TRANSFORMING RURAL LIVELIHOODS IN INDIA

Findings from NRETP and NRLM evaluation

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Executive summary

Introduction

Sustained growth in rural incomes requires a transition to a non-agrarian economy capable of significant increases in wages and employment. This transition often faces structural obstacles: small village populations and low levels of schooling help explain the continued dependence on agriculture and corresponding low incomes. These features shrink local market size to raise the costs of delivering credit, livelihood training and other services. Traditional income-enhancing policies do not address these fundamental constraints. Instead, they seek new ways to deliver inputs to small groups of relatively poor households, producing only modest income gains.

In 2011, the Government launched the Deen Dayal Antyodaya National Rural Livelihood Mission (NRLM), marking a major policy shift for rural income growth. Unlike traditional approaches, NRLM tackles the structural barriers to a non-agricultural transition through a multi-phased, large-scale program. As of March 2025, the programmecovered 745 districts and 7,144 blocks across India's 28 states and 6 Union Territories, reaching over 91 million women.

Its first phase establishes a federation of community institutions that links households within and across villages. The base unit of the federation, the Self-Help Group (SHG), typically consists of about 10 women who live in close proximity to each other. SHGs are federated at village level into Village Organizations (VOs) and across adjoining villages into Cluster Level Federations (CLFs). As the programmeexpands to cover additional villages and more households, VOs and CLFs grow in size. Full coverage of all villages and target households occurs gradually over an 8—10-year period.

NRLM's second phase uses the extended network created by the federation to implement new income-enhancing arrangements and interventions. The largest of these is the National Rural Economic Transformation Project (NRETP), introduced in 2019—almost a decade after NRLM began. NRETP follows a similar incremental rollout, initially targeting investments to a relatively small set of villages and households.

This phasing, together with prior investment in the federation, addresses structural barriers and creates potential for large returns to narrowly targeted interventions. The federation lowers the delivery costs across many small villages, reducing disadvantages of small market size. For example, training can be given to CLF office-bearers, who then train office bearers at lower levels. The federation's scale also builds links between members of different socio-economic and educational backgrounds, helping those with limited schooling to benefit.

NRLM's evolution over time affects evaluations of its impact. First-phase studies estimate returns to federation growth in the absence of significant income-enhancing interventions like NRETP, while second-phase studies estimate the combined impact of the federation plus NRETP. Thus, the first-and second-phase results are not directly comparable because they evaluate different programme packages.

Both study types matter policy. For example, determining if the additional costs of income-enhancing interventions are justified requires knowing whether similar benefits

result from Phase 1 investments in the federation alone. Likewise, policymakers need to understand if investing in the federation is necessary to ensure returns on the second layer of income-enhancing interventions.

This study therefore provides two sets of causal estimates of NRLM's impact on income, consumption, and other household welfare measures, along with a descriptive analysis of programme functioning. The first set estimates the impact of the foundational investment in the federation of community institutions on household outcomes over the medium-run (about eight years) relative to the short-run (about four years). These investments exclude income-enhancing investments introduced in NRLM's later stages. Our second set of estimates measures the returns to the combined investment in the federation and the income-enhancing investments undertaken under NRETP.

The difference between these two sets of estimates does not separate NRLM's impact through income-enhancing interventions from those that are purely a consequence of the growth of the federation. Consider the case of an income intervention that confers gains only on a few households. NRLM's set of community institutions may allow these gains to "spillover" to improve the incomes of a larger number of households because of factors such as social learning and information dissemination among members. In such cases, it is hard to disentangle the combined effect of the federation and of income-enhancing investments.

A unique NRETP sub-component; the Model Cluster Level Federation (MCLF) program, aims to ensure CLFs operate as NRLM guidelines intend. Implemented in roughly one cluster per NRETP block, MCLF provides additional funding to CLFs, primarily to cover salaries for the required cluster-level staff. This creates NRETP clusters that differ in federation strength yet are similar in other respects (for example, the scale of NRETP investments). Differences in outcomes between MCLF and non-MCLF clusters therefore indicate the importance of federation strength.

Evaluations of other sub-programs offer the opportunity for additional policy insights. In particular, preliminary results from an on-going evaluation of a second sub-component, the Integrated Farming Cluster (IFC), discussed in this summary, suggest policies that could enhance returns to second phase of income-enhancing investments.

Methodological approach

Our analysis builds on an earlier study of NRLM conducted in 2019 using survey data on households in 9 states.[1] The study sample was divided across NRLM's early blocks, those in which the programme commenced around 2011-12, and late blocks in which NRLM was introduced in 2015 or later. Of the 25,860 households surveyed in 2019, 23,178 were re-surveyed in 2024[2]. Though the 2019 survey was designed prior to policy decisions regarding the choice of NRETP blocks or MCLF clusters, 58% of the sample of early blocks were included in NRETP. Of NRETP sample clusters, 23% were MCLFs.[3]

[1] These are: Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, Maharashtra, Odisha, Rajasthan, West Bengal and Uttar Pradesh.

[2] 10.4% of households present at baseline (2019) could not be followed at endline (2024).

[3] The division of the sample into early and late blocks and of clusters into NRETP and MCLF clusters varies in regression samples, due to the need to ensure the comparability of treatment and control samples. For examples, states in which all early blocks were included in NRETP were dropped from the analysis of NRETP impacts due to the absence of a control sample for that state.

The lack of a sample dating back to NRLM's start (in 2011) combined with the fact that its coverage extended to all households and villages by 2024 implies that we cannot estimate NRLM's "full" impact on households from its start to its current stage. We can, however, use the 2019 and 2024 surveys to estimate NRLM's impact in the medium relative to the short term. Because the 2019 survey was conducted prior to NRETP's launch, the two surveys also enable credible estimates of NRETP's impact over this five-year period.

We estimate causal impacts as the difference in the five-year growth in income, consumption and other household outcomes in "treatment" samples and that in a comparable "control" sample. NRLM's early blocks serve as the treatment sample for our analysis of the program's medium-term effects. By 2019, at the time of the first survey, NRLM had been running in these blocks for about 8 years. Households in late blocks, exposed to the programme for four years by 2019, constitute the control sample.

To evaluate NRETP's impact, we restrict our analysis to the early block sample and compare the change in outcomes in NRETP blocks (treatment) to those in non-NRETP early blocks (control). Similarly, estimates of MCLF's impact compare households in MCLF clusters of NRETP blocks (treatment) to households in non-NRETP early blocks (control). To contrast our MCLF results to NRETP implementation in non-MCLF clusters, we re-estimate NRETP's impact using the same control sample but redefining the treatment sample to include only households in non-MCLF NRETP clusters.

Overview of findings: implementation

Federations: We document unprecedented federation growth since NRLM's inception. Between 2019 and 2024 membership of SHGs and VOs in CLFs in our sample states rose sharply: the share of surveyed VOs reporting CLF membership increased from 62% to 79%. MIS data supports this increasing trend of federation growth at the national level as well.

NRETP: Survey data on household participation in Producer Enterprises (PE) or Producer Groups (PG), smaller production clusters and other new institutional arrangements supported by NRETP confirm NRETP's narrowly targeted nature. Data from village surveys reveals that 23% of NRETP villages report the presence of livelihood institutions promoted under NRETP. This data accords with available MIS data on producer groups. Even in states such as Maharashtra that favor producer groups, the proportion of NRETP villages reporting functioning PGs is approximately 25%.

CLFs: 2024 survey data on CLF performance indicators such as the number of functioning sub-committees, cluster-level staff and trainings for office bearers suggest difficulties in meeting mandated performance standards in this period of high federation growth. 52% of CLFs in our survey reported functioning sub-committees for monitoring VOs and SHGs. 21% of CLFs have Livelihood committees. In most respects, Model CLFs perform better than their counterparts in other blocks. For example, the proportion of model CLFs reporting a livelihood sub-committee (58%) far exceeds the proportion in non-MCLF NRETP clusters (19%). Similarly, while 58% of model CLFs report up-to-date Minutes Registers, only 26% of non-MCLFs do so.

The functioning of a CLF and its member units requires both administrative capacity and financial resources. Sub-committees, for example, are managed and operated by boards that consist of CLF office-bearers and block and cluster-level staff. Conducting their operations also requires funds for travel, meetings and other items of expenditure. This suggests that any advantage of model CLFs may be a consequence of the additional funds provided to them to meet necessary expenditure, including staff salaries.

Our 2024 survey data reveals that model CLFs received larger amounts of Community Investment Funds (CIF) per SHG. This is surprising, given programme guidelines which mandate that each SHG get the same amount of CIF funds, regardless of the block in which they are located. However, on-going research on model CLFs suggests that these differences in CIF funding existed in 2019. Thus, the growth in CIF funding in MCLF clusters between 2019 and 2024 is like that in other clusters.

SHGs: While the body of this report includes extensive information on the functioning of SHGs, this summary highlights one particularly noteworthy feature: member exits and entries. Most SHGs report some members choosing to leave the SHG, particularly in the case of older SHGs. These members are usually replaced by new members. Our survey data reveal that new members tend to be younger and more educated, so that member entry and exit alter the socio-economic profile of SHG members.

Overview of findings: impact

NRLM Federation: Comparing the impact of the federation in the medium- relative to the short-term, our estimates suggest an average increase of 8.5% in per capita household expenditure and a 10% increase in household income in constant INR. Thus, even in the absence of significant layering of income-enhancing investments, the continued expansion of the federation improves consumption and income.

These improvements, however, do not appear to represent a structural transformation that reduces the importance of the agricultural sector and improves that of the non-farm sector. The increase in consumption, for example, primarily reflects increased expenditure on food items. There is no increase in borrowing for productive investments or in women's occupational patterns. There is an increase in the proportion of male family members who work as skilled non-agricultural laborers, a sector that accounted for a small proportion of working males in 2019. Thus, the growth in employment in this sector is not sufficient to generate large changes in the economy.

NRETP: While our analysis of NRETP over the 2019-24 period suggests similar improvements in per capital consumption, the program's impact on household income significantly exceeds that of non-NRETP blocks. The highest estimate, from a range of regression specifications, suggests that NRETP increased household income by 27% over this 5-year period.

This significant growth in incomes may reflect NRETP's greater success in reducing reliance on the agricultural sector. Households in NRETP blocks increase their expenditure on non-food items, devoting a smaller share of total expenditure to food. Ownership of assets used for production also increases as do loans for these investments and for working capital requirements. NRETP also increases the participation of men and women in the workforce. For women, these increases are

primarily in the family farm. Men, however, report large increases in their hours of work in the market for unskilled non-agricultural labor, a relatively large sector that accounted for 32% of the male workforce in 2019.

MCLF: Comparing outcomes in MCLF clusters of NRETP blocks to that in other clusters reveals that the increase in income in NRETP blocks primarily reflects income growth in MCLF clusters. Our estimates suggest income gains ranging from 12 to 33% (across different regression specifications) in MCLF clusters, while non-MCLF clusters of NRETP blocks record smaller improvements, ranging from 6-10%. Similarly, consumption growth in MCLF clusters (11-17%) exceeds that in non-MCLF NRETP clusters (4-10%).

Social outcomes: Our report also estimates NRETP's impact on a range of social outcomes such as women's membership in networks and their norms and beliefs on topics such as work participation and gender roles. Because survey questions to measure these outcomes were only included in the 2024 survey, we estimate NRETP's impact through a simple comparison of outcomes in NRETP blocks relative to non-NRETP early blocks. [4] One striking result is that NRETP lowers the proportion of women who hold "regressive" beliefs regarding women's participation in the work force and women's social and economic roles relative to men. A second is that NRETP helps increase the size of a woman's network, measured as the number of friends she can turn to for help or advice in a variety of fields.

Interpretation

Taken together, our results suggest that targeted investments in livelihoods and income, such as those supported by NRETP, are most likely to generate structural change and rapid income growth. While the continued growth of the federation in the absence of livelihood interventions still supports small consumption loans, investments in productive assets and the growth of the non-agricultural sector require targeted livelihood interventions.

The importance of the federation*.* Multiple factors can explain the large income gains in NRETP clusters, despite the program's targeted nature. One explanation is that households who benefit directly from NRETP investments raise their demand for hired labor, conferring gains on other households. Alternatively, spillover benefits to other households may reflect gains from NRLM's phase-1 investments in expanding and strengthening federations.

Our evaluation of MCLF helps explain pathways. Higher income returns in MCLF clusters imply that these CLFs differ from those in other clusters. Data discussed in the body of this report suggest that this advantage does not reflect additional investments under NRETP[5] or greater access to CIF and other funds. This rules out the possibility that the advantage of MCLF clusters reflects higher levels of investment and hence labor demand, relative to that in other clusters.

[4] The similarity of households in these blocks, as measured by 2019 survey data on socio-economic outcomes, suggests the validity of this comparison. We do not evaluate NRLM's medium- to short-run impact for these outcomes because of significant differences in 2019 outcomes across households in early blocks and late blocks

[5] We note, however, that this statement is based on MIS data on producer groups and warrants additional research.

Instead, the data suggest that MCLF clusters differ from others primarily in their additional staff strength and administrative capacity and, consequently, in their performance. Put differently, consistent with the program's objective, the model CLF programme strengthens the federation so that it better meets expected performance standards. This supports the view that strong federations help magnify the benefits of narrowly targeted income interventions, validating NRLM's strategy of first investing in the growth and development of the federation and then layering on income-enhancing interventions on mature federations.

We note, however, that our surveys provide data on relatively few CLFs. Additional research, based on more extensive CLF surveys, are required to substantiate our inferences.

Improving income gains Because NRETP investments target villages with good market access, they frequently result in activities being clustered in a set of adjoining villages. Despite this, the fact that NRETP benefits relatively few households in any given village limits income gains.

The Integrated Farming Cluster (IFC) programme provides evidence on the improvements possible with a greater scale of activity in a set of adjoining villages. The provides new production activities to approximately 100 households in each of three villages that form a IFC cluster, a number that contrasts with the 15-30 members of a village that benefit from the formation of a producer group. Equally important, it supports enterprises that serve existing farm and non-farm enterprises either through backward or forward linkages. This coordinated push improves the profitability of all enterprises and helps strengthen local markets.

Our preliminary estimates of Maharashtra's experience with IFC suggest that income returns are higher in clusters that feature a concentration of livelihood activities. However, we also find that villages engage with markets other than those in defined IFC clusters; it is the level of activity in all surrounding villages that matter.

As with our inferences regarding the importance of the federation, we note that our research on IFC is in its preliminary phases and that it is restricted to a small number of villages in Maharashtra. More research is required to support these claims.

Policy recommendations and the way forward

1. **Ensure adequate CLF staff and administrative capacity:** Our evaluation of the Model CLF programme suggests that income-enhancing interventions have their largest impact when implemented in clusters with strong CLFs. The data suggest that a primary reason for this is the ability of MCLFs to ensure staff strength and hence high administrative capacity. This suggests the importance of prioritizing the availability of adequate cluster-level staff. We note that staff strength and measures of performance in MCLFs, though higher than that in other clusters, still leave room for improvement.
2. **Emphasize managerial skills:** Data on weak book-keeping practices, even in new livelihoods institutions such as Producer Groups that are aided in their operations by cluster-level staff, suggest the importance of management training. Managerial skills facilitate accurate book-keeping but also improve the

functioning of federation units. For example, our data suggest that available funds are not always used to finance needed expenditure and that very few CLFs use available funds to hire CRPs and other staff. Improved managerial skills may ensure that funds are utilized to improve performance. Training in business skills may be more important in this regard than financial literacy training.

3. **Monitor bank-linkage effects on CLF financial sustainability**. The concluding chapter of this report suggests other features of the programme that may affect the sustainability of the federation, such as reductions in interest income that accompany a shift towards greater reliance on bank loans.
4. **Keep institutions dynamic:** The entry and exit of members helps keep SHGs vibrant through the introduction of younger members with higher levels of schooling. Membership drives to solicit new members should be encouraged, with the intent of placing new members in existing SHGs rather than forming new SHGs. The transition of membership within a household should also be encouraged.
5. **Transition SHGs from primarily credit providers to engines of income and social growth:** NRLM's impact on informal sector interest rates and access to bank loans implies that the value of SHGS as a source of loans will fall over time. This requires SHGs to transition to other roles so as to ensure the value of membership. Income growth and strengthened local markets suggest a growing role for SHGs in knowledge transfer and information dissemination. To develop this role, we recommend greater use of the federation for information dissemination and learning, similar to the model used in the Visioning exercises conducted by model CLFs. In particular, we suggest the introduction of training in life skills through a federation-intensive process.
6. **Maximise returns to income-enhancing investments through geographic focus.** Isolated investments scattered across villages that benefit just a few households are unlikely to have large effects. Our preliminary results from IFC suggest that a coordinated "big push" in productive activity in clusters of adjoining villages are likely to have large effects. These clusters may, by necessity, include villages in different administrative clusters and even in different blocks. That is, the focus should be on an appropriately defined local market rather than on an arbitrarily selected set of 3 villages within any given cluster.

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Abbreviations and acronyms

Abbreviation	Full Form
AAP	Annual Action Plan
ATT	Average Treatment Effect on the Treated
BC	Business Correspondent
BL	Baseline
CB-farm	Farm Capacity Building
CB-NF	Non-farm Capacity Building
CEF	Community Enterprise Fund
CIF	Community Investment Fund
CIS	Community Investment Support
CLF	Cluster Level federation
CRP	Community Resource Person
DMMU	District Mission Management Unit
EB	Early Block
EV	Early Village
FNHW	Food, Nutrition, Health and WASH
FSF	Food Security Fund
GDP	Gross Domestic Product
GP	Gram Panchayat
HQ	Headquarter
HRF	Health Risk Fund
IBCB	Institutional Building and Capacity Building
iCRP	Internal Community Resource Person
IFC	Integrated Farming Clusters
IHCB	Institutional and Human Capacity Building
INR	Indian Rupee
IPW	Inverse Probability Weighting
ITT	Intention to Treat
LFPR	Labour Force Participation Rate
LH	Livelihood
MCLF	Model Cluster Level Federation
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
MIS	Monitoring Information system
N	Number of Observations
NRETP	National Rural Economic Transformation Project
NRLM	National Rural Livelihoods Mission
NRLP	National Rural Livelihoods Project
OSF	One Stop Facility
PDS	Public Distribution System
PE	Producer Enterprise
PG	Producer Group
PRI-CBO	Panchayati Raj Institutions – Community Based Organizations
RA	Regression Adjusted
RF	Revolving Fund
SC	Scheduled Caste

Abbreviation	Full Form
SGSY	Swarnjayanti Gram Swarozgar Yojana
SHG	Self-Help Groups
SMMU	State Mission Management Unit
SRLM	State Rural Livelihood Mission
ST	Scheduled Tribe
SVEP	Start-up Village Entrepreneurship Programme
ToT	Treatment on Treated
VO	Village Organisation
VGF	Vulnerability Gab Fund
VRF	Vulnerability Reduction Fund
WASH	Water, Sanitation and Hygiene

1. Introduction

The National Rural Livelihoods Mission (NRLM) was initiated in 2011, at a time when the Indian economy was growing at a relatively fast rate but with this growth characterized by high and persistent poverty. In the decade 1998-2008, India's GDP growth rate was 7.2%. However, poverty also increased significantly in this period: the number of households living on less than INR 62.5 ($1.25) also grew by 3.5 crores over this period.[6] In this context, the NRLM was formed to promote inclusive growth with significant reductions in poverty through expanding livelihood opportunities for socially and economically disadvantaged groups. As detailed later in this report, the approach represented a paradigm shift from conventional welfare-based approaches to a rights-based approach with strong community involvement to ensure a change in civic society.

NRLM planning documents noted the severe challenges that had to be overcome to achieve this objective. Of these, the first was the lack of effective institutional platforms that ensured the poor a collective voice and bargaining power, factors required for an enabling environment sensitive to their needs and priorities. In the absence of such a platform, the lives of India's poor and particularly her women would always be dictated by others.

A second challenge was that the rural poor constituted a set of "scattered and fragmented producers and users of services", and hence suffered from the considerable disadvantage and diseconomies that followed from such fragmentation. Small farm size and lack of an institutional platform resulted in limited integration with markets; NRLM's implementation plan noted that the total marketed surplus of foodgrains at the project's onset was estimated to be 52% of total production, with 65% of the sale of agricultural commodities being conducted within the village.

Underlying this lack of market integration was the high cost of delivering services to rural households, given small village sizes and low levels of infrastructural development. Lack of access to formal credit was a primary constraint: In 2009, only 18% of poor households reported access to credit from formal sources.

A third challenge was the riskiness of the rural environment. This was a consequence of weather-related risks and their effect on the variance of agricultural and hence rural incomes. But it also importantly reflected limited investment in water, sanitation, and other local public goods affecting health. At NRLM's start, 15% of household expenditure was on health, and concerns about food security and health dominated the minds of the rural poor, affecting their investment choices and hence their prospects for significant improvements in income.

To these identified challenges, we add the dismally low levels of schooling of rural households, particularly rural women. In the 9 study states of this report, the mean female literacy rate in 2011 was just 54%.[7] It was even lower amongst the poorer households of these villages, who were the targeted population under NRLM. Even a

[6]These data and the references to the programme's implementation plans in this section are from Government of India, Ministry of Rural Development, National Rural Livelihoods Mission: Programme Implementation Plan.

[7] These data are from India's 2011 census.

decade later, at the time of our 2019 survey, 46% of women in our survey over the age of 18 lacked formal schooling. The proportion of women with more than 8 years of schooling was just 27%. Compounding the disadvantage of low schooling were gender disparities in schooling and other socio-economic indicators. In comparison to women in our survey, only 28% of males lacked formal schooling and 37% had 8 or more years of schooling.

In this context, those charged with formulating a plan for significant reductions in poverty recognized that a new approach was required. This approach would necessitate moving away from one that focused on ensuring asset ownership by individual households to one that simultaneously addressed capacity and governance constraints. This recognition followed a common thread in evaluations of earlier group-based programmes that related their failures to the insufficient development of capacity amongst rural households, which in turn hindered their ability to make profitable use of credit but also impaired the functioning of government programmes due to the prevalence of elite capture.

The model that emerged from these deliberations, the National Rural Livelihood Mission, is remarkable in its departure from conventional models and in its innovativeness. The points of departure are many; we note just a few of them here.

A first striking point of departure is NRLM's recognition that movements out of poverty would require 7 to 10 years; a long-term perspective was necessitated, and this span of time would likely include phases in which short-run advances were limited. A second point of departure was its staggered interventions or treatments. Given the existing low capacities of poor households, the most effective approach would require layering interventions over the course of the project's life cycle with new treatments being added only when certain "triggers" were met. Third, the programme recognized the importance of scale for poverty alleviation. It thus targeted not just the universal coverage of all villages in high-poverty blocks and districts, but the universal coverage of all poor households within each village. A fourth particularly noteworthy innovation was the approach to addressing the administrative capacity constraints that normally bedevil programmes that operate at scale, particularly the proposed scale of NRLM. This was the development of a community cadre comprising SHG members with relatively high levels of schooling, who were trained and subsequently charged with the responsibility of ensuring the programme's growth at the extensive and intensive margin. Growth at the extensive margin took the form of the promotion of the federation of community institutions across all villages and blocks. Growth at the intensive margin required the nurturing of each unit of this institutional architecture, ensuring the capacity and training of SHGs and their members and their access to programmatic financial and other inputs.

In its focus on scale, the Government implicitly acknowledged the importance of "aggregate" constraints that thwart movements out of poverty. Economists conventionally think of aggregate constraints as the resource constraints that determine the budgets of different institutions, including governments. However, the aggregate constraints that bind social and economic opportunities for the poor also include those imposed by the neighbourhoods they inhabit and by the geographies within which they conduct their activities. The rich and the poor are divided by the depth, scale, and the "richness" of

their neighbourhoods and geographies. Growth requires extending these boundaries, thereby allowing individuals to benefit from new opportunities and experiences. One dimension of this extension is referred to as “marketisation,” increased participation in markets for outputs and inputs, including labour markets. Market-driven approaches recognize that incomes grow by extending the boundaries of exchange. But market exchange requires addressing an additional aggregate constraint that comprises collectively held norms and beliefs. These include social norms that restrict occupational changes and mobility, norms that particularly bind women. In that sense, a market-driven approach requires a simultaneous focus on social change. NRLM is unique in its attempt to simultaneously address both economic and social change, an approach that its emphasis on scale enables.

Several noteworthy social and economic interventions were introduced over the course of the programme, including the SHG bank-linkage programme and the “Special Convergence Fund” introduced in 2016 to promote convergence with welfare programmes such as the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) and the Pradhan Mantri Awas Yojana. Perhaps the most notable additional intervention, however, was the launch of the National Rural Economic Transformation Project (NRETP) in 2019. This approach was layered on early NRLM blocks with the most mature Cluster Level Federations and focused on supporting these CLFs and their member SHGs to undertake the investments required to significantly enhance incomes.

This study provides summary statistics and descriptive evidence on changes in outcomes for households, Cluster Level Federation, and Self-help Groups between survey years and across different block types (NRETP blocks, NRLM’s early blocks, and its late blocks). We supplement this descriptive analysis with regressions that seek to identify causal impacts. Our primary focus is the impact of NRLM and NRETP on household consumption and income and a set of additional household outcomes including the labour force participation of household males and females. This analysis includes an evaluation of the impact of both programmes on an index of women’s role in intra-household decisions and an index measuring their self-efficacy or confidence. For the NRETP sample, we also evaluate the Model CLF programme and include an analysis of additional measures of women’s empowerment. Using data we collected on SHGs, we support the household-level findings with an analysis of the impact of NRETP and NRLM on some SHG-level outcomes.

The rest of this report is organized as follows. Chapter 2 describes broad features of NRLM and NRETP. Chapter 3 discusses the data. Our methodological approach is described in Chapter 4. This chapter separately details our approach to evaluating NRLM and that used to evaluate NRETP. Chapter 5 provides summary statistics for households, cluster-level federations, and self-help groups. The results of our empirical analysis are in Chapter 6. The last chapter (Chapter 7) brings together our findings to help interpret the impact of the National Rural Livelihoods Mission. It also includes a set of policy recommendations, based on our findings.

2. NRLM and NRETP

2.1 Introduction

This chapter briefly describes the National Rural Livelihoods Mission (NRLM) and the National Rural Economic Transformation Project (NRTP), discussing features that affect their implementation and their impact on households. Our discussion of NRETP is more detailed here, as the baseline evaluation report already provides a comprehensive overview of NRLM. (Kochar, Barooah, Jain, Singh, Nagabhushana, Narayanan, Sarkar and Shah (2020).

2.2 The National Rural Livelihoods Mission (NRLM)

2.2.1 Introduction

The Government of India, in 2011, initiated the National Rural Livelihoods Mission (NRLM)[8] to enhance the incomes of rural women and their households and improve women's socio-economic position. Its stated mission was "to reduce poverty by enabling the poor households to access gainful self-employment and skilled wage employment opportunities, resulting in appreciable increases in their incomes on a sustainable basis through building strong grassroots institutions of the poor (Government of India 2015)."

A federation of community institutions is at the heart of NRLM. The basic unit of the federation is a Self-Help Group (SHG) comprising approximately 10 women drawn from the same residential neighbourhood of a village. SHGs are therefore small and socio-economically homogeneous. SHGs in a village combine to form a Village Organization (VOs) with VOs within a "cluster" federated into Cluster Level Federations (CLFs). For administrative purposes, NRLM divided each of the country's administrative blocks into three to four clusters each of which comprises approximately 8-10 Gram Panchayats or 25-30 villages.

SHGs primarily serve as savings and lending groups, collecting small amounts of savings from members in weekly meetings and using accumulated funds to support "internal" loans to members. Weekly savings amounts are generally as low as INR 10 per member. These internal resources are augmented through a one-time grant of INR 15,000 (named "Revolving Funds (RF)") and through larger Community Investment Grants (CIF). The amount of CIF varies across states and over time. While initial guidelines suggested a maximum of INR 1,10,000 per SHG, new guidelines issued in 2021 recommended RF of INR 20,000 to 30,000 per SHG. The CIF limit was also increased to INR 1.5 lakhs per SHG. The guidelines stated that new SHGs, those formed in 2022 or later, and those that had not previously received CIF funding, be provided with this higher amount, while older SHGs should be allocated the difference between 1.5 lakhs and the amount of CIF that they had already received. SHGs also receive training in SHG norms, basic book-keeping, financial literacy, and in a variety of other subjects over time. The organization of the poor into groups greatly reduces the fixed costs of both fund delivery and training.

[8] The programme is formally named *Deendayal Antyodaya Yojana – National Rural Livelihoods Mission (DAY-NRLM).*

The primary trigger within NRLM that provides SHGs access to additional programme inputs is federation into a VO. This allows VOs to serve as intermediaries who channel additional resources and trainings to SHG members. For example, a VO-mediated SHG-bank linkage programme provides SHG members access to loans from banks. VOs also control a "Vulnerability Reduction Fund" and other funds that help insure SHG members against idiosyncratic reductions in income and other shocks. VOs provide and oversee training for SHG members in various fields including the preparation of business plans required to access CIFs. Perhaps the most important of their responsibilities is monitoring the performance of SHGs. This is done by grading SHGs' achievement against five targeted outcomes or *Panchsutras*: regular meetings, savings, loans, repayment of loans, and maintenance of books of record.

In turn, VOs are graded by CLFs, with CLFs having overall responsibility for monitoring and supporting the activities of the federation. Additionally, an important distinguishing mission of CLFs is to promote "convergence" between the activities of the federation and that of other Government departments and institutions engaged in rural development programmes. Because these programmes generally operate at a geographical level that exceeds the village, most frequently that of the Gram Panchayat, the CLF with its broader geographical jurisdiction is well suited for this role. Its coverage of several Gram Panchayats and villages also makes it the ideal unit to support interventions that require economies of scale. Thus, livelihood initiatives were expected to be implemented at the level of the CLF. Economies of scale also make the CLF the ideal unit for the management of training programmes; they can facilitate a cascading training system through which master trainers who operate at the level of the CLF can in turn train others at the VO and SHG level.

Taken together, the three-tiered federation of SHGs, VOs, and CLFs is commonly referred to as NRLM's "social institutions," entrusted with the development of social or community capital within village economies and the set of adjoining villages. Social capital is strongest amongst SHG members, a consequence of weekly meetings which allow them to become familiar with each other's economic circumstances and plans for the future. All SHG members in a village interact with each other through annual VO General Body meetings. However, the ties between the President and Vice President of each SHG with their counterparts in other SHGs of the village are stronger, since they are members of the Executive Body of the VO that meets weekly. They have even more regular interactions with sub-groups of Executive Committee members, through their participation in different VO sub-committees, each of which meets weekly. Similarly, the President and Vice President of each VO meet with their counterparts of other VOs in CLF executive committee meetings, while all CLF members interact through annual General Body meetings. While the set of SHG members with frequent interactions with members of other SHGs is small, the rotation of office bearers in all three institutions is an important means of ensuring the development of social capital amongst all SHG members.

On the administrative side, a critical innovation is NRLM's development of a "community cadre." While VOs were responsible for ensuring full coverage of poor households within the village, coverage across all villages in NRLM blocks and districts or growth at the programme's extensive margin was the responsibility of members of this cadre. In its infancy, the spread of the programme across villages in early blocks was accomplished

by recruiting a set of 'external' Community Resource Persons (CRPs) from states such as Andhra Pradesh, Kerala, and Bihar with a history of successful SHG programmes and from 'resource blocks' within each state. At the time of village entry, they identified SHG members with relatively high levels of education and leadership skills and recruited them to join the community cadre. After extensive training, these internal Community Resource Persons (iCRPs), viewed as NRLM's 'external' drivers, assumed responsibility for the spread of the programme in other villages of the cluster and the block. Similarly, growth of each SHG at the "internal" margin, in the form of improvements in capacity and skills, was overseen by NRLM's 'internal' drivers, members of the community cadre from the village or other villages of the cluster who worked with VOs and CLFs to ensure the quality of each SHG.

Before deployment, each member of the community cadre was required to satisfy a minimum participation criterion, defined in terms of the number of weeks of membership in a SHG (approximately one and a half years). Thus, deployment occurred approximately two years after recruitment. The size of the community cadre increased with the geographic scale of the programme, enabling the faster growth of SHGs within villages in later years of the programme, as well as the faster coverage of villages within a cluster.

In summary, NRLM used a "group" approach to poverty reduction. This approach, however, differed substantially from traditional "group" approaches used in microfinance and other financial inclusion programmes in that it enabled an *expansive* social network that combined small homogeneous groups into much larger and more heterogeneous networks. This expansive network enables returns to scale in economic and social transactions, providing the means for increasing income growth and reducing poverty. For example, the federation of SHGs in and across villages lowers transaction costs, facilitating access to bank loans and to other programmes. The creation of an expansive network that stretches across villages also ensures access to high human capital in the form of highly skilled CRPs. In principle, the operation of the programme at scale helps address two of the constraints considered critical for income growth: a credit constraint and a human capital constraint.

2.2.2 Evaluation of the National Rural Livelihoods Project (2019)

NRLM was initially piloted as the National Rural Livelihoods Project (NRLP) in a set of 400 blocks in 100 high-poverty districts in 13 states that accounted for 85% of the rural poor, so as to provide "proof of concept."[9] Half of these blocks were chosen based on the proportion of population living below the poverty line, the other half based on the strength of existing community institutions, including the SHGs developed under the precursor to NRLM, the *Swarnjayanti Gram Swarozgar Yojana* (SGSY). We refer to these as 'early blocks' (EBs). NRLM subsequently scaled up the programme beyond these 'intensive blocks' where NRLP had already initiated activities to the remaining 'non-intensive' blocks. As activities were the same, the two essentially differed in the duration of exposure to the programme.

Results from an impact evaluation of NRLP are in Kochar et al. (2020). Lacking baseline data on NRLP households, this study implemented a cross-sectional difference-in-

[9] These are the states of Assam, Bihar, Chhattisgarh, Jharkhand, Gujarat, Maharashtra, Madhya Pradesh, Odisha, Rajasthan, Uttar Pradesh, West Bengal, Karnataka and Tamil Nadu.

difference methodology, identifying the impact of an approximately 2 ½ year difference in exposure to the programme in the short run (after about 5 years of implementation) by exploiting the programme's phasing across blocks of the district and across villages of each block. Identifying "early villages" (EV) in each block, the study compared the difference in a set of outcomes across early and late villages of early blocks to the same difference in late blocks. This double-difference controls for the purposive selection of early blocks and a non-random phasing of the programmes across villages within a block. A critical methodological innovation of this study was allowing for heterogeneity in programme effects across early and late blocks (and villages) as a consequence of variation in implementation. Specifically, the study controlled for differences in the social capital that existed at the start of the programme in early and late blocks, a difference that implied differences in the effectiveness of the programme across early and late blocks of the same "age" or years of exposure to the programme.

The evaluation concluded that NRLP caused significant improvement in household incomes (around 19%) through the increased number of livelihood sources. The study also documented improvements in wage incomes. There was limited impact on households' ownership of productive assets or income earned from agriculture, livestock, and nonagricultural enterprises. The study found that household access to SHG credit improved as a result of NRLP. There were significant declines in high-cost informal debts and in the importance of the informal credit sector.

2.3 The National Rural Economic Transformation Project (NRETP)

2.3.1 Introduction: Differences between NRETP and NRLM

While NRLM, since its inception, included components to improve incomes of member households, an intensive targeting of this objective came with the introduction of the National Rural Economic Transformation Project (NRETP) in 2019. The Project provided INR 3250 crores, INR 1625 as an IBRD loan, and INR 1625 from the Government of India's budgetary resource, between April 2019 and June 2024.[10]

NRETP's objective was to scale the economic transformative initiatives introduced in NRLM (World Bank 2018). Because it builds on NRLM's social platform, it was introduced in a relatively narrow geography drawn from 100 districts with the highest amount of social mobilization and group capitalization. These were primarily (but not exclusively) NRLP blocks. Within this set, NRETP targeted even smaller sub-groups for specific programmes. For example, its Institutional Building and Capacity building (IBCB) component targeted 600 CLFs and 2000 VOs in 150 blocks of selected states.[11]

NRLM actively promoted the financial inclusion of rural households, anticipating that enhanced access to credit and accompanying general equilibrium improvements in rural credit markets would foster investments in productive assets and, consequently, income

[10] The programme was restructured in December 2020 in response to the COVID pandemic, primarily to enable pilot projects on Health and Nutrition, supporting migrants and supporting new projects such as Integrated Farming Clusters which targeted reductions in households' vulnerability to macro-shocks.

[11] Selection of blocks for this sub-component was based on a set of well-specified observable characteristics that included the functioning of at least 75% or more of the potential VOs targeted for formation under NRLM.

growth. Recognizing that poor households may place a greater priority on funding essential expenditures and on reducing consumption variability, it placed no restrictions on the end-use of loans. This was also true of bank loans that it helped SHG members access.

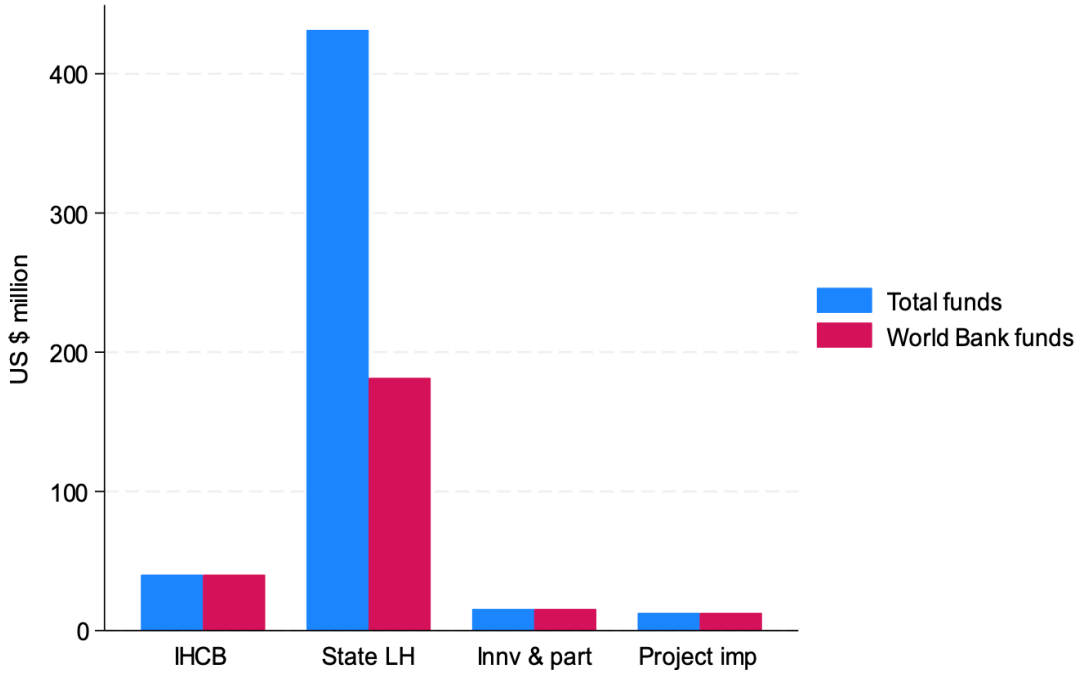
NRETP departs from this approach in that it provides funds that are specifically targeted to productive capital investments. Figure 1 helps understand NRETP's approach. It graphs the distribution of allocated (total) programme funds and, of this total, the funds provided by the World Bank, under four broad heads: Institutional and Human Capacity Building (IHCB); State Livelihood Support; Innovations and Partnership Support; and Project Implementation Support. The largest component is for State Livelihood Support that funds the following: State Rural Livelihood Missions (category B1 in NRLM and NRETP budget documents), Institution Building and Capacity Building (B2), Community Investment Support (B3), and Special Programmes. Of these categories, Community Investment support accounts for 36% of the total allocation, with Institution Building and Capacity Building (IBCB) receiving 35%. State Livelihood Missions receive 29% of total funds, while funding for Special Programmes is negligible.

Broadly speaking, funds for Institution Building and Capacity Building (IBCB, category B2) enable improvements in human capital through technical support, training, exposure visits, awareness camps, honorariums for staff including Community Resource Personnel, and other related expenditure. Of the total NRETP funds allocated for IBCB, 76% was allocated to cover the costs of Block Mission Management Units with the remainder supporting the strengthening of Higher Order Federations through technical support and capacity building. Funding under the head of Community Investment Support (B3) enables investments in infrastructure, working capital, and other items by new "livelihood" institutions (and their members) or to individual SHG members in the form of loans. The almost equal division of expenditure between IBCB and Community Investment Support indicates the equal priority placed under NRETP for improvements in human and physical capital.

The new focus on livelihoods under NRETP is best seen by comparing its budgetary allocations with NRLM's for the two major categories of State Livelihood support, Institution Building and Capacity Building (B2) and Community Investment Support (B3) and their sub-components. State Annual Action Plans (AAP), which separately record expenditures under NRLM and NRETP, enable this comparison. For example, we use the AAP of Rajasthan to demonstrate the focus of NRETP on livelihoods compared to NRLM in Figure 2.[12]

[12] Using data from other states does not change the conclusions of this discussion.

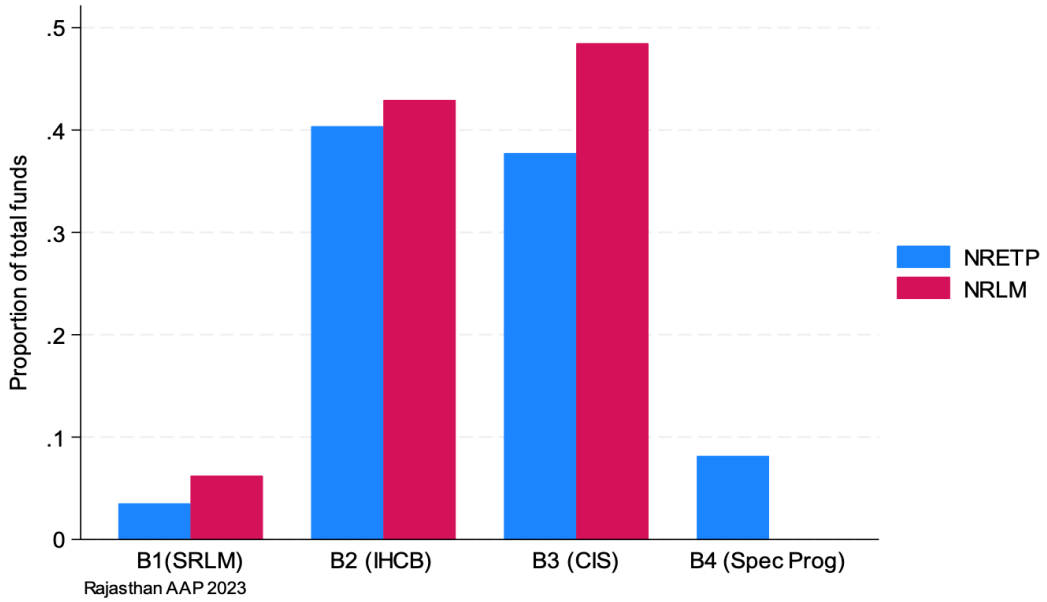
Figure 1: NRETP broad budgetary classifications



Source: The World Bank (2018).

Figure 2 suggests a similarity in funding patterns under NRLM and NRETP for broad categories of expenditure. However, details of expenditure under these sub-categories reveal their significant differences. Figure 3 plots the proportion of total B2 and B3 funding by subcategory. The first 6 items (from SMMU/DMMU to “CB-NF” or Non-farm capacity building) are sub-components of Institutional and Human Capacity Building (B2), while the remaining items fall under B3 (Community Investment Support).

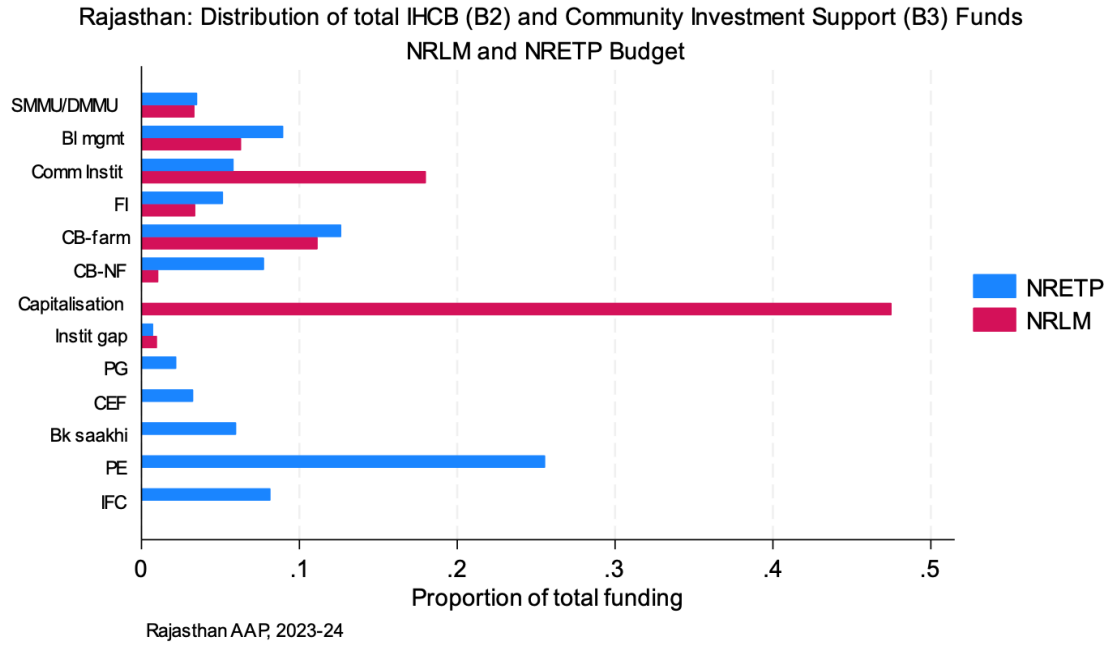
Figure 2: Comparison of NRETP and NRLM budgetary expenditures, broad categories



While NRLM and NRETP both fund Institutional and Human Capacity Building, the vast majority of NRLM funding is for the Capitalization of the set of community institutions through Revolving (RFs) and Community Investment Funds (CIFs). Details of the amounts allocated under NRLM budget reveal that CIF and RF are the biggest heads of funds. For example, looking at the 2022-2023 Annual Action Plan of Rajasthan, we see that 64% of the total capitalization funds went to CIFs for CLFs while RFs to SHGs accounted for 30.6%.

The second most important component of the NRLM budget is "Community Institutions" which supports SHG, VO and CLF formation, their start up and facilitation costs and capacity building costs for these institutions and for on gender, FNHW (Food, Nutrition, Health and WASH) and social initiatives.[13] Again, using Rajasthan as an example, the majority of these funds under NRLM were devoted to social mobilization and CRP rounds (78% of the budget for this item in the 2022-23 Annual Action Plan).

Figure 3: Proportion of total expenditure IHCB and Community Investment Support by sub-head, Rajasthan 2023-24 (Rajasthan AAP 2023)



NRETP funds these same categories only minimally, devoting most of its budget to specific livelihood sub-projects under Community Investment Support (B3) such as Producer Groups (PGs), Community Enterprises (CEF), Producer Enterprises (PE), and special programmes such as Integrated Farming Cluster (IFC). While NRETP funds also enable capacity building, this is primarily devoted to the development of capacity in the farm and non-farm sectors (CB-farm and CB-NF in figure 3).

NRETP also funds the development of community institutions (the third sub-category of "Comm Instit" in figure 3) primarily through a new programme for strengthening cluster-

[13] The different sub-categories under B2 differ slightly for NRLM and NRETP budgets. To ensure comparability, we have included expenditures under categories B2.6 through B2.10 on capacity building for various initiatives (model CLF, Gender, FNHW, social initiatives and PRI-CBO convergence) in this category.

level federations, the “model CLF” programme. This programme identifies a set of 600 CLFs, approximately one CLF in each of 150 selected NRETP blocks, to serve as proof-of-concept and resource block to other blocks. Model CLFs are intended to be premier institutions, operating at a superior level to significantly enhance the performance of their member VOs and SHGs. The funding support for model CLFs promotes their transition to the use of modern monitoring, operating, and accounting procedures such as regular audits and the maintenance of standard books of accounts.[14] These systems help enforce accountability and hence promote economic exchange in larger markets. Funding is also intended to help broaden the activities of CLFs, with each model CLF expected to implement one or more interventions in areas such as food, nutrition, health, and WASH (FNHW), social inclusion, gender-related activities, or convergence activities with other departments.

Thus, the new funding provided under NRETP enables the targeting of funds and human capital for the specific purpose of enhancing livelihoods. It is, of course, possible that this distribution of funds is not a consequence of a new emphasis on livelihoods enabled by NRETP funding but instead a division of NRLM’s pre-existing priorities across the two programmes. Examining expenditures under NRLM prior to the initiation of NRETP rules out this hypothesis. Figure 4 provides details on NRLM’s budgetary allocations in Rajasthan in 2017-18, prior to the onset of NRETP, using data from the state’s Audits of NRLM. It confirms that, prior to NRETP, the vast majority of NRLM funds were spent on the development of the set of community institutions.

Disaggregated data on expenditure under Community Investment Support (B3) from NRETP’s Project Implementation Plan (2018) provides information on the sub-projects that NRETP supports and their importance as reflected in budgetary provisions. Figure 5 graphs this data (for all NRETP states). It reveals that NRETP funds accrue primarily to new “livelihood” institutions in the form of Producer Enterprises, Producer Groups and other production groups. These institutions are distinct from the set of “social institutions” developed and supported by NRLM (SHGs, VOs and CLFs). They are, however, linked to the set of social institutions in a variety of ways. We will discuss these institutions in more detail later in this chapter.

[14] Funding to model CLFs takes several forms. First, they are provided funds under the budget for Investment Building and Capacity Building (B2) for undertaking the rating of units of the federation and for training, exposure visits, vision building and other capacity building initiatives. Second, they are provided Community Investment Support funds for infrastructure investments and for making up the shortfall between their current operational income and the amount required to operate at the desired level. Each model CLF is provided a grant of INR 2.5 lakhs for investments in infrastructure and an additional INR 20 lakhs for “viability gap” funding.

Figure 4: NRLM Fund Disbursement under Community Investment Support, 2017-18.

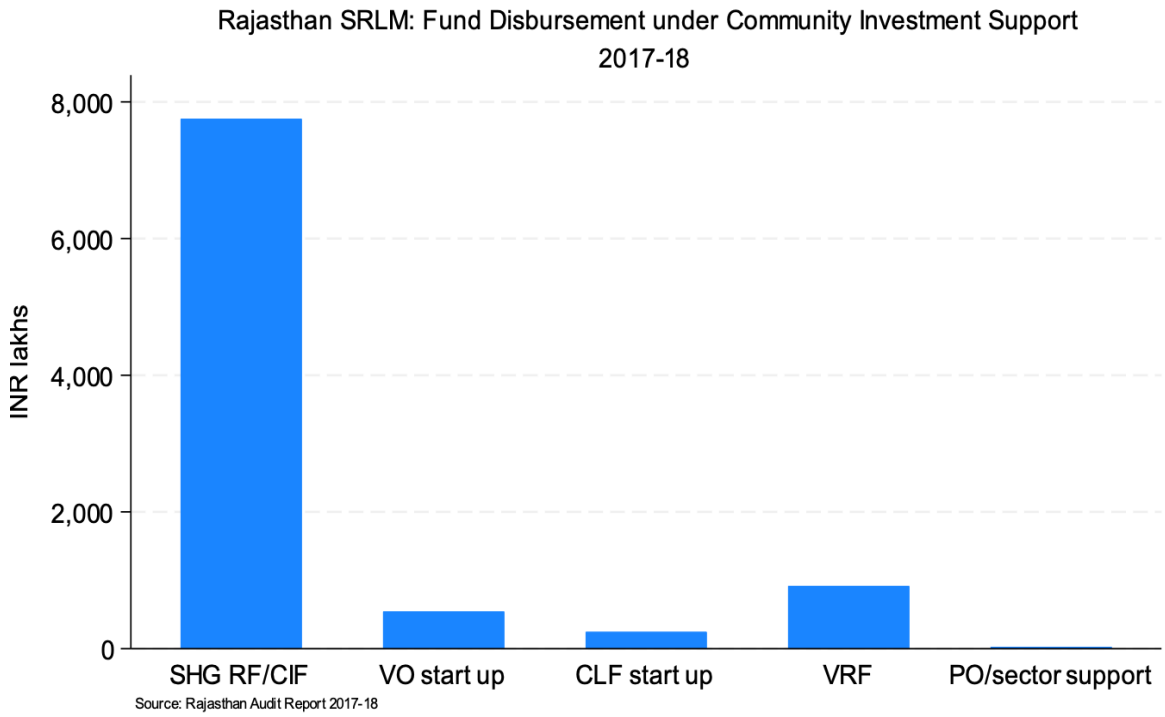
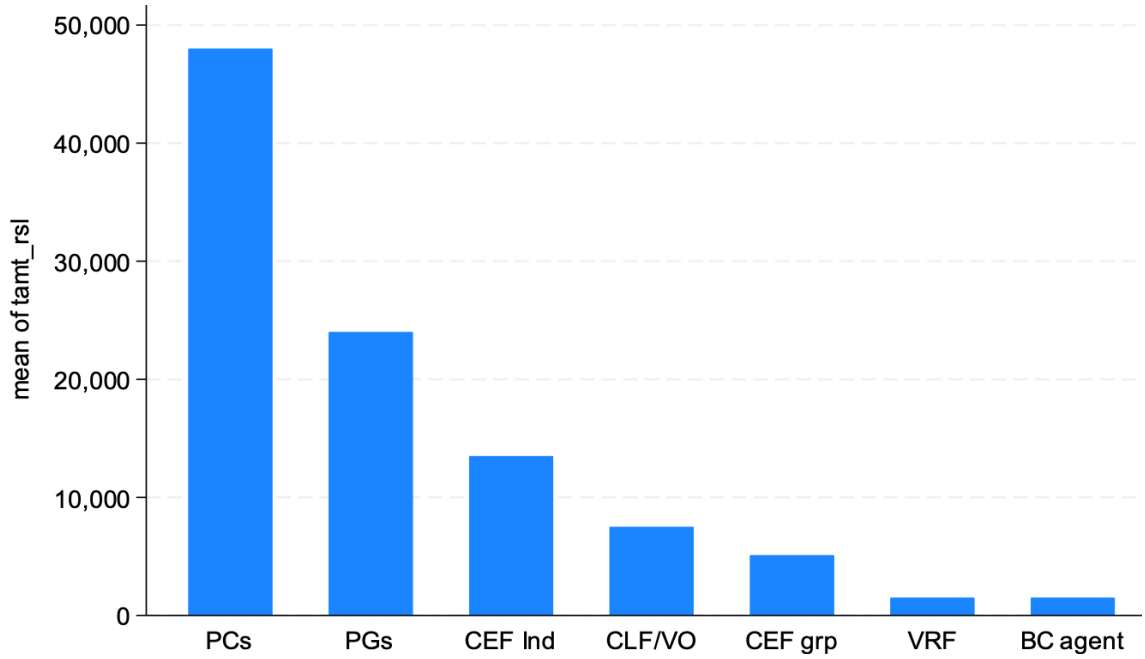


Figure 5: Total NRETP Budgetary Allocation under Community Investment Support (B3)



Note: The broad categories represent the following: PCs (Producer Companies), PGs (Producer Groups), CEF Ind (Community Enterprise Fund for individuals) CLF/VO Investment Support to Higher Order Federations);

CEF grp (Community Enterprise Funds for groups); VRF (Vulnerability Reduction for VOs and CLFs); BC agent (Investment support for equipment for BC agent). Source: NRETP PIP 2018

2.3.2 Complementarities in physical and human capital investments

Despite the clear demarcation of funds for investments in physical capital (under Community Investment Support) and human capital (Institutional and Human Capacity Building), the programme recognizes and builds on their complementarity.

