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Microcredit Access and Multidimensional Poverty Dynamics: Longitudinal Evidence from Indian Households

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Abstract

Microcredit is one of the significant mechanisms of financial inclusion for the alleviation of household poverty in developing economies. Its links with multidimensional poverty dynamics are, however, not fully understood. The present study analysed the relationship between Micro credit borrowing and multidimensional poverty of Indian households with longitudinal data from 2016-2019. Multidimensional poverty scores were used to measure household deprivation, descriptive statistics, poverty transition analysis, and household fixed-effects regression were used to explore the patterns and differences in borrowing over time. The results showed significant decreases in average poverty scores for those who borrowed and those who did not borrow. Borrowers saw a drop of 0.1496 to 0.1496, while the non-borrowers saw a drop of 0.1554 to 0.1554. A negative value for the association between microcredit borrowing and multidimensional poverty was found through fixed-effects estimation programme, as it was statistically significant ($\beta = -0.005519$) and the estimated value was relatively small. A provisional poverty threshold was used to identify poverty transitions, using a sample of households at both ends of the poverty distribution, which found 437 exits and 49 entries. These results indicate that the participation in microcredit is complementary but not a substitute to other poverty alleviation policies in order to tackle structural deprivation. Integrated Financial Inclusion, Livelihood Development and essential service interventions are still needed. More longitudinal studies are needed to validate causal relationships and assess long-term improvements to households' well-being.

Keywords: Microcredit, Multidimensional Poverty, Poverty Dynamics, Financial Inclusion, Longitudinal Analysis

1. Introduction

Despite the economic growth, financial inclusion and access to basic services, poverty is a recurring problem in India. Most poverty measures focus on income and consumption, neglecting the many disadvantages that affect families' circumstances. Multidimensional poverty offers a more comprehensive analytical tool as it takes into account deprivation in education, health, living standards and other dimensions of social and economic status. However, it is critical to analyse multidimensional poverty beyond the headcount to gain insights into the distribution of economic disadvantages among households and into variations in poverty intensity (Alkire et al., 2021). Despite the significant strides India has made in eradicating poverty, geographical disparities and access gaps in key services still have an impact on development results (NITI Aayog, 2023). They show the need to assess the extent of poverty and the socioeconomic processes driving household welfare and deprivation dynamics over time.

The link between economic development and multidimensional poverty is not straightforward: while an improvement in the overall economic situation does not automatically mean a fairer distribution of welfare, the opposite may be true. Economic growth can create jobs and raise standards of living, but the benefits of economic growth for employment and living standards are not always experienced by all socioeconomic groups or in all geographical areas. The link between multidimensional poverty and economic growth in India shows the significance of measuring development using indicators other than the aggregated economic growth (Bao & Liao, 2024). Regional inequalities also affect the levels of household deprivation due to variations in infrastructure, employment prospects, public services, and institutional availability. India's multidimensional poverty levels profile the disparities in development outcomes at state level (Jagadeshwaran et al., 2022). Furthermore, the inequity in caste is linked to inequity in a household's socioeconomic opportunities and deprivation, highlighting the continued relevance of structural disadvantage in understanding household poverty (Pradhan et al., 2022).

A dynamic view of poverty needs to take account not just of static poverty measures, but of the evolution of household deprivation over time. Household can become out of poverty because of better employment, education or livelihood means but others stay persistently poor or face economic reversal. The analysis of multidimensional child poverty emphasizes the need to look at the dimensions of child poverty across population groups and time (Pradhan & Pradhan, 2023). Other disparities and forms of deprivation faced by the urban poor, such as unemployment,

housing conditions, and unequal access to basic services, are also unique to their context (Mohanty & Vasishtha, 2021). Additionally, for multidimensional poverty measurement, one needs to pay attention to the choice of the indicators of deprivation that are socially relevant as it is necessary to have a poverty indicator that captures the living conditions and the household needs (Pomati et al., 2024). These views underscore the use of longitudinal analytic methods that enable one to detect poverty entry and exit and take into account household socioeconomic differences in poverty persistence.

