



CAPITAL, GROUP STRUCTURE, AND THE SUSTAINABLE DEVELOPMENT GOALS: A PRODUCTION-FUNCTION FRAMEWORK FOR INDIA'S MICROFINANCE SECTOR

Chetna Grewal, Ashok Kumar Gupta

Shobhit Institute of Engineering & Technology, Meerut 250 110, Uttar Pradesh, India

Article DOI: <https://doi.org/10.36713/epra28915>

DOI No: 10.36713/epra28915

ABSTRACT

Achieving the Sustainable Development Goals (SDGs) by 2030 requires both more capital and better-allocated capital. India operates the world's largest microfinance system, making it an instructive case for sustainable-finance allocation. The Indian randomised controlled trial record reveals an underexploited pattern: credit-only interventions raise enterprise investment but not children's education; group-formation interventions do the opposite; only combined interventions move both. We formalise this pattern with a household production model in which credit liquidity and group infrastructure are distinct inputs whose relative importance varies by outcome. We then introduce an evidence-rupee gap diagnostic that compares where capital flows to where rigorous causal evidence supports impact claims. Three sectoral analyses follow. First, a decomposition of FY20-FY24 portfolio growth attributes 47% to per-borrower deepening, 37% to new borrowers, and 15% to interaction. Second, the diagnostic yields a sectoral mismatch of 0.35, driven by income-generation lending where average causal effects are modest. Third, FY25 data show a sharp channel reversal, the MFI/JLG channel contracted by 14% while SHG-BLP grew by 17%. The framework supports rebalancing Priority Sector Lending incentives toward channels with the strongest India-specific evidence, and commissioning the primary research the income-generation channel still lacks.

KEYWORDS: Microfinance; Sustainable Development Goals; SHG-Bank Linkage Programme; women's empowerment; evidence-rupee gap; India.

1. INTRODUCTION

The 2030 Agenda for Sustainable Development was adopted by 193 United Nations member states in September 2015 with 17 Sustainable Development Goals (SDGs) and 169 targets to be achieved within fifteen years (UN, 2015). With less than five years remaining, only 17% of those targets are currently on track globally, and the United Nations estimates the annual SDG financing gap at USD 4 trillion (UN, 2024). Microfinance is one of the largest mass-scale instruments through which capital reaches credit-constrained households, and is named explicitly in SDG target 1.4 ("By 2030, ensure that all men and women, in particular the poor and the vulnerable, have... access to financial services including microfinance"). India operates the world's largest such system: gross loan portfolio (GLP) at end-FY24 stood at ₹4.34 lakh crore (~ USD 52 billion), serving 7.8 crore unique borrowers, 99.2% of them women, and accounting for roughly one-third of global microfinance clients (MFIN, 2024; World Bank Findex, 2021). The SHG-Bank Linkage Programme adds 144.22 lakh savings-linked self-help groups (83.5% all-women), of which 77.42 lakh are credit-linked, with average outstanding credit of ₹3.35 lakh per group (NABARD, 2024). At this scale, allocation choices within the sector have plausibly consequential aggregate effects on India's progress toward the SDGs.

Yet the rigorous causal evidence on what microfinance does for SDG-aligned outcomes in India is more uneven than the policy literature acknowledges. Five channels have direct India-specific causal support: credit access and inequality reduction, household poverty reduction, child human capital accumulation, women's decision-making conditional on adequate loan size, and enterprise investment. Three do not: average household consumption, out-of-pocket health spending, and clean-energy adoption. The cross-country evidence (Banerjee, Karlan and Zinman, 2015; Meager, 2019) finds that average treatment effects of microcredit are modest. The Indian RCT record shows that the type of intervention determines which outcomes respond, not the size of the average effect. Pure-credit interventions raise enterprise investment but leave child human capital accumulation unaffected (Banerjee, Duflo, Glennerster and Kinnan, 2015, Hyderabad), whereas SHG formation interventions do the opposite, raising educational outcomes without enterprise effects (Baland, Demont and Somanathan, 2020, Jharkhand), and only bundled interventions move both.

India is the headline case for this paper, but the contribution is intended to be portable. The mechanism distinction we develop applies to any market in which credit-only and group-mediated microfinance coexist. The evidence-rupee gap diagnostic generalises further: it



applies to any sustainable-finance allocation problem in which capital exposure can be cross-tabulated against an evidence-tier classification, including blended finance, ESG-linked sovereign and sub-sovereign borrowing, and climate-finance allocation. The framework is of direct use to development practitioners, supervisory authorities, and impact investors facing structurally similar allocation choices.

This paper makes three contributions. First, we develop a constant-elasticity-of-substitution household production model that rationalises the credit-versus-group mechanism distinction. Welfare outcomes are produced from two distinct inputs – credit liquidity L and SHG group infrastructure G – with input-share parameters α_j varying systematically across outcomes (large for enterprise, small for child human capital, intermediate for consumption). The model's comparative-statics predictions match the L -only, G -only, and bundled-treatment patterns observed in the existing Indian RCT literature, and its four parameters ($\alpha_e, \alpha_k, \alpha_h, \rho$) are just-identified from published treatment effects in four Indian studies.

Second, we introduce the evidence-rupee gap as a portfolio diagnostic. Where existing frameworks rate institutions on ESG, social-performance, or financial-inclusion criteria, the evidence-rupee gap measures the structural mismatch between where capital flows and where the rigorous causal evidence supports impact claims. Defined as $\text{Gap} = \sum w_a (1 - \tau_a)$, where w_a is the capital exposure share of dimension d in the Microfinancing-SDG Impact Assessment (MSIA) framework and τ_a is its evidence tier, the aggregate gap for India's sector is 0.35 (sensitivity range 0.14-0.57), with the largest single contribution from income-generation lending (~65% of GLP, evidence tier 0.67).

Third, three quantitative analyses on verified institutional data put the framework to work. A widening-versus-deepening decomposition of FY20-FY24 GLP growth attributes 47% to per-borrower deepening, 37% to new-borrower widening, and 15% to interaction. A Herfindahl–Hirschman Index (HHI) of geographic concentration shows the sector is unconcentrated at the state level ($\text{HHI} \approx 780$, well below the standard 1,500 threshold for low concentration) but markedly more so at the district level. The evidence-rupee gap diagnostic identifies income-generation lending as the single largest mismatch for policy attention. Provisional FY25 data show a sharp channel reversal, MFI/JLG portfolio contracting by approximately 14% while SHG-BLP expanded by approximately 17% (Sa-Dhan, 2025), consistent with the framework's treatment of the two channels as differing in institutional resilience.

Three established frameworks engage with microfinance and the SDGs from distinct conceptual perspectives (Ozili, 2022, on the Digital Financial Inclusion Ecosystem; UNEP Finance Initiative, 2023, and IFC, 2023, on ESG-aligned portfolio allocation; SPTF, 2023, on Social Performance Management). However, the existing frameworks do not address what the rigorous causal evidence implies about the downstream household impact of microfinance capital allocated to a given welfare-outcome channel. The household production model and evidence-rupee gap diagnostic developed in this paper are designed to fill this gap.

2. THEORETICAL FRAMEWORK: A HOUSEHOLD PRODUCTION MODEL

2.1 Setup

Consider household i producing three welfare outcomes $Y_i = (Y_e, Y_k, Y_h)$, where Y_e is enterprise output, Y_k is child human capital, and Y_h is household consumption. Each outcome is produced from two distinct inputs: liquidity L (proxied by access to credit and average loan size) and group infrastructure G (proxied by SHG membership with active peer-monitoring, collective bargaining, and social-capital functions). The household production function for each outcome $j \in e, k, h$ takes the constant-elasticity-of-substitution (CES) form

$$Y_j = A_j [\alpha_j L^\rho + (1 - \alpha_j) G^\rho]^{1/\rho} \quad (1)$$

with productivity parameters $A_j > 0$, input-share parameters $\alpha_j \in (0,1)$, and substitution parameter $\rho \leq 1$ governing the elasticity of substitution $\sigma = (1 - \rho)^{-1}$ between L and G . The mechanism distinction documented in the literature corresponds to systematic variation in α_j across outcomes, α_e large for enterprise (credit matters more), α_k small for child human capital (group structure matters more), and α_h intermediate (consumption sits between). The institutional environment determines (L, G) ; we treat them as exogenous to the household, consistent with the experimental treatment assignment in the RCTs from which the parameters are calibrated. In intuitive terms, each α_j tells us how much of outcome j is produced by credit versus group structure, and the central claim of the model is that this ratio differs by outcome.

