIES) conducted by the Philippine Statistics Authority (PSA). The study's analyses are limited to assessing the effect of accessibility to microfinance as there are no available panel dataset on actual products and services availed by clients of microfinance institutions at the time of study.

Given the dataset, we consider 2003 as the *pre-intervention* period when there are absolutely no microfinance-oriented banks (MOBs) established in any municipalities and 2006 and 2009 as the *post-intervention* periods when MOBs have been established. We then define those households living in a municipality with a MOB both in 2006 and 2009 as the treatment group or *continuing clients*. The control group or *never clients* are those households who reside in municipalities with no MOBs.

Along with these household categories, we further identify the *immediate*, *incremental*, and *total* (or *net*) effects of longer MOB presence in municipalities. Effects derived from *continuing* households in 2006 are considered as *immediate* because these households became exposed to microfinance only after 2004 while those in 2009 represent *incremental* effects (i.e., effects that are added to the initial, immediate effects). The combined estimates for 2006 and 2009 of *continuing* households represent the *total* (or *net*) impact of access to microfinance through MOBs.

To obtain deeper insights into heterogeneity, we further disentangle these impacts depending on poverty level of the recipient as microfinance programs typically target poor individuals and also because much of the literature predicts that the impacts of microfinancing may differ depending on the economic class of the recipients (Attanasio et al., 2015; Banerjee, Karlan, & Zinman, 2015; Banerjee & Mullainathan, 2010; Crèpon, Devoto, Duflo, & Parienté, 2015; Dichter & Harper, 2007; Hulme & Mosley, 1996; Khandker, 1998; Kondo, Orbeta, Dingcong, & Infantado, 2008; Tarozzi, Desai, & Johnson, 2015).

Primary outcomes of interest are the probability of and income from wage work and self-employment as well as real expenditures[1] (i.e., food, medical care, alcoholic beverage & tobacco, and education) because microfinance providers target micro-entrepreneurs and the widely used proxies for poverty are income and consumption.

The main challenge in using observational panel data is the endogeneity problem associated with self-selection as well as sample attrition. To address these concerns, we employ a difference-in-differences (DID) household fixed effects (FE) technique combined with inverse-probability-weighted (IPW). The DID-FE addresses the non-random selection of municipalities and households based on their observable attributes as well as time-invariant unobservable attributes (e.g., inherent ability, industriousness, or geographical landscape of the municipality, including climate and susceptibility to natural disaster) that may affect a household's decision to avail microfinance and MOB's choice of location. Meanwhile, the IPW accounts for the sample selection associated with households dropping out of the survey. Finally, we employ the methodology developed by Oster (2019) and Altonji, Elder, and Taber (2005) to check the robustness of treatment effects from the IPW DID-FE model against unobserved confounders.

Results indicate that access to microfinance through MOBs provides households with opportunity to be entrepreneur but there is no evidence that real consumption increased. Moreover, the effects on self-employment regress when the presence of MOB in a municipality is long-term. We also find no significant effect on real expenditures of poor

1 Consumption and expenditures are used interchangeably in this study.

households, but entrepreneurial activities increased albeit temporary, relative to non-poor families.

The rest of this paper is organized as follows. Section 2 offers a brief background on MOBs in the Philippines and the study's data. Section 3 outlines estimation strategy. The results are reported in Section 4. Section 5 performs test on omitted variables. Lastly, Section 6 concludes the paper and provides implications of the findings.

2. Data and Context

2.1 Establishment of MOBs

We use a unique event in the Philippines - when the BSP in 2001 and 2005 issued Circular Nos. 273 and 505, respectively - to evaluate the impact of longer MOB presence in municipalities on household welfare. BSP Circular No. 273, dated 27 February 2001, partly lifted the moratorium on the establishment of new banks, allowing new banks that are microfinance oriented to locate in places not fully served by existing rural banks or MOBs. On one hand, BSP Circular No. 505, dated 22 December 2005, allowed qualified MOBs and branches of regular banks to establish branches anywhere in the Philippines. Since then, MOBs have been established to provide financial services that cater primarily to the credit needs of the basic[2] and/or disadvantaged sectors for their microenterprises and small businesses. This event is unique in that commercial banks ventured into microfinance and opened MOBs in the country. This also formalized mandated loans to basic sectors primarily for their microenterprises and small businesses to enable them to raise their income and improve their living standards (BSP, 2001).

Banks started establishing MOBs only in 2004 (BSP, 2005).[3] Most of these branches can be found in the capital or in cities and first-class municipalities[4] of the three geographic island groups (i.e., Luzon, Visayas, and Mindanao) of the country (Figure 1).

In Figure 2, we present client and loan portfolio of MOBs to determine if there are any systematic patterns of client self-selection and MOB location. Most microfinance programs claim that their primary goal is to alleviate rural poverty by delivering credit and other financial services to poor households. Such selective targeting may be useful to increase the efficacy but would threaten the identification strategy when we simply compare households with or without access to microfinance through MOBs. This issue will be revisited later (Section 3: Estimation Strategy).

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[2] The Social Reform and Poverty Alleviation Act of 1997 (or Republic Act No. 8425) defined basic sectors as farmer-peasants; artisanal fisherfolk; workers in the formal and informal sectors; migrant workers; indigenous peoples and cultural communities; women; differently-abled persons; senior citizens; victims of calamities and disasters; youth and students; children; and urban poor.

[3] The MOB established beginning 2004 are newly created microfinance-oriented banks and are not a conversion of a regular bank.

[4] Based on the Department of Finance (DOF) Order No. 23-08 dated 29 July 2008, this class of municipalities has the highest average annual income at PHP 45 million (USD 0.88 million) or more but less than PHP 55 million (USD 1.08 million). The peso-dollar rate used is the period average for 2003, 2006, and 2009 posted by the BSP on its website.

Statistics in Figure 2 confirms that the clients served by MOBs are from low-income households. Their loan portfolio is comprised of agricultural, microfinance[5], small and medium enterprise, and individual loans, which typically have short-term (up to 365 days) maturity.

2.2 Data

The primary data source is the FIES for the year 2003, 2006, and 2009 collected by the PSA. The FIES is a nationwide household survey conducted every three years and provides information on the level of consumption by item of expenditure as well as sources of income in cash and in kind. It also includes statistics on family size; occupation, age, and level of education of the household head; and other housing characteristics.

The surveys for 2003, 2006, and 2009 comprised 42,094, 38,483, and 38,400 households, respectively, covering all 17 administrative regions in the country. The administrative regions were also the survey's primary sampling unit (PSU). It used two-stage sampling with stratification at the PSU level. In the first stage, random samples of enumeration areas (EAs) or *barangays* were selected within sampled PSUs (or each region) with probability proportional to EA size (i.e., total number of households); in the second stage, random samples of households were selected within sampled EAs.

However, only 6,529 households or approximately 16 percent of the original sample are used in this study to construct a balanced panel dataset for the period 2003, 2006, and 2009. According to the PSA, the reasons for the small proportion of households that remained in the surveys are that some households felt that the nature of the data being collected is sensitive, some relocated between data collection times, or data collection procedures are aversive or costly to the household being surveyed.

We also use statistics on the number of banks and MOBs in the municipalities compiled by the BSP for the periods 2003, 2006 and 2009. In the dataset, it is observed that it was only in 2004 that banks started to set up MOBs. As stated earlier, the BSP partially lifted the moratorium on the establishment of new banks in 2001, which paved way for MOBs to be set up in municipalities. There are 24 municipalities that have MOBs. Of these, 21 have only 1 MOB established in the area, 2 municipalities have 2 MOBs each, and 1 municipality has 3 MOBs. Two municipalities out of the 24 have no other access to formal financial institutions but MOBs.