Thus, the financial sustainability of CLFs and hence their ability to run business and training programmes (for all three tiers of the federation) and to effectively conduct their operations depends on their financial resources and strength. While CLFs receive significant programmatic funds for this purpose, variation across CLFs in their resource base reflects differences in the engagement of member SHGs in federation-supported income-earning activities. CLFs share interest payments on SHG loans to members. They also receive a share of the profits earned by any federation-supported enterprise and are paid a rental fee for any CLF-owned assets used by these enterprises.

On the flip side, the returns to investments in livelihoods by SHG members depend significantly on the capacity of NRLM's social institutions, particularly CLFs. This is because of the primacy of CLFs in implementing NRETP's livelihood activities, in the form of selection of beneficiaries, the preparation of business plans, oversight of CRPs, and the monitoring of programmes. Improvements in the managerial ability and capabilities of CLFs thus enable improvements in the incomes of member households.

2.3.3 The Model CLF programme

While NRETP provided livelihood funding and support to all CLFs in NRETP blocks, it provided additional support to a set of 600 "Model CLFs" intended to serve as "Centres of Excellence." Each NRETP block was to have at least 1 Model CLF (MCLF).

Model CLFs were intended to be self-managed, self-reliant, and financially sustainable, with strengthened governance structures, administrative capacity, and business and financial management practices. Going forward, the programme envisaged Model CLFs serving as a resource and training institutions for other CLFs.

Recognizing that the objective of developing self-sufficient and financially sound CLFs may require additional funds, all model CLFs were provided with "Viability Gap" Funding up to a maximum of INR 20 lakhs per CLF. Additionally, model CLFs were also provided with funding for Infrastructure support to ensure that they had the office space and facilities required to function effectively. All 600 Model CLFs received INR 2.5 lakhs for office infrastructure.[15]

NRLM also supported Model CLFs in non-NRETP blocks, but to a far reduced extent. Thus, the programme envisaged 10 model CLFs per state.[16] However, Viability Gap funding and Infrastructure Funds were only available to MCLFs in NRETP blocks.

2.3.4 Geographical variation in NRETP's footprint

Given hard budgetary constraints for each sub-project, NRETP ensures the productivity of expenditures by selectively distributing funds across states, blocks, and villages.

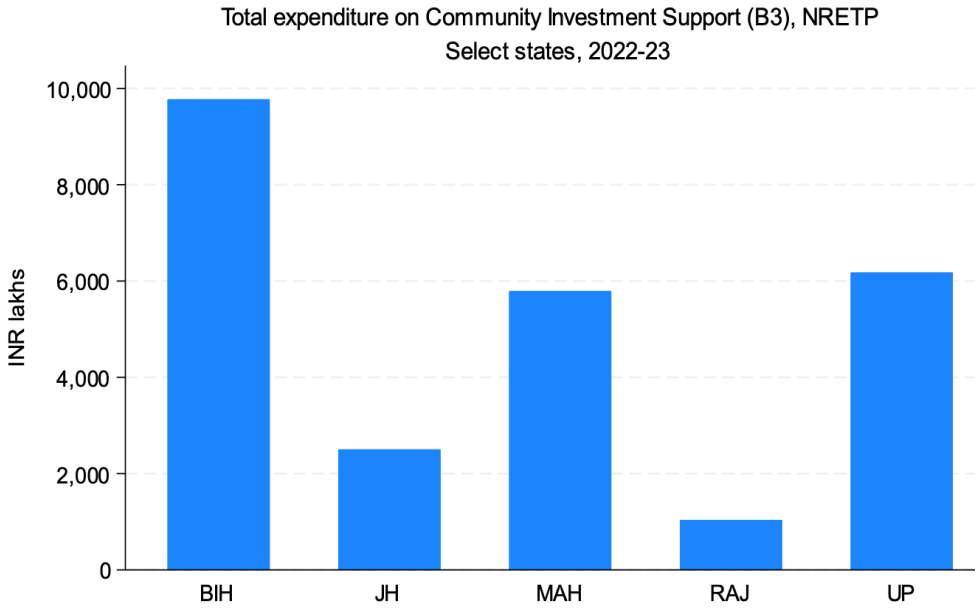
[15] The Model CLF programme also envisaged that 150 Model CLFs would operate training centers for members of NRLM institutions. These CLFs were provided with an additional 8 lakhs in infrastructure support.

[16] This applied to the 13 major states; more MCLFs were planned for the North-eastern and North-western states.

Programme guidelines require states to undertake scoping and baseline studies to identify potential groups or individual beneficiaries. This is followed by the preparation of detailed business plans with the help and guidance of (external) technical support agencies that clearly identify expected profits and the assumptions underlying these calculations. Final decisions regarding the types and numbers of specific projects and investments are included in each State's Annual Action Plans and subsequently approved by NRLM.

Consequently, both the number of livelihood activities supported under NRETP and their distribution vary across states, blocks, and villages, reflecting differences in the profitability of each project across different socio-economic and geographical units.[17] Data from 2022-23 Annual Action Plans (AAPs) for select states demonstrate these differences. Figures 6 and 7 graph differences in total and per (NRETP) SHG funding under component B3 (Community Investment Support) for 5 NRETP states, respectively.[18] While states such as Bihar (215,579 NRETP SHGs in 2022-23) dominate total funding because of the large number of SHGs in the state, the per ('000) SHG figures show that livelihoods support per SHG is highest in Uttar Pradesh followed by Maharashtra. More to the point, these figures demonstrate the significant variation across states in livelihood funding, a consequence of guidelines which provide funding only against the profitability of the project as documented in business plans.

Figure 6: Expenditure on Community Investment Support, NRETP, select states 2022-23

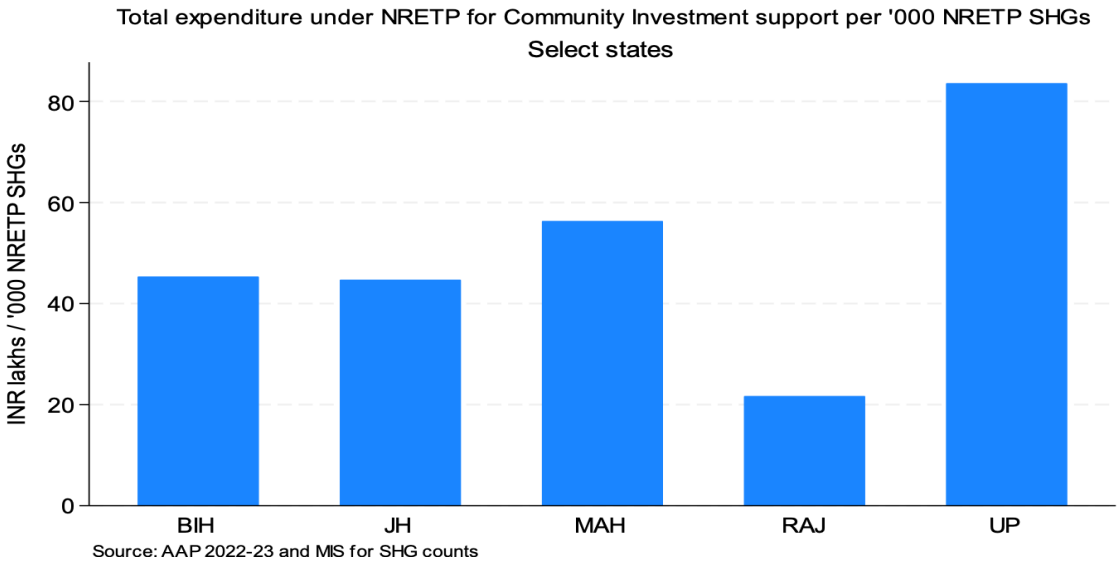


Note: Data are from each state's 2022-23 Annual Action Plan.

[17] Programme guidelines allow funds to be reallocated across states, if necessary. Thus, guidelines for cluster projects state that if some states are unable to use their allocated funds in NRETP's first year, then these funds may be offered to other states with viable projects on a first-come, first-served basis. As a consequence, the total funding of a given state may exceed the maximum amount initially prescribed.

[18] The per SHG amounts are based on the number of SHGs in NRETP blocks, and hence are referred to as "NRETP SHGs."

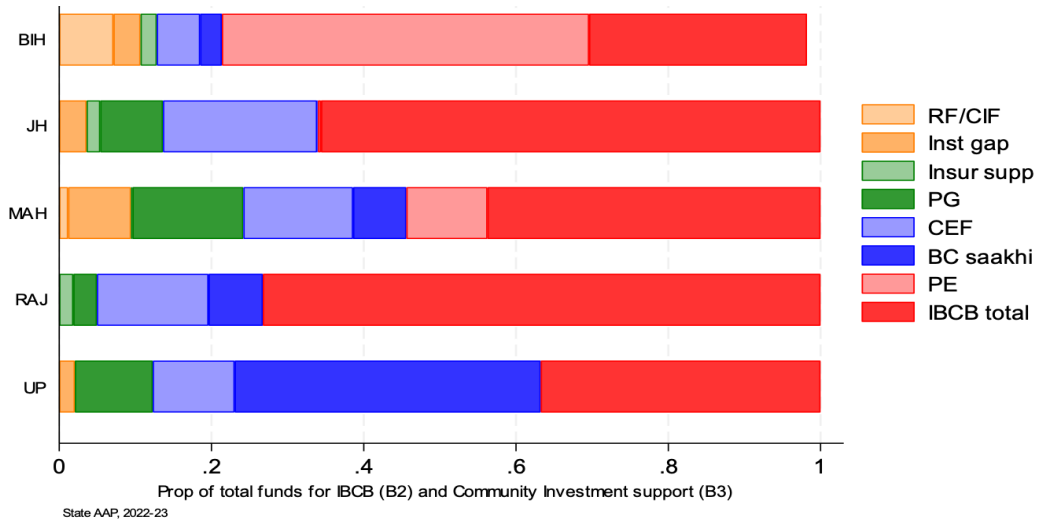
Figure 7: Per SHG Expenditure on Community Investment Support, NRETP, select states 2022-23



Note: Expenditures are total amounts per SHGs in NRETP blocks of the state, drawn from the 2023 Annual Action Plans for the state in question.

Differences across states arise not just in the total amount of funding but also in the sub-projects that are funded. Figure 8 graphs the proportion of total funds (AAP 2022-23) under IBCB (B2) and Community Investment Support (B3) for total IBCB investments and for sub-projects under Community Investment funds.[19] States such as Rajasthan and Jharkhand accord far greater attention to institutional and capacity building (IB/CB) than do other states. States also vary in the investment projects they prioritize. While Uttar Pradesh emphasizes investments in financial inclusion agents (*BC Sakhis*), Maharashtra has prioritized investments in producer groups and community enterprises.

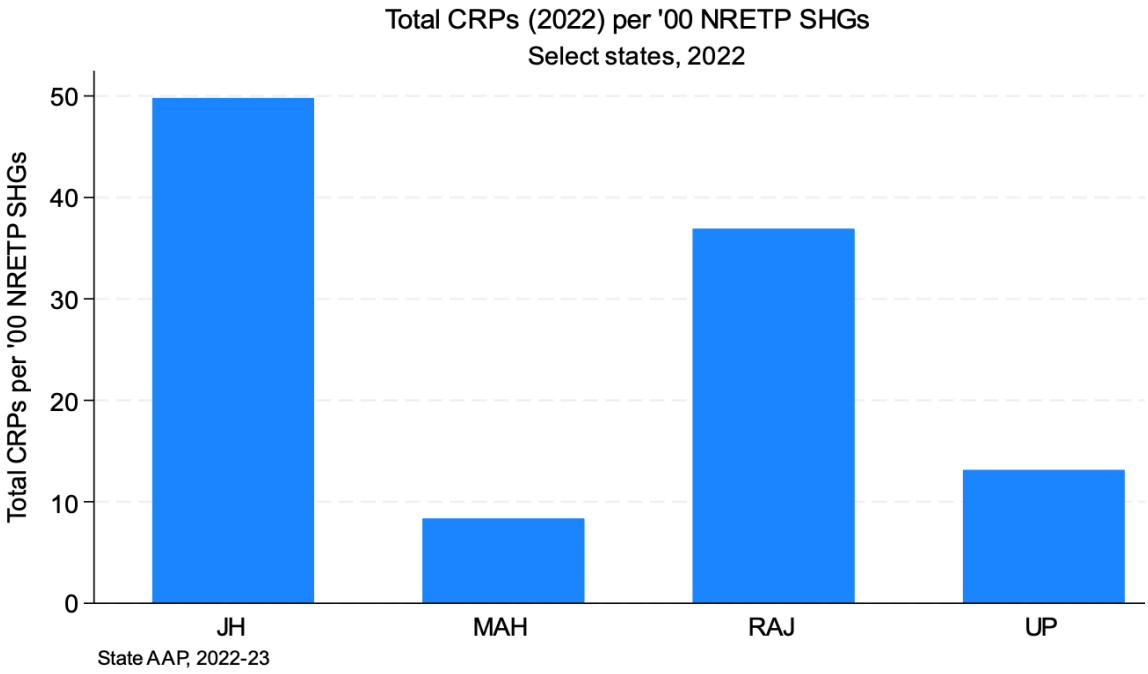
Figure 8: Proportion of total IBCB and Community Investment Support Funds by sub-categories and state



[19] While states such as Uttar Pradesh provide a breakdown of expenditure under IBCB, most states do not. Consequently, the figure graphs total expenditure under this head.

Finally, states also differ in the magnitude of human capital investments, as revealed in the total number of "livelihood" CRPs that support livelihood activities. Figure 9 plots the number of CRPs assigned to farm livelihoods by various states, as of 2022, per '00 NRETP SHGs, revealing the clear difference in the emphasis on human capital support.[20] The figure confirms the greater emphasis on IB/CB in Rajasthan and Jharkhand revealed in figure 8.

Figure 9: Number of Farm Livelihood CRPs per '00 NRETP SHGs, various states



2.3.5 Ensuring incentives: NRETP's institutional arrangements

It would be misleading to think of NRETP simply as an extension of NRLM that provides targeted funds for productive assets and for enhancing members' capacity for productive investments. Critical to an evaluation of the programme is the understanding that it explicitly promotes a new set of institutional arrangements through a set of sub-projects, each with its own distinctive guidelines and rules. In this context, our use of the term "Institutional" follows the academic literature which describes "Institutions as the set of constraints that structure political, economic, and social interaction"(North 1991). As North notes, institutions, along with budget and human capacity constraints, define transaction and production costs and hence the profitability and feasibility of economic exchange. They shape incentives. Thus, as history has repeatedly shown us, even large investments and expenditures on human capital will have little impact on outcomes if the institutional arrangements under which they are delivered do not adequately address agency constraints.

An implication of this statement is that the aggregate and distributional impact of NRETP's sizeable investments in physical and human capital will reflect its institutional arrangements; the same budgetary allocation will deliver different results if implemented under alternative institutional arrangements.

[20] Farm CRPs are: Krishi Sakhis, Pashu Sakhis, Van Sakhis, Udyog Mitras, Matsya Sakhi and Master CRPs for Agriculture and livestock. Data are from 2022 Annual Action Plans.

NRETP hosts a large number of institutional arrangements, each intended to address varying agency constraints. The differences in institutional arrangements in NRETP's sub-projects are considerable. A basic and critical difference relates to the unit of implementation: group versus individual. While the majority operate through groups, some also support individuals. Even within the set of group-based initiatives, differences exist in features commonly believed to be important determinants of a group's success, namely its size and the socio-economic and ethnic homogeneity of its members. In contrast to the "affinity" Self Help Groups promoted by NRLM, NRETP promotes "common activity" groups that constitute members engaged in the same activity. Consequently, though group members are homogenous in terms of activity, they may differ significantly in terms of affinity.

Sub-projects also differ in terms of the obligations of members, governance structures, and sharing rules, all institutional features that affect economic incentives. For example, a general feature of these subprojects is that newly created assets are the property of the Cluster Level Federation, which is paid a rent for its use.[21] This feature affects the willingness of households to augment infrastructure and capital costs from their own funds or through bank loans. Payment mechanisms also affect incentives. Thus, funds to "model CLFs" are released in three tranches tied to CLF performance against criteria such as the growth and development of member SHGs and VOs, maintenance of books of records, audits, leadership rotation, and use of funds.

Finally, we emphasize the point that institutional arrangements directly affect incomes, in addition to their indirect effect through their impact on investment incentives. For example, group arrangements enable operating at scale. Consequently, group size affects marketing and training costs, amongst others. Affinity groups also enable learning from others, fostering externalities that can significantly improve incomes and profitability.

We discuss below some of NRETP's sub-projects and their institutional architecture, emphasizing points that impact incentives and returns.

Producer Companies and Enterprises, the largest line item in NRETP's budget, are registered (formal) institutions that aggregate the output of producer households across blocks and villages through a set of varying collection arrangements.[22] This sub-project supports a variety of different institutional arrangements for the collection of output at the level of the village, for funding working and fixed capital, for equity and profit sharing, and for technical service support and investments in human capital in the form of administrative staff and community resource personnel. The large scale of aggregation enabled by PEs suggests the potential for significant cost reduction in transportation, marketing, and related costs through scale.

The impact of scale, however, will reflect the profitability and incentive structure of different PE models. For example, a common collection arrangement adopted by PEs is a collection center assigned to a few villages managed by a single individual, the *Sanchalika.* The extent of aggregation, then, is determined by the geographical coverage

[21] Loans also enable investments in small individually-operated assets when individual ownership is required, as in the case of sewing machines in sewing clusters.
[22] NRETP provided funding for 40 PEs.

of each center, but also, importantly, by the payment she receives and the extent to which it rewards efforts to increase aggregation. Alternative collection arrangements, such as the use of a producer group for the purpose, differ in the incentives they provide.

Producer Groups, 12,000 of which were planned under NRETP, are the informal counterparts of PEs that share their objective of improving incomes through exploiting economies of scale in transportation and through value-added investments such as in the sorting and grading of agricultural outputs. They are unregistered enterprises that are significantly smaller in size, drawing their membership from SHG members of the same village. Their size limits aggregation: they are expected to engage primarily in local markets. Diverse types of PGs (collection versus production) feature different profit and equity sharing arrangements. Unlike PEs that are governed by a Board of Directors, governance structures in PEs are voluntary, with responsibility resting on an elected President and Vice-President. The relatively small size of PGs can reduce the collective action problems that such voluntary governance entails, but this may be undermined if members differ significantly in terms of socio-economic characteristics such as landownership and education. Other institutional arrangements that are likely to affect profitability are group liability for working capital loans and the absence of equity sharing.

NRETP also funds non-agricultural enterprises (CEF) at the individual (CEF Ind) and group (CEF grp) level through programmes such as the Start-up Village Entrepreneurship Programme (SVEP), One Stop Facility (OSF), and through support for artisan and sectoral production clusters.[23] OSF is a business facilitation-cum-incubation Center, while SVEP promotes nano- and micro-enterprises. SVEP funding is intended to support 7,500 individuals and 1,500 groups in 500 blocks, while OSF served an additional 350 blocks. Both programmes provide individual and group enterprises with working and human capital support. Clusters similarly bring together groups of women to exploit economies of scale in training, mentorship, and the provision of other inputs such as artificial insemination, vaccinations, and other services for livestock and small animal enterprises. NRETP funds also enable “hard” infrastructural investments in common facilities, production, and service centers.

A more recent addition to the set of NRETP sub-projects is the Integrated Farming Cluster (IFC), which promotes a variety of livelihoods across a few carefully selected contiguous “clusters” of villages, with each cluster comprising approximately three villages. Each IFC block targets the phased or staggered formation of 3-4 clusters. Selected households within each cluster of villages are provided support to promote a variety of livelihood activities, with these activities in turn being integrated to provide forward- and backward-linkages. As an example, the cluster promotes investments in forward-linking enterprises such as collection centers and in backward-linking enterprises such as poultry- and buck-rearing units and soil testing centers. IFC thus departs from other sub-projects in that the agglomeration or concentration of activities it promotes in adjacent villages has the potential to significantly increase the size of the local market, addressing the “aggregate demand” constraint that affects the profitability of local or “place-based” programmes.

[23] NRETP provides INR 15 crores to each participating state for setting up and operationalizing a maximum of five clusters (NRETP Non-farm Enterprise Guidelines 2022).

2.3.6 Ensuring incentives: Agency problems in Labour Markets

While our discussion above relates to agency problems in production, these problems are equally severe in labour markets. In NRETP, this raises questions regarding the effectiveness of the community cadre and other local staff whose contributions to desired outcomes, improvements in member incomes, and their capabilities are difficult to measure and monitor.

As is generally the case, NRETP seeks to address agency constraints in labour markets through a system of incentive payments. The general practice is for members of the community cadre, including Livelihood CRPs (Krishi and Prani mitras as an example), to be paid a fixed amount augmented by variable payments for the tasks that they perform. For example, Pashu Sakhis are typically responsible for a variety of tasks, including handholding support to households in production, imparting training to goat rearers on best practices, promoting investments in improved infrastructure, vaccination, deworming, and other health-related services for animals, and marketing support. To ensure the implementation of this wide range of activities, the fixed salary of Pashu Sakhis is augmented by task-based incentives. In *Jeevika*, for example, Pashu Sakhis are compensated for the provision of first aid (Rs 10 per goat), deworming (Rs. 5 per goat), vaccination (Rs 8 per goat), insemination (Rs. 30 per goat), households who switch improved infrastructure (Rs. 25 per household), and, additionally, for surveys of goat rearers (Rs 10 per household) and any requested case studies.[24] While intended to ensure the Pashu Sakhi's attention to these tasks, the extent of tasks that are compensated in this way provides CRPs the opportunity to select from amongst them, keeping in mind the need to ensure overall satisfaction with her performance and her own income requirements. The extent to which this happens, and how it affects overall service delivery, is an empirical question on which there is scant evidence.

The primary implication of the significant dependence on incentive pay for CRPs is a well-known implication of the productivity of local service providers: It will depend on the size of the market if operations exhibit decreasing average costs (Marshall 1920; Young 1928). Thus, poorer villages will be less well served, since recruitment and retainment will both be issues. Further, particularly as regards the recruitment of a livelihood cadre that must be trained in sector-specific skills, high turnover will significantly increase the costs of the programme due to the need for more frequent training (assuming timely replacement of those who leave). Unfortunately, limited evidence is available on the totality of payments received by CRPs, and how this varies geographically across villages, blocks, and states.

2.3.7 Ensuring Incentives: The interplay between NRETP's livelihood institutions and NRLM's social institutions

As noted in the introductory paragraphs of this chapter, NRETP's institutions are layered over NRLM's federation of community institutions, with NRETP blocks purposively chosen on the basis of their development of social capital. This affects incentive constraints and hence outcomes in several ways. We close this chapter with a discussion of the links between NRLM's social institutions and NRETP's livelihood institutions and their importance for incentives and outcomes.

[24] Bihar Rural Livelihoods Promotion Society. 2018. Policy Note on Pashu Sakhi (Ref: BRLPS/Project/463/13/Vol. II/794.

First, overlaying NRETP on NRLM's social institutions allows NRETP's livelihood institutions to rely on the social capital of NRLM's institutions to ensure contractual adherence. The extent to which this is possible, of course, varies with the size of the NRETP institution; social capital will be less effective in large institutional arrangements such as PEs and far more effective in small arrangements such as those which promote enterprises that run by individual SHGs. The ability to use social capital to improve performance also applies to CRPs; they may be more diligent in their activities because they serve members of their own SHGs as well as those of neighbouring SHGs. Social reputation is an important determinant of behaviour.

Second, a significant benefit of NRLM's institutions is their role in the dissemination of information on NRETP's livelihood initiatives and in the selection of beneficiaries. Our extensive fieldwork across NRETP states validates the importance of this feature. CLFs pass on information on livelihood opportunities to VOs who in turn pass it on to SHGs. And, both CLFs and VOs play an important role in the selection of beneficiaries for different projects such as sector-specific cluster enterprises. Attention to selection, in turn, helps address the asymmetric information constraints that adversely affect performance in production and labour markets.

These "social" systems of information dissemination and selection also serve another important function: they promote "buy-in" and build widescale support for the programme, even when opportunities are unequally distributed across village households.[25] As an example, selection for a specific activity-based cluster requires prior experience in the activity in question. The selection of beneficiaries in an open forum that includes all SHG members helps explain this criterion and promotes overall acceptance and support for NRETP interventions. CLF and VO information dissemination and information sessions also help address equity concerns by drawing member households' attention to potential spillover benefits. Thus, though the opportunity to operate an egg collection center may be offered to just one SHG or one SHG member, such forums enable a discussion on the benefits of this center to all egg producers.

This last point underlies a third important benefit of layering NRETP's livelihood institutions on top of a set of social institutions, and of limiting their (initial) implementation to blocks and villages where these social institutions are well-developed. The extent to which SHGs cover the village population, or village scale, determines the spillover benefits from livelihood programmes. Livelihood programmes, even when targeted at select households within a village, can affect the entire local market through general equilibrium effects on prices. However, they are likely to have larger effects on SHG members through social learning and demonstration effects. For example, the probability of a SHG member initiating an entrepreneurial activity if other members of her own SHG have already taken this step will likely be higher than that of other village households who are not similarly linked.

They also determine the impact of NRETP and NRLM on social goods whose consumption is governed by a set of social norms that frequently inhibit women's economic participation. The recruitment of CRPs can, for example, significantly challenge social norms that minimize women's economic participation, generating a

[25] Information dissemination occurs through two channels: CLF and VO meetings, and through CRP discussions with SHG members.

spillover benefit to women as they consider engaging in productive activities outside the home. Factors such as CRPs' footprint in the village in question, their remuneration, and other work-related conditions affect such choices.

Equally important spillovers exist in the development of capabilities. The fact that SHGs, VOs, and CLFs combine to form a large, expansive social network enables a multiplier effect from investments in the capabilities of leaders of this network, such as CLF executive committee members, to other members through several channels. First, such investments directly enhance the profitability of any livelihood enterprises that they are engaged in. When these are group enterprises, as they frequently are, then any newly acquired knowledge and skills also enhance the knowledge of their fellow SHG members. Second, because CLF committee members have oversight and managerial responsibility for all the enterprises run by SHGs in the CLF, improvements in their knowledge base benefit members of other SHGs as well.

The two channels described above are conventional methods by which learning disseminates within an organization, spreading from the managerial level to other levels. However, NRLM's social fabric enables an additional channel: The rotation of leadership in SHGs, VOs, and CLFs. This considerably speeds the pace at which learning is disseminated. Current members of CLFs and VOs, at the end of their tenure, return to regular SHG members. Conversely, current members of SHGs have a high probability of serving on the executive committees of VOs and CLFs, and hence of directly benefitting from the training provided to these members.

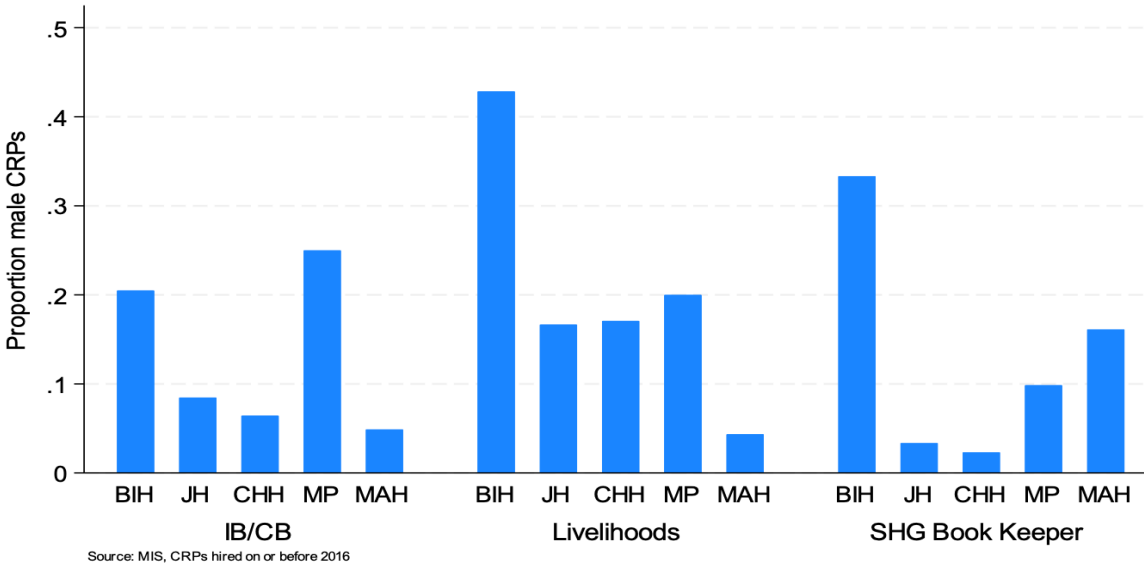
Whether such spillovers exist in practice is an empirical question, one that may reflect underlying village characteristics such as its size and the degree of socio-economic fragmentation amongst village households. In our field work, we visited many villages where satisfaction with the operation of CLFs is low and concerns regarding elite capture are frequently expressed.[26]

Such concerns also affect the operations of CRPs. These community cadre positions require applicants to meet a minimum education level, one that varies by task. These levels are sometimes hard to meet, particularly when the position is at the level of a village. In such cases, state guidelines enable the hiring of males, usually requiring them to be related to SHG members. Thus, state administrators face a choice: They can ensure an adequately sized CRP pool that can help implement NRETP's objectives in full or they can restrict selection to female CRPs who may be best placed to ensure trust and hence learning.

Preliminary evidence on this issue comes from MIS data on CRPs by their position and across states. Figure 10 graphs these data for CRPs who were hired in 2016 or earlier.[27]

[26] Some of these issues were discussed in our first evaluation of NRLM (Kochar et al , 2020).
[27] The data come from NRLM's Management Information System (MIS). Unfortunately, the data for some, but not all states, do not include CRPs hired in recent years. To ensure comparability, we therefore restrict attention to a few states and to CRPs hired on or before 2016.

Figure 10: Proportion of Male CRPs by state and thematic area



Source : NRLM MIS

2.4 Review of evidence on NRLM

The genesis of NRLM in its current form lies in a number of early models implemented by states. Barooah and Banerjee (2024) take stock of recent evidence on NRLM and SHG models, distinguishing between the findings of the early studies and emerging evidence. Early studies on the programme provide strong support that NRLM SHGs are effective in improving household and women's financial inclusion, savings, access to, and use of formal credit (Datta, Deininger, and Liu (2015), Pandey, Gupta, and Gupta (2019) all of which are the direct outcomes that the programme targets. Kochar and colleagues (2020) in their evaluation of the programme in nine states show that SHG households in areas that were early implementers of the programme reported almost 27% higher amounts of total savings than those that were late implementers. The evidence shows that this is achieved by providing SHG members savings options with the SHG and through opening bank accounts. Credit access is achieved through provision of direct SHG loans and linkages to formal credit networks.

SHG credit further impacts the village credit markets and impacts the informal credit sector. This is by studies such as those of Hoffman and colleagues (2016), Deshpande and Khanna (2021), and Pandey, Gupta, and Gupta (2019), Kochar and colleagues (2020), which have demonstrated that the introduction of NRLM SHGs impacts informal loan markets by bringing in competition and reducing interest rates. Consequently, there is a decline in household indebtedness in high-cost loans.

Recent evidence points to some impact of NRLM on livelihood options and income. (Kochar et al., 2020), Pandey, Gupta, and Gupta (2019) demonstrate that NRLM led to an increase in the number of income sources and household livelihoods options. There is good evidence that NRLM has a positive impact on women's labour force participation and employment in paid jobs (Pandey, Gupta, and Gupta,2019). Unlike earlier studies (such as Deininger and Liu, 2015, Desai and Joshi, 2015), emerging evidence shows that NRLM has positive impacts on household income. Kochar and colleagues (a.2020) report a 19% increase in household income among SHG households. This is determined

by the maturity of SHGs and linkage to the federation. As the programme matures and federation linkages are strengthened, SHGs are able to leverage higher amounts of programme funds and formal loans and take up convergence activities with other livelihoods programmes which may result in income enhancements. A recent review of NRLM by Deshpande (2022) provides a historical perspective of the programme from its original conception and the variations adapted by states. The study summarises recent evidence with similar conclusions on economic impacts increasing over time as institutions are scaled and strengthened.

There is compelling evidence that the programme significantly enhances women's collective agency and social capital. Diaz-Martin and colleagues (2022) argue that the main benefits of women's groups are the platform they provide to reach many women and foster social connections between women. Similarly, Deshpande and Khanna (2021) observe that programme members were more likely to attend Gram Sabha and Mahila Sabha meetings, with attendance rates increasing by 12 and 17 percent points, respectively. Palaniswamy, Parthasarathy, and Rao (2019) report a comparable trend in Tamil Nadu, where women's participation in Gram Sabha meetings saw a notable rise.

2.5 Conclusion

Focusing on NRETP, this chapter describes the broad features of its implementation that are likely to affect its impact and help interpret the results of the empirical analysis presented in this report. NRETP differs from NRLM in its explicit targeting of funds and human capital to enhance the livelihoods of SHG households. However, these targeted resources are not uniformly distributed across SHG households; their allocation is demand-driven and therefore varies within and across geographies. In other words, the distribution and use of NRETP funds differ based on the socio-economic characteristics of households, as well as the socio-economic context of villages, clusters, and blocks.

Nevertheless, the fact that NRETP is layered on top of the vast social network created by NRLM suggests that the programme's economic and social spillovers are likely to be significantly greater than if NRLM had not preceded it. Additionally, NRETP benefits from NRLM's federation of community institutions in multiple ways, including more effective dissemination of information and better screening of beneficiary households.

This chapter also highlights the importance of the institutional arrangements fostered under NRETP. Since the programme delivers resources through these institutions, its overall effectiveness depends critically on the functioning of these institutional structures.

3. Sampling and Data

Our evaluation of NRETP and NRLM builds on a two-year panel data set of households and SHGs. We start this chapter by describing the baseline data and then move to a discussion of the endline data. Prior to doing so, we note that the design of any study requires choices regarding topics to be covered and modules. Since our evaluation was charged with the responsibility of evaluating NRLM's impact on incomes, this necessitated the inclusion of a comprehensive and detailed income module. This module required over an hour for completion for those households reporting engagement in agricultural or non-agricultural family enterprises.

Budgetary restrictions and a corresponding upper limit to the amount of time available in any given village to field all modules, in conjunction with the need to provide estimates of income and consumption, meant that we were unable to field separate modules to provide information on the significant number of state-specific innovative programmes in several fields, despite their innovativeness and widely perceived value. Examples include programmes in livelihoods and Food, Nutrition, Health and WASH such as Jharkhand's Joint Action for Sustainable Health and Nutrition (JASHN) and Peer Group Counselling Programmes and Jeevika's Agricultural Entrepreneur Programme. For the same reason, this study does not evaluate other programmes that come under NRLM such as the One Stop Facility (OSF). Finally, time and budgetary constraints also limited our ability to undertake Focus Group Discussions (FGDs) to provide qualitative information on the insights and function of even those programmes that we do provide information on, including the model CLF programme.

3.1 Baseline sample and data

The baseline survey for this report was conducted between the months of March to May 2019. Details of the survey, including its geographical coverage and state-specific sample sizes, are in Kochar et al (2020) and hence are only briefly discussed here.

The survey covered 9 of the 13 states in which the National Rural Livelihoods Project (NRLP) was implemented. In two of these states, Bihar and West Bengal, the survey team was asked to continue an existing evaluation trial. Thus, the selection of households in these states was dictated by the earlier study. For the remaining 7 states, lacking baseline data, we implemented a cross-sectional difference-in-difference regression exploiting the staggered entry of the programme across early and late blocks of each state and across early and late villages within each cluster of the block. This methodology was facilitated by the lists provided to us by each State Rural Livelihood Mission identifying early and late entry blocks of the state. We selected pairs of early and late blocks in each district. Using extensive administrative data which identified administrative clusters of each block and provided information on the date of entry into each village, we then selected two clusters in each block and two early and two late villages in each cluster. Table 1 summarizes the sample from the nine states.

Table 1: Sample sizes across 9 states [Baseline]

States	Blocks	Villages	Households	SHGs	VOs	CLF
Rajasthan	14	115	3,346	667	95	16
Uttar Pradesh	10	86	2,398	444	29	5
Jharkhand	12	108	2,858	559	83	8
Odisha	12	94	2,794	564	81	39
Chhattisgarh	12	98	2,801	565	80	11
Madhya Pradesh	12	101	2,877	581	66	12
Maharashtra	12	99	2,851	569	47	14
Bihar	16	265	5870	1294	230	15
West Bengal	16	144	1462	429	48	11
Total	116	1,110	27,257	5,672	759	131

3.1.1 Selection of households

The sample households in the study were drawn from SHGs in the village. We randomly selected two SHGs from amongst those formed at the time of entry into the village in each village. These two early SHGs that were included in our sample are called “index SHGs” in our evaluation. Our survey design called for the inclusion of all members of these “index” SHGs in the household survey. In practice, the absence of key household members from the village at the time of the survey meant that, on average, five members per SHG were surveyed, with three or more members surveyed in approximately 80 percent of SHGs. The total sample of households linked to an SHG is 14,641 (excluding the sample from Bihar and West Bengal).

In addition to members of the identified SHG, we also surveyed five randomly selected households from within the neighbourhood or hamlet in which most SHG households live, in order to understand participation choices and to examine spillover effects. Since these five households were randomly selected from the neighbourhood of index SHGs, they sometimes included members of other SHGs, including those that are co-opted or not part of the NRLP. Of the total of 5,284 households in the sample of households that were part of the index SHGs, (excluding Bihar and West Bengal in which the sample was predetermined by the baseline sample), we find that 60 percent were not part of any SHG and the remaining 40 percent were part of different SHGs.

3.1.2 SHG modules

A distinguishing feature of our study was the collection of detailed data on SHGs through a SHG module. This module was canvassed on approximately 6 SHGs in each village, the two “index” SHGs and four other SHGs randomly selected from each village using the state’s administrative list of existing SHGs at the time of our survey. With the onset of field work for the study, it became apparent that a number of selected SHGs were no longer functioning while others existed only on paper. In all cases where SHGs once existed, it was possible to identify member households from available records. Our survey includes such members. While data on the current operations of the SHG were not available, information on SHG age was available from MIS records.

3.2 Endline sample and data

The baseline sample was re-surveyed between the months of April and July in 2024. Unfortunately, this survey coincided with India's national elections, requiring the data collection team to navigate the Model Code of Conduct, which restricts village gatherings from the announcement of elections until their conclusion. As a result, data collection in Odisha was impacted, limiting coverage to only half of the original sample. Table 2 presents data on the number of survey villages, households, SHGs, VOs, and CLFs in each state. Detailed information on the surveyed districts and sample sizes by district can be found in Appendix Table A2.

Table 2: Sample sizes across 9 states [Endline]

States	Blocks	Villages	Households	SHGs	VOs	CLFs
Rajasthan	14	115	3187	633	114	27
Uttar Pradesh	10	86	2254	418	78	20
Jharkhand	12	107	2694	533	108	22
Odisha	6	48	1346	269	50	19
Chhattisgarh	12	98	2727	561	97	25
Madhya Pradesh	12	101	2829	473	80	24
Maharashtra	12	99	2687	568	91	26
Bihar	16	265	5497	1301	251	32
West Bengal	16	140	1423	392	136	31
Total	110	1,059	24,644	5,148	1,005	226

Note: Sample sizes from nine states, with a reduced Odisha sample. The sample also covers a small proportion of replacement households and SHGs spread across the states.

We note that the 2019 survey was *not* intended to be a baseline for the evaluation of NRETP; the selection of blocks and villages for our study was done prior to NRETP's start and hence was not informed by NRETP's geographical coverage. This implies that NRETP was implemented in only a subset of the 2019 blocks. More critically, as noted in Chapter 2 that describes key features of NRETP, the project is demand-driven so that NRETP investments are found only in villages in which SHGs demand such investments. The Methodology chapter that follows provides information on how survey blocks divide into various treatment samples.

3.2.1 Sample drop-outs.

The effective baseline household sample targeted for the 2024 survey was 25,860, following a reduction in the Odisha sample for reasons outlined in the previous section. The survey team attempted to revisit 25,860 households, of which 23,178 could be covered in the endline survey in 2024. Thus, the drop-out rate from our sample is 10.37%[28].

Following the reduction of the Odisha sample, the target sample of SHGs for the 2024 survey was 5,393. The survey team attempted to revisit all 5,393 SHGs, of which 4,680 (sample survey drop-out rate 13.22%) were the final panel SHG sample covered in the endline survey.

Most of the analysis of this report is based on the panel of households and SHGs, following regression tests that revealed balance in attrition across different treatment samples. These regression results are reported in the Methodology chapter of this report.

However, households and SHGs that could not be resurveyed were replaced by others, generating a repeated cross-sectional survey of identical size in baseline and endline. Detailed protocols were established by the evaluation team to ensure accurate replacements for drop-out households, self-help groups (SHGs), and other institutional samples. These protocols were implemented by the data collection agency and monitored daily by the evaluation team.

[28] All attempts were made to cover or track these households. However, a number of factors, such as temporary or permanent migration, made it difficult to trace them.

For the seven states (excluding Bihar and West Bengal), household replacements were conducted randomly, mirroring the baseline sample methodology. Specifically, an SHG-linked household was replaced with another household from the same SHG, while a non-SHG-linked household was replaced with another randomly selected household from the same hamlet or neighbourhood. In Bihar and West Bengal, the original sample protocol was followed, with households being replaced randomly within the same hamlet or neighbourhood.

SHGs across all nine states were replaced within the same village, ensuring similarity in age, with selections made from the available MIS list.

3.3 Questionnaires

The survey instruments for the 2024 NRETP study were adapted from the 2019 NRLM Evaluation (Kochar et al., 2020), ensuring comparability across five core modules: Integrated Household (including the Women's Module), Self-Help Groups (SHG), Village Organization (VO), Cluster Level Federation (CLF), and Village. The main respondent of the household module was the household head, often a prime-aged man. The respondent of the women's module was the prime-age woman, in most cases a current or past SHG member. Given the focus on NRETP, the survey also included a module on Producer Groups (PG). The original survey plans called for data collection of at least one producer group in each village. In practice, because of NRETP's targeted nature, data was collected only on 76 PGs. As previously noted, this small number reflects the fact that the 2019 selection of villages and blocks was done prior to the implementation of NRETP and hence does not constitute an ideal baseline for NRETP. Additionally, we also administered an abbreviated household survey to members of the community cadre. This survey was administered to 3 CRPs in each village.

The 2024 household survey was specifically designed to keep key modules from the 2019 survey intact, such as the consumption module, household rosters, and modules relating to labour force participation in the last month, so as to ensure the comparability of data across survey rounds. Income modules also followed the same format, but with the addition of questions relating to marketing source, input procurement source, and the availability of "hand-holding" and mentoring support. These questions were inserted given the emphasis within NRETP on the provision of such inputs. Similarly, though the 2019 sections of the women's questionnaire were repeated in the 2024 survey, additional sections were included to provide a more detailed analysis of the programme's effect on women's empowerment. These included sections on women's norms and beliefs, their opinions on their welfare and status, and their impressions on generational change. It also included a section intended to assess women's financial and business literacy.

In a similar vein, the 2019 SHG, VO, and CLF modules remained unchanged, with additional sections incorporated to capture information on new inputs and resources provided under NRETP. The SHG module was expanded to include details on bank linkage, SHG livelihood funds, and other NRETP-supported inputs. Similarly, the CLF module was updated to provide more comprehensive information on CLF funds, livelihood funds, and newly introduced inputs under NRETP. Both SHG and CLF surveys included a new section intended to provide information on enterprises run by the institution in question. Again, this insertion reflected a policy push under NRETP to

promote enterprises run by SHGs and CLFs. As with PGs, however, the targeted nature of NRETP resulted in very few SHGs and CLFs reporting such enterprises. Our survey included information on just 31 SHG-run enterprises and 28 CLF-run enterprises.

Appendix Table A3 lists all outcome variables used in the analysis, providing definitions as required.

3.4 Data collection: Training, oversight, and monitoring

3ie partnered with Vrutti both as a research collaborator and for data quality assurance. Vrutti played a key role in overseeing data quality by monitoring the fieldwork conducted by the data collection agency. 3ie and Vrutti conducted a week-long training session for the data collection team, Sambodhi Research & Communications Pvt. Ltd. In addition to the standard training imparted to the data collection firm on the relevant schedules, the training included intensive sessions on NRLM and NRETP to ensure that the field team was fully knowledgeable about the programme and hence able to understand the details asked for in the different modules. The training also included two days of field practice. Following standard practice, training was provided through a cascading design, with 3ie conducting a week-long session with Trainers (Training of Trainers) who then subsequently trained members of the field team.

3ie and Vrutti also put in place an elaborate system to ensure oversight and to monitor the data work and hence ensure data quality. Key measures included:

- Logical sequence checks to identify inconsistencies in responses.
- Enumerator-wise dashboards for real-time data quality monitoring.
- Audio and text audits to assess response accuracy.
- Field monitoring (at least one round per enumerator) to oversee data collection.
- Flagging poor-performing enumerators (who were later dropped by the data collection agency) based on quiz results from training sessions, high error rates, and other quality indicators.
- Spot checks and back-checks for 5% of household and women respondents.

Additionally, the field monitoring team tracked enumerator performance over time, rating them based on data quality. A sample tracking sheet was developed to manage replacements and minimize attrition, ensuring the preservation of the baseline sample. The data collection agency received regular weekly feedback to improve performance and address emerging challenges.

3.5 Data Cleaning

The data was cleaned by the data collection firm, using investigators' diaries and repeat phone calls to correct for missing values and outliers.

As is well known, collection of data on income is particularly prone to error, primarily because many farm households consume a significant share of their produce. With falling land sizes, significant numbers of households report no marketed sales at all. Though the survey asked households the value of their total output, so as to allow the calculation of profits even in the absence of market sales, this question was frequently left unanswered in those cases where there was no marketed output at all. For this reason, we replaced agricultural output prices (in all cases) with the average village price

(by crop and by season). Livestock profits are subject to the same difficulty, but the relatively limited output from this enterprise (frequently just milk) allowed a simpler correction by using data on the value of home production from the consumption module. Livestock income was therefore calculated as the sum of the revenue from sales and from home production. Regressions on household income and consumption remove the top and bottom 1% of values, as do regressions on loan amounts.

4. Methodology

4.1 Research questions and objectives

This evaluation study has two main objectives. The first is to evaluate the causal impact of the National Rural Economic Transformation Project (NRETP) on a set of household incomes and on the federation of community institutions on which the programme is built (Self Help Groups, Village Organization, and Cluster Level Federation). As is standard, our evaluation tests the null hypothesis that the programme has no impact on household outcomes ($H_0: \beta = 0$). Rejection of the null suggests a significant impact.

Policy interests, however, extend beyond establishing a statistically significant impact of the programme. As discussed extensively in Chapter 2, NRETP represents a significant departure from NRLM (National Rural Livelihoods Mission) in terms of its approach to increasing household incomes. NRLM's focus was the development of a set of affinity-based community institutions to address the agency problems that underlie financial market failures and ensure the social capital required to empower women and enhance their economic opportunities. In contrast, NRETP is built on the hypothesis that improving incomes requires addressing a different set of constraints such as the aggregate demand constraints arising from low-income local markets and land market and entrepreneurial constraints that prevent enterprises from operating at scale. Though it draws on NRLM's set of community institutions, it builds on these to promote a different set of "livelihood" institutions that draw on newly formed activity-based groups.

This raises the important policy question of whether these new arrangements are required for improvements in income or whether addressing credit constraints through affinity-based institutions will serve the same purpose, once they mature and operate at scale. The evaluation of NRETP, particularly when based on a comparable set of non-NRETP blocks from NRLM, combines the effects of these different institutional arrangements with that of additional resources provided under NRETP and hence does not provide evidence on these issues.

The separate identification of these two models is enabled by the availability of two years of data (conducted at the start and end of NRETP) and by the staggered implementation of NRETP and NRLM. As noted earlier, NRETP blocks represent a subset of the NRLP blocks that served as a proof-of-concept for NRLM. NRLM, however, remained in progress after the onset of NRETP, targeting full coverage of households and villages by 2024. This meant that the process of full federation of community institutions (SHGs into VOs and VOs into CLFs) continued in this period with the growing resources of all levels of the federation supporting the activities of member households.

Staggered and continued implementation therefore generates three sets of blocks: those implementing NRETP; a second set of “early” NRLM blocks which initiated implementation of NRLM at the same time as NRETP blocks and in which NRLM continues to function but without the additional resources provided under NRETP; and a set of “late” NRLM blocks. These data therefore offer an opportunity, similar to that in experimental evaluation designs with multiple treatment arms, to isolate the impact of targeting livelihoods through activity-based institutional arrangements and funds targeted for productive purposes relative to an approach that focuses on addressing credit market imperfections. While studies that use multiple treatment arms are common, there are very few in which these arms enable evaluation of two distinct approaches to poverty reduction on a scale.

We start this section by describing the broad methodological approach we propose for both studies. We provide summary statistics that suggest the feasibility of its broad approach and suggest modifications required to ensure identification.

4.2 Baseline (2019) survey and design and endline (2024) survey

Our analysis is based on a two-year panel of households surveyed in 2019 (between the months of March to May) and in 2024 (April to June). The first survey year, 2019, corresponds to the start of NRETP and hence constitutes a baseline for the programme, while the 2024 survey serves as its endline, conducted just prior to the programme’s official closure (June 2024).

Unfortunately, no uniform baseline survey was conducted at NRLP’s start (2011).[29] Our estimates of the causal impact of NRLP in its early years therefore exploited the cross-sectional variation in exposure to the programme, a consequence of its phasing across two dimensions: blocks of a district and villages within a block. Specifically, we implemented a cross-sectional difference-in-difference regression, comparing the change in outcomes between early and late villages of early blocks to the same change in late blocks.

To enable this strategy, our sample included an early block and a late block in each survey district of 7 states, with coverage of 5-6 districts in each state. Within a block, the programme operates through administrative “clusters” of approximately 30 villages, with villages within a cluster being phased into the programme over a two-to-four-year period. The study selected two “early” villages and two “late” villages within a cluster, resulting in 8 villages in each block. Because of the faster pace of implementation in late blocks, the difference in years of exposure between early and late villages in early blocks (approximately 4 years) exceeded that in late blocks (approximately 2 years). The study therefore estimated the impact of approximately two years of additional exposure to the programme, in early stages of its life cycle.

In addition to these 7 states, our sample also includes households from Bihar and West Bengal. These are states for which the 2019 sample does not fit into the design described above, which selected households from early and late blocks and from early

[29] Baseline studies were conducted in most states, but these differed in survey instruments, methods of selection of the sample, and in modules. For most states, definitions of key variables such as income and consumption differed, making it impossible to pool the data in an informative way.

and late villages within each block. For both these states, we were asked to resurvey households that had been identified for earlier evaluations conducted in each of these states. While the West Bengal evaluation used a propensity-matched sample of treatment and control villages, the Bihar evaluation randomized gram-panchayats into treatment and control groups. The survey sample in West Bengal is relatively small (1,462 households). Bihar, however, constitutes a relatively large sample (5,872 households), divided across 7 districts and 16 blocks. The state's livelihood programme, *Jeevika,* was initiated in all these blocks by 2012, at the same time as the initiation of the programme in early blocks of other states.

The methodology of the 2019 baseline study was designed before NRETP was introduced, and NRETP's rollout across districts and blocks was not influenced by the availability of the 2019 survey data. As a consequence, NRETP was not implemented in all early blocks of the 2019 survey. Thus, though every survey district has an early and a late block, NRETP blocks do not exist in all districts. The table below provides information on the number of NRETP blocks, early blocks, and late blocks by state. In all states, with the exception of Maharashtra and West Bengal, the state sample includes NRETP blocks and early blocks. In Bihar, the sample is divided between NRETP blocks and early blocks, with the former dominating the latter.