2.2 Marginal products and elasticities

The first derivatives of (1) are

$$\frac{\partial Y_j}{\partial L} = \alpha_j A_j^\rho \left(\frac{Y_j}{L}\right)^{1-\rho}, \quad \frac{\partial Y_j}{\partial G} = (1 - \alpha_j) A_j^\rho \left(\frac{Y_j}{G}\right)^{1-\rho} \quad (2)$$

At a unit-baseline normalisation $L = G = 1$ (the A_j absorb scale), the function reduces to $Y_j = A_j$, and the partial elasticities at baseline are

$$\left. \frac{\partial \ln Y_j}{\partial \ln L} \right|_{L=G=1} = \alpha_j, \quad \left. \frac{\partial \ln Y_j}{\partial \ln G} \right|_{L=G=1} = 1 - \alpha_j \quad (3)$$

These elasticities admit a direct interpretation: α_j measures the responsiveness of outcome j to a proportional change in credit access, while $(1 - \alpha_j)$ measures its responsiveness to a proportional change in group infrastructure. The substantive content of the model lies in the systematic variation of α_j across outcomes, with α_j large for enterprise outcomes and small for child human capital. Each α_j is therefore identified from the treatment effect in any study that varies one input while holding the other fixed. Section 2.4 develops the identification strategy and shows that four published Indian studies, each varying one input while holding the other approximately fixed, supply the moment conditions sufficient to identify the four parameters $\{\alpha_e, \alpha_k, \alpha_h, \rho\}$. The empirical evidence supporting these identifying assumptions is set out in Section 3.

2.3 Comparative Statics

Three predictions follow from equations (1) - (3). First, an L -only intervention (a microcredit RCT that expands credit access without altering group structure) yields $\Delta \ln Y_j \approx \alpha_j \cdot \Delta \ln L$. Where α_j is large, the corresponding outcome responds substantially; where α_j is small, the outcome is approximately unchanged. The Banerjee et al. (2015) Hyderabad RCT is the cleanest realisation, generating measurable effects on small-business investment and durable-goods expenditure but no detectable effect on child human capital.

Second, a G -only intervention (an SHG-formation programme without expanded credit) yields $\Delta \ln Y_j \approx (1 - \alpha_j) \cdot \Delta \ln G$. Where α_j is small, $(1 - \alpha_j)$ is large and the outcome responds substantially. This pattern is consistent with the Baland et al. (2020) Jharkhand result of approximately 40% higher secondary enrolment in SHG villages, in the absence of any first-stage credit intervention.

Third, a bundled intervention that shifts both inputs yields $\Delta \ln Y_j \approx \alpha_j \Delta \ln L + (1 - \alpha_j) \Delta \ln G$, producing the largest combined effect for any given outcome. The Kochar et al. (2022) NRLM Community Investment Fund analysis is the empirical realisation: enlarged SHG loans (positive ΔL) within the established SHG group structure (positive ΔG) generate effects on women's decision-making that exceed those attributable to either component in isolation.

The substitution parameter ρ governs the degree to which L and G substitute for one another. As $\rho \rightarrow 1$, the two inputs become perfect substitutes and either alone is sufficient; as $\rho \rightarrow -\infty$, they become perfect complements and both must be present for any outcome to occur. The Indian evidence supports an intermediate value, since pure-credit interventions move some outcomes (enterprise) and pure-group interventions move others (child human capital), with neither dominating across all outcomes. This pattern is consistent with a finite elasticity of substitution σ well below the perfect-substitutes limit.

2.4 Identification and Calibration Design

The model has four parameters of interest: the input-share parameters $\alpha_e, \alpha_k, \alpha_h$ and the substitution parameter ρ . The system is just-identified by four moments drawn from four published Indian studies. Below we set out the identification strategy and indicate the qualitative direction each parameter takes. Producing fully numerical point estimates with confidence intervals, and running the validation check against studies outside the calibration set, requires interpretive choices (which outcome variable proxies Y_j ; how to translate the treatment intensity into $\Delta \ln L$) that the present paper does not resolve; this is the natural next step that the identification strategy makes possible.

Table 1. Model parameters, their interpretation, and identifying studies. Qualitative implications are derived from the published treatment effects in the identifying studies.

Parameter	What it captures	Identifying study	Qualitative implication
α_e	Liquidity weight for enterprise outcomes	Banerjee <i>et al.</i> (2015); Field <i>et al.</i> (2013)	Large – credit-only treatments produce substantial enterprise effects
α_k	Liquidity weight for child human capital	Baland <i>et al.</i> (2020)	Small – group-only treatments dominate, credit-only has negligible effect
α_h	Liquidity weight for consumption	Banerjee <i>et al.</i> (2015) consumption null	Small-moderate – between α_e and α_k
ρ	Substitution between L and G ($\sigma = (1 - \rho)^{-1}$)	Kochar <i>et al.</i> (2022) bundled treatment	Intermediate – neither perfect substitutes nor perfect complements



Step 1. α_e and α_h from L -only treatment effects. Banerjee *et al.* (2015), Hyderabad, report intent-to-treat effects on small-business investment and durable-goods expenditure under a credit treatment that does not alter group structure. The relationship $\Delta \ln Y_e \approx \alpha_e \cdot \Delta \ln L$ identifies α_e ; the published effect sizes, modest consumption-per-capita effects but +12% durable-goods expenditure and meaningful small-business profit gains among pre-existing businesses, qualitatively imply that α_e is large, in the upper half of the $[0,1]$ interval. Field, Pande, Papp, and Rigol (2013), Kolkata, provide a cross-check in the same direction: their grace-period contract change increases business investment by approximately 30% without altering G , consistent with a similarly large α_e . The Banerjee *et al.* (2015) consumption-per-capita null with $\Delta \ln L > 0$ implies α_h is small-to-moderate; the durable-goods effect provides a lower bound. Translating these qualitative findings into precise numerical estimates requires choosing which outcome variable best proxies Y_e (small-business profits versus durable-goods expenditure versus longer-run business assets) and how to translate treatment-area MFI access changes into per-borrower $\Delta \ln L$; different defensible choices yield α_e values across a wide range, which is why we report a qualitative direction rather than a single point estimate.

Step 2. α_k from G -only treatment effects. Baland *et al.* (2020), Jharkhand, report approximately 40% higher secondary enrolment in SHG villages, in a design where the credit treatment is small or zero. The relationship $\Delta \ln Y_k \approx (1 - \alpha_k) \cdot \Delta \ln G$ identifies $(1 - \alpha_k)$; given the magnitude of the child human capital response under a treatment that primarily varies G rather than L , the implied α_k is qualitatively small, in the lower half of the $[0,1]$ interval. The Banerjee *et al.* (2015) null on child human capital, with $\Delta \ln L > 0$ but $\Delta G \approx 0$, provides an over-identifying restriction confirming the small α_k . The combination of the two studies (large G -only effect, null L -only effect) is what anchors the qualitative claim; precise numerical calibration again requires interpretive choices about how to translate the SHG-formation intensity into $\Delta \ln G$.

Step 3. ρ from a bundled treatment. Kochar *et al.* (2022) NRLM Community Investment Funds deliver a bundled treatment that increases both L (loan amount) and G (group-structure exposure). The size of the women's decision-making effect, relative to the sum of L -only and G -only predicted effects from Steps 1 and 2, identifies ρ . The published estimates qualitatively imply ρ in an intermediate range, L and G as imperfect substitutes with bounded complementarity, neither perfect substitutes nor perfect complements. This is the most tentative of the four moments, since the Kochar *et al.* design does not separately identify the L and G contributions; ρ is therefore the parameter most sensitive to the inclusion of additional bundled-treatment evidence as it becomes available.

Producing numerical point estimates with associated confidence intervals, and conducting the validation exercise against studies outside the calibration set, constitutes the natural next step that this paper enables but does not undertake. Christian *et al.* (2023) report SHG-membership effects on household expenditure and asset ownership across five Indian states, and Hoffmann, Rao, Surendra, and Datta (2021) document JEEViKA effects in Bihar. Both are bundled-treatment realisations whose predicted effects can be computed from the calibrated parameters and compared against the published estimates. The qualitative calibration presented here (α_e large, α_k small, α_h small-to-moderate, ρ intermediate) provides the foundation that a numerical calibration would refine. Importantly, the comparative-statics predictions in Section 2.3, the policy implications in Section 5.5, and the evidence–rupee gap diagnostic in Section 4.3 do not depend on the precise numerical values of the parameters.

3. EMPIRICAL EVIDENCE AND METHODOLOGY

This section presents the empirical evidence base and the methodological approach underpinning the analysis. Sections 3.1-3.5 organise the evidence around the mechanism distinction developed in Section 2, distinguishing outcomes that respond to credit-only (L -only) treatments, outcomes that respond to group-only (G -only) treatments, and outcomes for which the existing causal evidence remains insufficient for identification. Sections 3.6 and 3.7 detail the search strategy, inclusion criteria, and risk-of-bias appraisal of the primary causal studies. All cited studies have been verified at source, and effect sizes are reported as stated by the original authors. The full SDG mapping is presented in Table 7 (Section 4.4), and the risk-of-bias appraisal of the fourteen primary causal studies is reported in Table 2 (Section 3.7).