The opening of MOBs in 2004 allows us to identify the treatment and control groups in terms of time (i.e., *pre-intervention* and *post-intervention* periods) and units (i.e., *continuing* and *never clients*). The *pre-intervention* period is set at 2003 when there are absolutely no MOB established yet in municipalities, while 2006 and 2009 are considered as *post-intervention* periods as MOBs had been established in municipalities by then.

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[5] The types of loan are agriculture, education, housing, health, microbusiness, capital/start-up capital, multipurpose, salary, life insurance, hospitalization, pension, motorcycle, and so on. Based on BSP Circular No. 694 dated 14 October 2010, microenterprise loans refer to small and short-term loans granted to the basic sectors, on the basis of the borrowers' cash flow, for their microenterprises and small businesses. The principal amount of a microenterprise loan can be generally pegged at PHP 150,000 or USD 3,325.23. The foreign exchange rate used is the average for 2010 at PHP 45.11, posted by the BSP on its website.

Based on the status of MOBs in each municipality, we classify households into a control group or *never clients* who reside in municipalities with no MOB in *pre-* and *post-intervention* periods while the treatment group or *continuing clients* are those that live in municipalities with MOBs both in 2006 and 2009. Of the 6,529 households surveyed, 36.33 percent (2,372 households) were classified as *continuing* households.

2.2.1 Descriptive Statistics

Table 1 provides descriptive statistics on household and municipality attributes across the three waves of the survey to show a snapshot of the circumstances *before* (2003) and *after* (2006 and 2009) the issuance of BSP Circular Nos. 273 and 505. In the first survey (2003), none of the households and municipalities had access to microfinance because no MOBs had been established. In the second (2006) and third (2009) surveys, MOBs could be seen in some municipalities. The proportion of self-employed is statistically larger in pre-MOB presence period. There is no statistically significant difference in the share of wage workers between pre- and post-MOB presence periods. Meanwhile, the average income from wage work and entrepreneurial activities is higher in post-MOB bank presence period. It is also evident that spending on medical care is higher during post-MOB presence period while expenditure on food and alcoholic beverage & tobacco is lower. Lastly, no statistically significant difference between pre- and post-MOB presence period is noted in education expenditure.

For household attributes, proportion of males, age of the household head, household's assets, and households that own a house is statistically higher while family size is lower after the establishment of MOBs. Education level of the household head is not statistically different between pre- and post-MOB presence periods. Lastly, the number of poor households and bank[6] density in the municipalities are higher post-MOB presence while population is not statistically different between pre- and post-MOB presence periods.

3. Estimation Strategy

To identify the impact of MOB presence on various household activities and welfare, we employ an IPW DID-FE model to address the endogeneity problem associated with self-selection as well as sample attrition, which are common to any observational data where treatment status may not be randomized. The decision of MOBs on where to establish their branches is never entirely random. Some MOBs choose to situate themselves in less poor municipalities and where there is better complementary infrastructure to guarantee loan repayment or profitability. In fact, in the data analysis section, we discussed that most MOBs are situated in the capital or in cities and first-class municipalities (Figure 1). This could be a result of the BSP allowing establishment of MOBs only in places not fully served by existing rural banks or MOBs. Nevertheless, some MOBs are also established in places that are

6 Banks comprise of head offices, branches, extension offices, and other banking offices.

unserved or underserved by financial institutions. The dataset also indicates that third, fourth, and fifth-class municipalities or relatively poor municipalities[7] too have MOBs.[8]

In addition, the choice of whether a household avails microfinance products and services are not determined by chance. Households living in municipalities where MOBs are present may share similar socio-economic and cultural backgrounds (e.g., religion, ethnicity, or income source) but have different levels of enterprising capacity leading to different probabilities of their decision to avail microcredit. The selection bias arises because these unobservable characteristics may also affect outcomes of interest such as employment, income, and consumption. For example, households who are risk-takers (an attribute that is difficult to measure, if not impossible) have a higher tendency to self-select into microfinance borrowing, but such households are also expected to have higher income and expenditures even without microfinance.

The IPW DID-FE model addresses the selection bias on the following aspects. First, the DID-FE addresses the non-random selection of municipalities and households on the basis of their observable attributes as well as time-invariant unobservable attributes (e.g., inherent ability, industriousness, or geographical landscape of the municipality, including climate and susceptibility to natural disaster) that may affect households' decision to avail microfinance and MOBs' choice of location.

Although we control selection on observable and time-invariant unobservable attributes in DID-FE, there may be other factors that may still confound the estimates. We combine DID-FE with IPW to address the remaining concerns on sample selection associated with households dropping out of the survey, which are typically observed in longitudinal observational data. Finally, we employ the methodology developed by Oster (2019) and Altonji et al. (2005) to determine whether there are still unobserved confounders in the IPW DID-FE.

3.1 DID-FE model

We use the event when the BSP partially lifted the moratorium on the establishment of new banks in 2001 to evaluate the impact of access to microfinance through MOB presence in municipalities. This regulatory policy led to the opening of MOBs in 2004. With this event, we can estimate the following household FE in a DID regression, which compares households with and without MOBs in 2003 (*pre-intervention*) and in 2006 and 2009 (*post-intervention*):

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7 Third-class municipalities are defined as those earning an average annual income of PHP 35 million (USD 0.69 million) or more but less than PHP 45 million (USD 0.88 million), fourth-class municipalities are those earning an average annual income of PHP 25 million (USD 0.49 million) or more but less than PHP 35 million (USD 0.69 million), and fifth-class municipalities are those that have obtained an average annual income of PHP 15 million (USD 0.29 million) or more but less than PHP 25 million (USD 0.49 million).

8 For example, there are MOBs established in Buug, Zamboanga Sibugay, Santa Josefa, Agusan Del Sur (3rd class municipalities); Dapa, Surigao Del Norte, Danao, Bohol, Madrid, Surigao Del Sur, Calamba, Misamis Occidental, Braulio Dujali, Davao Del Norte (4th class municipalities); and Santa Teresita Batangas (5th class municipality).

$$y_{imt} = \beta_i + \delta_1(TREAT_{im}\ X\ POST_t) + \delta_2(TREAT_{im}\ X\ POST_t\ X\ dum09) + \gamma_t + \pi^* X'_{imt} + \rho^* Z'_{mt} + \varepsilon_{imt} \quad (1)$$

where y_{imt} is the measure of activities and welfare for household i residing in municipality m at time t, including: 1) real[9] household expenditure on food, medical care, alcoholic beverage & tobacco, and education; 2) household head is employed or self-employed; and 3) income from wage & salary or entrepreneurial activities. Real expenditures and income are transformed to inverse hyperbolic sine (or arcsinh)[10] to retain zero values because some households do not spend on certain goods and services or may not be earning momentarily. We are interested in evaluating the employment status of the household head as microfinance programs are intended to enhance self-employment activities. We use income and consumption as they are common indicators of poverty or wellbeing.

$TREAT_{im}$ is our treatment variable for continuing clients, which equals 1 for households i living in municipalities m that had at least one MOB and 0 otherwise. *Never clients* are the control group that includes households living in municipalities that do not have MOBs. $POST_t$ is a dummy that equals 1 for years 2006 and 2009 (*post-intervention*) and 0 for year 2003 (*pre-intervention*). $dum09$ is a dummy that equals 1 for observation year 2009.

There are several potential threats to the validity of the DID-FE model. First, the location of MOBs is not random over municipalities and time as described earlier. Note that the BSP only restricted the establishment in areas not fully served by rural banks or MOBs, so we would expect that their establishment may depend on some pre-existing characteristics of their potential clients and municipality. In Table 2, we compare the baseline characteristics in 2003 of *continuing* households and the municipality that they reside in to *never clients*. *Continuing* households are more likely to be headed by older adults and the proportion of male or self-employed household head is lower compared to never clients. In terms of municipality attributes, continuing households reside in municipalities that have large number of poor families and banks. To deal with this non-random selection of households and MOBs, we included a set of household attributes X'_i and municipal characteristics Z'_m. Household characteristics include sex, age, age squared, and education level of the household head, family size, and ownership of house and/or lot and financial assets[11]. The municipality controls are population, number of banks, and poor households that have influence on MOB's choice of location. These observed controls comprised of demand-side factors for the reason they are exogenous – determined prior to the policy intervention. Supply-side factors are not considered because they are endogenous as they are mostly driven by household's choice of lender (i.e., outcome variable that also indicates level of competition and concentration in the credit market) and risk/return profile of the borrower.

