Does Long-term Access to Microcredit Lead to Women Empowerment?

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Abstract[4]

In this paper, we examine whether long-term access to microcredit leads to improvements in women's empowerment and explore intra-household bargaining power (IHBP) as a key underlying mechanism for the same. We use administrative data from a microfinance institution and adopt a quasi-experimental methodology by statistically matching their comparable long-term and new female microfinance clients using coarsened exact matching. We also conduct incentivized lab-in-the-field experiments with client couples to measure IHBP of women as a potential mechanism for women empowerment. We find that long-term access to microcredit has no significant impact on women's empowerment across key dimensions – decision-making, control over resources, and gender attitudes. Benchmarking our effect sizes against prior studies, we demonstrate that the null is both precise and credible. We attribute this result to a lack of improvement in our potential mechanism of IHBP among long-term female clients and show that our experimentally elicited IHBP measures are strongly predictive of women empowerment outcomes in the expected direction, affirming their construct validity. These findings suggest that long-term access to microcredit, even when sustained for over a decade, does not by itself transform women's status within the household, highlighting the need for credit-plus approaches that address social norms and strengthen women's bargaining position directly. Our findings are thus relevant for over 140 million women microfinance clients across developing countries, where entrenched gender norms still shape how financial access translates, or fails to translate, into women's empowerment.

JEL codes : C93, D13, D14, J16, O12

Keywords: Microcredit, women empowerment, intra-household bargaining power, mechanism, multidimensional poverty index, coarsened exact matching

Study pre-registration: This trial is pre-registered at the AEA RCT Registry

RCT ID - AEARCTR-0007922 (https://www.socialscienceregistry.org/trials/7922)

IRB approval number is #063-021(Monk Prayogshala Institutional Review Board on June 10, 2021)

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[4] Acknowledgements: The authors are grateful for comments and suggestions from Indradeep Ghosh, Utteeyo Dasgupta and Tanika Chakraborty.

1. Introduction

The microfinance movement began with considerable hope and enthusiasm for its potential to empower women and alleviate poverty. The theoretical foundation linking microcredit to women's empowerment is rooted in the implicit belief that access to financial resources will facilitate women's involvement in income-generating activities, enhance their control over household resource allocation and decision-making (Vaessen et al., 2014). On the other hand, the literature on intra-household bargaining theory suggests that women's ability to affect household resource outcomes crucially depends on their relative control over those resources and fallback options (Balasubramanian, 2013). In contexts where gender norms rigidly assign men greater authority within households, even increased economic contributions may not translate into meaningful shifts in bargaining power for women. Norms are socially enforced and slow to change, often requiring individuals to weigh the social costs of deviation (Andreoni et al., 2021). Research highlights that social expectations, cultural beliefs, and interpersonal dynamics play a central role in maintaining such norms (Bicchieri, 2023; Bicchieri et al., 2021, 2023; Bicchieri & Dimant, 2023). Consequently, norm change is a complex, gradual process that may not be catalyzed by any single intervention such as microcredit. Indeed, a series of randomized evaluation studies conducted across six countries found little to no effect of microcredit on women's empowerment, at least in the short run (Banerjee et al., 2015). Whether long-term access to microfinance can gradually mitigate the entrenched gender norms still remains an open empirical question. We address this gap in the literature by combining quasi-experimental methods with experimental measures of IHBP to test whether long-term-term access to microfinance improves women's position within the household and strengthens empowerment outcomes.

For this purpose, we partner with a Non-Banking Microfinance Institution (MFI) that provides microcredit to women from low-income households in India. India hosts one of the world's largest and fastest-growing microfinance markets, with non-bank MFIs managing over ₹3.5 trillion INR (173 billion USD in PPP) in outstanding loans and more than 70 million active borrowers, primarily women, impacting approximately 300 million families (approximately the population of USA which was 340 million as of 2024) (MFIN, 2023). This scale makes India a strategic setting for examining the overall effects of microcredit on women's empowerment. Moreover, while our data come from India, the dynamics we study – microfinance-led empowerment amidst entrenched gender norms – are relevant across many developing countries. With over 140 million microfinance clients globally, the majority of them women (D'Espallier et al., 2011; Dichter, 2023), our findings speak to broader policy debates in regions like South Asia, Sub-Saharan Africa, and Latin America where similar institutional and cultural conditions persist.

Through our partnership with the MFI, we obtained access to its administrative data and applied a three-step inclusion criterion to define our study sample i.e., the participants must be (i) female microcredit customers with Joint Liability Group loans, (ii) aged 18–55 and married, and (iii) residing with their spouse in either Thanjavur or Pudukkottai districts of Tamil Nadu, India. We then classified customers into two groups: 'Long-term Clients,' defined as women in their seventh loan cycle or higher, implying over a decade of microcredit access at the time of the study, and 'New Clients,' defined as women in their first loan cycle, with less than one year of exposure. Since microcredit participation is self-selected, these groups may differ systematically, making direct comparisons vulnerable to selection bias. Therefore, to mitigate such potential bias, we use a statistical matching technique called Coarsened Exact Matching (CEM), in which we match the customers across the two groups to make them more comparable on important observable characteristics, with the key difference being their tenure as a microcredit customer with our partner MFI. We use this identification strategy to examine differences in women empowerment measures between the long-term and new clients of microcredit. Given the stickiness of gender norms as explained before, we contribute to the existing literature on microfinance by capturing the long-term impact of microcredit as opposed to the existing literature of impact evaluation studies that typically look at the short-term impacts over a one- to three-year period (Banerjee et al., 2015; Cai et al., 2023). Therefore, our methodological approach is well-positioned to explore whether sustained access to microcredit can drive meaningful shifts in women's empowerment over time. To the best of our knowledge, ours is the first paper to study the long-term impact of microcredit on women's empowerment over a decade-long period.

Another key contribution of this paper lies in evaluating women's IHBP as a mechanism through which long-term access to microcredit may influence various dimensions of empowerment. While much of the microfinance literature focuses on outcomes such as income or business growth, we situate the impact of microcredit within the broader intra-household resource allocation literature. Traditional economic models treat the household as a unitary entity, assuming that all income and resources are pooled and allocated by an altruistic household head who maximizes the collective utility of the household, reflecting a unified set of preferences. However, empirical research has challenged this assumption, highlighting that households are spaces of both cooperation and conflict, where men and women often hold divergent preferences and may behave strategically to pursue their individual interests (Ashraf, 2009; Bjorvatn et al., 2020). In contrast to the unitary household models, cooperative and non-cooperative bargaining models acknowledge these differences and suggest that the outcomes of intra-household decision-making depend on the relative bargaining power of each member (Agarwal, 1997; S. J. Lundberg et al., 1997; Manser & Brown, 1980). In a complementary perspective, Lundberg & Pollak (1993) introduce the "separate spheres" model, which posits that household members operate within distinct domains of responsibility and decision-making based on socially constructed gender roles. These roles, though not explicitly negotiated, shape the bargaining landscape and influence how decisions over joint goods and activities are made.

Our theory of change builds on this framework: the extent to which long-term access to microcredit empowers women depends critically on whether it strengthens their IHBP (Balasubramanian, 2013). This raises a central empirical question: *does sustained exposure to microfinance improve women's bargaining power within the household?* While theoretically salient, empirical evidence on this relationship remains limited, and our study seeks to address this gap in the literature. A further contribution of our research lies in its methodological innovation in measuring IHBP. Rather than relying solely on self-reported survey data (Gerritzen, 2014), we use incentivized artefactual or lab-in-the-field experiments to elicit IHBP. Specifically, we conduct ultimatum games with female microcredit clients and their spouses, drawing on a tradition of experimental economics to elicit strategic behavior in bargaining settings (Güth et al., 1982; Kagel & Roth, 1995; Levitt & List, 2007). This lab-in-the-field approach enables us to capture the IHBP more accurately. Survey-based measures of household decision-making and control over resources are often prone to limitations. These include discrepancies in responses between household members due to differing perceptions, inaccuracies resulting from the presence of other household members during the interview, social desirability bias and variations in how questions are interpreted (Acosta et al., 2020). By contrast, our experimental approach offers a more robust and credible way to elicit intra-household dynamics and assess whether long-term access to microcredit can shift household bargaining outcomes in favor of women (Bulte et al., 2016; Iversen et al., 2006; Lenjiso et al., 2016; Munro, 2018).

