

**ASSESSING LONG -TERM CREDIT IMPACTS FROM THE TIMING OF  
MEMBERSHIP IN MICROFINANCE**

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**Abstract:** *This paper uses the concept of composite future counterfactuals to assess the long-term impact of farm households' participation in microcredit. A four wave panel data spanning over ten years for credit-eligible rural households in Ethiopia is used to assess impact of (timing of) membership on consumption. New in this method is that only households that did not participate up to the time of participation are considered as candidates for controls. Further, to account for counterfactuals between timing of membership and outcome measurement period in a panel data setting where only the outcome variable is time-varying, potential future paths of individuals in the control group are considered. The propensity score method is used to adjust for initial differences between participants and controls. The combined methodological innovation enables us to overcome biases due to selection as well as problems of accounting for dropouts and new participants inherent in microfinance impact assessments. Results suggest that the timing of membership matters: the earlier the onset of membership the better the effect. Results are robust compared to standard matched pair wise effects. Such comparisons suggest that not accounting for future counterfactuals, for the most part, overestimate impact.*

**Key words:** *microfinance, impact, dropouts, composite counterfactuals, Ethiopia*

## **1. Introduction**

In recent years, microfinance is seen as a beacon of hope to help eradicate poverty and has been at the center of policy making in many developing countries. A central element in microfinance is providing small but progressively larger and repeated loans to those that lack the required collateral to access conventional lenders. Loans are expected to help lift borrowers out of vulnerability and poverty over time. In the case of Ethiopia, repeated loans are primarily intended to bridge short term working capital requirements so as to gradually build assets and improve the ability to mitigate aggregate shocks. If successful, such loans would eventually trickle down into measurable welfare gains such as increases in consumption (e.g., Menon, 2006), or reducing vulnerability to economic hardships (Morduch, 1998). Nevertheless, many years since these programs are in operation, questions still remain if and to what extent these successive loans have been successful in achieving their intended goals.

Existing studies focus on evaluating before and after effects, regardless of the timing of participation and dynamics between participation and outcome measurement periods<sup>1</sup>. There are however differences among target households when it comes to benefiting from availability of credit. One major difference is that not all targeted households start to use credit at the same time and in the same intensity (Berhane and Gardebroek, 2009). For some reasons, some join earlier than others; still some remain members for long time while others dropout quickly. As a result, the effect of microfinance credit varies across different client pools and therefore evaluating the trickled down effects of credit requires measuring the relative impacts across these pools (Karlan and Goldberg, 2007). The aim of this paper is to evaluate the long-term impacts of MFI credit by overcoming heterogeneities across periodical participants pools. Of particular interest is whether

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<sup>1</sup> A recent study emphasizes the issue of timing in evaluations is “as important but relatively understudied” (King and Berhrman, 2009).

and how differences in the timing (e.g., early versus late membership) of membership impacted livelihoods, particularly in the face of economic distresses such as droughts, after accounting for pre- and post-entry differences. This provides an insight into how Microfinance Institutions (MFIs) can improve the design and timing of their loan products given heterogeneities in entry and loyalty of target clients (Karlan and Goldberg, 2007).

Evaluating such effects is however an arduous task not only because pertinent data spanning over sufficiently long periods is scarce but also because obtaining an appropriate ‘control group’ to identify effects over time given heterogeneities due to the timing of participation is difficult (Karlan, 2001). Microfinance impact studies thus far have focused on either experimental (e.g., Karlan and Zinman, 2007) or quasi-experimental cross-sectional designs (e.g., Pitt and Khandker, 1998, Coleman, 1999), or classic two-period panel data fixed-effects methods (e.g., Tedeschi, 2008) to investigate causal credit effects. Cross-sectional designs are useful to tease out biases due to individual borrower as well as MFI (e.g., program placement) selection characteristics inherent in such programs. They however lack the time-dimension required to capture lasting credit effects. King and Behrman (2009) emphasize the duration and timing of evaluation matter in program impact assessments. Likewise, although the classical fixed-effects method captures long-term effects when panel data is available, it has fundamental flaws when applied to repeated observations that go beyond the classic two-period case. First, in the case of dichotomous treatment, fixed-effects model works on the condition that individuals change treatment status (i.e., assumes treatment status is reversible) across time (Wooldridge, 2002:637-38). However, reversibility of treatment status means that impact estimates are biased because dropouts from previous borrowings are included in the control group (contamination-effect) and excluded from the treated group (attrition-effect). An appropriate impact assessment includes dropouts in the comparison group and the control group includes only untreated

individuals (Karlan, 2001). Second, in time-varying treatments with more than two-period observations, counterfactuals need to account for potential future paths of individuals in the control group (Brand and Xie, 2007). The fixed-effects method simply compares participants and non-participants pair wise and does not account for such future paths.

The classical parametric evaluation literature is thus silent about these effects and time dimensions in treatments except that agents are exposed to one of two possible conditions of the treatment at a given time and outcomes are measured subsequent to exposure (Brand and Xie, 2007). Owing to the difficulty of establishing appropriate counterfactuals when both the treatment and outcome variables are time-varying, long-term impact evaluations in many applications remain challenging even when panel data is available. Recent developments in nonparametric methods offer alternative ways to handle such identification problems. A body of literature in epidemiology (e.g., Robins, Hernan, and Brumback, 2000) and sociology (Brand and Xie, 2007) exploits the conceptual apparatus of the ‘potential outcome approach’ in experimental causal inference and extends it to non-experimental panel data. The strategy involves establishing a composite of ‘forward-looking composite counterfactuals’ for each group in each loan-cycle, considering participation as an *irreversible* treatment. These composite counterfactuals combine weighted averages of those who will borrow later between the treatment and the outcome measurement period and those who will never borrow by the end of the outcome measurement periods. This alternative method is used in this paper to overcome the difficulty of identifying credit impact from a four-wave panel data that covers ten years. The data comes from (non-) borrower households of a rural microfinance in Tigray, northern Ethiopia.