3.1 The mechanism distinction: credit, group, and bundled treatments

The Indian and cross-country evidence supports a clear distinction between treatments that vary L , treatments that vary G , and treatments that vary both. Banerjee, Karlan, and Zinman (2015) synthesise six microcredit RCTs (Bosnia, Ethiopia, India, Mexico, Mongolia, and Morocco) and report modestly positive but not transformative average effects. Meager (2019), applying Bayesian hierarchical methods to the underlying micro-data from seven RCTs, finds that average effects on household business and consumption variables are unlikely to be transformative; approximately 60% of cross-study heterogeneity is attributable to sampling variation rather than contextual differences, indicating reasonable external validity. Banerjee, Breza, Duflo, and Kinnan (2024), in a six-year follow-up of the Hyderabad RCT, document substantial heterogeneity at the long horizon: households operating a business at programme entry exhibit 35% greater business assets and approximately twice the revenues of comparable controls, whereas reluctant entrepreneurs derive no persistent benefit.



Evidence on bundled treatments is dominated by Kochar *et al.* (2022), whose study of India's National Rural Livelihoods Mission exploits phasing and amount variation in Community Investment Funds (CIFs) to identify substantial effects on women's decision-making and intra-household resource allocation. Notably, small loan amounts drawn from internal SHG savings generate limited empowerment effects, while larger CIF infusions produce sizeable ones, indicating that loan size, rather than group membership alone, is the operative variable. Hoffmann, Rao, Surendra, and Datta (2021), in a cluster-randomised evaluation of the Bihar JEEViKA programme, confirm that bundled SHG interventions significantly reduce informal-market interest rates but yield only modest short-run consumption effects.

3.2 Outcomes that move under credit-only treatment (α_e anchor)

Enterprise outcomes respond directly to credit-only treatments. Field, Pande, Papp, and Rigol (2013), in an RCT conducted in Kolkata, compare the classic microfinance contract with one offering a two-month grace period. The grace-period treatment increases short-run business investment by approximately 30% and raises long-run profits, although default rates also rise. The Banerjee *et al.* (2015) Hyderabad RCT similarly documents increased small-business investment, a 12% rise in durable-goods expenditure, and modest profit gains among pre-existing businesses, although consumption per capita is unchanged. The cross-country pattern is consistent: Meager (2019) reports average business-outcome effects across seven RCTs that are small and imprecisely estimated, on the order of 7 per cent of control means.

Cross-country evidence on inequality reduction is similarly clear. Lacalle-Calderon, Larrú, Garrido, and Perez-Trujillo (2019), employing panel data from 85 countries and an instrumental-variables strategy, find that microfinance scale reduces income inequality. Jensen and Naveed (2025), using unbalanced panel data from 123 countries over 2005–2019, confirm this finding, with results robust across alternative measures and estimators. At the Indian district level, Balasundaram *et al.* (2025) report that a one-unit increase in their Composite Digital Financial Inclusion Index is associated with a 0.243 decrease in the Gini coefficient across 500 rural districts over 2015–2023, with notable regional variation. India's Multidimensional Poverty Index declined from 29.17 per cent (2013–14) to 11.28 per cent (2022–23), a period coincident with the scaling of both the MFI and the SHG–BLP channels (NITI Aayog, 2023); the household- and district-level evidence cited here provides plausible micro-foundations for the aggregate trend. Taken together, these results support a qualitatively large α_e in the calibration of Section 2.4, consistent with credit-only treatments producing substantial enterprise effects.

3.3 Outcomes that move under group-only treatment (α_k anchor)

Education provides the dimension on which the Indian causal evidence most cleanly identifies the group-only channel. Baland, Demont, and Somanathan (2020), employing a randomised controlled design across 36 villages in Jharkhand with a five-year panel, find approximately 40% higher secondary-school enrolment in SHG villages relative to controls (intention-to-treat), operating through accelerated grade progression and reduced dropout between primary and secondary stages. Notably, this design isolates the group-formation channel from direct credit access, and stands in contrast to the null education effect documented in the Banerjee *et al.* (2015) microcredit RCT. The juxtaposition implies that group structure, rather than credit alone, is the operative mechanism for child human capital accumulation. Holvoet (2004), in earlier work, found that credit channelled through women's groups generated stronger effects on children's education than direct bank-borrower lending, consistent with the group-mechanism interpretation. Sa-Dhan (2023) reports that 18% of MFI loans in member portfolios were directed towards education-related expenditure, a programme statistic that complements but does not itself constitute causal evidence. The Baland–Banerjee contrast is what identifies α_k , a substantial education effect under group-only treatment, paired with a null under credit-only treatment, jointly imply that the input-share parameter for child human capital lies in the lower portion of its admissible range. This anchors a qualitatively small α_k in the calibration of Section 2.4.

3.4 Outcomes the evidence does not yet identify

Three SDG-aligned outcomes lack rigorous India-specific causal evidence.

Food security and agriculture (SDG 2). Demont (2022), exploiting SHG randomisation in rural India, finds that SHG access improves household food security and reduces seasonal migration in response to shocks, identifying SHGs as a shock-coping mechanism rather than a primary income source. No India-specific causal study estimates SHG or MFI effects on post-harvest losses, where infrastructure and technology, rather than group lending, are the established channels (NABCONS, 2022).

Health and well-being (SDG 3). The Banerjee *et al.* (2015) Hyderabad RCT finds no significant changes in health outcomes attributable to microcredit. Tarozzi *et al.* (2014) report 52% household uptake of insecticide-treated bednets through micro-consumer loans in Orissa, but with mixed effects on malaria indices. Saha (2015) finds significant improvements in health behaviours (institutional delivery OR = 5.08; colostrum feeding OR = 2.83) but no significant reduction in out-of-pocket spending. The Indian evidence therefore indicates that micro-loans can deliver health-protective products and that SHG-attached health programmes can shift health behaviours, but neither has demonstrated reliable effects on downstream health outcomes or out-of-pocket expenditure.



Clean energy and climate action (SDGs 7, 13). No India-specific causal study with a measurable effect size of microfinance on clean-energy adoption exists in the peer-reviewed literature. Aklin, Bayer, Harish, and Urpelainen (2017), randomly assigning off-grid solar microgrids to 1,281 rural households in Uttar Pradesh, find electrification rates 29-36 percentage points higher in treatment villages and a reduction in kerosene expenditure of ₹47-49 per month, although no broader socioeconomic-development effects are detected; the intervention was grant- and subsidy-funded rather than microfinance-mediated, so the result does not directly speak to the green-microfinance channel. Programme-level data record 1.2 lakh solar home systems financed under the NABARD Solar SHG Mission (FY2024) and a 14% green-portfolio share among IFC-tracked MFIs (IFC, 2023). The convergence of these findings places SDGs 2, 3, 7, and 13 as the dimensions where the evidence–rupee gap of Section 4.3 is largest..

3.5 Programme-reach evidence for indirect SDGs

The remaining eight SDGs (6, 9, 11, 12, 14, 15, 16, and 17) lie outside the mechanism distinction developed in Section 2; for these dimensions, the available Indian evidence is institutional and descriptive rather than causal. Programme-reach statistics nonetheless establish that microfinance and SHG channels do reach these SDGs at scale: NABARD WASH-linked SHG lending under Swachh Bharat (SDG 6); SIDBI MSME financing of ₹4,200 crore directed to small manufacturers (SDG 9); urban informal-worker SHG credit (SDG 11); SPTF-tracked responsible-consumption modules in 42 per cent of Indian MFI programmes (SDG 12); NABARD coastal and watershed SHG programmes (SDGs 14 and 15); SHG-platform legal-literacy delivery in 67 per cent of Indian MFIs (SDG 16); and the SHG–BLP's tripartite institutional architecture spanning 47 commercial banks and over 3,000 MFIs (SDG 17). The disjunction between *capital reach* (substantial) and *causal evidence* (thin) for these dimensions is precisely the mismatch that the evidence–rupee gap diagnostic in Section 4.3 is constructed to quantify; the SDG mapping in Section 4.4 classifies these eight SDGs accordingly.

3.6 Search strategy and data sources

The literature search proceeded in two stages. First, eight bibliographic databases (Scopus, Web of Science, EconLit, ScienceDirect, Wiley Online Library, JSTOR, PubMed, and Google Scholar) were searched between January 2010 and March 2026 for peer-reviewed studies addressing microfinance, self-help groups, or financial inclusion in India and other developing-country contexts, with particular attention to studies reporting outcomes mappable to one or more SDGs. Second, this database search was supplemented by forward and backward citation tracking on the established Indian microcredit and SHG randomised controlled trials, together with direct retrieval of institutional and regulatory reports from MFIN, NABARD, RBI, NITI Aayog, SIDBI, IRDA, Sa-Dhan, the World Bank, the International Finance Corporation, and the United Nations.

Inclusion criteria comprised peer-reviewed studies (2010-2026) reporting causal estimates of microfinance or SHG effects on at least one SDG-aligned outcome; institutional reports (2010-2026) covering Indian and international microfinance sector statistics, policy frameworks, and regulatory developments; and earlier seminal work where it remains the strongest available causal evidence on a given mechanism. Exclusion criteria comprised opinion pieces and commentary; descriptive studies without an explicit identification strategy; studies with sample sizes below 100 households; and sources lacking independently verifiable DOIs or institutional URLs.