Table 3 clearly reveals differences in the overall sample size across NRETP, early, and late NRLM blocks, and differences across states in their representation in each of these three types of blocks. Bihar and Maharashtra both have a large number of NRETP blocks. In Maharashtra, this is because the state implemented NRETP in all its erstwhile early blocks. Our sample blocks for Maharashtra therefore divide into NRETP and late blocks, without any representation by the state in the early block sample. As a consequence, Maharashtra lacks the control blocks required for the NRETP evaluation. Table 3 also shows that treatment and control samples are unbalanced for both the NRETP and the NRLM evaluation. For any given sample size, a balanced sample with an equal number of treatment and control blocks increases statistical power. However, in unbalanced samples, dropping treatment blocks to achieve balance will reduce power.

Table 3: Distribution of blocks, by state and type, in the survey data

State	Number of NRETP blocks	Number of EB (non-NRETP)	Number of late blocks	Total blocks
Rajasthan	3	4	7	14
Bihar	13	3	--	16
Jharkhand	2	4	6	12
Odisha	4	2	6	12
Madhya Pradesh	2	5	5	12
Maharashtra	6	--	6	12
Chhattisgarh	8	2	2	12
Uttar Pradesh	2	3	5	10
West Bengal	1	7	8	16

4.3 Broad Methodological Approach: Difference-in-difference

Exploiting the availability of two years of data across blocks that vary in their implementation of NRETRP and NRLM, our evaluation of both programmes is broadly based on a difference-in-difference methodology, described below.

Using notation from the potential outcomes literature, let $Y_{it}(0,0)$ be the potential outcome for household i in year t if its block of residence is untreated in both periods, with $Y_{it}(0,1)$ being the potential outcome if NRETP is implemented in the block in the second year. For notational simplicity, and following the literature, we let $Y_{it}(0) = Y_{it}(0,0)$ and $Y_{it}(1) = Y_{it}(0,1)$. The causal impact of the programme on households in treated blocks is given by the average treatment effect on the treated (ATT):

$$(1) \qquad ATT = \tilde{\beta} = \mathbb{E}\left[Y_{i,2}(1) - Y_{i,2}(0) \middle| NRETP_i = 1\right]$$

The fundamental problem of causal inference is that, in any given period, we only observe households in one of the two potential states (treated or untreated), rendering impossible a calculation of $\tilde{\beta}$ based on observable data. This requires an imputation of outcomes for treated observations that would have been obtained in the absence of treatment. The availability of baseline and endline data allows improved estimates of counterfactuals. Specifically, we use a difference-in-difference regression that estimates the required counterfactual using the trend in outcomes (without treatment) for the control sample and the availability of pre-programme data on outcomes for treated samples from the baseline survey. The identifying assumption is that in the absence of the programme, the change in outcomes in treatment and control blocks would have been the same. This "parallel trends" assumption assumes similarity in output *growth* across treatment and control blocks, while allowing for selection based on the pre-programme *level* of observed and unobserved covariates.[30] If this assumption holds, then any higher growth in treatment blocks represents the causal impact of the programme ($\tilde{\beta}$).[31] The parallel trends assumption is:

$$(2) \qquad \mathbb{E}\left[Y_{i,2}(0) - Y_{i,1}(0) \middle| T_i = 1\right] = \mathbb{E}\left[Y_{i,2}(0) - Y_{i,1}(0) \middle| T_i = 0\right]$$

[30] Equation (2) relates to potential outcomes and hence cannot be tested. In practice, researchers most commonly support this assumption by testing for parallel "pre-trends" in treatment and control regions prior to the onset of the programme. A recent literature suggests the pitfalls of this approach, noting its sensitivity to functional form (Roth and Sant'Anna 2023) and the low power associated with this test (Bilinski and Hatfield 2018; Freyaldenhoven et al. 2019; Roth 2022). These tests typically involve a null hypothesis of equal pre-trends and hence, as conventionally designed, have a high probability of type II error: A failure to reject the null provides only weak evidence that group-specific pre-trends are parallel.

[31] Identification also requires a "no anticipation" assumption, which rules out decisions made on the basis of anticipated future benefits. Recent research also addresses identification in staggered programmes that are introduced in different regions at different times. In such cases, the control sample is frequently also treated, but at a lower "intensity." If so, causal identification requires an additional assumption regarding the homogeneity of treatment effects (de Chaisemartin and D'Haultfoeuille 2023, 2020; Goodman-Bacon 2021, Abraham and Sun 2018).

In equation (2), T_i is an indicator variable that takes the value 1 if block i is a treatment block (NRETP block for the NRETP evaluation and early NRLM block for the NRLM evaluation). The basic difference-in-difference equation for outcomes (y) for household i residing in block b at time t is:

$$Y_{ibt} = \beta_0 + \beta_1 T_b * POST_t + \beta_2 POST_t + X_i'\beta_3 + B_b + u_{ibt} \quad (3)$$

In this regression, T is an indicator for treatment blocks, while *POST* takes the value 1 for observations in the endline sample. B is a set of block fixed effects, which controls for any residual selection into NRETP blocks based on time-invariant variables. X is a set of covariates at the village level. These include a basic set of household controls, namely the number of adult males and females in three different age groups (20-40, 40-60, and above 60), an indicator for whether the household has land and for whether it is a member of a scheduled caste and tribe, and the highest level of education of an adult female member of the household. In extensions of the basic difference-in-difference framework described below, the set of covariates is expanded to include village-level determinants of the pace of implementation of NRLM.

The coefficient β_1 on the interaction of the treatment and endline indicators (T and POST in equation (3)) measures the impact of treatment, identified as the difference in growth rates of the outcome in treatment blocks relative to control. It is this coefficient that we report in the regression tables of Chapter 6. It is important to understand exactly what is being identified. Take the case of a variable whose value falls between baseline and endline surveys. Female labour force participation rates may offer one such example. Here, a positive treatment effect, as represented by the coefficient β_1, may be consistent with estimates of the magnitude of female labour force participation in treatment blocks that are lower in endline relative to baseline values. In such cases, a positive treatment effect takes the form of a reduction in the downward trend of the outcome in question.

The credibility of estimates based on difference-in-difference regressions depends on the plausibility of the parallel trend's assumption. In most cases, researchers address this by selecting a set of control blocks that are similar to treatment blocks in socio-economic characteristics such as population, education, infrastructure, and poverty levels, but which were, for some reason, not included in the programme. Identification of suitable control blocks for the NRETP evaluation faces an additional obstacle in that the programme is layered on top of NRLM, a programme which is expected to affect outcomes in all the villages in which it operates, with returns that likely vary across geographies and time. This requires treatment and control blocks to be similar not just in socio-economic characteristics but also in terms of their implementation of NRLM.[32]

Credible estimates of NRETP's impact are possible because NRETP was introduced in a subset of NRLM's early blocks, with the sample of NRLM early blocks from which NRETP blocks exhibiting a high degree of homogeneity in socio-economic conditions at the start of the programme.[33] The selection of NRETP blocks was primarily done at the administrative level above the block, the district, with the programme selecting 100

[32] NRLM early and late blocks obviously differ in the duration of the programme as well. Understanding the impact of this difference is the objective of our evaluation of the programme.
[33] NRETP was introduced in 100 or NRLM's 161 early districts, and in 410 out of 584 early blocks.

districts on the basis of existing degree of mobilization and capitalization under NRLM and hence on the maturity of NRLM's federation of community institutions. While this likely meant some differences between NRETP blocks and the residual set of early blocks, we show (in the next section) that these differences were minimal for the blocks of our 2019 survey, both in terms of socio-economic variables but also in terms of the status and trend of implementation of NRLM.

The appropriateness of a difference-in-difference methodology for an evaluation of NRETP also derives from the fact that the control sample (non-NRETP blocks) is untreated for the duration of the study. Consequently, the canonical difference-in-difference 2x2 matrix applies: A treatment sample that is untreated at baseline and treated by endline and a control sample that is untreated throughout.

Nevertheless, concerns regarding the validity of the parallel trends assumption for NRETP blocks remain. These concerns apply even more so to an evaluation of NRLM based on a comparison of early NRLM and late NRLM blocks, given their socio-economic differences. Compounding this concern, the control sample for the NRLM evaluation (late blocks) is treated, albeit to a lower degree, in both survey rounds. We address our treatment of these concerns later in this section, following our presentation of summary statistics that evaluate the extent to which the three sets of blocks differ in socio-economic characteristics and programme implementation.

4.4 Methodology for outcome variables available only at endline

While we primarily focus our attention on variables such as household consumption and labour force participation rates that are available in both endline and baseline surveys, we also include analysis on a subset of outcomes that were measured only in the endline surveys. These are measures of women's status, including data on their subjective gender-related norms and beliefs and measures of their subjective welfare. Lacking baseline data, we use matching methods, restricting our analysis to the impact of NRETP because of the very close match between the treatment (NRETP) and control (early NRLM blocks) samples for this evaluation.

4.5 Baseline Balance

Our methodology requires balance in terms of household variables and programme implementation. We first demonstrate balance in covariates in 2011, at the start of NRLM. We then also provide evidence on the pace of implementation of NRLM over time, since 2011, for different types of blocks. Further evidence on balance for the samples used in each of the studies (NRETP and NRLM) is provided in subsequent sub-sections.

4.5.1 The similarity of socio-economic conditions in 2011, prior to implementation of NRLM:

We use data from the 2011 census to test the similarity of villages in different block types by characteristics related to the selection of blocks (village population, proportion of the population from scheduled castes and tribes, and female literacy rate) as well as a wide range of measures of development such as measures of household consumer assets (TV, quality of homes), access to services (outlet for the Public Distribution System), and remoteness (distance to the block capital). Testing for the similarity of villages in the

sample helps evaluate the suitability of linear regressions: If covariates are similar, then the assumption of a linear relationship for the sample is more plausible.

We evaluate differences in these variables across villages in different types of blocks (NRETP, early NRLM, and late NRLM) using normalized variables, or the differences in averages by treatment status (NRETP in the NRETP-early block comparison, and Early block in the early-late block comparison) scaled by the square root of the sum of the variances. As noted by Imbens and Wooldridge (2009), this is a scale-free measure of differences and hence unaffected by variation in sample size.[34] They suggest, as a rule-of-thumb, that concern regarding the sensitivity of the regression to different forms is justified if the normalized differences exceed 0.25.

Table 4 compares normalized differences in village characteristics across NRETP and early blocks, and across early and late blocks, using data from the 2011 census. The data reveal the close similarity in NRETP and early blocks: For a relatively large list of variables, the differences do not exceed 0.25 for any. The only variables for which this difference is relatively large (but still less than the 0.25 cutoff) are measures of household assets (TV ownership and the quality of the home residence). In contrast, there is a significant difference between early and late blocks. Variables such as village population, households of permanent structure, and village infrastructure (presence of a bank branch in the village) suggest larger differences between early and late blocks than exist between NRETP and early blocks.

Table 4: Tests of normalized differences in village characteristics by block type, survey villages

Variable	NRETP blocks	Early blocks	Late blocks	Difference in normalized variables	
				NRETP and early blocks	Early and Late blocks
Village population	3,120.53	2,444.40	1,494.33	0.107	0.254***
	(3185.25)	(2415.07)	(1233.54)	(0.159)	(0.095)
Village prop SC/ST	0.39	0.38	0.47	0.143	-0.027
	(0.33)	(0.29)	(0.32)	(0.171)	(0.15)
Female literacy rate	0.47	0.51	0.54	-0.058	-0.114
	(0.14)	(0.15)	(0.15)	(0.189)	(0.153)
Female LFPR (main worker)	0.20	0.17	0.20	0.037	0.13
	(0.19)	(0.17)	(0.21)	(0.187)	(0.118)
Percentage of village homes of permanent structure	30.11	34.17	31.48	-0.222	0.346*
	(21.09)	(27.82)	(25.36)	(0.257)	(0.174)
Percentage of hholds with TV	9.14	15.63	18.90	-0.256*	0.23
	(10.80)	(16.97)	(16.40)	(0.152)	(0.20)
Percentage of hholds who use banking facilities	48.15	44.94	53.82	-0.078	0.17
	(26.26)	(28.57)	(31.45)	(0.147)	(0.12)

[34] Following Imbens and Wooldridge (2009), the normalized differences is calculated as:

$\triangle_x = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{S_0^2 - S_1^2}}$ where for w=0,1, $S_w^2 = \sum_{i:W_{i=w}} \frac{\left(X_i - \bar{X}_w\right)^2}{(N_w - 1)}$

Variable	NRETP blocks	Early blocks	Late blocks	Difference in normalized variables	
				NRETP and early blocks	Early and Late blocks
Proportion of villages with PDS outlet	0.69	0.53	0.57	0.188	-0.014
	(0.47)	(0.50)	(0.50)	(0.132)	(0.095)
Prop, of villages with bank in village	0.15	0.14	0.09	0.043	0.157*
	(0.36)	(0.35)	(0.29)	(0.111)	(0.090)
Distance to block capital (kms)	18.66	13.56	16.00	0.138	0.043
	(18.90)	(11.85)	(13.32)	(0.103)	(0.123)
Sample size	343	292	359	635	651

Note: Figures in parentheses are standard deviations for data on variable means (columns 1-3) and standard errors for data on the difference in normalized variables clustered at the level of the block (columns 4-5). Regressions include state fixed effects. Data are for sample villages. Calculations are based on all villages in the respective block type. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Tests of normalized differences in household characteristics by block type, survey villages (2019 survey)

Variable	NRETP blocks	Early blocks	Late blocks	Difference	
				NRETP and early blocks	Early and Late blocks
Income	70,832.99	71,034.22	63,202.33	-0.031	0.048
	(70,258.33)	(69,007.62)	(68,629.11)	(0.078)	(0.087)
Number income sources	2.49	2.44	2.33	0.033	0.195**
	(1.18)	(1.18)	(1.24)	(0.083)	(0.090)
Per capita household exp	22,124.93	22,259.68	24,766.36	-0.010	-0.064
	(15,200.71)	(14644.33)	(16,764.47)	(0.083)	(0.072)
Number of migrants	0.40	0.31	0.32	0.098	-0.012
	(0.83)	(0.71)	(0.75)	(0.100)	(0.087)
Prod. Assets (Rs)	12,471.93	19.862.55	21,047.37	-0.156	0.066
	(135,028.75)	(54,637.48)	(56,985.09)	(0.099)	(0.072)
Consumer assets (Rs)	71,990.13	70,569.01	90,740.84	-0.032	0.011
	(135,028.75)	(126,871.89)	(149,060.77)	(0.087)	(0.067)
Mother – total hours of work (incl. domestic)	2,356.09	2,187.49	2360.76	0.059	0.111*
	(1183.80)	(1057.59)	(1260.99)	(0)	(0.058)
Father – total hours of work	1889.02	1,767.33	1841.63	-0.034	0.087
	(1247.61)	(1107.26)	(1340.29)	(0.079)	(0.069)
SHG member	0.81	0.77	0.72	-0.047	0.047
	(0.39)	(0.43)	(0.45)	(0.045)	(0.062)
Total Loan amount (all sources)	36,099.52	32,748.63	32,335.77	0.144	0.096
	(57,195.55)	(57838.62)	(59,126.09)	(0.121)	(0.098)
SHG loan amount	5,772.06	5198.34	4,100.86	0.078	0.257***
	(10,932.25)	(10532.57)	(9,047.12)	(0.060)	(0.094)
Informal loan amount	9,120.79	7660.73	4451.39	0.083	0.088
	(23824.45)	(22,038.19)	(16,625.09)	(0.089)	(0.089)

Note: Figures in parentheses are standard deviations for data on variable means (columns 1-3) and standard errors for data on the difference in normalized variables, clustered at the level of the block (columns 4-5). Regressions include state fixed effects. Data are for 2019 survey households. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Differences in household variables from the 2019 survey (Table 5) present a similar picture. There are no statistically significant differences in these values between NRETP and early blocks, indicative of the fact that both types of blocks were selected for early implementation of NRLM and followed a similar time profile for the roll-out of the programme and the provision of inputs. In fact, the difference between a large range of household outcomes across survey villages of these blocks never exceeds 0.12. In contrast, there are statistically significant differences between households in early and late blocks in terms of the number of income (livelihood) sources and in loan amounts. This is in line with the 2019 evaluation (Kochar et al., 2020) that documented differences in loan amounts and in income.[35]

4.5.2 Testing differences in programme implementation by block type

As discussed, a primary concern is not differences that remain stable across time between NRETP and early blocks, but the possibility that blocks could differ in the pace of implementation of the programme. The graphs below, however, suggest that NRETP and early blocks are similar in this regard. These graphs use data just for survey villages. In the appendix to this chapter, we provide graphs for *all* villages in survey districts. The same trends are maintained.

The first graph (figure 11) shows the cumulative number of SHGs in a village, averaged over villages, in the major states of our survey. The greater number of SHGs in Bihar and West Bengal reflects broader definitions of poor households and hence targeted SHG members. To account for this, the second figure (figure 12) represents a distribution function which plots the proportion of targeted SHGs within a village that were formed in the year in question.[36] This figure suggests that the process of SHG formation was largely completed by 2022.

[35] The methodological design controlled for the selection of blocks and villages, using the difference between early and late villages in early blocks, relative to control blocks, while also conditioning on differences in programme implementation. Thus, the differences across household outcomes in early and late blocks (without using the second level of differencing across villages) will not replicate the results of the 2019 evaluation.

[36] We use 2024 data on the number of SHGs in each village as the target number.

Figure 11: Growth in village SHGs by year and state

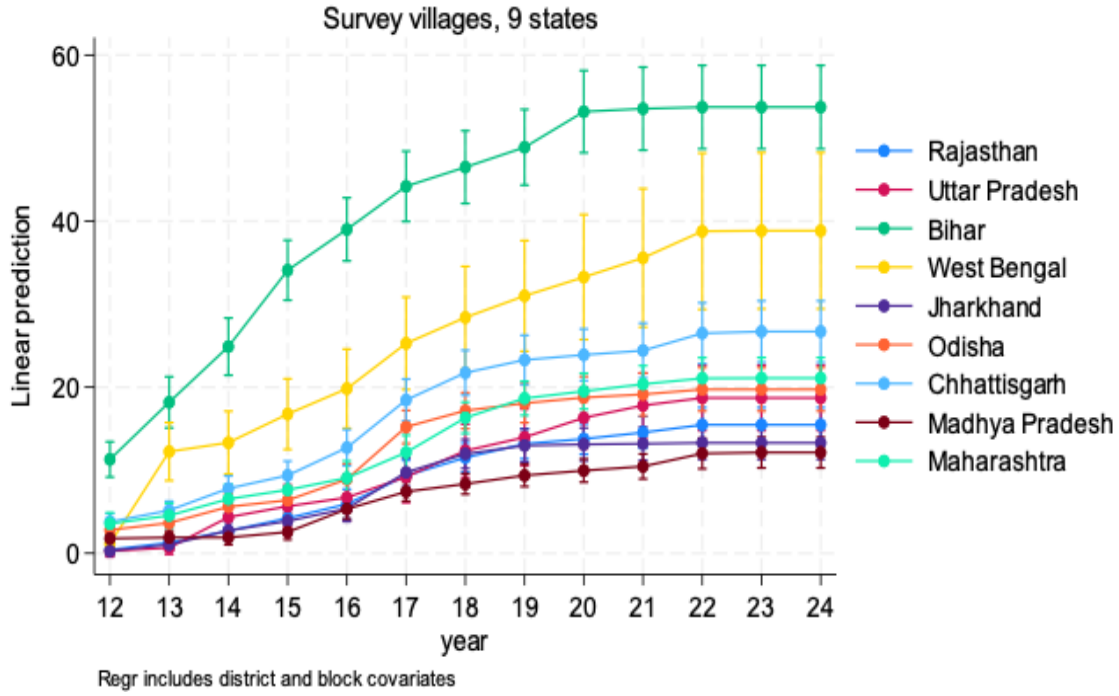


Figure 12: Proportion of targeted SHGs formed by year and state

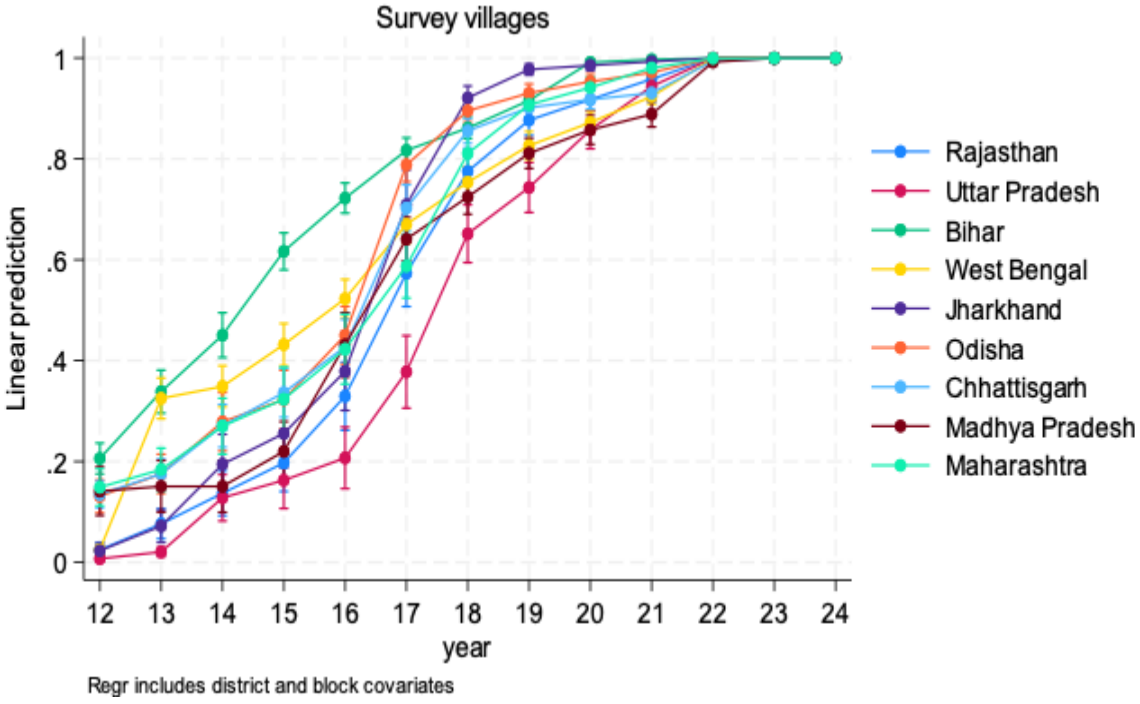


Figure 13: Pace of implementation by block type and year

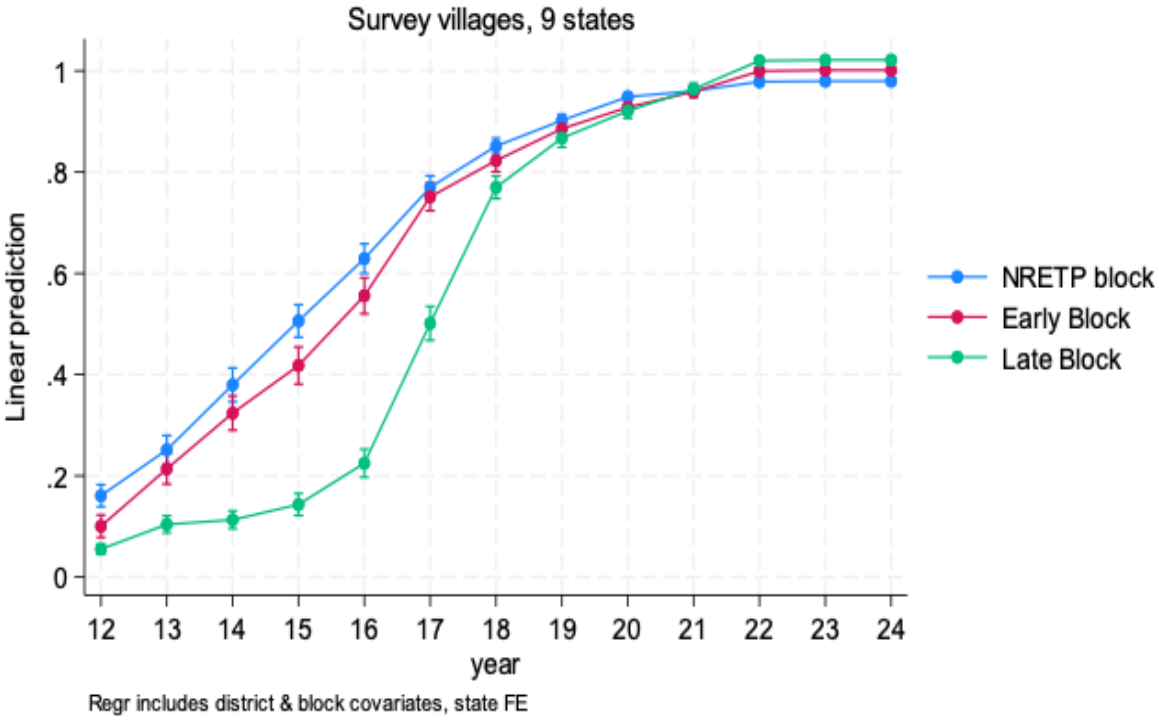
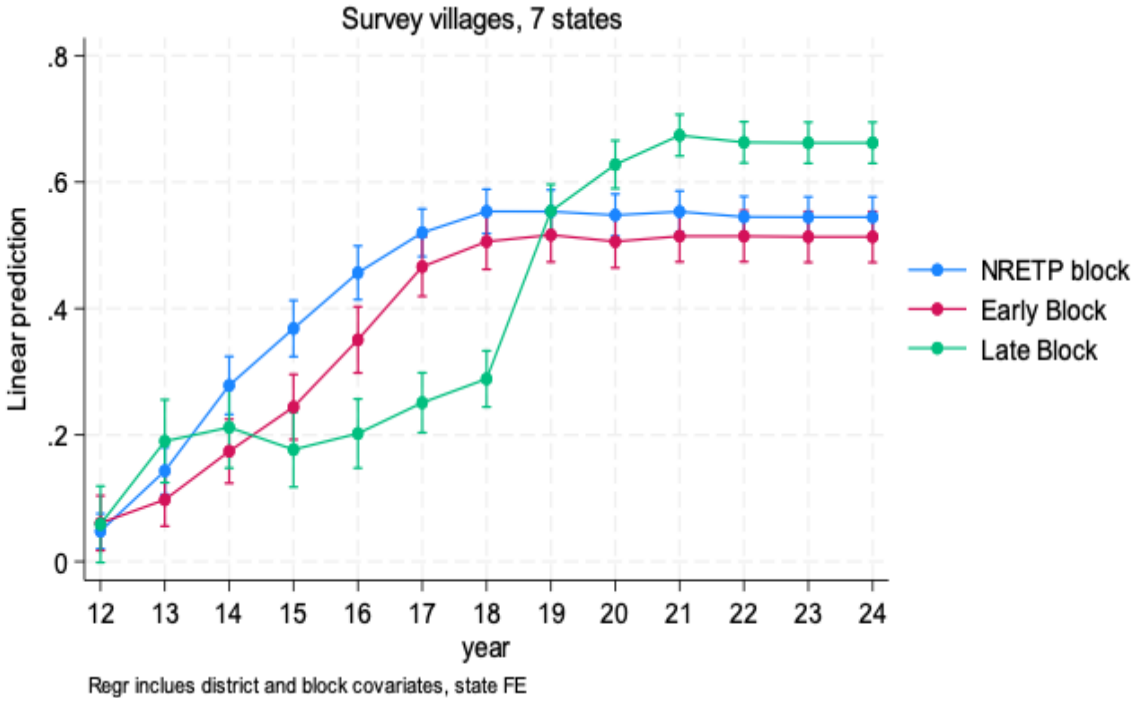


Figure 13 reveals the considerable variation in this age profile of implementation by block type, confirming an identical pace of implementation in NRETP blocks and other early blocks. In both these blocks, the growth of SHGs follows a concave path. In contrast, SHG growth in late blocks occurred at a much faster pace in early years (2016-2018), and then slowed down.

A better measure of the development of the federation is the proportion of SHGs that are federated into the highest level of the federation, the Cluster Level Federation. As noted in Chapter 1, NRETP relies heavily on the Cluster Level Federation for its implementation, and the selection of NRETP blocks is most likely to reflect the maturity of CLFs. Figure 14 charts the growth in the proportion of SHGs federated into CLFs across NRETP, early, and late blocks. As in previous graphs, this figure reveals the slower growth of CLF membership in early years of the programme and the subsequent higher pace of implementation (after 2018). Comparing NRETP to early blocks, while the proportion of SHGs federated into CLFs was approximately the same across these blocks from 2018 onwards, the pace of federation was higher in NRETP blocks in early years of the programme. Though this difference is relatively small, it does suggest that CLFs in NRETP blocks are older and hence more mature than their SHG counterparts.

Figure 14: Proportion of SHGs federated in CLFs by year and block type.



4.6 Identifying the causal impact of NRETP

4.6.1 Methodological Approach

Despite the similarity of villages in NRETP and Early blocks documented in tables 4 and 5, the differences in the pace of CLF formation, though slight, suggest the potential for a violation of the parallel trends assumption. This concern is particularly salient because NRETP implementation guidelines suggest the selection of NRETP blocks on the basis of the degree of maturity of NRLM's institutions.

If the covariates that likely generate differences in trends are observable, then the parallel trends assumption (equation 2) can be weakened to one that assumes "conditional parallel trends." This requires outcome trends in treatment and control regions, in the absence of the programme, to be equal *after* conditioning on possible confounding variables X_{it}. Thus, the identifying assumption changes to:

$$\mathbb{E}\left[Y_{i,2}(0) - Y_{i,1}(0) \middle| NRETP_i = 1, X_i\right] = \mathbb{E}\left[Y_{i,2}(0) - Y_{i,1}(0) \middle| NRETP_i = 0, X_i\right] \quad (4)$$

Under this assumption, valid inferences regarding NRETP's impact are possible, with estimators varying according to how well-specified the regressions for outcomes and treatment into NRETP are. A "regression adjustment" (RA) approach is preferred if the outcome equation is well-specified. RA methods (Heckman et al. 1997; Heckman et al. 1998) augment outcome regressions to include confounding variables whose values vary across treatment and control samples and whose impact on outcomes may differ across these samples. In contrast, inverse probability weighted (IPW) regressions correct for deviations from the parallel trends assumption by focusing on the probability of treatment. Combining the two, "doubly robust" methods enable consistent estimation if *either* the treatment equation or the outcome equation is correctly specified (Sant'Anna and Zhao 2020). Building on this literature, we provide RA, IPW, and doubly-robust

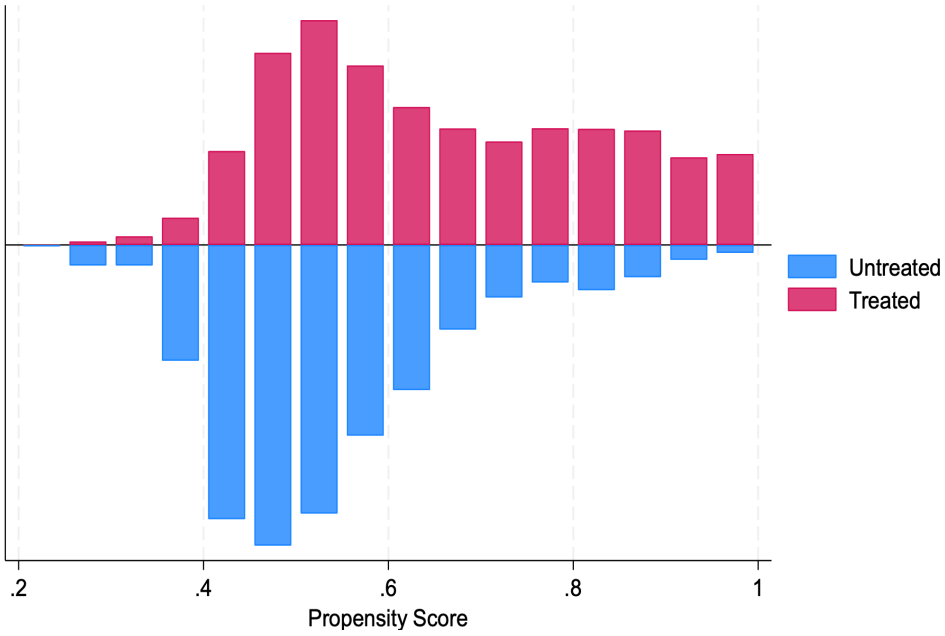
estimates of the impact of NRETP, in addition to that obtained from a “basic” difference-in-difference regression.

Our basic difference-in-difference regression includes amongst regression controls the set of variables that determined the selection of early NRLM blocks (as specified in programme implementation documents). These are village population, the proportion of the village from scheduled castes and tribes, female literacy rates, and village infrastructure. We take these variables from the 2011 Census, the same source used to identify NRETP (and early NRLM) blocks for implementation purposes. Second, we include determinants of the selection of NRETP blocks from amongst early blocks, specifically measures of the maturity of NRLM institutions in 2018, the baseline for NRETP. We do this using data from the programmes Management Information System (MIS), which provides year-level data on the programme and hence provides the information that was used to select NRETP blocks. We constructed the variables *vscale_18* and *clfscale_18,* defined respectively as the total age of all SHGs that exist in the village in 2018 and the total number of years of federation into CLFs for all these SHGs. These measures allow for variation in the year of formation of SHGs in each village and for variation in the year in which each SHG is federated into Cluster Level Federations. We focus on CLFs since it is this institution through which NRETP is implemented.

4.6.2 Overlap Condition

IPW and doubly robust regressions based on the propensity score require the satisfaction of an overlap condition. This requires the conditional probability of being in the treatment group to be bounded away from one, and the proportion of treated units to be bounded away from zero. We estimate the probability of treatment using the set of variables described above as covariates (village population, proportion from scheduled castes and tribes, female literacy rates, an index of village infrastructure, *vscale_18,* and *clfscale_18).* Figure 15 below suggests that this condition is met for NRETP blocks and non-NRETP early NRLM blocks (the control for our evaluation of NRETP).

Figure 15: Testing overlap for NRETP and early NRLM blocks.



4.6.3 Support for Identification: Sensitivity and Falsification tests

Lack of household data prior to 2011 prevents us from examining trends in household outcomes prior to the implementation of NRETP or from developing sensitivity tests based on bounds on pre-trends. However, as previously noted, the weakness of tests based on pre-trends suggests that other tests may be more informative.

We provide support for our methodological approach by examining whether the same results hold for treatment and control samples that are similar to the NRETP treatment and control sample, but without the implementation of NRETP. For this, we exploit the fact that the selection of NRETP was based on a set of observables, namely the maturity of NRLM institutions in 2018.

Specifically, our falsification tests use the set of control blocks (early NRLM but without NRETP) and divide them into two groups by the level of development of NRLM institutions. We use several different methods to construct these two groups. A first method divides the set of control blocks based on a propensity score, calculated on the basis of a probit regression of a NRETP block indicator on *clfscale_18* and *vscale_18,* as well as values of implementation status in 2015 (*clfscale_15* and *vscale_15*). The regression is run on all early blocks and used to predict the probability of being a NRETP block for all non-NRETP early blocks. Using this prediction, we divide the sample into those with a high and low probability of NRETP implementation. We then run robust difference-in-difference regressions, using the “advanced” sample of villages as treatment and the others as control. We then repeat this exercise, but now dividing blocks into groups with high and low levels of institutional development first on the basis of *vscale_18* and then based on *clfscale_18.*

These regression tests the impact of the scale or level of development of NRLM institutions in the absence of NRETP. If our estimates of NRETP are merely reflecting the greater development of NRLM institutions in NRETP blocks, then the results based on this division of the control sample (non-NRETP early blocks) should generate similar results.

We also conduct robustness tests, using different state samples and different sets of controls. For the latter, we include lagged values of *vscale* and *clfscale* (*vscale_15* and *clfscale_15*) as well as block-level variables (measures of female labour force participation rates, female literacy, and proportion of households from scheduled castes and tribes at the level of the block, constructed using 2011 census data).

4.7 Estimating the returns to sub-components of NRETP: the model CLF Programme

As discussed in Chapter 2, NRETP included several important sub-components. These constituted additional implementation-related treatments as well as new livelihood institutional arrangements. Amongst the former, the most significant is the model Cluster Level Federation intended to serve as a center of excellence with strengthened implementation capabilities and enhanced resources (details are in Chapter 2).

As in other NRLM / NRETP interventions, the model CLF programme constitutes a staggered intervention, initially intended to be implemented in just one cluster of each NRETP block. With the average NRETP block comprising four clusters, this suggests implementation in approximately one-fourth of all NRETP clusters. Because our initial

survey included at least two clusters in each block, our sample clusters and hence villages also reveal similar variation in the incidence of mCLFs. Approximately 27% of villages in NRETP blocks fall in mCLF clusters. Extending the sample to all NRLM Early Blocks, approximately 18% of sample villages are in MCLF clusters. This staggered intervention provides the potential for a credible evaluation of the mCLF programme.

One methodology for this evaluation would be to restrict attention to NRETP blocks and compare clusters with model CLFs to other clusters, using a difference-in-difference regression with cluster fixed effects. As always, identification relies on parallel trends, an assumption that is likely to be valid after conditioning on the baseline maturity of NRLM's community institutions, since the selection of model CLF clusters from amongst the otherwise very similar clusters of a block is primarily based on this criterion. However, since the model CLF programme is best viewed as an intensive version of NRETP, this methodology essentially estimates differences in treatment intensity and requires a no-treatment heterogeneity assumption. As discussed in greater detail in later subsections of this chapter that outline our methodology for evaluating NRLM, this assumes that in the absence of the model CLF programme, the returns to NRETP in MCLF clusters would have been identical to those in non-MCLF NRETP clusters. While this assumption is likely valid, a more serious concern is the potential for spillovers from mCLF clusters to other clusters of the block. Block implementers may prioritize model CLF clusters when allocating their resources (other than those specifically intended for model CLF clusters). The reverse is also possible: model CLF resources may substitute for normally available resources, enhancing their availability for non-mCLF clusters.

Using clusters in non-NRETP early blocks, the blocks used as the control sample for the NRETP evaluation allows us to circumvent these issues. Thus, we provide estimates of the impact of the model CLF programme by comparing the trend in outcomes across MCLF NRETP clusters to that in NRLM (non-NRETP) early blocks. We similarly present results from regressions that compare the trend in outcomes in non-MCLF NRETP blocks to those in non-NRETP early blocks. The first set of regressions estimates the returns to the NRETP + MCLF intervention, the intensive form of NRETP, relative to a control sample that lacks both programmes. The second estimates the returns to the less-intensive (no MCLF) NRETP intervention relative to the same control. For completeness, we also report results that compare the trend in outcomes in MCLF NRETP clusters to that in non-MCLF NRETP clusters. In the absence of spillover effects and under the no-treatment heterogeneity assumption, the results from this regression should approximate the difference in estimates from the two regressions described above.

4.8 Identifying the mid- to long-term causal impact of NRLM

4.8.1 Methodological Approach

Our identification of NRLM identifies the impact of the programme in its medium-to long run (the returns over a 5-year period after approximately 6 years of programme implementation) to those that obtain in the short run (the returns over a similar 5-yearear period approximately 2 years after the commencement of the programme). This focus is dictated by the lack of baseline data on outcomes prior to NRLM's start and hence the inability to identify treatment effects relative to those that would have obtained without the programme. The staggered nature of implementation and the consequent availability of a sample of blocks in which programme intervention started in 2017 (on average)

allows us to use this sample to construct counterfactual outcomes of impacts in the short run (for a five-year period, commencing two years after programme start).

We stress the implications of the lack of baseline data for the interpretation of the results of our NRLM evaluation: Our estimates evaluate whether outcome growth in the medium to long run persists at the same rate as in early years, or whether it increases or decreases relative to short-run trends. A finding of no impact of the programme in the medium- relative to short-run merely suggests a linear growth rate, with returns that are invariant over this period. A negative estimate from this study can still be consistent with positive returns to NRLM relative to that which would obtain in the absence of NRLM; it merely indicates that returns decline over time. Conversely, a finding of a positive effect suggests increasing returns over time. Layering new interventions (such as NRETP) over old treatments may generate increasing returns. But, decreasing returns are also possible. For example, households may use early access to credit provided by NRLM institutions to invest in productive fixed capital, the returns to which decline over time unless continuous improvements in productivity are possible.

4.8.2 Basic difference-in-difference regression:

We start our analysis of the impact of NRLM using broadly the same broad difference-in-difference regressions as for the NRETP analysis (equation 3), but with the treatment indicator T now taking the value 1 for Early NRLM blocks, and with the regression sample restricted to early and late blocks, with early blocks being restricted to those without NRETP. Additionally, we drop the variables used for the selection of NRETP blocks (*vscale* and *clfscale*) from amongst the regressors. These variables did not play a role in the selection of early and late blocks. More importantly, because our analysis of NRLM primarily captures the impact of increases in programme scale over time, these variables essentially represent lagged values of treatment, complicating any interpretation of results. Figure 16 below demonstrates overlap between the sample of early (treated) and late (untreated) blocks for this evaluation.

4.8.3 Treatment heterogeneity

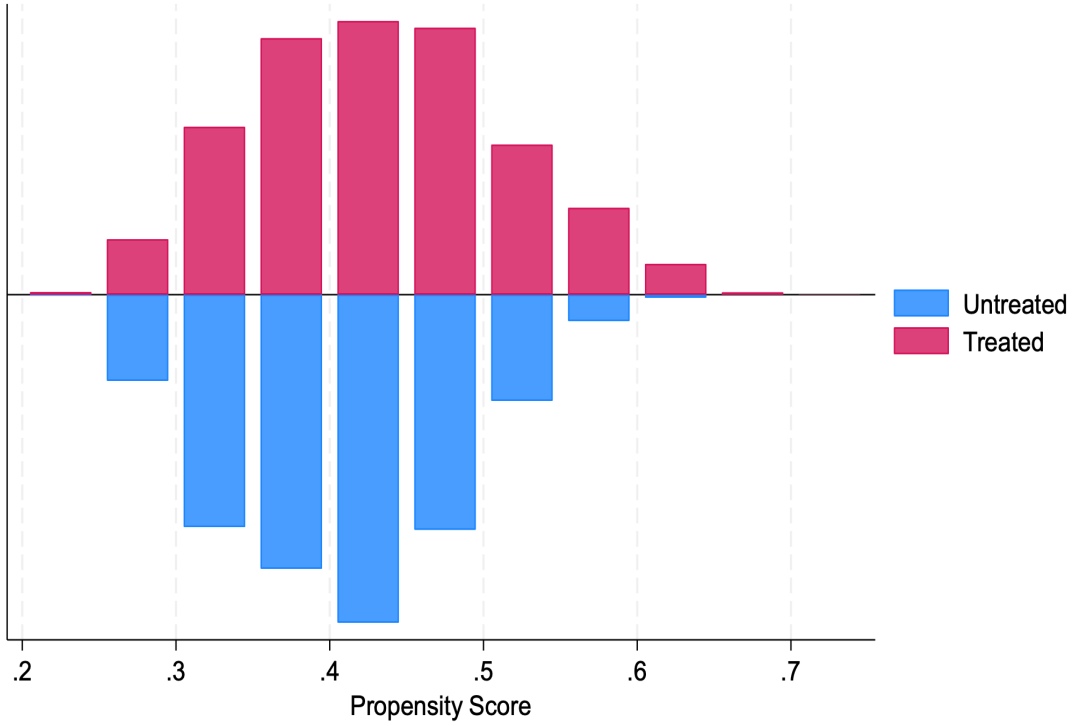
The fact that the control sample of our NRLM evaluation is also treated, albeit to a lesser extent than the treatment sample, affects the interpretation of the results but also the assumptions required to identify causal effects. In terms of interpretation, as previously discussed, any identified difference between treatment and control units measures the impact of the *same* difference in duration (intensity) in the medium to long-run relative to the short run.

The variation in treatment intensity across treatment and control samples of the NRLM evaluation also raises concerns regarding treatment heterogeneity. These vary with the nature of the treatment (binary or continuous) and the context, with the latter affecting the dynamic evolution of outcomes and hence the validity of assumptions regarding the variance of treatment effects over time and space. Since the challenges differ by policy and context, so do the solutions.[37] We therefore start by discussing the condition

[37] Much of the recent literature that considers contexts where control samples are treated in some or all periods focuses on binary treatments with heterogeneity in treatment between groups and over time. In such cases, the overall ATT estimate is hard to interpret and may be misleading, even suggesting negative treatment effects. In other designs, including continuous or multiple

required for causal identification of the relevant treatment effect and then consider the factors specific to NRLM that may cause a failure of this condition. Based on this, we outline our proposed strategy and provide evidence to support our approach.

Figure 16: Testing overlap for NRLM early and late blocks.



As before, we restrict attention to two groups (blocks), now defined by the time of programme entry. Let EB take the value 1 for early blocks, 0 for late-entry blocks. Let programme duration be given by $d\epsilon\{0,1,2\}$, where d=0 implies the short run (0 to 4 years), d=1 denotes the medium run (5 to 8 years), and 2 implies the long run (9-12 years). The potential outcome for household i in period t with long-term exposure to the programme is denoted as $Y_{i,}t(2)$, while the potential outcome in the medium-run is $Y_{i,t}(1)$. With this notation, the following equation defines the ATT parameter $\tilde{\beta}$, the impact of long-run exposure in early blocks relative to exposure over the medium-run:

$$\tilde{\beta} = \mathbb{E}\left[Y_{i,2}(2) - Y_{i,2}(1)\middle|EB_i = 1\right] \quad (5)$$

As always, the identification problem is that, in any given period, we only observe households' current outcomes. For households in blocks where the programme has been running for 8 years by period t=2, we observe long-run outcomes but not those that obtained over the medium term. Households in late blocks which enter the programme with a four-year lag offer the potential for identification. For these households, we observe $Y_{i.2}(1)$ in year t and $Y_{i.2}(0)$ in the first period t - 1.

treatments, biases can result even in the absence of treatment heterogeneity. Here, potential solutions will depend on the factors that cause bias.

The necessary identifying assumption is that the expected evolution of outcomes between the short and medium term is the same for both groups.

$$(6) \qquad \mathbb{E}\left[Y_{i,2}(1) - Y_{i,1}(0)\middle|EB_i = 1\right] = \mathbb{E}\left[Y_{i,2}(1) - Y_{i,1}(0)\middle|EB_i = 0\right]$$

With data on outcomes for the control group (late block) in the short and medium run, in years (t-1) and t respectively, the right-hand side of equation (6) is observed. The identifying assumption requires this observable trend to replicate the evolution of outcomes between the short and medium run for the treatment group. If so, the difference-in-difference regression identifies the difference in outcomes between the long and medium run. This is a stronger assumption than the parallel trends assumption: it requires that the impact of treatment in the medium run be the same in early and late blocks.

In discussing the validity of this assumption, much of the literature focuses on socio-economic characteristics, such as age or education, which may cause the impact of treatment on the trend rate of growth to vary across treatment and control groups when observed at similar lengths of programme duration. Such socio-economic factors are less important in NRLM, particularly in survey blocks, given that both early and late blocks belong to a target set of blocks selected from the population of all blocks in the country on the basis of a relatively small set of socio-economic factors. Though these conditions vary across treatment and control blocks, the variation is relatively small and unlikely to cause large differences in treatment effects. Instead, the primary factor influencing the impact of treatment in early and late entry blocks at a common programme duration such as the medium run is a programmatic factor: differences in implementation of the programme as it scales.

These implementation differences have long been considered to be an important determinant of the effectiveness of programmes that operate at scale and the primary factor that restricts generalizing from small pilots conducted at the start of a programme to its impact at scale (Banerjee et al., 2017). Little evidence exists on implementation constraints at scale and their influence on programme returns at a point in time or over time. Research that explicitly considers implementation constraints tends to focus on aspects related to the *design* of the programme rather than administrative capacity. Angrist and Meager (2023), for example, show that the heterogeneity in treatment effects across five different randomized studies of educational interventions is primarily explained by variation in the degree of implementation (intention-to-treat or treatment-on-the-treated) and the programme delivery model (teachers or volunteers). As in much of the literature, the implementation differences that Angrist and Meager focus on are cross-sectional differences in the design of the programme, such as the type of instructor, differences that are likely to be significant in comparisons of pilot studies implemented in different contexts. In a difference-in-difference context, such factors are likely to get netted out when taking differences for similar groups over time.[38]

[38] They also note the relevance of their results to instances of implementation *failure*: the possibility that the absence of a statistically significant impact of any programme may reflect an inability to implement it in important ways. If such failures exist, standard research methodologies confound the impact of programmatic inputs with implementation failures, making it hard to assess whether the programme would be worth pursuing if implementation could be improved.

A far greater concern in at-scale programmes evaluated over a relatively long period of time is a different set of implementation constraints, namely administrative capacity or the strength and quality of the administrative staff charged with implementing the programme. Most governments stagger the introduction of a programme across regions to work around capacity constraints, addressing them over time as the programme scales.

This *planned* variation in administrative capacity constitutes a confounding variable whose magnitude varies across treatment and control groups and over time. This implies that the trend in growth, at the same length of duration of the programme, will vary across treatment and control samples, causing a failure of the identifying condition (equation 6). In our instance, a standard difference-in-difference regression on a treatment indicator that takes the value 1 for long-run exposure will confound estimates of duration impact with that of differences in administrative capacity, as long as the impact of initial administrative capacity varies across years, as it is bound to do.

The resulting bias could be in either direction. While it is generally assumed that capacity constraints are more likely to bind as a programme scales, this need not necessarily be the case. NRLM provides an example. As discussed in Chapter 1, NRLM included initiatives to ensure that local administrative capacity improved over time. If so, the scale-up of the programme will be faster in villages of late-entry blocks relative to those in early blocks. Indeed, it is precisely this variation that underlies the evaluation methodology of our 2019 study and the triple-difference regression approach of this paper. Specifically, these methodologies exploit the greater difference in programme duration between early and late villages of early blocks relative to the same difference in late blocks, a difference that reflects the growth in administrative capacity over time. Late NRLM blocks and late villages within each block benefitted from a planned programmatic spillover from early blocks and villages, which enabled a growth in capacity over time.

Contexts such as NRLM where the violation of the identifying assumption reflects a measurable confounder suggest an approach analogous to conditioning on confounders to ensure parallel trends. The identifying assumption changes to a conditional parallel trends assumption, namely that equation (6) holds, conditioning on initial administrative capacity. In this case, RA methods allow for interactions of initial administrative capacity (at programme start) with time and treatment indicators.

4.8.4 Measuring initial programme capacity

Our measure of programme capacity relies heavily on the actual implementation of the programme and its approach to mitigate capacity constraints. As previously described, NRLM relied on members of a “community cadre” for the formation of SHGs, drawing members of this cadre from amongst existing SHGs in the district. For this, 1-2 “active women” were identified in each village at the time of entry, trained for two years, and then deployed in teams responsible for SHG and VO formation in remaining villages. The process was designed to ensure that local administrative capacity increased hand-in-hand with the expansion of the programme, enabling faster growth of SHGs and the federation in late-entry villages and blocks. It implies a built-in spillover from early to late blocks: For any given village entered in year t, the pace of growth of the federation reflected the number of villages within the district that had been entered in year (t-2) or earlier.

This suggests that the local administrative capacity for villages entered in time t reflects the number of villages within the district that were entered in year (t-2) or earlier.[39] This includes such villages in other blocks of the district, but also early-entry villages of the same block. Since the order of entry into villages within a block was based on village socio-economic characteristics such as the size of the targeted population of SHG members, measures of the order of village entry within a block are correlated with observable and unobservable village characteristics which may directly affect the pace of SHG development. They are also indicative of the characteristics of surrounding villages. For example, suppose that smaller villages are more likely to be entered later. Then, for any given village v, a large number of villages with prior entry within the block signals the size of village v but also suggests that it is surrounded by larger villages.

We therefore measure existing capacity for village v, at the onset of programme implementation in the village, using information only on villages in other blocks of the district and in other clusters of the same block. Specifically, using the programme's administrative database, we measure the number of SHGs in existence two years prior to the start of the programme in the village in question, restricting attention to SHGs located in other blocks of the same district (*dshgentry_2v*). We also include the number of villages in other clusters of the same block in which village v is located (*blventry_2v*), again restricting this count of villages to those in which programme entry started two years prior to the village in question.

To allow for treatment heterogeneity, we include an interaction of treatment (the EB indicator) and these two implementation indicators (*dshgentry_2v* and *blventry_2v*) as well as interactions of the indicator for the endline survey with these same terms.

Table 6 provides summary statistics on these measures of programme capacity for each of the three types of blocks of this study, NRETP blocks, non-NRETP early blocks, and late blocks. The data reveal the considerable variation in initial capacity, reflected by the scale of the programme two years prior to programme entry in the village in question. For example, the formation of SHGs in villages of our survey NRETP blocks was undertaken by a community cadre drawn from approximately 1007 SHGs that were formed in other blocks of the district at least two years prior to entry in the village in question. This figure is similar to that for non-NRETP early blocks (963). In striking contrast, villages in late blocks were able to draw on 3,700 pre-existing SHGs and hence a far larger pool of community resource persons. This explains the far faster scale-up of the programme in late blocks and the corresponding potential for a difference in treatment impact in these blocks.

[39] It also implies that identification is aided by a functional-form assumption: Capacity constraints are most binding for early villages of treatment blocks, a sample for which the number of already-entered villages in the district is essentially zero. This is not true in early villages of late blocks.

Table 6: Measures of initial programme capacity at the level of the village by block type

	NRETP blocks	Non-NRETP early blocks	Late blocks
dshgentry_2v	1007.47	962.51	3739.72
Number of SHGS formed in other blocks of the district prior to village entry	(1564.06)	(1349.75)	(5454.46)
blventry_2v	28.61	32.99	3.46
Number of villages entered in other clusters of the block prior to village entry	(39.56)	(40.45)	(11.01)
Sample size (number of villages)	195	160	310

Note: Standard deviations in parentheses.