Results indicate that compared to later participants, early participants are better off even after accounting for initial as well as future counterfactuals. Comparative results show that not accounting for future counterfactuals overestimate impact. It also suggests that the timing of

participation matters when it comes to the capacities credit provides to overcome economic distresses: the earlier the better. The contributions of this paper are threefold. First, we measure credit impact from long-term panel data accounting for counterfactuals in future pathways, reducing biases due to dropouts and time dimension. This contrasts with conventional methods that compare participants and non-participants pair wise. Second, the propensity score matching method is used to establish appropriate controls for participant groups in each period. Although this non-parametric method is not new, we believe, applying it to panel data to establish causality from sequential counterfactuals adds a new dimension to microfinance impact evaluations. Third, this paper provides additional evidence on selection bias, mainly due to the timing of decision to participate and changes in the composition of participants and non-participant, and underlines the danger of employing parametric impact assessments that naively compare participants and non-participants pair wise.

The rest of the paper is organized as follows. By way of describing the structure of the data set used, section 2 discusses the challenges to identify impact using conventional methods in time-varying settings. Section 3 introduces the concept of ‘forward-looking composite counterfactuals’. The techniques to overcome identification problems using this concept and its empirical implementation in this paper are discussed. Section 4 presents and discusses the results. Section 5 concludes.

## **2. Estimating long-term impacts of periodical participation in microfinance credit**

The main objective in this paper is to assess the long-term impact of credit with periodical participation of households, which in more than two-period panel data setting involve identification problems due to differences in the *timing of participation*. Before proceeding to discuss why these heterogeneities cause identification problems, it is essential to elaborate on the

dynamics of participation using the structure of the data set at hand. Therefore, section 2.1 presents the data set structure and section 2.2 discusses the challenges of identifying credit impact using conventional methods in more than the classic two-period settings. An alternative method proposed by Brand and Xie (2007) that exploits the timing of treatment and outcome measurement to mitigate these identification problems is discussed in section 3.

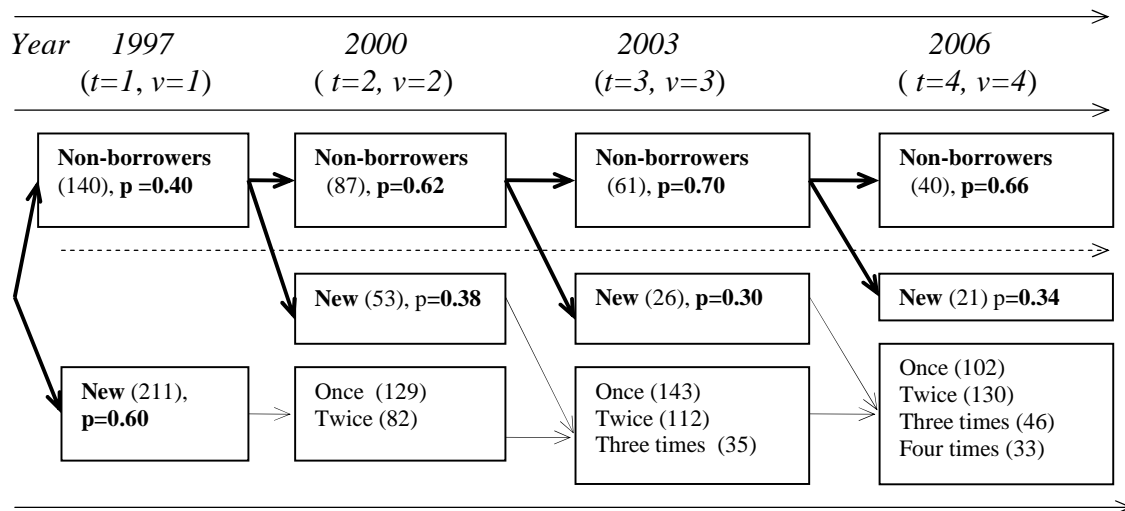
## 2.1 The structure of the data set used

Panel data used in this paper comes from farm households in Tigray, northern Ethiopia, whose livelihoods largely depend on rainfall based agriculture where production is only once a year. Data was collected during 1997-2006, in four-waves with a three-year interval. Sample households include participants and non-participants of the Dedebit Credit and Saving Institution (DECSI), a MFI that provides credit services in the Tigray region of Ethiopia since 1994.

*Table 1 Summary statistics of yearly household consumption expenditure and other variables used in the propensity score matching Method.*

<i>Variable name</i>	<i>Mean</i>	<i>Std.dev.</i>	<i>Min</i>	<i>Max</i>
Participation in program credit	0.450	0.498	0	1
Annual household consumption expenditure	3514	4271	229.82	72064
Family size	5.282	2.352	2	13
Male-headed (yes=1)	0.244	0.429	0	1
MFI Branch office close enough (yes=1)	0.762	0.426	0	1
Poorer village (yes=1)	0.239	0.427	0	1
Age of household head	52.875	14.852	19	92
Size of land owned (in <i>tsimad</i> =0.25 ha.)	4.408	3.835	0.25	10.5
Non-farm income dummy	0.742	0.438	0	1
Participation in extension programs (yes =1)	0.165	0.371	0	1
Micro-dam availability	0.514	0.499	0	1

First on trial basis in selected villages, but since 1997 it is present in almost all villages. The official launch coincided with the first wave of this study. Respondent households were selected using a multi-level sampling procedure. First, 16 villages were selected to represent regional differences, including access to credit. Second, 25 households were randomly selected from each village. Of the total 400 households, 351 are included in the analysis, a total of 1404 observations for the balanced four-year panel. The remaining were excluded because they either became non-targets (outliers) over time, mainly due to old age or dropped out from the survey. Respondents were surveyed on several household- (e.g., annual consumption levels, participation in MFI credit), village- (whether or not village had access to basic infrastructure) and MFI-level (e.g., ease of access to MFI credit) characteristics. Expenditure values (in local prices) on major household (food and non-food) consumption items were collected. Table 1 provides summary statistics of annual household expenditure and other variables used in the analysis.



Note: number of participants in parentheses,  $t$  = participation period,  $v$  = outcome measurement period,  $p$  = transition probabilities

Figure 1. Borrowing participation transition of sample households, 1997-2006

An important issue in this data set for empirical identification is that households joined the MFI at different times during the survey. Of the sample households, 211 participated early (in 1997), while many others joined in later years. So, participation status of members fluctuated over the years. Some members dropped out after participating only once and others continued up to four times. Figure 6.1 presents the number (in parentheses), proportion and frequency of participation in each year. The fact that households switched their status over the survey years makes it possible to apply conventional (e.g., fixed-effects) methods to estimate the impact of participation. However, as will be made clear in section 2.2, these switches also make it difficult to establish appropriate controls for participants in each year.