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9 The amount of expenditure is deflated by consumer price index with base year of 2012.

10 The inverse hyperbolic sine transformation can be expressed as $arcsinh(x) = \log(\sqrt{X^2+1} + x)$. Bellemaret and Wichman (2020) explain that applied econometricians frequently transform a variable to an arcsinh because it "approximates the natural logarithm of a variable and allows retaining zero-valued observations".

11 Financial assets owned comprised dividends and investments, interest from bank deposits and loans to other households, amount deposited in banks/investments, and profits from sale of stocks and real property.

Additionally, we included household fixed effects β_i to effectively account for the time-invariant unobserved household attributes. For example, entrepreneurial ability and risk preference may greatly influence a household's decision to avail microfinance products and services. According to Berg, Shahe Emran, & Shilpi (2013), less risk averse, and highly skilled households are more likely to engage in productive activities such as non-farm enterprises, and households with higher entrepreneurial ability are more likely to borrow. As such, households that are risk-takers with better entrepreneurial skills are more likely to avail microfinance through MOBs. We cluster the standard errors at the municipality-year level to allow for an arbitrary covariance structure within municipality across time as the error term ε_{imt} might be correlated across households within a municipality at a specific time period.

The identification strategy is based on the common trends assumption. Note that the dataset has just one pre-MOB period in 2003, which prevents the testing (indirectly) of the parallel trends assumption using multiple pre-intervention periods. To mitigate the concern, we control for time trend γ_t that captures temporal changes in the outcome variables that are common to all households, which reduces estimation bias, if any, originating from violation of the common trends.

The coefficient δ_1 is the estimated *immediate* causal effect of MOB presence for *continuing* households and δ_2 captures *incremental* effect. The sum of δ_1 and δ_2 pertains to *total* (or *net*) treatment effect. That is, if access to microfinance through MOB presence has a true lasting positive effect on *continuing* households, then we should find statistically significant *total* (or *net*) positive impact of δ_1 and δ_2 as well as the corresponding *F*-statistic. But if we observe a statistically insignificant *F*-statistic, then longer access to microfinance diminishes gains or even regress. These coefficients underscore the sensitivity of the impact with respect to the length of access to microfinance, which can be very valuable in designing effective microfinance programs, products, and services.

We also determine the heterogeneous effects depending on the poverty level of the household. It is important to disentangle these effects as much of the literature predicts that the impacts of microfinancing may be influenced by economic class of the recipients and also because microfinance programs typically target poor individuals.

3.2 IPW DID-FE model

To obtain internally valid estimates, sample selection bias, arising out of the possibility of non-random dropping out of households from the survey across treatment and control groups, is another concern that needs to be addressed. In the data subsection of the chapter, we discussed that the household panel dataset approximately represents 16 percent of the original sample in 2003, 2006, and 2009. It is important to account for those who drop out of the survey, especially if attrition is non-random so that the remaining sample can be representative of the original population (Barry, 2005).

We checked if there are any systematic differences in the pre-intervention (2003) demographic and other socioeconomic characteristics of households that remained in the follow-up surveys in 2006 and 2009 and were, thus, used as our study sample (*stayers*) and those who did not (*attritors*). Table 3 indicates that there are significant differences in the

outcome variables and attributes between attritors and stayers—except in spending on alcoholic beverage & tobacco and education as well as in income from entrepreneurial activities. We also analyzed the probability of stayers regressed on treatment dummy as well as a range of household and municipality attributes. Table 4 shows that the coefficient of the treatment dummy is never statistically significant. However, a test of joint significance shows that the covariates are jointly correlated with stayer status.

To deal with this potential sample selection bias, we take the DID-FE model a step further by combining it with IPW as outlined by Hirano, Imbens, and Ridder (2003). The weights are estimated by fitting a logistic model of the probability of the stayer household, which is defined as:

$$Prob(STAYERS_i = 1) = \frac{\exp(\delta X_i)}{1 + \exp(\delta X_i)} \quad (2)$$

where i indexes households. The variable $STAYERS_i$ is a dummy equaling 1 for household i that is successfully interviewed until the 2006 and 2009 surveys and 0 otherwise. X_i is a vector of household characteristics such as household head's age, sex, and education level, as well as family size and house ownership from 2003 FIES that includes households who dropped out of the survey (see Appendix Table A1 for the results).

We then check whether the weighting by the inverse propensity score creates an appropriate control group. The means of the observable baseline characteristics are balanced after weighting by the inverse propensity scores. Results in Appendix Table A2 suggest that there is no significant difference in the means of the baseline characteristics between stayers and attritors once the means are weighted using the inverse propensity scores. We also perform a balancing check within the stayer sample, between never clients (control group) and the continuing clients (treatment group). The results of the exercise in Appendix Table A3 indicate that there is no significant difference in the means of the baseline characteristics between households that live in a municipality with MOB and those that did not.

3.3 Selection on Unobservable Attributes

While we controlled for selection bias on the basis of observable attributes, time-invariant unobservable attributes, and households dropping out of the survey, there may be unobservable factors like time-variant attributes (e.g., dynamic learning effects and productivity of households and municipalities) that can still confound the estimates. To address this concern of endogeneity associated with self-selection because of time-variant unobserved factors, we employ the methodology developed by Oster (2019) and Altonji et al. (2005). Oster's restricted estimator is used which assumes: 1) equal selection ($\tilde{\delta} = 1$) or that the unobservable and observables are equally related to the treatment and 2) the relative contributions of each observed controls to the treatment must be the same as their contribution to the outcome variable. Given this, we can calculate an approximation of the bias-adjusted treatment effect with:

$$\beta^{*\prime} = \tilde{\beta} - \left[\dot{\beta} - \tilde{\beta}\right] \frac{Rmax - \tilde{R}}{\tilde{R} - \dot{R}} \quad (3)$$

where $\dot{\beta}$ is the coefficient resulting from the short regression of outcome variable on treatment and the R-squared from that regression as $\dot{R}$. $\tilde{\beta}$ is the coefficient from the intermediate regression of outcome variable on treatment and observed controls and the R-squared as $\tilde{R}$. Finally, Rmax is the hypothetical R-squared from a regression of outcome variable on treatment, observed controls and not observed. In this study, $\mathrm{R_{max}} = \min\{1.3\tilde{R}, 1\}$. Oster (2019) explains that "$1.3\tilde{R}$ is a cut-off value derived from a sample of 76 results from randomized 27 articles from top journals which allow at least 90.0 percent of the results would remain robust against unobservable selection bias".

We then estimate a set of bounds for β based on Oster's restricted estimator to conduct the robustness test. One bound is $\tilde{\beta}$ (corresponding to those in IPW DID-FE with all observable controls included); the other bound is a restricted bias-adjusted coefficient $\beta^{*\prime}$, which is the value of β when $R^2 = R_{max} = \min\{1.3\tilde{R}, 1\}$ and $\tilde{\delta} = 1$. With these two bounding assumptions, we can define a bounding set as $[\tilde{\beta}, \beta^{*\prime}(\min\{1.3\tilde{R}, 1\})]$. If this set excludes 0, the results from the controlled regression can be considered robust to omitted variable bias. Additionally, when the bounding set (or identified set) is within the confidence intervals of the controlled effect $\tilde{\beta}$, it implies that the omitted variables are unlikely to drive the results.