Financial inclusion has become a critical element of development strategies seeking to enhance the economic participation and strengthen the resilience of households. Financial services can help people save and invest, smooth consumption, and deal with unexpected economic problems. Financial inclusion and digital payment systems are especially important for boosting financial resilience of economically vulnerable populations (Demirgüç-Kunt et al., 2022). In this context, microcredit offers households with difficulties accessing mainstream banking small-scale loan opportunities. Microfinance institutions and self-help groups in India have become important avenues for providing credit to financially excluded groups. But the promise of microcredit is contingent on loan usage, the repayment requirements, financial ability of the household, and the presence of productive economic opportunities. Therefore, the borrowing participation does not necessarily reflect on the socioeconomic welfare improvement.

Household features, institutional availability, and community financial arrangements are important factors affecting household participation in microcredit. The role of financial inclusion among households in India was studied by analyzing the participation patterns of the members in the self-help groups organized around microfinance institutions, which suggests that participation in and duration of a microfinance self-help group are crucial factors (Ahmad et al., 2020). Self-help groups can also actively play a part in the socioeconomic development by providing a platform for collective participation, financial awareness, and access to resources related to livelihoods (Kandpal, 2022). However, the impact of microcredit interventions is partly conditional on the type of loan and the financial possibilities of the borrowers. In India, experimental evidence shows that it is important to carefully examine individual credit-line programs and not to take the benefits of credit-line programs for granted (Aragón et al., 2020). Given the above considerations, it is suggested that the link between microcredit borrowing and multidimensional poverty should be investigated, based on household level observations made over several time periods.

Although there has been a rise in studies of financial inclusion and poverty reduction, there are still questions about the link between access to microcredit and intra-household changes in poverty status. Comparisons across cross-sections cannot resolve the issue of whether the disadvantage is ongoing or changing within the family over time. Moreover, there may be systematic differences between borrowers and non-borrowers on factors that affect their likelihood of borrowing and their likelihood of being poor, which could introduce selection bias. Longitudinal econometric analysis provides a chance to analyze the dynamics of poverty at the household level and to account for the unobserved heterogeneity that can occur at the household level over time. Therefore, this study examines the dynamics of Microcredit Borrowing and Multidimensional Poverty of Indian Households from 2016 to 2019 based on longitudinal observations. The study aims to provide empirical evidence to development economics and financial inclusion research by studying poverty transitions and estimating household fixed-effects models. The study addresses the following three research objectives:

1.To examine the association between microcredit borrowing and multidimensional poverty among Indian households.

2.To assess longitudinal changes in household deprivation, including poverty persistence, entry, and exit during 2016–2019.

3.To evaluate the robustness of the microcredit–poverty relationship using household fixed-effects econometric models and socioeconomic control variables.

2. Materials and Methods

2.1. Study Design and Data

A quantitative longitudinal research design was used in this study to explore the relationship between micro-credit access and multi-dimensional poverty among Indian households in the period 2016–2019. Secondary data at the household level was derived from the Consumer Pyramids Household Survey (CPHS). The analytical data set included 47,437 household-years, consisting of 32,880 distinct households. Household identification codes (HH_ID) and indicators of survey years helped observations to be connected across survey periods. A total of 23,731 borrowings and 23,706 non-borrowings were included in the sample. Households were categorized based on the microcredit loan they reported borrowing from either a self-help group (SHG) or a microfinance institution (MFI) (Maharana & Shaw, s2026). The number of years that households

were observed in the panel varied. To understand the differences in poverty and over time, descriptive statistics and longitudinal econometric methods were used.