## **2.2 Problems of identifying credit impact in long panels with periodical participation**

A straightforward method to estimate impact of periodical participation would have been to exploit the panel nature of the data and use the fixed-effects method. This method uses the time-varying nature of the treatment variable (i.e., participation) across observation periods to identify impact pair wise. Particularly, it exploits the fact that units change their treatment status across observation periods (Chamberlain, 1984: 1247-1317). In the case of borrowing, such status changes involve two-way transitions of members between participation and non-participation status over time, which essentially assumes *reversibility* of the treatment. In other words, when previous borrowers dropout at some point, they become part of the control group as if their previous participation does not have an effect on their outcome. Moreover, the fixed-effects method does not use variations of households that do not change status (i.e., always participants and never participants) in explaining outcome variables.

There are therefore three types of biases that arise in using standard parametric methods, such as the fixed-effects method, in panel datasets of more than two periods with dichotomous

treatment as in our setting. First, not all participant households have become members of the MFI at the same time. For some reasons, some have joined earlier than others (see Figure 6.1). In other words, there are heterogeneities among the four *new* participant groups due to the timing of membership. One reason is that selection criteria by both the MFIs and participants might have changed over time (Tedeschi and Karlan, forthcoming). Moreover, even the degree of participation over the years varies across members; some have continued to participate while others have dropped out. Second, estimates are biased if dropping out is non-random (Karlan, 2001)<sup>2</sup>, i.e. if dropouts are those who became worse off or better off due to the program. Third, since they were once in the treated (participant) group, dropouts may contaminate the control group carrying over the effect of the treatment to the control group, particularly when the effect of the treatment lasts longer than the treatment period as in borrowing used to acquire durable inputs, e.g., oxen or draft animals. Thus, although long-term panels can be advantageous to capture long-term impacts in many applications, in this particular application the use of such periodical participation and the resulting two-way transition yields biased estimates. As such, partly owing to these problems, most credit impact assessments are limited either to the two-period classic panel data methods or quasi-experimental cross-sectional methods that compare ever-participants to never-participants on pooled data.

### **3. Empirical method**

This section presents an alternative empirical method that overcomes the challenges of identifying impact of periodical participation in credit discussed in section 2.2. Section 3.1 briefly

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<sup>2</sup> Karlan, 2001 discusses the nature of the bias in cross-sectional designs that exclude dropouts from the treatment group. Tedeschi and Karlan (forthcoming) measure the extent of this bias using quasi-experimental method for two-period panel data from Peru.

introduces a method proposed by Brand and Xie (2007) and its implementation. Section 3.2 discusses the Propensity Score Matching (PSM) method that is used to implement this method.

### **3.1 The forward-looking sequential counterfactual method**

A central issue in our setup is that treatment effects are nonreversible and therefore our interest is to identify the causal effect from the timing of participation in credit on outcomes measured at several points in time subsequent to the treatment. However, when outcomes are measured at different periods other than just subsequent to treatment, it is no longer clear what the appropriate control group should include because the control group varies depending on the gap between the timing of the two events. The concept of ‘forward looking sequential counterfactuals’ proposed by Brand and Xie (2007) provides a framework to construct appropriate counterfactuals for treatments with lasting effects that vary over time. This concept is useful in applications where (a) exposure to treatment can take place at any point in time but once treated the effect stays on, and (b) the effect of the treatment varies over time subsequent to treatment, regardless of whether or not the treatment is repeated.

In this approach, the control group for individuals treated at  $t$  whose outcome is measured at  $v$  is composed of individuals that are (i) untreated by  $t$  but are treated any time up to  $v$ , (ii) never treated up to the end of the observation period but can be potentially treated any time in the future. Thus, individuals that participated prior to  $t$  can no longer serve as controls at  $t$  and the only controls for individuals that have participated at  $t$  are therefore those that have never participated up to  $t$ . However, control individuals at  $t$  may or may not participate after  $t$ . Likewise, participants at  $t$  would have had the same potential paths after  $t$  had they not participated at  $t$ . E.g., a household that participated in 1997, in our case, would have had two possible paths (i.e., participate or not) in subsequent loan cycles had this household not participated in 1997. This

means, if outcome is measured in 2006, this household would have had three other participation chances up to 2006. Brand and Xie (2007) argue not accounting for such counterfactual possibilities biases impact measurement and therefore an appropriate counterfactual outcome must include all potential outcomes of the future paths of the control units considered. This is done by assigning transition probability weights to each potential future path of the controls (see Figure 6.1). A forward-looking sequential approach therefore composes a ‘composite’ of counterfactuals that are weighted combinations of those individuals later treated and those individuals never treated.

However participant and non-participant groups may also differ in their pre-treatment characteristics and participation may be based on these pre-treatment characteristics, in which case estimates are biased even after accounting for future paths. This problem is dealt using the propensity score method assuming the conditional independence assumption discussed in section 3.2. Under this assumption, the Average Treatment Effect on the Treated (*ATT*) of participation in borrowing at time  $t$ ,  $d=t$ , on annual household consumption expenditure,  $C$ , measured at time  $v$ ,  $v \geq t$ , is calculated using forward-looking counterfactual approach as:

$$E(\Delta C_v^{d=t} | X) = E(C_v^{d=t} | X) - E(C_v^{d>t} | X) \quad (1)$$

where the LHS is the *ATT* of participation in borrowing at  $d=t$  conditional on  $X$ , a vector of exogenous (or pre-treatment) characteristics that determine participation. The terms on the RHS are expected annual consumption expenditure after  $d=t$ , conditional on  $X$ , for participant and non-participant groups at  $v$ , respectively. In our case, these two terms are calculated using PSM, given as the average treatment effects on the participants and non-participants had the latter participated (more on this in section 3.2). The difference between the two provides the average treatment effect on the treated (*ATT*). Note that  $d>t$  in  $E(C_v^{d>t} | X)$  indicates that those in the control group

are not treated until  $t$  but may or may not be treated up to  $v$  and this term is a composite of non-participants' future outcomes expected between  $t$  and  $v$ . Depending on the causal question asked, this term is decomposed into its future components. That is, decomposition depends on the treatment ( $d=t$ ) as well as the outcome measurement,  $v$  periods considered. Note that decomposition is needed only if  $v>t$ . Otherwise, (1) is reduced to standard pair wise comparison between participants and non-participants.