We note that these village-specific variables vary across villages, even villages with the same programme start date. That is, the variation does not merely reflect variation across villages in programme start date; these covariates will vary across two villages with the same programme start date but located in different districts. Appendix figure B1 attests to this, plotting the growth in the number of villages entered by year for all districts in a sample of our survey states. These plots show the variation that the pace of formation of SHGs in two villages, with the same entry year, one with programme entry in 2012 and another with entry in 2014, would significantly differ, depending on the district in which they were located.

4.9 Outcomes

For both NRETP and NRLM, we report results from a common set of household outcomes: household income, household expenditure, the diversity of income sources, measures of food diversity, the value of production and consumption assets, measures of financial inclusion including access to loans and loan amounts, and measures of women's empowerment and economic status including female labour force participation and occupational choice that are common to both survey rounds. As previously discussed, we also provide regression estimates of the impact of NRETP on a set of measures of female empowerment and women's status, using data only from the endline surveys.

This report also includes some analysis of the impact of NRETP and NRLM on SHG quality, using data from the SHG module that was canvassed in both survey rounds. We concentrate on measures of SHG quality, described in detail in the Summary Statistics chapter of this report. We also examine each programme's impact on member entry and exit and hence on member composition. The broad methodology used for the SHG level analysis is the same as that for the household analysis. Specifically, our analysis of the impact of NRETP on SHG performance uses difference-in-difference regressions to compare outcomes across SHGs in NRETP blocks and those in NRLM's early blocks. We examine the impact of NRLM by contrasting changes in outcomes for SHGs in NRLM's early blocks relative to late blocks, with the same set of controls for treatment heterogeneity as used in the household-level analysis.

4.10 Attrition from sample

4.10.1 Household follow-up survey

Household attrition from the baseline 2019 sample in our survey is exceptionally low, at 10.37%, a likely consequence of COVID-19 that significantly reduced out-migration from rural to urban India. There is also no evidence of treatment-level variation in attrition. Table 7 reports results from a regression of an indicator variable for attritted households on an indicator for treatment blocks for the two studies (NRETP and NRLM), a set of block-level indicators used in the main regressions of this paper and state fixed effects. The regression, run on the baseline sample, reveals no effect of treatment on the probability of attrition.

In addition to household attrition, the interpretation of results will be affected if treatment causes migration of members within each sample, resulting in differences in demographics. To assess the importance of this concern, Table 8 reports results from regressions which test if household demographics had remained the same across baseline and endline by treatment status. We examine the impact of treatment on household size and on a set of three gender-by-age groups, males ages 20-40, males ages 40-60, males above the age of 40, and the same set of three groups for women. We regress these outcomes on the interaction of the treatment indicator (NRETP and NRLM early blocks) and block fixed effects, separately for the two different regression samples. The results in Table 8 reveal a significant effect at the 10% level for males in the 20-40 and 40 and higher age groups in the NRETP sample.

Table 7: Testing differential household attrition by treatment status, NRETP and NRLM

	NRETP sample	NRLM sample
Coefficient on Treatment	-0.0159	0.0241
indicator (NRETP/NRLM)	(0.0124)	(0.0176)
Sample size	14,413	11,642

Note: regressions are run on baseline sample and test for differences in attrition across treatment samples at baseline. NRETP sample is NRETP and NRLM (non-NRETP) early blocks. NRLM sample is (non-NRETP) NRLM early and late blocks. Standard errors, clustered at the level of the village, in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A second regression for each treatment sample adds on the set of households (indicator for SC/ST households, maximum education level at baseline, and landlessness at baseline) and block-level variables used in the main regressions of this paper, with the latter interacted with an endline indicator. With these controls, the change in adult males aged 20-40 and the age group 40 and higher is no longer statistically significant.

These findings suggest that any effect of NRETP or NRLM identified in our main regression results is unlikely to be the consequence either of differences in sample attrition or because NRLM affects household demographics.

Table 8: Testing differential impact of treatment status on trends in household demographics

	NRETP sample: coefficient on Treatment x Endline		NRLM sample: coefficient on treatment x endline	
	Base regression	With additional controls	Base regression	With additional controls
Household size	-0.0578	0.0490	0.0171	-0.0130
	(0.0491)	(0.0495)	(0.0526)	(0.0521)
Number of males:				
age: 20-40	0.0249	0.0218	0.00537	0.00922
	(0.0206)	(0.0214)	(0.0224)	(0.0225)
age: 40-60	-0.0200*	-0.00303	-0.00172	0.00570
	(0.0113)	(0.0118)	(0.0123)	(0.0126)
age: over 60	-0.0144*	-0.00857	0.00277	0.00203
	(0.00775)	(0.00849)	(0.00837)	(0.00866)
Sample size	27,657	27,657	21,297	21,297

Note: all regressions include blocked fixed effects. Additional controls are the interaction of the endline indicator with the following block-level variables: population, proportion from scheduled castes and tribes, female literacy, and infrastructure index. Standard errors, clustered at the level of the village, are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.10.2 SHG follow-up survey

The 2019 survey targeted 5,672 SHGs, approximately 6 in a village. Of these, 5,393 (95%) were targeted at endline after dropping part of the Odisha sample. Out of these, we were able to follow 4,680 (87%) SHGs at the endline.

The survey team was given instructions to follow up on all SHGs that were defunct at baseline, given that NRLM attempts to “revive” such SHGs. Thus, the 2024 survey does include 491 SHGs, 10% of the panel SHGs interviewed in both rounds, that were defunct at baseline. An additional set of SHGs, 482 or 12% of the SHGs that were functioning at baseline and included in the 2024 survey, were found to be non-functioning at endline.

Concerns about the SHG sample thus take two forms. First, there is the usual concern regarding attrition and whether it is balanced across treatment and control groups. A second concern relates to functioning SHGs. Since some regressions restrict analysis to functioning SHGs, the concern is whether the functioning SHGs that were dropped in the second round are balanced across treatment and control groups.

To address these concerns, Table 9 reports results from two different regressions. Both regressions are run on all SHGs included in the baseline survey and use only baseline data. The regressions differ in their dependent variable. The dependent variable for the first regression is an indicator variable for attritted SHGs, SHGs included in the 2019 survey that were not in the 2024 survey. The second uses an indicator variable that takes value 1 for functioning SHGs that were not included in the 2024 survey.

The first two columns of the table report results for the NRETP sample. The next two repeat these regressions for the Early Block sample, replacing the NRETP indicator with

the EB indicator. For each dependent variable, we report results from three different regressions. The first regression includes only an indicator for NRETP blocks and state fixed effects, with standard errors clustered at the level of the village. The second regression includes all the village and block-level controls used in the household analysis.[40] We also include two additional SHG-level controls. The first is an indicator variable that takes the value 1 if the SHG was formed by Cluster Resource Persons (CRPs) from the same or other districts, 0 if formed by the VO, by active women of the village, by NGOs, or any other non-NRLM institution. The second is a set of fixed effects for the year in which the SHG was formed. A third regression replaces the SHG start-year fixed effects with a quadratic in the SHG's age.

Regressions for both the NRETP sample and the EB sample suggest that attrition is balanced across treatment samples: The NRETP (EB) indicator is statistically insignificant in all regression specifications. This remains true when we examine the effect of treatment on the sample of functioning SHGs that were not resurveyed in 2024.

Table 9: Testing differential SHG attrition across samples, NRETP

Dependent variable: Attrition SHGs between survey years (SHGs that were in baseline but not surveyed in endline)

Regression type	NRETP sample: Coefficient on indicator for NRETP block		NRLM sample: Coefficient on early block	
	Sample 1	Sample 2	Sample 1	Sample 2
No additional controls	0.00316	-0.000788	0.0255	-0.00358
	(0.0159)	(0.0101)	(0.0204)	(0.0120)
Add controls & indicator variables for SHG start year	0.00799	0.00466	0.0130	-0.00614
	(0.0165)	(0.0115)	(0.0292)	(0.0156)
Add controls & quadratic in SHG age in months	0.00896	0.00533	0.0143	-0.00379
	(0.0167)	(0.0115)	(0.0289)	(0.0156)
Sample size	2857	2857	2030	2030

Note: Sample 1: All SHGs in the baseline survey, baseline data only. Sample 2: Restricts sample to functioning SHGs in the baseline. Standard errors, clustered at the level of the village, in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[40] Village level variables are village population; the proportion of the village population from scheduled castes and tribes; the female literacy rate; and a village infrastructure index. Block-level variables include the block counterparts to these variables as well as measures of block wealth (the mean of the total number of good-quality houses in each village of the block) and the proportion of the block male population employed in the non-agricultural labour market. As in the household analysis, all variables are from the 2011 Census. The regressions also include interactions of the village infrastructure index with measures of programme scale: *vscale_v15, vscale_v18, clfscale_v15,* and *clfscale_v18.*

5. Summary Statistics and Descriptive Analysis

This chapter presents summary statistics for households, the primary female respondent of the household, and for NRLM's community institutions. The summary statistics chapter of our baseline report (Kochar et al., 2020) provided detailed information on village statistics based on data from the 2011 Census. Some of that data is reproduced in the Methodology Chapter of this report (Chapter 4) to examine baseline balance across villages in the three block types of interest: NRETP blocks, early (non-NRETP) NRLM blocks, and late blocks. Given this prior extensive discussion, this chapter primarily discusses changes over time in household outcomes and discusses data on SHGs and CLFs. In the interests of brevity, we discuss results for the overall sample without distinguishing outcomes for the three different types of blocks.

As was the case in our 2019 report, the analysis of this chapter does not establish causal effects but instead provides broad information on households and particularly NRLM's community institutions, highlighting findings of broad interest which suggest the need for further research. For household outcomes, the intent is merely to provide a snapshot of the sample at baseline and endline, and to note broad time trends in the main outcomes over the years.

For SHGs and CLFs, however, we provide a further disaggregation of data for the different treatment blocks. These simple comparisons across blocks do not provide causal evidence of the programme's effect but instead suggest potential explanations or pathways for the results of the next chapter. We note that many of the tables of this section relate to the endline study, since the same level of detailed data was not collected at baseline. While summary statistics cannot be used to infer causal impacts, this is particularly true of data which is only available at one point in time. Contrasting outcomes in early to late blocks, for example, may confound the programme's impact with that of pre-existing differences in the data.

5.1 Households

5.1.1 Basic household socio-economic statistics

Table 10 provides data on the key socio-economic household variables for panel households, those that were surveyed in both survey years. As expected, time-invariant variables such as the proportion of households from scheduled castes and tribes and the proportion of landless households are approximately the same across survey years. The proportion of scheduled castes and tribes is 0.63 in 2019 and 0.61 in 2024, while the proportion of landless households is 0.41 in 2019 and 0.42 in 2024 in both survey years.

Other socio-economic characteristics of households change over time. Household size declines marginally from 5.3 in the baseline study (2019) to 5.0 in 2024. The average amount of land owned per household increases slightly from 1.03 acres to 1.26. Larger increases occur in education. The number of completed years of education for the household male and female over the age of 18 with the highest schooling attainment increases by almost one year, from 6.7 to 7.5 for males and from 4.6 to 5.7 for females.

Table 10: Household Summary Statistics, Panel Households

	Baseline (2019)	Endline (2024)
Household size	5.270	4.991
	(2.146)	(2.146)
Scheduled caste or tribe	0.633	0.619
	(0.482)	(0.486)
Highest schooling years, household adult male	6.680	7.507
	(4.817)	(4.827)
Highest schooling years, household adult female	4.640	5.657
	(4.868)	(5.129)
Prop landless	0.416	0.421
	(0.493)	(0.494)
Land size (acres)	1.029	1.262
	(2.218)	(7.465)
Annual income (real INR)	68194.1	66601.5
	(102504.2)	(116294.3)
Per capita monthly household expenditure (real INR)	17,823.70	20,661.10
	(21,656.00)	(26,477.70)
Share of food in items of monthly expenditure	0.66	0.67
	(0.15)	(0.16)
Share of food in total expenditure	0.45	0.51
	(0.17)	(0.17)
Proportion of home-produced consumption exp to total food	0.223	0.238
	(0.228)	(0.252)
Count of types of food items consumed	12.11	12.99
	(2.846)	(3.785)
Counts of all consumption items	17.01	19.26
	(3.991)	(5.384)

Note: Figures are mean values, standard deviations in parentheses. Data is for panel households, surveyed in 2019 and 2024. Sample size is 23,177 in each survey round.

The survey data suggest a significant increase in household per capita expenditure in real terms, from INR 18,000 to INR 20,600. Household income, again in constant INR, however, remains approximately the same (INR 68,000 in 2019 and INR 67,000 in 2024). Reflecting the constancy of household income, the share of food in items of regular expenditure (food and non-food items bought regularly every month) increases, from 0.66 to 0.67. However, an alternative measure of expenditure diversity, a simple count of the types of items (food and non-food) purchased by households, increases from 17 to 19 across survey years.

5.1.2 Income sources, productive assets, and occupational distributions

Table 11 provides information on the number of income sources, sources of income, and the ownership of “productive” assets used in income enterprises. For purposes of counting the number of different sources of income, we distinguish between male and female earnings in casual labour markets and in salaried employment. Given this, the average household reports close to 3 sources of income. This number is relatively similar across survey years (2.8 at baseline and 2.9 at endline).

To assess sources of household income, we construct indicator variables which take value 1 if the household reports any income from the source in question. These variables (Table 11) suggest the continued importance of agriculture across survey years, with the proportion of households reporting earning some agricultural income being 0.55 in 2019 and 0.57 in 2024. However, in terms of this measure, employment in the casual (non-salary) labour market, either as skilled labour or unskilled labour, is of greater importance. At baseline, 63% of households reporting some male labour market earnings, while 40% report such earnings from female members. This percentage declines over time for males, falling to 58% by endline. In contrast, it increases to 45% for females. Employment in the formal (salary) sector remains small for both men and women. In 2024, the proportion of households reporting males earning a salary was 11%. The corresponding percentage for women was just 5%.

Table 11: Household income sources

	Baseline (2019)	Endline (2024)
Number of income sources	2.832	2.872
	(1.299)	(1.546)
Households reporting (any) earnings from:		
Agriculture	0.548	0.565
	(0.498)	(0.496)
Livestock	0.504	0.529
	(0.500)	(0.499)
Other non-agriculture enterprises	0.118	0.113
	(0.323)	(0.317)
Male wage earnings (casual)	0.632	0.583
	(0.482)	(0.493)
Female wage earnings (casual)	0.403	0.452
	(0.490)	(0.498)
Salary earnings (male)	0.146	0.111
	(0.353)	(0.315)
Salary earnings (female)	0.0435	0.0473
	(0.204)	(0.212)
Assets		
Proportion households reporting any productive assets	0.472	0.558
	(0.499)	(0.497)
Average number of productive assets	1.972	2.611
	(3.556)	(3.575)
Average value of productive assets,	17758.8	16445.2
(constant INR)	(51257.1)	(53641.7)

Note: Survey data. Household means standard deviations in parentheses. Data are for panel households.

The data reveal a significant increase in the proportion of households reporting ownership of any productive assets between the baseline (47%) and endline (55%) surveys.[41] The average number of (productive) assets owned by households also

[41] Data are on assets are over all sample households, including those who do not own any assets.

increases across survey years, but to a smaller extent, rising from 2.0 at baseline to 2.6. This smaller increase, relative to the growth in the number of households reporting ownership of *some* assets, suggests that households may have also sold off some of their assets. This is reflected in the slight decline in the total value of all productive assets owned (in constant INR), from INR 18,000 in baseline to INR 16,000 at endline.

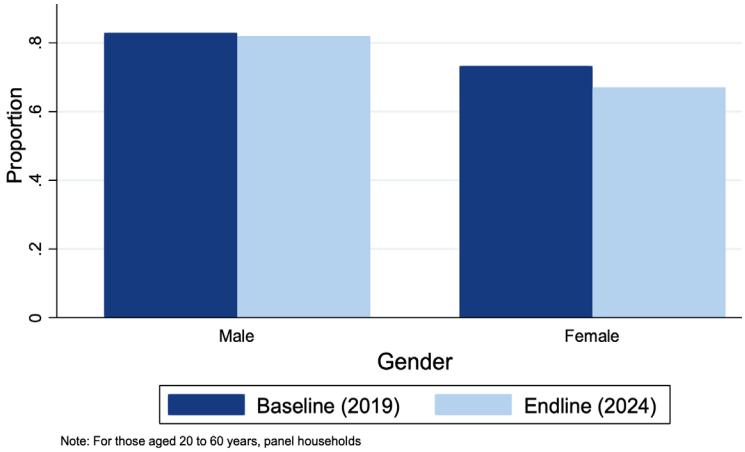
Labour force participation rates are calculated as the proportion of adult members (ages 20-60) of each gender reporting any productive work. While male labour force participation rates remain relatively constant, female labour force participation rates fall from 0.73 in 2019 to 0.67 in 2024 (table 12). The data on labour force participation rates for males and females in each survey year is graphed in figure 17.

Table 12: Labour force participation and primary occupation distribution by gender

	Male		Female	
	Baseline (2019)	Endline (2024)	Baseline (2019)	Endline (2024)
Labour Force Participation Rate	0.829 (0.376)	0.820 (0.384)	0.733 (0.442)	0.671 (0.470)
Occupation distribution				
Own agriculture work	0.286 (0.452)	0.242 (0.428)	0.290 (0.454)	0.272 (0.445)
Livestock and non-agriculture enterprises	0.133 (0.340)	0.172 (0.377)	0.391 (0.488)	0.371 (0.483)
Agriculture labour	0.067 (0.251)	0.134 (0.341)	0.140 (0.347)	0.212 (0.409)
Non agriculture labour - unskilled	0.316 (0.465)	0.257 (0.437)	0.111 (0.314)	0.075 (0.264)
Non agriculture labour - skilled	0.094 (0.292)	0.100 (0.300)	0.018 (0.132)	0.014 (0.117)
MGNREGS	0.003 (0.0577)	0.005 (0.0697)	0.013 (0.112)	0.016 (0.127)
Salary	0.099 (0.299)	0.089 (0.285)	0.037 (0.190)	0.034 (0.182)
Community Cadre	--	0.000 (0.0216)	--	0.005 (0.0724)
N	21866	23590	21066	21257

Note: Individual means for those reporting productive work, standard deviations in parentheses. Data are for panel households.

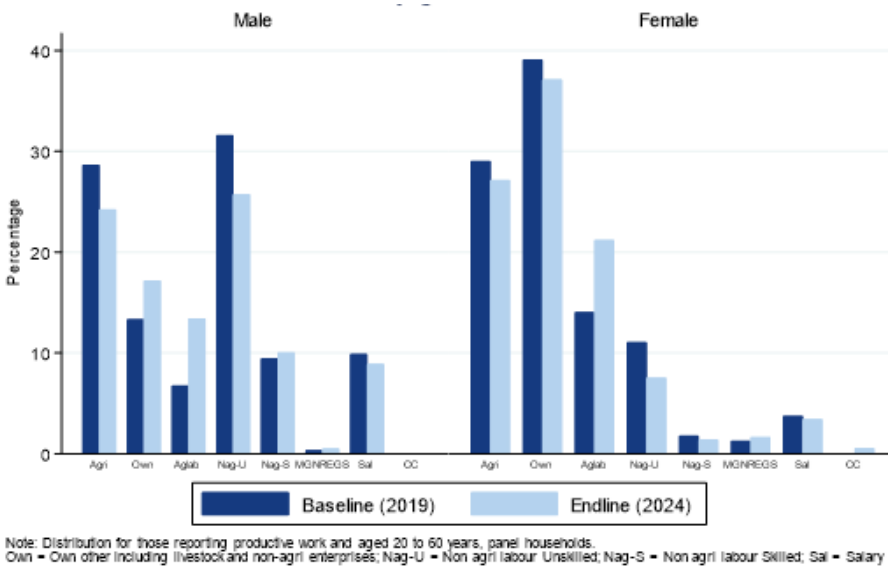
Figure 17: Male and Female Labour force participation rates, 2024 and 2019



Note: For those aged 20 to 60 years, panel households

Using data at the level of individual members of each household, Table 12 provides information on the primary sector of occupation for individual males and females (ages 20 to 60). These data are graphed in Figure 18. The statistics in Table 12 disaggregate employment in the casual wage market, distinguishing between the market for agricultural labour, non-agricultural unskilled labour, and non-agricultural skilled labour. Supporting the findings of the previous table, the primary source of employment for men is the unskilled non-agricultural market, with 32% of males reporting this to be their primary occupation. The second most important primary occupation is own farm work (29%) in 2019. The dominant primary occupation for women, however, is livestock and other non-agricultural enterprises. 39% of women at baseline report this to be the primary source of employment. Employment in own farms is also significant, accounting for 29% of primary occupations. Taken together, employment in family enterprises (agriculture and non-agriculture) accounts for 68% of women's primary occupations but only 42% of primary occupations for men. This difference finds its counterpart in the unskilled labour market (agriculture or non-agriculture). While unskilled casual employment represents 25% of primary occupations for women, it accounts for 44% of the primary occupations of men.

Figure 18: Occupational distribution of primary activities, by survey round and gender



Note: Distribution for those reporting productive work and aged 20 to 60 years, panel households.
Own = Own other including livestock and non-agri enterprises; Nag-U = Non agri labour Unskilled; Nag-S = Non agri labour Skilled; Sal = Salary

Comparing the data for 2019 with that for 2024, the proportion of men reporting primary employment in a family enterprise other than family farms increases from 13% to 17%, as did employment in the agricultural labour market (7% to 13%). These increases come at the expense of declining employment on own farms and the labour market for unskilled non-agricultural labour, with the latter being most pronounced. Women, too, increased their primary employment in the agricultural labour market by 7 percentage points (14% to 21%). Countervailing this, the proportion of women reporting all other sources of employment declined, albeit marginally.

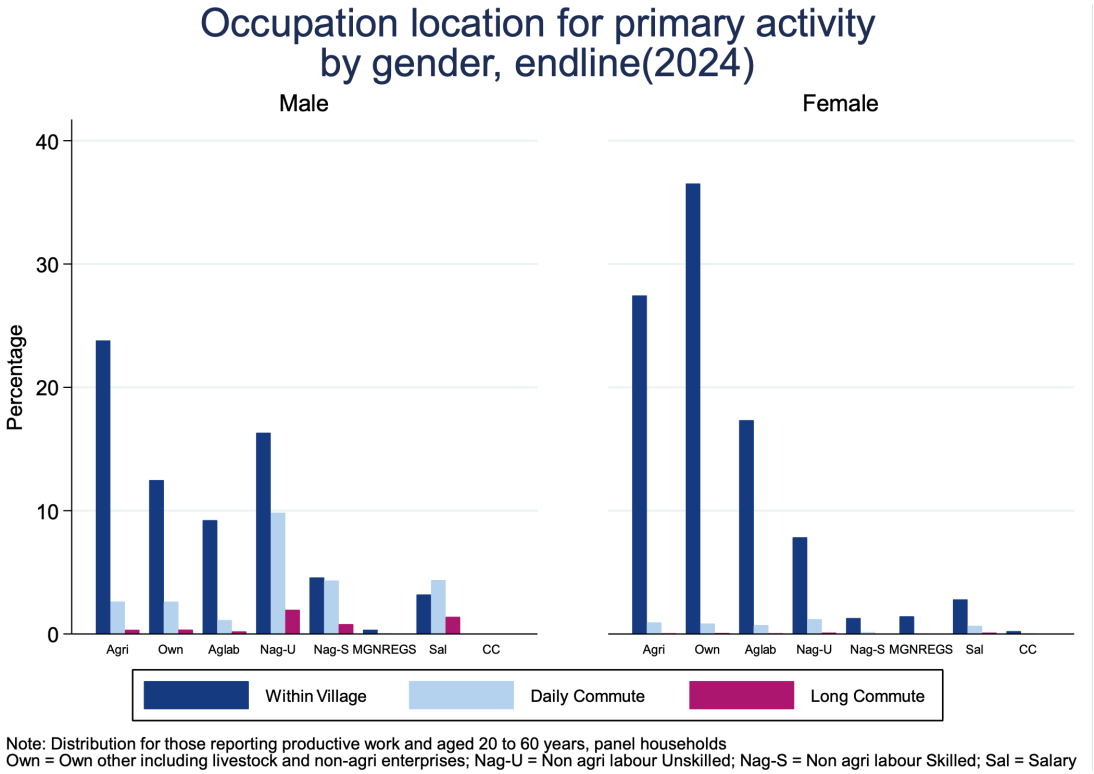
Defining structural transformation as a shift from agricultural to non-agricultural employment (including livestock and other non-agricultural family enterprises), the data suggest only marginal change for men and a reverse shift *towards* agriculture for women. For men, the proportion reporting primary employment in their own farms or in the agricultural labour market increases by 1% between survey years, from 36% in 2019 to 37% in 2024. The corresponding change for women is 43% in 2019 to 48% in 2024.

Structural transformation can also be alternately defined as a shift from home production, in agricultural and non-agricultural enterprises within the homestead, to wage market employment outside the home, in the casual market (skilled or unskilled) or the formal market. In this sense, too, the transformation of the rural economy remains minimal. In 2019, 42% of men and 57% of women reported their primary employment to be in family-owned enterprises run from their homestead (own-farm or other). The corresponding percentages for 2024 are 41% (for males) and 58% (females). These numbers do not include engagement in domestic chores. Accounting for this, the decline in female labour force employment across survey years suggests a significant reverse shift from market to home production for women, in excess of that for men.

Our survey is amongst the few to collect detailed data on the location of employment for each activity type. These data enable an assessment of the geographical reach of the labour markets for men and women, and hence a third dimension of structural transformation. This is a significant dimension, representing whether employment occurs within a village or whether geographical boundaries in employment are extending outwards. Despite its importance, relatively little data exist to examine its extent.

The data, graphed in figure 19, reveal that the vast majority of employment in the agricultural labour markets occurs within the village for both men and women, as expected. Not surprisingly, this is also true for employment in farm and non-farm family enterprises. However, a significant share of male non-agricultural employment, in both the unskilled and skilled markets, requires (daily) commuting to other villages. Such commuting is insignificant for women.

Figure 19: The location of primary activities by gender



Note: Distribution for those reporting productive work and aged 20 to 60 years, panel households
Own = Own other including livestock and non-agri enterprises; Nag-U = Non agri labour Unskilled; Nag-S = Non agri labour Skilled; Sal = Salary

This provides an explanation for the limited growth in female employment in rural areas of the country and for the lack of structural transformation, particularly for women. With declining farm sizes, increased employment must necessarily come from the non-agricultural sector. Such employment is likely to be concentrated in larger villages and nearby towns. Men are better able to take advantage of these opportunities than are women. This difference implies that labour markets are gendered; the determinants of **employment will differ for men and women.**

5.1.3 Measures of food, nutrition and health (FNHW) and investments in related infrastructure

Our detailed survey data on consumption expenditures (Table 13) enables us to calculate an index of food diversity following guidelines by the Food and Agriculture Organization (2010). This index measures whether the household reports consumption of items in a variety of food groups, such as grains, beans, milk and products, vegetables, and fruits. As is conventional, our measure is based on food intake over the past 24 hours, as reported by the prime-age woman interviewed for the women's module. The data reveal a significant improvement in dietary intake, with the index increasing from 0.16 at baseline to 0.24 at endline.

Table 13: Household Food, Nutrition, Health (FNH) and Infrastructure for Water, Sanitation and Hygiene (WASH)

	Baseline (2019)	Endline (2024)
Food diversity index	0.160	0.235
	(0.367)	(0.424)
WASH infrastructure (consolidated score on availability of bathroom, kitchen, flush toilet, piped water and lpg)	1.508	1.628
	(1.315)	(1.410)
Bathroom in house	0.327	0.425
	(0.469)	(0.494)
Kitchen (dedicated room for cooking)	0.453	0.418
	(0.498)	(0.493)
Flush toilet	0.423	0.401
	(0.494)	(0.490)
Piped drinking water	0.151	0.210
	(0.358)	(0.407)
LPG for cooking	0.153	0.174
	(0.360)	(0.379)
ill-health (endline only)		
Proportion of households reporting episodes of illness by any member, last 12 months	--	0.395
		(0.489)
Mean number of days of usual activity lost across all household members, last 12 months	--	14.80
		(42.48)
Proportion of households reporting illness by child aged 11 or younger, last 12 months	--	0.411
		(0.492)
Proportion of households reporting episodes of child illhealth requiring visit to doctor	--	0.360
		(0.480)

Note: Survey data. Household means, standard deviations in parentheses. Data are for panel households

Both survey rounds also collected information on household infrastructure that pertains to access to water, sanitation, and hygiene (WASH). This includes data on whether the household reports a bathroom and a kitchen within the house, the availability of a flush toilet and piped drinking water, and the use of LPG for cooking. Combining these measures into a simple index with a maximum score of 5, household-level WASH infrastructure remains low (1.6 at endline and 1.5 at baseline), but suggests a slight improvement between survey years.

In percentage terms relative to the baseline value, the greatest improvement was in investments in piped drinking water sources within the household. The percentage of households reporting access to piped water increased by 40% between the survey rounds, from 15% at baseline. We note that our survey period coincides exactly with the baseline and endline of the Government's *Jal Jeevan Mission*, a programme intended to provide individual tap connections to all rural households. Similarly reflecting the government's focus on investments in toilets, the second largest increase is in the availability of a toilet within the household (30% increase between survey years). We note again that our summary statistics reflect these broad improvements that have

occurred across the country, and are not indicative of the impact of NRLM or NRETP on such investments.

While the baseline survey did not include any measures of household health, the endline survey collected simple data on whether individual members of the household reported episodes of ill-health and the number of days of (usual) activity lost as a consequence of these episodes. 40% of households reported a member suffering from ill-health during the past year, resulting in an average of 15 days of activity loss. 41% of households reported an episode of illness by a child aged 11 years or younger. Of these episodes, 36% required consultation with a doctor.

5.1.4 Women's contraception and gender-based violence

Table 14 provides data on women's uses of contraception and some aspects of gender-based violence. These data were collected in the endline survey, but not at baseline. Approximately half (49%) of married women aged 49 years or younger report the use of some method of contraception. This percentage is lower than the 67% reported in the National Family Health Survey 2019-20 (NFHS-5). However, our data pertains to the poorest households in blocks that are amongst the most disadvantaged blocks of the country, while the NFHS data are aggregates for the entire population, including urban areas.[42]

Our data do, however, accord with NFHS in that they support the finding that female sterilization remains the most popular form of contraception. In our survey, 34% of married women under the age of 49 report sterilization. NFHS 5 data, for all married women in the country (including women residing in urban areas), reveal that 38% of women reported sterilization in 2019-20.

Table 14: Women's contraception use and measures of Gender Based Violence (endline only)

	2024
A. Contraception	
Proportion of married women aged ≤49 years reporting current use of contraception by self or partner	0.490 (0.500)
Proportion of married women aged<=49 years reporting female sterilization	0.336 (0.472)
B. Gender Based Violence	
Proportion reporting perceived increase in violence against women since COVID-19	0.215 (0.410)
Willingness to seek support from SHG/VO/CLF in the event of any episode of gender-based violence within household	0.420 (0.494)
Feel SHG/VO/CLF/CRP are equipped to support and guide in cases of gender-based violence	0.599 (0.490)

Note: Survey data from women's module. Responses are from a prime-age woman in the household. Question 2 on willingness to seek help from SHG for intra-household violence asked only of women who were alone for the interview. Standard deviations in parentheses. Data are for women from the panel survey.

[42] Disaggregated data from NFHS at the level of individual states similarly do not correspond to our state-level figures, since our data come from the poorest households of disadvantaged blocks.

Understanding the difficulty in collecting accurate information on gender-based violence (GBV)through an all-purpose survey such as ours, the survey questions on this topic were designed to be broad, querying women on their perceptions of GBV in the village in the past five years and their opinions on whether the SHG provided a means to address this issue. 22% of women felt that GBV in the village had increased since COVID-19. Encouragingly, a relatively high proportion of women (42%) felt that they could seek support from NRLM's set of community institutions in the event of any episode of GBV within the household. An even higher percentage (60%) opined that SHGs, VOs, and CLFs were equipped to support women who encountered any intra-household GBV.

5.1.5 Household financial outcomes

Table 15 reports provide survey data on the proportion of households that report borrowing by purpose from all sources, distinguishing between loans from SHGs, the formal sector, informal sector, and relatives and friends. To ensure a complete picture, the data is based on information on loans that are currently outstanding as well as all loans that were taken in the three years prior to the survey year but paid off at the time of the survey. Including "closed" loans provides a more accurate representation of short-term loans taken for a duration of a year or less. All loan amounts are in constant INR, calculated by using the CPI for the year in which the loan was taken. SHG loans include loans from "internal" SHG savings and through the SHG-bank linkage programme that provides funds to the SHG for on-lending to individual members. Table 15 also provides data on loan purpose for the three major categories reported by households: Production loans, loans for education and health expenses, and for regular food and non-food items of food consumption.

The proportion of households reporting any loan falls significantly across years, from 77% at baseline to 69% at endline. This decline is particularly manifest in loans for regular items of food and non-food (monthly) expenditure. Additionally, fewer households report borrowing for education and health expenses in 2024 relative to 2019. We note, however, that in the absence of data on episodes of ill-health at baseline, it is difficult to interpret this decline. The smaller percentage of households reporting loans for this purpose at the time of the endline survey may reflect an improvement in health status, one that we would expect given the increase in the availability of bathrooms and piped drinking water reported earlier.

The proportion of households reporting loans for productive purposes remains approximately the same between baseline (25%) and endline (28%). However, this small change masks larger changes in the source of "productive" loans. The data reveal a large increase in the proportion of households reporting productive loans from SHGs (12% to 21%), with small declines in this percentage for all other sources, including direct loans from the formal sector (from 9% at baseline to 5% at endline).

Table 15: Household borrowing status

	Baseline (2019)	Endline (2024)
Proportion reporting loans		
Any loan (all purposes)	0.770	0.693
	(0.421)	(0.461)
Prop. reporting loans by source:		
SHGs (incl bk linkage)	0.445	0.546
	(0.497)	(0.498)
Formal sector	0.173	0.138
	(0.378)	(0.345)
Informal Sector	0.232	0.0594
	(0.422)	(0.236)
Relatives & friends	0.280	0.128
	(0.449)	(0.334)
Prop. reporting loans by purpose		
Production	0.254	0.275
	(0.435)	(0.447)
Regular food & household consumption	0.289	0.118
	(0.453)	(0.323)
Education & health expenses	0.308	0.210
	(0.462)	(0.407)
Prop. reporting production loans by source		
SHGs	0.118	0.210
	(0.323)	(0.407)
Formal sector	0.0852	0.0548
	(0.279)	(0.228)
Informal Sector	0.0442	0.0131
	(0.206)	(0.114)
Relatives & friends	0.0529	0.0253
	(0.224)	(0.157)

Note: Household means standard deviations in parentheses. Sample: Panel households. The data represents the proportion of all sample households reporting currently outstanding loans or loans closed within the last three years from any given source / purpose. Sample size is 46,354 (over both survey rounds).

Table 16 reveals that in contrast to the decline in the proportion of households who borrow (for any purpose), the average loan amount, per household, has increased in real terms across survey years, from INR 16,000 in 2019 to an average of INR 22,000 in 2024. This reflects an increase in the average SHG loan (from INR 7,000 in 2019 to INR 12,000 in 2024). The average real loan amount per household borrowing from the formal sector remains approximately flat (INR 28,000 in 2019 and in 2024), as do loan amounts from the informal sector and from relatives and friends.[43]

[43] We note that the data reflect the loan amount per borrowing household in the respective year and hence do not provide information on the change in loan amounts over time for any given household.

Comparing across sectors, while an average SHG loan in 2019 was far less than the average loan amount from any given source, this difference had significantly narrowed by 2024. For example, the average SHG loan in 2019, at INR 7,000, was less than half of the average informal sector loan (INR 15,000). By 2024, the difference in average loan size was approximately INR 2000 (INR 12,000 for SHGs and INR 14,000 for informal sector loans). However, the average loan size of a formal sector loan far exceeds the amount borrowed from other sectors, suggesting the dominance of formal banks as a source of large loan amounts. These loans are individual loans, in contrast to the joint liability loans from banks that households access through the SHG bank linkage programme.

The data on loan amounts by purpose reveal very little change in real value across survey years (table 16). Loan amounts for production purposes (an average of INR 17,000 in 2024) far exceed loans for regular items of expenditure (INR 5,000) and even for health or education costs (INR 12,000). However, the last panel of data in this table reveals significant changes in productive loan amounts by sector. In 2019, the average productive loan from the formal sector, at INR 24,000, far exceeded the average loan from SHGs (INR 7,000), the informal sector (INR 7,000), and from relatives and friends (INR 8,000). However, the size of the average productive loan from the formal and informal sector, and from relatives and friends, fell between survey years. In contrast, the size of the average SHG loan for productive purposes almost doubled. Thus, by 2024, while the informal sector and loans from family and friends represented an insignificant source of loans for productive purposes, both in terms of their incidence and in terms of loan amounts, productive loans from SHGs increased in importance across both these dimensions.

The endline survey separated SHG loans from internal savings and SHG loans through the bank linkage programme and also asked households about their use of bank Mitra's / Sakhi and business-correspondent community resource persons (BC Sakhi). As previously noted, bank Mitra's and Sakhis are Community Resource Persons (CRPs) who are located at bank branches to help SHGs and their member households access their accounts for savings or for loans. BC Sakhis, in contrast, are authorized to undertake financial transactions at the point of service and hence offer branchless banking options to households. These services were minimal at the time of the baseline survey.

Table 16: Household mean loan amounts, borrowing households only

	Baseline (2019)	Endline (2024)
Mean loan amount (real INR)	16376.0	21,635.50
	(24230.1)	(30,519.00)
Mean loan amount by source:		
SHGs (incl bk linkage)	6903.7	11,862.10
	(8884.6)	(12,454.30)
Formal sector	28492.9	28,087.90
	(33630.9)	(29,933.90)
Informal Sector	15080.8	14,451.30
	(19078.5)	(14,458.60)

	Baseline (2019)	Endline (2024)
Relatives & friends	13452.2	13,524.30
	(18342.4)	(16,409.20)
Mean loan amount by purpose		
Production	17852.1	17,205.80
	(23408.0)	(20,828.80)
Regular food & household consumption	3599.4	5,207.50
	(5263.2)	(5,859.30)
Education & health expenses	10489.3	12,057.40
	(24889.6)	(29,697.80)
Mean loan amount of production loans by source		
SHGs	6730.0	11,182.60
	(6788.8)	(10,557.30)
Formal sector	24367.9	22,558.80
	(22878.2)	(17,847.50)
Informal Sector	7436.6	2,869.00
	(7225.9)	(1,737.70)
Relatives & friends	7721.2	6,028.20
	(7519.5)	(4,661.80)

Note: Loan amounts are for households that report currently outstanding loans or loans closed in the last three years for that purpose or source. All amounts are in constant INR, deflated by consumer price index for the year in which the loan was taken. Household means standard deviations in parentheses. Sample: 33,888 survey data, panel households.

The sample survey data on the proportion of households reporting borrowing from SHG internal funds or through the bank linkage programme in Table 17 relates to those who report either an outstanding loan from the SHG (from internal funds or any other source) or a loan that was repaid within the last three years. For SHG borrowers, loans from internal funds dominate, at 62 percent of such households, while loans through the bank linkage programme stood around 40%.The average loan amount from the latter (INR 14,000) far exceeds the average loan amount borrowed from internal funds (INR 8,000). Turning to loans for productive purposes, SHG borrowers use SHG loans and the bank linkage programme to an equivalent degree, with 18% of SHG borrowers reporting productive loans from the bank linkage programme and 20% reporting borrowing for this purpose from internal funds. However, the average size of a loan for production purposes from the bank linkage programme (INR 12,000) exceeds that from internal funds (INR 8,000).

The bottom panel of Table 17 provides information on the use of bank Mitra’s and BC agents for households. Restricting attention to households who report savings accounts in formal banks, the data reveal that 13% of them report using a BC to access savings. Use of bank Sakhis, placed in bank branches, for accessing bank loans is far more prevalent, with 47% of those who borrow from banks reporting using the services of a bank Sakhi.

Table 17: Programme-related household financial outcomes (2024 values only)

Outcome	Mean value (std. deviation)
SHG bank linkage	
Proportion of total SHG borrowers reporting SHG bank linkage loans	0.395 (0.490)
Proportion of SHG borrowers reporting bank linkage loans for production	0.174 (0.379)
Average loan amount, bank linkage, borrowing households only	14006.6 (12,316.90)
Average loan amount for production, bank linkage, borrowing households only	11941.1 (9,296.6)
SHG internal funds	
Proportion of SHG borrowers reporting loans from SHG internal funds	0.623 (0.49)
Proportion of SHG borrowers reporting loan from SHG internal funds for production	0.202 (0.40)
Average loan amount, SHG internal funds, borrowing households only	8083.3 (8,757.70)
Average loan amount for production, SHG internal funds, borrowing households only	8194.5 (7,911.60)
Use of Bank Mitra (sakhi) or BC agent for bank transactions	
Accessing bank savings (As proportion of households with bank savings)	0.130 (0.336)
Accessing bank loans (As proportion of households reporting loans through bank linkage or directly from banks)	0.465 (0.499)

Note: Data are from the 2024 survey. Data on the proportion of households reporting loans (from internal funds or through bank linkage) is for households reporting loans from SHGs. Loan amounts are in real INR, borrowing households only. Usage of BC agent or Bank Mitra for savings and loan access is as a proportion of households reporting savings or loans from banks, respectively. Standard deviations in parentheses.

Data on whether the household reports investments in life, accident, ill-health, and income insurance are in table 18. Income insurance measures the household's access to insurance for crop-loss and other income shocks. Consistent with the government's emphasis on insurance, the data reveal significant increases in all types of insurance, with the exception of insurance against income loss, which increased but to a lesser extent. Combining the data across insurance types, 38% of households report investments in an insurance programme, compared to 15% at baseline.

The final two rows of this table provide information from questions included in the women's module, administered to a prime-age woman in the household to evaluate her financial and business knowledge. Their responses suggest relatively low levels of both financial and business literacy, with scores of 43% and 30%, respectively.

Table 18: Household Access to Insurance & women's financial literacy

	Baseline (2019)	Endline (2023)
Proportion households reporting having:		
Any insurance	0.149	0.379
	(0.357)	(0.485)
Life insurance	0.073	0.158
	(0.261)	(0.365)
Accident insurance	0.0180	0.111
	(0.133)	(0.314)
Health insurance	0.056	0.191
	(0.230)	(0.393)
Insurance against crop loss or any other income loss	0.024	0.060
	(0.151)	(0.238)
Women's financial & business literacy scores		
Financial literacy score (%)	--	42.55
		(21.59)
Business literacy score (%)	--	29.59
		(26.15)

Note: Household means standard deviations in parentheses. Sample: Panel households. Financial and business literacy scores are only available for the 2024 sample.

5.2 Cluster Level Federations (CLFs)

5.2.1 Financial Resources

Table 19 provides data on CLFs from the 2024 survey, distinguishing between CLFs in the three types of study blocks (NRETP, Early Block, and Late Block). In NRETP blocks, we further distinguish between Model CLFs (MCLFs) and "other" CLFs. The data in this chapter omits data on CLFs in West Bengal and Odisha. Because CLFs in these states operate at the level of the Gram Panchayat, they are very different from those in other states. Additionally, we exclude the few MCLFs in early blocks (12) and late blocks (5) so as not to confound the statistics for the typical block in these two categories.

The number of SHGs and consequently VOs associated with CLFs is significantly higher in MCLF clusters, relative to non-MCLF clusters in NRETP blocks and to CLFs in early and late blocks. Our survey data reveal that the average MCLF cluster in NRETP blocks has 648 SHGs. In comparison, the number of SHGs in non-MCLF NRETP clusters is 518, with early and late blocks covering 466 and 323 SHGs, respectively.

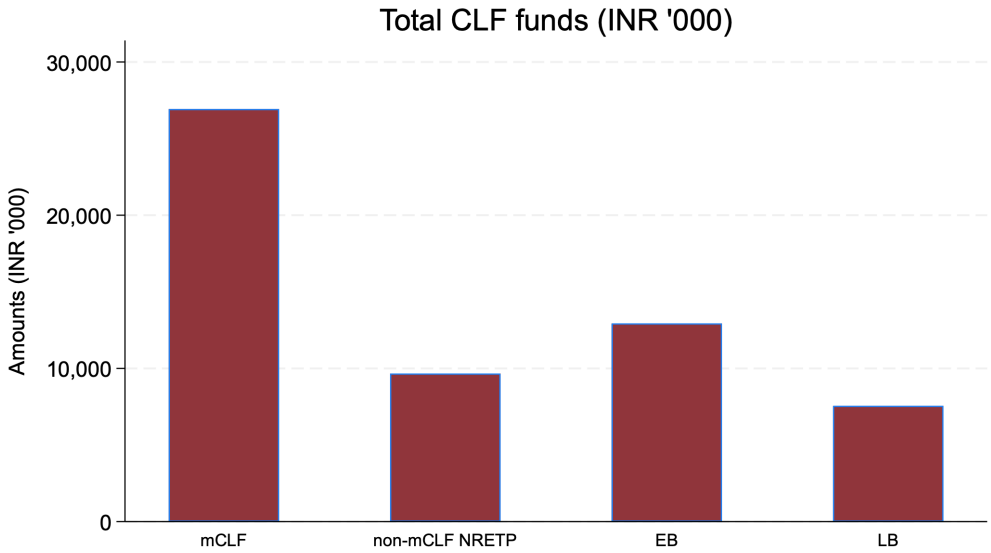
Table 19: CLF funding

	NRETP		EB	LB	All
	MCLF	other			
Number affiliated SHGs	647.9 (250.5)	518.1 (274.6)	466.1 (168.2)	323.4 (118.0)	465.8 (234.6)
Number affiliated VOs	45.03 (19.45)	37.00 (20.61)	33.97 (11.24)	24.09 (8.52)	33.48 (16.85)
Total funds					
Total funds (INR '000)	26932.9 (29669.9)	9670.8 (8075.8)	12134.3 (11064.6)	7424.7 (6898.6)	13493.3 (17950.5)
CIF (INR '000)	14,824.10 (24,257.46)	3,706.4 (5,268.89)	7398.1 (8342.4)	3889.4 (4364.6)	7204.6 (13611.3)
VGF (INR '000)	1,749.54 (2,121.92)	93.65 (358.50)	--	--	439.7 (1280.2)
Infrastructure fund	410.70 (875.49)	31.65 (75.78)	34.57 (100.7)	54.46 (107.1)	132.4 (462.0)
Livelihood Funds INR ('000)	2,020.61 (3,386.38)	1,142.26 (1,326.89)	190.4 (508.0)	199.4 (661.2)	808.5 (1957.0)
Total funds per SHG					
Total funds per SHG (INR)	42,405.84 (36,862.96)	20,106.78 (14,865.76)	25168.0 (19865.2)	25067.0 (21284.7)	28377.8 (25931.5)
CIF funds per SHG	21,932.57 (28,667.98)	8,607.63 (11,466.02)	15302.6 (15603.0)	14845.6 (18070.1)	15519.5 (20134.6)
VGF funds per SHG	2,731.53 (2,674.99)	155.42 (682.86)	--	--	688.1 (1765.4)
Infr funds per SHG	819.2 (1923.0)	65.37 (151.3)	93.68 (301.9)	159.1 (328.7)	288.4 (1014.0)
Livelihood funds per SHG	4289.23 (7992.11)	2458.97 (2960.80)	344.7 (904.1)	555.7 (1990.7)	1760.2 (4569.3)
Number	36	27	30	56	149

Source: Data on the number of affiliated SHGs and VOs is from the LoKos MIS data. All the other data is from the 2024 survey. Funding data is cumulative funds received since the formation of CLF. Data excludes West Bengal and Odisha. Data for early and late blocks omit any MCLF clusters. Standard deviations are in parentheses.

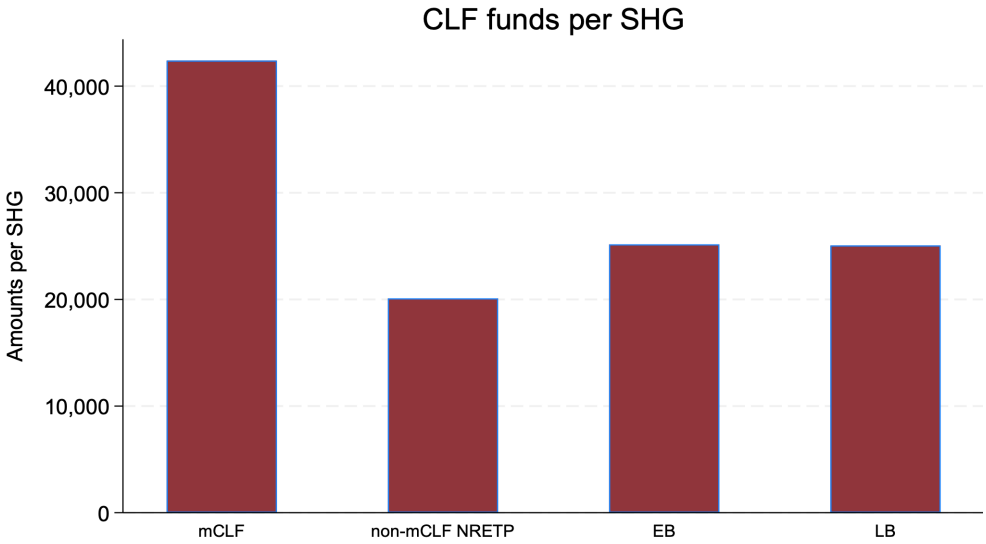
Correspondingly, the total funding available to NRETP CLFs, graphed in figure 20, is greater than the funding reported by CLFs in Early and Late Blocks. The average MCLF NRETP cluster reports a total of INR 27,000 in funding, with the corresponding figure for non-MCLF NRETP clusters, early and late blocks being 9,670, 12,134, and 7,435 respectively (all data are in INR '000). Figure 21, which plots the total funds per SHG received by CLFs, reveals that these differences remain after allowing for the variation in the number of SHGs across different cluster and block types. The average amount of funds per SHG in model CLF clusters is INR 42,000, while funds per SHG in non-MCLF NRETP blocks is just 20,000, an amount that is marginally less than the average amount provided to SHGs in early and late blocks (approximately 25,000).

Figure 20: Total funding per CLF by broad block categories



Excl Odisha & WB, sample size=149

Figure 21: CLF funds per SHG

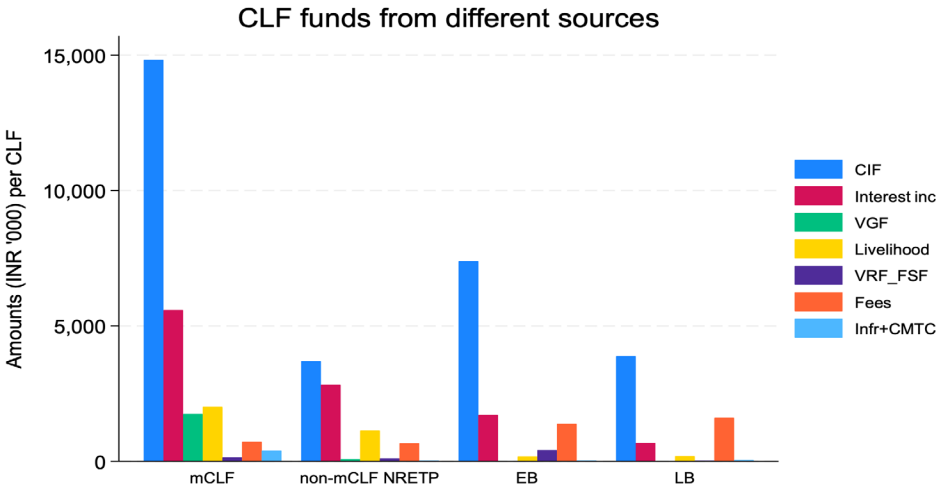


Excl Odisha & WB, sample size=149

Figure 22 graphs total funding by source, while figure 23 reports source-wise amounts per SHG. For this purpose, the data in Table 19 on CIF, Vulnerability Gap Funds (VGF), and funds for infrastructure development (including CMTCs or Community Managed Training Centres) and livelihood programmes are augmented by data on income (interest income on deposits, Vulnerability Reduction and Food Security funds (VRF, FSF), and membership fees) Both figures reveal that the difference in total funding across CLFs across different types of clusters and blocks primarily reflects differences in the amount of Community Investment Funds (CIF).[44] Model CLFs also receive more interest income and funding in the form of Viability Gap Funds. Finally, they report greater receipt of funds earmarked for livelihood programmes.

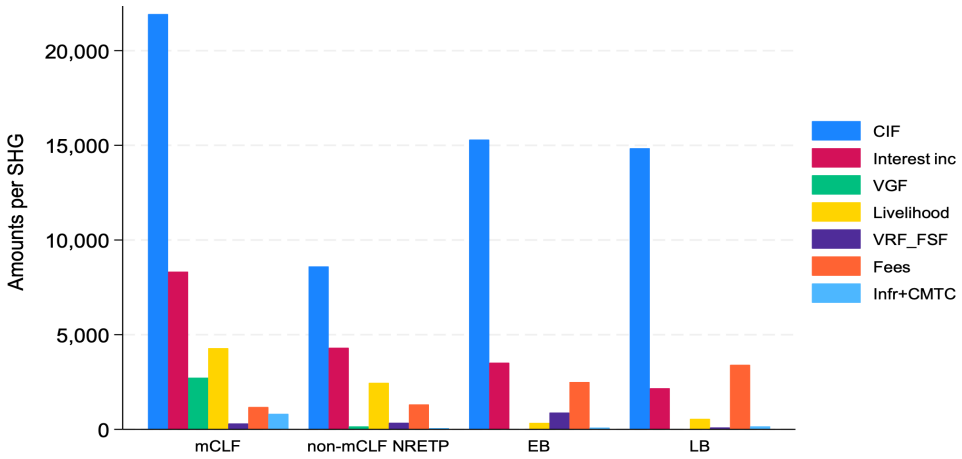
[44] These data are for total CIF funding received by the CLF, the sum of payments in different tranches.