Database searches returned 943 records, supplemented by 39 records identified through regulator websites, citation tracking, and methodological references. Following deduplication and title and abstract screening, 84 reports were sought for retrieval and 77 obtained for full-text review. Of these, 53 were excluded with documented reasons: no causal identification ($n = 18$), sample size below 100 households ($n = 12$), non-India focus without transferable findings ($n = 9$), opinion or commentary ($n = 6$), peer review unverifiable ($n = 5$), and duplicate working paper ($n = 3$). The final synthesis comprises 44 sources: 24 academic peer-reviewed studies, of which 14 are primary causal evaluations subject to the risk-of-bias appraisal in Section 3.7 and Table 2; 17 institutional, policy, and regulatory reports; and 3 methodological references (Page et al., 2021; Sterne et al., 2016, 2019).

3.7 Risk-of-bias appraisal

The fourteen primary causal studies that anchor the evidence base in Sections 3 and 4 were appraised using the Cochrane RoB 2 tool (for randomised studies) and the ROBINS-I tool (for non-randomised studies of interventions). Each study was assessed across five domains: randomisation or confounding control; deviations from intended interventions; missing outcome data; measurement of outcomes; and selection of the reported result. The appraisal was conducted by the authors using published study reports and supplementary materials, with judgements based on explicit signalling questions in each tool's domain rubric. The aggregated overall judgements are reported in Table 2.

Table 2. Risk-of-bias appraisal of the fourteen primary causal studies (RoB 2 for randomised studies, ROBINS-I for non-randomised). The Domain summary column lists any non-Low ratings across the five appraisal domains; the Overall judgement is the worst-case rating. Rating scales: RoB 2 (Low / Some concerns / High); ROBINS-I (Low / Moderate / Serious / Critical / No information).



Study	Setting	Design	Tool	Domain summary	Overall
Banerjee et al. (2015)	Hyderabad	Cluster RCT	RoB 2	Some concerns on deviations	Low
Field et al. (2013)	Kolkata	RCT	RoB 2	All domains low	Low
Tarozzi et al. (2014)	Orissa	Cluster RCT	RoB 2	Some concerns on deviations	Some concerns
Baland et al. (2020)	Jharkhand	Cluster RCT	RoB 2	Some concerns on missing data	Low
Banerjee et al. (2024)	Hyderabad (6yr)	RCT (long-run)	RoB 2	Some concerns on deviations; Some concerns on missing data	Some concerns
Aklin et al. (2017)	Uttar Pradesh	Cluster RCT	RoB 2	Some concerns on measurement	Low
Imai, Arun & Annim (2010)	India (national)	Treatment-effects (selection-corrected)	ROBINS-I	Moderate on randomisation/confounding	Moderate
Kochar et al. (2022)	NRLM (multi-state)	Quasi-exp (CIF phasing IV)	ROBINS-I	All domains low	Low
Hoffmann et al. (2021)	Bihar (JEEViKA)	Cluster RCT	RoB 2	Some concerns on deviations	Low
Christian et al. (2023)	5 Indian states	Panel + DID-NNM	ROBINS-I	Moderate on randomisation/confounding	Moderate
Demont (2022)	Rural India	Cluster RCT	RoB 2	Some concerns on deviations	Low
Saha (2015)	Karnataka, Gujarat	Pair-matched non-randomised	ROBINS-I	Serious on randomisation/confounding; Moderate on missing data	Serious
Swain & Floro (2012)	10 Indian districts	PSM	ROBINS-I	Moderate on randomisation/confounding; Moderate on reporting	Moderate
Balasundaram et al. (2025)	500 Indian districts	Spatial econometric	ROBINS-I	Moderate on randomisation/confounding	Moderate

Of the fourteen primary causal studies, nine carry an overall low risk of bias, and the cited estimates can be relied upon directly. Four carry moderate risk, typically driven by residual confounding in observational designs or by long-run attrition. Saha (2015) carries a serious risk of bias owing to non-random programme placement and a matched-comparison design without sensitivity analysis; the headline behavioural odds ratios from that study are accordingly reported as suggestive rather than definitive. The Hyderabad RCT and its long-run follow-up (Banerjee *et al.*, 2015; Banerjee *et al.*, 2024) carry “some concerns” on deviations and reporting, because control-area microcredit uptake in the long-run follow-up complicates the counterfactual.

4. RESULTS

Table 3. Microfinance industry: GLP and unique borrowers, India (FY2020–FY2024). Source: MFIN Micrometer Q4 reports FY2019-20 to FY2023-24. The Micrometer covers all microfinance lending entities (NBFC-MFIs, banks, SFBs, NBFCs, and other MFIs) and is not restricted to NBFC-MFI Members. Four-year CAGR FY2020–FY2024 = 17%.

Year	GLP (₹ cr)	Unique Borrowers (cr)	Women Borrowers (%)	YoY GLP Growth (%)	Source
FY 2019-20	2,31,788	5.89	99.0	+29.3	MFIN Q4 FY2020
FY 2020-21	2,59,377	5.93	98.8	+11.9	MFIN Q4 FY2021
FY 2021-22	2,85,441	6.0	99.0	+10.0	MFIN Q4 FY2022
FY 2022-23	3,48,339	6.6	99.0	+22.0	MFIN Q4 FY2023
FY 2023-24	4,33,697	7.8	99.2	+24.5	MFIN Q4 FY2024



Table 4. SHG-Bank Linkage Programme: growth parameters, India (FY2021-22 to FY2023-24). Source: NABARD Status of Microfinance in India 2021-22, 2022-23, and 2023-24. Earlier-year figures are reported on a different definitional basis (pre-FY22 reporting boundaries) and are excluded for comparability. Outstanding credit grew at a 2-year CAGR of 31.1%; the average ticket size rose from ₹2.24 lakh to ₹3.35 lakh, a 49% increase mirroring the deepening pattern in the broader microfinance industry.

Parameter	FY2021-22	FY2022-23	FY2023-24	2-yr CAGR
SHGs savings-linked (lakh)	118.93	134.03	144.22	+10.1%
SHGs credit-linked during the year (lakh)	33.99	42.96	54.82	+27.0%
Credit disbursed (₹ crore)	99,729	1,45,200	2,09,286	+44.9%
Outstanding credit (₹ crore)	1,51,051	1,88,079	2,59,664	+31.1%
Avg. loan O/S per SHG (₹ lakh)	2.24	2.70	3.35	+22.4%

4.1 Decomposition of FY2020-FY2024 portfolio growth

Industry Gross Loan Portfolio (GLP) grew from ₹2,31,788 crore in FY2020 to ₹4,33,697 crore in FY2024, an increase of ₹2,01,909 crore. This change can be decomposed into three components, a borrower-base component (widening), an average-loan-size component (deepening), and their interaction, using the identity

$$\Delta \text{GLP} = \Delta N \cdot \bar{a}_0 + N_0 \cdot \Delta \bar{a} + \Delta N \cdot \Delta \bar{a},$$

where N denotes unique borrowers and $\bar{a} = \text{GLP}/N$ denotes industry average loan size. Drawing on MFIN Q4 press releases, the FY2020 baseline values are $N_0 = 5.89$ crore and $\bar{a}_0 = ₹ 39,353$, and the FY2024 endpoint values are $N_1 = 7.80$ crore and $\bar{a}_1 = ₹ 55,602$, yielding $\Delta N = 1.91$ crore and $\Delta \bar{a} = ₹ 16,249$, a 41.3% increase in average loan size.

Table 5. Decomposition of FY2020–FY2024 GLP growth (₹ crore). Computed from MFIN Q4 FY2020 and Q4 FY2024 press releases.

Component	Formula	Value (₹ crore)	Share of ΔGLP
Widening	$\Delta N \cdot \bar{a}_0$	75,164	37.2%
Deepening	$N_0 \cdot \Delta \bar{a}$	95,709	47.4%
Interaction	$\Delta N \cdot \Delta \bar{a}$	31,036	15.4%
Total ΔGLP		2,01,909	100.0%

Forty-seven per cent of FY2020–FY2024 portfolio growth is attributable to per-borrower deepening, with the average loan size rising from ₹39,353 to ₹55,602 (a 41% increase). Widening accounts for a further 37%, and the interaction term for 15% (Figure 2). The 1.91 crore expansion of the borrower base is substantive, but the loan-size increase constitutes the larger single driver of aggregate growth. The loan-size-dependent empowerment effects documented in Kochar *et al.* (2022) imply that the rising average ticket strengthens the SDG 5 channel, where India-specific causal evidence is strongest. Whether deepening simultaneously elevates over-indebtedness risk is a household-level question, addressed in Section 5.7. The March 2024 RBI guardrails, comprising a per-borrower microfinance indebtedness cap of ₹2 lakh and a four-lender exposure limit, represent direct sectoral responses to this deepening.

