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Rural non-farm employment in Uttar Pradesh, India: drivers and impact

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Abstract The agriculture sector is facing disguised unemployment and the workforce is migrating from the farm sector to the non-farm sector. This study examines rural non-farm employment patterns in Uttar Pradesh, India, to identify the drivers of household employment choices and the impact of increased income levels on poverty. The shift from the agricultural sector to the non-farm sector—across all expenditure and landholding classes—is drastic. If non-farm employment increases, household income rises and rural poverty falls. Promoting crop diversification—and providing extensive infrastructure, financial, and technological support—could help localized micro-enterprises engage in post-harvest activities.

Keywords Non-farm employment, rural sector, rural transformation, agriculture, income, livelihoods, poverty, Uttar Pradesh, India

JEL codes E24, P25, O13, O18, P36

India's rural sector is undergoing a transformation within and beyond the agricultural sector (Mishra and Singh 2019). The non-farm sector includes all the economic activities undertaken outside the agricultural sector (mining, construction, trade, business); its share of rural employment has grown significantly, and its capacity to absorb additional labour has plateaued (Basant and Kumar 1989; Visaria 1995; Chadha and Sahu 2002; Mukhopadhyay and Rajaraman 2007; Kumar 2009; Panda 2017).

The non-farm sector's share of rural employment grew from 23% in 1993–94 to 36% in 2011–12, and the share of farm workers in the rural workforce fell from 77% in 1993–94 to 73% in 2004–05 and 64% in 2011–12. Between 2011 and 2015, the number of farm jobs fell by 26 million while non-farm jobs rose by 33 million, according to a report by the McKinsey Global Institute on India's labour market (Woetzel, Madgavkar, and Gupta 2017).

India's Periodic Labour Force Survey highlights that, as of 2017–18, only 44% of the country's workforce was engaged in agriculture and related activities. Between 2011–12 and 2017–18, primary-sector employment in rural India fell from 59.4% to 55% among men and from 74.9% to 73.2% among women (MOSPI 2019).

A strong non-farm sector provides farming households opportunities to expand their income sources, improve agricultural productivity, and increase food consumption expenditure (Ruben 2001; Clover 2003; Mishra, Mottaleb, and Mohanty 2015). Increased participation in non-farm sector activities can be viewed as a promising path toward eradicating poverty and generating income in rural areas (Woldenhanna and Oskam 2001; Matshe and Young 2004; Oseni and Winters 2009; Gibson and Olivia 2010; Mishra et al. 2014).

Rural non-farm employment (RNFE) discourages urban migration and promotes the development of small-scale industries that use local resources, including a revival of traditional crafts (Mishra and Singh 2019). Engagement in off-farm activities is viewed as a tool for reducing income uncertainty (Anang and Yebaoah 2019).

Several studies analyse the trends and patterns of RNFE in India (Lanjouw and Shariff 2004; Jha 2006; Pradhan 2008; Lanjouw and Murgai 2009; Kumar et al. 2011; Reddy et al. 2014), but most are based on national survey data, and therefore present a macroeconomic perspective; few focus on the drivers and impact of RNFE. India comprises several states, different agro-climatic conditions, and infrastructure networks; rural employment and RNFE exhibit patterns that differ within and across states.

This is particularly pertinent for Uttar Pradesh (UP), India's most populous state. Were UP a separate nation, it would be the world's fifth most populous country (behind China, India, the US, and Indonesia). Moreover, agriculture contributed 26.7% of the state's gross value-added (GVA) in 2017–18 (IBEF 2018); the sector provides employment to as much as 55% of the rural population (Mamgain and Verick 2017). Few studies focus on the RNFE in the state, however (Singh 1994; Srivastava 1999; Ranjan 2009).

Employment patterns have shifted drastically across India since the implementation of the Mahatma Gandhi National Rural Employment Guarantee Act, 2005 (MGNREGA); and a comprehensive, disaggregated study is essential in understanding the transformation of the rural workforce (Mishra and Singh 2019) and in developing a strategic framework for rural development, including the implications for poverty. In this context, this study examines the pattern and trends of RNFE in UP, identifying the drivers of household employment choices and the impact of increased household income levels on poverty.

Data

The National Sample Survey Organisation (NSSO) conducts Employment and Unemployment Surveys. This study is based on unit-level data from three rounds: the 50th round (1993–94), covering 9,006 households; 61st round (2004–05), covering 7,872 households; and the 68th round (2011–12), covering 5,916 households. This provides a representative picture of the UP.

The survey provides information on the 'principal industry of activity' to which the households are affiliated to obtain the major portion of their income. The socio-demographic and economic variables included are household size, religion, caste, monthly per capita expenditure (MPCE) on food and non-food items, and asset ownership. The survey provides comprehensive information on each household member (age, gender, education, training, employment status at principal, and subsidiary levels, types of job contracts, availability of social security benefits, method of payment, and level of unemployment).