Figure 22: Proportion of funds for different subheads, by block type



Excl Odisha & WB, sample size=149

Figure 23: CLF funds per SHG from different sources



Excl Odisha & WB, sample size=149

5.2.2 Other features: Subcommittees, training and CRPs

Table 20 provides information on other aspects of CLF functioning that likely impact their member VOs and SHGs and SHG members. A first such factor is the availability of functioning subcommittees which oversee the operations of the Federation in their area of operation.[45] A second is the extent to which office bearers have benefitted from training in different areas. A third is the availability of CRPs. The first two features are described in Table 20 and graphed in Figures 24 and 25. Data on CRPs is in Table 21 and Figure 26.

The proportion of CLFs reporting functioning committees for monitoring SHGs and VOs and for overseeing the Community Based Recovery Mechanism (SBRM) is equally high amongst model CLF clusters, non-MCLF NRETP clusters and early blocks, and lower in late blocks. Model CLFs, however, have a clear advantage over other clusters and blocks in the formation of social action and livelihood committees. For example, 58% of model CLFs report the existence of a Social Action Committee and 31% report on

[45] Unfortunately, in the all-purpose surveys conducted for this report, the collection of details of operating sub-committees and the other aspects broadly described in this section could not be collected, because of constraints on survey length and interview duration.

functioning Livelihood Committees. In contrast, only 37% of non-MCLF NRETP clusters have Social Action Committees while the percentage with a Livelihood Committee is significantly lower (19%).

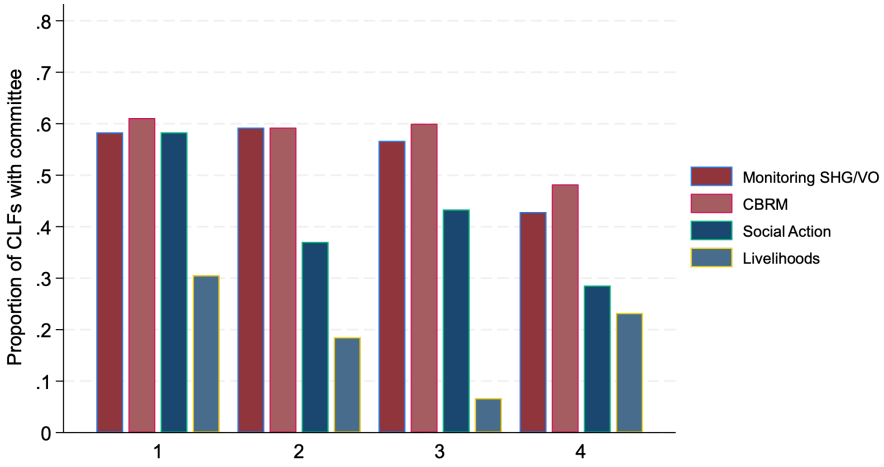
The greater focus on livelihoods is also apparent in the data on training in the same table (table 20). 78% of MCLFs report that their office bearers have received training in this area. In contrast, such training is reported by just 52% of non-MCLF NRETP clusters and 30% of CLFs in early and late blocks. A high proportion of CLFs in all NRETP blocks, MCLF and non-MCLF, report training in social action (89% and 85%, respectively). This percentage is smaller in early (73%) and late (64%) blocks.

Table 20: CLFs: Sub-committees and training by block type

	NRETP		EB	LB	All
	MCLF	other			
Sub-Committees					
Monitoring	0.583	0.593	0.567	0.429	0.523
committee	(0.500)	(0.501)	(0.504)	(0.499)	(0.501)
Social Action	0.583	0.370	0.433	0.286	0.403
committee	(0.500)	(0.492)	(0.504)	(0.456)	(0.492)
Livelihood	0.306	0.185	0.0667	0.232	0.208
Committee	(0.467)	(0.396)	(0.254)	(0.426)	(0.407)
Trainings to Office Bearers					
Any trainings	1.00	0.93	0.93	1.00	0.97
	(0.00)	(0.27)	(0.25)	(0.00)	(0.16)
Social action	0.889	0.852	0.73	0.64	0.76
training	(0.319)	(0.362)	(0.45)	(0.48)	(0.43)
Livelihood training	0.78	0.52	0.30	0.30	0.46
	(0.42)	(0.51)	(0.47)	(0.46)	(0.50)
Number	36	27	30	56	149

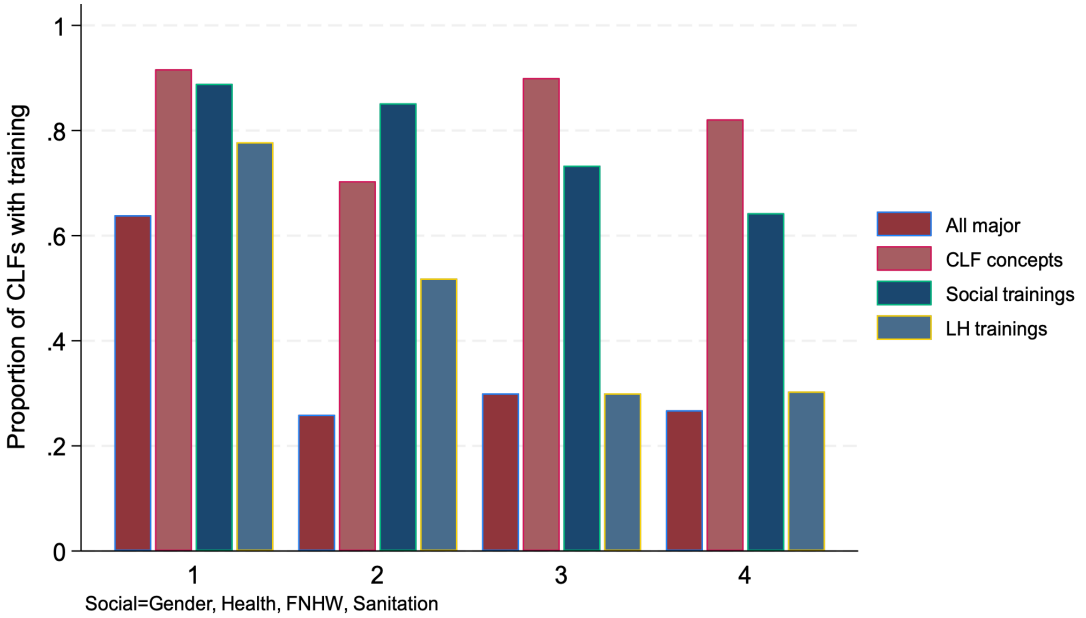
Source: 2024 survey data. The data on subcommittees relates to functioning subcommittees. Training data is for any training in the past 5 years organized for office bearers. Standard deviations in parentheses.

Figure 24: CLF sub-committees by block type



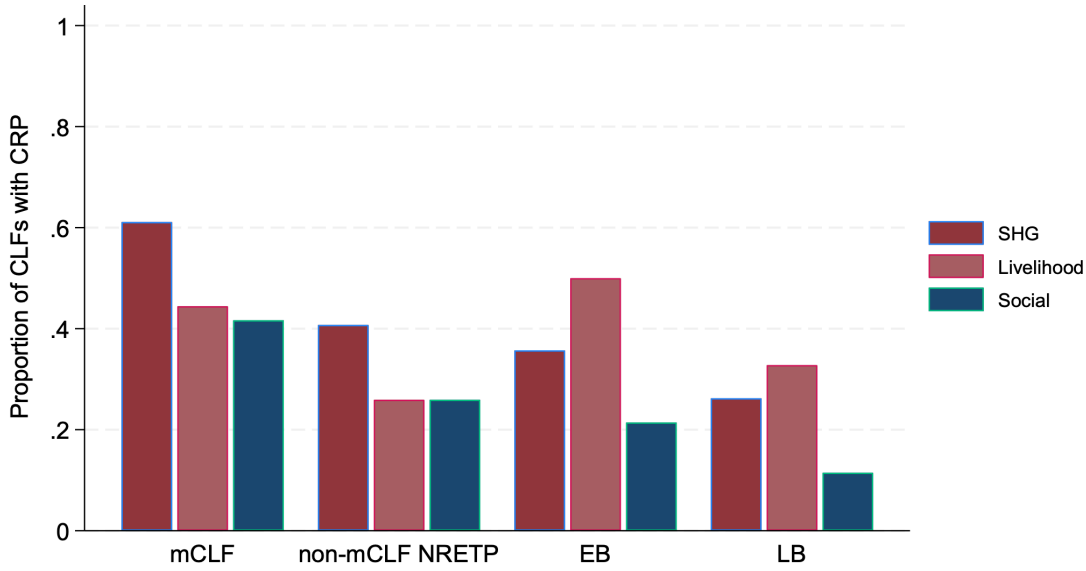
Excl Odisha & WB, sample size=149

Figure 25: Proportion of CLFs reporting training by training and block type



Sample size=149

Figure 26: Number of CRPs per CLF, by block type



Excl Odisha & WB, sample size=149

Data on CRPs also reveal significant differences across cluster and block type (Table 21). Model CLFs report marginally more CRPs (an average of 4.1) than available to non-MCLF NRETP clusters (3.4), early (3.6) and late (2.8) blocks. With the exception of livelihood CRPs, model CLFs are more likely to have CRPs that oversee and monitor SHGs and VOs, and social action CRPs.[46] 44% of model CLFs report the availability of a Livelihood CRP, with clusters in Early Blocks leading in this regard (53%).

[46] These include CRPs responsible for any social programme, maternal and child health, other health concerns, FNHW, and gender issues. Livelihood CRPs include those for business development (Udyog Sakhi), agriculture (Krishi Sakhi or Udyog Krishi Sakhi), livestock (Pashu Sakhi), and other livelihood areas (Matsya Sakhi, Vanopai Sakhi, etc.).

Data on CRPs' years of work experience and years on the current job in Table 21 reveal that those in model CLF clusters have approximately an additional year of experience relative to their counterparts in non-MCLF clusters and almost double the experience of those in late blocks. The same applies to their tenure in the current job. The advantage in experience in MCLF clusters relative to non-MCLF NRETP clusters is noteworthy, since programme years are identical across these two types of clusters.

Table 21 also provides data on the proportion of CRPs who report receiving payments from different sources (project funds, CLF funds and from members of the community). The receipt of payments from project funds and from the CLF is significantly higher for MCLFs. In all clusters and blocks, however, a negligible proportion of CRPs report receiving payments from the community (5% for all CRPs and for CRPs in MCLFs). In terms of amounts, the mean payment amount received from project funds and CLFs, for CRPs who report such payments, is approximately equal, reflecting fixed pay scales for CRPs. The mean amount received from the community is approximately half this amount. In combination with the very low percentage of CRPs who report payments from the community, the data suggests that the community cadre as a whole remains overwhelmingly dependent on project and CLF funds.

The last panel of data in this table uses data from a survey of CRPs in the village at the time of the survey. Sample sizes varied across cluster types and are much lower in model CLF clusters than in others.[47] This raises concerns regarding the comparability of the data across clusters. For this reason, we focus our discussion on the average data for all CRPs (across cluster types), reporting results from a set of questions that evaluate their financial literacy. These questions are the same as those administered to prime-age women through the women's module and hence the results can be compared. For this sample of CRPs as a whole, financial literacy scores average 60%, significantly higher than the average reported for women in the household survey (43%). This difference suggests that CRPs can play a significant role in enhancing women's financial literacy.

Data on training reveal that the proportion of interviewed CRPs who received any financial training is low (an average of 20%). Though these CRPs exclude those explicitly involved in financial inclusion activities, such as Bank Sakhis and Mitras, their value either as community mobilizers or as livelihood CRPs could be enhanced with financial literacy training. The last row of the table suggests that CRPs with financial literacy training have higher test scores. This evidence is suggestive of the value of training but does not provide causal evidence of such a link.

[47] The total number of CRPs surveyed was 231 in model CLF clusters and 594, 516 and 597 in other NRETP clusters, early blocks and late blocks respectively. We drop the 5% of this sample who are Bank Sakhis, Bank mitras or BC agents.

Table 21: CLFs: Community Resource Persons (CRPs) by block type

	NRETP		EB	LB	All
	MCLF	other			
Total CRPs	4.11	3.41	3.63	2.82	3.40
	(1.37)	(1.80)	(1.40)	(1.90)	(1.73)
Any CRP - SHG monitoring	0.61	0.41	0.37	0.27	0.40
	(0.49)	(0.50)	(0.49)	(0.45)	(0.49)
Any CRP – social action	0.42	0.26	0.20	0.089	0.22
	(0.50)	(0.45)	(0.41)	(0.29)	(0.42)
Any CRP - Livelihoods	0.44	0.26	0.53	0.30	0.38
	(0.50)	(0.45)	(0.51)	(0.46)	(0.49)
Mean work experience (yrs)	6.20	5.39	4.87	3.46	4.80
	(2.58)	(2.68)	(1.76)	(1.23)	(2.30)
Mean years current job	5.14	4.74	4.07	3.47	4.25
	(1.95)	(1.94)	(1.72)	(1.26)	(1.80)
Proportion CRPs reporting payments from					
Project funds	0.78	0.62	0.69	0.50	0.63
	(0.36)	(0.49)	(0.41)	(0.44)	(0.43)
CLF	0.33	0.23	0.29	0.23	0.27
	(0.31)	(0.36)	(0.35)	(0.38)	(0.35)
Community	0.05	0.07	0.04	0.03	0.05
	(0.12)	(0.21)	(0.09)	(0.15)	(0.15)
Mean annual payments from					
Project Funds	51,593.0	60,783.8	31,849.0	30,000.61	41,576.3
	(29,745.9)	(50,437.2)	(22,270.3)	(18,739.0)	(31,844.9)
CLF	52,220.18	40,491.67	51,518.18	24,041.67	46,337.1
	(22.016.61)	(18,207.03)	(21,269.5)	(17,876.3)	(22,318.3)
Community	20,799.56	50,070	26,737.5	13,236	21,599.8
	(20.015.64)	(.)	(20,815.81)	(5,517.47)	(18.102.08)
Number	36	27	30	56	149
Data on individual CRPs					
Financial literacy score (%)	54.73	60.00	59.52	61.16	59.60
	(22.38)	(21.66)	(22.73)	(22.73)	(22.43)
Prop. Received financial training	0.190	0.205	0.159	0.221	0.196
	(0.394)	(0.404)	(0.366)	(0.415)	(0.397)
Financial lit score, with fin training	59.74	66.39	64.81	62.77	64.02
	(22.49)	(20.20)	(21.32)	(22.38)	(21.51)

Source: 2024 survey data. Standard deviations in parentheses. Mean payments are for CRPs who report receipt of payments. Mean years of experience and years on current job are means across all CRPs in the CLF. Data on individual CRPs are from surveys of village CRPs excluding the 5% who are FI CRPs. Sample sizes (by column) are: 231, 594, 516, 597, & 1938 (total). Sample size for those with financial training: 44, 122, 89, 132, and 380 (total).

Put together, our data on CLFs suggest a sizeable advantage enjoyed by model CLFs, compared even to those in other NRETP clusters, not just in terms of financial resources but also in other aspects such as the existence of subcommittees, training, and the availability of CRPs. Surprisingly, non-MCLF NRETP clusters appear to have little advantage over early and even late blocks in terms of fund availability, with their primary advantage being in the availability of livelihood and social action subcommittees and the training provided to office bearers in these areas.

These non-financial factors are of considerable importance, particularly given the targeted nature of investments in livelihoods in all NRETP clusters. Thus, even though producer groups do not exist in all villages of NRETP blocks, SHG households in all villages benefit from the availability of CRPs and from the training and other activities organized by subcommittees. Livelihood CRPs, for example, operate as extension officers responsible for visiting individual households to provide sector-specific information, organizing field demonstrations and trainings, and providing continuous on-field support in the adoption of improved practices.[48]

In concluding this section, we note that the baseline 2019 survey did not collect the same detail of data on Cluster Level Federations. Consequently, we lack information on trends in CLF financial and non-financial resources and, particularly, on any differences in these trends. It is this differential that is important for any differential trends across clusters identified through regression analysis. Because model CLF clusters are selected on the basis of the level of maturing of NRLM's community institutions, it is very likely that these same differences across CLFs existed, to some degree, at the time of the baseline survey. This emphasizes the point made in the introductory paragraphs of this chapter: The data in this section cannot be interpreted as evidence of causal impacts.

Additionally, it is possible that even level differences in CLF resources, governance, and training may not trickle down to SHGs. To examine this, we discuss SHG-level data collected in both rounds of our survey.

5.3 Self Help Groups (SHGs)

In this sub-section, we report data from the SHG module of our survey canvassed to approximately 6 SHGs in each survey village. The data and figures relate to different samples. While most frequently restricted to panel SHGs who were surveyed in both years, some tables are based on the totality of SHGs in the endline data (including replacement SHGs), while others restrict attention to functioning SHGs in the panel.[49] The data are drawn from the SHG module of the survey. As previously described, this module contains information on SHG resources, but also details of the socio-economic characteristics of SHG members and of the loans that they received from SHGs in the past three years. Because these loan details are available for all SHG members, they provide a more comprehensive view of SHG lending behaviour than is available from the household survey.

5.3.1 Membership and the strength of the Federation

Prior to discussing data collected in the SHG module, we report data from the (women's module) household questionnaire regarding membership in SHGs so as to understand trends in SHG membership amongst poor households in the village, the target population from which survey households were drawn.

Recalling that our sample is over-representative of SHG households; with the exception of Bihar and West Bengal, 20 of 30 households surveyed in a village were selected from

[48] The responsibilities of Farm Livelihood CRPs is detailed in the Ministry of Rural Development's (2020) *Advisory on Engagement of Community Resource Persons in Farm Livelihood Promotion (FLH-CRP).*

[49] The Methodology chapter of this report (Chapter 4) includes a discussion on attrition and functioning SHGs.

amongst SHGs in the village, with the remaining being non-SHG members from the same hamlets. The Bihar and West Bengal samples came from earlier randomized evaluations. Though households were randomly selected for the survey, the majority of them were drawn from hamlets that favoured poor households who were the target households under the programme.

Correspondingly, the proportion of (prime-age) women interviewed for the women's module of our survey reporting SHG membership at baseline is high (68%). This percentage remains the same at endline. We also asked women who were not currently SHG members if they had ever been a SHG member. At baseline, only 19% of women reported affirmatively. By endline, this percentage had increased to 31%, suggesting a high level of turnover in membership in recent years. We provide and discuss additional data on this, as well as on other SHG characteristics, in this sub-section.

Restricting attention to panel SHGs that were functioning in both survey rounds, Table 22 reveals little change in the broad features of SHGs over time. Thus, the average number of members of a SHG was 11.5 in baseline, falling marginally to 11.1 by endline. Similarly, the proportion of SC/ST members decreased just slightly across years, from 0.61 in baseline to 0.60 at the time of the endline survey.

The same table reveals continuing growth of the federation of community institutions, with accompanying institutional features. At baseline, 82% of SHGs reported membership in VOs. This percentage increased to 91% by endline. The growth in VO membership in CLF as demonstrated in our sample is particularly impressive, increasing from 62% at baseline to 79% by endline. Accompanying this growth, the percentage of SHGs who report being linked to banks increased from 40% to 74%. SHGs are also involved in supporting members to access government schemes through the process of convergence. In 2024, 77.6% of SHGs report supporting members in accessing government schemes, a sharp increase from just 39.57% of SHGs at baseline. While we do not have the comparable information for baseline, at endline, of the SHGs reporting convergence, 79% report supporting access to livelihood schemes.

Table 22: SHG broad features and federation membership

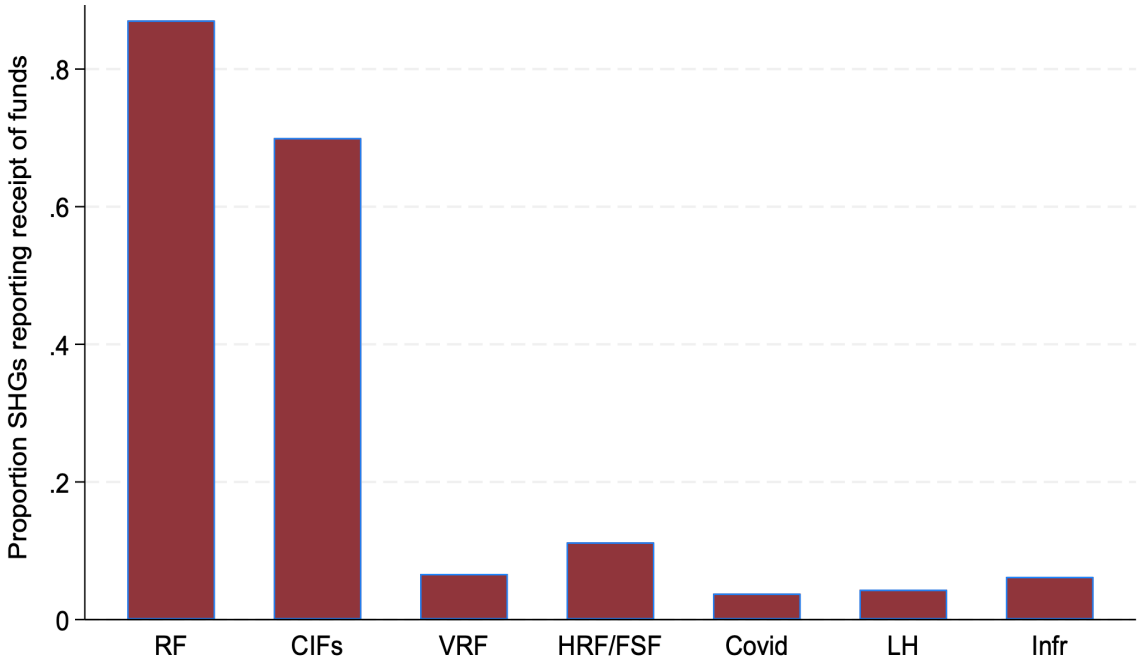
	Baseline (2019)	Endline (2024)
Total members	11.47	11.10
	(1.453)	(1.483)
Proportion SC/ST	0.611	0.595
	(0.431)	(0.434)
Proportion of SHGs reporting		
VO membership	0.824	0.907
	(0.381)	(0.290)
CLF membership	0.615	0.787
	(0.487)	(0.410)
Bank linkage	0.405	0.737
	(0.491)	(0.440)

Note: Sample means, with standard deviations in parentheses. Sample: Functioning panel SHGs. Combined sample size is 8,235.

5.3.2 SHG resources

Given the differences in the resource position of CLFs across different programme blocks, we now turn to data that explores the same for SHGs. Figure 27 documents the proportion of SHGs reporting the receipt of funds by fund type based on endline data for all SHGs (panel and replacement SHGs at endline). As expected, SHGs primarily receive programme funds in the form of Revolving Funds (RF) and Community Investment Funds (CIF). These are also the funds whose awareness is highest. Far fewer SHGs report receiving funds from other sources, including the Vulnerability Reduction Fund (VRF), the Health Risk and Food Security Funds (HRF/FSF), any special Covid-specific funds, funds earmarked for Livelihood investments, and Infrastructure funds.

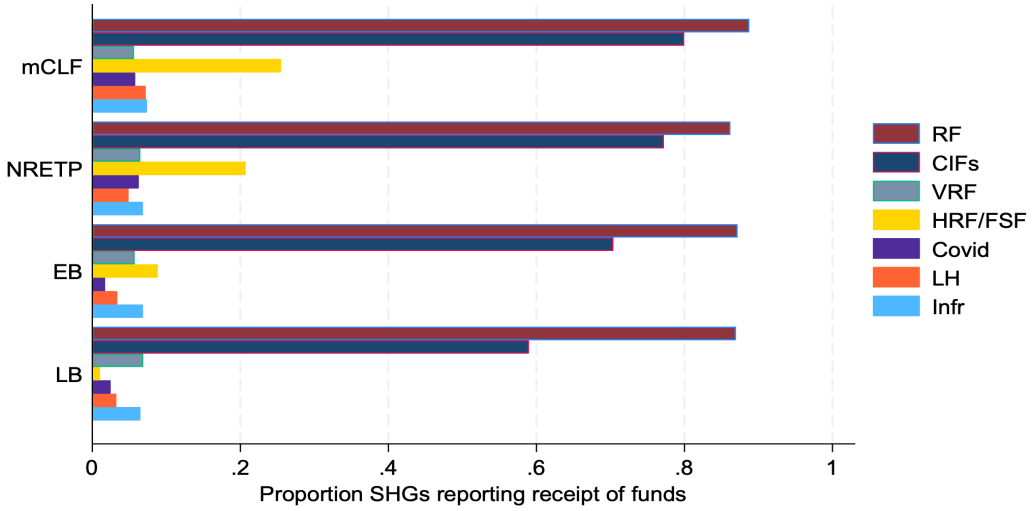
Figure 27: Proportion SHGs reporting receipt of funds by fund type



Note: All SHGs at endline (including replacement SHGs)

Figure 28 repeats this figure for the same sample but now comparing the importance of different sources of funding across block types. While the proportion of SHGs reporting Revolving Funds is similar across all blocks (model CLF, non-model CLF NRETP, Early Blocks, and Late Blocks), SHGs are more likely to report CIF funds and funds for Livelihood Investments. It is worth noting that though a greater proportion of SHGs in model CLF blocks report the receipt of such funds, this proportion is also greater for SHGs in other NRETP blocks. Thus, in sharp contrast to the CLF-level data of the previous sub-section, the SHG-level data show a difference in the resource position of SHGs in non-model NRETP clusters and those in clusters of early and late blocks.

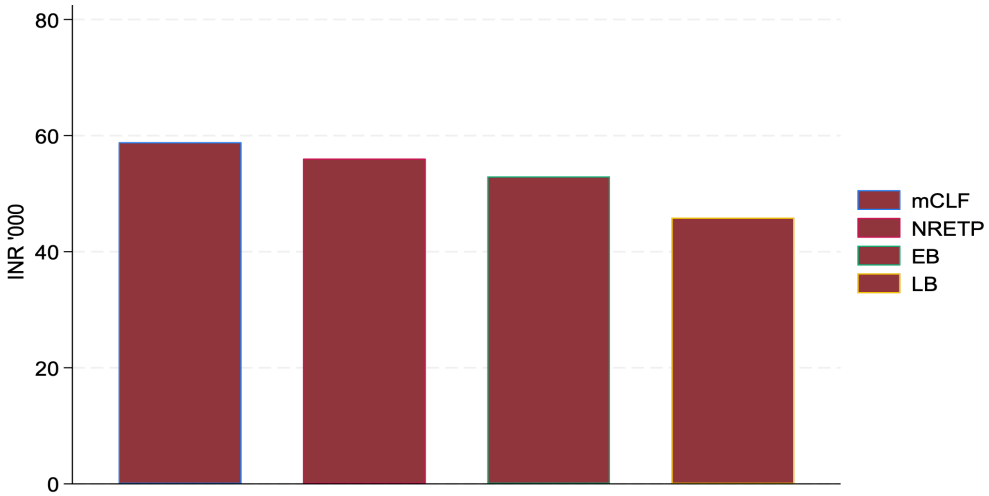
Figure 28: Proportion of SHGs reporting receipt of funds by fund and block type



Note: All SHGs at endline (including replacement SHGs)

Figure 29 reveals that the higher percentage of CLFs in NRETP blocks that report receiving Community Investment Funds has not come at the cost of the average amount of CIF funding. Rather, there are only minimal differences in the amount of CIF funding across SHGs from different types of clusters. This accords with programme guidelines that stipulate a common standard for the CIF funds for each SHG regardless of the type of cluster or block in which they are located. Across all cluster and block types, the average amount of CIF funds provided to each SHG is INR 60,000. This falls short of the current recommendation of INR 150,000 per SHG, which came into effect at the end of 2021.[50] Despite the fact that the SHGs in our sample are older SHGs, formed prior to 2021, the new guidelines suggested that older SHGs should be provided with "top-up" funds so as to ensure that each SHG received a totality of INR 150,000 in CIF funding. Our data suggests that this increase has not been achieved.

Figure 29: Average CIF funds per SHG, by block type



Note: All endline SHGs (panel and replacement)

[50] This change was previously discussed in Chapter 2.

A final source of funds for SHGs, a source that has been growing in importance, relates to funds from banks through the SHG-bank linkage programme. Table 23 provides some information on this programme using data on SHGs surveyed in the endline (2024) survey. Because the programme was still in its early stages at the time of the baseline survey, that survey did not collect these same details.

The data reveal a very high proportion of survey SHGs linked to banks through this programme. 68% of all SHGs surveyed at endline report bank linkage, with little variation in this percentage across NRETP blocks, NRLM Early blocks, and NRLM late blocks. The total loan amount disbursed to members through bank linkage funds varies more, but favors SHGs in late blocks. The mean amount reported by SHGs in our sample is approximately INR 98,000 in NRETP blocks, compared to INR 1,15,000 in late blocks.[51]

Table 23: Details of bank linkage by cluster and block type, endline survey (2024)

	MCLF clusters	Non-MCLF NRETP clusters	Early Blocks	Late Blocks	Full sample
Prop. SHGs bank linked	0.700 (0.459)	0.703 (0.457)	0.672 (0.470)	0.659 (0.474)	0.681 (0.466)
Total amount disbursed through bank linkage (INR)	98150.4 (196773.8)	79737.8 (216707.7)	94167.6 (246706.4)	114704.2 (282273.8)	97572.3 (244351.0)
Bk mitra available at bank branch?	0.686 (0.464)	0.618 (0.486)	0.537 (0.499)	0.459 (0.498)	0.558 (0.497)
Bank Mitra resides in same village as SHG?	0.161 (0.368)	0.202 (0.401)	0.165 (0.372)	0.161 (0.368)	0.173 (0.378)
Sample size	759	1,249	1,114	1,496	4,618

Note: Sample means, with standard deviations in parentheses. Sample: All SHGs surveyed at Endline. Loan amounts are in real INR.

A particular focus of NRLM in recent years has been the push to ensure “hand-holding” support for SHG members in transacting with banks through the appointment of bank Mitra’s. Bank Mitra’s are generally SHG members with higher levels of education who have been provided with the necessary training required for this role. They are placed at bank branches so as to serve any SHG member who needs help while at the bank in undertaking her transactions. Our endline survey included a question on whether a bank Mitra was available at the bank branch at which the SHG conducted its transactions. The responses (table 23) suggest that such support is greater in MCLF (68%) and non-MCLF NRETP (62%) clusters, falling off in early (54%) and late (46%) blocks. The survey also asked if the bank Mitra was from the same village that the SHG was located in for the sample as a whole. 17% of SHGs reported that she was, with little variation in this amount across blocks.

5.3.3 SHG lending

The resources available to SHGs affect members’ access to loans. Table 24 provides details of the lending behaviour of panel SHGs that were functioning in each of the two survey years, for the sample as a whole and by cluster and block type.

[51] All loan amounts are in real INR.

The top panel provides information for the baseline year (2019). The proportion of members reporting loans in the three years prior to the survey is highest amongst SHGs in late blocks (79%), but also high for those in MCLF clusters (74%). The greater incidence of lending in late blocks suggests that loan activity is at its highest in a SHG's formative year, with lending declining as the SHG matures. Mean loan amounts at the time of the baseline survey were, however, the smallest for these SHGs. Given that the data discussed above suggests that SHGs in late blocks have equal access to the bank linkage programme and to Community Investment Funds, these relatively small loan amounts suggest a preference for frequent borrowing of small amounts in relatively young SHGs. This hypothesis is supported by the greater incidence of borrowing to finance regular consumption expenditures reported by these SHGs. Amongst the SHGs in the remaining three types of clusters, there is little variation at baseline in terms of the amount of the loan or the incidence of borrowing for either production or consumption purposes.

While the proportion of SHG members reporting loans in the last three years did not change significantly across survey rounds, there was a marked increase in the mean loan amount (in real terms) and in the proportion of households reporting borrowing for productive purposes. This increase came at the expense of borrowing for consumption purposes, with the proportion of borrowers reporting consumption loans falling significantly. However, while the differences in loan activity and behaviour over time are marked, a striking fact is the similarity in these outcomes across SHGs in MCLF, non-MCLF NRETP, early, and late blocks.

Table 24: Details on SHG lending

	MCLF clusters	Non-MCLF NRETP clusters	Early Blocks	Late blocks	Full sample
Baseline					
Proportion of members receiving a loan, last 3 years	0.744 (0.437)	0.628 (0.484)	0.639 (0.481)	0.794 (0.405)	0.704 (0.456)
Mean loan amount (real INR '000)	5.211 (9.717)	4.689 (6.936)	4.910 (7.940)	2.894 (5.165)	4.243 (7.300)
Prop, reporting loan for productive purposes	0.203 (0.302)	0.184 (0.314)	0.233 (0.332)	0.208 (0.32)	0.207 (0.319)
Proportion reporting loans for food and regular consumption items.	0.22 (0.321)	0.186 (0.312)	0.197 (0.339)	0.457 (0.421)	0.283 (0.378)
Endline					
Proportion of members receiving a loan, last 3 years	0.769 (0.422)	0.694 (0.461)	0.676 (0.468)	0.775 (0.417)	0.728 (0.445)
Mean loan amount (real INR '000)	10.850 (9.465)	9.561 (9.612)	9.263 (9.760)	8.902 (9.043)	9.499 (9.468)
Prop, reporting loan for productive purposes	0.451 (0.389)	0.43 (0.417)	0.426 (0.421)	0.523 (0.422)	0.462 (0.417)
Proportion reporting loans for food and regular consumption items.	0.138 (0.243)	0.0861 (0.204)	0.0944 (0.207)	0.183 (0.295)	0.127 (0.246)

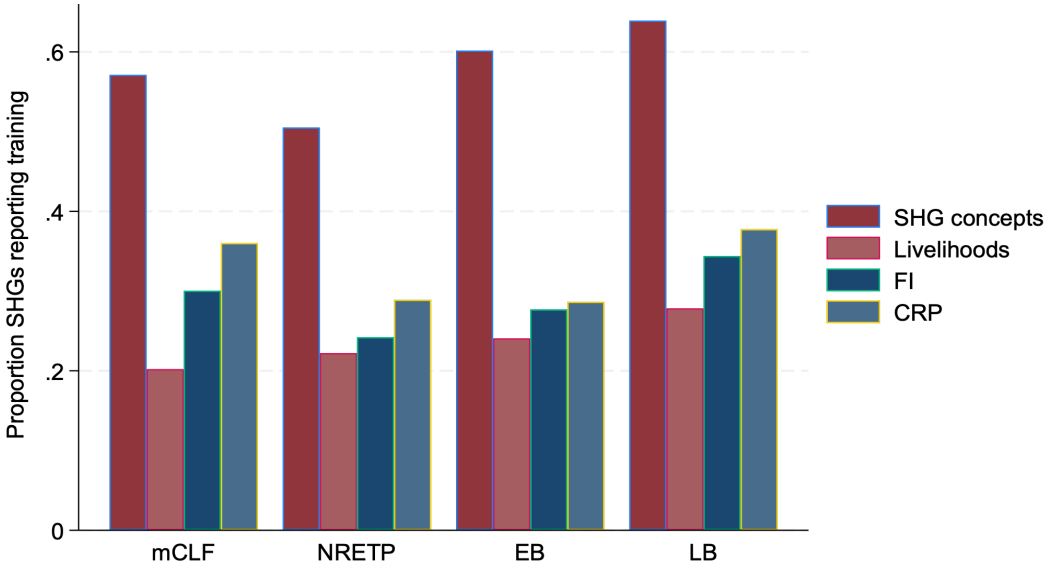
Note: Data are the mean values for all functioning panel SHGs used in regression analysis (sample size 3,893 at baseline). Standard deviations in parentheses.

We caution that these summary statistics should not be taken as indicative of any causal effect of NRETP. One reason for this is the existing differences at baseline. Second, because NRETP blocks were selected on the basis of higher levels of maturity of the federation of NRLM community institutions, and given that implementation of the programme started at the same time in NRETP and early blocks, there are likely to be differences in the trend rate of growth of the programme in these two blocks, differences that may partially explain the better performance of SHGs in NRETP blocks at the endline survey. Our regression analysis takes these potential differences into account, and hence provides credible evidence of causal effects.

5.3.4 Trainings

As is the case in the loan data discussed above, data on the trainings received by SHGs in different blocks, graphed in figure 30, also suggest far greater equality than that revealed in the CLF data. In fact, a higher proportion of the younger SHGs in late blocks report trainings in SHG concepts, including training on the maintenance of SHG books and on SHG procedures and norms of governance. Other forms of training show little variation across blocks. This includes financial trainings on the preparation of credit plans, financial literacy, and on SHG bank linkage. It is also true of trainings provided to SHG members to help their employment as members of NRLM's community cadre ("CRP trainings"). Surprisingly, the proportion of SHGs reporting livelihood training is lowest in model CLF clusters (0.20) and highest in late blocks (0.28).

Figure 30: Trainings received by SHGs, endline sample



Note: All SHGs in endline sample, including replacement SHGs.

5.3.5 SHG quality as measured through Panchsutra scores

We measure SHG quality or performance as in the last survey, based on variables that measure performance against the five quality standards or *Panchsutras* that are used for this purpose within the programme: performance in lending to members, member saving, loan repayment, attendance in meetings, and SHG book-keeping. The Panchsutra score is a composite index that aggregates performance across these dimensions for each SHG. We construct various alternative measures of the Panchsutra score, which assess SHG adherence to each dimension with relatively greater or lesser stringency.

Table 25 provides descriptions of the different components used to construct the Panchsutra scores. For meetings, savings, and repayment, we allow for variation in norms over time and across states by defining both a “stringent” and a less stringent measure. For example, a stringent measure of performance regarding meetings takes the value 1 if the SHG has weekly meetings, 0 otherwise. As noted in the academic literature, the frequency of meetings helps develop social and reputational capital amongst members. However, as these levels of social capital develop, SHG members may not feel the need for such regular meetings. Reflecting this, many states have reduced prescribed norms regarding the regularity of meetings. As a consequence, data across survey years may suggest a drop-off in quality as measured by the most stringent measure. This drop-off, however, reflects changing needs over time and is frequently sanctioned by the respective state ministry.

Table 25: Description of Components of the Panchsutra Score

Variable	Rationale
1. Weekly Meetings	
A The SHG has set a weekly frequency for meetings	NRLM’s Guidelines called for weekly SHG meetings at the inception of the programme.
B The SHG has set a weekly, fortnightly, or monthly frequency for meetings	In some states, such as West Bengal, SHGs have a norm of meeting monthly rather than weekly. This measure allows for state-level variation in the prescribed frequency of meetings.
2. Weekly Savings	
A The SHG has set a weekly frequency for savings	This is the stringent measure of weekly savings, requiring that SHGs have save within the SHG every week.
B The SHG has set a weekly, fortnightly, or monthly frequency for savings	A lenient measure of savings frequency allows for the variation in the frequency of regular meetings.
3. Regular Loaning	
A The SHG has disbursed at least one loan to members between April 2018/23 and the date of survey	We take this as a measure of regular lending. The cutoff of April of the year prior to the survey is chosen in order to align the baseline and endline figures
4. Regular Repayment	
A The SHG has a penalty for non-repayment of loans	The existence of a system to penalize non-repayment indicates that SHGs actively discourage loan default and provide an incentive for repayment.
B The SHG has set a monthly, fortnightly, or weekly frequency for loan repayment	This more lenient measure recognizes that the time set for repayment can also influence the repayment rate, even without a penalty.
5. Regular Bookkeeping	

Variable	Rationale
The SHG has updated at least one of the following books of accounts between August 2018/23 and the date of survey: 1. Cash Book 2. Minutes Book 3. Loan Ledger 4. Savings Ledger 5. SHG Bank Passbook	Maintenance of up-to-date records indicates that SHGs are actively tracking and recording their activities. The types of books of accounts and the time period were chosen to align the data between the baseline and endline surveys, and correspond to approximately one year before the date of the survey.

Using the set of indicators in Table 25 , we develop three different Panchsutra scores. The most stringent measure, *Panchsutra 1,* is the sum of 1A, 2A, 3, 4A, and 5 and accords closely to guidelines at the programme's start (weekly meetings, weekly savings, regular lending, penalty for non-repayment, and regular book-keeping). A less stringent measure, *Panchsutra 2,* replaces the norm of weekly meetings and savings with option B (monthly meetings and savings), but retains other indicators. The least stringent, *Panchsutra 3,* replaces all the more stringent options in *Panchsutra 1* with the weaker indicators (1B, 2B, 3, 4B, and 5), including replacing the penalty for non-repayment of loans with a monthly, fortnightly, or weekly set norm for loan repayments.

Table 26 provides information on the averages of each type of *Panchsutra* score across SHGs surveyed in both baseline and endline rounds. It therefore omits most SHGs that were non-functioning ("defunct" SHGs) identified in the baseline round. It reveals that SHG quality is relatively low, with the mean score in our first measure, *Panchsutra 1*, the most stringent measure, being just 3 out of 5 at baseline. SHG quality by this measure marginally declined to 2.7 by endline. The less stringent measures, *Panchsutra 2* and *3,* yield higher scores, 3.2 and 4.0 at baseline. The first score remains the same at the time of the endline survey (3.2), while the second improves marginally to 4.1. Thus, allowing for the relaxation of *Panchsutra* norms over time, as has taken place in reality, reverses the decline in SHG quality that is suggested if we do not allow for changing norms.

Looking at the performance across individual dimensions of the *Panchsutra*, the data reveals that weekly meetings were slightly less common at endline (70%) than at baseline (72%), but monthly or more frequent meetings were more common (93% at endline vs 82% at baseline). The regularity of savings follows a similar pattern, with weekly savings being less common (67% vs 70%) but including monthly and fortnightly savings frequency, SHGs are more regular at endline (96%) than at baseline (87%). The proportion of our sample SHGs engaging in lending has reduced between baseline and endline, going from 62% to 47% of SHGs doing so. Of the SHGs lending, relatively few SHGs had penalties for loan non-repayment (approximately 15%) and this remained closely consistent between baseline and endline, but a monthly or greater set frequency for loan repayment was more common at endline (97%) than at baseline (87%). However, the regularity of bookkeeping has declined, falling from 78% at baseline to 73% at endline.

An SHG is considered "defunct" if it is not engaging in any of the 5 *Panchsutras*. Both survey rounds collected data on whether SHGs were defunct or not. In the baseline

survey, we identified survey SHGs from the programme's Management Information System (MIS). Defunct SHGs are therefore those that existed in official records but, in practice, were not engaged in any activity. Of SHGs identified for the baseline survey, 13% were found to be defunct.

As previously noted, most of these were not resurveyed in 2024. To calculate defunct rates for the endline survey, we restrict attention to SHGs that were functioning at baseline but not at endline. The data suggest that 13% of SHGs that were functioning at baseline had ceased to do so at endline, a percentage equal to that of SHGs found to be defunct at baseline (as identified using the programme's Management Information System). The proportion of defunct SHGs, therefore, remains relatively stable.

Since a SHG is considered defunct if it fails to meet its expected norms of *Panchsutras*, the classification of defunct SHGs essentially represents a discrete indicator drawn from the *Panchsutra* score, identifying SHGs with a score of 0 or close to zero. Many other SHGs also report minimal activity, making them very similar to non-functioning SHGs. Using our measure of *Panchsutra* score, we can identify very weak SHGs, using other cutoffs. Thus, table 20 also reports the proportion of SHGs with Panchsutra scores of 1 or less. For the most stringent score, *Panchsutra type 1,* this percentage was 18% in baseline, declining to 16% by endline. This therefore suggests an improvement in SHG quality at the lower end of the distribution, even using this measure. The improvement in SHG quality at the low end of the distribution is particularly marked if assessed using less stringent measures, *Panchsutra 2* and *Panchsutra 3.* Thus, at baseline, 14% of SHGs reported a Panchsutra 2 score of less than 1 while 12% fall below this cut-off on the basis of the Panchsutra 3 score. These percentages fell to 5% and 2%, respectively, by endline. We note that these scores are calculated for the sample of panel SHGs and hence omit the defunct SHGs at baseline that were not re-surveyed in 2024. Assuming that these SHGs fell below the cut-off, including them in the baseline data but excluding them from endline (so as to properly assess changes in functioning status in the four years prior to the survey year) would further reduce baseline quality.

Taken together, the data suggest an improvement in SHG quality from baseline to endline, accompanied with a significant increase in the proportion of SHGs that are federated into VOs and CLFs and the growth of bank linkage. The latter suggests significant growth in SHG resources over time.

Table 26: Summary Statistics on SHG Panchsutra Scores and their Components

	Baseline (2019)	Endline (2024)
Regular Meetings		
1A: SHG has weekly meeting frequency	0.719	0.703
	(0.449)	(0.457)
1B: SHG has monthly, fortnightly or weekly meeting frequency	0.822	0.928
	(0.383)	(0.258)
Regular Savings		
2A: SHG has weekly savings frequency	0.696	0.669
	(0.460)	(0.471)
2B: SHG has monthly, fortnightly or weekly savings frequency	0.869	0.961
	(0.338)	(0.194)
Regular Loaning		
3: SHG has disbursed at least one loan to members between April 2018/23 and date	0.617	0.471
	(0.486)	(0.499)
Regular Repayment		
4A: SHG has penalty for non-repayment of loan	0.151	0.145
	(0.358)	(0.352)
4B: SHG has monthly, fortnightly, or weekly loan repayment schedule	0.873	0.966
	(0.333)	(0.182)
Regular Bookkeeping		
5: At least one book of accounts updated between August 2018/23 and date of survey	0.778	0.728
	(0.416)	(0.445)
Panchsutra Scores		
Score Type 1 [1A + 2A + 3 + 4A + 5]	2.961	2.717
	(1.474)	(1.251)
SHG Has Type 1 Panchsutra Score of 1 or below	0.184	0.160
	(0.388)	(0.367)
Score Type 2 [1B + 2B + 3 + 4A + 5]	3.236	3.234
	(1.410)	(1.035)
SHG Has Type 2 Panchsutra Score of 1 or below	0.138	0.047
	(0.345)	(0.211)
Score Type 3 [1B + 2B + 3 + 4B + 5]	3.958	4.054
	(1.585)	(0.994)
SHG Has Type 3 Panchsutra Score of 1 or below	0.115	0.022
	(0.318)	(0.146)

Note: Sample is panel SHGs. Standard errors in parentheses; *Books of accounts considered include: Cash Book, Minutes Book, Loan Ledger, Savings Ledger, and SHG Bank Passbook. Sample size is 4680.

Figures 31 and 32 allow us to assess differences in SHG quality, as measured by Panchsutra scores, across the different types of programme blocks and across survey years. Figure 31 presents data on the most stringent score, *Panchsutra 1,* while figure 32 does so for the least stringent, *Panchsutra 3.* The data are for panel SHGs that are functioning (scores greater than 0) in both rounds, omitting defunct SHGs.

For both scores, the data reveal that SHG quality, as reflected in these scores, has declined over time in non-NRETP blocks, with the greatest decline being in late blocks and using the most stringent Panchsutra score. We note, however, that these data do not condition on other relevant qualities of SHGs, including the difference in age between SHGs in late blocks and in early blocks. Our regression analysis includes such controls and hence identifies causal programme effects. The graphs in these tables are merely indicative of overall trends over time and blocks.

Figure 31: Panchsutra Score Type 1, Functioning SHGs BL and EL

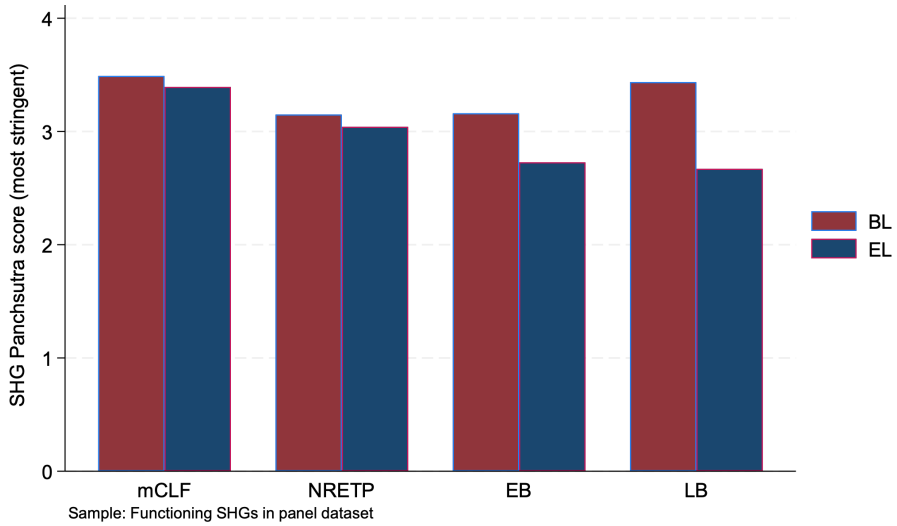
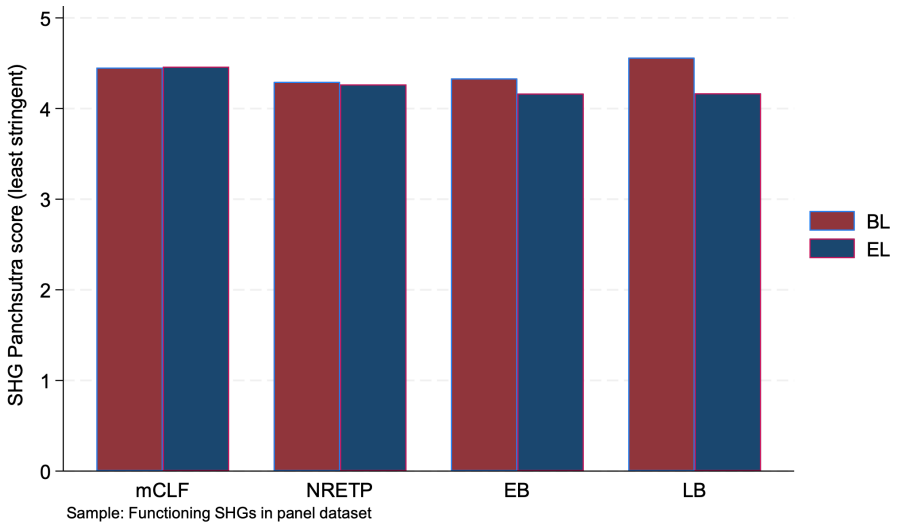


Figure 32: Panchsutra score type 3, functioning SHGs BL and EL



5.3.6 Changes in SHG composition

We close by discussing an important aspect that affects the dynamic functioning of SHGs, one that has received relatively little attention in literature. This is the degree of turnover or “churn” in SHG membership.

Our data suggest a large degree of churn in SHG membership (table 27). In both rounds of the survey, SHGs were asked whether members had left in the past three years and, if so, the number that had done so. The data reveal that while 28% of SHGs reported

member exit at baseline, this percentage increased to 47% by endline. On average, SHGs reported the exit of 0.5 member over 3 years at baseline. By 2024, this number had increased to 1.1.

Table 27: SHGs entry and exit, survey years

	Baseline (2019)	Endline (2024)
SHGs reporting member exit (last 3 years)	0.284	0.474
	(0.451)	(0.499)
Number of members reported exiting	0.535	1.055
	(1.170)	(1.748)
Proportion of SHGs reporting member entry, last 3 years	0.121	0.178
	(0.326)	(0.383)
SHG members – mean education years	2.831	3.211
	(2.225)	(2.472)
SHG members mean age	37.99	42.17
	(4.956)	(5.093)

Note: mean characteristics, standard deviations in parentheses. Data are for all functioning panel SHGs, surveyed at baseline and endline.

The exit of members need not imply that the SHG is functioning poorly; it may be a consequence of changes in the members' socio-economic status or lifecycle changes in the need for loans and credit. Indeed, given that the programme started in 2011, it would be surprising if member exit had *not* occurred. Supporting this view, data from the SHG module which asked for reasons for member exit reveals that the primary reason is the migration of household members and their families.

Upon member exit, the usual practice is to add on new members. Identifying new members as all who joined the SHG 6 months or more since its formation and within 3 years of the survey date, 12% of SHGs reported new members at baseline, while 18% did so by endline. The relative constancy in membership size suggests that member exit is balanced by member entry.

However, to the extent that new members differ from other members in socio-economic composition, changing membership will change the socio-economic profile of SHG members. The data in table 27 support this hypothesis, revealing an increase in the mean schooling years of SHG members between survey rounds. SHG mean age also increases, though this increase over time is expected given the difference in survey years.

We can relate this difference to the entry and exit of members using data on the socio-economic characteristics of those who exited SHGs between baseline and endline and new members who joined the SHG between the two survey rounds. These data are in table 28. The first two columns provide information on the SHG members at baseline who were still in the SHG at the time of the endline survey ("stayers") and also on those who left. The last two columns of the table provide information on the socio-economic composition of "old" SHG members at the time of the 2024 survey, as well as the "new" members who joined the SHG between two survey rounds. The data on "stayers" and "existing members" (columns 1 and 3) are provided as a point of reference; we expect

time-invariant characteristics such as schooling years and SC/ST membership to be constant, with age increasing in line with the time difference between survey years.

The first two columns of the table reveal that members who leave are very similar to those who stay in age, education, and caste (scheduled caste or not). The difference between new members and existing members in 2024 is much larger. New members are significantly younger than existing members and have more schooling.

Table 28: Socio-economic characteristics of exiting and new members

	Baseline (2019)		Endline (2024)	
	Members who stayed	Members who left	Existing members	New members
Member's characteristics				
Age	37.71	39.10	42.76	38.60
	(10.38)	(11.77)	(10.71)	(11.39)
Schooling years	2.67	2.09	2.93	4.50
	(3.99)	(3.71)	(4.05)	(4.68)
SC/ST	0.57	0.49	0.61	0.54
	(0.50)	(0.50)	(0.49)	(0.50)
Sample size	44,243	15,718	44,243	9,303

Note: Data relate to members of functioning panel SHGs. Variable means, with standard deviations in parentheses.