We illustrate this decomposition using two causal research questions in this paper. First, consider 'what is the effect of *early* (1997) participation ( $t=1$ ) in credit on annual household consumption measured in 2006 ( $v=4$ )?' As shown in Figure 6.1, in this specific problem, there are three possible paths for households who did not participate by  $t=1$ : to participate at  $t=2$ , to participate at  $t=3$ , to participate at  $t=4$  or not to participate at all,  $d>4$ . Let the probability to participate at any future path  $t$  be given by  $p(t)$ , otherwise  $q(t)=1-p(t)$ . Ignoring  $X$  for now, the composite term can be decomposed into its path dependent additive components as follows (Brand and Xie, 2007):

$$E(C_v^{d>t} | X) \cong E(C_4^{d>1} | X) = [p(2) \cdot E(C_4^{d=2})] + [q(2) \cdot p(3) \cdot E(C_4^{d=3})] + [q(2) \cdot q(3) \cdot p(4) \cdot E(C_4^{d=4})] + [q(2) \cdot q(3) \cdot q(4) \cdot E(C_4^{d>4})] \quad (2)$$

where the terms in square brackets of the *RHS* give the weighted ATT of participation at  $t=2$ ,  $t=3$ , and  $t=4$  and non-participation by  $t=4$ , respectively, measured at  $v=4$ . Note that the transition probabilities  $p(t)$  and  $q(t)$  in (2) assign the likelihood of individuals to transit to one of the two paths (participate or not participate) at  $t$  conditional on being non-participant prior to  $t$ ; i.e.,  $p(t) = \text{prob}(d=t | d \geq t)$  and  $q(t) = 1 - p(t)$ . We therefore use the probability of being in the participant group in each path such that  $p(t) + q(t) = 1$  (Brand and Xie, 2007). Combining eq. (1)

and eq. (2) gives the ATT of *early* participation in MFI borrowing on household consumption expenditure measured in 2006.

$$\begin{aligned}
ATT_t &= E(\Delta C_v^{d=t} | X) = E(C_v^{d=t} | X) - E(C_v^{d>t} | X) \\
&= E(C_4^{d=t} | X) - \{p(2) \cdot E(C_4^{d=2}) + q(2) \cdot p(3) \cdot E(C_4^{d=3}) \\
&\quad + q(2) \cdot q(3) \cdot p(4) \cdot E(C_4^{d=4}) + q(2) \cdot q(3) \cdot q(4) \cdot E(C_4^{d>4})\}
\end{aligned} \tag{3}$$

Second, consider the causal question, ‘what is the effect of *late* (e.g., in 2003) participation ( $t=3$ ) on annual consumption expenditure measured in 2006 ( $v=4$ )?’ As before, the composite term in (1) is decomposed into its components<sup>3</sup>. For non-participants at  $t=3$  where  $v=4$  (see Figure 6.1), there is only one chance to participate before the survey period ends: to participate or not to participate at  $t=4$ .

$$E(C_v^{d>t} | X) \cong E(C_4^{d>3} | X) = [p(4) \cdot E(C_4^{d=4})] + [q(4) \cdot E(C_4^{d>4})] \tag{4}$$

Combining eq. (1) and eq. (4) gives the ATT of *late* participation (in 2003) in MFI borrowing on household consumption expenditure measure at  $v=4$  (i.e., in 2006).

$$\begin{aligned}
ATT_3 &= E(\Delta C_4^{d=3} | X) = E(C_4^{d=3} | X) - E(C_4^{d>3} | X) \\
&= E(C_4^{d=3} | X) - \{p(4) \cdot E(C_4^{d=4}) + q(4) \cdot E(C_4^{d>4})\}
\end{aligned} \tag{5}$$

This procedure is implemented for all ten possible counterfactual constructions in this paper. A complete computation for all these possibilities is given in appendix 1A. Comparative results are summarized in the results section from which the causal effect of e.g. *early* versus *late* participation can be made by comparing results obtained from (3) and (5).

Note however that although non-reversible, participation in borrowing is repeatable. The time-varying treatment proposed by Brand and Xie (2007) does not give a way to incorporate the

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<sup>3</sup> Analyzing the effect of participation at  $d=t, t+1, \dots T$  on outcomes measured at  $v=t, t+1, \dots T$  follows the same procedure. For a general formula that can be used in many other applications, the interested reader is referred to Brand and Xie (2007).

*ATT* of *repeat-borrowers* because treatment is assumed non-reversible and non-repeatable, or simply the treatment state is an *absorbing state* and once treated, individuals remain in the treatment state. The method discussed so far therefore provides the gross effect of credit after the onset of participation. To substantiate results from this method, effects of repeat-borrowing and dropping out are analyzed pair wise. These results are provided in section 4.3.

### **3.2 Propensity score matching method**

The composite counterfactual method discussed in section 3.1 gives a way to construct appropriate *future controls* for each participant group in each treatment period. However, participant and non-participant households in each treatment period may not be directly comparable because participant households may self-select (or, be selected) into the program based on initial differences, including the outcome of interest, in which case the mean outcome of the two groups differ even in the absence of the program. Therefore, before proceeding to future counterfactuals, initial comparability must be established to avoid initial selection bias, at least, based on some common observable characteristics.