To isolate strategic bargaining from altruistic motives, we supplement the ultimatum game with an incentivized dictator game. We also include a risk preference elicitation task to account for variation in risk attitude, which could influence offers and acceptances in bargaining games. Together, these experiments provide a more credible and behaviorally grounded measure of IHBP than conventional surveys (Bulte et al., 2016; Iversen et al., 2006; Lenjiso et al., 2016; Lowes, n.d.; Munro, 2018). In addition to the experimental data, we conduct a detailed household survey capturing demographics, financial access, household income and expenditure, women's empowerment, and key well-being indicators such as education, health, and living standards. This allows us to examine both the proximate mechanism (bargaining power) and the downstream effects of microcredit on broader welfare outcomes. Finally, we assess changes in multidimensional poverty using the Multidimensional Poverty Index (MPI) – a framework increasingly used by development agencies and governments to track poverty across multiple dimensions (NITI Aayog, 2023; UNDP, 2023). By combining behavioral games, survey data, and welfare metrics, our study contributes to the literature on microcredit and empowerment, while also offering new tools for evaluating the long-term social impacts of financial inclusion.

Our main finding is that long-term access to microcredit does not increase women's IHBP and, correspondingly, has no significant effect on broader measures of women's empowerment. We empirically test our theory of change and show that the IHBP outcome variables elicited through the ultimatum games significantly predict various women empowerment indices in the expected directions. This empirical link supports the central mechanism we propose. Thus, to the best of our knowledge, our paper is the first in the literature to provide a behavioral and empirically grounded explanation for the limited impact of microcredit on women's empowerment observed in prior randomized evaluations such as Banerjee et al. (2015). To strengthen our results, we conduct two complementary robustness checks. First, in our ex-ante Coarsened Exact Matching, we were constrained by the set of observables available in the administrative data. Thus, to further improve comparability between long-term and new clients, we conduct an ex-post Propensity Score Matching (PSM) analysis using a richer dataset from our primary household survey and find consistent results. Second, we use machine learning algorithms trained on a richer set of pre-treatment variables that are drawn from administrative data recorded at clients' first loan cycle, to predict who is likely to become a long-term client. We then compare actual long-term clients with new clients classified as "potential long-term clients", based on selected probability cutoffs to make a more like-to-like comparison. Across different models and cutoffs, results remain robust, reinforcing that our main findings are not driven by baseline differences in client characteristics or model-specific artifacts.

Our findings yield three key policy implications. First, microcredit on its own may be insufficient to empower women or shift intra-household bargaining dynamics. A more holistic approach—one that combines access to formal finance with interventions aimed at enhancing women's skills, building social networks, and supporting sustainable livelihoods—is likely to be more effective in transforming women's lives and improving their overall well-being. Second, while microcredit may not significantly drive empowerment, it remains valuable as a financial tool for smoothing household consumption and managing short-term income fluctuations (Merfeld & Morduch, 2023). To enhance its utility, microcredit contracts should be better tailored to the specific cash flow needs of clients. Evidence suggests that customized financial products, designed to meet the diverse needs of different client segments, outperform standardized, one-size-fits-all microcredit offerings (Cai et al., 2023). Finally, targeted credit interventions aimed at enterprise creation and expansion can support women's economic agency, particularly among those with entrepreneurial aspirations. In this regard, India's social protection programs—such as centrally and state-sponsored rural livelihoods initiatives—offer promising models. These programs integrate access to credit with market linkages, business training, and livelihood support, and have shown positive impacts on women's decision-making power and household socioeconomic outcomes (Hoffmann et al., 2018; Kochar et al., 2022). These findings reinforce the value of a "credit-plus" approach in empowering women from low-income households.

2. Empirical Design and Strategy

2.1 Empirical Design

2.1.1 Quasi-experimental Design

Given our central research question of studying the long-term impact of microcredit over a decade-long period, a randomized evaluation would not be feasible for our purpose. Therefore, we adopt a quasi-experimental methodology involving a CEM technique to identify the impact of long-term access of microcredit. (Reinisch et al., 1995; Stuart, 2010). For this purpose, we leveraged administrative data from our partner MFI, which includes detailed information on client demographics (age, gender, marital status, education), loan characteristics (amount, type, tenure, interest rate, branch), and household attributes (caste, religion, income, size, asset ownership). Based on loan history, we bifurcated the customer data on the basis of when they adopted microcredit into two groups - 'Long-term Microfinance Clients' and 'New Microfinance Clients'. Since each JLG loan cycle lasts for an average of 2 years, customers who were in their seventh loan cycle or more had access to microcredit for about 14 years as opposed to the counterfactual group who were in their first loan cycle at the time of the study.

As the customers self-selected when to take microcredit, long-term microfinance clients could be systematically different from new microfinance clients. To mitigate this selection bias, we use CEM to select the best-matched sample of long-term clients with new clients (Reinisch et al., 1995; Stuart, 2010). CEM techniques ensure that units across the two groups (long-term clients and new clients) are similar, based on relevant observable characteristics. It increases the likelihood that the differences in outcomes between the two groups can be causally attributed to the intervention being studied. So, it is important to include the pre-treatment covariates in the matching procedure that affect both the treatment (time of adoption of microcredit) and the outcome (women empowerment and IHBP) simultaneously (Heckman et al., 1997; Rubin & Thomas, 1996), but those variables that are affected by the treatment (such as occupation, income of the customer) need to be avoided (Frangakis & Rubin, 2002; Greenland, 2003; Rosenbaum, 1984). Thus, the covariates that we selected from the administrative dataset for matching are age, education, caste, religion, and household size. [5]

CEM is a type of stratification matching method in which the continuous covariates are first coarsened into different bins, and then exact matching is applied to these coarsened covariates. [6] CEM creates

[5] We were of course, constrained by the set of variables that were available in the administrative data to select the matching variables. In order to address this limitation, we conduct an ex-post matching exercise with a wider set of variables, as a robustness check.

[6] To arrive at the final sample, we tried different types of matching methods such as propensity score matching (PSM), nearest neighbor matching, optimal pair matching, optimal full matching, caliper matching, exact matching. Ultimately, we found that CEM provided the best balance and a satisfactory sample size, making it the most appropriate choice for our study.

different subclasses or strata based on the different combinations of the selected covariates and then exactly matches each long-term client unit with its corresponding new client unit. [7] It drops any subclasses that do not contain at least 1 unit from each of the two groups. Therefore, it does not require a separate region of common support, unlike other matching techniques. Moreover, it also meets the congruence principle as it operates in the space where the covariates were created and measured (Iacus et al., 2012; King et al., 2011). In order to control for potential heterogeneity among customers between the two districts Thanjavur and Pudukkottai, we matched long-term and new clients within districts but not across districts (Heckman et al., 1998; Heckman et al., 1997). Our final sample consisted of 360 customer couples with 180 long-term client couples matched with 180 new client couples across 185 villages in the two districts.

2.1.2 Experimental Design

To elicit IHBP for our study subjects, we conduct Ultimatum Game (UG) experiments with spouses across both the long-term and new client groups. Typically, in a UG, two players are allocated a sum of money that can be divided between them. The player 1 (proposer) makes an offer to the responder (player 2), and the responder can choose to accept or reject this offer. In our UG, player 1 is given ₹400 (19.72 USD in PPP)[8] to allocate between them and their spouse (player 2). They can propose any amount between ₹0-400 (both included). Player 2 decides what the minimum amount that they would accept is. If player 1's offer is equal to or higher than the minimum acceptable amount by player 2, i.e., player 2 accepts the offer, then both player 1 and player 2 receive the amounts allocated by player 1. If player 1's offer is lower than the minimum acceptable amount by player 2, i.e., player 2 rejects the offer, then both receive zero. In our experiment, we randomly assign spouses to assume the role of player 1 or 2. We also use the strategy method whereby we ask player 2 to decide whether to accept or reject for each potential allocation by player 1. It allows us to estimate the minimum acceptable amount for player 2. According to standard game theory prediction, player 1 should offer any amount slightly higher than 0 so that the payoff for player 2 becomes greater than 0, and player 2 should accept the offer. Moreover, any higher amount given by player 1 to player 2, as well as player 2's refusal to accept a low but positive amount, can be interpreted as higher bargaining power for player 2 (Thaler, 1988; Lowes, 2022). Thus, given the nature of the UG, the higher the allocation by the proposer to the responder, the lower the proposer's bargaining power and vice versa. Similarly, the higher the minimum amount accepted by the responder, the higher the responder's bargaining power and vice versa (Lowes, 2022). Thus, the amounts proposed or expected depend on the players' perception of their own and their partner's bargaining power.