Meanwhile, Altonji et al. (2005) suggested a ratio of the impact of unobserved variables relative to the observed explanatory variables that would be needed to fully explain the treatment effect of MOB presence on some household welfare outcome measures. We denote this ratio by δ^0. A hypothetical $\delta^0 > 1$ suggests that the treatment effect can be considered robust to unobserved confounders and that the unobservables would have to be δ^0 times strongly correlated than observables for the unobservables to explain the treatment effects.[12]

4. Results and Discussions[13]

We present results from IPW DID-FE specification in Table 5 where the estimated coefficients for income and real expenditures have been transformed[14] to elasticities in percentage change for arcsinh-linear specification with dummy independent variables.

4.1 Effects of MOB Presence on All Income Households

Panel A of Table 5 shows that there is no evidence of impact on real consumption for *continuing* households. Nonetheless, we see *immediate* gains of 2.80 percentage points on the likelihood of self-employment and of 0.44 percent on entrepreneurial income in 2006. These, however, regressed as an *incremental* reduction of 4.30 percentage points in the

[12] Khan, Nakano, and Kurosaki (2019) interpret $\delta < 0$ as the coefficient increasing in magnitude due to the controls. And that while this does not indicate that the coefficient is unstable, it suggests that the method is not informative regarding omitted variable bias.

[13] We also conducted simulation on households that live in municipality with MOB only in 2006 (*dropouts*) and in 2009 (*newcomers*). For brevity and adherence to the manuscript format requirements, results for dropouts and newcomers were not included but are available from the authors upon request.

[14] See Bellemaret and Wichman (2020) for the derivation of elasticity. The non-transformed treatment effects are reported in Table 6.

probability of self-employment and of 0.31 percent in entrepreneurial income in 2009 are noted. The *net* impact on self-employment is statistically not different from zero according to joint *F*-tests shown in Panel A of Table 5. This is probably because the typical businesses set up by microfinance clients in the Philippines are susceptible to closure because they are mostly small-scale production or distribution of goods and services (e.g., sari-sari store or small grocery/convenience store, ambulant/rolling stores, hair dressing, barbering, tailoring, tire repair, etc.)[15], which generates low, seasonal, or irregular income and faces stiff competition with big or organized establishments that offer comparable and lower-priced products and services (Milgram, 2005).

4.2 Heterogeneous Effects of MOB Presence

We now turn to the heterogeneous effects of MOB presence on poverty level of the household. A household is considered poor if it is categorized under the first to third national income decile. The PSA groups families into two income strata, the Bottom 30% and the Upper 70%. The Bottom 30% grouping is used as a proxy for those falling below the poverty line. It refers to the lowest 30 percent of the total households in the per capita income distribution, arranged in descending order.

We assess whether the establishment of MOBs reduces poverty, as claimed by the proponents of microfinance under the impression that the poor are just financially constrained but can otherwise have high return to investment (Kaboski & Townsend, 2012).

4.2.1 Bottom 30% Income Households

In Panel B of Table 5, it can be noted that there is also no significant effect on real expenditures of *continuing* households. They nonetheless enjoy an *immediate* increase in 2006 on the likelihood of being self-employed and in entrepreneurial income of 7.1 percentage points and 1.23 percent, respectively. However, a negative *incremental* effect on self-employment income of 0.60 percent is noted in 2009. And while households reap *incremental* increase in wage work of 5.80 percentage points in 2009, they experience *incremental* decrease in wage income of 0.40 percent. The immediate benefit of MOB presence on entrepreneurial activities is not unusual and consistent with the findings of Crèpon et al. (2015) suggesting that the lesser preference for wage work is a byproduct of increased income from self-employment activities because households in this circumstance have strong disutility with casual (day) labor or stable salaried work. That is, there is a change in household activity towards self-employment and away from wage work. Banerjee, Karlan, et al. (2015) further explained that microcredit affords the poor more freedom in their choice of occupation.

Meanwhile, the incremental decrease in entrepreneurial and wage income as well as increase in likelihood of wage work are likely because households no longer have access to microfinance, their microbusiness activities may have diminished, and salaried work is now preferred.

[15] Karlan and Zinman (n.d.) contends that these are the usual clients of microfinance providers in the Philippines, such as First Macro Bank.

4.2.2 Upper 70% Income Households

As for the impact on the Upper 70% income or non-poor households, results in Panel C of Table 5 indicate that no significant impact on the welfare of *continuing* non-poor households are recorded. These results may not be entirely surprising as microfinance does not have an effect on those who are too unproductive to be entrepreneurs and the funds lent are too small to substantially affect the livelihood of the highly skilled and non-poor borrowers (Buera et al., 2012).

5. Tests on Omitted Variables

We investigate the robustness of our estimated coefficients to other unobserved factors that might contribute to the non-random selection of our households into our treatment group and MOB location using the Oster (2019) and Altonji et al. (2005) approaches. The estimated coefficients for income and real expenditures shown in Table 6 are not the elasticities or percent change but for the arcsinh transformation. Overall, the value of several δ^0 and/or the coefficient bounds point to robustness in all our statistically significant estimates.

For instance, the coefficient bound interval (-0.043, -0.038) for the effect of MOB presence on likelihood of self-employment in Panel A of Table 6 does not contain 0 and is within the confidence interval of the controlled effect, which implies that the estimate is robust. Similarly, the value of $\delta_2^0 = 8.42$ indicates that unobservables must be 8.42 times as important as the control variables to drive the treatment effect to 0. Since this value is greater than 1, the effect can be considered robust to selection on unobservables. Regarding the other estimates that either have bound intervals containing 0 or have $\delta^0 < 1$, we still do not consider these a major enough concern for our results to be claimed false positive as they are insignificant coefficients.

6. Conclusion

This study utilizes a nationally representative panel dataset drawn from the 2003, 2006, and 2009 FIES for the Philippines to analyze whether access to microfinance through establishment of MOBs in municipalities affects various measures of household welfare such as engagement in wage work and self-employment activities, wage and entrepreneurial income, and real expenditure on food, medical care, alcoholic beverage & tobacco, and education.

Deviating from the previous literature, this study examines not only the impact of *long-term* MOB presence in a municipality but also the differentiation of the impact into *immediate, incremental,* or *total* (*net*) effects. Furthermore, heterogenous effects by poverty level is also examined. We employ DID-FE and IPW to control for endogeneity problem associated with self-selection as well as sample attrition.

Results suggest that long-term MOB presence have an immediate positive impact on households' engagement in and income from entrepreneurial activities. However, these benefits diminish or even regress over time. We find similar results among poor households. That is, there are immediate gains in entrepreneurial income and activities but the incremental effects either regress or wane. No significant effects are also noted on real expenditures of poor households. Lastly, non-poor families do not benefit from access to microfinance.

These findings show that the benefits of using microfinance products and services are not evenly distributed among households, which prompts a rethinking of the role of microfinance in basic development outcomes for poor households. For those who have access to microfinance through MOBs, while it raises the likelihood of households being microentrepreneurs, it does not fuel an escape from poverty. Real expenditures do not increase for those who live in municipalities with long-term MOB presence. Similarly, income does not increase in the long run.

As such, access to microfinance through MOBs may not be as "transformative" as its proponents claim it to be. However, by providing opportunities to open or expand existing microbusinesses, it reduces vulnerability of clients, who would otherwise have been wage workers had not they received it. It affords households to make intertemporal choices, including the freedom to choose which income-generating activities to undertake.

While we cannot identify the root causes of the subtle impacts of microfinance, it seems likely that the diminishing or regressive impacts of longer presence of MOBs may be attributable to the smaller amounts of loans offered to microfinance clients, which are not large enough to cover borrowing costs or expand existing microbusinesses, as well as unprofitable businesses that microfinance clients choose to open. If this is the case, from a policy standpoint, there would be a need to *facilitate graduation of microfinance clients*. It would be necessary to facilitate microfinance clients to borrow higher amounts of working capital, based on their financial needs. This kind of initiative is currently being implemented in the Philippines by CARD Mutually Reinforcing Institutions (CARD MRI), which provides microloans and assists its clients who have evolved into medium- or large-scale entrepreneurs and are in need of larger loans from universal/commercial and thrift banks.