To deal with this problem, we use the Propensity Score Matching (PSM) technique that has gained popularity in recent years for its potential to remove substantial amount of bias from non-experimental data (e.g., Dehejia and Wahba, 1999). This technique helps to adjust for initial differences between a cross-section of participant and non-participant groups by matching each participant unit to a non-participant unit based on ‘similar’ observable characteristics. An advantage of PSM is that it summarizes all the differences in a single dimension, the propensity score, which is then used to compute treatment effects non-parametrically. The propensity score conveniently summarizes the conditional probability of participation given pre-treatment or exogenous characteristics (Rosenbaum and Rubin, 1983). An important assumption on which this

technique builds is the Conditional Independence Assumption (CIA), which states that selection is solely based on observable characteristics and potential outcomes are independent of treatment assignment<sup>4</sup>. Under the assumption that initial differences between the two groups determining participation are captured by observable characteristics, the participants' counterfactual mean outcome had they not been participated is identified by non-participants' mean outcome. Besides CIA, another condition in PSM is the Common Support requirement, which ensures that individuals compared from the participant and non-participant groups are, to begin with, comparable. Specifically, it ensures individuals with the same observable characteristics have a positive probability of being in both participant and non-participant groups (Heckman, LaLonde, and Smith, 1999: 1865). This requirement can be imposed such that estimation is performed on individuals that have common support. The average treatment effect on the treated (*ATT*) is therefore given by the difference in mean outcome of matched participants and non-participants that have common support conditional on the propensity score.

The following practical steps are followed to implement the PSM technique in this paper. The first step is to predict the propensity score for each group in each period using a probit model. Justifying the CIA requires that only variables that simultaneously influence the participation decision and consumption outcome but that themselves are not affected by participation are included (Heckman, Ichimura, and Todd, 1998). As such, variables included in our specifications are either measured before treatment or carefully selected exogenous characteristics. Specifications vary across participant groups, accounting for heterogeneities due to 'timing of participation'. Since there are four observed treatments (loan cycles) whose outcomes are

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<sup>4</sup>Obviously, this is a strong assumption and there may be bias due to unobservables. Given the complexity of the problem we try to handle in this paper, we hope that this bias maybe empirically less important compared to the magnitude of bias that this method eliminates.

measured four times, a total of thirty distinct matching specifications, one for each cross-section, are needed to construct the ten composite counterfactuals (see section 3.1).

The second step is to choose a method by which weights are assigned for matching. Four different matching algorithms are available in the literature (see Caliendo and Kopeinig, 2005). Throughout the paper Kernel Matching (KM) is used. A major advantage of the KM method is that it ensures low variance because it uses weighted averages of all individuals in the control group to construct the counterfactual outcome. Its drawback is however the possibility of bad matches because it uses full information. A recommended solution is to properly impose the common support upon implementation (Heckman, Ichimura, and Todd, 1998, 1998). Once the propensity score is estimated and used to compute the matching, the third and critical step is to perform a ‘balancing test’ to check if the matching procedure was effective, i.e. to test if matching balanced observable covariates across treated and control groups. A t-test on equality of means in the treated and control households suggests the extent to which the difference in the covariates between the treated and control groups have been eliminated so that any difference in outcome variable between the two groups can be inferred as coming mainly from the treatment (Heckman and Smith, 1995).

#### **4. Results and discussions**

This section presents results based on methods discussed in section 3. Before proceeding to the main results, a pair wise comparison between matched and unmatched households discussed in section 4.1 highlights the bias due to initial differences. The main results are provided in section 4.2 where after matching among participants and non-participants in each loan cycle, average participation effects using composite counterfactuals are compared to average participation

effects from simple pair wise comparisons. Finally, as a robustness check, section 4.3 provides comparative results between matched composite and unmatched pair wise comparisons.

#### **4.1 Matched versus unmatched pair wise comparisons**

The effect of participation for both matched and unmatched households is given in table 2 This table gives a simple pair wise comparison of average treatment effect of participants as compared to non-participants (controls) in each year with and without matching. Note that in this table each new participant group's (i.e.,  $t=1,..4$ ) annual consumption is observed over subsequent observation years (i.e.,  $v=1, \dots 4$ ). E.g., average annual consumption of new participants in the first observation year ( $t=1$ ) is given under  $v=1$  to  $v=4$ , hence, the table is diagonal. There are two columns under each observation year, which give average impact estimates for the same participant group with and without matching. Comparing the matched against unmatched estimates for the same participant group (in each  $t$ ) gives the bias reduction after appropriately accounting for initial differences using the matching method. It can be observed that the average effect on each *new* participant's annual consumption (see diagonal) is higher for the unmatched than for the matched. E.g., for new participants at  $t=1$ , average annual consumption increased by ETB 476 before matching but after matching, the increase is reduced to ETB 398. As such, comparing the new participants (on the diagonal of the table) against their appropriately matched controls reduces the average impact. One implication is that compared to an average non-participant that constituted the unmatched controls, better off households have self-selected into the program in each year. Clearly, comparing the new participants in each year against non-participants without accounting for initial differences, in our case, overestimate impact. The bias remains even after entry (off-diagonal). However, the direction of bias differs from year to year.

*Table 2 Simple pair wise comparisons between matched and unmatched households*

*Average participation effects on yearly household consumption expenditure*

Timing of participation	1997 (v=1)		2000 (v=2)		2003 (v=3)		2006 (v=4)	
	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched
t=1	398.045*** (109.118)	475.671*** (112.671)	529.716* (281.947)	506.302* (282.546)	371.162** (146.650)	268.145* (1.820)	1487.966*** (546.147)	1663.482*** (540.301)
t=2			133.156 (428.498)	258.850 (380.228)	-296.506 (263.564)	-439.124* (247.017)	1457.280* (871.109)	1135.41** (751.849)
t=3					717.044* (462.315)	739.875** (378.987)	497.059 (1178.491)	1398.763** (918.440)
t=4							429.150 (1591.532)	2041.472*** (934.478)

Note: \*\*\*, \*\*, \*, significant at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses.

## 4.2 Matched composite versus matched pair wise comparisons

The pair wise comparison of participation effects between matched and unmatched groups in the previous section suggests that matching reduces a significant part of bias due to differences prior to entry. However, it does not account for how participating households would have fared in subsequent years if they had not participated. Such effect is captured by the composite counterfactual estimated according to methods provided in section 3.1 and 3.2 (detail calculations are given in appendix 1A). Main results are given in table 3. For comparison purposes, matched pair wise effects are also provided for each outcome measurement period along with the composite effects. The columns in table 3 provide these comparative results for each group of participant ( $t=1,..4$ ) and in each outcome measurement period ( $v=1,..,4$ ). Note that standard errors are not given for composite results because they are calculated from several matching results according to methods in (2) and (4) (see appendix 1A).