[7] For example, the continuous variable age is converted into age classes and education into three literacy categories.

[8] IMF's 2023 implied PPP conversion rate.

In this game, high allocation by the proposer can also be motivated by their altruism or risk aversion, while the responder's rejection of the offer can be motivated by non-cooperation (Croson & Gneezy, 2009). However, the incentive structure of the game at least partially controls for these other potential factors that might influence behaviour, and makes the players objectively predict the bargaining position of the other party (Lenjiso et al., 2016). Moreover, we also administer a dictator game and a risk game to control for altruism and risk aversion among subjects. To control for altruism, we conduct a standard dictator game. In this game, player 1 is asked to allocate ₹400 (19.72 USD in PPP) between themselves and player 2 (their spouse). Similar to the ultimatum game, player 1 can propose any amount between ₹0-400 (both included). However, unlike the ultimatum game, in this game, player 2 has no agency and has to accept the amount allocated by player 1. According to standard game theory prediction, player 1 shouldn't offer anything to player 2 as player 2 has no control over the outcome of the game, and therefore any amount greater than zero sent by player 1 to their counterparts can be viewed as altruism (Hoffman et al., 1996). Player 1 (2) for the ultimatum game continued to be player 1 (2) for the dictator game. We used a "pay one randomly'' mechanism where one of the two games was randomly selected for payment. The subjects were informed about this before the start of the experiment. We chose this "pay one randomly" payoff mechanism as it helps in eliciting true responses by avoiding wealth effects and hedging (Charness et al., 2016).

Finally, we administered a risk elicitation game among our study participants (Gneezy & Potters, 1997). Each respondent, i.e., both the husband and the wife, was given ₹50 (2.46 USD in PPP) for completing the survey. The subjects could keep ₹50 for themselves, or they could use that money to participate in an incentivized risk game where they were offered a chance to invest their earnings of ₹50 from the survey into a lottery. They could invest any amount between ₹0-50 in the lottery, where they would receive triple the amount of money invested with a 50% probability or zero otherwise. The roll of a die decided the outcome of the lottery. If an odd number appeared on the die, the respondent won the lottery, and if an even number appeared, they lost. In this game set-up, the lower they invest, the more risk-averse they are.

2.2 Empirical Strategy

2.2.1 Women Empowerment Indices and Intra-household Bargaining Power

To estimate the effects of long-term microcredit access on women's empowerment, we construct four indices capturing various dimensions. First, the Access to Resource Index (ARI) combines ten indicators reflecting women's access to both financial and non-financial resources, including contraceptive awareness, SHG membership, independent purchases and mobility, access to family assets, hygiene products, personal savings, autonomous bank use, and paid work. Second, the Gender

Perceptions Index (GPI) aggregates nine items capturing attitudes toward gender norms, such as views on financial control, the relative value of daughters, respect for women, and acceptance of women earning more than their husbands. Third, the Decision-Making Index (DMI) is constructed from eight indicators of women's influence in household decisions regarding consumption, health, fertility, children's education and marriage, savings, borrowing, and voting. Finally, the Women's Empowerment Index (WEI) aggregates all items from the three sub-indices to reflect an overall multidimensional empowerment measure. We apply Principal Component Analysis (PCA) [9] to construct these four indices, a common method in studies of women's empowerment (OECD, 2008; Vyas & Kumaranayake, 2006). PCA weights the components based on their contribution to the underlying variation in the data (Ewerling et al., 2017; Sharaunga et al., 2016), avoiding arbitrary weighting.

To study the impact of long-term access to microcredit on women's empowerment across the four dimensions, we employ a fractional regression strategy to estimate the model:

$$Y_i = T_i\beta + X_i\delta + U_i$$

where $Y_i \epsilon [0,1]$ denotes the dependent variable (ARI, GPI, DMI, or WEI), T_i is a treatment indicator for long-term microcredit clients, and X_i is a vector of pre-treatment covariates (religion, caste, household size, education, years married, spousal age gap, number of females in the household, income, landholding, number of outstanding loans, and BMI). Here, β denotes our coefficient of interest, δ denotes the vector of coefficients to be estimated, and U_i denotes the random disturbance term.

We also construct two experimental measures of intra-household bargaining power using lab-in-the-field experiments: Amount Allocated to Spouse (AAS) and Acceptable Minimum Amount (AMA) [10]. These serve as outcome variables in analogous fractional regression models estimated on the matched sample obtained via coarsened exact matching.

2.2.3 Multidimensional Poverty Index

The Multidimensional Poverty Index (MPI) captures household deprivation across various aspects of well-being beyond just income or consumption (Alkire & Foster, 2011) [11]. Given growing evidence that microcredit often fails to improve traditional household outcomes like income or spending, recent work has called for broader measures of impact (Merfeld & Morduch, 2023; UNCDF, 2022; UNSGSA,

[9] PCA is a dimensionality reduction technique used to reduce the number of variables in the data set. It takes n correlated variables from an initial set and creates uncorrelated components, where each component is a linear weighted average of the initial set of correlated variables.
[10] Henceforth the abbreviations and full forms of these two variables are used interchangeably.
[11] The MPI based on the Alkire-Foster method is the most widely used non-monetary poverty index in the world (Godinot & Walker, 2020). It captures overlapping deprivations in health, education, and living standards and has been used by UNDP in its Human Development Report since 2010 (UNDP, 2010).

2021). In response, we adopt a multidimensional poverty lens to assess how microcredit affects overall household well-being. [12]

For our analysis, we construct two dependent variables from the Multidimensional Poverty Index (MPI). The first is the Deprivation Score, a continuous variable ranging from 0 to 1. The second is a binary variable Poor, indicating whether a household is classified as poor (1) or not (0), based on a standard poverty cut-off. To estimate the impact of long-term microcredit access on multidimensional poverty, we use a fractional regression model for the Deprivation Score, and a logistic regression for the binary Poor outcome:

$$\ln\left(\frac{\Pr(Y_i = 1)}{\Pr(Y_i = 0)}\right) = T_i\beta + X_i\delta + U_i$$

Here, T_i is a treatment indicator equal to 1 for long-term clients and 0 for new clients, and X_i includes covariates such as religion, caste, household size, years since marriage, spousal age gap, number of women in the household, household income, landholdings, and outstanding loans. β denotes our coefficient of interest, δ denotes the vector of coefficients to be estimated, and U_i denotes the random disturbance term.

3. Results

3.1 Women Empowerment Indices

We examine the effects of long-term access to microcredit on women's empowerment- WEI and its constituent indices DMI, ARI, GPI. The results are presented in Table *1*, where every second column represents a model with control variables corresponding the model in the column that precedes it. Columns (7) and (8) in Table *1* shows the results of Fractional regression on the WEI, which is a composite of DMI, ARI, and GPI. The rest of the columns show the results of fractional regression on the other three dimensions of women's empowerment: DMI, ARI, and GPI. Columns 2, 4, 6 and 8 of Table *1* show the results of the model, including demographic and behavioral controls. We find that the coefficients for long-term clients for each of the indices- DMI, ARI, GPI and WEI are statistically insignificant. It indicates that long-term clients of microcredit are no different from newer clients in terms of their levels of empowerment measured through the four indices.