Analytical framework

The analyses cover gainful employment activities, categorized as crops; livestock; other farm activities (forestry, fisheries, agricultural services); and non-farm activities (including all non-farm activities within the secondary and tertiary sectors). Agricultural labour—among the most important economic activities for rural people—is included in the 'other farm' activities.

To analyse the level of employment, we use the 'usual status' concept of employment, in which the share of employment is obtained by adding the respective shares of workers employed in a sector or sub-sector in terms of their principal status and subsidiary status. We examine the employment trends by comparing the shares of employment across sectors and subsectors over time.

We explore the variations in employment shares across household categories on the basis of income levels (using MPCE as a proxy variable) and land ownership status. We classify the households by expenditure group into five quintile groups of MPCE. We categorize landownership or farm size into landless (<0.5 hectare [ha]); marginal (>0.5–1.0 ha); small (>1.0–2.0 ha), medium (>2.0–4.0 ha); and large (>4.0 ha).

Methodology

Various observed and unobserved characteristics of participation in non-farm employment activities determine household consumption expenditure. We employ the two stage least squares instrumental variable (2SLS-IV) regression. An ordinary least squares (OLS) regression would lead to biased results based on unseen endogeneity; so, we use a Hausman test to check for endogeneity.

Household employment decisions are affected by many unobserved factors, including entrepreneurial spirit, family lineage, and peer pressure. Since the Hausman test indicates endogeneity, we implement an instrumental variable (IV) regression. An IV must be uncorrelated with the error term and correlated with the independent variable (X). The IVs implemented in the model are the share of households in the total rural workforce engaged in self-employment, regular salaried or wage-based employment, casual employment, and all forms of RNFE. The IV is calculated at the village level for each type of non-farm employment. Thus, a 2SLS-IV regression is considered a better option because it accounts for the issues of heterogeneity.

The 2SLS-IV regression follows a two-stage estimation procedure. In the first stage, the dependent variable is a binary variable, $RNFE_i$, which is regressed against a set of independent variables, X_i. We use a simple logit model to estimate this relationship, which takes the functional form:

$$RNFE(k)_i = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum \beta_i X_i + u_i \qquad (1)$$

where,

$RNFE_i$ is a binary variable depicting the primary activity of the i^{th} household and taking value 1 for the non-farm sector and 0 otherwise;

k indicates a subset of $RNFE_i$, which includes SE, CAS, REG, and ALL, depending on the type of non-farm activity undertaken by the household.

RNFE (SE) indicates self-employment in the non-farm sector,

RNFE (REG) indicates regular salaried/wage-based employment in the non-farm sector,

RNFE (CAS) indicates casual employment in non-farm sector, and

RNFE (ALL) includes all the forms of RNFE.

On the right-hand side of equation (1),

p shows the probability that a household will engage in the non-farm sector to derive its chief source of income,

β_i represents the regression coefficients to be estimated, and

X_i is a vector of explanatory variables comprising socio-economic and demographic household features (age, gender, caste, education, household size, and land).

The error term u_i is assumed to be normally distributed, and the model is estimated through a maximum likelihood approach.

In the second stage of the 2SLS-IV regression, we fit the household expenditure function for assessing the impact of RNFE on household consumption expenditure. The functional form for the second stage is

$$MPCE_i = \alpha + \delta d(k)_i + \gamma X_i + \varepsilon_i \qquad (2)$$

where

$MPCE_i$ denotes MPCE of the i^{th} household, and

$d(k)_i$ is a dummy variable indicating whether a household engages in non-farm sector employment or not, assuming a value of 1 in the respective cases as k varies from SE to ALL, and 0 otherwise.

X_i is the same vector of explanatory variables used in Equation (1), and

ε_i is the error term assumed to be normally distributed.

A propensity score matching (PSM) algorithm has been widely used when the treatments are binary, but PSM with a binary treatment is often prevented in observational studies where the treatment variables may not be binary or categorical (Bia and Mattei 2008). Hirano and Imbens (2004) advanced PSM to cases where treatment variables are continuous by allowing estimation through the dose response function (DRF) technique. This new approach is known as the generalized propensity score matching (GPSM).

Non-farm employment is rising; to judge its effect on household income and poverty levels in rural UP, we use the GPSM approach to estimate the DRF for various levels of non-farm employment (the treatment) on the sample households' MPCE and poverty status (outcomes). We use IV regression estimates to eliminate the potential for bias arising from unobserved heterogeneity. The generalized propensity score is defined as the conditional probability (r(t,x,)) of receiving a particular treatment level given the pre-treatment variables (Imbens 2000). Mathematically, it can be written as

$$r(t,x) = pr(T = t|X = x) = E\{D(t)|X = x\} \quad (3)$$

Next, to compute the average treatment effect for each level of treatment, we set a dose response function:

$$E\big(Y(t)\big) = \frac{1}{N}\sum_{i=1}^{N} \beta\{t, r(t, X_i)\} \quad (4)$$

Results and discussion: trends in shares of employment across sectors and sub-sectors

We observe a direct relationship between non-farm sector employment and expenditure quintiles and an inverse relationship between crop sector employment and expenditure quintiles (Table 1)—implying that as household expenditure rose, crop sector employment fell, and non-farm sector employment rose.