There are two important findings in this exercise. First, regarding the main causal question of comparing the effect of early versus late participation, the composite counterfactual results suggest that early participants have consistently fared better than late participants. Specifically, after accounting for both initial differences and potential future changes in the composition of participants and their controls, long-term participants have enjoyed relatively higher average annual consumption than short-term participants. In table 3, this can be seen by comparing the composite effects for each new participant group (i.e., at each  $t$ ) against its preceding participant column wise. Note that the composite effect, for the most part, declines going from top (early participants) to bottom (late participants) in each column. One reason is that the effect of borrowing lasts longer than the specific period it refers to and that long- rather than short-standing participants are more likely to enjoy higher effects in terms of capacity to smooth consumption over time. Another is since participation is state dependent, at least, in this

data set (see results in chapter three); the chances of repeat participation and hence further increases in consumption are higher for early than late participants.

Second, in contrast to simple pair wise effects, the composite effects provide conservative results in all comparisons except for the initial year<sup>1</sup>. This is because the composite effects take future potential counterfactuals into account whereas the pair wise estimates do not. In other words, not accounting for future potential counterfactuals overestimates impact. This is so because not participating in any earlier year does not preclude the possibility of participating in any later year and given positive effects of participation, not accounting for these chances of later participation overestimates impact of early participation. This can be elaborated using the most early participants (i.e.,  $t=1$ ) whose outcome is measured in four period. The composite effect in the last outcome measurement period ( $v=4$ ) takes into account the fact that some of their matched controls (i.e., non-participants at  $t=1$ ) have been able to participate at  $t=2$ ,  $t=3$  or at  $t=4$ . This reduces the average effect from ETB 1488 to ETB 1238. Clearly, the difference is the counterfactual for early participants had they not participated at  $t=1$ . Thus, failing to account for the different future pathways between participation and outcome measurement periods overstates the effect of (early) participation.

Obviously, many factors other than borrowing dictate changes in consumption levels over time and, with a slight downturn in 2003, average consumption increased between  $v=1$  and  $v=4$  for both participants and non-participants, albeit at different pace. Specifically, except in the bad year 2003 in which case there was a consumption downturn, the pair wise causal effects, for the most part, overestimate impacts because the counterfactual paths are not taken into account.

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<sup>1</sup> Note that in each initial year, the pair wise effect is the same as the composite effect because  $t=v$  and there is no need to account for future potential counterfactual.

Table 3 Matched composite versus matched pair wise comparisons

Household consumption expenditure measurement period								
Timing of participation	1997 (v=1)		2000 (v=2)		2003 (v=3)		2006 (v=4)	
	Composite	Pair wise	Composite	Pair wise	Composite	Pair wise	Composite	Pair wise
t=1	<b>398.045</b>	398.045*** (109.118)	<b>388.733</b>	529.716* (281.947)	<b>859.674</b>	371.162** (146.650)	<b>1238.704</b>	1487.966*** (546.147)
t=2			<b>133.156</b>	133.156 (428.498)	<b>-568.872</b>	-296.506 (263.564)	<b>524.370</b>	1457.280* (871.109)
t=3					<b>717.044</b>	717.044* (462.315)	<b>-292.578</b>	497.059 (1178.491)
t=4							<b>429.150</b>	429.150 (1591.532)

Note: \*\*\*, \*\*, \*, significant at the 1%, 5%, and 10% levels, respectively. Standard deviations in parentheses.

Evidently, conventional parametric impact assessments that compare ‘ever participants’ to ‘never participants’ without considering the timing of the decision to participate and the different potential future pathways an individual household might have followed in the absence of the program would yield biased estimates.

Finally, given the relatively longer period the data set covers, including two drought years (1999/2000 and 2003) in between, it is interesting to see the implications of the effects of these differences in timings of participation on household consumption and hence relative capacity to cope with vulnerability during and after the drought years. Composite effects of participation in the first three periods i.e., at  $t = 1, 2,$  and  $3,$  on annual consumption during the last three outcome measurement periods, i.e.,  $v = 2, 3,$  and  $4,$  are of interest here. Compared to controls, results suggest that the average annual consumption of the earliest ( $t=1$ ) participants has increased steadily, including during and post drought years. Intuitively, sufficient time is needed for the cumulative impact of credit to take effect (King and Behrman, 2009). This is however not the case for later ( $t=2$  and  $t=3$ ) participants. In fact, although both participant groups have seen increased average consumption in the year they participated (which happened to be the drought years for both), in both cases, it has declined a year after participation (post drought years). A possible explanation for this is that households might have diverted loans to smooth consumption in the drought years, a common phenomenon despite DECSI’s claims of ‘productive’ use of credit. A study on the same MFI by Borchgrevink et al., (2005:68-69) finds indications of use of credit given for production purposes diverted to consumption during drought periods. This is also inline with the claim in chapter three that for households that are borrowing risk constrained, credit might be only useful as a last resort in times of distress. Moreover, the fact that loans are repaid after one year seems to explain the relative decline in participant households’ consumption in the post drought periods. Nevertheless, for the  $t = 2$  participants, the result suggests this decline

has been reversed in 2006<sup>1</sup>. It can therefore be concluded that relative to non-participants, earlier participants gained better capacities to cope with shocks and the earlier the better. This conclusion has to be taken with caution though because the results explicitly compare variations of average consumption due to credit and not overall consumption variability due to shocks.

### **4.3 Effects of changes in the composition of treatment and control groups in time-varying treatments**

In sections 4.1 and 4.2 interest centered on the effect of timing of first-time participation in MFI borrowing on annual household consumption in subsequent years. Thus, the analysis was mainly based on entry, considering borrowing as an irreversible regime, i.e., once households participate, they remain members thereafter. However, there are borrowing dynamics after this entry event took place. Particularly, once in the borrowing regime, some households participated repeatedly, and others participated occasionally or never repeated at all. Details about these dynamics are given in Figure 1. This section presents effects of such borrowing dynamics, mainly effects of dropping out and repeat-borrowing in a particular year. Due to the complexity of applying composite counterfactuals, effects are analyzed pair wise. However, comparative results are provided such that the biases in handling dropouts discussed in section 2.2 are also evaluated.