Such changes in SHG membership over time affect the interpretation of measures of SHG quality, including Panchsutra scores. Our observed changes in membership over time imply that the institution is in constant flux. Consequently, calculations of the Panchsutra score at two different points of time imply aggregations over different sets of members. This complicates the interpretation of the summary statistics of this section, as well as the regression results of the next chapter.

5.4 Livelihood Institutions

Our survey questionnaires also included modules designed to understand broad features of livelihood institutions, namely enterprises run by CLFs or SHGs and Producer Groups (PGs), institutions promoted under NRETP. The methodology chapter of this report (Chapter 4) notes that the targeted nature of NRETP livelihood investments suggests that these institutions exist only in a few clusters and villages. Not only does their incidence vary across villages in a state, but also across states. PGs, for example, exist to a larger measure in states such as Maharashtra and Jharkhand but are of relative insignificance in other states.

Reflecting this, the survey provides information on very few CLF and SHG enterprises, a total of just 31 and 28, respectively. Additionally, survey questions relating to their functioning were frequently not answered. For this reason, the information we provide primarily relates to funding.

Data for CLF enterprises (Table 29) suggests that they draw their funding, an average of INR 7 lakhs per CLF, primarily from loans provided by the supporting CLF. Loan funds

are also more important to SHGs than are grants. However, in contrast to CLF enterprises, SHG enterprises primarily receive loans from banks (refer to Table 20). Though they also receive loans from CLFs and through convergence programmes with other ministries, these sources of loans are small relative to bank loans. Convergence funds are, however, the most important source of grants for SHG enterprises.

The data reveal that a relatively high proportion of CLF enterprises report having received training (74%). This percentage is lower for SHG enterprises (54%).

In terms of profits, the average profit reported by CLF enterprises is negative, while the average SHG enterprise reports a profit of INR 21 lakhs. This difference may partly reflect age. Of SHG enterprises, the majority started functioning in 2022 (32%) with 8% starting in 2023. In contrast, 18% of CLF enterprises started functioning in 2023.

Turning to Producer Groups, we restricted attention to those formed under NRETP (that is, to those formed after 2019). The majority were established in 2022 (35%), with 75% being older (starting between 2020 and 2022).

The data on Producer Groups (table 30) reveal an average membership size of 26. The majority of PGs (63%) are involved in collection functions, such as aggregating agricultural output to enhance market prices and access. About 46% of PGs are engaged in a business. Examples include PGs that operate tailoring (stitching) enterprises, shops of different kinds, and those that engage in processing or some other form of manufacturing. Among these PGs, 44% operate as both collection and producer PGs. 35% of PGs are engaged in other operations such as input procurement, providing training to members, providing production and consumption loans, and serving as a source of information for better practices regarding the production of commodities produced by members.

In terms of governance indictors, PGs do relatively well in holding regular meetings and maintaining books of account. However, only 41% of surveyed PGs report having developed a Business Plan, a document that is necessary to access working capital loans from the programme. 16% of PGs report at least one member exit since their inception.

Data on funds and their source are only available for approximately one-third of surveyed SHGs (25 out of 75). For these reporting SHGs, loans from CLFs dominate loans from banks, with the average amount of CLF loans per reporting SHG being 1.35 lakhs. A smaller percentage of PGs (8 out of 75 or 11%) report receiving loans through programmes operated by other ministries (a process referred to as “convergence”). For those who do, however, the amount is sizeable, averaging 2.62 lakhs. These PGs also report an average of INR 25,000 by way of grants through convergence programmes. And, 17 of 75 PGs report receiving grants for Infrastructure (from all sources).

Table 29: CLF and SHG enterprises

	CLF enterprises	SHG enterprises
Total number of institutions in our survey (*total number of CLFs or SHGs)*	226	5148
Total number running an enterprise	31	28
Funding – Loans (INR)		
From SHGs	-	32,802.1
		(95,746.3)
From VOs	-	3,542.9
		(13,268.2)
From CLFs	6,94,673.7	12,500.00
	(12,35,096.4)	(46,398.0)
From Banks	-	10,28,750.00
		(47,08,133.9)
Through Convergence (Government)	-	10,821.4
		(56,676.5)
Funding – Grants (INR)	-	-
From SHGs		
From VOs	-	-
From CLFs	-	535.7
		(2834.7)
From Banks	-	-
Through Convergence (Government)	-	39,285.7
		(1,59,488.3)
Other indicators		
Proportion reporting any training	0.742	0.536
	(0.445)	(0.508)
Profit (INR)	-2,19,028.2	21,38,439
		(76,26,229)
	(1090311)	

Note: Figures in parentheses are standard deviations

Table 30: Data on Producer Groups

	PG Details
Total number of PGs in our survey	76
Of (1) Prop that are in NRETP blocks	0.75 (0.435)
Proportion that are collection PGs	0.63 (0.485)
Proportion that are production PGs	0.46 (0.501)
Proportion engaged in both production and collection	0.45 (0.50)
Average number of members	25.884 (8.77)
(over 26 PGs reporting membership)	
Governance: Proportion of PGs with	
Business Plan	0.41 (0.49)
Regular meetings	0.64 (0.48)
Member attrition	0.16 (0.37)
Books of account	0.68 (0.47)
Funding – Loans (including working capital loans), reporting PGs only	
From Project	43,800 (80,380.35)
(number reporting=25)	

	PG Details
From VOs (number reporting=25)	8,000 (40,000)
From CLFs (number reporting=25)	1,34,966.2 (1,15,516.8)
From Banks (number reporting=25)	8,000 (40,000)
Through Convergence (number reporting=8)	2,62,600 (2,62,060.8)
Funding – Grants (including infrastructure grant), reporting PGs only	
Through convergence (number reporting=8)	25,000 (70,710.68)
Infrastructure Grant (Number reporting=17)	72,250.76 (56,981.18)

Note: Standard deviations in parentheses.

6. Results

This chapter commences with results from our evaluation of NRLM (section 6.1) and NRETP (section 6.2), starting with the former. Section 6.3 of this chapter discusses results that compare outcomes in model CLF clusters to other NRETP clusters, while section 6.4 describes results from regressions that examine the potential role of credit and human capital constraints. The last two sections discuss the impact of both programmes on SHG quality and other SHG attributes (section 6.5) and measures of women's empowerment (section 6.6).

6.1 NRLM

As previously described, NRLM is built on the premise that movements out of poverty require 7 to 10 years with injections of inputs or "treatments" at regular intervals so as to constantly enhance the returns to its institutional architecture. With such continuous investments, the decreasing returns to scale to physical capital that normally thwart sustained improvements in income may be reduced and even reversed. We discuss our results within this broad framework, informing research on the determinants and constraints to income growth by doing so.

Following the methodological approach outlined in Chapter 4, we evaluate NRLM by comparing the change in outcomes in "Early" NRLM blocks to those in "Late" blocks, with these two types of blocks differing in the length of implementation of the programme. Early blocks commenced implementation between 2011 and 2014, while late blocks initiated the programme between 2015 and 2017.[52] As a consequence, the average difference in years of exposure between early and late blocks is four years. This implies that, at the time of the endline survey, the programme has been running for an average of 11 years in early blocks and 7 years in late blocks.

[52] Some blocks started implementation prior to NRLM's official launch, through state-specific programmes.

As noted in our Methodological Chapter, the fact that the control (late) blocks have also experienced a significant length of implementation implies that our results identify NRLM's impact *over time*. Specifically, we estimate the difference in returns from 6 years of implementation (at the time of the 2019 survey) relative to 2. If the identifying assumptions for difference-in-difference regressions maintain, then our results are indicative of the change in outcomes that are achieved by early blocks from their implementation over the medium-run relative to achievements, *in these same blocks,* in their early years. If returns are initially high, tapering off over time as the productivity of early investments declines, then our identified impact of longer NRLM duration will be negative. This does not mean that the returns are low, merely that they have declined over time. Correspondingly, a positive effect suggests returns that increase over time.

6.1.1 NRLM: Impact on SHG membership

We start by discussing results from regressions which test the impact of (the duration of) NRLM on the probability of SHG membership. If SHG membership increases over time in NRLM blocks, then any identified difference in returns in the middle-to-long run relative to the short-run could be a consequence of a growth in membership rather than a change in the outcome in question for the average household.

Table 31 reports results from two regressions. The first uses the basic set of controls described in the Methodology Chapter (Chapter 4). The second adds controls for treatment heterogeneity. The table reports coefficients from the interaction of treatment with the endline indicator, coefficients that are indicative of treatment effects. It also reports the coefficient on the Endline indicator, which reveals trends over time. Both regressions suggest that SHG group sizes are declining over time. However, there is no difference in the rate of decline across early and late blocks, implying no difference in the change in SHG group size over a four-year period in the medium-to-long run, relative to the short run. It is therefore unlikely that any identified impact on household-level outcomes is a consequence of changes in SHG group size over the programme's life cycle.

Table 31: NRLM: Probability of SHG membership

Regression specification	NRLM	
	Basic controls	Add heterogeneity
With EB indicator		
EB*endline	0.0133	-0.00809
	(0.0245)	(0.03)
Endline	-0.591***	-0.553***
	(0.0844)	(0.09)

Note: Standard errors, in parentheses, are clustered at the level of the village. Sample size: 19,310

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.1.2 NRLM: Impact on consumption and incomes

Table 32 provides estimates from various specifications of difference-in-difference regressions on (ln) per capita household expenditure and household income. All values are in constant INR. The first two columns present results for regressions on (ln) per capita real household consumption. The coefficient on the interacted term EB*endline

represents the increase in (ln) consumption under NRLM in the medium run relative to the counterfactual increase for the same set of early block villages over the short run. Since the dependent variable is (ln) per capita real consumption, the coefficient is the difference in (ln) per capita consumption or, equivalently, the growth rate of consumption. Thus, the percentage growth in consumption in the medium run relative to the short run is approximately 7.7%. Allowing for treatment heterogeneity, this increases to 8.5%.

The last two columns of table (table 32) provide estimates of the programme's impact on household income in the medium-run relative to the short-run. Allowing for treatment heterogeneity, the results suggest that NRLM increased (real) incomes by INR 5,600 in the medium run, relative to the short-run. That is, incomes continued to grow over time as the programme matured. Calculated as a percentage of the counterfactual income for this same set of villages in the short-run (constant INR 56,754), our results suggest a 10.14% increase over the counterfactual (short run). Appendix C shows the percentage increase in income over baseline (constant INR 63,000), which amounts to close to a 9% increase. The programme's impact on incomes in the medium-run relative to the short-run is thus equivalent to its impact on consumption.

These estimates underscore the importance of allowing for treatment heterogeneity. As noted in our Methodological chapter, the pace of implementation was significantly faster in late blocks, a consequence of the ability of late blocks to draw on the social capital created in early blocks. Including the measures of capacity available to late blocks when they commenced implementation thus corrects for this spillover effects. With this, the coefficient on the interaction of EB and the endline indicator increases, particularly for income.

Table 32: NRLM: Impact on household consumption and income, different specifications

Regression specification	(ln) household consumption (real INR)		Total household income (real INR)	
	Basic controls	Add heterogeneity controls	Basic controls	Add heterogeneity controls
Eb*endline	0.0772**	0.0846**	-219.4	5612.33**
	(0.03)	(0.04)	(2165.1)	(2,843.53)
Endline	0.464***	0.542***	24367.0***	22092.54**
	(0.10)	(0.11)	(8986.7)	(9,065.60)

Note: all values are in constant INR. Standard errors, in parentheses, are clustered at the level of the village. Sample size:19,111 for consumption regressions and 18,064 for income.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.1.3 Heterogeneity in returns: per capita household consumption

Table 33 reports results that allow the medium-run impact of NRETP to vary across households and villages.

A first result is that the impact of NRLM in the medium run is greater for SHG members, suggesting that other village households benefit less than SHG members in the medium run. A second important finding is that the programme is inclusive; the returns over time

are higher for households with lower education, and for the poorest households. Additionally, the returns to landless households are similar to those achieved by landowning households. The gains for SC/ST are no different from other castes.

Mirroring these results, regressions that allow for heterogeneity by village characteristics reveal that returns are higher for remote villages. We also compare outcomes across villages that offer large markets for producers relative to those that offer small markets, using the total number of houses built of permanent structures as our measure of market size.[53] This measure captures both a higher mean value of house quality and size (total number of households). We find that the medium-run returns to NRLM relative to the short-run are, in fact, higher in villages that have smaller market size.

A final village indicator examines the impact of bank linkage at baseline. Using data from the SHG modules canvassed at baseline, we calculate the proportion of village SHGs that were "bank linked" through the programme at baseline. We then run separate regressions for villages in which no SHG reports being bank-linked and the remaining set of villages. The regression results suggest that average consumption amongst sample households is significantly higher in villages where some SHGs have been linked to banks, providing their members with access to larger resources.

Our final set of characteristics are of important policy relevance. While NRLM stipulates clear guidelines about the formation of SHGs in terms of their size and composition, guidelines for VOs are not so stringent. A general guideline is that each VO should have between 10-20 SHG members. This guideline is difficult to meet in small villages which host fewer than 10 villages; villages with under 5 SHGs are common. In such cases, a common practice is to federate these SHGs with those in a nearby village to create a suitably large VO. There is little evidence, to date, on how this affects programme outcomes. To evaluate this, we use administrative data for all villages in the block and for all VOs to calculate the mean number of villages served by each VO in the block. We also similarly calculate the mean (membership) size of all VOs in the block. Our regression finds that though the mean size of block VOs does not affect medium returns under NRLM, multi-village VOs reduce the programme's impact on consumption. This could be because SHG members of such VOs face greater transaction costs in engaging with VOs, a factor that may reduce the "quality" of the VO. Additionally, multi-village VOs may embody lower social capital, given that social capital increases with the frequency of interactions.

Table 33: NRLM: Heterogeneity in consumption impact by household and village characteristics

	Diff-in-diff coefficient (eb * endline)	Regression F statistic	Sample size
Household characteristics			
Shg member at baseline	0.106**	45.02	13,860
	(0.05)		
Non-member at baseline	0.03	19.19	5,251
	(0.06)		
SC/ST	0.08	40.35	11,904
	(0.05)		

[53] Data are from the 2011 census.

	Diff-in-diff coefficient (eb * endline)	Regression F statistic	Sample size
Other caste	0.06 (0.06)	21.85	7,207
(highest) Female Educ >=5 years	0.05 (0.04)	30.80	9,914
Female education < 5 years	0.1215** (0.05)	38.51	9,197
Land owners	0.07 (0.05)	44.44	13,055
Landless	0.09080* (0.05)	21.65	6,056
Poorest quartile of households (BL ln per capita hhexp)	0.1158** (0.06)	66.12	4,825
Top ¾ quartiles	0.00857 (0.04)	29.18	14,286
Village characteristics			
Early village	0.03 (0.052)	66.43	9,576
Late village	0.1230* (0.0744)	37.68	9,535
Block HQ distance <=15 kms	0.05 (0.05)	10,328	10,328
Block HQ distance > 15 kms	0.1276** (0.061)	31.10	8,783
Total village homes of permanent structure <=median value	0.870* (0.05)	40.92	11,602
Total village homes of permanent structure >median value	0.003 (0.07)	26.31	7,509
Villages with bk linkage at BL	0.1399** (0.065)	30.61	7,834
Villages without bk linkage	0.0128 (0.051)	37.31	11,277
VO characteristics[*]			
Size (Number of affiliated SHGs)	-0.0005 (0.011)		
Indicator for multi-village VO	-0.2145** (0.0913)	45.39	16,938

Note: In all cases with the exception of VO characteristics, reported results are from separate difference-in-difference regressions for each type (such as landowners versus landless). Results for VO characteristics are from the same difference-in-difference regression which includes the following triple interactions: EB*endline*VO size, EB*endline*I(multi-village VO). All regressions include controls used for basic difference-in-difference regressions, with standard errors clustered at the level of the village. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.1.4 NRLM: Other outcomes

Table 34 reports results from other outcomes, commencing with the programme's impact on income earned through different sources. The results suggest that increases in income are primarily a consequence of improvements in wage incomes, though the impact on wage incomes is imprecisely measured and is statistically insignificant at the 10% level. Additionally, we find that the increase in consumption appears to be largely a consequence of greater expenditure on monthly food items.

The bottom panel of this table reports a strongly significant reduction in borrowing to finance production needs over time. Because the comparison is to the early years of the programme, this suggests higher investments in capital in the programme's early years, with investments tapering off over time. In contrast, borrowing to finance expenditure on food and regular-use items increases significantly in the medium-run relative to the short-run, as does borrowing for this purpose from SHGs. For both overall loans and SHG loans, the increase is statistically significant at the 1% level.

Results relating to overall labour force participation as well as participation in specific sectors are in Table 35 Overall, the results suggest little change over the programme's medium run, relative to the short run, in women's labour force participation, hours, or their sectoral participation. In contrast, total hours of work reported by males decline significantly. In terms of their sectoral participation, there is a significant increase in the probability of male participation in the market for skilled non-agricultural labour, while there is a shift from participation in the formal (salary) sector, but to a lesser extent.

Table 34: NRLM Additional outcomes

Outcome	eb* endline	
	Coeff	Regr .F
Components of income		
Agricultural income	702.59	7.88
	(3306.67)	
Livestock income	523.91	6.05
	(922.61)	
Total wage income	3,576.34	36.25
	(2,592.17)	
Wage labour income	3,384.93	31.81
	(2,156.05)	
MNREGA income	-24.01	7.12
	(301.41)	
Salary income	3,221.93	11.96
	(2,270.80)	
(ln) Food exp per capita (real INR)	0.0970**	68.67
	(0.04)	
(ln) non-food daily items, per capita	0.05	45.64
	(0.06)	
(ln) non-food annual items, per capita	0.11	30.00
	(0.07)	
Home cc (INR)	81.22	33.83
	(78.80)	
Mkt cc (INR)	149.9	25.50
	(152.2)	
Food share of monthly consumption items	0.01	11.08
	(0.01)	
Number of income sources	-0.136	72.64
	(0.105)	
Count of consumption items	0.137	30.89
	(0.369)	
Any life insurance	-0.018	11.76
	(0.022)	
Any health insurance	-0.027	11.08
	(0.027)	

Outcome	eb* endline	
	Coeff	Regr .F
WASH infrastructure	-0.069	21.64
	(0.075)	
Any production loans	-0.0852***	13.47
	(0.026)	
Any production loan, SHGs	-0.0881***	11.56
	(0.024)	
Consumption loans	0.0752***	27.38
	(0.027)	
Any consumption loans, SHGs	0.0928***	17.81
	(0.026)	
Assets		
Productive assets - number	0.49	8.69
	(0.761)	
Productive assets – value	6870.2	7.58
(constant INR)	(6995.220)	
Consumer assets - number	0.220	88.28
	(0.200)	
Consumer assets - value	3905.410(3229.660)	22.04

Note: sample size is 19,310

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35: NRLM Programme effects on labour force participation

	Coefficient on EB * endline	
	Females	Males
LFPR	-0.0165	-0.0192
	(0.02)	(0.02)
Total hours of work	-0.48	-15.45*
	(6.00)	(8.61)
Own farm	0.045	0.0222
	(0.0324)	(0.0341)
Other hhold enterprise	0.0218	0.0022
	(0.028)	(0.0253)
Ag lab	-0.0162	-0.0179
	(0.0138)	(0.018)
Unskilled non-ag labour	-0.00175	-0.037
	(0.0158)	(0.0255)
Skilled non-ag labour	--	0.0326**
		(0.0157)
Salary	--	-0.0254*
		(0.0129)
Sample size	26,101	24,186

Note: all regressions include controls for treatment heterogeneity. Other household enterprises include livestock, fisheries, and non-agricultural household enterprises. Standard errors, in parentheses, are clustered at the level of the village. Sample size is 26,101 for regressions on females, 24,186 for regressions on males.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.1.5 Overview of NRLM's medium-run impact

Our estimates support the hypothesis that consumption and income increase over NRLM's medium run relative to its short run. The total impact of NRLM by 2024 is the sum of income (and consumption) increases in the short run and those achieved between the short and medium run. This report identifies the latter, but the absence of baseline data from years prior to NRLM's start renders identifying the short-term effects beyond the scope of this evaluation.

Our finding that income and consumption returns to NRLM *increase* over time is important and significant. A growing literature in economics recognizes that the effects of programmes, particularly those supporting credit access and financial inclusion, vary over time and are frequently highest at early stages, particularly for income. This is generally attributed to an early push for ensuring loans for productive purposes and declining returns to such investments over time. This accords with our findings related to productive loans. Other studies suggest similar effects, with an increase in aggregate or programmatic resource constraints causing a similar time-profile in productive investments (Buera, Kaboski, and Shin 2021). However, while productive lending falls off in the NRLM sample, income is nevertheless higher in the medium run relative to the short run.

The heterogeneity in returns that we identify helps explain relatively low average returns. The data suggest that the poor and those from lower socio-economic backgrounds been amongst the major beneficiaries of the programme. This inclusive nature of NRLM may come at the cost of larger increases in income if households with higher education are more productive. This tradeoff is, of course, well known, but one that is less relevant in the context of programmes such as NRLM whose stated objective is to reduce poverty. In such cases, the equity-efficiency tradeoff will always favour equity objectives. More importantly, the results of our evaluation suggest that significant improvements in both income and consumption are possible, even when programmes target the poorest households.

Our results also reveal higher consumption levels over time, financed by a growth in consumption loans. Since households could borrow for either production or consumption, the growth in consumption loans at the expense of those for production suggests a reduction in the extent to which credit constraints bind. While such a reduction would cause consumption to increase, their continued prevalence would explain the lack of borrowing for productive purposes.

It may be surprising that access to credit continues to be an important factor, given that community investment funds (CIFs) provided to CLFs are a grant-in-perpetuity, intended to allow for continuous borrowing amongst SHG members. Moreover, both NRLM and NRETP SHGs have been "bank-linked" to a similar extent, suggesting the availability of even greater access to loans. However, economic theory cautions that joint liability groups may deter individual members from investing, because all members are liable in the event of default by any one member (Fischer 2013). Indeed, during field work, this view was commonly expressed by SHG members. Thus, while the pool of savings available to SHGs provides some insurance against idiosyncratic income shocks, it is insufficient to cover the risks that may be associated with large investments by any given member of the magnitude required for significant improvements in income. The solution

offered by economic theory is to allow all SHG members to have an equity stake in investments undertaken by any member. This is a feature of joint SHG enterprises, but such enterprises are rarely found in NRLM SHGs.

This leaves SHGs preferring to borrow from programmatic funds provided through the CLF. The funds that are currently available to NRLM CLFs may be insufficient to finance large productive loans. Indeed, the support for NRETP and, in particular, for the model CLF programme, builds in part on the recognition that the federation of community institutions lacks the financial and other resources required for large improvements in income. Our evaluation of NRETP and the model CLF programme, discussed below, sheds light on this hypothesis.

6.2 NRETP

6.2.1 NRETP: Impacts on SHG participation and consumption

As with our evaluation of NRLM, we start our analysis of NRETP by examining its effects on participation in SHGs. The results in Table 36 suggest that the implementation of NRETP did not affect SHG membership, echoing our earlier results for NRLM.

Table 37 provides estimates of NRETP's impact on household consumption using different regression methodologies. The estimates are relatively consistent across specifications. These include estimates from double-robust methods (Sant'Anna and Zhao 2020) and from models that correct for potential deviations from the parallel trends assumption by modelling the conditional expectation function (regression adjustment) or the treatment equation (inverse probability weighting).

All specifications suggest a strong, significant effect of NRETP on per capita household consumption growth, with the estimates ranging from 8 to 14 %. These are similar to our estimates of the impact of NRLM in the medium run relative to the short run (8.5%). The next two rows of the table report the robustness of the estimates to variation in sample size and to an alternative expanded control set. For the former, we drop observations for the state of Odisha, for which the sample is considerably unbalanced. This may affect the match between treatment and control blocks and hence the credibility of the parallel trends assumption, even after weighting and regression adjustment. Doing so marginally increases the magnitude of the estimate across all specifications so that it now ranges from 12 to 15%. Again, the estimates are remarkably consistent across specifications. The last row expands the set of controls to include measures of the households' demographic composition and lagged measures of programme scale from 2015. The results are highly robust to this change in controls.

The finding of a strong effect of the programme on consumption is in sharp contrast to estimates of the impact of micro-finance programmes, particularly those measured at early stages. The collection of such studies in Banerjee et al. (2015) notes only modest impacts of a wide variety of microfinance programmes on consumption, with many such programmes having no statistically significant effect. In a similar vein, our earlier evaluation of NRLM (Kochar et al., 2020) and an early evaluation of Jeevika (Hoffman et al., 2021) also found no effect on consumption.

Table 36: NRETP: Probability of SHG membership

Regression specification	Treatment effect
Difference in difference	0.00676
	(0.0227)
Double robust	-0.00170
	(0.0268)
Regression adjusted	0.00315
	(0.0679)
IPW	-0.0588
	(0.0431)

Note: Standard errors, in parentheses, are clustered at the level of the village. Sample size: 24,968

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 37: NRETP: Impact on (ln) per capita household expenditure

	Basic diff-in-diff	Double robust	Regr adjust (RA)	IP weighted
	(1)	(2)	(3)	(4)
Ln per capita household exp (real INR)				
Full sample (omit MH)	0.0825***	0.1058***	0.1264***	0.1363***
	(0.0305)	(0.0308)	(0.0325)	(0.0392)
N	24,710			
Drop ODI	0.1273***	0.1212***	0.1444**	0.1538***
	(0.0290)	(0.0331)	(0.0640)	(0.0357)
N	22,993			
Add additional controls	0.0834**	0.1096***	0.1415***	0.1420***
	(0.0306)	(0.0297)	(0.0325)	(0.0391)
N	24,710			

Note: Estimates in column 2 are Sant'Anna and Zhao's (2020) improved doubly robust difference-in-difference estimator based on inverse probability of tilting and weighted least squares; col 3 (RA) are regression-adjusted estimates and col 4 are from inverse probability weighted difference-in-difference estimators with stabilized weights (Sant'Anna and Zhao, 2020). The basic set of controls includes household size, an indicator for SC/ST and for landless households, the maximum level of schooling of a female member of the household at baseline, village population, proportion of the population from scheduled castes and tribes, village female literacy rate, and a village infrastructure index. It also includes the scale of SHGs and CLFs in the village in 2018, as defined in the paper. These latter variables model the probability of treatment. The extended set of controls adds on household demographics and measures of programme scale in 2015. All regression errors are clustered at the level of the village.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2.2 Falsification test

We note that this estimated effect does *not* represent the longer duration of NRLM in NRETP blocks since the treatment (NRETP) and control (Early NRLM) blocks of our study share a common period of programme duration and because NRLM continues to be implemented in control blocks. The blocks differ only in the introduction of NRETP in treatment blocks. Correspondingly, the estimates of this table are representative of a causal impact of NRETP on household consumption, over and above the impact of the extended duration of NRLM. Nevertheless, even if treatment and control blocks started

implementing the programme at the same time, it is possible that the two types of blocks differ in programme intensity, or the scale of the programme in the villages of the block. If so, it is possible that our estimate of NRETP's impact identifies the effect of programme intensity, rather than the inputs provided under NRETP.

We address this concern through a falsification test. For this, we report results from regressions that include a measure of programme intensity, an indicator for endline observations, and the interaction of the two. The coefficient on the interaction variable tests for intensity effects. We measure intensity in three ways, first by a propensity score, second by the scale of SHGs in the village (the total number of SHG years of all village SHGs), and lastly by the scale of CLFs (the total number of years of federation in CLF across all SHGs in the village). If the NRETP effect reflects differences in programme intensity between treatment and control villages, then household expenditure in high intensity villages of control blocks should exceed that of low intensity villages.

Table 38 finds that this is not the case. The coefficient on the interaction of programme intensity and the endline indicator is never statistically positive; we fail to reject the null hypothesis of no (positive) effect of programme intensity. This suggests that our estimates of the impact of NRETP correctly identify the programme's impact.

Table 38: Falsification tests for NRETP impact: Differences in control (early blocks) by programme intensity (scale)

	Basic diff-in-diff	Double robust	Regr. adjusted	IP weighted
Propensity score	-0.0301	-0.0312	0.0184	-0.0062
(N=9945)	(0.04)	(0.08)	(0.10)	(0.09)
Vscale	0.0013	0.0159	0.0635	0.0780
(N=9945)	(0.04)	(0.04)	(0.09)	(0.07)
Clfscale	-0.0210	-0.0132	0.0010	-0.0116
(N=9945)	(0.05)	(0.05)	(0.05)	(0.04)

Note: Regressions are run on non-NRETP Early block sample, dividing the sample in two by propensity score and by the initial (2018) scale of SHGs in the village (*vscale_18).* Sample size is 9,945.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2.3 Heterogeneity in NRETP's impact on household expenditure

Table 39 reports difference-in-difference estimates of the differential impact of NRETP by household, village, and programme characteristics.

A first finding is that the programme, like NRLM, is highly inclusive. Thus, returns are greater for members of scheduled castes and tribes and for less educated women. But, in contrast to NRLM, this difference does not exist when comparing across the poorest households and the less poor or by landownership. The impact on landless households is greater in magnitude than on landowners and statistically significant for the former but not the latter.

Additionally, the programme's impact on non-members (at baseline) is greater in magnitude than its impact on SHG members. Second, NRETP's impact is larger in villages that are closer to markets or are likely to have larger markets of their own. Thus,

consumption increases more in villages close to the block capital. It is also significantly higher in villages with larger markets, as measured by the total number of good-quality houses. These findings are consistent with a literature which suggests that growth opportunities are likely to have higher returns in areas with better access to markets, so that an increase in income-earning opportunities may initially increase geographical inequalities.

Similar to NRLM, consumption is higher in villages with prior bank-linked SHGs. There is, however, no difference in returns between villages in which the programme started earlier than others in the block (early villages) and those that started later. And, also as was the case for NRLM (table 33), the results relating to VO characteristics find that multi-village VOs significantly reduce consumption. In contrast, VO size has a statistically insignificant effect.

Table 39: NRETP Heterogeneity in consumption impact by household and village characteristics

(dependent variable: ln per capita household expenditure)

	Diff-in-diff coefficient (NRETP * endline)	Regression F statistic	Sample size
Household characteristics			
Shg member at baseline	0.0677* (0.03)	82.53	16,833
Non-member at baseline	0.116*** (0.04)	49.91	7,877
SC/ST	0.089** (0.04)	72.47	16,400
Other caste	0.06 (0.04)	44.01	8,310
(highest) Female Educ >=5 years	0.0503 (0.0374)	46.58	10,659
Female education < 5 years	0.1109*** (0.03)	82.39	14,051
Land owners	0.06 (0.0381)	56.34	13,118
Landless households	0.105*** (0.04)	69.15	11,592
Poorest households	0.0166 (0.0360)	123.22	6,437
Less poor	0.0289 (0.0300)	57.80	18,273
Village characteristics			
Early village	0.0942** (0.04)	57.59	12,421
Late village	0.07 (0.04)	68.09	12,289
Villages with BL bank linkage	0.0806** (0.04)	65.52	13,805
Villages without bank linkage	0.0904* (0.0495)	53.28	10,905

	Diff-in-diff coefficient (NRETP * endline)	Regression F statistic	Sample size
Block HQ distance <=15 kms	0.107*** (0.036)	73.66	15,598
Block HQ distance > 15 kms	0.052 (0.055)	54.01	9,112
Total village homes of permanent structure <=median value	0.024 (0.046)	47.40	11,279
Total village homes of permanent structure >median value	0.143*** (0.044)	77.48	13,431
*VO characteristics**			
Endline*NRETP block	0.287 (0.221)	87.65	24,366
Size (Number of affiliated SHGs)	0.008 (0.011)		
Indicator for multi-village VO	-0.2327** (0.11)		

Note: In all cases with the exception of VO characteristics, reported results are from separate difference-in-difference regressions for each type (such as landowners versus landless). Results for VO characteristics are from the same difference-in-difference regression which includes the following triple interactions: NRETP*endline*VO size, NRETP*endline*I(multi-village VO). All regressions include controls used for basic difference-in-difference regressions, with standard errors clustered at the level of the village. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2.4 NRETP: Household Income, hours of work, and sectoral labour outcomes

Table 40 reports regression results of the programme's impact on (total) household income, using different regression specifications. The results reveal a positive effect of NRETP on household income, an effect that is statistically significant at conventional levels (5% or less in all cases). As for household consumption, the results are robust to different regression methodologies. The second row of results shows that they are also robust to variations in the sample (removing observations for the state of Odisha) and to variations in the set of controls.

The impact on income is sizeable. The estimates in the first row vary from INR 11,000 (difference-in-difference) to INR 18,000 (regression adjusted). At the low end, the INR 11,000 increase amounts to an improvement of 16% in real incomes relative to the counterfactual of incomes for treated households at baseline in the absence of NRETP. This percentage increases to 23% for the double-robust estimate (INR 15,600) and to 27% for the regression adjustment estimate (Appendix D). These increases are significantly larger than the estimated 9-10% increase in the medium-run impact of NRLM relative to the short-run.

This significant improvement in income distinguishes NRETP from other financial inclusion programmes, suggesting the importance of the additional resources provided under the programme. As described in earlier chapters, this infusion takes the form of augmented access to financial and human capital. It also includes new institutional arrangements that provide the potential for additional improvements in productivity.

Table 41 provides estimates of the programme's impact on different components of income. All specifications suggest that NRETP improved agricultural incomes. The double-robust specification also reveals improvements in wage incomes and incomes from livestock enterprises, with the increase in wage incomes coming from earnings in both the casual labour market and salaries.

Results of the programme's impact on labour force participation (table 42) support the finding of an improvement in wage incomes. Unlike the NRLM findings, labour force participation and total hours of work of both males and females increase significantly as a consequence of NRETP. The increase in women's LFPR reflects greater female participation in own-farm activities. For men, the increase is primarily a consequence of greater involvement in the unskilled non-agricultural labour market, with a (smaller) decline in participation in the agricultural labour market.

Given the evidence in Chapter 5 on the extent to which males participate in the non-agricultural labour markets of adjoining villages, this growth of male non-agricultural labour is a testimonial to the importance of the programme's scale. As a consequence of their work-mobility, men, and hence their households, can benefit from increases in labour demand in adjoining villages. On the flip side, however, the continued importance of local agricultural markets for female employment suggests their sustained dependence on conditions in the local village economy and the growing disparities in labour markets for males and females.

Table 40: Regressions on total household income (constant INR)

	Basic diff-in-diff	Double robust	Regr adjust (RA)	IP weighted
	(1)	(2)	(3)	(4)
Total household income (real INR)				
Full sample (omit MH)	10909.0***	15541.3**	18038.82**	11872.1**
(N=24,654)	(3,927.70)	(6,695.21)	(7,151.8)	(5,565.10)
Drop ODI	11354.4**	16063.6**	19373.9**	11269.7**
N (22,914	(4322.3)	(7,151.5)	(7,785.0)	(5,016.1)
Add additional controls	10687.7***	14894.0**	19,092.1	11969.7**
(N=24,648)	(3,864.2)	(7,195.9)	(18,353.2)	(5,560.0)

Note: Estimates in column 2 (double robust) are Sant'Anna and Zhao's (2020) improved doubly robust difference-in-difference estimator based on inverse probability of tilting and weighted least squares; col 3 (RA) are regression-adjusted estimates and col 4 are from inverse probability weighted difference-in-difference estimators with stabilized weights (Sant'Anna and Zhao 2020). The basic set of controls includes household size, an indicator for SC/ST and for landless households, the maximum level of schooling of a female member of the household at baseline, village population, proportion of the population from scheduled castes and tribes, village female literacy rate, and a village infrastructure index. It also includes the scale of SHGs and CLFs in the village in 2018, as defined in the paper. These latter variables model the probability of treatment. The extended set of controls adds on household demographics and measures of programme scale in 2015. All regression errors are clustered at the level of the village.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 41: NRETP: Components of income

	Diff-in-diff	Double robust	Regr adjusted	Std. IPW
Agricultural income	4144.7*	3424.59**	6678.8***	4004.9***
	(2135.9)	(1,716.73)	(2,357.40)	(1,449.40)
Livestock	495.2	1201.3**	1415.4**	1119.51*
	(457.6)	(591.0)	(654.29)	(587.50)
Total wage income	2839.0	6412.921***	5864.4**	4,921.00
	(1765.0)	(2,407.80)	(2,633.0)	(3,997.40)
Components of wage income				
Wage income	2054.1	4547.1**	4906.0**	4,320.00
	(1586.9)	(1,923.41)	(2,254.41)	(2,984.10)
MGNREGA	-273.12	-315.6*	-482.5**	-125.90
	(201.62)	(191.03)	(214.01)	(199.00)
Salary	1858.71	4325.5***	3354.4*	2,531.50
	(1334.51)	(1,639.45)	(1,760.20)	(1,850.80)

Note: sample size for all regressions is 24,654

Table 42: NRETP impact on labour force participation, hours, and sectoral participation

	Females	Males
LFPR	0.0400**	0.0295**
	(0.0182)	(0.0124)
Hours of work	6.539*	12.91***
	(3.418)	(4.786)
Sectoral participation		
Own farm	0.0317	0.0310
	(0.0205)	(0.0218)
Own household	0.0320*	-0.0145
	(0.0187)	(0.0180)
Agricultural labour	0.000670	-0.0421***
	(0.0132)	(0.0140)
Unskilled non-ag labour	0.0144	0.0603***
	(0.0106)	(0.0179)
Skilled non-ag labour	--	-0.00263
		(0.0102)
Salary	--	0.0028
		(0.00825)

Note: Difference-in-difference regressions. Sample size is 33,659 for females and 30,580 for males. Female employment as skilled non-agricultural labour and in the formal (salary) sector is insignificant.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2.5 NRETP: State-level variation in treatment heterogeneity

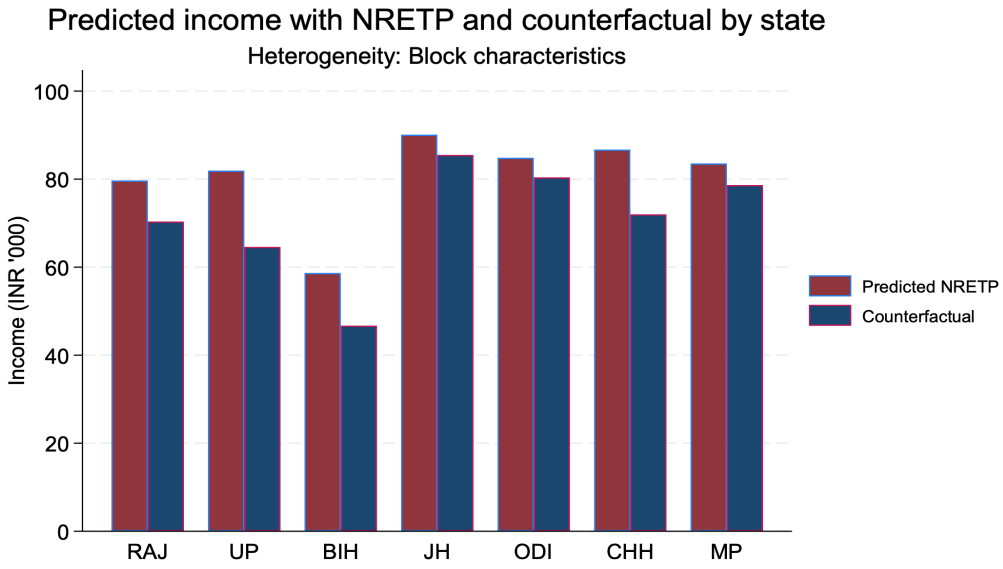
The fact that socio-economic conditions related to market access differentially affect the returns to the programme suggests corresponding differences in the programme's

impact across states as a consequence of state-level variation in these conditions. That is, variation in the programme's impact across states will exist because of initial differences in socio-economic context, even if implementation and implementation quality were similar across all states.

We demonstrate the magnitude of such effects by plotting predicted and counterfactual incomes across states in the regression sample, allowing for heterogeneity along various dimensions. Figure 33 allows for heterogeneity in three block-level measures: female literacy rate, the presence of a bank in the village (using data from the 2011 census), and the mean size of village markets (our measure based on the total number of good-quality houses).[54] It reveals a larger impact of the programme in Bihar and Uttar Pradesh, followed by Chhattisgarh and Rajasthan. The impact is slightly less in Madhya Pradesh, while Jharkhand and Odisha reveal only marginal programme effects.

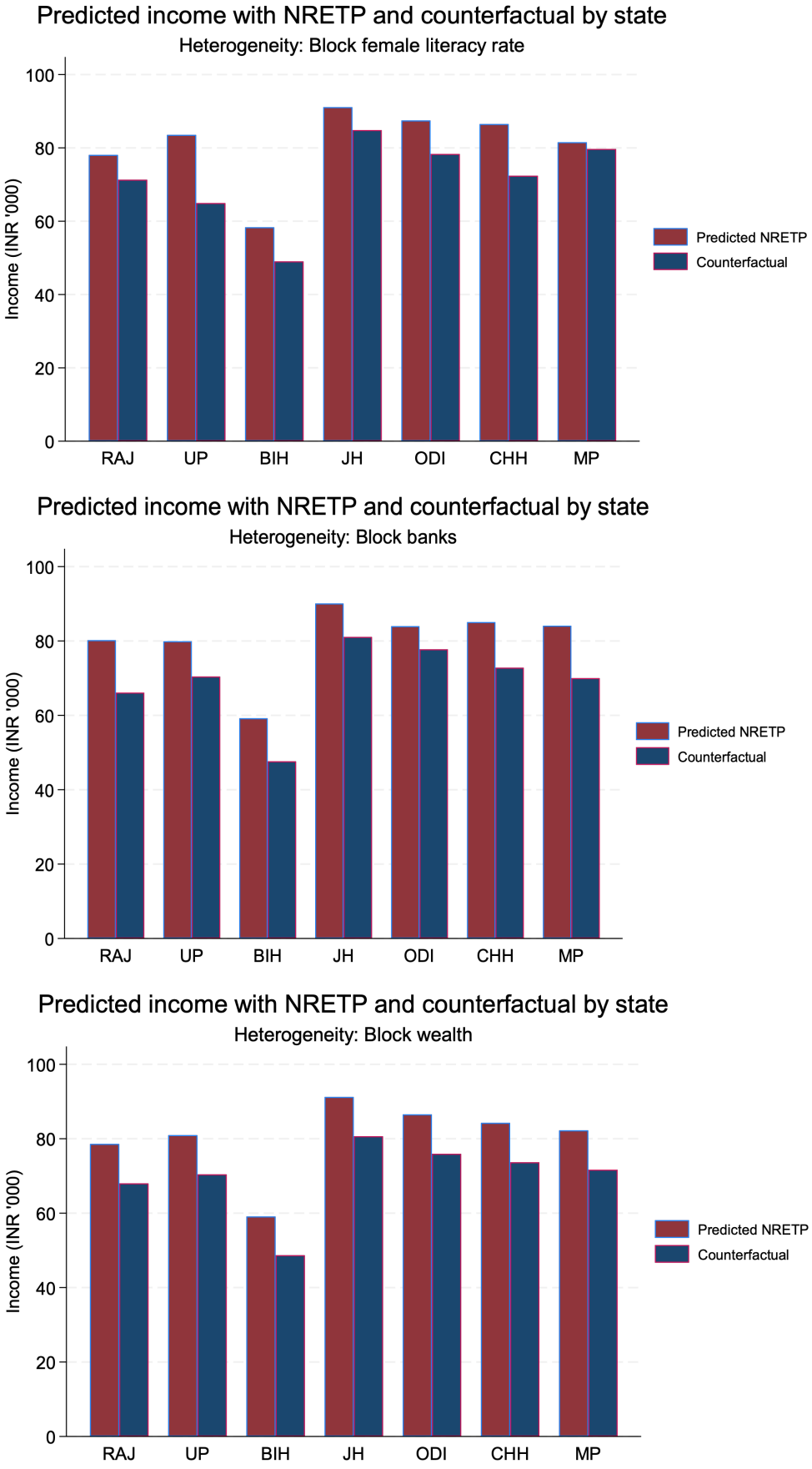
Figure 34 plots separate graphs for each of these block-level characteristics. The first, by block female literacy rate, reveals that Uttar Pradesh's advantage is primarily a consequence of the higher female literacy rate in this state. Initial bank infrastructure provides a greater advantage to Rajasthan, Madhya Pradesh, and Chhattisgarh (the second figure). In contrast, the last figure reveals that Bihar's advantage reflects its larger market size. This is because market size incorporates both the (population) size of the village market and any increase in mean incomes. The much higher village population size in Bihar results in a larger estimate of market size. Data from India's 2011 census reveal an average size of 2,058 in 2011 (across all villages in the state). In contrast, the average village population size is just 917 in the remaining states of our sample. Amongst our survey villages too, the average village population size is 4,400 in Bihar but just 1,700 in the remaining states.

Figure 33: State-level variation in income improvements under NRETP with heterogeneity in block market-related characteristics



[54] We recognize the significant changes in bank infrastructure that have occurred since 2011, a consequence of the Government's efforts to ensure access to banks across India's villages. Nevertheless, the 2011 data serve as a baseline for NRLM. The results, in fact, reveal that these baseline levels have predictive power for consumption and income regressions.

Figure 34: State-level differences in income improvements, by block characteristics



6.2.6 NRETP: Additional outcomes

A final set of results (table 43) explores NRETP's impact on other household outcomes. The table presents results from difference-in-difference and double-robust regressions, with both regression methodologies generating generally similar results.

Again, there are significant contrasts with the NRLM results. A first striking effect is the large and significant increase in non-food (regular) consumption. As a consequence of this increase, the share of food in monthly consumption falls significantly. This decline is generally viewed as indicative of an improvement in household welfare. A second such measure, the number of consumption items reported by the household, also significantly increases.

Differences between the two programmes are also apparent in their impacts on assets. NRLM increased the number and value of productive assets, though the impact was statistically insignificant at conventional levels. In contrast, NRETP appears to reduce the number of productive assets that households report, but significantly increases their value. There is no statistically significant effect on the number of consumer assets or their values.

Finally, both regression methodologies suggest an increase in the number of productive loans, but with these effects being statistically significant only in the difference-in-difference specification. We provide additional information on productive loans in our analysis of SHGs in later sections of this chapter.

Our comment on the disincentives to investment in joint liability groups applies as much to NRETP SHGs as it does to NRLM SHGs. During field work in NRETP blocks, we asked members of PGs about their level of satisfaction with the programme and which aspects they would like to see improved. A common response was a request for greater infrastructure grants, on the grounds that members were unwilling to use bank loans for this purpose, given concerns regarding joint liability. Additionally, because members of PGs are frequently associated with different SHGs, they stated that it would be wrong to approach their own SHG for loans that would benefit members of other SHGs. The general point made in our discussion on NRLM SHGs remains: joint liability groups may create disincentives for large investments, with members preferring to borrow smaller amounts and / or to use available funds for their working capital needs.

Table 43: NRETP: additional outcomes

Outcome	Basic difference-in-difference	Double robust
(ln) Food exp per capita (real INR)	0.04	0.100***
	(0.0307)	(0.0287)
(ln) non-food daily items, per capita (real INR)	0.206***	0.2570***
	(0.0387)	(0.0378)
(ln) non-food annual items, per capita (real INR)	0.0130	-0.0594
	(0.0501)	(0.0558)
Home cc (real INR)	136.4**	323.0***
	(61.28)	(56.93)
Mkt cc (real INR)	74.60	709.42
	(159.13)	(441.6)
Count of consumption items	0.732***	1.117***
	(0.268)	(0.298)

Outcome	Basic difference-in-difference	Double robust
Food share of monthly consumption items	-0.0317***	-0.0354***
	(0.0067)	(0.0067)
Number of income sources	-0.184**	-0.179**
	(0.0785)	(0.0882)
Any life insurance	0.0065	0.0063
	(0.0119)	(0.0118)
Any health insurance	0.0497**	0.0371**
	(0.0209)	(0.0182)
WASH infrastructure	-0.126**	0.0010
	(0.0545)	(0.0639)
Any production loans	0.0511***	0.0170
	(0.0188)	(0.0160)
Any production loan, SHGs	0.0569***	0.0149
	(0.0174)	(0.0172)
Consumption loans	0.00316	0.00658
	(0.0190)	(0.0182)
Any consumption loan, SHG	0.0210	0.0176
	(0.0172)	(0.0156)
Assets		
Productive assets, number	-1.724***	-3.140***
	(0.582)	(1.083)
Productive assets, value(real INR)	21580.6*	20665.6**
	(12545.6)	(9285.8)
Consumer assets, number	-0.0527	0.0871
	(0.133)	(0.131)
Consumer assets, value	1,686.0	222.40
	(2,041.9)	(3100.66)

Note: All regressions use the basic set of controls described in the text. Sample size is 24,713 for items related to consumption (top and bottom 1% removed), 24,968 for other outcomes. Standard errors, clustered at the level of the village, in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.3 The impact of the Model CLF programme (MCLF)

Details of our methodological approach for evaluating the model CLF programme are in the Methodological Chapter (Chapter 4). Regression results from difference-in-difference regressions for both consumption and income, as well as from alternative regression methodologies, are in Table 44. The first column of results compares outcomes in MCLF clusters to those in NRETP clusters, exploiting the fact that the model CLF programme was, on average, implemented in just one cluster of each NRETP block. As discussed in the Methodological chapter, these estimates of the additional impact of MCLF in NRETP blocks will be biased downwards if there are spillover effects to other clusters of the same block and may also be biased due to treatment heterogeneity. Column (2) addresses these concerns by comparing outcomes in MCLF clusters to those in non-NRETP Early blocks, providing estimates of the combined effect of MCLF and NRETP, relative to the control sample of Early blocks. To disentangle the effects of MCLF and NRETP, column 3 repeats these regressions, but now using non-MCLF NRETP clusters as treatment, and therefore identifying the effect of NRETP but without the additional resources provided to model CLFs.

The results reveal a sizeable additional effect of MCLFs relative to NRETP clusters. On average, across different specifications, the additional percentage increase in consumption is approximately 8-9%, with the percentage effect of MCLF relative to NRLM Early blocks ranging from 11% to 17% while the percentage effect of NRETP relative to the NRLM Early blocks varies from 4% to 10%.

The effect on incomes appears even larger. The increase in (real) INR in MCLF clusters relative to NRLM Early blocks ranges from INR 7,000 to 17,000. In contrast, the corresponding increase as a consequence of NRETP varies from INR 3,000 to 6,000. Converting these figures to a percentage increase as a consequence of treatment relative to a counterfactual endline income in the absence of treatment suggests that, at the low end of estimates, NRETP increases incomes by 6% while the MCLF programme increases it by 12%. The inverse-probability weighted regressions (IPW) imply an increase of 10% for NRETP and 25% for MCLF, while the regression adjusted estimates (RA) suggest improvements of 10% and 33% for NRETP and MCLF respectively.

While the additional impact of MCLF is high, we note that our results still suggest significant income and consumption benefits to households in non-MCLF clusters of NRETP blocks relative to those in early blocks. While it is beyond the scope of this project to detect the factors underlying these differences, the summary statistics of Chapter 5 suggest several factors that we elaborate on in sub-section 6.4 of this chapter below.

Table 44: Comparing MCLF to NRETP income and expenditure regressions

	MCLF vs. NRETP block	MCLF vs. EB	NRETP vs EB
(ln) per capita household exp			
Difference-in-difference (basic)	0.0491 (0.0342)	0.1094*** (0.0345)	0.0428 (0.0364)
Double robust	0.0864** (0.0365)	0.172** (0.0687)	0.0992** (0.0410)
RA	0.0865 (0.9150)	0.1406** (0.0690)	0.09 (0.0623)
Std. IPW	0.0773** (0.0365)	0.1632** (0.0701)	0.0975** (0.0413)
Sample size	14,789	14,791	17,926
Income			
Difference-in-difference (basic)	6404.41** (3080.09)	6917.41** (3213.58)	3115.79 (3180.56)
Double robust	5606.18* (3325.83)	16834.8*** (6124.40)	5925.86 (4171.09)
RA	6528.4** (3238.5)	15222.96** (644.13.)	5358.49 (6,321.25)
Std. IPW	6332.2* (3320)	11983.8* (7228.27)	5016.50 (4591.83)
Sample size	14,679	14,701	17,822

Note: The estimates are based on dividing the NRETP block into two sets of clusters, those with model CLFs and those without. Estimates in column 1 compare model CLF NRETP clusters to other NRETP clusters without model CLF, with the total sample being restricted to NRETP blocks. The second column compares model CLF NRETP blocks to early blocks (without NRETP). The third column compares other NRETP clusters (without model CLF) to early blocks without NRETP. All regressions include the same set of regressors used for the evaluation of NRETP. Standard errors, clustered at the level of the village, in parentheses.

6.4 Testing for credit and human capital constraints

6.4.1 Methodology

Our discussion above suggests that credit constraints may still bind for households in NRLM villages while being relaxed for those in NRETP blocks. We explicitly test this hypothesis below, using specifications that derive from Euler equations. In the absence of credit constraints, inter-temporal optimization implies that the change in consumption over two periods will reflect changes in preference shifters and income and taste shocks, but will be unaffected by lagged income. Conversely, if credit constraints are binding, then the Lagrange multiplier associated with the borrowing constraint will be strictly positive, implying higher consumption growth for credit-constrained households (Zeldes 1989). Consequently, consumption growth will be negatively correlated with variables that affect credit access due to their impact, such as lagged values of household exogenous income.

Implementation of this test requires assumptions regarding utility. Assuming that utility is of the constant relative risk aversion form, Euler equations generate an estimating equation in which the change in (ln) per capita household consumption can be expressed as a function of the change in variables affecting preferences, with all time-invariant determinants being removed as a consequence of the differencing.