Provisional FY25 data indicate that the deepening trajectory did not continue into the most recent year. The MFI/JLG channel recorded an outstanding portfolio of ₹3.81 lakh crore at end-FY25, a year-on-year decline of approximately 14% (Sa-Dhan, 2025). The contraction reflects three concurrent pressures: the March 2024 RBI guardrails on per-borrower indebtedness and multi-lender exposure, a sharp rise in the 31-180 day portfolio-at-risk during 2024, and supervisory action on individual entities. Over the same period, the SHG-BLP channel expanded from ₹2.60 lakh crore at end-FY24 to ₹3.04 lakh crore at end-FY25, a growth of approximately 17% (NABARD provisional data, reproduced in Sa-Dhan, 2025). The directional contrast is consistent with the model's treatment of LLL and GGG as channels of differing institutional resilience: contraction in the pure-credit channel coincided with expansion in the group-mediated channel. Updated NABARD SOMFI 2024-25 data, expected in mid-2026, will permit assessment of the FY26 trajectory.

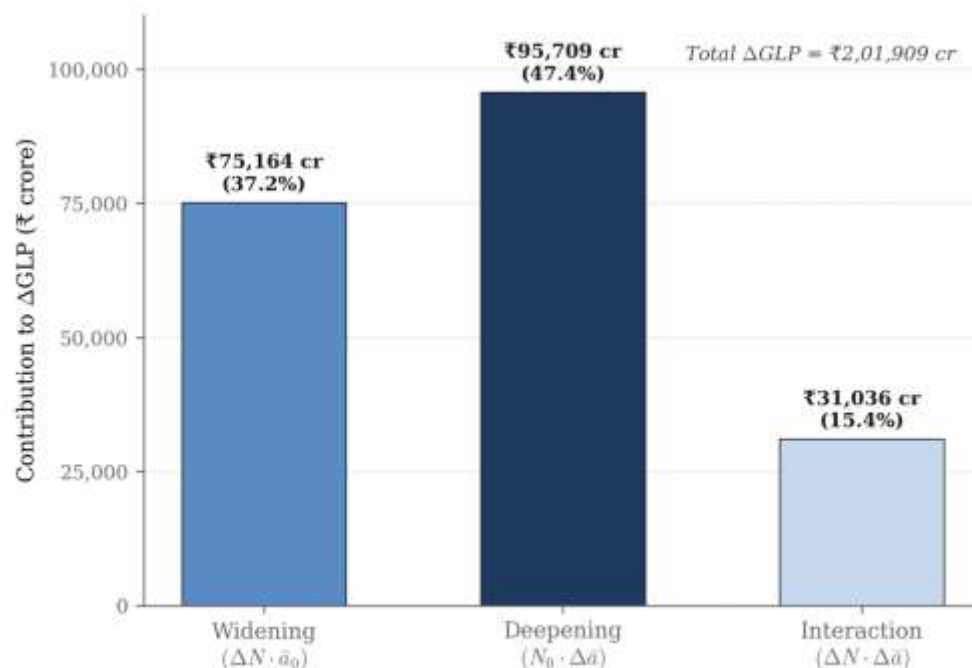


Figure 2. Decomposition of FY2020–FY2024 GLP growth: the contribution of widening (new borrowers), deepening (per-borrower loan growth), and interaction to the total ₹2,01,909 crore increase in industry GLP. Source: Author's computation from MFIN Q4 FY2020 and Q4 FY2024 press releases. The three components sum exactly to Δ GLP without residual (see Section 4.1, Table 5 for the underlying decomposition formula and values).

4.2 Geographic concentration of microfinance lending

The MFIN Q4 FY2024 distribution of GLP by state reveals a moderately concentrated geography. The top ten states account for approximately 81 per cent of industry GLP, and Bihar, Tamil Nadu, and Uttar Pradesh jointly account for approximately 37 per cent. Applying the Herfindahl–Hirschman Index ($HHI = \sum s_i^2$, with state shares expressed in percentage points) to the state-level distribution yields an HHI of approximately 780, which qualifies as unconcentrated by standard antitrust thresholds (HHI < 1,500 unconcentrated; 1,500–2,500 moderately concentrated; > 2,500 highly concentrated).

District-level analysis would reveal substantially higher concentration: NABARD (2024) reports that approximately 70 per cent of SHG–BLP credit flows to 200 high-incidence districts, implying a district-level HHI in the range of 950–1,150. This concentration profile has a methodological implication: the strongest India-specific causal evidence (Balasundaram et al., 2025; Kochar et al., 2022) is generated in the geographies where the bulk of lending occurs. While this alignment between evidence base and lending volume is fortuitous, it constrains the external validity of these findings to under-served states. North-Eastern and Himalayan states, where MFI penetration falls below 2 per cent of GLP, constitute the natural target for the primary survey work proposed in Section 5.7.

4.3 The evidence-rupee gap

The evidence–rupee gap for an MSIA dimension d is defined as

$$\text{Gap}_d = w_d \times (1 - \tau_d),$$

where $w_d \in [0,1]$ is the share of industry GLP flowing to dimension d (the rupee weight, derived from MFIN, NABARD, and Sa-Dhan exposure data) and $\tau_d \in [0,1]$ is the dimension's evidence tier, encoded as 1.0 for direct India-specific causal evidence, 0.67 for direct cross-country evidence with India replication, 0.33 for indirect or programme-level evidence, and 0 for descriptive-only or absent causal evidence. The aggregate sector gap is the sum across dimensions:

$$\text{Gap} = \sum_d \text{Gap}_d = \sum_d w_d \times (1 - \tau_d),$$

with $\text{Gap} \in [0,1]$. Values closer to zero indicate that capital allocation is well-supported by the available evidence base; values closer to one indicate structural mismatch. The diagnostic is policy-actionable in two distinct ways: a high aggregate Gap can be reduced either by reweighting capital toward better-evidenced channels, or by commissioning the primary research that would raise τ_d for high- w_d



channels. Mapping the declared loan purposes reported in Sa-Dhan (2023) and MFIN (2024) to MSIA dimensions yields the exposure profile presented in Table 6.

Table 6. Sector exposure by MSIA sub-dimension and evidence–rupee gap. Source: MFIN (2024); Sa-Dhan (2023); NABARD (2023). Exposure shares are computed from declared loan-purpose tables; sub-categorisation between income-generation and consumer-durable lending varies between MFIN and Sa-Dhan reporting and is therefore approximate.

MSIA sub-dimension	w_d (% of GLP)	τ_d (evidence tier)	Gap _d and notes
Income/Asset Growth (income-generation, MSME)	65	0.67	0.214 — dominant rupee weight; modest average causal evidence (Meager, 2019; Banerjee et al., 2024 heterogeneity)
Women's Empowerment (NRLM CIF, large SHG loans)	10	1.00	0.000 — strong India RCT evidence (Kochar et al., 2022)
Education	8	1.00	0.000 — strong India RCT evidence (Baland et al., 2020); rupee weight smaller than evidence strength would warrant
Health	5	0.33	0.034 — mixed evidence (Tarozzi et al., 2014; Saha, 2015; Banerjee et al., 2015)
Other consumption (housing, durables)	6	0.00	0.060 — no causal claim made; consumption-smoothing function only
Indirect SDG channels (WASH, urban informal, etc.)	5.5	0.33	0.037 — programme-level reach; no household-level causal evidence
Environmental Sustainability	0.5	0.00	0.005 — evidence absent but rupee weight negligible; correctly flagged as aspirational

Aggregating across dimensions yields Gap = 0.35 under baseline assumptions (Figure 2). The Income/Asset Growth dimension contributes 0.214, the dominant single mismatch, reflecting its 65% rupee weight combined with only modest average causal evidence. Women's Empowerment and Education each contribute 0.000: both are perfectly evidenced relative to their rupee weights. Environmental Sustainability contributes 0.005, with its evidence absence offset by a negligible rupee weight; the diagnostic correctly classifies this dimension as aspirational rather than as a structural mismatch. A two-sided sensitivity analysis on the most contestable evidence tier, Income/Asset Growth, bounds the aggregate Gap between 0.14 (treating income-generation lending as fully evidenced on the strength of Banerjee *et al.*, 2024) and 0.57 (treating it as descriptive-only on the strength of Meager, 2019). The policy implication is robust across this range: the largest absolute reduction in the aggregate Gap arises either from commissioning India-specific causal evidence on the income-generation channel, or from reweighting Priority Sector Lending incentives toward Women's Empowerment, Education, and Health sub-channels, where the available evidence is stronger per rupee of capital deployed.