Table 4 presents comparative results of (i) including dropouts in control groups but not in treatment groups (comparison 1) in contrast to including them in treatment groups but excluding them from the control groups (comparison 2). This comparison shows the bias in using the standard fixed-effects method that would naively include dropouts in control groups; (ii) excluding dropouts from both and excluding new participants from treatment groups (comparison

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<sup>1</sup> For  $t = 3$  participants, the effect in subsequent years is not known because the observation period does not allow for this.

Table 4 Effects of repeat-participation and changes in the composition of participants: matched and unmatched pair wise Comparisons

Average participation effects (ATT) on yearly household consumption expenditure									
Composition of treatment & control groups	Treatment periods	1997 (v=1)		2000 (v=2)		2003 (v=3)		2006 (v=4)	
		Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched
<b>Comparison 1:</b>	<i>t=1</i>	398.045*** (109.118)	475.671*** (112.671)	529.716* (281.947)	506.302* (282.546)	371.162** (146.650)	268.145* (1.820)	1487.966*** (546.147)	1663.482*** (540.301)
<u>Treatment group:</u> Repeat and new participants at <i>t</i>	<i>t=2</i>			443.185 (371.215)	590.496* (363.088)	-191.687 (223.447)	-240.763 (179.716)	2350.142*** (695.203)	2382.831*** (694.100)
<u>Control group:</u> Non-participants at <i>t</i> (dropouts excluded)	<i>t=3</i>					-32.794 (294.988)	492.149** (211.200)	2113.532*** (708.526)	2886.439*** (722.815)
	<i>t=4</i>							1058.209 (970.112)	1656.060 (1347.406)
<b>Comparison 2:</b>	<i>t=1</i>	398.045*** (109.118)	475.671*** (112.671)	529.716* (281.947)	506.302* (282.546)	371.162** (146.650)	268.145* (1.820)	1487.966*** (546.147)	1663.482*** (540.301)
<u>Treatment group:</u> Repeat and new participants at <i>t</i>	<i>t=2</i>			388.838 (307.474)	305.734 (285.217)	-235.219 (143.111)	-326.401 (148.135)	1371.132*** (591.648)	1548.644*** (544.875)
<u>Control group:</u> Non-participants at <i>t</i> (dropouts included)	<i>t=3</i>					301.201** (150.605)	386.784*** (149.853)	1177.210** (581.238)	1620.214*** (552.194)
	<i>t=4</i>							1129.253* (771.022)	1311.087* (756.857)
<b>Comparison 3:</b>	<i>t=1</i>	398.045*** (109.118)	475.671*** (112.671)	529.716* (281.947)	506.302* (282.546)	371.162** (146.650)	268.145* (1.820)	1487.966*** (546.147)	1663.482*** (540.301)
<u>Treatment group:</u> Only repeat participants at <i>t</i>	<i>t=2</i>			790.598* (488.708)	804.851* (426.080)	-130.691 (240.557)	-112.555 (215.603)	3148.094*** (838.369)	3189.090*** (776.011)
<u>Control group:</u> Non-participants at <i>t</i> (dropouts excluded)	<i>t=3</i>					-208.260 (318.011)	348.360* (208.593)	2193.486*** (752.784)	3273.235*** (733.314)
	<i>t=4</i>							1190.914 (2177.474)	1837.332 (1410.308)

Note: \*\*\*, \*\*, \*, significant at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses.

3, table 4). In comparison 3, only repeated participants are compared to their periodical non-participant counterparts. This is can be used as reference for comparisons 1 and 2. Besides, this last comparison provides the effect of repeated participation on outcomes measured in different periods.

Comparing comparison (1) and (2) in table 4, shows that including dropouts in control (but not in treatment) groups biases impact even after adjusting for initial conditions using matching. However, the direction of the bias depends on the relative condition of dropouts in each year, which in turn may depend on the economic conditions in the year before. That is, in years when dropouts are those that have become worse off after participation, excluding them from the treatment group overstates impact. On the other hand, in years when dropouts are better off households, excluding them from treatment groups overstate impact both due to attrition and contamination effects. For participants in 2000, result shows that excluding dropouts from the treated groups and including them in the control group understates impact in all outcome measurement periods (see matched columns, table 4). On the contrary, excluding dropouts from the treatment group (including them in the control group) overstates impact because not only were relatively worse off participants selectively dropped out in the bad year 2003, but also the new participants in the same year were relatively better off. The latter can be seen by comparing the average participation effect of ETB 717 for matched new participants (table 3) and ETB 302 for matched new and repeat participants (table 4) in 2003. The same is true to participants in 2006. This means, there is not only a strong selection processes at work but also the direction of selection depends on the underlying economic conditions households face in each period. Note that in the unmatched case, the same comparison provides a different picture, concealing the selection processes.

Lastly, the last part of table 4 (comparison 3) provides the effect of repeated participation, excluding dropouts and new participants. Once again, comparing the veteran participants to their non-participant counterparts by excluding dropout overstates impact even when new participants are excluded, e.g. for participants in 2000, because only worse off participants dropped out systematically. Thus, for the most part, results in comparison 3 are higher than in comparison 1, which are in turn, for the most part higher than results in comparison 2, reflecting the consistency of the results obtained.

## **5. Conclusions**

This paper dealt with the methodologically challenging question of assessing the impact of differences in the timing of membership in microfinance credit using a four-wave panel data covering ten years that comes from a rural microfinance in Ethiopia. Specifically, main questions addressed include (a) whether or not early participation, as opposed to late participation, matters in terms of increases in average annual household consumption, (b) a methodological issue of consideration of potential future path ways of control groups when the timing of participation and outcome measurement are different, and (c) overcoming impact estimation biases due to the dynamics of borrowing, mainly dropouts and new entrants.

In the empirical methodology the paper argued that parametric impact assessment methods such as the fixed-effects method may yield biased estimates when the treatment variable is dichotomous and units are observed more often than in the classic two-period panel data case because such methods exploit on individuals being “on” and “off” the treatment over time, which contaminates the impact estimate. An alternative method is used that treats participation in credit as an irreversible regime and identify impact from the timing of onset of participation. As such, only non-participant households up to the time of entry of participants are considered as

candidates for control. The propensity score matching is used to balance potential initial heterogeneities among participants and non-participant controls.