[12] In our study, the MPI is composed of three dimensions- education, health, and standard of living. For each household, the indicator is assigned a score of 1 if it meets the deprivation cut-off and 0 otherwise. An equal weight of 1/3 is applied to each dimension. We calculate the deprivation score for each household by taking a weighted sum of the number of deprivations, so that the deprivation score for each household lies between 0 and 1. The higher the score, the higher the deprivation. Finally, in order to identify a household that is multi-dimensionally poor, we use a second cut-off or threshold, which as per the Alkire-Foster methodology is called the poverty cut-off. India's national MPI follows the poverty cut-off of 0.33 used in the global MPI measure (NITI Aayog, 2023). Consequently, any household that receives a score of 0.33 or higher is identified as poor.

Since our outcome variables are PCA-based indices, we approximate standardized effect sizes by dividing the treatment coefficients by the control group means. The resulting standardized effects are –0.044, –0.071, –0.028, and –0.043 SDs for the DMI, ARI, GPI, and WEI, respectively. These are statistically insignificant and an order of magnitude smaller than policy-relevant thresholds which is typically in the range of 0.14–0.3 SD (Haushofer & Shapiro, 2016; Ismayilova et al., 2018). Thus, we treat these nulls as credible and informative: the estimates are precise, and we can rule out economically meaningful impacts of microfinance alone on women's empowerment. This result is also supported by a meta-analysis of 25 empirical studies by Vaessen et al. (2014) and by a series of randomized evaluations on the impact of microcredit on women empowerment measures and women's decision-making ability (Banerjee et al., 2015).

An analysis of control variables shows that being Hindu (relative to other religions) is associated with a 2.08 percentage points (pp), 0.16pp, and 0.12pp reduction in DMI, GPI, and WEI, respectively. A higher number of females in the household is linked to 0.42pp–0.47pp lower scores across DMI, GPI, and WEI. Additionally, a greater number of outstanding loans is associated with small increases in empowerment (ranging from 0.04pp to 0.09pp), while higher risk aversion corresponds to a modest 0.002pp increase across all empowerment indices.[13]

Table 1: Fractional regression results for Women Empowerment measures

	Decision-Making Index		Access to Resource Index		Gender Perceptions Index		Women-empowerment Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-term Clients	-0.033	-0.034	-0.023	-0.021	-0.022	-0.017	-0.036	-0.029
	(0.030)	(0.028)	(0.015)	(0.014)	(0.032)	(0.029)	(0.031)	(0.028)
Hindu Religion	-	-2.084***	-	-0.047	-	-0.163**	-	-0.118**
		(0.173)		(0.033)		(0.074)		(0.058)
Caste (Base category - General)								
Scheduled Caste	-	-0.028	-	-0.005	-	-0.047	-	-0.047
		(0.036)		(0.016)		(0.035)		(0.036)
Other Backward Castes	-	0.008	-	0.03	-	0.002	-	-0.019
		(0.040)		(0.020)		(0.040)		(0.040)
Family size	-	0.002	-	0	-	0.012	-	0.01
		(0.019)		(0.009)		(0.020)		(0.019)
Education (Base category - No formal education)								
Class 1-5	-	0.06	-	-0.034	-	0.074	-	0.057
		(0.049)		(0.023)		(0.047)		(0.047)
Class 6-9	-	0.06	-	0.005	-	0.048	-	0.049
		(0.038)		(0.019)		(0.038)		(0.038)
Class 10-12	-	0.061	-	0.004	-	0.01	-	0.046
		(0.039)		(0.018)		(0.042)		(0.040)

[13] To check for the robustness of our results to different functional forms, we also run an OLS regression and include cluster fixed effects to control for possible unobserved time-invariant differences and find that the results are similar to Table 1.

Vocational Training, Graduation, or Postgraduation	-	-0.035	-	-0.035	-	-0.122	-	-0.068
		(0.068)		(0.034)		(0.078)		(0.074)
Years since marriage	-	0.003	-	0	-	0.001	-	0.003
		(0.002)		(0.001)		(0.002)		(0.002)
Age difference of spouses	-	-0.004	-	-0.002	-	-0.003	-	-0.005
		(0.004)		(0.002)		(0.004)		(0.004)
No. of females in HH	-	-0.042*	-	-0.003	-	-0.047**	-	-0.043*
		(0.023)		(0.010)		(0.024)		(0.023)
Total HH income (in ₹)	-	-0.000002	-	-0.000002	-	-0.000003	-	-0.000003
		(0.000001)		(0.000001)		(0.000002)		(0.000002)
HH land holding (in sq. ft.)	-	0.00000002	-	0.00000008	-	0.00000009	-	-0.00000002
		(0.0000003)		(0.0000001)		(0.0000003)		(0.0000003)
Number of outstanding loans of the household	-	0.077***	-	0.038***	-	0.093***	-	0.075***
		(0.018)		(0.007)		(0.016)		(0.016)
Risk attitude	-	0.003***	-	0.001***	-	0.002**	-	0.003***
		(0.001)		(000)		(0.001)		(0.001)
BMI	-	-0.004	-	-0.002	-	0.000	-	-0.001
		(0.004)		(0.002)		(0.004)		(0.004)
New Client Mean	0.779	0.779	0.295	0.295	0.616	0.616	0.681	0.681
Observations	360	360	360	360	360	360	360	360
Pseudo R2	0.001	0.078	0.001	0.015	0.0004	0.06	0.001	0.062

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2 Mechanism: Intra-household bargaining power (IHBP)

This subsection examines the impact of long-term access to microcredit on IHBP, as our theory of change hypothesizes IHBP to be an important mechanism through which long-term access to microcredit could manifest in the form of women's empowerment across multiple dimensions. Our first outcome variable for analysis is the AAS, where player 1 subjects are asked to allocate ₹400 (19.72 USD in PPP) among themselves and their spouse, such that they get the money only if their spouse agrees to their proposed allocation. The columns (1) to (4) in Table 2 show the results for female client subjects and their husbands. It presents two columns comprising a model with (1) no controls, and (2) Demographic, BMI, and Behavioral controls for the husbands of female clients, and the corresponding models for the female clients are presented in Columns (3) and (4).

We find that long-term female clients, on average, allocated 4-5pp more money to their spouses than the newer female clients. The effects for the female clients are higher than the husbands (Columns (1) and (2) are comparable to Columns (3) and (4) respectively) and are significant at p-value<0.01 level for Column (4), and at p-value<0.05 level for Column (3). For the husbands of long-term clients, the effects are significant at p-value<0.10 for Column (2). Our results suggest that long-term female clients have lower IHBP than the newer female clients, as they are willing to allocate a significantly higher amount to their spouses. Garikpati et al. (2017) discuss mechanisms that may explain our results. According to their analysis, microfinance loans may strengthen existing social norms around power dynamics in the household. Consequently, the woman's docility and lack of agency might be exploited to enforce payments, while the husband might use the lion's share of the loan amount.

We now note the significant control variables in Columns (2) and (4) in Table 2. For husbands, belonging to Scheduled Castes or Other Backward Castes is associated with allocating 5.6pp and 9.2pp less to their spouses, respectively, compared to the General caste. An additional loan is linked with a 2.6pp increase, and lower risk aversion is associated with a slight increase in AAS. Higher income and primary or secondary education are linked with lower allocations. For female clients, years of marriage are negatively associated, while more loans and more female members are positively associated with AAS.

Our second outcome variable for analysis is the AMA, where player 2 subjects are asked the minimum amount they would be willing to accept from their spouse. The coefficient of interest corresponds to the variable 'long-term clients' in our models. From Table 2, we find that the husbands of long-term female clients, on average, accepted a 7.6pp to 9.6pp higher minimum amount than the husbands of newer female customers. As shown in Column (6), the average spouse of the long-term client group accepted 9.6pp higher minimum amounts than the spouses of the new client group. The effect in Column (5) may be interpreted in the same way. These effects are highly statistically significant at $p\text{-value}<0.05$ level for Column (5) and $p\text{-value}<0.01$ level for Column (6).

In contrast, long-term female clients accepted a minimum of 0.3pp to 1.4pp lower from their spouses, on average, than newer female clients, and these effects are not statistically significant. Thus, our results suggest that while long-term female clients do not have higher IHBP compared to new clients, husbands of the long-term clients have higher bargaining power in the household as they are, on average, willing to accept a higher minimum amount from their spouses compared to husbands of new clients. This finding is in line with (Balasubramanian, 2013), where the author suggests that women are often forced to part ways with microcredit funds upon their husbands' instruction, which limits their control over the use of loans. It may lead to the woman being worse off after getting microcredit, since a default on her husband's part would now be reflected as a reduction in her credibility in the credit market. Research also highlights the increase in debt distress among female microfinance borrowers who largely bear the social and financial cost of repayment and are responsible for juggling debt from various sources (Guerin, 2014), potentially leaving them worse off due to sustained access to microcredit.