Comparing results for 1993–94 with those for 2011–12, in the lowest expenditure quintile, employment in the crop sector fell from 78.9% to 55.3%, while employment in the non-farm sector rose from 16.5% to 37.7%. In the second expenditure quintile, the share of households employed in the crop sector fell from 74.9% to 52.6%, while the share of employment in the

Table 1 Share of employment in UP by sector and expenditure quintile, 1993–94 to 2011–12

Sector	Employment share (%)			Change (%)	Compound annual growth rate (%)
	50th Round 1993–94	61st Round 2004–05	68th Round 2011–12		
Lowest quintile					
Crops	78.9	67.5	55.3	–30.0	–2.1
Livestock	4.2	7.3	6.2	47.9	2.3
Other farm	0.3	0.1	0.8	133.0	5.1
Non-farm	16.5	25.2	37.7	128.2	5.0
Second quintile					
Crops	74.9	64.0	52.6	–29.9	–2.1
Livestock	6.9	10.4	8.3	21.2	1.1
Other farm	0.3	0.2	1.9	576.2	11.9
Non-farm	18.0	25.4	37.2	107.5	4.4
Third quintile					
Crops	71.1	62.3	52.6	–26.0	–1.8
Livestock	9.6	12.2	8.2	–14.4	–0.9
Other farm	0.4	0.5	1.4	228.9	7.3
Non-farm	19.0	25.0	37.8	99.6	4.2
Fourth quintile					
Crops	70.6	62.6	59.0	–16.3	–1.1
Livestock	8.4	12.9	9.0	6.6	0.4
Other farm	0.3	0.2	2.0	625.1	12.4
Non-farm	20.7	24.3	30.0	44.7	2.2
Highest quintile					
Crops	66.8	60.7	55.5	–16.9	–1.1
Livestock	10.2	15.3	8.5	–16.9	–1.1
Other farm	0.5	0.3	2.3	413.3	10.1
Non-farm	22.5	23.6	33.7	49.6	2.4
All groups					
Crops	72.9	63.5	54.9	–24.8	–1.7
Livestock	7.6	11.5	8.0	4.5	0.3
Other farm	0.4	0.3	1.6	367.1	9.5
Non-farm	19.1	24.7	35.6	86.3	3.7

Source: Authors' calculations based on NSSO data

non-farm sector grew from 18.0% to 37.2%. In the third expenditure quintile, the share of households employed in the crop sector fell precipitously, from 71.1% to 52.6%, while employment in the non-farm sector rose from 19.0% to 37.8%. In the fourth expenditure quintile, non-farm sector employment increased from 20.7% to 30.0%, and employment in the crop sector declined from 70.6% to 59.0%. Finally, in the highest expenditure quintile, the share of employment in the non-farm sector increased from 22.5% to 33.7%, while the share of employment in the crop sector fell from 66.8% to 55.5%.

Secondly, crop sector employment declined over the time, followed by a rise in the share of RNFE (Table 1). The overall share of crop sector employment declined from 72.9% in 1993–94 to 54.9% in 2011–12. Over the same timeframe, the share of non-farm employment increased from 19.1% to 35.6%. Both the livestock and other farm sectors recorded mixed responses. Overall, employment in the livestock sector increased from 7.6% in 1993–94 to 11.5% in 2004–05, but it declined to 8.0% in 2011–12. The share of sample households employed in other farm activities declined from 0.4% in 1993–94 to 0.3% in 2004–05 but increased to 1.6% in 2011–12.

Interestingly, landless households or marginal landholders have a large share in non-farm employment (Table 2). In 2011–12, the employment participation