The results of the propensity score matching indicate that matching participants and non-participants on some basic pre-treatment characteristics reduces substantial amount of selection bias. Comparisons between matched and unmatched average treatment effects suggests that over the years ‘better off’ households tend to participate. The results from the main analysis indicate that early than late participants enjoyed higher average annual consumption over time. Comparing the composite effects against simple pair wise effects, the composite effects provide conservative results because they take future counterfactuals into account. Thus, not accounting for potential future path ways overstates impact. The results also suggest that compared to their respective control groups, credit has had better shock cushioning effect for earlier than later participants.

The analysis has also considered effects of the dynamics of borrowing once in the borrowing relationship. Particularly, pair wise effects of repeat-borrowing and dropping out are considered in a comparative way. Results suggest including dropouts in control (but not in treatment), as in fixed-effects, biases impact even after adjusting for initial conditions using matching. However, the direction of the bias depends on the relative condition of dropouts in each year. Further, the comparative analysis indicates that because of the selection processes at work when individuals dropout or repeat, impact assessments that compare participants and non-participants, covering longer periods but only adjusting for initial conditions but not for dynamics in mean time are likely to be biased.

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**Appendix 1A.**

**Calculating ATT based on composite counterfactuals:**

1)  $t=1$  and  $v=1$

$$\begin{aligned} ATE_1 &= E(\Delta C_v^{d=t} | X) = E(C_1^{d=1} | X) - E(C_1^{d>1} | X) \\ &= 1960.363 - 1562.318 \\ &= 398.045 \end{aligned}$$

2)  $t=1$  and  $v=2$

$$\begin{aligned} ATT_2 &= E(\Delta C_v^{d=t} | X) = E(C_2^{d=1} | X) - E(C_2^{d>1} | X) \\ &= E(C_2^{d=1} | X) - \{p(2) \cdot E(C_2^{d=2} | X) + q(2) \cdot E(C_2^{d>2} | X)\} \\ &= (2950.014) - \{(0.38)(2643.837) + (0.62)(2510.682)\} \\ &= 388.733 \end{aligned}$$

3)  $t=1$  and  $v=3$

$$\begin{aligned} ATT_3 &= E(\Delta C_v^{d=t} | X) = E(C_v^{d=t} | X) - E(C_v^{d>t} | X) \\ &= E(C_3^{d=1} | X) - \{p(2) \cdot E(C_3^{d=2} | X) + q(2) \cdot p(3) \cdot E(C_3^{d=3} | X) \\ &\quad + q(2) \cdot q(3) \cdot E(C_3^{d>3} | X)\} \\ &= (2383.919) - \{(0.38)(1889.588) + (0.62)(0.30)(2960.391) \\ &\quad + (0.62)(0.70)(2243.347)\} \\ &= 859.674 \end{aligned}$$

4)  $t=1$  and  $v=4$

$$\begin{aligned} ATT_4 &= E(\Delta C_v^{d=t} | X) = E(C_4^{d=1} | X) - E(C_4^{d>1} | X) \\ &= E(C_4^{d=1} | X) - \{p(2) \cdot E(C_4^{d=2} | X) + q(2) \cdot p(3) \cdot E(C_4^{d=3} | X) \\ &\quad + q(2) \cdot q(3) \cdot p(4) \cdot E(C_4^{d=4} | X) + q(2) \cdot q(3) \cdot q(4) \cdot E(C_4^{d>4} | X)\} \\ &= (7604.657) - \{(0.38)(6691.062) + (0.62)(0.30)(5961.886) \\ &\quad + (0.62)(0.70)(0.34)(6537.704) + (0.62)(0.70)(0.66)(6108.554)\} \\ &= 1238.704 \end{aligned}$$

5)  $t=2$  and  $v=2$

$$\begin{aligned} ATT_5 &= E(\Delta C_v^{d=t} | X) = E(C_2^{d=2} | X) - E(C_2^{d>2} | X) \\ &= 2643.837 - 2510.682 \\ &= 133.156 \end{aligned}$$

6)  $t=2$  and  $v=3$

$$\begin{aligned}
 ATT_6 &= E(\Delta C_v^{d=t} | X) = E(C_3^{d=2} | X) - E(C_3^{d>2} | X) \\
 &= E(C_3^{d=2} | X) - \{p(3) \cdot E(C_3^{d=3} | X) + q(3) \cdot E(C_3^{d>3} | X)\} \\
 &= (1889.588) - \{(0.30)(2960.391) + (0.70)(2243.347)\} \\
 &= -568.872
 \end{aligned}$$

7)  $t=2$  and  $v=4$

$$\begin{aligned}
 ATT_7 &= E(\Delta C_v^{d=t} | X) = E(C_4^{d=2} | X) - E(C_4^{d>2} | X) \\
 &= E(C_4^{d=2} | X) - \{p(3) \cdot E(C_4^{d=3} | X) + q(3) \cdot p(4) \cdot E(C_4^{d=4} | X) \\
 &\quad + q(3) \cdot q(4) \cdot E(C_4^{d>4} | X)\} \\
 &= (6691.062) - (0.30)(5961.886) + (0.70)(0.34)(6537.704) \\
 &\quad + (0.70)(0.66)(6108.554) \\
 &= 524.370
 \end{aligned}$$

8)  $t=3$  and  $v=3$

$$\begin{aligned}
 ATT_8 &= E(\Delta C_3^{d=3} | X) = E(C_3^{d=3} | X) - E(C_3^{d>3} | X) \\
 &= 2960.391 - 2243.347 \\
 &= 717.044
 \end{aligned}$$

9)  $t=3$  and  $v=4$

$$\begin{aligned}
 ATT_9 &= E(\Delta C_4^{d=3} | X) = E(C_4^{d=3} | X) - E(C_4^{d>3} | X) \\
 &= E(C_4^{d=3} | X) - \{p(4) \cdot E(C_4^{d=4} | X) + q(4) \cdot E(C_4^{d>4} | X)\} \\
 &= (5961.886) - \{(0.34) \cdot (6537.704) + (0.66) \cdot (6108.554)\} \\
 &= 292.578
 \end{aligned}$$

10)  $t=4$  and  $v=4$

$$\begin{aligned}
 ATT_{10} &= E(\Delta C_4^{d=4} | X) = E(C_4^{d=4} | X) - E(C_4^{d>4} | X) \\
 &= 6537.704 - 6108.554 \\
 &= 429.150
 \end{aligned}$$