Finally, looking at the control variables in Column (6), for husbands of female clients, having an additional family member is associated with a 4.5pp, and one-unit higher risk aversion is associated with a 0.3pp lower AMA. In Column (8), for female clients, lower risk aversion is associated with a 0.2pp lower AAS.[14]

In addition to the analysis split by gender, we conduct pooled regression analysis for each of AAS and AMA, such that both the clients and their husbands are part of the same regression sample. The results depicted in Table A. 1 reveal that, on average, compared to new clients, long-term clients and their husbands have significantly lower bargaining power as measured using AAS and no significant difference in IHBP as measured by AMA. Juxtaposed to Table 2, this means that the significant increase in AAS in the pooled game, is driven more by the female population (coefficient in Column (4) is greater than Column (2)), while the increase in AMA for men is offset by a decrease in AMA for women (Column (6) is positive while Column (8) is negative), resulting in null results in case of the pooled regression. Together, these results suggest that long-term exposure to microfinance loans does not improve intra-household bargaining power for women.

Table 2: Fractional regression results for IHBP outcomes

	Amount Allocated to Spouse				Acceptable Minimum Amount			
	Husbands of female clients		Female clients		Husbands of female clients		Female clients	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-term clients	0.022	0.035*	0.040**	0.049***	0.076**	0.096***	-0.003	-0.014
	(0.019)	(0.018)	(0.019)	(0.019)	(0.033)	(0.031)	(0.034)	(0.033)
Female	-	-	-	-	-	-	-	-
Hindu religion	-	-0.034	-	0.088	-	0.083	-	-0.058***
		(0.105)		(0.055)		(0.078)		(0.001)
Caste (Base category – General)								
Scheduled Caste	-	-0.056***	-	-0.013	-	-0.005	-	0.011
		(0.021)		(0.021)		(0.041)		(0.036)
Other Backward Castes	-	-0.092***	-	0.011	-	0.036	-	0.069
		(0.025)		(0.025)		(0.047)		(0.043)
Family size	-	0.011	-	-0.017	-	-0.045**	-	0.018
		(0.015)		(0.012)		(0.021)		(0.027)
Education (Base category - No formal schooling)								
Class 1-5	-	-0.040	-	-0.072**	-	-0.001	-	-0.027
		(0.039)		(0.032)		(0.052)		(0.057)
Class 6-9	-	-0.067***	-	-0.027	-	-0.027	-	0.032
		(0.024)		(0.024)		(0.043)		(0.044)
Class 10-12	-	-0.024	-	-0.048*	-	-0.007	-	-0.008
		(0.027)		(0.027)		(0.046)		(0.047)
Vocational Training, Graduation or Post Graduation	-	0.009	-	-0.034	-	-0.123	-	0.009

[14] To check for the robustness of our results to different functional forms, we also run a Tobit regression and include cluster fixed effects to control for possible unobserved time-invariant differences and find that the results are similar to Table 2.

		(0.031)		(0.038)		(0.082)		(0.120)
Years since marriage	-	-0.001	-	-0.003**	-	-0.003	-	0.002
		(0.002)		(0.002)		(0.002)		(0.003)
Age difference of spouses	-	0.002	-	-0.004	-	-0.001	-	0.008
		(0.003)		(0.004)		(0.007)		(0.006)
No. of females in HH	-	0.011	-	0.029**	-	0.045	-	-0.014
		(0.018)		(0.012)		(0.028)		(0.029)
Total HH income (in ₹)	-	-0.000001**	-	0.0000004	-	0.000002	-	0.0000002
		(0.0000004)		(0.000001)		(0.000002)		(0.000002)
HH land holding (in sq. ft.)	-	-0.0000001	-	0.0000001	-	0.0000002	-	0.000001
		(0.0000002)		(0.0000001)		(0.0000002)		(0.0000004)
Number of outstanding loans of the household	-	0.026**	-	0.024**	-	-0.017	-	0.027
		(0.010)		(0.009)		(0.015)		(0.018)
BMI	-	0.004	-	0.007	-	0.005	-	-0.009
		(0.003)		(0.005)		(0.008)		(0.006)
Altruism	-	0.0001	-	-0.0001		-0.003***		-0.002**
		(0.0002)		(0.0003)		(0.001)		(0.001)
Risk aversion	-	0.001*	-	0.0001	-	-0.001	-	-0.027
		(0.0005)		(0.001)		(0.052)		(0.057)
New Client Mean	0.694	0.694	0.671	0.671	0.391	0.391	0.463	0.463
Observations	168	168	192	192	192	192	168	168
Pseudo R2	0.000	0.014	0.002	0.010	0.004	0.023	0.000	0.019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The coefficient on Hindu Religion cannot be calculated as there are only Hindu men in the population with a non-missing value for the amount allocated to spouse variable.

3.3 Testing our Theory of Change: Does IHBP Explain Women Empowerment?

To test whether IHBP explains women's empowerment, we estimate a series of fractional regression models using the two IHBP measures: AAS and AMA as explanatory variables, and the four women's empowerment indices (DMI, ARI, GPI, WEI) as dependent variables. Each specification includes a model without controls followed by a model with demographic and behavioral controls. Since lower AAS and higher AMA indicate greater bargaining power, we expect AAS to be negatively correlated and AMA positively correlated with women's empowerment.

Results from our regression analysis are presented in Table 3. In line with our theory of change, we find that the coefficient on AAS is negative and statistically significant at p-value<0.1 level for DMI (-0.255), i.e., a 1pp increase in the AAS is associated with a 0.255 unit decrease in DMI (Column (2) in Panel 1 of Table 3), suggesting that women who allocate a higher amount to their spouse in the ultimatum game – indicating lower bargaining power – also report lower decision-making authority. Although the coefficients for other indices are not statistically significant, they are directionally consistent. In contrast, AMA is positively and significantly associated with ARI, GPI, and WEI, even after adding controls (Panel 2 in Table 3), which is in line with our theory. This suggests that women who accept a higher minimum amount in the ultimatum game – a signal of higher IHBP – also report higher empowerment in access to resources, gender attitudes, and overall. It implies that women's bargaining power measured through AMA significantly explains multiple dimensions of women's empowerment. Therefore, taken together, the outcome variables AAS and AMA hold significant explanatory power in determining women empowerment, in line with our theory of change of IHBP as a key mechanism for women empowerment.

Table 3: Fractional regressions to test if Intra-Household Bargaining Power explains women empowerment

	Decision-Making Index		Access to Resource Index		Gender Perceptions Index		Women-empowerment Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel 1								
Amount Allocated to Spouse	-0.156	-0.255*	0.055	-0.023	0.018	-0.062	-0.104	-0.196
	(0.140)	(0.136)	(0.079)	(0.082)	(0.131)	(0.129)	(0.139)	(0.133)
New Client mean	0.779	0.779	0.295	0.295	0.616	0.616	0.681	0.681
Observations	192	192	192	192	192	192	192	192
Pseudo R2	0.002	0.137	0.0002	0.021	0.00002	0.081	0.001	0.097
Panel 2								
Acceptable Minimum Amount	0.153	0.137	0.146***	0.133***	0.265***	0.220***	0.155*	0.157*
	(0.093)	(0.097)	(0.042)	(0.049)	(0.088)	(0.085)	(0.092)	(0.093)
New Client mean	0.779	0.779	0.295	0.295	0.616	0.616	0.681	0.681
Observations	168	168	168	168	168	168	168	168
Pseudo R2	0.005	0.071	0.005	0.015	0.011	0.059	0.004	0.058
Demographic and Behavioral Controls	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Columns (1), (3), (5), and (7) have no controls, Columns (2), (4), (6), and (8) show results with demographic and behavioral controls, such as religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, and risk aversion of the customer.