Table 2 Share of employment in UP by sector and farm size, 1993–94 to 2011–12

Sector	Employment share (%)			Change (%)	Compound annual growth rate (%)
	50th Round 1993–94	61st Round 2004–05	68th Round 2011–12		
Landless (<= 0.005 ha)					
Crop	38.9	31.1	19.7	–49.4	–3.9
Livestock	8.6	10.9	4.2	–51.2	–4.1
Other farm	0.3	0.6	2.6	664.1	12.7
Non-farm	52.2	57.3	73.5	41.0	2.0
Marginal (0.006–1.0 ha)					
Crop	82.6	63.1	54.3	–34.3	–2.4
Livestock	8.3	10.7	8.0	–3.8	–0.2
Other farm	0.1	0.3	1.9	3,614.8	23.7
Non-farm	9.0	26.0	35.9	296.9	8.5
Small (1.0–2.0 ha)					
Crop	83.0	74.9	73.7	–11.2	–0.7
Livestock	6.0	13.1	11.0	85.2	3.7
Other farm	0.1	0.2	0.0	–78.0	–8.5
Non-farm	10.9	11.8	15.2	39.7	2.0
Medium (2.0–4.0 ha)					
Crop	82.6	74.3	82.0	–0.8	–0.1
Livestock	8.3	15.4	6.5	–20.9	–1.4
Other farm	0.1	0.1	0.0	–100.0	–100.0
Non-farm	9.0	10.2	11.5	26.7	1.4
Large (> 4.0 ha)					
Crop	84.3	76.9	72.6	–13.9	–0.9
Livestock	7.7	13.6	12.9	67.9	3.1
Other farm	0.0	0.1	0.0	–100.0	–100.0
Non-farm	8.0	9.4	14.6	82.1	3.6
All groups					
Crop	72.9	63.5	54.9	–24.8	–1.7
Livestock	7.6	11.5	8.0	4.5	0.3
Other farm	0.4	0.3	1.6	367.1	9.5
Non-farm	19.1	24.7	35.6	86.3	3.7

Source: Authors' calculations based on NSSO data

rate for landless people was highest in non-farm activities (73.5%) and lowest in the crop sector (19.7%). Households with marginal landholdings had the highest share of employment in the crop sector in 1993–94 (82.6%) and in the non-farm sector in 2011–12 (35.9%).

Across all five categories of landholding, non-farm employment increased while crop sector employment fell. The share of households with marginal landholdings in non-farm employment grew 8.5%, the largest rate of annual growth. The share of the landless in crop sector employment fell the most (–3.9%) because the crop sector alone cannot provide marginal and landless farmers sustainable earnings, and the profitability of the agricultural sector declined.

The results for the livestock and other farm sectors are mixed (Table 2): the employment share in the livestock sector fell sharply for landless households and households with marginal and medium-size landholdings, but the share of households with small and large landholdings increased. Households with medium-size landholdings had the largest share of employment in the livestock sector (15.4%, 2004–05); landless households had the smallest share (4.2%, 2011–12). Between 1993–94 and 2011–12, engagement in other farm activities grew 12.7% per annum for landless households and 23.7% per annum for marginal landholders. The employment share in other farm activities declined among households with small, medium-size, and large landholdings. Between 1994–95 and 2011–12, the share of crop sector employment fell 1.7% per annum for the sample as a whole, but there was an increase in the annual employment share in the livestock sector (0.3%), other farm sectors (9.5%), and non-farm sectors (3.7%) (Table 2).

Lanjouw and Shariff (2002) associate regional disparities in farm/non-farm employment with variations in such factors as education levels, land ownership, population density, and the prevailing agricultural wage rates. We examined these imbalances by analysing the shares of farm and non-farm employment across the four regions of UP: central, western, eastern, and southern (Table 3). In 1993–94, central UP had the largest share of farm employment (82.6%) and western UP the smallest (80.3%). Unsurprisingly, the share of non-farm employment was the smallest in central UP (17.4%) and the largest in western UP (19.7%). In 2004–05, southern UP recorded the largest share of farm employment (81.3%), while western UP recorded the largest share of non-farm employment (29.1%). In 2011–12, central UP recorded the largest share of farm employment (68.1%), and western UP the largest share of non-farm employment (38.8%).

The compound annual growth rate (CAGR) changed for both farm and non-farm employment; the change in farm activities was greatest in western UP (–1.6%) and in non-farm activities greatest in southern UP (4.3%). The smallest annual changes in the employment share occurred in the farm sector in central UP (–1.1%) and in the non-farm sector in eastern UP (3.4%).

Household non-farm employment: disaggregated patterns

Panda (2017) notes the heterogeneous nature of RNFE: the non-farm sector includes all rural economic activities except agriculture, livestock, fishing, and hunting. Table 4 presents the shares of RNFE in UP by subsector. In 1993–94, manufacturing contributed the largest share (32.0%) and financial services the lowest (0.4%). In 2004–05, manufacturing contributed the

Table 3 Share of employment in UP by sector and region, 1993–94 to 2011–12

Region	50th Round (1993–94)		61st Round (2004–05)		68th Round (2011–12)		Compound annual growth rate (%)	
	Farm	Non-farm	Farm	Non-farm	Farm	Non-farm	Farm	Non-farm
Western	80.3	19.7	70.9	29.1	61.2	38.8	–1.6	4.1
Central	82.6	17.4	77.3	22.7	68.1	31.9	–1.1	3.7
Eastern	80.6	19.4	76.7	23.3	65.6	34.4	–1.2	3.4
Southern	82.3	17.7	81.3	18.7	63.7	36.3	–1.5	4.3
Total	**80.9**	**19.1**	**75.3**	**24.7**	**64.5**	**35.6**	**–1.3**	**3.7**