2.2. Variable Measurement

The Multidimensional Poverty Score (MDPS) was used as the main outcome variable for multidimensional poverty. Scores were higher the more deprived the household was. A multidimensional poverty score adjusted for vulnerability (VMDPS) was also analyzed to characterize vulnerability of households. The binary variable brw_shg_mfi indicated whether a household participated in a SHG or MFI (binary 1) or did not participate in SHG or MFI (binary 0). This indicator did not reflect credit eligibility or availability of loans, but borrowing participation. Household socioeconomic variables consisted of family size, dependency ratio, employment indicators, occupational status and other demographic variables available. Such characteristics were utilized to describe sample composition and to adjust econometric specifications. No attempt was made to reconstruct the poverty indicator weights underlying the original poverty scores, which were instead retained.

2.3. Poverty Dynamics

Longitudinal poverty dynamics were analysed by comparing poverty scores by survey years using multidimensional poverty scores. Average MDPS values were determined for borrowers and non-borrowers of loans for the year. Repeated observations were identified using house numbers and a sample of end-point matched households was created by selecting households that were observed in 2016 and 2019. The poverty transitions were estimated provisionally based on the MDPS threshold of one-third. There were four groups identified: persistently poor, poverty exit, poverty entry and persistently non-poor. Transition frequencies were computed based on baseline borrowing status. To separate the aggregate temporal trend from observed within-household changes, the change in the poverty score for each household was considered. The provisional poverty criterion needed to be checked with respect to the original index documentation.

2.4. Econometric Analysis

Household fixed-effects regression was applied to estimate the association between microcredit borrowing and multidimensional poverty while controlling for time-invariant household characteristics. The model was specified as:

$$MDPS_{it}=\beta_1 Microcredit_{it}+\gamma' X_{it}+\alpha_i+\lambda_t+\varepsilon_{it}$$

where MDPSitrepresented multidimensional poverty for household iin year t; Microcredititindicated borrowing participation; Xitrepresented time-varying socioeconomic controls; αi denoted household fixed effects; and λt represented survey-year fixed effects. Baseline and adjusted specifications were estimated. The adjusted model incorporated dependency ratio, household employment, formal occupational status, and family-size indicators. Standard errors were clustered at the household level to account for within-household dependence. Regression coefficients, standard errors, p-values, and 95% confidence intervals were reported.

2.5. Robustness Tests

Robustness was assessed by comparing baseline and covariate-adjusted fixed-effects estimates. Coefficient direction, magnitude, statistical significance, and confidence intervals were examined across specifications. Household observation frequencies were calculated to evaluate panel coverage and identify potential limitations associated with unbalanced observations. Statistical analysis and figure generation were conducted using Python, including Pandas, NumPy, Matplotlib, and regression procedures. Statistical significance was evaluated at the 5% level. Because microcredit participation was observational rather than randomly assigned, estimated coefficients were interpreted as associations, not causal effects.

3. Results

3.1. Household Characteristics

The analytical sample consisted of 47,437 household-year observations from 32,880 distinct Indian households in 2016–2019. Of these observations, 23,731 (50.03%) were Microcredit borrowers from Microfinance Institutions or Self Help Groups and 23,706 (49.97%) were Non-Borrower households. The average size of the household consisted of one more person for the borrowers than the non-borrowers (3.70 vs 3.49). The dependency ratios were 0.330 and 0.327, respectively. The average scores of the MDPS (0.1829) and VAPS (0.2957) were lower for

borrowing households than for the non-borrowing households (0.1868 and 0.2940, respectively). These descriptive differences suggest differences in deprivation patterns and household characteristics, but do not imply causality or a causal link between borrowing and poverty.

Table 1. Household characteristics by microcredit borrowing status

Indicator	Borrowers	Non-borrowers	Overall
Observations	23,731	23,706	47,437
Sample proportion (%)	50.03	49.97	100.00
Mean MDPS	0.1829	0.1868	0.1849
Mean VMDPS	0.2957	0.2940	0.2949
Mean household size	3.70	3.49	—
Mean dependency ratio	0.330	0.327	—

3.2. Temporal Trends in Multidimensional Poverty

Multidimensional poverty declined consistently across the four observation years. The overall mean MDPS decreased from 0.2641 in 2016 to 0.1525 in 2019, indicating a substantial reduction in measured deprivation. Among borrowers, the mean score declined from 0.2687 to 0.1496, whereas non-borrowers experienced a reduction from 0.2595 to 0.1554. Borrowing households initially exhibited higher average deprivation but recorded lower scores during 2018 and 2019. Annual sample sizes increased from 5,397 observations in 2016 to 16,837 in 2019. Consequently, these descriptive trends should be interpreted cautiously because changes in sample composition may partly influence the observed differences.