Second, *complement credit with client, entrepreneurship, or business development services*. Credit should be accompanied by complementary development services such as linking entrepreneurs to markets (e.g., agricultural value-chain financing, market matching, or trade fairs); training in product development and marketing; and entrepreneurship education. Such initiatives would foster product diversification, integrate microfinance borrowers into broader and high value markets, and enhance borrowers' business skills, thereby enabling borrowers to run their business profitably, increasing business opportunities, and avoid business closures.

This study establishes the role of microfinance in reducing vulnerability of households. It is hoped that these findings will encourage further empirical studies on the issues involved in advocating microfinance as an effective tool for poverty reduction, and lead to better micro- and macro-prudential policies towards a financially self-sustainable microfinance industry that will provide a wide range of products and services.

We suggest examination of whether the magnitude will increase, and whether the direction of the impacts will be the same: 1) if actual MOB borrowing of households are used instead of MOB presence and 2) in the presence of non-government organization (NGO) microfinance providers in municipalities where there are MOBs. Our study was not able to account for actual borrowing of households from MOBs and NGO microfinance providers due to the absence of readily available information about their locations.

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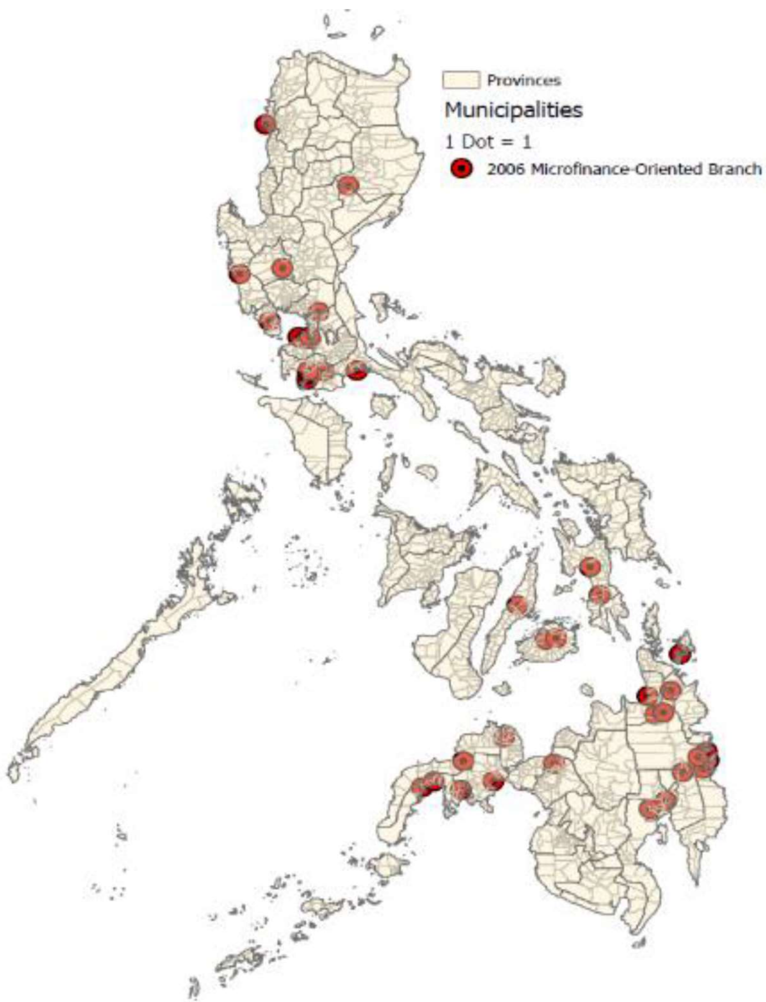
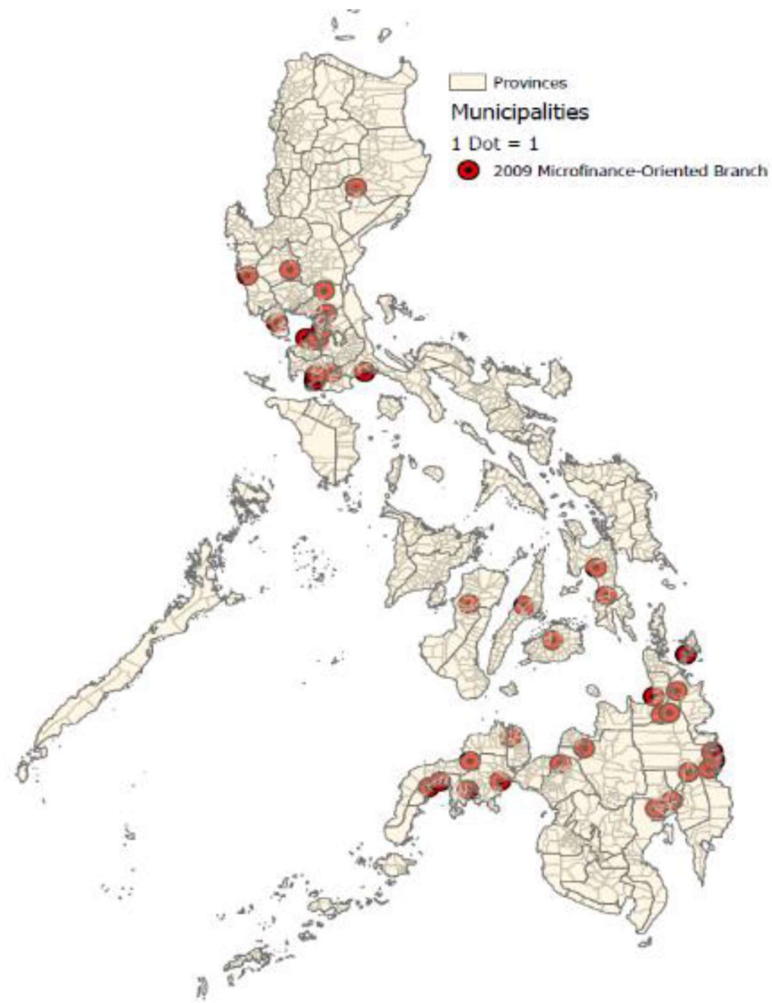
Figure 1: Geographical Distribution of Microfinance-Oriented Banks in the Philippines

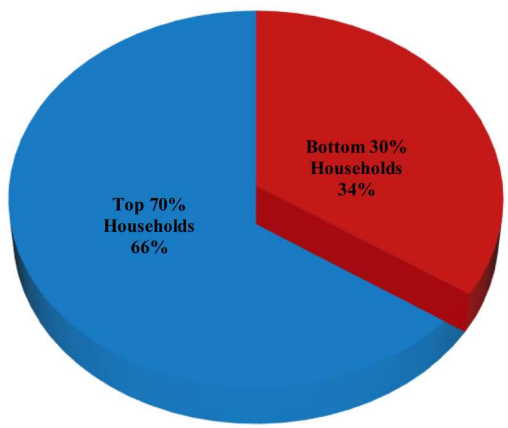




Source of Data: Bangko Sentral ng Pilipinas; data plotted by the Authors.