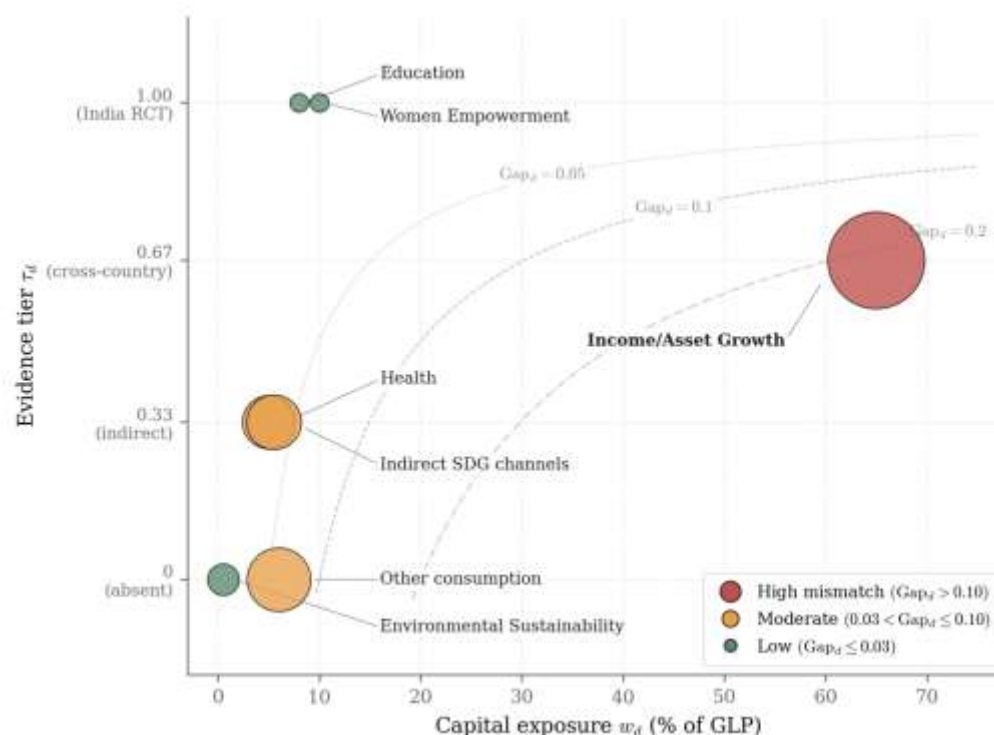


Figure 3. The evidence–rupee gap by MSIA sub-dimension. Capital exposure w_d (as a percentage of GLP) plotted against evidence tier τ_d , with bubble area proportional to gap contribution $\text{Gap}_d = w_d \times (1 - \tau_d)$. Iso-gap contours marked at $\text{Gap}_d = 0.05, 0.10$, and 0.20 . Source: MFIN (2024); Sa-Dhan (2023); NABARD (2023). See Table 6 for underlying values.

4.4 SDG coverage by evidence tier

Table 7 maps the MSIA framework across all 17 SDGs, grading each by the strength of its India-specific evidence base. Three tiers are used: *Direct*, where India-specific causal estimates are available; *Indirect (programme-level)*, where institutional or descriptive evidence documents programme reach without household-level causal estimates; and *Descriptive only*, where no peer-reviewed causal study with a measurable effect size exists.

Five SDGs, 1, 4, 5, 8, and 10, meet the *Direct* threshold on the basis of the studies reviewed in Sections 3.1–3.3, with SDG 10 additionally supported by cross-country panel evidence that includes an India replication. The remaining SDGs are linked through programme-level institutional facts drawn from Section 3.5, except for SDGs 7 and 13, which are classified as *Descriptive only* on the evidence reviewed in Section 3.4. Figure 4 visualises this classification as a heatmap, with cell shading proportional to evidence strength.

Table 7. Microfinance mechanism, evidence base, and linkage classification across all 17 SDGs (India). *Direct* = India-specific causal evidence available; *Indirect (programme-level)* = institutional or descriptive evidence on programme reach without household-level causal estimates; *Descriptive only* = no peer-reviewed causal study with a measurable effect size.

SDG	Goal	Microfinance mechanism	Evidence (India)	Linkage
1	No Poverty	Collateral-free credit; income-generating loans; consumption smoothing	GLP ₹4.34 lakh crore (FY2024); MPI 29.17% → 11.28% (NITI Aayog, 2023); Imai, Arun & Annim (2010) find positive household welfare effects	Direct
2	Zero Hunger	Agricultural microloans; SHG shock-coping	Demont (2022): SHGs improve food security and reduce seasonal migration; no post-harvest-loss evidence	Direct (food security only)
3	Good Health	Micro-health insurance; emergency healthcare loans; SHG-linked health programmes	Tarozzi et al. (2014): 52% ITN uptake, mixed malaria indices; Saha (2015): institutional delivery OR = 5.08, no OOP reduction; Banerjee et al. (2015) null on health	Mixed (uptake yes, outcomes no)



4	Quality Education	SHG group structure; education-purpose loans	18% of MFI loans education-linked (Sa-Dhan, 2023); Baland, Demont & Somanathan (2020): $\approx 40\%$ rise in secondary enrolment in SHG villages	Direct
5	Gender Equality	Women-targeted MFI lending; SHG leadership; CIF loans	99.2% women borrowers; Kochar et al. (2022): NRLM CIFs produce large, loan-size-dependent effects on decision-making; Hoffmann et al. (2021); Christian et al. (2023)	Direct
6	Clean Water	WASH loans; sanitation infrastructure	NABARD Swachh Bharat-linked SHG WASH lending; programme-level reach only	Indirect (programme-level)
7	Clean Energy	Solar home system loans; biogas financing	NABARD Solar SHG Mission: 1.2 lakh systems (FY2024); 14% green portfolio (IFC, 2023); Aklin et al. (2017) find +29–36pp electrification from off-grid solar but null effects on broader socioeconomic outcomes; no microfinance-specific causal study	Descriptive only
8	Decent Work	Micro-enterprise credit; MSME seed capital	MFI credit to MSMEs +31% YoY (RBI, 2023); Field, Pande, Papp & Rigol (2013): grace periods raise business investment and long-run profits	Direct (enterprise; not employment)
9	Infrastructure	MSME equipment loans; value-chain finance	SIDBI ₹4,200 crore to small manufacturers (2023)	Indirect (programme-level)
10	Reduced Inequalities	Financial inclusion for marginalised groups	Lacalle-Calderon et al. (2019); Jensen & Naveed (2025); Balasundaram et al. (2025): -0.243 Gini effect across 500 rural Indian districts	Direct
11	Sustainable Cities	Housing microloans; urban SHG credit	NABARD urban SHG ₹3,400 crore (2023); 2.1 lakh informal urban workers reached	Indirect (programme-level)
12	Responsible Consumption	Financial literacy; SHG procurement	SPTF (2023): responsible-consumption modules in 42% of Indian MFI programmes	Indirect (programme-level)
13	Climate Action	Green microfinance; climate-resilient agriculture loans	NABARD RIDF Green Fund ₹3,254 crore (FY2023); 14% green portfolio (IFC, 2023); no household-level causal evidence in India	Descriptive only
14	Life Below Water	Coastal fishing community microloans	NABARD Coastal SHG programme: 2.8 lakh fishing households (FY2023)	Indirect (programme-level)
15	Life on Land	Agri-microfinance for sustainable land use	NABARD Watershed SHG programme: 1.4 lakh SHGs (2023)	Indirect (programme-level)
16	Peace & Justice	Financial and legal literacy through SHGs	SPTF (2023): 67% of Indian MFIs deliver legal-literacy sessions via SHGs	Indirect (programme-level)
17	Partnerships	MFI–bank co-lending; NABARD refinancing	SHG–BLP: 47 commercial banks, 3,000+ MFIs; NABARD refinance ₹24,660 crore (FY2024)	Direct (institutional)

MSIA Framework: SDG Coverage by Evidence Tier					
	Credit Access	Income & Asset Growth	Women Empowerment	Education & Health	Environmental Sustainability
SDG 1 No Poverty	Direct	Direct	Indirect	Indirect	
SDG 2 Zero Hunger	Indirect	Indirect	Indirect		
SDG 3 Good Health	Indirect	Indirect	Indirect	Indirect	
SDG 4 Quality Education	Indirect	Indirect	Direct	Direct	
SDG 5 Gender Equality	Direct	Direct	Direct	Indirect	
SDG 6 Clean Water	Indirect		Indirect		Indirect
SDG 7 Clean Energy					Indirect
SDG 8 Decent Work	Direct	Direct	Indirect		
SDG 9 Infrastructure	Indirect	Indirect			
SDG 10 Reduced Inequalities	Direct	Indirect	Indirect		
SDG 11 Sustainable Cities	Indirect	Indirect	Indirect		
SDG 12 Resp. Consumption					Indirect
SDG 13 Climate Action					Indirect
SDG 14 Life Below Water	Indirect	Indirect			Indirect
SDG 15 Life on Land	Indirect	Indirect			Indirect
SDG 16 Peace & Justice			Indirect		
SDG 17 Partnerships	Inst.				

Direct: India-specific causal evidence
 Indirect: programme-level reach
 Direct: institutional (e.g. SHG-BLP)
 Descriptive only / no linkage

Figure 4. MSIA framework: SDG coverage by evidence tier (based on Table 7). Cell shading indicates the strength of the available India-specific evidence for each SDG–dimension combination.