3.4 Other Potential Mechanism: Women's Labour Force Participation

In this section, we examine another potential mechanism – women's labor force participation (WLFP) – that could explain why long-term access to microcredit fails to improve women's empowerment. WLFP is frequently identified as a key pathway through which economic interventions influence intra-household dynamics and decision-making (Heath et al., 2024; Iregui-Bohórquez et al., 2024). Specifically, we focus on two measures: the likelihood of being self-employed and being engaged in paid work. The theory of change follows the idea that greater economic participation, particularly through self-employment, translates into increased autonomy and decision-making power. We begin by examining whether women who have had long-term access to microcredit are more likely to be self-employed than new clients.

We apply a logit regression model given the binary nature of this variable (1 if the woman is self-employed and 0 otherwise). The columns (1) and (2) in present the regression results from this analysis (both with and without demographic and behavioral control). We report the marginal effects for easier interpretation of results. We find that the coefficient for the long-term client group is not statistically significant in columns (1) and (2). It implies that there is no significant difference in women's likelihood of being self-employed between the long-term and new client groups. We next move to examine differences in engagement with paid work for female microcredit customers across the two groups-long-term and new client groups. The columns (3) and (4) in Table 4 present the regression results for women engaging in paid work as the outcome of interest. Across columns (3) and (4), although the coefficient for the long-term customer group is positive, it is not statistically significant. It implies that there is no significant difference in women's likelihood of being engaged in paid work between the long-term and new client groups. Overall, our results indicate that long-term access to microcredit does not improve women's likelihood of being engaged in paid work or being self-employed. Given these results, the absence of sustained positive effects of microcredit on WLPF along with IHBP can also potentially explain its limited impact on women's empowerment.

Table 4: Logit regression results for other potential outcomes

	Self-employed		Paid work	
	(1)	(2)	(3)	(4)
Long-term Clients	-0.011	-0.028	0.033	0.043
	(0.036)	(0.033)	(0.030)	(0.029)
New Client Mean	0.115	0.115	0.894	0.894
Observations	303	303	360	358
Pseudo R2	0.0005	0.188	0.006	0.201
Demographic and Behavioral Controls	No	Yes	No	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Demographic and behavioral controls includes religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, and risk aversion of the customer.

3.5 Multidimensional Poverty Index (MPI)

In this section, we regress our measures of MPI on customer type and other controls to determine the effect of microcredit loans on multidimensional poverty. There are two dependent variables in this analysis. The dependent variables are MPI deprivation score and Poor at 0.33 cut-off. These regressions are run at the household level. As per construction, a higher MPI Deprivation Score corresponds to higher poverty. Therefore, a negative coefficient on long-term microfinance clients will suggest that customers with longer exposure to micro-credit loans are less poor than newer customers who have relatively shorter exposure to microfinance loans. Since we run a fractional logistic regression model for this analysis, because our MPI deprivation score is a fraction, we report the marginal effects in columns (1) and (2) in Table 5. Table 5 shows that the coefficients on long-term clients (Column (1) with no controls, and Column (2) with household controls) are not statistically significant. This implies that long-term microcredit clients are not significantly better off than newer customers when it comes to multidimensional poverty. The control variables reveal that higher education, the number of females, and being a Hindu are associated with lower poverty levels, whereas more outstanding loans are associated with higher poverty levels.

Following the MPI literature, we put a cut-off of 0.33 on the MPI deprivation score and call any household above this cut-off as poor, and any household below it as non-poor (Suppa & Kanagaratnam, 2025). Thus, Poor at 0.33 cut-off is a binary variable and takes the value 1 when the household is classified as poor, and we employ a logistic regression method for this analysis. Once again, we report marginal effects in columns (3) and (4) in Table 5, as the usual coefficients are difficult to interpret. **Error! Reference source not found.** shows that the coefficients on long-term clients in both models (Column (3) with no controls, and Column (4) with household controls) are not statistically significant. It again implies that long-term clients of micro-credit are not significantly better off than newer customers when it comes to multidimensional poverty. The control variables reveal that higher education is associated with lower poverty levels, whereas being Scheduled Caste or Other Backward Caste or having outstanding loans are associated with higher poverty levels.

Table 5: Fractional Logistic Regression for MPI Outcomes

	MPI Deprivation Score		MPI Poor at 0.33 cutoff	
	(1)	(2)	(3)	(4)
Long-term clients	-0.015	-0.018	-0.039	-0.035
	(0.014)	(0.013)	(0.052)	(0.049)
New Customer Mean	0.314	0.314	0.439	0.439
Observations	360	360	360	360
Pseudo R2	0.000	0.011	0.001	0.121
Household controls	No	Yes	No	Yes

Robust standard errors in parentheses
Household controls include religion, caste, household size, years since marriage, spousal age gap, number of women in the household, household income, landholdings, and outstanding loans

4. Robustness Checks

4.1 Propensity Score Matching to Improve Comparability among Microfinance Clients

To address baseline imbalance and potential selection concerns, we adopted a matching strategy by implementing Coarsened Exact Matching (CEM) ex-ante. However, we were constrained by the set of observables available in the administrative data. To further improve comparability and account for underlying household heterogeneity, in this section, we conduct an ex-post Propensity Score Matching (PSM) analysis using a richer dataset from our primary household survey. It allows for a more like-for-like comparison between long-term and new clients. We use nearest neighbor matching with four neighbors to match on a broader set of covariates that are not affected by the duration of access to microcredit, including religion, caste, family size, education, years since marriage, age difference between spouses, number of females in the household, and the customer's risk attitude. After matching, we restrict the sample to observations within the region of common support and apply a four-nearest-neighbor algorithm.

Subsequently, we re-estimate our primary outcomes—fractional regressions for women's empowerment indices (Table *6*), and Fractional regressions for the AAS, and the AMA (Table 7) – using the matched sample and controlling for the aforementioned covariates. Results in Table *6* indicate no statistically significant differences in empowerment outcomes between long-term and new clients across any of the four indices. This suggests that prolonged exposure to microcredit does not lead to measurable improvements in women's empowerment. These findings reinforce the results of our primary analysis show in Table *1*.

Table 6: Average Treatment Effect of long-term access to microcredit on different dimensions of women empowerment

	Decision-Making Index	Access to Resource Index	Gender Perceptions Index	Women-empowerment Index
	(1)	(2)	(3)	(4)
Long-term clients	-0.042	-0.022	-0.025	-0.040
	(0.030)	(0.015)	(0.032)	(0.030)
New Customer Mean	0.782	0.294	0.617	0.682
Observations	344	344	344	344
Pseudo R2	0.048	0.007	0.031	0.039
Demographic and Behavioral controls	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Demographic and Behavioral controls include religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, and risk attitude of the customer.

Table 7 presents the effect of long-term microcredit access on household bargaining power, as captured through AAS and AMA. We find that both long-term female clients and their husbands allocate a higher amount to their spouses compared to the new clients and husbands of new clients. However, in AMA, the coefficient on females is statistically insignificant, showing no difference in IHBP with new clients, but is highly statistically significant and positive for husbands, indicating that husbands of long-term clients demand more money from their spouses as compared to husbands of new clients, and so have a higher bargaining power. These findings also reinforce the results of the primary analysis shown in Table *2*.

Table 7: Average treatment effect of long-term access to microcredit on bargaining power

	Amount Allocated to Spouse		Acceptable Minimum Amount	
	Husbands of female clients	Female clients	Husbands of female clients	Female clients
	(1)	(2)	(3)	(4)
Long-term clients	0.035*	0.055***	0.101***	0.004
	(0.020)	(0.020)	(0.031)	(0.033)
New Customer Mean	0.688	0.667	0.392	0.462
Observations	159	185	185	159
Pseudo R2	0.011	0.007	0.018	0.018

Demographic and Behavioral controls	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Demographic and Behavioral controls include religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, and risk attitude of the customer.