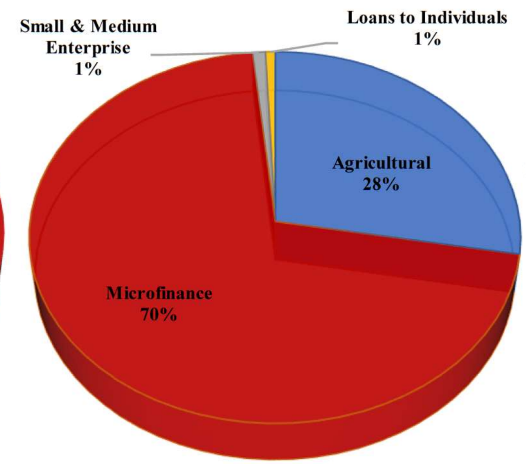
Figure 2 Client and Loan Portfolio of Microfinance-Oriented Banks in the Philippines

(a) MFI Borrowers: By Income Decile
(For the Period 2011, In Percent)



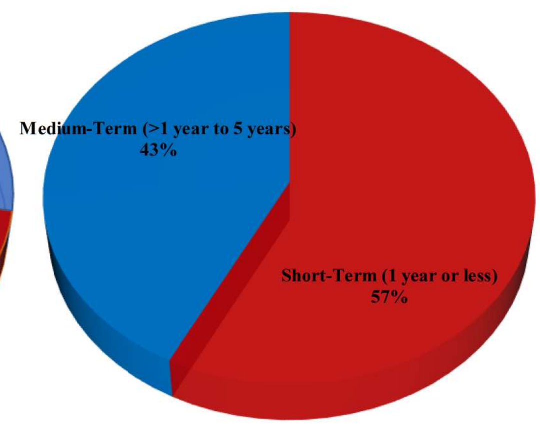
Source of Data: Annual Poverty Indicator Survey (APIS); Philippine Statistics Authority

(b) Gross Loan Portfolio: By Type
(As of 2010, In Percent)



Source of Data: Bangko Sentral ng Pilipinas

(c) Maturity of Loans (As of 2010, In Percent)



Source of Data: Bangko Sentral ng Pilipinas

Notes: The earliest statistics on microfinance-oriented banks consolidated by the BSP is in 2010 while the APIS prior to 2011 do not have information on household borrowing from microfinance institutions.

Table 1: Summary Statistics

	Pre-MOB Presence 2003 Mean (1)	Standard Deviation (2)	**Post-MOB Presence** 2006 Mean (3)	Standard Deviation (4)	2009 Mean (5)	Standard Deviation (6)	**Difference** (Pre-MOB vs Post-MOB) **t-statistics** (7)
Outcome Variables							
Employment Status							
Employed	0.36	0.48	0.34	0.48	0.36	0.48	1.52
Self-employed	0.50	0.50	0.50	0.50	0.46	0.50	2.90***
Household Income							
Wage and Salaries	56,369.59 (USD1,039.97)	94,018.38	63,205.71 (USD1,231.74)	111,780.3	75,177.68 (USD1,578.13)	118,238.00	-8.33***
Entrepreneurial Activities	35,246.49 (USD650.26)	70,653.33	42,228.30 (USD822.93)	89,198.04	42,228.30 (USD886.46)	48,297.92	-7.81***
Real Household Expenditures (2012=100)							
Food	828.43	517.22	799.922	514.13	780.75	458.45	4.95***
Medical Care	34.16	117.09	50.55	237.09	59.25	289.97	-7.59***
Alcoholic Beverage & Tobacco	33.28	41.43	30.26	40.58	30.13	36.72	5.02***
Education	77.15	230.67	83.28	250.88	76.31	213.59	-0.75
Household Attributes							
Household Head Sex (1=male; 0=female)	0.85	0.35	0.83	0.37	0.81	0.40	-6.15***
Household Head Age	47.50	13.83	50.01	13.48	52.18	13.38	-17.29***
Household Head Education	7.58	16.89	7.76	17.15	7.98	17.44	-1.11
Family Size	5.07	2.15	5.01	2.20	4.86	2.19	4.21***
Amount of financial assets owned	5,148.51 (USD94.99)	33,505.34	6,619.99 (USD129.01)	74,965.86	8,479.13 (USD177.99)	61,808.68	-3.29***
House and/or land ownership (1=yes; 0=no)	0.74	0.44	0.78	0.41	0.77	0.42	-4.75***
Municipality Attributes							
Population	190,209.10	390,665.60	193,823.10	398,088.20	197,505.70	405,651.90	-0.91
Number of poor families	55,856.50	41,826.13	63,818.40	46,868.97	66,878.94	45,808.56	-14.43***
No. of banks	143.03	195.50	151.09	203.91	164.24	213.68	-4.83***
Observation				6,529			

Notes: MOB = microfinance-oriented banks. The numbers in the table are rounded-off to the nearest two decimal places. Financial assets owned comprised of dividends and investments, interest from bank deposits and loans to other households, amount deposited in banks/investments, and profits from sale of stocks and real property. Employed refers to those working for private household, private establishment, and government while self-employment comprised of self-employed without any employee and employer in own family-operated farm or business. Banks comprised of head offices, branches, extension offices, and other banking offices. The peso-dollar exchange rate used for the pre-MOB presence is the average for 2003 at PHP 54.20 and for the post-MOB presence is the average for 2006 at PHP 51.31 and in 2009 at PHP 47.64, posted by the BSP in its website.

Table 2: Pre-MOB Presence Comparison of Household and Municipality Attributes

	Never Clients (1)	Continuing Clients (2)	Difference (3)
Outcome Variables			
Employment Status			
Employed	0.35	0.37	-0.03
Self-employed	0.53	0.47	0.05***
Household Income			
Wage and Salaries	55,135.34	59,214.45	-4,079.11
Entrepreneurial Activities	36,781.61	34,339.37	2,442.24
Real Household Expenditures (2012=100)			
Food	827.64	836.97	-9.33
Medical Care	33.90	35.51	-1.61
Alcoholic Beverage & Tobacco	32.82	33.15	-0.33
Education	78.03	78.31	-0.28
Household Attributes			
Household Head Sex (1=male; 0=female)	0.86	0.84	0.02*
Household Head Age	46.97	48.19	-1.22***
Household Head Education	7.53	7.514	0.02
Family Size	5.10	50.38	0.59
Amount of financial assets owned	4,731.58	5,934.36	-1,202.77
House and/or land ownership (1=yes; 0=no)	0.75	0.76	-0.01
Municipality Attributes			
Population	217,966.9	151,005.8	66,961.17
Number of poor families	45,816.10	68,679.18	-22,863.08***
No. of banks	123.71	177.05	-53.34*

Notes: MOB = microfinance-oriented banks. Column (1) reports group mean for each variable of those households that live in a municipality without MOBs (or "never clients") while those with MOBs both in 2006 and 2009 (or "continuing") are reported in Column (2). The results of the *t*-test for differences in the means with standard errors clustered at the municipal level of these households are presented in Column (3). The Philippines has four levels of administrative divisions – regions, provinces, cities and municipalities, and barangays – the highest level is regions and lowest is barangays. The numbers in the table are rounded-off to the nearest two decimal places. Household income and financial assets owned are in Philippine peso. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 3: Stayers versus Attritors

		Stayers group			Stayers - Attritors	
	Obs	Obs	Mean	Standard Deviation	Difference	*p*-value
Outcome Variables						
Real Household Expenditures (2012=100)						
Food	42,094	6,529	828.53	517.29	-11.84*	0.09
Medical	42,094	6,529	34.16	117.09	-3.91**	0.03
Alcoholic Beverage & Tobacco	42,094	6,529	33.27	41.43	0.41	0.47
Education	42,094	6,529	77.11	230.66	-0.94	0.77
Employment Status						
Employed	42,094	6,529	0.36	0.48	-0.04***	0.00
Self-employed	42,094	6,529	0.50	0.50	0.04***	0.00
Household Income						
Wage and Salaries	42,094	6,529	56,372.69	94,018.08	-4,205.26***	0.00
Entrepreneurial Activities	42,094	6,529	35,259.15	70,661.03	32.14	0.99
Household Attributes						
Household Head Sex (1=male; 0=female)	42,094	6,529	0.85	0.00	0.02***	0.00
Household Head Age	42,094	6,529	47.51	13.83	1.46***	0.00
Household Head Education	42,094	6,529	7.58	16.89	-1.03***	0.00
Family Size	42,094	6,529	5.07	2.15	0.28***	0.00
Financial assets owned	42,094	6,529	5,148.51	33,505.34	-2,178.34***	0.01
House and/or land ownership (1=yes, 0=no)	42,094	6,529	0.74	0.44	0.06***	0.00