Following Zeldes (1989), we run separate regressions for households in NRETP blocks and in non-NRETP early blocks, under the assumption that the latter are more likely to be credit-constrained. Assuming that credit-constrained households' access to credit reflects their income, we test for the significance of baseline household income in both samples, using the sum of salary income and transfer income for this purpose so as to avoid issues related to the endogeneity of income from other sources such as agriculture and other family enterprises.

We also test whether credit access reflects a human capital constraint. Allowing for human capital spillovers across SHGs in a village, we test whether the proportion of SHG members in the village with 8 or more years of schooling, as estimated from SHG modules that provide education details for all members, significantly affects the change in consumption. Thus, our tests provide information into the nature of credit constraints. In economies with limited growth opportunities, we expect credit access to be affected by household income. However, within this sample, we do not expect credit access to vary across villages to differ in human capital. In contrast, the constraints that affect credit access and hence the growth chart of livelihoods changes as economies grow. In high-growth economies, lack of human capital may constitute a binding constraint.

These tests, since they are based on different samples (NRETP and non-NRETP early blocks), also require addressing selection bias caused by this variation in sample. We therefore employ a Heckman selection correction, identifying NRETP blocks, as before, by using lagged variables of the programme's scale (*vscale, clfscale).*

6.4.2 Results

The regression results are in Table 45. All regressions include the same set of household and village controls used in previous regressions. We provide results from regressions that include baseline household income only, and from an extended regression that

includes both baseline income and the education of village SHG members. For each of these two specifications, the top panel of results omits block fixed effects while the lower panel includes them.

The results reveal that Mill's ratio, used to correct for sample selection, is a significant determinant of outcomes in regressions without block fixed effects. When block fixed effects are included, it is significant at the 10% level only for the last regression on the NRETP sample. These results confirm that selection of NRETP blocks is based on block-level variables that are time-invariant in this sample and are swept away through block fixed effects.

The primary result from this regression is that the change in consumption in non-NRETP blocks is importantly affected by (baseline) household income, suggesting that access to credit is a function of household income in such samples.[55] This suggests that households in NRLM blocks continue to be credit constrained, even in the medium run. In contrast, baseline income does not affect consumption growth in NRETP blocks. But, levels of village human capital do. This result is consistent with models that predict a shift from binding credit constraints to binding human capital constraints in the process of structural transformation of the economy (Galor and Moav 2004). This evidence suggests that the growth of consumption for NRETP households is no longer constrained by binding credit constraints. Instead, consumption growth is constrained more greatly by access to human capital.

The growing importance of human capital constraints suggests the need for greater attention to livelihood trainings. The findings of the summary statistics chapter are relevant here. While CLFs in NRETP blocks are far more likely to report receiving livelihood training, relative to those in early and late blocks, this is not the case for SHGs in these different blocks.

Table 45: Testing for credit constraints

With Samples	Household baseline income (salary + transfer)	Proportion of village SHG members with >= years of schooling	Mill's ratio
Income only			
NRETP sample	-0.0001	--	0.13***
	(0.0002)		(0.05)
Non NRETP sample	-0.001***	--	-0.12**
	(0.0002)		(0.06)
With block fixed effects			
NRETP sample	-0.0001	--	0.0001
	(0.0001)		(0.06)
Non NRETP sample	-0.001***	--	-0.10
	(0.0001)		(0.07)
Income and village education			
NRETP sample	-0.0001	-0.15*	0.13***
	(0.0002)	(0.15)	(0.05)

[55] This result, though generally taken as suggestive of credit constraints, can also be a consequence of precautionary behaviour and the unwillingness to borrow to finance either consumption or production as a consequence of continued exposure to risk.

With Samples	Household baseline income (salary + transfer)	Proportion of village SHG members with >= years of schooling	Mill's ratio
Non NRETP sample	-0.001***	0.04	-0.13
	(0.0002)	(0.09)	(0.06)
With block fixed effects			
NRETP sample	-0.00017	-0.46***	0,002
	(0.00013)	(0.11)	(0.06)
Non NRETP sample	-0.001***	0.03	-0.13*
	(0.0002)	(0.11)	(0.07)

Note: Sample size is 12,251 for NRETP blocks and 12,437 for non-NRETP blocks. In addition to lagged income and village education, all regressions include household demographic controls (the number of household members in 6 gender-by-age groups), the maximum level of education of an adult female member of the household, an indicator for households from scheduled castes and tribes, and a set of village covariates (village population, proportion from scheduled castes and tribes, village infrastructure index, and village female literacy rates). For each specification, the first set of results omits block fixed effects, while the lower panel includes them.

6.5 Impact of NRETP and NRLM on SHGs

This section provides empirical evidence on NRETP and NRLM's effect on the quality of SHGs, focusing on measures of SHG functioning and on (constructed) quality scores that closely follow the standards stipulated by the programme in the form of *Panchsutras.* We follow this with a discussion of dynamic aspects of SHGs, specifically changes in the composition of their members, and evaluate each programme's effect on these changes.

6.5.1 Impact on SHG functioning and quality

Evaluating the impact of NRETP and NRLM on SHGs' functioning status requires us to include non-functioning SHGs in both the baseline and the endline regression sample. For this, we drop SHGs that were non-functioning at baseline from the endline sample. Consequently, the set of SHGs that are non-functioning in the endline sample are just those that stopped functioning between survey rounds. To similarly measure the SHGs that stopped functioning in the years prior to the baseline survey, we include all SHGs that were non-functioning at baseline in the baseline sample.[56] Thus, both survey rounds include SHGs that stopped functioning in the years prior to the relevant survey year.

A SHG is considered as non-functioning or defunct within the programme if it fails to perform the five expected roles of SHGs: savings, lending, regular repayment, regular meetings, and maintenance of books. Thus, defunct SHGs are those at the tail end of the distribution of SHG scores, generally identified using a cut-off score of 0 but including some which still reported some minimum activity.

Recognizing that defunct SHGs represent those at the low-end of the Panchsutra distribution, we also evaluate SHG quality on the basis of other cut-offs. For this, we define an alternative measure of functioning SHGs which takes the value 1 if the Panchsutra score exceeds 1. The results are in table 46. The top panel of the table provides results for the NRETP sample while the bottom panel relates to the NRLM panel. Within each panel, the first row reports the coefficient on the Endline indicator and hence on the trend in SHG quality between survey rounds. The second row reports the

[56] This includes those that were not roe-surveyed in 2024.

interaction of the relevant treatment indicator with the endline indicator, and hence tests for a different effect by treatment status. A significant coefficient on the interaction terms suggests a causal effect of treatment.

The results suggest an improvement in SHG quality over time, particularly for SHGs in the NRLM sample. However, the causal effects are quite different from the long-term trend. For NRETP, the coefficient on the interaction of the endline and NRETP indicator is negative in both specifications and significantly so when using the weaker indicator (Panchsutra score >1), suggesting lower quality in NRETP blocks relative to the control sample of early NRLM blocks. For the NRLM sample, the coefficient on the interacted term is statistically insignificant, implying that there is little change in SHG quality between the short and medium-run.

Since the Panchsutra score reflects a SHG's overall quality, we can also test the effect of each programme on the overall score, rather than its effect on the tail of the distribution. The results are in table 47. The first three columns provide results for the three scores described in the summary statistics chapter, *Panchsutra* 1 to 3, with *Panchsutra* 1 being the most stringent and *Panchsutra* 3 being the least. As earlier discussed, each of these scores combines five index variables which note whether the SHG is achieving standards against the 5 norms. The last column of table 47 uses an alternative index, based on continuous measures of the SHG's performance against each norm.

The first panel of results reveals that the coefficients on the interaction of NRETP and the endline indicator are negative in three of the four specifications, but statistically insignificant in all cases. To test if the programme's impact on SHG quality differs in model CLF clusters, the second panel repeats this regression for the MCLF sample. Treatment SHGs in this sample are those that fall in MCLF clusters of NRETP blocks, while the control sample remains SHGs in non-NRETP blocks. While the coefficient on the interaction of treatment and the endline indicator is statistically insignificant in three out of the four regressions, it is marginally significant (at 10% level) and negative in one specification. Thus, while the results generally suggest an insignificant effect of NRETP on SHG quality, the statistically significant negative coefficient in column 2 of table 46 (Panchsutra score >1) and in the regression on Panchsutra 2 in table 47 imply negative effects on SHG quality by some measures.

The opposite is true for SHGs in the NRLM sample. Here, the coefficients on all outcome variables reported in Table 47 are positive, with the coefficient on the continuous measure of Panchsutra scores being statistically significant at the 5% level. Thus, while the general impression is of little change in SHG quality between the short and medium-run, there is some evidence of improvement by at least one measure.

Table 46: SHG functioning status and Panchsutra scores

Sample & Methodology	SHG functioning?	Panchsutra score 1 >1
NRETP sample		
Endline coeff	0.292***	0.120
	(0.0818)	(0.0749)
Endline*NRETP block	-0.0389	-0.106***
	(0.0268)	(0.0339)
NRLM sample		
Endline coeff	0.277*	0.731***
	(0.154)	(0.122)
Endline * EB	0.0405	-0.0427
	(0.0433)	(0.0437)

Note: For NRLM and NRETP regressions, the sample is all SHGs in the baseline (including those who attritted). For the endline, the sample is all panel SHGs that were functioning at the baseline. Regression samples for NRETP and NRLM include only states with representation in both treatment and control blocks. All regressions include the full set of control variables and a quadratic in the SHG's age in months. The NRETP sample size is 5,153. The NRLM sample size is 3,507.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 47: SHG functioning status and Panchsutra scores, based on alternative continuous variables

Sample & Methodology	Panchsutra 1	Panchsutra 2	Panchsutra 3	Panchsutra continuous
NRETP sample				
Endline coeff	0.378	0.821***	1.201***	0.835***
	(0.258)	(0.257)	(0.284)	(0.294)
Endline*NRETP block	-0.110	-0.156	-0.164	0.101
	(0.117)	(0.116)	(0.119)	(0.134)
MCLF sample				
Endline coeff	0.670**	1.061***	1.459***	1.171***
	(0.319)	(0.320)	(0.356)	(0.356)
Endline*MCLF cluster	-0.212	-0.271*	-0.351**	-0.0679
	(0.144)	(0.140)	(0.148)	(0.157)
NRLM sample				
Endline coeff	1.649***	2.015***	3.194***	0.954
	(0 .455)	(0.428)	(0.485)	(0.601)
Endline*Early Block	0.0601	0.125	0.153	0.365**
	(0.162)	(0.147)	(0.161)	(0.180)

Note: The dependent variable in columns 1-3 are Panchsutra rankings based on a discrete score that takes values of 1 to 5, with the scores varying in terms of the stringency of norms as described in the text, with Panchsutra 3 being the least stringent. The last column, Panchsutra continuous, is an alternative continuous score which combines continuous measures of SHG performance along the 5 Panchsutra norms. For all regressions, the sample is all SHGs in baseline (including those who attritted). For endline, the sample is all panel SHGs that were functioning at Baseline. Regressions on MCLF sample are restricted to MCLF clusters in NRETP blocks with the control being clusters in Early Blocks. All regression samples include only states with representation in both treatment and control blocks. All regressions include the full set of control variables and a quadratic in the SHG's age in months. NRETP sample size is 5,153. NRLM sample size is 3,507, and MCLF sample size is 2,997.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.5.2 Programme effects on member entry and exit, member characteristics, and loans

One potential explanation for these differing effects is the fact that the SHG is not a fixed entity. Thus, when evaluating the effect of NRETP or NRLM on SHG quality and restricting our attention to functioning SHGs, we are essentially considering the programme's effect on an entity or institution that itself is changing between survey years. This change is a consequence of member entry and exit, summary statistics on which were provided in Chapter 5.

Table 48 reports regressions that are restricted to panel SHGs, those surveyed at both endline and baseline. As in the previous table, the first two columns apply to the NRETP evaluation while the remaining two evaluate the impact of NRLM, using the early block (EB) indicator. Within each sample, the first column reports the coefficient on the interaction between the treatment and the endline indicator, while the second column reports the coefficient on the endline indicator and is thus indicative of the trend rate in the outcome in question between the two survey years.

The first two rows of the table suggest a striking difference between NRETP and NRLM. SHGs in NRETP blocks are more likely to have member exit as well as entry. While the coefficient on member exit is statistically insignificant, that on member entry is significant at the 5% level. In contrast, SHGs in NRLM blocks are less likely to have either member entry or member exit, with the coefficient on member exit being statistically significant at the 1% level. We note again that all results for the NRLM sample represent a comparison between outcomes in the short run and the end run, so that the interpretation differs from that which applies to the NRETP sample. For NRLM, the regressions suggest that SHGs remain relatively stable over time.

The higher degree of churn in NRETP SHGs suggests that SHGs in NRETP blocks are more likely to experience changes in the characteristics of their members relative to those in (control) NRETP blocks. This is confirmed in the next panel of results that relates to SHG size (total number of members) and characteristics. Neither NRLM nor NRETP directly causes changes in members' education years or age. Instead, any significant effect of treatment (the NRETP or NRLM indicator) in these changes is a consequence of the impact of treatment on entry and exit and the different socio-economic characteristics of new entrants relative to new exits. Put differently, the treatment indicator reflects the impact of treatment on member entry and exit.

Not surprisingly, then, given the earlier results on entry and exit, the composition of SHGs changes significantly as a consequence of NRETP, with a decline in mean age and an increase in years of schooling relative to SHGs in the control sample. While the interpretation of results for the NRETP sample differs from that in the NRLM sample, the NRLM sample suggests a decline in the mean schooling of members between the short and medium run.

The last panel of Table 48 examines the impact of the two programmes on the proportion of members reporting loans in the 3 years prior to the survey year. The regressions suggest no impact of NRETP on the probability of borrowing (and hence on the probability of borrowing for production or consumption purposes). In contrast, NRLM causes an increase in the probability of a member reporting a loan over time, with this increase taking the form of greater borrowing for consumption purposes.

As in the results of the previous panel, these coefficients combine any effect of each programme on the borrowings of a given member as well as the programme's effect on the composition of borrowers. With limited turnover in NRLM SHGs, the regression results are more likely to be indicative of an increase in borrowing for the average member. For NRETP SHGs, however, the coefficients are harder to interpret since they combine the effect on old members to that on new members.[57]

Table 48: NRETP & NRLM: Member entry and exit and SHG characteristics

	NRETP sample, regression coeff		NRLM sample, regr coeff	
	NRETP block x Endline	Endline	EB x Endline	Endline
Member entry & exit				
Any member exit?	0.022	0.127	-0.175***	0.196
	(0.0369)	(0.0949)	(0.0612)	(0.175)
Any new members, last 3	0.0585**	-0.0240	-0.0324	-0.0325
years?	(0.0265)	(0.0746)	(0.0411)	(0.136)
Member size & characteristics				
Total members	-0.0266	-0.691***	0.0757	-0.908**
(SHG size)	(0.0858)	(0.221)	(0.118)	(0.420)
Mean age	-0.907***	3.246***	-0.342	2.622*
	(0.291)	(0.804)	(0.453)	(1.431)
Mean schooling years	0.252**	0.742***	-0.388***	0.148
	(0.102)	(0.25)	(0.138)	(0.416)
Loans				
Prop. members reporting	-0.000152	0.0348	0.165***	-0.0295
any loan, last 3 years	(0.0446)	(0.109)	(0.0559)	(0.200)
Prop. members reporting	0.0387	0.232***	-0.0491	0.384**
loans for production	(0.0320)	(0.0831)	(0.0529)	(0.162)
Prop. members reporting	0.0280	-0.0576	0.265***	-0.165
loans for consumption	(0.0221)	(0.0621)	(0.0374)	(0.141)

Note: Regression sample is functioning SHGs in panel. Sample size is 4,548 for NRETP regression, 2839 for NRLM regressions. NRLM regressions use years of NRLM in the block

6.6 Results on measures of Women's socio-economic status, norms and beliefs

Our strongest results on measures of women's empowerment relate to indices of women's intra-household decision making, their confidence or self-efficacy, food diversity based on 24-hour recall and on a measure of fertility timing, the number of children in early reproductive years. The women's questionnaire in both baseline and endline years included a set of questions that allow us to construct these indices, with this set remaining unchanged over survey years.[58] We also collected extensive data on other measures of women's norms and beliefs, status and empowerment in the endline study. Because of the lack of baseline data, our analysis of these additional outcomes relies on matching methods. As a consequence, we restrict this analysis to NRETP villages, given the close match between NRETP and Early blocks. The differences between early and late blocks render the identification of causal effects of the impact of NRLM over the medium to long run more difficult.

[57] The results reflect aggregate outcomes for all SHGs in the panel, but with outcomes including those for new and old members.

[58] We include our discussion of food diversity in this section, since the data was collected as part of the woman's module.

6.6.1 Difference-in-difference estimates of women's decision making, confidence and food diversity

Table 49 reports results from different specifications of the decision-making and confidence indices, attesting to their robustness, and of the food diversity index. These indices were described earlier in the appendix to Chapter 2 of this report. For decision-making, the first index is a more exacting measure, recording whether women reported being "mostly" or "entirely" responsible for decision-making in each of 26 areas. The second is based on the mean score reported by women across all of these areas, with scores ranging from a low of 1 ("little to no input") to 5 ("entirely my input"). The first "confidence" index reflects women's dealings with government officials, SHG members, and their confidence in their ability to make decisions about health or give advice on health to other women. The second index drops these latter two questions. The first row of the table reports results for the full NRETP sample. The second restricts it to just MCLF clusters while the third row provides data on non-MCLF NRETP clusters. The last row describes outcomes for the NRLM sample.

The results in Table 49 suggest strong effects of NRETP on women's decision-making and positive, but not statistically significant effects on confidence-making for the sample as a whole. Unlike earlier results which suggest a differential effect of MCLF and non-MCLF NRETP programmes on household consumption and income, the results in Table 49 suggest that all NRETP blocks, MCLF and non-MCLF, report improvements in women's decision-making to an equivalent degree. Because the treatment and control blocks for the analysis of NRETP are characterized by similar durations of exposure to NRLM institutions, the results suggest that layering on a livelihood focus in blocks which are otherwise similar significantly increases a woman's intra-household bargaining power.

The programme's differ in their effect on women's self-efficacy or confidence. Here, it is the non-MCLF clusters that report significant effects of the programme. The impact of programme inputs in MCLF clusters on women's confidence is statistically insignificant.

The results on the NRLM sample, in the bottom panel of the same table, suggest that women's bargaining power does not increase with the four additional years of exposure between the short and medium run. It may be the case that improvements in decision-making role occur early in the programme and then are sustained through the medium run. This appears unlikely, if only because a real change in a woman's position within a household requires a change in norms of behaviour for both men and women. Changing norms requires time.

Finally, our results suggest an absence of statistically significant effects of the three programmes on food diversity.

As always, these results represent the *difference* in outcomes between the treatment sample in question and the control, the proper measure of the programme's impact. In many instances, the overall trend in the outcome in question is negative, so that a positive treatment effect may essentially mean a reversal in the decline. That is the case for both decision-making and confidence indices for all samples, as is evident from the coefficient on "endline" reported in the second row of each panel of results. For food diversity, however, our estimates a strong positive time trend between survey rounds, but an insignificant effect of any of the three programmes (MCLF, non-MCLF NRETP, or NRLM).

We close this discussion by noting that the significant difference in women's decision-making ability in NRETP relative to NRLM blocks that lack the same livelihood focus support the view that improvements in women's (intra-household) bargaining power require increases in their ability to support themselves independently. We note, however, that NRETP builds on NRLM's social capital. Consequently, it is certainly possible that NRLM's social capital enables improvements realized under NRETP. Put differently, the same results may not obtain under programmes that support income-enhancing investments but without a similar investment in social capital. While the results we provide on NRLM suggest no sustained improvement in women's bargaining power in the absence of the resources provided to NRETP villages, our results on NRETP reflect a combined effect of investments in social capital and in market capital (NRETP investments); disentangling the two is a topic that we leave to future research.

Table 49: The impact of NRETP and NRLM on women's decision making. self-efficacy and food diversity

Sample / Coefficient on	Decision making index (top scores)	Decision making mean score	Confidence index	Confidence index omitting health scores	Food diversity index
NRETP + MCLF sample					
NRETP * endline	0.062***	0.148***	3.017	3.120	-0.002
	(0.017)	(0.035)	(2.406)	(2.508)	(0.020)
Endline	-0.061*	-0.341***	-9.151*	-9.615*	0.116***
	(0.036)	(0.070)	(5.165)	(5.211)	(0.043)
MCLF sample					
MCLF*endline	0.070***	0.178***	-3.348	-2.231	-0.015
	(0.020)	(0.042)	(3.125)	(3.243)	(0.024)
Endline	-0.069	-0.362***	-11.495*	-12.585**	0.083*
	(0.043)	(0.086)	(6.035)	(6.166)	(0.048)
Non- MCLF NRETP sample					
NRETP * endline	0.066***	0.146***	6.942***	6.345**	0.012
	(0.019)	(0.040)	(2.682)	(2.793)	(0.024)
Endline	-0.086**	-0.378***	-6.714	-7.104	0.148***
	(0.042)	(0.083)	(6.124)	(6.214)	(0.052)
NRLM sample					
NRLM EB * endline	-0.009	-0.051	0.158	1.199	-0.040
	(0.022)	(0.044)	(3.558)	(3.640)	(0.031)
Endline	-0.103**	-0.274***	-9.762	-9.866	0.170**
	(0.045)	(0.099)	(8.868)	(9.372)	(0.085)

Note: The decision-making index in the first column is the mean over a set of indicator variables that records the woman's decision-making role over a set of 26 topics, with the indicator taking the value 1 if the woman responds that decisions in that area are mostly or entirely made by her. The second decision making index is the mean over scores (1 to 5) across all 26 question areas. The first confidence index includes responses to questions relating to women's level of comfort in dealing with various government officials (Gram Panchayat members, bank officers, etc) and two questions regarding whether she is confident in recognizing signs of ill-health in her children or in giving health advice to others. The last indicator drops these health-related questions. Sample sizes: 23,316 for full NRETP regressions; 14,540 for MCLF; 17,585 for non-MCLF NRETP; and 17,363 for NRLM regressions. Standard errors, clustered at the level of the village, are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.6.2 Results on NRETP's impact on early fertility

Table 50 provides estimates of the impact of MCLF and NRETP on the number of births reported by a woman in her early reproductive years. For this, we compare the number of births of relatively young cohorts of women, identified by their age in the baseline survey, between two survey rounds. We focus on young cohorts since the programme cannot impact fertility outcomes of older women who are no longer actively considering having children.

For such young cohorts, we obviously lack data on completed fertility histories. However, a large and well-established early literature in economics documents the impact of increased birth spacing and hence fewer children in early reproductive years on a woman's total fertility rate, with longer birth intervals and hence fewer children in early years predicting a lower total fertility rate (Heckman, Hotz, and Walker 1985). Existing research also establishes that job market opportunities available to young women reduce their number of desired children (Jensen 2012).

Another advantage of focusing on early fertility choices is that it minimizes concerns regarding under-reporting due to the exit of older children due to marriage, household separations, or job opportunities. Thus, the youngest cohort we consider, those aged 20-29 at baseline, are of ages 25-34 at baseline. If we assume that women have children immediately following marriage and a marriage age of 18, this implies that her oldest child will be in the age range of 7-16 at baseline. Since this represents an upper bound, concerns regarding child exit are minimal for this sample, and only slightly greater for the 5-year older cohort ages 25-35 at baseline. Additionally, we minimize concerns regarding child exit by using data on those who left the household between survey rounds to provide accurate measures of the number of children reported by a woman in the endline survey, adding such exits to the reported number of resident children.

The results suggest a statistically significant reduction in the number of children born in early reproductive years in MCLF clusters but not in other NRETP clusters. The magnitude of the impact is relatively similar for both cohorts.

Table 50: The impact of NRETP and NRLM on early fertility choices: Number of children reported by young women

Methodology / sample	Coefficient on Endline * Treatment sample, by women's age at baseline	
	20-29	25-35
Difference-in-difference regression		
NRETP + MCLF sample	0.0119	-0.0495
	(0.0591)	(0.0397)
NRETP only	0.1020	0.0135
	(0.0673)	(0.0394)
MCLF only	-0.145*	-0.153***
	(0.0763)	(0.0490)

Note: Survey data on two cohorts, ages 20-29 and 25-35, panel. Dependent variable is the number of women who reside with the mother in the survey year, corrected for member exit between baseline and endline surveys. Estimates are from difference-in-difference regressions which compare the change in the number of children across survey years, for a given cohort, rin treatment samples relative to control. Standard errors, clustered at the level of the village, the level of the village, are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.6.2 NRETP's impact on measures of women's empowerment and norms at endline

We next turn to results from our analysis of 2024 data on measures of women's empowerment and related outcomes.

Table 51 provides evidence of covariate balance for the variables used to calculate the propensity score for selection into NRETP blocks, listing the unweighted (raw) and weighted difference in the mean value of variables in treatment and control blocks and the variance ratio. It also provides the χ^2 statistic for the null hypothesis that the differences are significant. The test statistic rejects this hypothesis at conventional levels. The balance between treatment and control samples is visually demonstrated in figure 35. To validate the robustness of our results to methodological choices, we provide estimates from double-robust regressions, as well as from regressions which use regression adjustment and inverse-probability weights to identify causal effects.

Table 51: Women's regressions: covariate balance in treatment

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
flitrate_v	-0.166	0.06	0.78	1.01
Vscale_v18	0.49	-0.10	1.93	0.60
Clfscale_v18	0.65	-0.05	3.96	0.80

Note: sample size is 11,378 The χ^2 statistic for the null hypothesis that the differences are significant is 3.13 (0.54)

Figure 35: Sample balance for women's status regressions

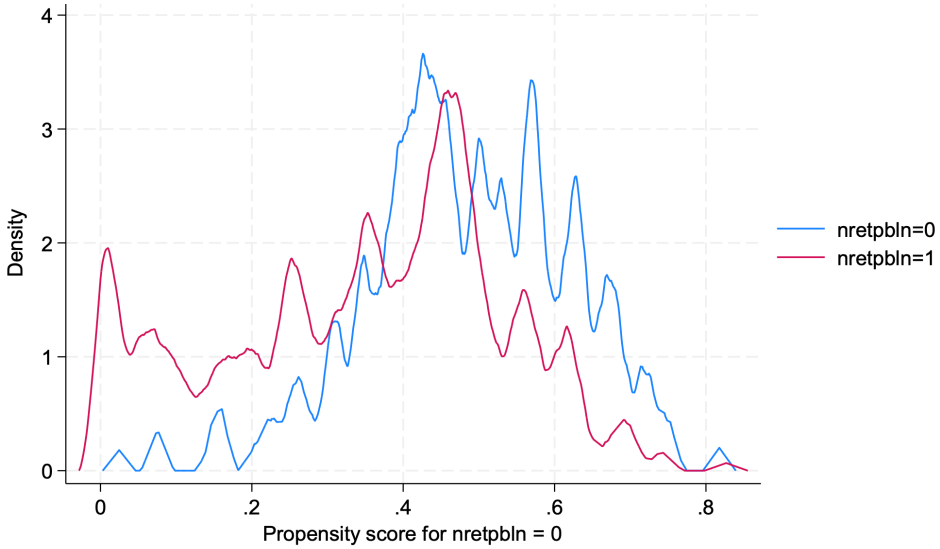


Table 52 provides an overview of the impact of NRETP on women's status, describing the impact on the aggregate score in questions relating to measures of network size, regressive norms relating to gender, a financial literacy index, her knowledge of existing government insurance programmes, beliefs regarding changes in socio-economic conditions across generations, her subjective opinion of her welfare, and broad questions relevant to civic engagement.

The layering of a livelihood focus targeted to women over NRLM's set of community institutions has a strong impact on women's networks, norms, and beliefs. The data reveal an increase in the size of women's networks, measured as the number of women she feels she can rely on for help and support across a number of dimensions. It also reduces the prevalence of regressive gender norms.

Our next set of outcomes relate to women's financial inclusion and knowledge. Women's response to standard financial literacy questions (drawn largely from the Reserve Bank of India's financial literacy test), compiled as an index, suggests both low levels of financial literacy and a lack of programme impact on this index. Women's knowledge of existing government insurance programmes is, however, higher in NRETP clusters relative to non-NRETP early blocks, particularly of the Jan Dhan programme (PMJDY), a programme intended to enhance financial inclusion.

Our survey included questions to assess women's opinions of their welfare and the quality of life, asking them about their current level of satisfaction with their consumption (on essential items and on durables and recreational expenditures), consumption vulnerability, house quality, their own contributions to family income and to their social lives and friendships. While women in NRETP clusters generally report higher levels of current satisfaction than their counterparts in NRLM early clusters, this effect is not statistically significant at conventional levels. Follow-up questions on whether they believe they are currently better off than they were five years ago do, however, elicit statistically significant positive effects.

A last set of questions on women's expectations of future change reveal no statistical difference between women's expectations of future welfare, along these dimensions, for women in NRETP and early NRLM blocks. We also find no difference between women in these two types of blocks in terms of their perceptions of improvement in their socio-economic welfare relative to their mothers (at the same age).

We emphasize that these results compare NRETP blocks to other early blocks at a similar stage of development of NRLM's community institutions. One implication of our results is that improvements in norms relating to workforce participation and women's involvement in economic activities are increased through programmes that place greater emphasis on livelihoods and enable women's participation in income-earning opportunities. Conversely, women's subjective well-being may be more closely associated with the development of social capital that occurs through NRLM's community institutions.

Our survey included a few questions related to women's overall views regarding civic society and engagement. We find that women in NRETP blocks are more accepting of socio-economic inequality in society, as gauged from answers to a question which asked if they thought a society characterized by greater equality was a better society. A greater acceptance of inequality is characteristic of nations with growing incomes. A second question asks if governments are responsible for ensuring their citizens' welfare. The response to this question suggests a small difference in beliefs regarding government responsibility across women in NRETP treatment relative to control. All blocks, statistically significant at the 10% level in one specification.

Table 52: Different indices of women's beliefs and welfare

	Double robust	Regression adjustment	Inverse Probability weights	Potential outcome mean (IPW-RA) (NRETP block=0)
Network size (number of friends)	0.307** (0.130)	0.404*** (0.131)	0.307** (0.144)	2.99 (0.09)
Index of regressive norms	-1.924** (0.931)	-1.387* (0.774)	-1.754* (1.004)	35.42 (0.80)
Financial literacy index	-0.104 (0.835)	1.183 (0.867)	0.081 (0.849)	40.15 (0.71)
Knowledge of PMJJBY	0.0260 (0.0158)	0.0190 (0.0168)	0.025 (0.017)	0.210 (0.01)
Knowledge of PMJDY	0.059*** (0.0191)	0.0365* (0.0194)	0.0612*** (0.0203)	0.25 (0.01)
Generational change – better off than mother	-1.628 (1.485)	-0.522 (1.464)	-0.630 (1.624)	49.31 (1.18)
Subjective welfare index – current status	1.792 (2.294)	-0.216 (1.802)	1.704 (2.856)	45.87 (2.05)
Subjective welfare index – compare to 5 years ago	4.064* (2.356)	2.50 (1.993)	5.863** (2.75)	44.59 (2.10)
Subjective welfare index_ - expectation of future	1.450 (2.015)	-0.341 (1.599)	1.222 (2.088)	64.70 (1.80)
More equal society is better	-0.0441** (0.0197)	-0.0483** (0.0199)	-0.0383* (0.0197)	0.36 (0.02)
Govts are responsible for citizen's welfare	-0.0399 (0.0251)	-0.0252 (0.0206)	-0.0492* (0.0271)	0.40 (0.02)

Note: Indices are defined as follows. Subjective welfare: How satisfied are you with current consumption of basic needs, non-basic needs, quality of home, ability to protect consumption from shocks, your contribution to income, your friendships, and leisure time (5 levels, from less than I would like to very satisfied). Generational Change: relative to your mother, do you think you are better off with respect to: Overall household income, your control of income, your ability to spend on consumption, individual access to savings, ability to choose occupation, drudgery work, child care, elderly care, freedom, respect by husband, leisure time, friendships, general happiness. Sample size is 11,383. Standard errors, clustered at the level of the village, in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.6.4 Detailed responses

Regressive norms. Responses to the individual questions that constitute the score on change in terms of holding gender norms that are regressive suggest that the

improvement is largely a consequence of greater acceptance of women's work and a corresponding revision of norms relating to female work (table 53). There is also a reduction in regressive gender norms as they apply to different expectations of boys and girls.

Networks. In addition to asking women to state the size of their social networks, or the number of women that they interact with frequently and can approach for help across a variety of dimensions (reported in table 54), we also asked questions regarding the number of friends they can approach for help and information on specific topics such as income opportunities, help in case of a shortage of daily consumption needs, and emotional support. A first question asked women to state how many women she could approach for help in each area. A second question asks if any of these women are members of her SHG or any NRLM livelihood institution such as producer groups.

We find no statistical difference (across broad groups) in the size of women's networks on these disaggregated areas (table 54 across women in treatment and control blocks). However, there is clear evidence that SHGs in NRETP relative to early NRLM blocks contribute to strengthening women's networks, particularly as regards information on economic opportunities and emotional support when required.

Beliefs affecting savings. Table 55 reports results from questions that provide information on women's savings and consumption incentives. Overall, we find little evidence that these preferences differ between the NRETP and early NRLM samples, other than responses to the question of whether women intend to live with their sons in old age. Here, the NRETP sample reports a statistically significantly lower expectation, indicative of expectations of their ability to support their old age expenditures by themselves.

Table 53: Details of regressive norms (Double robust estimates)

	Coefficient	Potential outcome mean (NRETP block=0)
Importance of home / domestic responsibilities	-0.00938 (0.0104)	0.55 (0.01)
Women's roles	-0.00773 (0.00903)	0.47 (0.01)
Gender equality for children	-0.0274** (0.0131)	0.24 (0.01)
Norms regarding women's work	-0.0152* (0.00903)	0.44 (0.01)
Norm: Brides should not work	-0.0230 (0.0187)	0.47 (0.02)

Note: Sample size is 11,383. Standard errors, clustered at the level of the village, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 54: Networks (IPW-RA): Number of friends (average)

	How many friends can you discuss these issues with?	Of this number, how many are in your SHG / PG?
Income (share worries / information on income)	-0.0215(0.083)	0.182*** (0.0647)
Emotional needs (share dreams, worries, overall support)	-0.0394(0.076)	0.101*(0.061)
Sharing (help with consumption needs, child care)	-0.0467(0.068)	0.0744 (0.060)
Help with ill-health / information (health, birth control)	-0.114 (0.208)	0.0255 (0.0603)
Overall index	-0.036 (0.0726)	0.0769 (0.0604)

Note: Sample size is 11,383. Standard errors, clustered at the level of the village, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 55: Preferences affecting financial behavior & financial knowledge (IPW-RA)

	Coefficient	Potential outcome mean
Consumption preferences	0.00177	0.27
(prefer to spend money today rather than save)	(0.0218)	(0.02)
Need for precautionary savings – important to	0.0293	0.695
have a plan for income shocks	(0.0196)	(0.02)
Need for old-age savings	-0.00774	0.88
	(0.0114)	(0.01)
Intend to live with son in old age?	-0.0459***	0.87
	(0.0132)	(0.01)
Business literacy	-0.0184	0.31
	(0.0115)	(0.01)

Note: Sample size is 11,383. Business literacy: knowledge of books of accounts, assets versus liabilities, fixed capital versus working capital. Standard errors, clustered at the level of the village, in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7. Conclusions, Pathways, and Policy Recommendations

7.1 Conclusions

7.1.1 Caveats

This study represents an endline evaluation of the National Rural Livelihoods Mission based on two survey rounds of data collection. The first round was conducted in 2019, while the second round, the Endline survey, was conducted in 2024 to coincide with the closure of the NRETP. Thus, the first survey round does not constitute a true baseline for the NRLM, since it was not undertaken prior to the programme's start. It does, however, represent a baseline for NRETP.

While this study was charged with identifying causal impacts of NRLM and NRETP, the lack of a true baseline for NRLM affects what we can and cannot identify. Our general approach uses a "difference-in-difference" methodology which identifies the impact of treatment by comparing outcomes across "treated" and "control" blocks. Under a set of identifying assumptions, detailed in Chapter 3 of this report, this approach separates the causal impact of the programme from one that reflects underlying trends in outcomes common to the economy and controls for time-invariant characteristics of treatment blocks which may cause differences in their outcomes relative to those in control blocks, even in the absence of the programme.

To identify the impact of NRLM, the 2019 survey design exploited the phasing of the programme across India's blocks, ensuring survey coverage of equal numbers of "early" blocks, those in which implementation started between 2011 and 2014, and "late" blocks with the onset of implementation planned after 2015. Early blocks were taken as treatment blocks, while late blocks served as a control sample. Using late blocks to serve as a counterfactual for what outcomes would have been in early blocks in their formative years, difference-in-difference regressions for the NRLM sample identify the change in outcomes in the medium run (approximately given as a five-year period commencing (on average) 6 years after the programme's start for early blocks) relative to the short run (a 5-year period commencing about 2 years after the programme's start).

This has implications for the interpretations of the results of our study, particularly in light of the fact that NRLM constitutes a staggered intervention in which "social" interventions, the formation and development of SHGs in particular, but also Village Organizations, occur early in the programme's life cycle, and livelihood-enhancing investments occur late. If social change in the form of the development of networks occurs in the programme's formative years, i.e. in its short run, then we should expect little change in these measures between the medium and short run. Similarly, there might be little change in income between the short run and the medium run if income interventions are concentrated in a few targeted areas in late phases of implementation. Put differently, there are few expectations of what the change in outcomes would be between the medium and short run for a wide range of indicators; as emphasized earlier in this section, NRLM was built on the premise that movements out of poverty would take 10 years and that the pace of change may not always be linear.

There was, however, a clear expectation that significant change would follow the implementation of the entire package of inputs, specifically those components intended

to be layered in a final stage, once Cluster Level Federations had achieved the desired level of maturity. These were the “Livelihood interventions” implemented under NRETP whose market focus required implementation at the level of CLFs and not that of village economies. For several reasons, primarily the impact of COVID, the implementation of these livelihood approaches has been slow, with progress in most cases commencing only in 2021 and after.

The 2019 and 2024 surveys constitute “true” baselines and endlines for NRETP, thus providing the potential for a robust evaluation of its causal impact. However, the programme’s delayed implementation has several implications for our evaluation. The primary amongst them is that our endline study was conducted at a time when the reach of interventions implemented under NRETP remains low. NRETP was, in any case, targeted at only a few of the existing NRLM blocks. But, within these blocks, the programme’s footprint by 2024 primarily took the form of financial support to CLFs for livelihood activities but also for livelihood and other trainings and for funds intended to ensure safety nets (the Health Risk Fund and the Food Security Fund). Chapter 4 of this Report notes the limited reach of new institutional arrangements, such as Producer Groups and Enterprises. These, and other institutional arrangements, such as sector-specific cluster approaches and Integrated Farming Clusters, are currently in place only in relatively few villages. IFC, as an example, was initiated with a delay of several years, with coverage of only about 6-9 villages of implementing blocks at the time of our survey. None of these villages were represented in our sample. As another example, the large-scale Prouder Enterprises that were promoted under NRETP and, in fact, constituted the single-most important item in the NRETP budget, were formed in blocks that were again not adequately represented in our study.

The under-representation of villages which supported NRETP’s new producer institutions is a consequence not just of their currently small numbers but also the fact that the 2019 study was not intended to be a baseline for an evaluation of NRETP. For this reason, it did not specifically sample villages that were slated for these new institutions.

This implies that our evaluation of NRETP primarily identifies the impact of the additional resources provided to CLFs to support livelihoods amongst member SHGs. We expect that the programme’s impact will be greater once the new livelihood institutions are put in place. Identifying their impact will require further research.

7.1.2 Major findings: Income and Expenditure

The primary result from our impact evaluation is the sizeable impact of both programmes on household per capita consumption. This impact is matched by a similarly significant improvement in household income in the NRETP sample, with the income increase in the NRLM sample being positive but more modest. As emphasized throughout our report, the results for NRETP represent increases in the five-year period 2019 to 2024 over matched early blocks at a similar stage of institutional development, but lacking the livelihood interventions of NRETP. The corresponding figures for NRLM represent a dynamic effect, namely changes in the medium run relative to the short-run, with the latter counterfactual identified by outcome growth in late blocks with a 4-year shorter duration of exposure to the programme. For the NRLM sample, the growth in consumption is estimated at 10% over this period. Per capita consumption growth in the NRETP sample is similar in magnitude, with estimates ranging from 8 to 14%. We

estimate Income growth (relative to the counterfactual) in the NRLM sample to be 9%. It is significantly higher in the NRETP sample, with estimates ranging from 17 to 27% across different methodological specifications. Regression methodologies that are robust to various forms of mis-specification (“double robust” difference-in-difference regressions) suggest that the improvement in income in the NRETP sample relative to non-NRETP early blocks is 27%. This is a sizeable increase.

A separate identification of income and consumption increases attributable to the Model CLF (MCLF) programme suggests that a major share of the improvements in NRETP blocks stem from the model CLF programme. Comparing villages in MCLF clusters to their counterparts in non-NRETP blocks reveals (per capita) expenditure increases of 10 to 17%. The corresponding range for improvements in consumption in non-MCLF NRTP blocks relative to early blocks is 4 to 11%. The impact of the MCLF programme on incomes is significantly larger. Our estimates suggest that the improvement in income in MCLF clusters relative to non-NRETP early blocks is 32%, while the corresponding figure for NRETP blocks (relative to the same early blocks) is 10%.

Because these interventions were introduced only in early blocks, all of which were at the same level of maturity of NRLM’s federation of community institutions, our survey samples do not allow us to identify whether these large increases were a consequence of the prior social development achieved through these institutions. This is a topic we leave for future research.

7.1.3 Social change

Much of our analysis on indicators of social change and women’s empowerment is based on variables that were only collected in the endline survey. We accordingly restrict our analysis to a comparison of NRETP and NRLM blocks, given that these two samples are well-matched.

Perhaps the most significant finding is that women in NRETP households report an increase in their network size, with much of this increase reflecting relationships forged with other members of their SHG. This finding suggests the programme’s success in achieving one of its primary objectives: strengthening community ties and improving women’s collective voice. We also find improvements in other social indicators, such as a reduction in the extent to which regressive norms relating to women’s participation are maintained.

We note that these results stem from a comparison of NRETP to NRLM early blocks and hence to villages characterized by the same level of maturity of SHGs and their federations. In this report, we make no attempt to evaluate social change across villages which differ in the period of their exposure to the programme, leaving this to future research. Given this, our results relate to social change that stems as a consequence of improvements in economic opportunities.

The exception to this approach relates to measures of women’s intra-household decision-making role, self-reported measures of her confidence in her interactions with fellow SHG members and her dealings with bank officials, government officers, and other village-level functionaries, and to measures of diversity in food intake. We collected data that allow us to construct decision-making, confidence, and food diversity indices in both

survey rounds, using identical survey questions. This allows us to evaluate changes in these indices in the NRLM sample and in the NRETP sample. As always, our results for NRLM are indicative of changes in the programme's effect over time, while our results for NRETP compare outcomes to a counterfactual no-treatment state.

We find statistically significant improvements in women's intra-household bargaining power in the NRETP sample. This result supports the view that improvements in women's intra-household decision-making roles stem only from policies that augment her ability to earn income and, correspondingly, her "outside" options. Confidence indices are also higher, but the difference is not statistically significant at the 10% level. In contrast, there is no improvement in these indices in the NRLM sample. We also find no change in food diversity indices in either NRETP or NRLM regressions.

7.1.4 Impact on SHGs

Using data from a panel of SHGs surveyed in both years, we also report results of each programme's impact on SHG quality. The primary measure we use for this analysis is a measure designed to reflect performance across five norms or *Panchsutras,* the norms used within the programme to rank SHGs. Because we construct this measure from data on SHGs' operations, we report results from a series of measures.

For this purpose, we expand the sample to include those SHGs who were found to be non-functioning or defunct at the time of the baseline study as well as those who stopped functioning between survey rounds. We find an upward trend in SHG quality between survey rounds. For the large part, however, neither programme has a statistically significant effect on SHG quality. We note, however, that estimated effects, though insignificant, are more frequently negative for the NRETP sample and more consistently positive for the NRLM sample. And it is only for the NRLM sample that we find a positive significant effect using one measure of the Panchsutra score.

In our discussion of SHGs, we emphasize that they represent institutions whose membership changes over time, with member entry and exit. This implies that the performance of SHGs, when evaluated at two different points of time, compares institutions whose membership – and hence socio-economic profile – may have changed. Evaluating each programme's effect on member entry and exit, we find that NRLM SHGs report less member exit in the medium-run relative to the short-run, and no significant addition of members in this same period. NRETP SHGs, in comparison to the control sample, are characterized by significantly greater growth of membership. New members are more educated, resulting in a significant increase in the mean schooling attainment of these SHGs.

These changes in SHG composition may play a role in explaining the increase in productive loans in NRETP SHGs, given that educated members are much more likely to borrow for productive purposes. Reflecting the lack of change in membership, we find that NRLM SHGs report greater loans for consumption purposes between survey rounds, with production loans declining. These results, derived from SHG data, confirm the household regressions which found an increase in consumption loans in the NRLM sample and an increase in production loans in the NRETP sample.

7.2 Understanding Pathways

What explains the relatively large effect of MCLF and NRETP on household incomes and the smaller effect on incomes in the medium-run under NRLM? Are there explanations which are consistent with the increase in agricultural incomes and with the labour force participation patterns discussed in previous sections? We address these questions by first relating our findings to different theoretical models of economic growth, drawing insights from them on potential pathways. We close by focusing on the model CLF programme and describing our understanding of factors underlying its effect.

7.2.1 Using economic theory to interpret results

"Buffer stock" models and those that assume a precautionary motive for savings (Carroll 1997, Deaton 1990) carry the implication that households will refrain from borrowing large amounts for productive purposes, conserving their savings and access to credit to maintain consumption in periods of low income. Even in periods of high income, expectations of income losses in future periods will reduce productive borrowing if credit constraints can be expected to bind then.

Even without productive investments, such models still predict income growth in the local economy. While households may be unwilling to borrow large amounts to finance lumpy investments in capital, greater access to credit may increase their borrowing for consumption items. In turn, any credit-fueled increase in the (local) demand for food or other consumer items will cause farmers and local producers to increase output in response to increased demand. Such growth is most likely to favour the agricultural economy, since relatively poor households are likely to favour food purchases over non-food items.

If the increase in demand and hence in local prices is limited, farmers' responses will similarly be muted, favouring low-cost ways of increasing output. This could take the form of small changes in cropping patterns in line with any changes in the demand for specific items. Farmers may also borrow small working capital loans to cover the costs of storing crops for sale in later periods when prices are higher. In both these scenarios, agricultural profits may increase, even in the absence of large productive investments, though to a small extent.

The predictions of this model apply well to financial inclusion programmes that initially offer small loans or that target a small number of households and hence are limited in scale. As programme duration increases, improvements in savings and access to larger loans may increase productive investments, but only if available savings or loans are sufficient to cover unexpected declines in income or consumption shocks such as ill-health.

The medium- and long-run impact of any such programme will depend on the dynamics of fund delivery. Kaboski and Townsen (2012, for example, note that the positive impact of many financial access programmes on household consumption and income is confined to their early years. Continuous improvements require continuous injections of additional resources.

This model accords with our NRLM results of small increases in income and expenditure over time, but without significant structural transformation in the sources of household income and labour force participation, and hence without significant change in how households spend their income. Given that agricultural prices are strongly influenced by

national prices and policies, changes in the prices of agricultural products in local markets are likely to be small. This helps explain why the programme's benefits appear equally distributed across relatively wealth villages and others, and unaffected by distance to more remunerative markets.

We provide direct evidence on these hypotheses through regressions of the impact of both NRLM and NRETP programmes on the proportion of farm output that is sold and on cropping patterns. For cropping patterns, we look at the area under rice and millets in the Kharif season and under wheat in the Rabi season. Regressions on the proportion of output sold are over the set of households that report agricultural output in the survey year.

Since these regressions are restricted to cultivating households (in the year and by season), sample sizes are significantly smaller than those in the main regressions on household consumption and income. This raises valid concerns regarding whether the identifying assumptions required for unbiased estimates of programme effects in difference-in-difference regressions hold. Given these concerns, the results of this section are best viewed as suggestive.

With this qualification, the results in Table 56 suggest that NRETP significantly increased the marketisation of agricultural output. There is no such increase in marketed output in the medium-run relative to that in the short-run in NRLM villages. However, these villages record a significant reduction in the area under foodgrains, a reduction not found in NRETP villages. This accords with theories which maintain that households seek to diversify their food consumption as their resources or their access to credit to finance expenditure increases. If farmers respond to this shift in demand, agricultural incomes could increase even without significant additional expenditure on physical capital. Data collected in the 2024 survey on the point of sale for agricultural output supports this hypothesis. Farmers report that approximately 28% of their output is sold to village households or village traders.

Table 56: The effect of NRETP and NRLM on marketed output and cropping patterns

	Coefficient on interaction of treatment x Endline indicator		
	Proportion of total output sold	Proportion of cropped area under rice and maize, Kharif	Proportion of cropped area under wheat, Rabi
NRETP	0.0686***	-0.118	0.0464
	(0.0180)	(0.0975)	(0.0887)
Sample size	12,699	12,545	10,531
NRLM	0.00449	-4.913**	-5.531**
	(0.0201)	(2.134)	(2.473)
Sample size	12,284	12,227	10,167

Note: All regressions have the same set of controls used in regressions on household income and consumption. NRLM regressions include control for treatment heterogeneity. Regressions on marketed proportion are on the sample of households who report some agricultural output in the year. Regressions on area under rice and maize are on the sample of farmers who report cropping in the Kharif season, while regressions on cropped area under wheat are on farm households that report cropping in Rabi. Standard errors, clustered at the level of the village, are in parentheses.

In contrast to NRLM, NRETP and particularly the model CLF programme were explicitly intended to ensure access to sufficient financial and other resources. Our finding that this intervention substantially improved incomes supports other theoretical work that emphasizes the importance of credit access for entrepreneurial activity (Schumpeter 1912). The focus on capacity building in NRETP clusters and particularly those with a Model CLF also resonates with models that emphasize the importance of human capital and capacity for economic growth (Lucas 1988; Romer 1986).

Perhaps even more important to the interpretation of our results is a theoretical literature that emphasizes the importance of markets as a determinant of households' willingness to undertake high-cost investments that deliver increasing returns (Young 1928; Murphy, Shleifer, and Vishny 1989). As long as village economies, limited by low incomes, generate low demand for non-agricultural products, large investments in increasing returns technology are likely to be limited by (local) market size. This explains our finding that the returns to NRETP are greater in wealthier villages and in those that are closer to block capital and more remunerative markets.

Also relevant are models of economic geography (Krugman 1991), which suggest that increasing returns will result in a division of occupations across locations distinguished by market size. Non-agricultural investment will be more profitable when located in urban centers and large villages, with smaller villages specializing in agriculture. The occupational distribution of households in villages, particularly small villages, may then suggest a "reverse" structural transformation with increases in agricultural employment.

This appears to describe the current Indian scenario (Deshpande 2025). However, focusing on employment opportunities in villages of location yields a misleading picture of the economic conditions of village residents given growth in other villages and the increased integration of village economies with each other and with urban centers. The data in this report, which documents the importance of employment outside the village for the inhabitants of any given village, support this statement. Put differently, increased specialization in agriculture in village economies may lead to higher growth in larger regional economies, with villages within these larger geographies benefiting from spillovers.

Models of economic geography and those that emphasize locational spillovers are particularly relevant for the interpretation of our NRETP estimates. We earlier noted that our sample villages were selected prior to the implementation of NRETP and that, as a consequence of its highly targeted nature, included few households that report affiliation with the new set of NRETP livelihood institutions such as producer groups.[59] But these institutions are present in the village and in neighbouring villages of NRETP clusters. Thus, surveys of Village Organizations in our sample reveal that 23% of SHG members in NRETP villages report affiliation with NRETP livelihood institutions, with this percentage being 29% in MCLF clusters. The fact that these institutions exist within the village suggests that survey households are likely to benefit from general equilibrium effects on product prices and wages. Moreover, the significant improvements in road connectivity in rural India suggest that households in any given village will also benefit from entrepreneurial activity in more distant, larger villages and cities.

[59] Approximately 2% of survey households report affiliation with new NRETP livelihood institutions.

7.2.2 The impact of Model CLFs

Amongst the major results of this report is the significant impact of MCLFs on household income, consumption, and a variety of other outcomes. What explains this large effect?

We explore three alternative explanations, supporting them with reference to the statistics and regression results of this paper to the extent possible. The first reflects the data in Chapter 5 that reveal that MCLFs received larger CIF amounts and CIF amounts per SHG than their counterparts in other clusters. A second relates to administrative and human capacity constraints, as reflected in the staffing of CLFs and the availability of CRPs but also in other measures of administrative capacity. A final explanation is the possibility that MCLFs benefitted from direct NRETP livelihood institutions to a greater extent than CLFs in non-MCLF blocks of NRETP clusters.

Additional CIF

Our descriptive analysis of Cluster Level Federations in Chapter 5 suggests that a primary difference between MCLFs and CLFs in other clusters is their greater access to Community Investment Funds (CIFs) in absolute amounts and per SHG. This suggests that these additional financial resources may explain the increased borrowing for productive purposes that we observe amongst SHG members in MCLFs and hence the greater impact of MCLFs.

The greater amounts of CIF per SHG in model CLFs raise questions, given that programme guidelines require each SHG to receive the same funding amount.[60] One explanation relates to resource constraints at the level of SRLMs: They may not have the required funds. Supporting this view, the 2023-24 Annual Action Plan of Rajasthan's SRLM (*Raajeevika*) discusses the difficulties in providing CIFs to eligible SHGs. It notes that budget constraints allow funding to just 25,000 eligible SHGs from a total of 198,437 (just 12.6%), with each funded SHG receiving INR 75,000 rather than the recommended 1.5 lakhs. Other states are in a similar position, but these budgetary and administrative difficulties are not always discussed with the level of honesty and detail in *Raajeevika's* AAP (for which it should be commended).