4.2 Machine Learning to Improve Comparability among Microfinance Clients

In our CEM technique, we used only a selected set of observable characteristics to obtain a sample of comparable long-term and new clients. In this section, we incorporate a broader set of pre-treatment characteristics to strengthen comparability by making a more apples-to-apples comparison between long-term clients and potential long-term clients. These pre-treatment characteristics - including landholdings, individual and household income, occupation, and loan terms such as interest rate, instalment amount, sanctioned amount, and loan purpose- are recorded at the time the client first entered our MFI's database during their first loan cycle, ensuring they are not influenced by treatment status. We leverage the administrative data from 2008 (start of our MFI's operations) to 2020 for this analysis. By employing machine learning algorithms on this dataset, we use the larger set of characteristics at the date of joining, and build models to predict the probability that a given client will become a long-term client in the future.

We use these models to generate similar predicted probabilities for our main sample. After obtaining the predicted probabilities in our main sample, we classify all the clients (actual long-term and new clients) as Potential long-term clients using cut-off values. We then use the accuracy of prediction among the actual long-term clients to formulate a rationale for choosing the classification cut-off for the new clients. Clients with a predicted probability greater than the chosen cut-off value are classified as Potential long-term clients. However, based on the value of the cut-off, some actual long-term clients may not be classified as potential long-term clients. We try to minimize this error by choosing cut-off values so that 70% (henceforth cut-off value 70%) of our actual long-term clients are correctly classified as Potential long-term clients. We then proceed to compare the actual long-term clients with the new clients predicted as potential long-term clients based on our main outcomes of interest, namely the women empowerment indices and the measures of IHBP.

To check if our results are sensitive to the choice of cut-off we also check two additional cut-off values, such that 60% and 50% of the actual long-term clients are correctly classified. Table 8, shows the results for the women empowerment indices, at cut-off value 70%, based on predicted probabilities from three different machine learning models, shown in separate panels. The three panels use different machine learning models, such as ADA Boost, Balanced Bagging and RUS Boost model respectively. The columns (1) through (4) show the main coefficient of interest for the various measures of women empowerment. These results are comparable and qualitatively similar to the coefficients obtained in

Table 1. Furthermore, we also find similar results for cut-off values 60% and 50% are summarized in the Appendix Table A. 2.

Table 8: Long-term clients vs Potential long-term clients on Women Empowerment Indices

	Decision-Making Index	Access to Resource Index	Gender Perceptions Index	Women Empowerment Index
	(1)	(2)	(3)	(4)
Panel 1				
Long-term client	-0.212	-0.131*	-0.119	-0.157
	(0.174)	(0.075)	(0.137)	(0.140)
New Client Mean	0.780	0.299	0.624	0.684
Observations	344	344	344	344
Pseudo R2	0.076	0.015	0.057	0.059
Panel 2				
Long-term client	-0.217	-0.134	-0.081	-0.146
	(0.185)	(0.084)	(0.145)	(0.149)
New Client Mean	0.777	0.300	0.615	0.679
Observations	314	314	314	314
Pseudo R2	0.075	0.016	0.063	0.059
Panel 3				
Long-term client	-0.235	-0.121	-0.106	-0.168
	(0.174)	(0.076)	(0.136)	(0.140)
New Client Mean	0.781	0.298	0.621	0.684
Observations	344	344	344	344
Pseudo R2	0.075	0.015	0.057	0.059

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All the columns have demographic and behavioral controls, such as religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, and risk aversion of the customer.

The columns (1) and (2) in Table 9, show the results for the IHBP measure AAS, at cut-off value 70%, based on predicted probabilities from three different machine learning models shown in separate Panels. The three panels use different machine learning models, such as ADA Boost, Balanced Bagging and RUS Boost models, respectively. The columns (1) and (2) show the main coefficient of interest for female clients and their husbands, respectively. These results are comparable and qualitatively similar to the relevant coefficients obtained in Table 2. Furthermore we also find similar results for cut-off values 60% and 50% are summarized in the Appendix Table A. 3.

The columns (3) and (4) in Table 9, shows the results for the IHBP measure AMA, at cut-off value 70%, based on predicted probabilities from three different machine learning models shown in separated Panels The three panels use different machine learning models such as ADA Boost, Balanced Bagging and RUS Boost model respectively. The columns (3) through (4) show the main coefficient of interest for husbands of female clients and female clients, respectively. These results are comparable and qualitatively similar to the relevant coefficients obtained in Table 2. Furthermore, we also find similar results for cut-off values 60% and 50% are summarized in the Appendix Table A. 3 . Thus, the analyses reveal that our main results are robust to a choice of a larger set of characteristics, machine learning algorithms, and cut-off values.

Table 9: Long-term clients vs Potential long-term clients on the IHBP outcomes

	Amount Allocated to Spouse		Acceptable Minimum Amount	
	Husbands of female clients	Female clients	Husbands of female clients	Female clients
	(1)	(2)	(3)	(4)
Panel 1				
Long-term client	0.028	0.051***	0.094***	-0.025
	(0.021)	(0.019)	(0.033)	(0.036)
New Client Mean	0.701	0.670	0.392	0.469
Observations	157	187	187	157
Pseudo R2	0.014	0.008	0.024	0.024
Panel 2				
Long-term client	0.027	0.055***	0.091**	-0.040
	(0.022)	(0.021)	(0.035)	(0.037)
New Client Mean	0.698	0.664	0.395	0.473
Observations	141	173	173	141
Pseudo R2	0.014	0.009	0.021	0.027
Panel 3				
Long-term client	0.028	0.051***	0.096***	-0.025
	(0.021)	(0.019)	(0.032)	(0.036)
New Client Mean	0.701	0.670	0.392	0.469
Observations	157	187	187	157
Pseudo R2	0.014	0.008	0.024	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All columns include demographic and behavioral controls, such as religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, altruism and risk attitude of the customer.

5. Discussion and Policy Implication

In this study, we examine the impact of long-term access to microcredit on women's intra-household bargaining power and consequently, women's empowerment. Our main contribution is to study a key mechanism – IHBP- through which microcredit impacts women's empowerment. Our theory of change suggests that only when there are first-order effects in the form of improved levels of women's IHBP can microfinance lead to women empowerment. Our study shows that long-term access to microcredit does not improve women's IHBP and thus does not have any significant impact on women's empowerment measured through four indices- access to resources, decision-making, gender attitudes, and a composite index combining the three categories. We also find that women who have long-term access to microcredit are no more likely to be self-employed or engage in paid work than women who are in the first loan cycle at the time of our study. Taken together, we argue that the mechanisms described above drive the lack of effect of long-term access to microcredit on women's empowerment.

Our results suggest that long-term access to microcredit may not be adequate to mitigate sticky gender norms and shift IHBP, as the evolution of norms is a complex phenomenon and might not change with a single intervention such as microcredit. Our results also suggest that microcredit's potential of leading to transformative impact both at the household level as well as at the individual level in terms of women's empowerment, at least using conventional metrics, might be overstated. Instead, the impact of microcredit might be best studied in relation to households' ability to manage their finances and smooth consumption (Merfeld and Morduch, 2023). Given that microcredit loans are overwhelmingly used for regular household expenses as opposed to business investments, households typically do not see an increase in income, consumption or business revenue. However, low-income households value the ability to raise lump sums. Microcredit as a tool allows them to do just that by providing access to a relatively large lump sum that households can choose to use in multiple ways- lending to friends and family, repaying previous debt, household spending across multiple purposes such as weddings, health expenses, school fees, and other miscellaneous expenses, investing through other formal channels, etc.

Although our study is situated in Tamil Nadu, India, its implications extend well beyond this context. The conditions under which microfinance operates—gendered social norms, informal labor markets, and high female labor force dropout rates—are common across many low- and middle-income countries (LMICs). Globally, over 80% of microfinance clients are women, and institutions serve more than 140 million people, with particularly high concentrations in South Asia, Sub-Saharan Africa, and Latin America (D'Espallier et al., 2011; Dichter, 2023). For example, in Bangladesh, the share of female borrowers exceeds 90% (Heath et al., 2024); in Peru and Bolivia, similar patterns are seen under entrenched machismo cultures. In Sub-Saharan Africa, women comprise around 60% of borrowers (Mithika, 2025), with MFIs often being one of the few credit sources for rural women . These similarities suggest that the behavioral and intra-household dynamics we uncover may generalize to settings with parallel institutional and social features. Thus, our findings offer policy-relevant insights for improving the design of microfinance programs across LMICs with persistent gender inequality.