Table 2. Annual multidimensional poverty trends, 2016–2019

Year	Observations	Overall MDPS	Non-borrowers	Borrowers
2016	5,397	0.2641	0.2595	0.2687
2017	8,931	0.2216	0.2217	0.2214
2018	16,272	0.1719	0.1761	0.1676
2019	16,837	0.1525	0.1554	0.1496

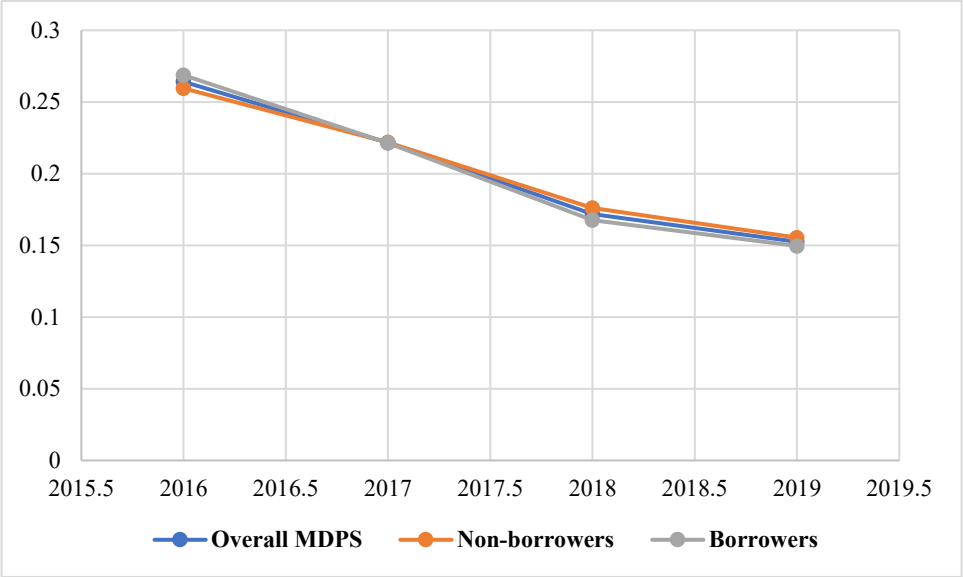

Figure 1. Annual multidimensional poverty scores by borrowing status

3.3. Household Poverty Transitions

Longitudinal poverty-transition analysis was conducted among 1,406 households observed in both 2016 and 2019. Their average multidimensional poverty score declined by 0.1129 points between the two periods. Using a provisional poverty threshold of MDPS ≥ 0.3333, 437 households transitioned from poverty to non-poverty, while 49 entered poverty. Another 134 households remained poor, and 786 remained non-poor throughout the endpoint comparison. Among baseline borrowers, 161 households exited poverty, compared with 276 baseline non-borrowers. These findings indicate considerable household mobility across poverty categories. However, the transition classifications remain conditional on validation of the poverty threshold against the original multidimensional poverty measurement framework.