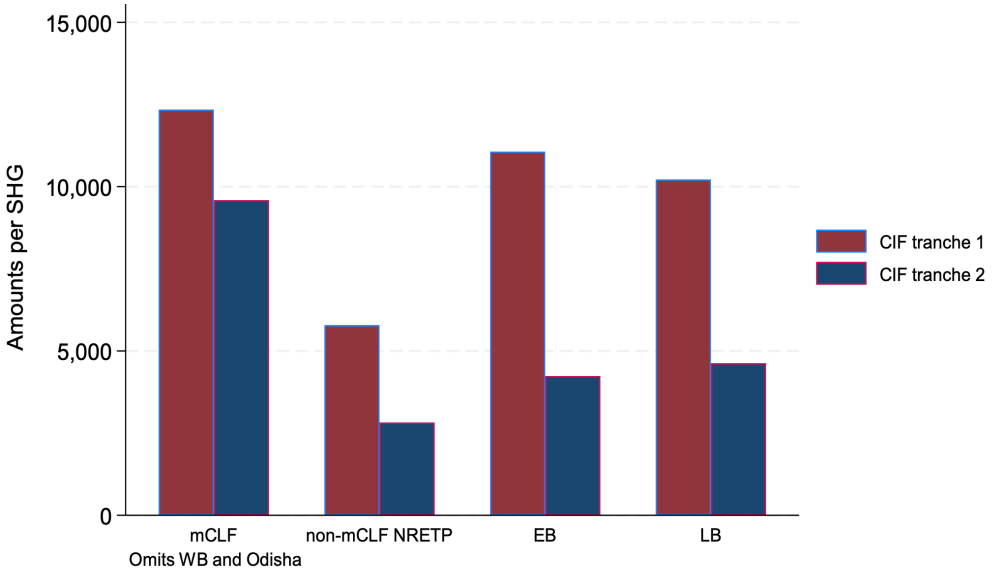
Resource constraints may explain the fact that CLFs, with the exception of model CLFs and, to a lesser degree, CLFs in other NRETP clusters, rarely lift the entirety of the CIF amount listed in programme guidelines, even prior to the revision of CIF guidelines in 2019. CIFs are distributed to CLFs in tranches, based on factors such as the repayment of existing loans and other measures of SHG quality. Figure 36 documents the significant variation in the receipt of CIF tranche 2 funds across CLFs by block type, with model CLFs doing much better in this regard, particularly relative to CLFs in early and late blocks.

One possibility, then, is that binding constraints on fund availability cause allocation decisions that favour MCLFs at the expense of CLFs in other clusters. This may apply both to financial resources and to human capital resources (CRPs). If so, the advantage

[60] Though, under revised guidelines, new SHGs are to receive INR 1.5 lakhs, the guidelines call for the difference between this amount and what each SHG received to be provided to all SHGs. Our data on CIFs relates to the totality of CIF funding available to the CLF since its formation. If older SHGs did indeed receive the incremental amount to which they were entitled, there would be no difference in CIF resources, on a per SHG basis, provided to each CLF.

of model CLFs comes at the cost of others, causing negative administrative spillovers. In this case, the greater increase in expenditure and income that we find in MCLF clusters reflects both the increased inputs that are available to MCLFs *and* reductions in inputs provided to other CLFs in the same block.

Figure 36: CLF Funds Per SHG By Tranche By Block type



This hypothesis assumes that SHGs are credit constrained, so that the larger amounts of CIF available in MCLFs enable the greater incidence of productive borrowing that we note in this sample. However, our analysis raises serious doubts about the validity of this assumption. For example, the loan data (Chapter 5) reveal that the average amount of a SHG loan is small. This is true even of loans through the bank linkage programme (average size of INR 14,000 in 2024 in real terms). SHG borrowings from this programme are not close to the annual credit limits to which they are entitled. Direct (individual) loans from formal banks are of larger magnitude (average of INR 27,000 in real terms in 2024). These facts suggest “demand-side” constraints on the incidence and amount of borrowing from SHG internal funds and the bank linkage programme, such as the previously discussed incentives to borrow in joint liability programmes.

Such demand-side constraints offer an alternative explanation for the failure of CLFs to avail of the full amount of the CIF funding they are entitled to. They may also help understand the fact that several SHGs, VOs, and CLFs maintain large balances, with lending being low relative to these balances. The issue of “idle funds” at the level of each of these community institutions has long been of concern and is frequently emphasized in the Annual Action Plans of different SRLMs.

Administrative capacity and human capital constraints

Improved administrative oversight and guidance can help reduce these adverse incentives, enhancing the demand for loans. If so, the higher levels of productive borrowing in MCLF clusters may reflect a reduction in “demand-side” constraints, due to higher administrative capacity, rather than the greater availability of CIF funding.

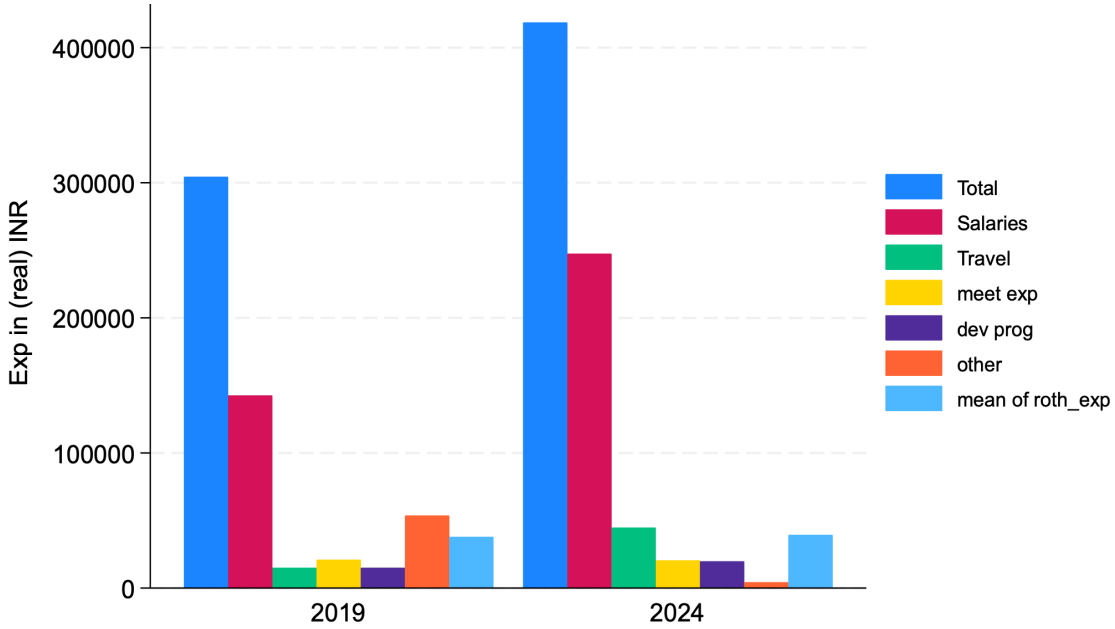
While our empirical analysis does not include regressions that establish the factors that underlie greater productive borrowing amongst MCLF households, we do provide

regression results which suggest that human capital constraints bind improvements in household consumption growth to a greater extent than credit constraints. If so, the greater borrowing reported by SHG members in model CLF clusters may be a consequence of improved administrative capacity and the greater availability of CRPs and other staff.

Supporting this view, we note our finding that member SHGs in model CLFs programme do not appear to be of higher quality than those in other clusters: There is no evidence that the MCLF programme or other NRETP interventions improve SHG performance as measured by Panchsutra scores. This again suggests that demand-side pathways may be of greater importance than supply-side determinants.

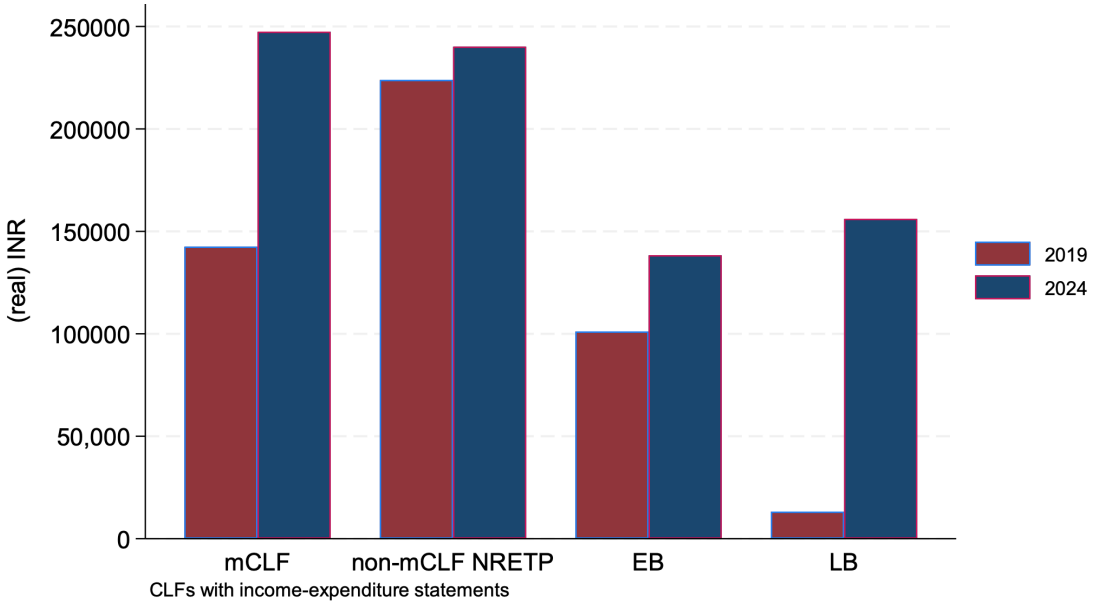
We provide additional support for this view through details of expenditure from CLF income-expenditure statements collected as a component of our survey. These data, graphed in figure 37, reveal that the primary items of expenditure for MCLFs are staff salaries and that this item is also the one that has recorded the greatest growth between 2019 and 2024. Expenditure on salaries dominates all other items of expenditure, including expenditure on development programmes.

Figure 37: Details of Expenditure (MCLFs)



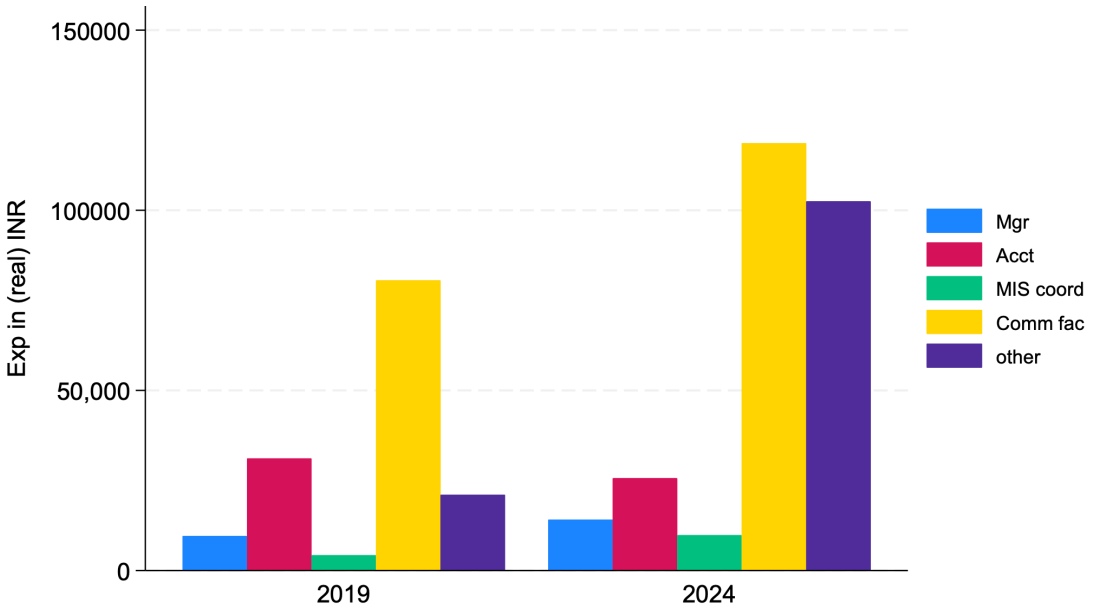
We also collected similar data on salary payments in other types of clusters, enabling a comparison of the growth in salary payments across clusters and blocks. We note, however, that the data for all cluster and block types is only based on CLFs that maintain income-expenditure statements. Attesting to their better administrative performance, 92% of model CLFs maintain these records. This percentage drops to 82% in other NRETP CLFs, 68% in early blocks, and 76% in lower blocks. This decline suggests that the numbers for non-MCLF clusters overstate the actual picture since they most likely ignore data for the worst-performing CLFs. That being said, figure 38 shows that the growth in expenditures on salaries is significantly higher in MCLF clusters than in other NRETP clusters. These increased payments constitute an important component of the changes that have happened in MCLF villages between survey rounds.

Figure 38: Salary Payments by CLFs, by CLF type and year



A final figure, figure 39, provides details of salary expenditure on different staff members in MCLFs across survey years. These data reveal that the greatest growth in staff strength has been in the number of Community Facilitators and in the "Other" category representing the employment of different community cadres.[61] This is in line with the evidence we presented in Chapter 6 of the greater availability of CRPs in MCLFs.

Figure 39: Details of Salary Expenses (MCLFs)



While our discussion has focused on staff and CRP availability, our comments apply more generally to other aspects of CLFs' administrative capacity. The data presented in this report suggest that model CLFs are more likely to have functioning sub-committees, experienced CRPs, and trained office bearers. These factors may be as important as

[61] Model CLF guidelines require them to invest in "higher order social capital" to the extent of 10 members per CLF.

staff strength in determining households' demand for loans. They are likely correlated with improved staffing: Sub-committees are unlikely to exist if CLFs lack the staff to form the necessary committees and ensure their effective functioning.

Taken together, the data suggest that the estimated advantage of MCLFs may reflect the programme's success in terms of its mandate: It was intended to serve as a "proof of concept" that attention to CLF guidelines and stipulated standards regarding staff, sub-committees, training, the maintenance of registers, governance, and a host of other quality-related factors pays dividends. The evidence suggests that this may, indeed, be the case.

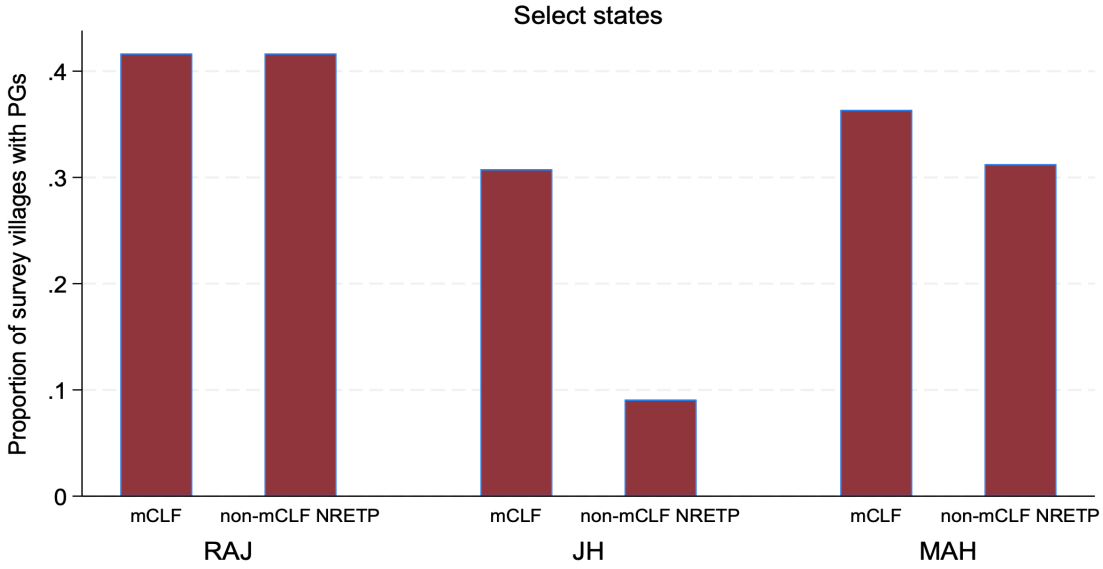
We do not establish a causal link between greater investments in staff and improved implementation, and the higher growth rates of consumption and income in MCLF clusters. Providing causal evidence would require some experimental variation in these inputs. Nevertheless, in combination with our regression results that suggest a reduction in the importance of credit constraints and growing human capacity constraints, these data suggest the distinct possibility that the superior performance of MCLFs is a consequence of their greater administrative capacity.

That being said, our data reveals considerable room for improvement. Thus, despite the fact that model CLFs outperform their counterparts in other clusters and blocks, only 31% report the existence of a Livelihood Sub-committee and just 44% report hosting a Livelihood CRP. Only 58% of model CLFs report an up-to-date minutes register (26% in non-MCLF clusters). If administrative advantages help explain the advantage of MCLFs, then future improvements will require additional attention to the quality of implementation.

NRETP's livelihood institutions

We provide some evidence on the hypothesis that MCLF clusters may benefit from the greater presence of NRETP's livelihood institutions using MIS data on all NRETP Producer Groups (PGs). Our analysis is restricted to the states of Maharashtra, Jharkhand, and Rajasthan, states where investments in PGs are sizeable. Figure 40 plots the proportion of survey villages in model CLF and other NRETP clusters that report the operation of at least one PG. The figure suggests that such differences exist in Jharkhand, but not in Rajasthan or Maharashtra. Lacking MIS data on the incidence of other livelihood interventions, we cannot state whether other states follow the pattern of Jharkhand, or of Rajasthan and Maharashtra. But the equality of investments across Rajasthan and Maharashtra suggests that differences in NRETP livelihood institutions are unlikely to explain the larger effects of MCLF clusters.

Figure 40: Presence of PGs in Survey Villages (MCLF and NRETP clusters)



In conclusion, the descriptive evidence discussed above, in conjunction with the data provided and previously discussed in Chapter 3, suggests to us that the difference in the performance of Model CLFs and others is largely a consequence of improvements in administrative capacity and staff strength of MCLFs. These improvements may directly affect the willingness of SHG members to borrow to a greater extent than enhancements in CIF, given the evidence that households' loan amounts are small and not close to the amounts they are eligible for from bank loan programmes or, indeed, from SHG internal resources.

7.3 Policy Recommendations

We restrict our policy recommendations to those emanating from findings of this report, but bolster them with qualitative findings from the extensive field work done in conjunction with the research of this project. Some of these recommendations require additional research, and we note where this may be the case.

The importance of attention to administrative capacity. The Radhakrishna Committee report, that evaluated the performance of NRLM's precursor, SGSY, noted that low capacity of SHGs at that time was the primary reason for the programme's poor performance. While administrative capacity has significantly improved, our data reveal that it remains low, with CLFs, VOs, and SHGs still operating at standards that fall short of guidelines, including those pertaining to staff and CRP strength...

This also applies to households' access to Bank Sakhi and other financial inclusion CRPs. Less than half of households borrowing from banks report the use of the services of Bank Sakhi. Use of business correspondents appears to be insignificant.

Our heterogeneity results find strong impacts of bank linkage, measured by the proportion of villages in the block with credit-linked SHGs at the time of the baseline survey. These effects are particularly strong in the NRLM sample. The data we present in Chapter 5 (Summary statistics) also reveals that NRETP SHGs were more likely to report the availability of Bank Mitras in bank branches.

Recent NRLM policies have argued for the rationalization and efficient deployment of CRPs across clusters. Whether this will generate the necessary improvements remains to be seen. We note that the impact of CRPs is an important area of future research, and that though we document the variation in CRP strength across CLFs, more research is required in this area.

A need for greater investments in "Market capital": investments in human capital, financial capital, and business acumen. A "financial literacy" module included in the Women's questionnaire allowed us to test levels of financial literacy and differences in levels across different types of blocks. We found generally low scores, with little block-level variation. Improvements in financial literacy, though long emphasized in NRLM, have not received the same level of attention as have other policy interventions. However, the regression analysis we present of the changing constraints in NRLM relative to NRETP blocks and the growing importance of investments in human capital emphasizes the need for priority action in this area.

Attention to the quality of NRLM's set of community and livelihood institutions. This concern stems from several findings of our report. First, the finding of growing "churn" in SHG membership in NRETP blocks suggests the need to allow for such dynamic changes in SHGs. These measures could include trainings in SHG concepts for new members. Given higher education rates of young entrants, it could also include training in bookkeeping and accounting. A second concern relates to findings that blocks with a high number of VOs whose membership is spread across villages do worse. While this may be necessitated by village size and other factors, our findings help identify potentially weak VOs that can be targeted for additional training and / or oversight and monitoring. Finally, our regression evidence reveals declines in SHG quality over time, as measured by Panchsutra scores, even in NRETP blocks.

We document that concerns are particularly manifest in Producer groups. Attempts to collect rigorous data on the Producer Groups in our sample frequently failed because of the lack of availability of any record books.

The sustainability of NRLM's federation of community institutions. While our data suggests that a few model CLFs have started running enterprises, such enterprises are negligible in other CLFs and in SHGs, even those in other NRETP and early blocks in which the programme has been running for over a decade. This undoubtedly reflects the lack of remunerative business opportunities for what would be relatively small enterprises.

However, earnings from enterprises reflect just one source of the financial sustainability of NRLM institutions. Other important sources are earnings from internal resources as well as payments from community members (SHG members and non-members) for the services of CRPs. We report evidence that the share of CRPs reporting payment for their services by community members is negligible. Increased convergence with other programmes could be a means for efficient use of existing resources.

We note, too, that loans through the bank linkage programme and those through the internal resources of the federation (in the form of loans supported by Community Investment Funds and Viability Gap Funding) have different implications for the financial

sustainability of NRLM institutions. Interest earnings on internally-funded loans are divided between SHGs, VOs, and CLFs. Our analysis of CLF budgets suggests that interest earnings are an important component of their resources. In contrast, loans made under the bank-linkage programme provide a source of income only to SHGs and not to the higher-level units of the federation. A shift from internal lending to increased reliance on bank loans therefore adversely affects the financial sustainability of the federation. These are policy matters that require consideration going forward.

Policy attention to factors underlying the lack of borrowing for productive investments. We find little evidence of increased productive investments in the medium-run relative to early years in the NRLM sample. While productive loans are greater in NRETP SHGs relative to their counterparts in non-NRETP early blocks, they are primarily given to more educated members. This may, of course, be a consequence of higher returns to the more educated and hence to differences in loan demand. Our field work, however, identified an additional set of constraints. Primary amongst them are concerns relating to risk and joint liability. While it is widely recognized that joint liability may cause members to discourage others from undertaking investments that might be risky, the strong social bonds amongst SHG members result in members themselves not undertaking such investments out of concern for the obligations they may be posing on others. The end result is the same: Low levels of investment and hence borrowing for investment in the most closely-knit groups. The lack of investment due to concerns relating to joint liability particularly affecting borrowing by producer groups comprising members from several SHGs.

One solution to such concerns is to support equity ownership by SHG members in the investments undertaken by fellow members. SHG-run enterprises, supported by the entire SHG membership, offer an example of such an arrangement. These enterprises are in their infancy, and follow-up research is required to examine their impact. An alternative to achieving the same effect of equity ownership is for SHG members to divide (a share) of their accumulated savings equally amongst all members. Through field visits, we found that SHGs commonly resort to this practice. However, this sharing is not equitable: The common practice is to divide the gains unequally, favouring members who have borrowed more on the grounds that they contribute more to SHG resources in the form of interest income. While this is true, it implies an absence of equity ownership with corresponding adverse effects on investment.

Our field work also identified other factors that may help interpret the findings of this report. A common practice reported by SHG members is to take “loans” through the SHG bank linkage programme, but with these loans being in name only. This is because of the fear that an absence of loan activity will cause a loss of access to future bank loans. As a consequence, bank loans show up in books of accounts, with the stated purpose being to support consumption expenditure, despite any real financial transactions occurring. A detailed analysis of such concerns requires additional research.

The sensitivity of loan information explains the relatively little research in this area. This remains an area where more evidence is needed.

Appendix A: Chapter 3

Table A1: Sample states and districts [Baseline sample]

State	District	Sample size
Bihar	Gaya	249
	Madhepura	2000
	Madhubani	402
	Muzaffarpur	925
	Nalanda	381
	Saharsa	983
	Supaul	930
Chattisgarh	Balrampur	466
	Bastar	474
	Gariyabad	475
	Raipu	469
	Rajnandgaon	470
	Surguja	447
Jharkhand	Giridh	989
	Latehar	478
	Palamu	479
	Paschimi Singhbhum	457
	Ranchi	455
Madhya Pradesh	Damoh	481
	Guna	480
	Narsimhapur	480
	Raisen	481
	Rajgarh	478
	Rewa	477
Maharashtra	Gadchiroli	480
	Jalna	479
	Nandurbar	932
	Solapur	480
	Yavatmal	480
Odisha	Kandhamal	479
	Korapur	450
	Mayurbhanj	474
	Rayagada	474
	Sambalpur	446
	Sundargarh	471
Rajasthan	Banswara	470
	Bhilwara	481
	Chittaurgarh	479
	Dungapur	960
	Udaipur	956
Uttar Pradesh	Allahabad	473
	Ambedkar Nagar	480
	Azamgarh	470
	Bijnor	479
	Chandauli	496

State	District	Sample size
West Bengal	Burdwan	372
	Maldah	361
	Paschim Medinipur	368
	South 24 Parganas	361
Total		**27,257**

Table A2: Endline sample [with reduced Odisha sample]

State	District	Sample Size
Bihar	Madhubani	358
	Supaul	878
	Madhepura	1922
	Sharsa	923
	Muzaffarpur	848
	Nalanda	351
	Gaya	217
Chhattisgarh	Surguja	430
	Rajnandgaon	456
	Raipur	462
	Bastar	467
	Balrampur	459
	Gariyaband	453
Jharkhand	Giridih	932
	Palamu	461
	Latehar	459
	Ranchi	428
	Pashchimi singhbhum	414
Madhya pradesh	Damoh	472
	Rewa	474
	Rajgarh	477
	Raisen	476
	Narsimhapur	455
	Guna	475
Maharashtra	Nandurbar	883
	Gadchiroli	440
	Yavatmal	453
	Jalna	440
	Solapur	471
Odisha	Sambalpur	415
	Sundargarh	468
	Kandhamal	234
	Rayagada	229
Rajasthan	Bhilwara	427
	Dungarpur	923

State	District	Sample Size
	Banswara	427
	Chittaurgarh	460
	Udaipur	950
Uttar Pradesh	Bijnor	475
	Allahabad	461
	Ambedkar Nagar	420
	Azamgarh	447
	Chandauli	451
West Bengal	Maldah	363
	Burdwan	369
	South 24 parganas	320
	Paschim Medinipur	371
Total		**24644**

Table A3: Main variables and their definitions

Variable	Description
Household Data	
Income and livelihoods	
Total household income (real INR)	Total real income earned by the household from any employment in the past 12 months. This includes agriculture, leased-out land, livestock, casual work, MGNREGA, salary, enterprise (both individual and group), transfer income, and other income sources. Transfer income includes assistance and remittances received and given in the form of cash or in-kind. Other income sources include government pension income, rental income from property, interest earned from financial assets, and the share of profit from a group enterprise, as well as income received as a community cadre of NRLM institutions, among others.
Agriculture income (real INR)	Total real income earned by the household from agriculture in the past 12 months. This does not include the income earned from leased-out land.
Livestock income (real INR)	Total real income earned by the household from livestock in the past 12 months from any livestock.
Total wage Income (real INR)	Total real income earned by household members from wage employment in the past 12 months. This includes casual work, MGNREGA, and salary income.
Wage labour income (real INR)	Total real casual wage employment income earned by the household members, either skilled or unskilled, including in-kind and bonus amount, in the past 12 months. This does not include MGNREGA and salary income.
MGNREGA income (real INR)	Total MGNREGA income earned by the household members, either skilled or unskilled, in the past 12 months.

Variable	Description
Salary Income (real INR)	Total salary income (includes dearness allowance, etc.) earned by the household members, including in-kind and bonus amounts, in the past 12 months.
Number of income sources	Total number of sources from which the household earned income. A total of 11 sources of income have been included. These include agriculture, livestock, enterprise (includes group enterprise), kitchen garden, MNREGA, community coordinator/cluster coordinator, transfer, male wage, female wage, male salary, and female salary income.
Consumption Expenditure	
(ln) Per capita household expenditure (real INR)	The total value of the household's annual expenditure on food, non-food daily items, and non-food annual items in the last month, divided by household size, converted into a natural logarithm value.
(ln) Food exp per capita (real INR)	The total value of the household's monthly expenditure on food items in the last month, divided by household size, is converted into a natural logarithm value. It includes the imputed value of all food items produced by the household as well as the value of PDS purchases.
(ln) Non-food daily items, per capita (real INR)	The same definition applies to non-food items, as explained for food items.
(ln) Non-food annual items, per capita (real INR)	The total value of the household's monthly expenditure on non-food annual items in the last 12 months, divided by household size, is converted into a natural logarithm value.
Home cc (Real INR)	The total consumption value of all goods produced by the household.
Market cc (Real INR)	The total consumption value of all purchased food items.
Food share of monthly consumption items	The share of food in the total expenditure by the household on monthly food and non-food items in the last month.
Count of consumption items	Count of the distinct number of consumption items, including food as well as non-food items, reported by the household.
Assets	
Productive assets – number	The sum of the number of productive assets owned by the household.
Productive assets – value (real INR)	The real total value of productive assets owned by the household.
Consumer assets - number	The sum of the number of consumption assets owned by the household.
Consumer assets – value (real INR)	The real total value of consumption assets owned by the household.
Labour Force Participation Rates	
LFPR - Females	The proportion of women aged between 20 and 60 years that were engaged in any income-generating work, including work in their own

Variable	Description
	farms or family-owned enterprises.
LFPR - Males	The same definition applies to LFPR-Male, as explained for LFPR-Female.
Loan	
Any Production Loan	Any loan taken to promote farm or non-farm enterprises in the past 2 years (2022 and 2023).
Any Production Loan, SHG	Same as above, restricted to loans from SHGs.
Any Consumption Loan	Loans taken to finance food purchases or any regular household expenditure in the past 2 years (2022 and 2023). Spending on education and health is excluded.
Any Consumption Loan, SHGs	Same as above, restricted to loans from SHGs.
SHG Data	
Panchsutra score 1	Calculated as the sum of the binary variables: whether the SHG had a weekly set frequency for meetings, a weekly set frequency for savings, had disbursed at least one loan between April 2018 (baseline) or April 2023 (endline) and the date of survey, had a penalty for loan repayments, and had updated at least one of the following books of accounts within the past year: Cash Book, Minutes Book, Loan Ledger, Savings Ledger, and SHG Bank Passbook
Panchsutra score 1 > 1	Whether or not the Panchsutra score 1 was greater than 1 for the SHG
Panchsutra score 2	Calculated as the sum of the binary variables: whether the SHG had a monthly, fortnightly, or weekly set frequency for meetings, a monthly, fortnightly, or weekly set frequency for savings, had disbursed at least one loan between April 2018 (baseline) or April 2023 (endline) and the date of survey, had a penalty for loan repayments, and had updated at least one of the following books of accounts within the past year: Cash Book, Minutes Book, Loan Ledger, Savings Ledger, and SHG Bank Passbook.
Panchsutra score 3	Calculated as the sum of the binary variables: whether the SHG had a monthly, fortnightly, or weekly set frequency for meetings, a monthly, fortnightly, or weekly set frequency for savings, had disbursed at least one loan between April 2018 (baseline) or April 2023 (endline) and the date of survey, had a monthly, fortnightly, or weekly set frequency for loan repayments, and had updated at least one of the following books of accounts within the past year: Cash Book, Minutes Book, Loan Ledger, Savings Ledger, and SHG Bank Passbook.

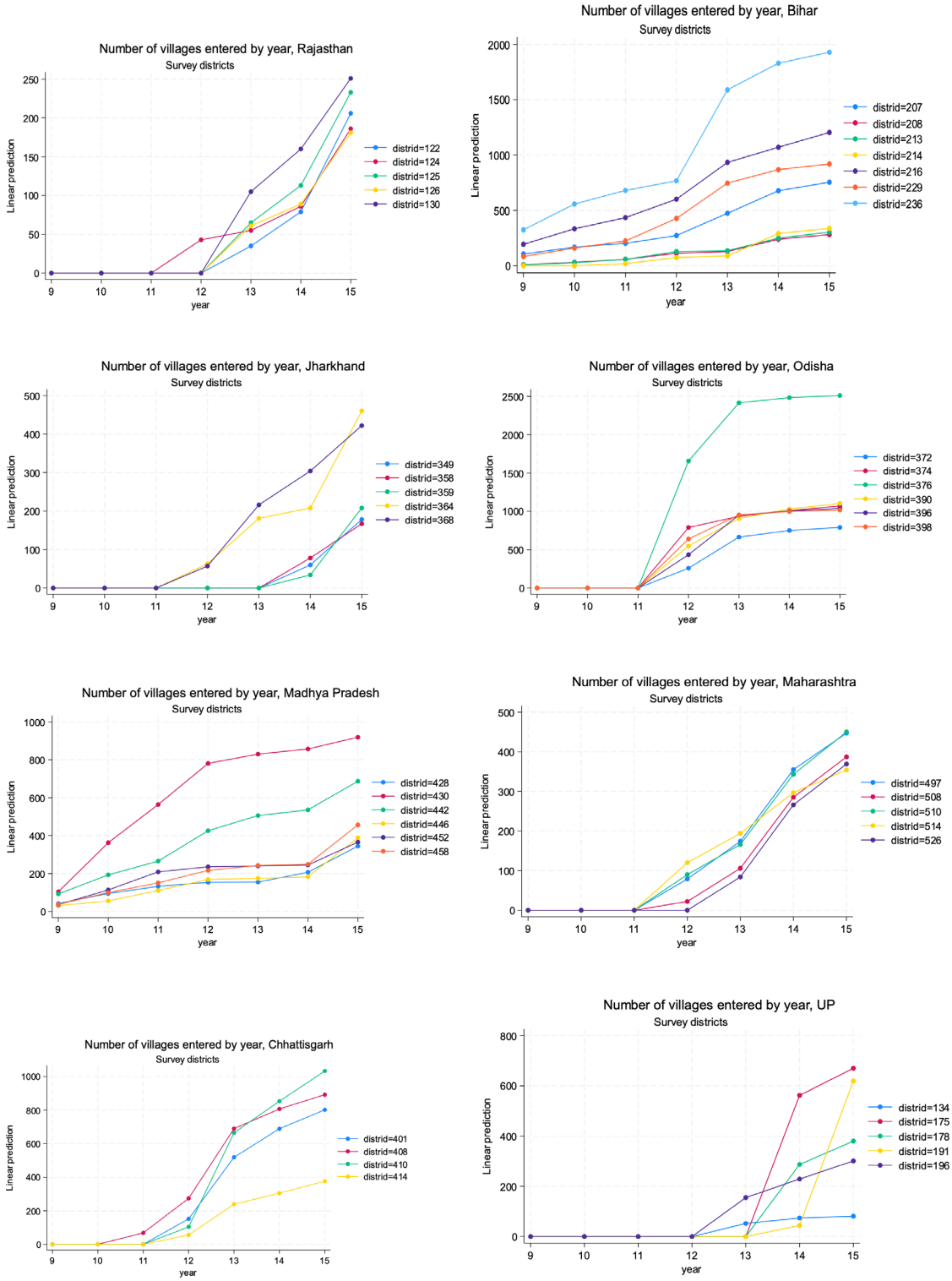
Variable	Description
Continuous Panchsutra	Calculated as the sum of the proportion of SHG members that had attended at least 12 meetings in the past year, the proportion of SHG members that had saved at least 12 times in the past year, the proportion of SHG members that had received a loan in the past year, the proportion of SHG members that had made some repayment towards a loan taken in the past year, and the proportion of the following books of accounts that were updated within the past year: Cash Book, Minutes Book, Loan Ledger, Savings Ledger, and SHG Bank Passbook
Women Data	
Indices of women's beliefs and welfare	
Network Size (number of friends)	Total number of friends women turn to (currently and in the past) for companionship, advice, help, and support in different matters.
Index of regressive norms	Based on the data, we defined the index of regressive norms as the percentage of cases (out of a total of 12 regressive norm indicators) for which women agree or disagree with a particular norm.
Financial Literacy Index	To assess the financial literacy of women surveyed, we defined the financial literacy index as the percentage of cases (out of a total of 9 financial literacy indicators) for which women were able to correctly answer questions on division, interest rate calculation, simple interest calculation, the difference between simple and compound interest, assess whether a particular loan or fund belongs to asset or liability.
Generational Change-better off than mother	To capture information on the generational change status of women with respect to their mothers, we asked the women respondents to share their perceptions regarding whether they perceived themselves to be better off than their mothers when they were approximately the same age. Based on the data, we defined the index as the percentage of cases (out of a total of 10 generational change indicators) for which women reported feeling better off than their mothers. The indicators are overall household income, your control over your own income, your ability to spend on consumption, access to savings, ability to choose an occupation, freedom, and mobility to do things on your own, hours of work on drudgery, general happiness and satisfaction with life, being treated with respect by your husband and leisure time.
Subjective welfare index – current status	To capture the information on subjective welfare well-being, we asked the women about their satisfaction with current levels of consumption, income, standard of living, and ability to spend time with friends. Based on the reported information, we define a subjective welfare index – current status as the percentage of cases (out of a total of 7 indicators) for which females felt that they were very satisfied or moderately satisfied with their current status.
Subjective welfare index – compared to 5	Subjective welfare index created similar to the one above, comparing the current status with how it was five years ago.

Variable	Description
years ago	
Subjective welfare index_ - expectation of future	Subjective welfare index created similar to the one above, comparing the expectation of future status in five years.
Decision-making index	To capture information on decision-making within the household, we asked the women respondents what they feel about their inputs in household decisions relating to household expenditure, borrowing, education, home improvements, and healthcare for children. Based on the reported information, we define a decision-making index as the percentage of cases (out of a total of 26 decisions) for which females felt that their inputs were important for that decision, i.e., either they provided most of the inputs or it was entirely their input.
Decision-making index (mean)	A second index is calculated as the mean value over all possible scores (1 to 5), with 1 implying little or no role.
Confidence index	An index calculated over 6 questions, which asked the woman if she was confident speaking in SHG meetings, in dealing with Gram Panchayat leaders, bank officers and health functionaries, and two additional questions that record her confidence in her children's health outcomes and providing health-related advice to others. For each question, the woman was assigned a score of one if she said she was confident in this area. The score is the percentage score across all questions.
Confidence index without health	Same as above, dropping the last two health-related questions.
More equal society is better.	Indicator variable, 1 if the women agree to the statement "Society is better off if people's incomes are more equal", and 0 if women agree to the statement "Society is better off if there are greater incentives for individual effort".
Govts are responsible for citizen's welfare.	Indicator variable, 1 if the women agree to the statement "Governments should take more responsibility to ensure that everyone is provided for," and 0 if women agree to the statement "People should take more responsibility to provide for themselves".
Regressive norms indicators	A-B question to reveal the women's attitudes regarding the importance of home / domestic responsibilities, women's roles, gender equality for children, and norms relating to women's work.
Networks	
Income (share worries/information on income)	The total number of friends with whom women can discuss any concerns they may have regarding household income, such as worries about whether it is enough to meet current and future consumption requirements, and they can reach out for new income opportunities for themselves. This is measured by summing the total number of friends for two indicators.
Emotional needs (share dreams, worries, overall support)	The total number of friends with whom women can reach out for support for emotional needs, which include worry about income, worries about any of her children, emotional support, hopes and dreams of the future, and visiting house regularly. This is measured

Variable	Description
	by summing the total number of friends for five indicators.
Sharing (help with consumption needs, child care)	The total number of friends with whom women can reach out in case of abuse from anyone in the village who needs help supervising children or cooking meals if required, and turn out to friends outside the house for buying daily items when needed for consumption purposes. This is measured by summing the total number of friends for three indicators.
Help with ill health/information (health, birth control)	The total number of friends with whom women can reach out for health and nutrition needs, serious health issues needing hospitalization and contraception, or matters relating to female health concerns. This is measured by summing the total number of friends for three indicators.
Overall Network Index	The total number of friends women reach out to for help with 13 indicators on social networks, as mentioned above.
Financial Behaviour & Financial Knowledge	
Consumption preferences (prefer to spend money today rather than save)	Indicator variable, 1 if the woman strongly agrees or agrees with the statement “I would prefer to spend money today rather than save it for consumption in later years,” 0 otherwise.
Need for precautionary savings – important to have a plan for income shocks.	Indicator variable, 1 if the women say Yes to the statement “Do you think it is important to have a plan to deal with unexpected decline in your income or unexpected need to spend more, or shocks as in the case of household emergencies such as ill-health of a primary earner, or crop failure, etc.?” and 0 if she says No
Need for old-age savings.	Indicator variable, 1 if women say Yes to the statement “Do you think it is important for all people to save some money for old age, that is when they are no longer able to work?” and 0 if she says No.
Intend to live with son in old age?	Indicator variable, 1 if women say she will “live with her son” to the statement “When you and your husband are no longer able to work, what do you think your residential / care arrangements will be?” and 0 if she says any other options
Business Literacy	To assess the business literacy of women surveyed, we defined the business literacy index as the percentage of cases (out of a total of 3 business literacy indicators) for which women were able to correctly answer questions on the difference between fixed and variable cost, assess whether a particular loan or fund belongs to asset or liability.

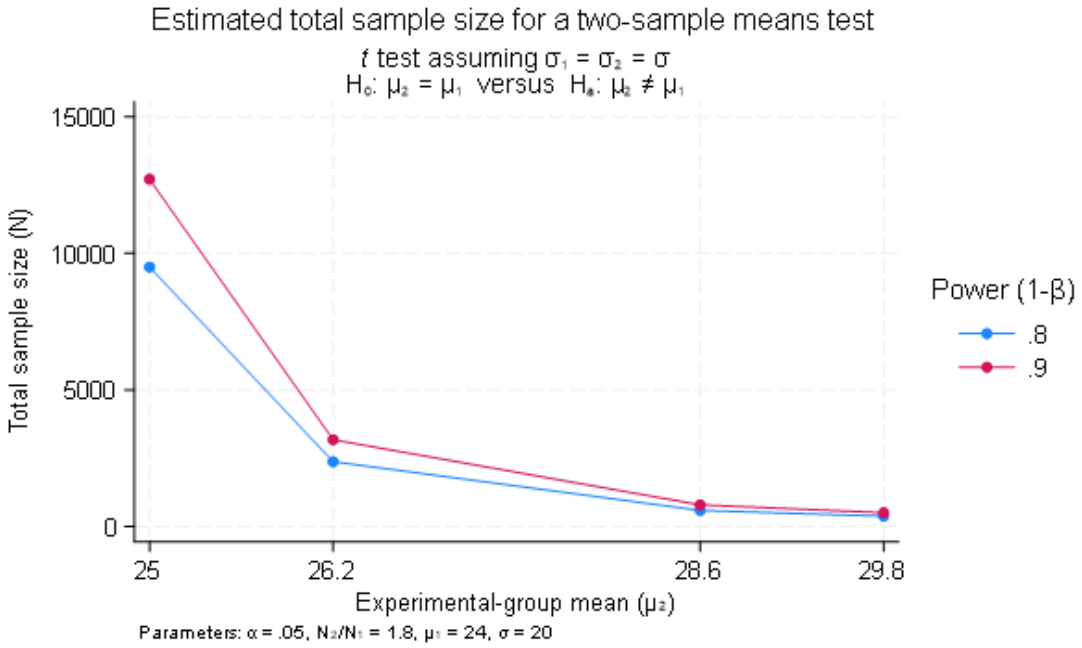
Appendix B: Chapter 4

Figure B1: Number of villages entered by year, survey districts and states



Power calculations

The extensive geographical coverage of the study and overall sample size suggests that the study is adequately powered to detect differences in mean per capita household expenditure even when the evaluation sample is restricted to NRETP (treatment) and early (control) blocks and given that the unbalance in these two samples. The graph below depicts the sample sizes required to detect improvements in expenditure of 5% (per capita household expenditure equal to INR 25 thousand), 10% (26.2), 20% (28.6)and 25% (29.8) relative to the baseline per capita household expenditure (INR 23.8 thousand, with standard deviation of 20). The ratio of treatment to control blocks, using NRETP and early blocks, is approximately 1.8, with a total sample size of 11,000.



Appendix C: Chapter 6

Impact of NRLM (Percentage Change Calculation from Baseline to Endline)

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
Total household income	Basic Controls	-219.4	63521.48	63388.82	-0.35%	-0.35%	18064
		(2,165.11)					
	Add Heterogeneity	5612.33**	63724.02	63124.79	8.81%	8.89%	18064
		(2,843.53)					
Agricultural income		702.59	7906.50	7187.67	8.89%	9.77%	19310
		(3,306.67)					
Livestock income		523.91	3835.11	3709.49	13.66%	14.12%	19310
		(922.61)					
Total wage income		3,576.34	41115.74	43602.85	8.70%	8.20%	19310
		(2,592.17)					
Wage labour income		3,384.93	29786.94	29999.41	11.36%	11.28%	19310
		(2,156.05)					
MNREGA income		-24.01	628.48	727.84	-3.82%	-3.30%	19310
		(301.41)					
Salary income		3,221.93	11963.90	15848.36	26.93%	20.33%	19310
		(2,270.80)					
Home cc (INR)		81.22	710.70	721.30	11.43%	11.26%	19,310
		(78.80)					
Mkt cc (INR)		149.9	2055.30	2019.27	7.29%	7.42%	19,310
		(152.20)					
Number of income sources		-0.136	2.69	2.78	-5.06%	-4.89%	19,310
		(0.105)					

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
Count of consumption items		0.137	16.81	16.48	0.81%	0.83%	19,310
		(0.369)					
WASH infrastructure		-0.069	1.28	1.47	-5.35%	-4.65%	19,310
		(0.075)					
Productive assets - number		0.49	2.611	2.265665	18.77%	21.63%	19,310
		(0.761)					
Productive assets – value (constant INR)		6,870.2	24174.86	25104.8	28.42%	27.37%	19,310
		(6,995.220)					
Consumer assets - number		0.220	5.05866	5.294818	4.34%	4.15%	19,310
		(0.200)					
Consumer assets - value		3,905.410	28308.87	27807.8	13.80%	14.04%	19,310
		(3,229.660)					
Total hours of work (Female)		-0.48	92.415	96.48589	-0.52%	-0.50%	26101
		(6.00)					
Total hours of work (Male)		-15.45*	188.30	187.1934	-8.20%	-8.25%	24186
		(8.61)					

Appendix D: Chapter 6

Impact of NRETP (Percentage Change Calculation from Baseline to Endline)

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
Total household income Real (Full Sample)	Difference in difference	10909.0***	67401.47	66776.49	16.19%	16.34%	24,654
		(3,927.70)					
	Double robust	15541.3**	67401.47	66776.49	23.06%	23.27%	24,654
		(6,695.21)					
	Regr adjust (RA)	18038.82**	67401.47	66776.49	26.76%	27.01%	24,654
		(7,151.8)					
	IPW	11872.1**	67401.47	66776.49	17.61%	17.78%	24,654
		(5,565.10)					
Total household income Real (Drop ODI)	Basic diff-in-diff	11354.4***	68607.06	68707.74	16.55%	16.53%	22,914
		(4,322.3)					
	Double robust	16063.6**	68607.06	68707.74	23.41%	23.38%	22,914
		(7,151.5)					
	Regr adjust (RA)	19373.9**	68607.06	68707.74	28.24%	28.20%	22,914
		(7,785.0)					
	IPW	11269.7**	68607.06	68707.74	16.43%	16.40%	22,914
		(5,016.1)					
Total household income Real (Add Additional Controls)	Basic diff-in-diff	10687.7***	67130.48	66966.59	15.92%	15.96%	24,648
		(3,864.2)					
	Double robust	14894.0**	67130.48	66966.59	22.19%	22.24%	24,648
		(7,195.9)					

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
	Regr adjust (RA)	19,092.1	67130.48	66966.59	28.44%	28.51%	24,648
		(18,353.2)					
	IPW	11969.7**	67130.48	66966.59	17.83%	17.87%	24,648
		(5,556.0)					
Agricultural income	Diff-in-diff	4144.7*	7384.07	5317.79	56.13%	77.94%	24654
		(2,135.90)					
	Double robust	3424.59**	7384.07	5317.79	46.38%	64.40%	24654
		(1,716.73)					
	Regr adjusted	6678.8***	7384.07	5317.79	90.45%	125.59%	24654
		(2,357.40)					
	Std. IPW	4004.9***	7384.07	5317.79	54.24%	75.31%	24654
		(1,449.40)					
Livestock	Diff-in-diff	495.2	2892.41	2711.14	17.12%	18.27%	24654
		(457.6)					
	Double robust	1201.3**	2892.41	2711.14	41.53%	44.31%	24654
		(591.0)					
	Regr adjusted	1415.4**	2892.41	2711.14	48.93%	52.21%	24654
		(654.29)					
	Std. IPW	1119.51*	2892.41	2711.14	38.71%	41.29%	24654
		(587.5)					
Total wage income	Diff-in-diff	2,839.00	42395.27	44936.29	6.70%	6.32%	24654
		(1,765.00)					
	Double robust	6412.921***	42395.27	44936.29	15.13%	14.27%	24654
		(2,407.80)					
	Regr adjusted	5864.4**	42395.27	44936.29	13.83%	13.05%	24654

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
		(2,633.0)					
	Std. IPW	4,921.00	42395.27	44936.29	11.61%	10.95%	24654
		(3,997.40)					
Wage income	Diff-in-diff	2,054.10	31458.66	34239.16	6.53%	6.00%	24654
		(1,586.90)					
	Double robust	4547.1**	31458.66	34239.16	14.45%	13.28%	24654
		(1,923.41)					
	Regr adjusted	4906.0**	31458.66	34239.16	15.60%	14.33%	24654
		(2,254.41)					
	Std. IPW	4,320.00	31458.66	34239.16	13.73%	12.62%	24654
		(2,984.10)					
MGNREGA	Diff-in-diff	-273.12	502.54	474	-54.35%	-57.62%	24654
		(201.62)					
	Double robust	-315.6*	502.54	474	-62.80%	-66.58%	24654
		(191.03)					
	Regr adjusted	-482.5**	502.54	474	-96.01%	-101.79%	24654
		(214.01)					
	Std. IPW	-125.90	502.54	474	-25.05%	-26.56%	24654
		(199.00)					
Salary	Diff-in-diff	1,858.71	12452.83	11490.1	14.93%	16.18%	24654
		(1,334.51)					
	Double robust	4325.5***	12452.83	11490.1	34.74%	37.65%	24654
		(1,639.45)					
	Regr adjusted	3354.4*	12452.83	11490.1	26.94%	29.19%	24654
		(1,760.20)					

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
	Std. IPW	2,531.50	12452.83	11490.1	20.33%	22.03%	24654
		(1,850.80)					
Total hours of work (Female)	Diff-in-diff	6.539*	83.57	68.98	7.83%	9.48%	33059
		(3.418)					
Total hours of work (Male)	Diff-in-diff	12.91***	178.02	179.94	7.25%	7.17%	30016
		(4.786)					
Home cc (real INR)	Basic difference-in-difference	136.4**	667.88	585.76	20.43%	23.29%	24719
		(61.28)					
	Double robust	323.0***	667.88	585.76	48.36%	55.14%	24719
		(56.93)					
Mkt cc (real INR)	Basic difference-in-difference	74.6	2213.09	2269.87	3.37%	3.29%	24719
		(159.13)					
	Double robust	709.42	2213.09	2269.87	32.06%	31.25%	24719
		(441.6)					
Count of consumption items	Basic difference-in-difference	0.732***	16.63	16.62	4.40%	4.40%	24719
		(0.268)					
	Double robust	1.117***	16.63	16.62	6.68%	6.68%	24719
		(0.298)					
Number of income sources	Basic difference-in-difference	-0.184**	2.84	2.77	-6.49%	-6.64%	24968
		(0.0785)					
	Double robust	-0.179**	2.84	2.77	-6.31%	-6.46%	24968
		(0.0882)					
WASH infrastructure	Basic difference-in-difference	-0.126**	1.33	1.26	-9.38%	-9.96%	24968
		(0.0545)					
	Double robust	0.001	1.33	1.26	0.08%	0.08%	24968

		1	2	3	1/2	1/3	
Variable	**Specification**	**Impact Coefficient**	**Predicted Baseline Control**	**Predicted Baseline Treatment**	**Percentage Change (I/BC)**	**Percentage Change (I/BT)**	**Sample Size (N)**
		(0.0639)					
Productive assets, number	Basic difference-in-difference	-1.724***	2.4	2.18	-71.94%	-78.97%	24968
		(0.582)					
	Double robust	-3.140***	2.4	2.18	-131.02%	-143.83%	24968
		(1.083)					
Productive assets, value (real INR)	Basic difference-in-difference	21580.6*	20681.83	17441.15	104.35%	123.73%	24968
		(12,545.6)					
	Double robust	20665.6**	20681.83	17441.15	99.92%	118.49%	24968
		(9285.8)					
Consumer assets, number	Basic difference-in-difference	-0.0527	5	4.78	-1.05%	-1.10%	24968
		(0.133)					
	Double robust	0.0871	5	4.78	1.74%	1.82%	24968
		(0.131)					
Consumer assets, value	Basic difference-in-difference	1,686.0	19071.91	17621.49	8.84%	9.57%	24968
		(2,041.9)					
	Double robust	222.4	19071.91	17621.49	1.17%	1.26%	24968
		(3100.66)					

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