5. DISCUSSION

5.1 What the rigorous evidence supports – and what it does not

Three claims that recur in the policy literature are inconsistent with this evidence base. First, the global average effect of microcredit on consumption is small (Banerjee, Karlan, and Zinman, 2015; Meager, 2019), and average household consumption per capita has not been shown to rise in India (Banerjee, Duflo, Glennerster, and Kinnan, 2015; Christian *et al.*, 2023). Second, the long-run Hyderabad follow-up (Banerjee *et al.*, 2024) reports that prolific entrepreneurs roughly double revenues at six years while reluctant entrepreneurs realise no persistent benefit, indicating that the average effect masks a policy-relevant distribution. Third, the effect of microcredit on health outcomes is null (Banerjee *et al.*, 2015), and SHG-attached health programmes shift behaviours without reducing out-of-pocket expenditure (Saha, 2015); enterprise investment rises, but per-borrower employment-creation effects remain modest in any credibly identified specification.



A further set of MSIA dimensions lacks any India-specific causal study with a measured effect size, namely microfinance and household clean-energy adoption (SDGs 7 and 13) and SHG/MFI participation in post-harvest losses (SDG 2). Programme architecture is real and expanding on both fronts, most visibly through the NABARD Solar SHG Mission and the NABARD-ICAR climate-resilient agriculture pilots. The framework retains these dimensions as descriptive-evidence-only and advances no quantitative claim about household impact pending primary causal work.

5.2 Engagement with the skeptical literature

Three streams of skeptical scholarship merit specific engagement. Bateman and Chang (2009) contend that microfinance has been promoted on institutional rather than evidentiary grounds, and that it fragments capital into low-productivity self-employment in lieu of supporting industrial transformation. The framework partly corroborates this critique: approximately 65% of GLP flows to income-generation lending, where average causal effects are modest. The long-run heterogeneity finding of Banerjee *et al.* (2024) nonetheless demonstrates that microfinance enables sustained enterprise scaling for a meaningful sub-population, and the SHG-BLP's 83.5% exclusively-women-led structure, with documented empowerment effects (Kochar *et al.*, 2022), constitutes a channel against which the structural critique offers no comparable rebuttal.

Duvendack *et al.* (2011), in the most-cited DFID-commissioned systematic review, conclude that the microfinance impact evidence base is methodologically weaker than the literature implies, with most studies compromised by selection bias or unaddressed endogeneity. The risk-of-bias appraisal in Section 3.7 takes this concern seriously: of fourteen cited studies, nine carry low risk, four moderate, and one serious, a more nuanced picture than either Duvendack *et al.*'s blanket pessimism or the practitioner literature's blanket optimism. The post-2015 RCT corpus, post-dating Duvendack *et al.* (2011), substantially strengthens the methodological foundation.

Morduch (2020) argues that the first-generation microcredit RCTs were not designed to estimate average effects of microcredit, focused instead on marginal borrowers in marginal locations, and have been systematically over-interpreted. The framework treats this as a binding constraint on inference: the cross-country "modestly positive, possibly negligible" finding describes the average effect of expanding microcredit to marginal customers across seven study sites, not the population effect of microfinance as an institution in India. India-specific causal evidence (Imai *et al.*, 2010; Balasundaram *et al.*, 2025; Kochar *et al.*, 2022) therefore remains the operative anchor in lieu of cross-country aggregation, and the primary survey proposed in Section 5.4 is designed to capture institutional-level effects.

5.3 Implications and limitations

For the Reserve Bank of India and NABARD, the calibrated framework supports refinement of Priority Sector Lending norms through weighted incentives directed at channels for which causal evidence is strongest (SDGs 1, 4, 5, and 10) and at channels for which loan size is the binding constraint on impact (SDG 5; Kochar *et al.*, 2022). For MFI practitioners, the framework functions as a portfolio-mix diagnostic. Because SHG group structure rather than credit alone appears to be the operative mechanism for child human capital accumulation, group-based delivery models warrant retention even where digital disbursement is feasible. For international development organisations, the framework offers a benchmark instrument that distinguishes documented impact from aspirational programme-level claims. The FY25 contraction in the MFI/JLG channel and the concurrent expansion in the SHG-BLP channel (Section 4.1) indicate that some of this rebalancing is already occurring through market and policy adjustments, which strengthens the feasibility of the proposed PSL refinements.

Four limitations bound these implications. First, the framework is a conceptual instrument and has not yet been validated against primary household-level data. Second, several MSIA dimensions, most notably Environmental Sustainability, rest on descriptive evidence alone. Third, the rigorous India causal literature is concentrated in a small number of well-identified studies; this is the appropriate evidence base, but it is narrower than the breadth of the policy literature implies. Fourth, the sector-exposure mapping in Table 6 relies on declared loan-purpose data from MFIs and Sa-Dhan that may diverge from actual end-use, and household-level use-of-funds tracking would refine the exposure shares. The headline analyses also have a temporal cutoff at FY24: Sa-Dhan's Bharat Microfinance Report 2025 documents a sharp FY25 channel reversal (Section 4.1), and the framework's predictions for the post-FY24 trajectory should be revisited as NABARD SOMFI 2024-25 and FY26 sector data become available.

5.4 Future directions

The framework and the model in Section 2 jointly generate four hypotheses for a primary survey of approximately 600 microfinance client households (NCR sample or comparable urban-rural mix, with sample size targeting 80% power to detect a 20-percentage-point treatment difference). Hypotheses are stated as predictions that primary-data analysis is designed to falsify.



H1 (loan-size threshold for empowerment) predicts that women's decision-making index, household-budget control, and asset-ownership rate increase with cumulative loan-cycle borrowing only above a threshold of approximately ₹40,000-50,000, with negligible effect below that threshold (replicating and quantifying Kochar *et al.*, 2022). H2 (group-structure dominance for child human capital) predicts that children's secondary-enrolment rates are higher in SHG-member households than in MFI-only borrower households, conditional on credit-access volume, with the model predicting $\alpha_k < \alpha_e$ (testing the Baland *et al.*, 2020 versus Banerjee, Duflo, Glennerster, and Kinnan, 2015 mechanism distinction). H3 (heterogeneity in enterprise returns) predicts that, conditional on receiving microfinance, households with prior business experience exhibit enterprise asset growth at least 25% higher than reluctant entrepreneurs over a 36-month horizon, with the effect concentrated in the upper quartile (testing Banerjee *et al.*, 2024 in an Indian urban context). H4 (clean-energy null) predicts that microfinance access has no measurable effect on solar-home-system, biogas, or clean-cookstove adoption when unbundled from subsidy or technology delivery (testing the SDG 7/13 channel presently classified as descriptive-evidence-only).

Beyond the proposed primary survey, five research priorities follow. First, numerical calibration of the production-function model of Section 2, assigning point estimates and confidence intervals to α_e , α_k , α_h , and ρ from the four identifying studies, and conducting the validation check against Christian *et al.* (2023) and Hoffmann *et al.* (2021), is the immediate next step that the present paper enables. The calibration requires interpretive choices regarding which outcome variable proxies each Y_j and how to translate treatment intensity into $\Delta \ln L$ and $\Delta \ln G$, and the articulation and defence of these choices is itself a research contribution. Second, a randomised or quasi-experimental study of green microfinance and clean-energy adoption in India, constructed as a microfinance-mediated replication of the Aklin *et al.* (2017) design that varies subsidy intensity against credit terms, would close the largest evidence gap in the SDG 7/13 channel. Third, replication of the Kochar *et al.* (2022) loan-size finding outside Bihar and Uttar Pradesh would strengthen confidence in the loan-size-as-binding-constraint interpretation of the empowerment channel. Fourth, long-term follow-up of the Baland *et al.* (2020) Jharkhand cohorts would establish whether the secondary-enrolment effect translates into completed schooling and labour-market outcomes. Fifth, a Bayesian hierarchical meta-analysis in the tradition of Meager (2019), restricted to India studies and stratified by MSIA dimension, would yield the first methodologically defensible pooled-effect estimates of microfinance impact in India.

6. CONCLUSION

This paper develops a household production model and an evidence-tier-based diagnostic that together map Indian microfinance to the seventeen Sustainable Development Goals. The framework supports a rebalanced Priority Sector Lending architecture: weighting incentives toward channels where India-specific causal evidence is strongest, and commissioning the primary research that the income-generation channel still lacks.

Author contributions

Both authors contributed equally to the conceptualisation, analysis, and writing of this paper.

Conflict of interest

The authors declare no conflict of interest.

Data availability statement

The institutional data analysed in this study are publicly accessible from the cited sources: the Microfinance Institutions Network (MFIN) Micrometer Q4 reports; the National Bank for Agriculture and Rural Development (NABARD) Status of Microfinance in India reports; the Reserve Bank of India regulatory notifications; the NITI Aayog SDG India Index; and Sa-Dhan's Bharat Microfinance Report 2025. All other data analysed are derived from the published peer-reviewed studies cited in the references. No new primary data were generated for this study.