Table 3. Household poverty transitions between 2016 and 2019

Transition category	Non-borrowers	Borrowers	Total
Persistently poor	100	34	134
Exited poverty	276	161	437
Entered poverty	36	13	49
Persistently non-poor	567	219	786
Total	979	427	1,406

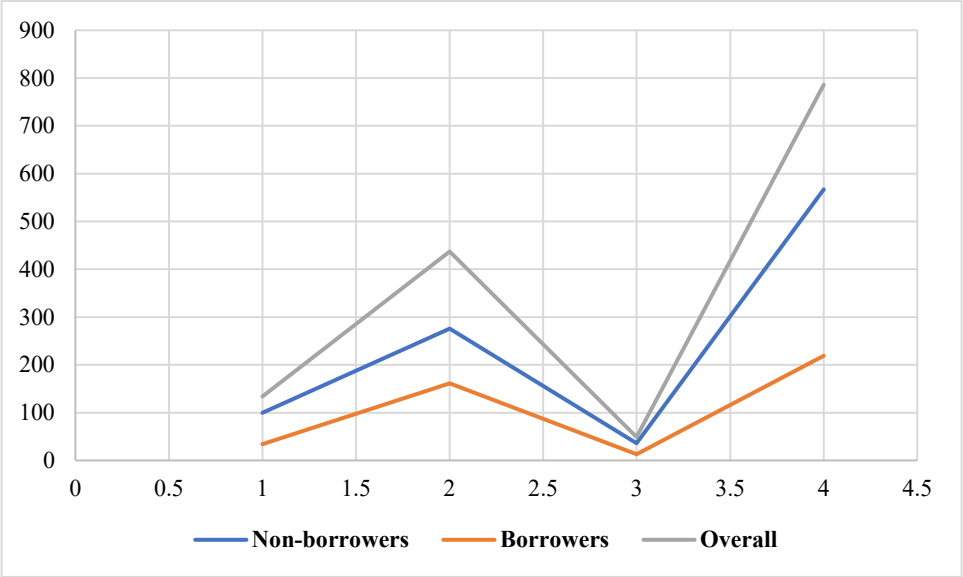

Figure 2. Distribution of household poverty transitions

3.4. Fixed-Effects Regression Results

Household fixed-effects regression identified a statistically significant negative association between microcredit borrowing and multidimensional poverty. The baseline model estimated a borrowing coefficient of −0.005519, with a household-clustered standard error of 0.001875 and a p-value of 0.003245. The corresponding 95% confidence interval ranged from −0.009195 to −0.001844. After incorporating socioeconomic controls, including dependency ratio, household employment, occupational status, and household size, the estimated borrowing coefficient remained −0.005519, with a standard error of 0.001874. The stability of these estimates indicates that the observed association was not materially altered by the included controls. Nevertheless, the coefficient represents a modest difference in multidimensional poverty scores and should not be interpreted as a causal treatment effect.

Table 4. Household fixed-effects estimates of microcredit borrowing

Model	Coefficient	Clustered SE	p-value	95% CI
Baseline	−0.005519	0.001875	0.003245	[−0.009195, −0.001844]
Adjusted	−0.005519	0.001874	0.003232	[−0.009193, −0.001846]

3.5. Panel Coverage and Robustness Assessment

The longitudinal dataset exhibited an unbalanced panel structure. Of the 32,880 unique households, 21,298 were observed for one year, 8,985 for two years, 2,219 for three years, and only 378 for all four years. This variation in observation frequency is relevant because households with shorter observation histories contribute less information about within-household changes. The fixed-effects estimates remained statistically significant after incorporating the specified socioeconomic controls, providing limited evidence of specification stability. However, the available results do not establish robustness to alternative poverty thresholds, sample restrictions, or time-varying unobserved confounding. Therefore, the findings should be interpreted as longitudinal associations rather than definitive evidence of the poverty-reducing effect of microcredit.