Source: Authors' calculations based on NSSO data

Table 4 Share of employment in U.P. by non-farm sub-sector, 1993–94 to 2011–12

Non-farm sub-sector	Employment share (%)			Compound annual growth rate (%)
	50th round 1993–94	61st round 2004–05	68th round 2011–12	
Mining and quarrying	0.9	0.7	1.1	0.8
Manufacturing	32.0	32.5	21.9	-2.2
Electricity, gas, and water supply	0.6	0.3	0.5	-1.8
Construction	10.9	20.7	42.8	8.4
Wholesale and retail trade	20.3	22.2	14.4	-2.0
Hotels and restaurants	1.5	1.5	1.7	0.6
Transport, storage, and communication	8.1	8.4	6.6	-1.1
Financial intermediation	0.4	0.4	0.5	1.1
Real estate, renting, and other business activities	0.5	1.1	0.3	-3.9
Public administration and defence	5.1	2.0	1.3	-7.9
Education	4.5	4.4	4.3	-0.3
Health and social services	2.4	1.4	0.6	-7.3
Other services activities	12.7	4.4	4.1	-6.4
Total	100.0	100.0	100.0	

Source: Authors' calculations based on NSSO data

largest share (32.5%) and the supply of electricity, gas, and water the lowest (0.3%). In 2011–12, construction represented the highest share of RNFE (42.8%) and real estate the lowest (0.3%).

Interestingly, the construction subsector recorded the largest overall positive change in its share of employment (8.4%). The largest decline occurred in public administration and defence (–7.9%). Overall, construction superseded manufacturing as a generator of RNFE. This may imply a deterioration in household skills, given that manufacturing can require specialized knowledge and skills. On the other hand, construction work (manual labour) in rural areas tends not to require specialized skills. This shift may also be attributable to the generation of employment through MGNREGA (Panda 2017).

Determinants of non-farm diversification and its impact on household expenditure

This section discusses the determinants of RNFE in UP and its impact on household expenditure.

Determinants of non-farm employment

Table 5 presents the results of the first stage of the 2SLS-IV regression, run on a total of 46,926 observations. The model simulates relationships among various forms of RNFE [RNFE (SE), RNFE (REG) RNFE (CAS), and RNFE (ALL)], and various household-level and location-specific factors, that determine household livelihood choices. All models include regional fixed effects, and the standard errors are robust and clustered at the village level. The results of the OLS regression are presented in Table A1 in the appendix.

The coefficient of age is positive and significant across all the models, but the coefficients for age squared are negative, implying that as a person ages, their efficiency decreases, as does their probability of employment. This result corroborates the findings reported in El-Osta and Morehart (2008) for the US and in Adeoti (2014) and Adeoye et al. (2019) for Nigeria.

The coefficient of household size is positive and significant for both RNFE (SE) and RNFE (ALL), indicating that as household size increases, so does the level of RNFE income from self-employment. On the other hand, the coefficient for household size is negative and significant for both RNFE (REG) and RNFE (CAS), indicating that increased household size is associated with lower income from salaried and casual employment.

Table 5 First-stage IV regression on the impact of RNFE on household expenditure

Dependent variable (RNFE = 1, otherwise =0)	First-stage regression coefficients			
	RNFE (SE)	RNFE (REG)	RNFE (CAS)	RNFE (ALL)
Age	0.006***	0.005***	0.001**	0.012***
	(0.001)	(–0.001)	(–0.001)	(0.001)
Age square	0.001***	–0.001***	–0.001***	–0.001***
	(–0.001)	(–0.001)	(–0.001)	(–0.001)
Household size	0.006***	–0.001*	–0.003***	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Household size square	–0.001	0.001	0.001***	0.001
	(–0.001)	(–0.001)	(–0.001)	(–0.001)
Land category (Base = Landless)				
Marginal	0.072***	–0.031***	–0.091***	–0.201***
	(0.010)	(0.006)	(0.008)	(0.010)
Small	0.178***	–0.043***	–0.141***	–0.377***
	(0.011)	(0.006)	(0.008)	(0.011)
Medium	0.208***	–0.054***	–0.146***	–0.425***
	–0.011	(0.006)	(0.008)	(0.012)
Large	0.233***	–0.064***	–0.137***	–0.452***
	(0.012)	(0.007)	(0.008)	(0.013)
Gender (Base = Male)				
Female	0.103***	–0.009***	–0.104***	–0.217***
	(0.005)	(0.002)	(0.004)	(0.006)
Education (Base = Illiterate)				
Primary	0.044***	0.027***	–0.013***	0.061***
	(0.005)	(0.002)	(0.004)	(0.006)
Middle	0.033***	0.042***	–0.028***	0.050***
	(0.006)	(0.003)	(0.004)	(0.007)
Secondary	0.026***	0.146***	–0.072***	0.105***
	(0.005)	(0.005)	(0.004)	(0.007)
Caste (Base = General and other)				
Scheduled castes or scheduled tribes	0.064***	–0.003	0.058***	–0.010*
	(0.005)	(0.002)	(0.004)	(0.006)
Instrumental variables				
Share of households engaged in RNFE(SE)	0.009***	–	–	–
	(–0.001)	–	–	–
Share of households engaged in RNFE(REG)	–	0.009***	–	–
	–	(–0.001)	–	–
Share of households engaged in RNFE(CAS)	–	–	0.009***	–
	–	–	(–0.001)	–
Share of households engaged in RNFE(ALL)	–	–	–	0.008***
	–	–	–	(–0.001)
Regional and year effect	Yes	Yes	Yes	Yes
Constant	0.006	–0.078***	0.172***	0.136***
	(0.016)	(0.009)	(0.011)	(0.017)
Observations	46,926	46,926	46,926	46,926
R-squared	0.195	0.170	0.226	0.287
Hausman Test (F-value)	20.20	63.25	100.98	136.94
Hausman Test (p-value)	0.001	0.001	0.001	0.001