Notes: Data source is 2003 FIES. Sample includes all households surveyed in 2003. The numbers in the table are rounded-off to the nearest two decimal places. Household income and expenditures as well as financial assets owned are in Philippine peso. Stayers are the households that were surveyed in 2006 and 2009. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 4: Probability of Household Stayed Until 2009 FIES

	Dependent Variable: HH stayers between 2003 and 2009				
	(1)	(2)	(3)	(4)	(5)
MOB presence	0.060	0.072	0.078	0.082	0.075
	(0.232)	(0.238)	(0.235)	(0.232)	(0.244)
Household attributes	No	Yes	Yes	Yes	Yes
Household expenditures	No	No	Yes	Yes	Yes
Employment status	No	No	No	Yes	Yes
No. of banks	No	No	No	No	Yes
Observations	42,094	42,094	42,094	42,094	42,094
***F*-stat (test of joint significance) - including treatment**		39.86	44.80	65.02	71.49
Prob>*F*		0.00	0.00	0.00	0.00
***F*-stat (test of joint significance) - excluding treatment**		25.00	29.59	31.54	38.19
Prob>*F*		0.00	0.00	0.00	0.00

Notes: HH = Household. Data source is 2003 FIES. Sample includes all households surveyed in 2003. The numbers in the table are rounded-off to the nearest two or three decimal places. Coefficients and standard errors (in parentheses) clustered at the municipal level are from a probit regression where the dependent variable is an indicator of whether the household stayed or not. The standard errors are also corrected by propensity score-matched. Household attributes are sex, age and education of the household head, financial assets owned, and house ownership. Household expenditures comprise of food, medical care, alcoholic beverage & tobacco, and education. Employment status refers to wage worker or self-employed. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 5: Effects of Microfinance-Oriented Bank Presence: IPW DID-FE

	Employment Status		Income		Real Expenditure			
	Employed	Self-employed	Wage & Salaries	Entrepreneurial Activities	Food	Medical Care	Alcoholic Beverage & Tobacco	Education
All Income Households								
Panel A: Treatment Group: Continuing Clients (With MOB in 2006 and 2009)								
Control Group: Never Clients (No MOB)								
CONTINUING x POST	-0.016	0.028*	0.079	0.444*	0.022	0.059	-0.069	0.002
	[-0.047, 0.014]	[-0.005, 0.061]	[-0.362, 0.520]	[-0.046, 0.933]	[-0.026, 0.069]	[-0.134, 0.253]	[-0.224, 0.086]	[-0.159, 0.162]
CONTINUING x POST x 2009	0.024	-0.043***	-0.015	-0.314**	-0.005	-0.001	-0.007	-0.034
	[-0.008, 0.055]	[-0.075, -0.011]	[-0.406, 0.376]	[-0.583, -0.046]	[-0.046, 0.037]	[-0.209, 0.206]	[-0.179, 0.166]	[-0.171, 0.103]
F-stat (test of joint significance)	0.16	0.68	0.11	0.00	0.48	0.31	0.73	0.13
R-squared	0.026	0.016	0.045	0.019	0.262	0.028	0.039	0.082
No. of Observations	18,825	18,825	18,825	18,825	18,825	18,825	18,825	18,825
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bottom 30% Income Households								
Panel B: Treatment Group: Continuing Clients (With MOB in 2006 and 2009)								
Control Group: Never Clients (No MOB)								
CONTINUING x POST	-0.043	0.071**	0.791	1.230**	0.052	-0.050	0.068	0.012
	[-0.100, 0.014]	[0.011, 0.131]	[-0.525, 2.107]	[0.006, 2.454]	[-0.038, 0.142]	[-0.284, 0.183]	[-0.226, 0.361]	[-0.192, 0.215]
CONTINUING x POST x 2009	0.058*	-0.047	-0.397*	-0.598***	-0.021	0.093	-0.036	0.052
	[-0.003, 0.118]	[-0.114, 0.019]	[-0.858, 0.063]	[-0.831, -0.365]	[-0.085, 0.043]	[-0.196, 0.382]	[-0.285, 0.212]	[-0.149, 0.254]
F-stat (test of joint significance)	0.25	0.56	0.04	0.12	0.70	0.08	0.05	0.36
R-squared	0.029	0.026	0.037	0.037	0.249	0.029	0.040	0.151
No. of Observations	6,234	6,234	6,234	6,234	6,234	6,234	6,234	6,234
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Upper 70% Income Households								
Panel C: Treatment Group: Continuing Clients (With MOB in 2006 and 2009)								
Control Group: Never Clients (No MOB)								
CONTINUING x POST	0.013	-0.004	-0.005	0.188	0.018	0.096	-0.091	0.043
	[-0.022, 0.049]	[-0.045, 0.038]	[-0.466, 0.455]	[-0.332, 0.708]	[-0.034, 0.070]	[-0.173, 0.364]	[-0.276, 0.094]	[-0.190, 0.276]
CONTINUING x POST x 2009	-0.010	-0.019	0.159	-0.193	0.000	-0.049	-0.037	-0.051
	[-0.044, 0.024]	[-0.056, 0.018]	[-0.396 0.713]	[-0.643, 0.257]	[-0.046, 0.046]	[-0.304, 0.206]	[-0.246, 0.171]	[-0.218, 0.115]
F-stat (test of joint significance)	0.04	0.94	0.42	0.02	0.34	0.10	1.23	0.01
R-squared	0.039	0.014	0.038	0.015	0.218	0.030	0.033	0.054
No. of Observations	12,591	12,591	12,591	12,591	12,591	12,591	12,591	12,591
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table 5: Continued