Table 5. Household panel observation coverage

Years observed	Households	Share (%)
1	21,298	64.77
2	8,985	27.33
3	2,219	6.75
4	378	1.15
Total	32,880	100.00

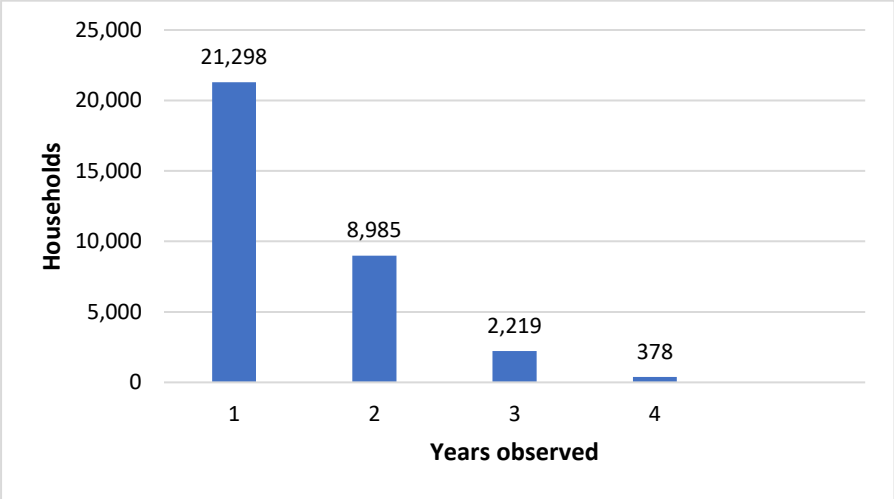

Figure 3. Distribution of households by panel observation frequency

4. Discussion

The present study examined the relationship between microcredit borrowing and multidimensional poverty among Indian households using longitudinal observations from 2016 to 2019. The results showed that there was a statistically significant negative relationship between multidimensional poverty scores and microcredit membership, indicating that the marginal impact of microcredit participation led to a reduction in multidimensional poverty. The estimated coefficient of −0.005519 was found to be stable in both the baseline and adjusted regression specifications, suggesting stability with the socioeconomic controls included. Nevertheless, this relatively low coefficient indicates that the effect of microcredit was not strong enough to solve the various aspects of poverty. The previous evidence has linked the involvement of microcredit with the improvement of the beneficiaries' socioeconomic status, mainly in terms of opportunities for productive activities and financial participation (Tiwari, 2023). The results of the present study, however, highlight the difference between statistical significance and meaningful benefits to household welfare. While microcredit can help alleviate poverty, its impact is likely to be contingent upon the wider socioeconomic environment and households' capacity to put borrowed funds to good use.

The longitudinal results showed that multidimensional poverty scores averaged significantly decreased from 2016 to 2019. The mean MDPS of borrowing households fell from 0.2687 to 0.1496, and that of the non-borrowers from 0.2595 to 0.1554. While on average being more deprived than non-borrowers in the years before they borrowed, they were on average less deprived than non-borrowers in subsequent years. While the patterns do indicate that microcredit participation might have a positive effect on the poverty trajectory, this cannot yet be attributed to micro-credit because of the changing composition of the sample and other economic factors. An analysis of the possibility of reducing poverty through microcredit in developing countries has also been explored, pointing to the relevance of financial services for economically disadvantaged groups (Félix & Belo, 2019). Household poverty exit analysis also found 437 cases of poverty being exited and 49 cases of poverty being entered during the transit between the two endpoints. These movements show the dynamic nature of multidimensional poverty as against its static nature. The gendered impacts of targeted microcredit in rural China have also been explored, with findings indicating that the positive effects of borrowing may differ across contexts and institutions

(Wu et al., 2024). Therefore, poverty changes must be viewed in context of socioeconomic heterogeneity and not just socioeconomic borrowings.

The results add to the growing body of research that has been conducted on the relationship between conventional measures of poverty and multidimensional measures of deprivation. Averaged results of poverty scores have decreased over the course of the study, but the amount of change varied by household, highlighting the need to track poverty in many dimensions of social and economic well-being. It has been shown through the research in selected areas of India that income-based and multidimensional poverty measures can create contrasting measures of household disadvantage (Roy & Chakraborti, 2023). This distinction must be noted as better access to credit or income-generating activity does not automatically result in better education, healthcare, housing or basic living conditions. The observed relationship between being in borrowing and being less poor in multidimensional poverty is also consistent with the overall hypothesis that financial involvement can foster household economic opportunities. Studies on the role of microfinance and women entrepreneurs in Pakistan have highlighted the link between the financial empowerment and sustainable poverty alleviation (Farooq et al., 2024). However, caution must be used in comparing the various studies due to methodological differences, institutional variations and household composition. The present analysis expands on this discussion by adding repeated observations of households and fixed effects estimation and keeping a conservative understanding of the estimated relationships.