Source: Authors' estimates; Robust errors are shown in parentheses; ***, **, * denote significance at the 1%, 5% and 10% levels, respectively; SE = self-employment, REG = salaried/wage-based employment, and CAS = casual employment.

Being female is positively associated with self-employment and negatively associated with salaried and casual employment. On the whole, results indicate that women are less likely to engage in RNFE, which is consistent with a study on UP by Mishra and Singh (2019).

Education, one of the most important factors in non-farm employment, is significant for all the four types of RNFE: self-employed, waged and salaried, casual, and the combination of the three types (all). The primary, middle, and secondary levels of education are positively associated with self-employment and salaried employment but negatively associated with casual employment. Scheduled Caste (SC) or Scheduled Tribe (ST) households are more likely to be self-employed or casually employed than to undertake salaried or wage-based employment.

In UP, landholding size is a major determinant of the pattern of RNFE; the coefficient for marginal, small, medium-size, and large landholdings is positive and significant for self-employment and negative and significant for salaried employment and casual employment. Overall, landholding size is negatively correlated with RNFE, which is consistent with results reported in Seng (2015) for Cambodia and Do et al. (2019) for Cambodia.

Impact of RNFE on household income

The results of the second stage of the 2SLS-IV regression highlight the effect of RNFE on household income (Table 6). We took household MPCE as a proxy for income levels to analyse this effect; to neutralize the impact of inflation, we converted the MPCE of different years to constant prices using 1993–94 as the base year.

The results were obtained by taking regional fixed effects; and standard errors are robust and clustered at the village level. The results show that the coefficients of self-employment, salaried–wage-based employment, casual employment, and total non-farm employment are positive and significant for MPCE. A unit rise in self-employed, regular waged and salaried, and casually employed households would raise their income, respectively, by 17%, 64%, and 43%.

Education determines a household's human capital and affects income levels. All categories of education have a positive and significant effect on income levels, which increase with an increase in education levels, which is consistent with findings of Al-Amin and Hossain (2019) for Bangladesh and Anang and Yeboah (2019) for Ghana. Age has a positive and significant impact on income levels.

The greater the age of household members, the higher the likelihood of higher income levels from RNFE. The size of landholdings also has a positive and significant impact on income levels across all four employment categories. Notably, as the size of landholdings and education levels increase, the level of income also increases for each category of RNFE. Caste has a significant impact on household income levels from RNFE. Unsurprisingly, SC and ST households earn less through RNFE than households from other social groups.

The role of rural non-farm diversification in reducing poverty

This section examines how non-farm employment affected household poverty over the study period. Poverty can be defined as a condition or state in which a household lacks the financial resources to obtain a minimum standard of living, and the income from employment is too low to fulfil the basic human needs. We calculate the difference between household income and the benchmarked minimum income level to determine the poverty level; to examine how it is affected by non-farm diversification, we use the GPSM and DRF algorithms to check for impact and robustness.

To test for the balance between the control and treatment groups, we divide the sample into three groups based on the distribution of the share of working members engaged in RNFE. Group 1 consists of sample households with less than 25% of their members engaged in RNFE; the corresponding percentages are 25–50% in Group 2 and more than 50% in Group 3.