Notes: MOB = Microfinance-Oriented Bank. DID-FE refers to difference-in-differences fixed effects. Treatment is defined as presence of MOBs in the municipality where the household is residing. Household expenditures are deflated by consumer price indices of the goods and services with base year of 2012. Weight is from logit model where the dependent variable is an indicator of whether the household stayed or not and the control variables are household head's age, sex, education, and family size as well as house ownership. The sample used to compute the weight includes households that dropped from the survey. Estimated coefficients for income and consumption are elasticities for the arcsinh-linear specification with dummy independent variables or in percentage change in the outcome variable due to the discrete change in treatment dummy = 0 to dummy = 1. The estimated coefficients for income and consumption expenditures that are not transformed into percentage change are presented in Table 6. Confidence intervals are in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Table 6: Robustness to Omitted Variable Bias of the Effects of Long-Term Microfinance-Oriented Bank Presence				
Dependent Variable	Identified Set $[\widetilde{\beta}, \beta^{*\prime}(min\{1.3\,\widetilde{R},1\}),1]$	Exclude Zero?	Within Confidence Interval?	δ^0 for β=0
	(1)	(2)	(3)	(4)
All Income Households				
Panel A: Treatment Group: Continuing Clients (With MOB in 2006 and 2009)				
Control Group: Never Clients (No MOB)				
Employment Status				
Employed				
CONTINUING x POST	(-0.016, -0.014)	Yes	Yes	6.221
CONTINUING x POST x 2009	(0.024, 0.022)	Yes	Yes	15.049
Self-employed				
CONTINUING x POST	(0.028*, 0.036)	Yes	Yes	-3.436
CONTINUING x POST x 2009	(-0.043***, -0.038)	Yes	Yes	8.421
Household Income				
Wages & Salaries				
CONTINUING x POST	(0.076, 0.105)	Yes	Yes	-2.699
CONTINUING x POST x 2009	(-0.015, -0.126)	Yes	Yes	-0.138
Entrepreneurial Activities				
CONTINUING x POST	(0.367**, 0.433)	Yes	Yes	-5.596
CONTINUING x POST x 2009	(-0.377*, -0.397)	Yes	Yes	-19.079
Real Household Expenditure				
Food				
CONTINUING x POST	(0.021, 0.030)	Yes	Yes	-2.424
CONTINUING x POST x 2009	(-0.005, 0.000)	No	Yes	0.954
Medical Care				
CONTINUING x POST	(0.057, -0.002)	No	Yes	0.965
CONTINUING x POST x 2009	(-0.001, -0.031)	Yes	Yes	-0.041
Alcoholic Beverage & Tobacco				
CONTINUING x POST	(-0.072, -0.023)	Yes	Yes	1.483
CONTINUING x POST x 2009	(-0.007, -0.019)	Yes	Yes	-0.577
Education				
CONTINUING x POST	(0.002, 0.002)	Yes	Yes	-7.487
CONTINUING x POST x 2009	(-0.035, -0.019)	Yes	Yes	2.208
Bottom 30% Income Households				
Panel B: Treatment Group: Continuing Clients (With MOB in 2006 and 2009)				
Control Group: Never Clients (No MOB)				
Employment Status				
Employed				
CONTINUING x POST	(-0.043, -0.055)	Yes	Yes	3.463
CONTINUING x POST x 2009	(0.058*, 0.053)	Yes	Yes	11.853
Self-employed				
CONTINUING x POST	(0.071**, 0.097)	Yes	Yes	-2.700
CONTINUING x POST x 2009	(-0.047, -0.038)	Yes	Yes	5.171
Household Income				
Wages & Salaries				
CONTINUING x POST	(0.583, 0.585)	Yes	Yes	-286.197

(Continued)

Table 6: Continued

Dependent Variable	Identified Set $[\widetilde{\beta}, \beta^{*\prime}(min\{1.3\,\widetilde{R},1\}),1]$	Exclude Zero?	Within Confidence Interval?	δ^0 for β=0
	(1)	(2)	(3)	(4)
CONTINUING x POST x 2009	(-0.507, -0.670)	Yes	Yes	-3.096
Entrepreneurial Activities				
CONTINUING x POST	(0.802***, 0.949)	Yes	Yes	-5.463
CONTINUING x POST x 2009	(-0.911***, -0.919)	Yes	Yes	-117.657
Real Household Expenditure				
Food				
CONTINUING x POST	(0.051, 0.051)	Yes	Yes	-71.543
CONTINUING x POST x 2009	(-0.022, -0.023)	Yes	Yes	-18.610
Medical Care				
CONTINUING x POST	(-0.052, -0.110)	Yes	Yes	-0.889
CONTINUING x POST x 2009	(0.089, 0.063)	Yes	Yes	3.464
Alcoholic Beverage & Tobacco				
CONTINUING x POST	(0.065, 0.093)	Yes	Yes	-2.371
CONTINUING x POST x 2009	(-0.037, -0.077)	Yes	Yes	-0.918
Education				
CONTINUING x POST	(0.011, -0.010)	No	Yes	0.530
CONTINUING x POST x 2009	(0.051, 0.035)	Yes	Yes	3.126
	Upper 70% Income Households			
Panel C: Treatment Group: Continuing Clients (With MOB in 2006 and 2009)				
Control Group: Never Clients (No MOB)				
Employment Status				
Employed				
CONTINUING x POST	(0.013, 0.022)	Yes	Yes	-1.496
CONTINUING x POST x 2009	(-0.010, -0.010)	Yes	Yes	-30.267
Self-employed				
CONTINUING x POST	(-0.004, -0.002)	Yes	Yes	1.862
CONTINUING x POST x 2009	(-0.019, -0.018)	Yes	Yes	15.431
Household Income				
Wages & Salaries				
CONTINUING x POST	(-0.006, 0.051)	No	Yes	0.098
CONTINUING x POST x 2009	(0.147, 0.043)	Yes	Yes	1.407
Entrepreneurial Activities				
CONTINUING x POST	(0.172, 0.217)	Yes	Yes	-3.908
CONTINUING x POST x 2009	(-0.214, -0.258)	Yes	Yes	-4.919
Real Household Expenditure				
Food				
CONTINUING x POST	(0.018, 0.031)	Yes	Yes	-1.331
CONTINUING x POST x 2009	(0.000, 0.004)	Yes	Yes	-0.028
Medical Care				
CONTINUING x POST	(0.091, 0.020)	Yes	Yes	1.287
CONTINUING x POST x 2009	(-0.050, -0.088)	Yes	Yes	-1.319
Alcoholic Beverage & Tobacco				
CONTINUING x POST	(-0.096, -0.024)	Yes	Yes	1.332
CONTINUING x POST x 2009	(-0.038, -0.050)	Yes	Yes	-3.124

(Continued)

Table 6: Continued

Education				
CONTINUING x POST	(0.042, 0.066)	Yes	Yes	-1.746
CONTINUING x POST x 2009	(-0.053, -0.031)	Yes	Yes	2.377

Notes: MOB = Microfinance-Oriented Bank. Results in column (1) reports the identified set and $\tilde{\boldsymbol{\beta}}$ is the treatment effect. The treatment effect of income and consumption expenditures are not in percent change but for the arcsinh-linear specification with dummy independent variables from the IPW DID-FE regression. Column (2) indicates whether the identified set excludes zero and Column (3) reports whether the estimated biased-adjusted coefficient is within the confidence interval of the estimated controlled effect $\tilde{\boldsymbol{\beta}}$. Column (4) is the computed $\delta^0 = \frac{(\tilde{\beta}-\beta^*)(\tilde{R}-R^0)}{(\beta^0-\tilde{\beta})(R_{max}-\tilde{R})}$ where β^0 is the treatment effect and R^0 is the R^2 value in the simple regression with no controls of outcome on treatment; $\tilde{\beta}$ and $\tilde{R}$ correspond to the regression with observable controls; and β^* is equal to zero (Khan et al., 2019). δ^0 is the Altonji et al. (2005) coefficient of proportionality that would be required to attribute the treatment effect entirely to the influence of unobservables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

Appendices

Table A1: Logit Estimates of Probability Household Stayed

Variable	**Coefficients**	**Robust Standard Error**
Household Head Sex (1=male; 0=female)	0.130***	0.040
Household Head Age	0.007***	0.001
Household Head Education	-0.003***	0.001
Family Size	0.055***	0.006
House and/or land ownership (1=yes, 0=no)	0.273***	0.031
No. of Observations	42,094	

Notes: Statistically significant at ***1%, **5%, and *10% level.

Table A2: Balance in Covariates Across Stayers and Attritors after Using Inverse Probability of Treatment Weights with the Propensity Score

	Mean in Stayers	Mean in Attritors	Standardized difference
Household Head Sex (1=male; 0=female)	0.84	0.84	-0.011
Household Head Age	46.37	46.27	0.007
Household Head Education	8.61	8.46	0.008
Family Size	4.84	4.84	0.002
Amount of financial assets owned	8,788.11	7,021.21	0.019
House and/or land ownership (1=yes, 0=no)	0.69	0.69	-0.007

Table A3: Balance in Covariates Across Continuing and Never Clients after Using Inverse Probability of Treatment Weights with the Propensity Score

	Mean in Continuing Clients	Mean in Never Clients	Standardized difference
Household Head Sex (1=male; 0=female)	0.48	0.51	-0.072
Household Head Age	50.38	50.05	0.025
Household Head Education	7.67	8.31	-0.038
Family Size	51.27	50.62	0.030
Amount of financial assets owned	10,283.52	7,046.96	0.052
House and/or land ownership (1=yes, 0=no)	0.78	0.77	0.016