The results of this study have implications for the financial inclusion and poverty reduction strategies in India. Even though there was a negative relationship between multidimensional poverty and use of microcredit, the coefficient was relatively small, suggesting that increasing the availability of credit to households does not guarantee a large impact on household welfare. Financial inclusion programmes need to thus include responsible lending, livelihood development, financial literacy, employment support, and access to essential services. MICROFINANCE INSTITUTIONS AND SELF-HELP GROUPS can enhance their developmental impact through help in using loans productively and lessening financial vulnerability in repayments. The study of microfinance and financial inclusion, poverty alleviation and sustainable development has also been explored in Sub-Saharan Africa, highlighting the importance of the wider institutional and developmental context (Osuma et al., 2025). However, policymakers should be aware that structural factors beyond financial access are important for poverty reduction within the household.

Microcredit programmes can be complemented by targeted interventions, such as education, health, employment insecurity, and regional inequalities. It would also be helpful to monitor multidimensional poverty outcomes over time, to be able to separate financial participation from durable gains in household living.

These findings should be viewed with a number of caveats. The first limitation of the observational research design was that it did not allow for causal inference, as microcredit borrowers could have unobserved attributes that affect poverty outcomes. Household fixed effects have been adjusted for time-invariant characteristics, but time-varying confounding may be present. Second, the analytical panel was significantly imbalanced and there were relatively small number of households in each of the four survey years. This differential coverage could have an impact on longitudinal comparisons or generalizability. Third, the poverty transition analysis was based on a provisional multidimensional threshold that needed to be validated with the original framework of measurement. Lastly, the study period did not include long-term results beyond 2019. More future research should rely on the extended household panels, more powerful causal identification methods, other poverty measures, and more in-depth ways of measuring borrowing intensity and loan use. Such approaches might help to explain conditions under which microcredit supports continued multidimensional poverty alleviation.

5. Conclusion

This study examined the relationship between microcredit borrowing and multidimensional poverty dynamics among Indian households using longitudinal data from 2016 to 2019. The results showed a significant difference in the overall average scores of multidimensional poverty over the period of observation, and an improvement in the current measured deprivation for all households, including both borrowing and non-borrowing. Borrowing households' poverty score was, however, slightly lower during the later survey years, which indicates a potentially positive relationship between microcredit access and household welfare. The negative relationship between microcredit borrowing and multidimensional poverty was also confirmed by household fixed-effects regression with the estimated coefficient of −0.005519 being statistically significant. This association was similar for every alternative specification, but the relatively small size of this association suggested that microcredit could be insufficient to help eradicate the unabated socioeconomic deprivation. There was also a significant amount of household poverty mobility in

the longitudinal analysis, with 437 households that "exited" poverty and 49 households that "entered" poverty at the same time that they were observed at both the beginning and end of the study, based on a provisional poverty classification threshold. These results illustrated the need to focus on the transitions in the poverty levels, and not just on overall poverty indicators. However, the data were collected with an observational design, were unbalanced, and there was a possibility for borrowers to select themselves. The study makes a contribution to development economics by combining microcredit participation, multidimensional poverty measure, and longitudinal analysis of the household in Indian context. The results of this process indicate that efforts to promote financial inclusion require to be complemented by the promotion of livelihood development, access to education, healthcare, and responsible lending. Future studies should use longer household panels, poverty lines based on empirical research and more powerful causal identification methods to assess the ability of microcredit to lead to stable gains in multidimensional household welfare.

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