Figure 1 presents the distributions of generalized propensity scores (GPS) within each group and compares the distributions. The distributions overlap—a condition necessary to satisfy the common support condition. Table A2 details the results for the GPS. The results show that age and household size have a positive and significant impact on the treatment variable. A unit rise in age will increase participation in RNFE 0.11 times; a unit rise in household size will increase it 0.58

Table 6 Second-stage IV regression on the impact of RNFE on household expenditure

Dependent variable (log MPCE)	Second-stage regression coefficients			
	RNFE (SE)	RNFE (REG)	RNFE (CAS)	RNFE (ALL)
RNFE (SE = 1, Other = 0)	0.173***	–	–	–
	(0.036)	–	–	–
RNFE (REG = 1, Other = 0)	–	0.642***	–	–
	–	(0.068)	–	–
RNFE (CAS = 1, Other = 0)	–	–	0.432***	–
	–	–	(0.052)	–
RNFE (ALL = 1, Other = 0)	–	–	–	0.393***
	–	–	–	(0.033)
Age	–0.001	–0.003***	–0.001	–0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Age square	0.001***	0.001***	0.001***	0.001***
	–0.001	–0.001	–0.001	–0.001
Household size	–0.081***	–0.079***	–0.079***	–0.082***
	(0.007)	(0.006)	(0.007)	(0.007)
Household size square	0.002***	0.002***	0.002***	0.002***
	–0.001	–0.001	–0.001	–0.001
Land (Base = Landless)				
Marginal	0.070***	0.085***	0.103***	0.158***
	(0.014)	(0.014)	(0.016)	(0.016)
Small	0.225***	0.228***	0.262***	0.381***
	(0.018)	(0.017)	(0.019)	(0.022)
Medium	0.379***	0.384***	0.411***	0.554***
	(0.021)	(0.019)	(0.021)	(0.024)
Large	0.500***	0.510***	0.525***	0.688***
	(0.026)	(0.024)	(0.025)	(0.029)
Gender (base = male)				
Female	0.066***	0.054***	0.096***	0.136***
	(0.007)	(0.006)	(0.008)	(0.010)
Education (base = illiterate)				
Primary	0.099***	0.086***	0.112***	0.073***
	(0.007)	(0.007)	(0.007)	(0.007)
Middle	0.177***	0.146***	0.193***	0.150***
	(0.008)	(0.009)	(0.009)	(0.009)
Secondary	0.338***	0.228***	0.371***	0.280***
	(0.010)	(0.014)	(0.011)	(0.011)
Caste (base = General and Other)				
Scheduled Castes or Scheduled Tribes	–0.117***	–0.129***	–0.165***	–0.123***
	(0.009)	(0.009)	(0.010)	(0.009)
Regional and year effect	Yes	Yes	Yes	Yes
Constant	5.868***	5.919***	5.793***	5.725***
	(0.037)	(0.035)	(0.038)	(0.039)
Observations	46,926	46,926	46,926	46,926
R-squared	0.251	0.216	0.204	0.178

Source: Authors' estimates; Robust errors are shown in parentheses; ***, **, * denote significance level at the 1%, 5% and 10% levels, respectively; SE = self-employment, REG = salaried/wage-based employment, and CAS = casual employment.

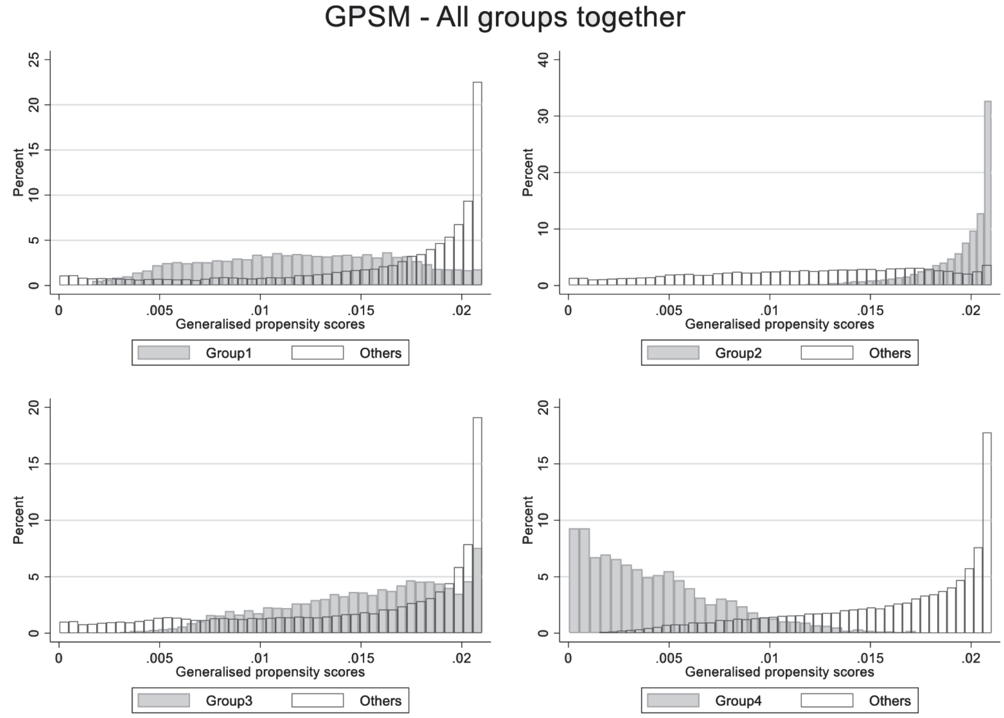

Figure 1 Common support condition
Source Authors' estimations

times. Contradictorily, age square (–0.001) and household square (–0.017) have a negative and significant effect on the treatment levels.