In particular, three policy implications emerge from our results. First, microcredit alone may not be enough to transform women's lives and their households' well-being. A holistic approach that focuses on enhancing skills, networks, and livelihoods in addition to access to formal finance and social protection can help the poor achieve socioeconomic resilience. For example, BRAC's "Targeting the Ultra-Poor" program found that a one-time boost of capital improves the condition of the poor even a decade later (Banerjee et al., 2021). [15] Similarly, impact evaluations of the government-led livelihoods program in India - National Rural Livelihoods Mission - which is also based on a holistic set of interventions, show positive effects on women's decision-making power and households' socioeconomic outcomes (Hoffmann et al., 2018; Kochar et al., 2022). Second, as MFIs might not have the capacity and resources to offer microcredit plus services, they could focus on ways in which their

[15] BRAC's ultra poor graduation approach is built on four foundational pillars- social protection, livelihoods promotions, financial inclusion and social empowerment- https://www.brac.net/program/wp-content/uploads/2020/02/Graduation-Overview.pdf

product can be made more suitable to match the financial needs and contexts of their clientele. These could take the form of innovation in both product and process design, such as flexibility in loan contracts (repayment flexibility, customized loan tenure, amounts, etc.), innovation in modes of loan disbursement and collection mechanisms, etc. It could, in turn, improve households' ability to manage their finances. Research shows a positive and significant impact on microfinance clients when loans are tailored to the specific needs of various categories of households rather than treating microfinance as one homogeneous product (Cai et al., 2023). Third, government policies that enable access to credit for enterprise creation and expansion can be a useful intervention for women from low-income households, given its potential to impact women's livelihood, well-being, and agency. However, identifying and targeting the right group of women for such an intervention is important, as the desire to be self-employed or to be an entrepreneur might not be universal.

Finally, our study has the following limitations. First, our study design is based on a quasi-experimental methodology involving a statistical matching technique to identify the impact of long-term access to microcredit. The matching is based on administrative data maintained by our implementation partner. However, the dataset is limited to only a small set of observables that describe basic individual and household characteristics. There could be other important household and individual characteristics that might potentially influence the timing of the adoption of microcredit that we are unable to account for in our matching technique, due to a lack of data. However, we conduct an ex-post PSM matching as well as a machine learning prediction model with a wider set of variables to mitigate this concern. Second, while we explore the role of women's agency and their IHBP in producing downstream effects for both the woman and her family, other contextual factors may also determine the way microcredit interacts with existing relationships within the household and between households. Finally, our approach to measuring women's empowerment relies on the standard economics literature, which defines women's empowerment in terms of bargaining power, control, and individual agency. However, empowerment as a concept may take multiple forms. Literature from the field of sociology and anthropology alludes to the concept of joint agency, joint action, joint commitments, and being interdependent, connected, and trustworthy as features that symbolize empowerment for poor women (Guérin, 2023; Kusimba, 2018). However, these limitations also provide important areas for further research. Future work could incorporate qualitative data to identify a broader set of contextual factors and understand empowerment directly from the perspective of women microcredit customers. Further research is also needed to understand the impact of microcredit on households' financial management and financial well-being, and finally, its role in shaping interdependencies both within and outside the household.

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APPENDIX

Table A. 1 Pooled Fractional Regression for IHBP outcomes

	Amount Allocated to Spouse		Acceptable Minimum Amount	
	(1)	(2)	(3)	(4)
Long-term clients	0.031**	0.039***	0.038	0.037
	(0.014)	(0.013)	(0.024)	(0.023)
New Customer Mean	0.682	0.682	0.426	0.426
Observations	360	360	360	359
Pseudo R2	0.001	0.008	0.001	0.012
Demographic and Behavioral controls	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Demographic and behavioral controls include religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, and risk aversion of the customer.

Table A. 2: Long-term clients vs Potential long-term clients on Women Empowerment Indices: Additional cut-off values

	Decision-Making Index		Access to Resource Index		Gender Perceptions Index		Women Empowerment Index	
	Cut-off value 60%	Cut-off value 50%	Cut-off value 60%	Cut-off value 50%	Cut-off value 60%	Cut-off value 50%	Cut-off value 60%	Cut-off value 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel 1								
Long-term client	-0.205	-0.174	-0.128*	-0.127*	-0.109	-0.092	-0.152	-0.129
	(0.174)	(0.174)	(0.076)	(0.076)	(0.137)	(0.138)	(0.140)	(0.141)
New Client Mean	0.778	0.774	0.298	0.298	0.621	0.619	0.682	0.678
Observations	342	339	342	339	342	339	342	339
Pseudo R2	0.075	0.078	0.015	0.015	0.057	0.059	0.059	0.061
Panel 2								

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-term client	-0.140	-0.130	-0.134	-0.106	-0.102	-0.125	-0.117	-0.126
	(0.193)	(0.212)	(0.094)	(0.101)	(0.158)	(0.173)	(0.159)	(0.179)
New Client Mean	0.763	0.750	0.296	0.284	0.616	0.609	0.669	0.662
Observations	289	268	289	268	289	268	289	268
Pseudo R2	0.080	0.083	0.017	0.017	0.072	0.078	0.065	0.069
Panel 3								
Long-term client	-0.192	-0.212	-0.127*	-0.123	-0.101	-0.104	-0.144	-0.154
	(0.174)	(0.175)	(0.077)	(0.078)	(0.138)	(0.138)	(0.141)	(0.141)
New Client Mean	0.775	0.776	0.298	0.296	0.619	0.619	0.679	0.679
Observations	340	338	340	338	340	338	340	338
Pseudo R2	0.075	0.078	0.015	0.014	0.057	0.058	0.059	0.060

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The three panels use different machine learning models such as ADA Boost, Balanced Bagging and RUS Boost model respectively.
All the columns have demographic and behavioral controls, such as religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, and risk aversion of the customer.

Table A. 3: Long-term clients vs Potential long-term clients on IHBP outcomes: Additional cut-off values

	Amount Allocated to Spouse				Acceptable Minimum Amount			
	Husbands of female clients		Female clients		Husbands of female clients		Female clients	
	Cut-off value 60%	Cut-off value 50%	Cut-off value 60%	Cut-off value 50%	Cut-off value 60%	Cut-off value 50%	Cut-off value 60%	Cut-off value 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel 1								
Long-term client	0.025	0.024	0.051***	0.052***	0.098***	0.098***	-0.030	-0.037
	(0.021)	(0.021)	(0.019)	(0.019)	(0.033)	(0.033)	(0.036)	(0.036)
New Client Mean	0.703	0.702	0.670	0.669	0.386	0.385	0.475	0.479
Observations	156	154	186	185	186	185	156	154
Pseudo R2	0.014	0.015	0.008	0.008	0.024	0.025	0.024	0.025
Panel 2								
Long-term client	0.023	0.024	0.050**	0.072**	0.078*	0.107**	-0.056	-0.063
	(0.022)	(0.024)	(0.021)	(0.031)	(0.041)	(0.048)	(0.037)	(0.038)
New Client Mean	0.703	0.705	0.670	0.659	0.409	0.378	0.500	0.497
Observations	132	128	157	140	157	140	132	128
Pseudo R2	0.012	0.011	0.008	0.009	0.016	0.017	0.027	0.027
Panel 3								
Long-term client	0.022	0.022	0.053***	0.054***	0.095***	0.103***	-0.031	-0.031
	(0.021)	(0.021)	(0.019)	(0.020)	(0.034)	(0.034)	(0.036)	(0.036)
New Client Mean	0.706	0.706	0.669	0.667	0.390	0.381	0.476	0.476
Observations	155	155	185	183	185	183	155	155
Pseudo R2	0.015	0.015	0.008	0.008	0.024	0.025	0.024	0.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The three panels use different machine learning models such as ADA Boost, Balanced Bagging and RUS Boost model respectively.
This table include demographic and behavioral controls, such as religion, caste, family size, education, years passed since marriage of the customer, age difference of the spouses, number of females in the household, total monthly household income, the landholding of the household, number of outstanding loans by the household, BMI, altruism and risk attitude of the customer.