REFERENCES

1. Aklin, M., Bayer, P., Harish, S. P., & Urpelainen, J. (2017). Does basic energy access generate socioeconomic benefits? A field experiment with off-grid solar power in India. *Science Advances*, 3(5), e1602153. <https://doi.org/10.1126/sciadv.1602153>
2. Baland, J.-M., Demont, T., & Somanathan, R. (2020). Child labor and schooling decisions among self-help group members in rural India. *Economic Development and Cultural Change*, 69(1), 1–39. <https://doi.org/10.1086/702792>
3. Balasundaram, E., Aranganathan, P., Cailassame, N. S. N., Mathiazhagan, A., Vinoth, A., & Gajendran, A. (2025). The impact of digital financial inclusion on income inequality in rural India: A spatial econometric and mixed-methods analysis. *The Indian Economic Journal*. <https://doi.org/10.1177/00194662251332866>
4. Banerjee, A., Breza, E., Duflo, E., & Kinnan, C. (2024). Can microfinance unlock a poverty trap for some entrepreneurs? Evidence from a six-year follow-up of a randomized controlled trial. NBER Working Paper No. 26346. <https://doi.org/10.3386/w26346>



5. Banerjee, A., Duflo, E., Glennerster, R., & Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. *American Economic Journal: Applied Economics*, 7(1), 22–53. <https://doi.org/10.1257/app.20130533>
6. Banerjee, A., Karlan, D., & Zinman, J. (2015). Six randomized evaluations of microcredit: Introduction and further steps. *American Economic Journal: Applied Economics*, 7(1), 1–21. <https://doi.org/10.1257/app.20140287>
7. Bateman, M., & Chang, H.-J. (2009). The microfinance illusion. Available at SSRN. <https://doi.org/10.2139/ssrn.2385174>
8. Christian, P., Kandpal, E., Palaniswamy, N., & Rao, V. (2023). Scale and sustainability: The impact of a women's self-help group program on household economic well-being in India. *Journal of Development Studies*, 59(11), 1745–1768. <https://doi.org/10.1080/00220388.2022.2154151>
9. Demont, T. (2022). Coping with shocks: How self-help groups impact food security and seasonal migration. *World Development*, 155, 105892. <https://doi.org/10.1016/j.worlddev.2022.105892>
10. Duvendack, M., Palmer-Jones, R., Copestake, J. G., Hooper, L., Loke, Y., & Rao, N. (2011). What is the evidence of the impact of microfinance on the well-being of poor people? EPPI-Centre, University of London. ISBN 978-1-907345-19-7.
11. Field, E., Pande, R., Papp, J., & Rigol, N. (2013). Does the classic microfinance model discourage entrepreneurship among the poor? Experimental evidence from India. *American Economic Review*, 103(6), 2196–2226. <https://doi.org/10.1257/aer.103.6.2196>
12. Hoffmann, V., Rao, V., Surendra, V., & Datta, U. (2021). Relief from usury: Impact of a self-help group lending program in rural India. *Journal of Development Economics*, 148, 102567. <https://doi.org/10.1016/j.jdeveco.2020.102567>
13. Holvoet, N. (2004). Impact of microfinance programs on children's education: Do the gender of the borrower and the delivery model matter? *Journal of Microfinance*, 6(2), 27–49.
14. IFC. (2023). Green Microfinance Guidelines: ESG Portfolio Standards for MFIs. International Finance Corporation. Washington, DC.
15. Imai, K. S., Arun, T., & Annim, S. K. (2010). Microfinance and household poverty reduction: New evidence from India. *World Development*, 38(12), 1760–1774. <https://doi.org/10.1016/j.worlddev.2010.04.006>
16. Imai, K. S., Gaiha, R., Thapa, G., & Annim, S. K. (2012). Microfinance and poverty – A macro perspective. *World Development*, 40(8), 1675–1689. <https://doi.org/10.1016/j.worlddev.2012.04.013>
17. IRDA. (2022). Annual Report 2021–22. Insurance Regulatory and Development Authority of India. Hyderabad.
18. Jensen, A. C. H., & Naveed, A. (2025). Assessing the role of microfinance in mitigating income inequality: New evidence from a global context. *Social Indicators Research*, 179(1), 371–397. <https://doi.org/10.1007/s11205-025-03608-8>
19. Kochar, A., Nagabhushana, C., Sarkar, R., Shah, R., & Singh, G. (2022). Financial access and women's role in household decisions: Empirical evidence from India's National Rural Livelihoods Project. *Journal of Development Economics*, 155, 102829. <https://doi.org/10.1016/j.jdeveco.2021.102829>
20. Lacalle-Calderon, M., Larrú, J. M., Garrido, S. R., & Perez-Trujillo, M. (2019). Microfinance and income inequality: New macrolevel evidence. *Review of Development Economics*, 23(2), 860–876. <https://doi.org/10.1111/rode.12573>
21. Meager, R. (2019). Understanding the average impact of microcredit expansions: A Bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics*, 11(1), 57–91. <https://doi.org/10.1257/app.20170299>
22. MFIN. (2024). Micrometer Q4 FY2023–24. Microfinance Institutions Network. New Delhi. <https://mfinindia.org>
23. Morduch, J. (2020). Why RCTs failed to answer the biggest questions about microcredit impact. *World Development*, 127, 104818. <https://doi.org/10.1016/j.worlddev.2019.104818>
24. NABARD. (2023). Status of Microfinance in India 2022–23. National Bank for Agriculture and Rural Development. Mumbai. <https://nabard.org>
25. NABARD. (2024). Status of Microfinance in India 2023–24. National Bank for Agriculture and Rural Development. Mumbai. <https://nabard.org>
26. NABCONS. (2022). Study to Determine Post-Harvest Losses of Agri Produce in India. NABARD Consultancy Services. New Delhi.
27. NITI Aayog. (2023). National Multidimensional Poverty Index: Progress Review 2023. Government of India. <https://niti.gov.in>
28. Ozili, P. K. (2022). Financial inclusion and sustainable development: An empirical association. MPRA Paper 113789 / SSRN 4086856. <https://mpra.ub.uni-muenchen.de/113789/>
29. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>
30. RBI. (2023). Framework for Acceptance of Green Deposits. Reserve Bank of India. <https://rbi.org.in>
31. RBI. (2023–24). Report on Trend and Progress of Banking in India 2023–24. Reserve Bank of India. <https://rbi.org.in>
32. Sa-Dhan. (2023). Bharat Microfinance Report 2023. Sa-Dhan. New Delhi. <https://sa-dhan.net>
33. Sa-Dhan. (2025). Bharat Microfinance Report 2025 (FY 2024–25 data). Sa-Dhan. New Delhi. <https://www.sa-dhan.net>
34. Saha, S. (2015). Effect of combining a health program with a microfinance-based self-help group on health behaviors and outcomes. *Global Health Action*, 8(1), 27535. <https://doi.org/10.3402/gha.v8.27535>
35. SIDBI. (2023). MSME Finance Report 2022–23. Small Industries Development Bank of India. Mumbai.
36. SPTF. (2023). Universal Standards for Social Performance Management (3rd ed.). Social Performance Task Force. <https://sptf.info>
37. Sterne, J. A. C., Hernán, M. A., Reeves, B. C., Savović, J., Berkman, N. D., Viswanathan, M., et al. (2016). ROBINS-I: A tool for assessing risk of bias in non-randomised studies of interventions. *BMJ*, 355, i4919. <https://doi.org/10.1136/bmj.i4919>
38. Sterne, J. A. C., Savović, J., Page, M. J., Elbers, R. G., Blencowe, N. S., Boutron, I., et al. (2019). RoB 2: A revised tool for assessing risk of bias in randomised trials. *BMJ*, 366, l4898. <https://doi.org/10.1136/bmj.l4898>



39. Swain, R. B., & Floro, M. (2012). Assessing the effect of microfinance on vulnerability and poverty among low income households. *Journal of Development Studies*, 48(5), 605–618. <https://doi.org/10.1080/00220388.2011.615917>
40. Tarozzi, A., Mahajan, A., Blackburn, B., Kopf, D., Krishnan, L., & Yoong, J. (2014). Micro-loans, insecticide-treated bednets, and malaria: Evidence from a randomized controlled trial in Orissa, India. *American Economic Review*, 104(7), 1909–1941. <https://doi.org/10.1257/aer.104.7.1909>
41. United Nations. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. United Nations General Assembly Resolution A/RES/70/1. <https://sdgs.un.org/2030agenda>
42. United Nations. (2024). *The Sustainable Development Goals Report 2024*. United Nations Department of Economic and Social Affairs. New York. <https://unstats.un.org/sdgs/report/2024/>
43. UNEP Finance Initiative. (2023). *ESG-Aligned Microfinance Guidelines*. United Nations Environment Programme Finance Initiative. Geneva.
44. World Bank. (2021). *The Global Findex Database 2021*. World Bank Group. <https://doi.org/10.1596/978-1-4648-1694-9>