Land owned categories have a diminishing and significant impact on the participation levels, indicating that higher the land size owned, lower the participation. Females also have a negative and significant impact on the treatments; a rise in the number of female-headed households will decrease treatment level by 0.98 units. Education plays a positive and significant role in determining the treatment level; higher the household's education level, higher the participation in the non-farm sector. Lastly, SC and ST households have a negative and significant impact on the treatment levels ("1.984). The constant terms in Equations 1 and 2 are significant.

Next, to estimate the conditional expectation of outcomes given the treatment and propensity scores, we regress the outcomes Y_i (poverty gap) on the share of non-farm employment (T_i) and the propensity scores (R_{-i}). We have included the second-order moments of treatment and scores and the interaction of T_i and R_i as explanatory variables. Figures 2–4 depict DRF and treatment functions of non-farm diversification on the poverty gap for sample households in the 50th, 61st, and 68th NSSO rounds—obtained using the bootstrapping technique.

The poverty gap among households falls initially but starts to rise over time. The DRF for the 1993–94 shows that as the treatment level increases, the poverty gap widens in rural UP (Figure 2, Table A3)—indicating that larger the number of people working in the farm sector, the prevalence of poverty rises. In the late 20th century, people were not aware of non-farm employment opportunities and they were restricted to agricultural activities. Also, many rural households are illiterate. Agriculture provides seasonal employment, for about half the year; so, a large share of the rural population is unemployed for nearly half the year, and the poverty gap widens for poor households.

Over time, rural households, along with the government, began exploring other means of earning their livelihoods, and non-farm employment practices developed—leading to an increase in RNFE and rural earnings and, indirectly, to a reduction in poverty. The DRF for the 61st survey round (2004–05) shows that the poverty gap shrinks as the level of treatment increases (Figure 3, Table A3. The DRF for the 68th

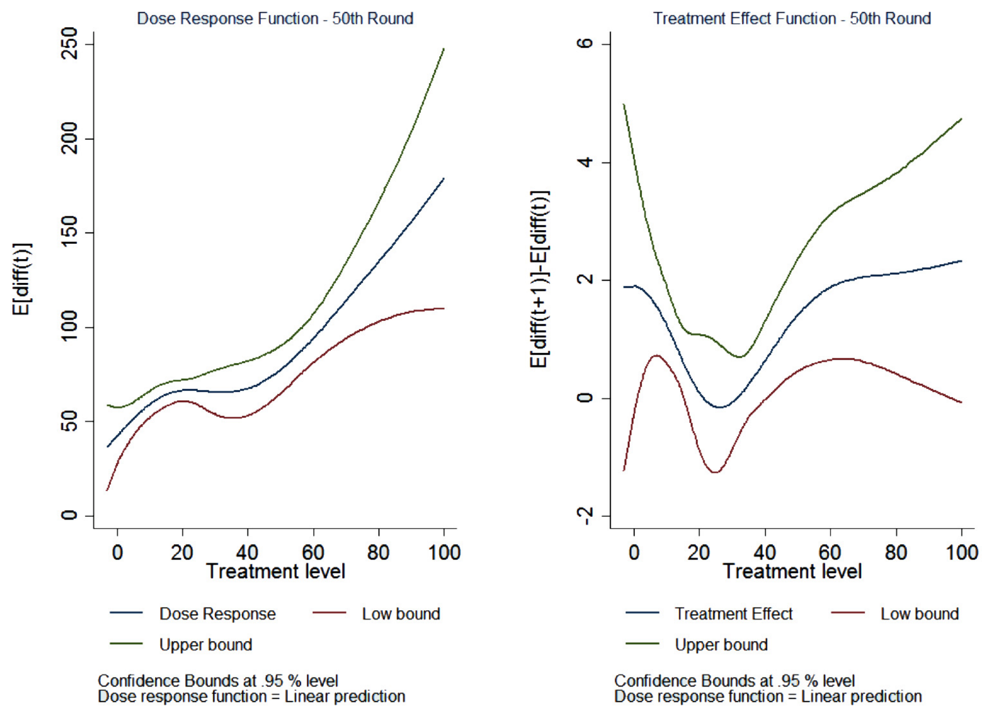

Figure 2 DRF and marginal treatment function of rural non-farm diversification on the poverty gap for sample households in the 50th survey round, 1993/94
Source Authors' estimations.

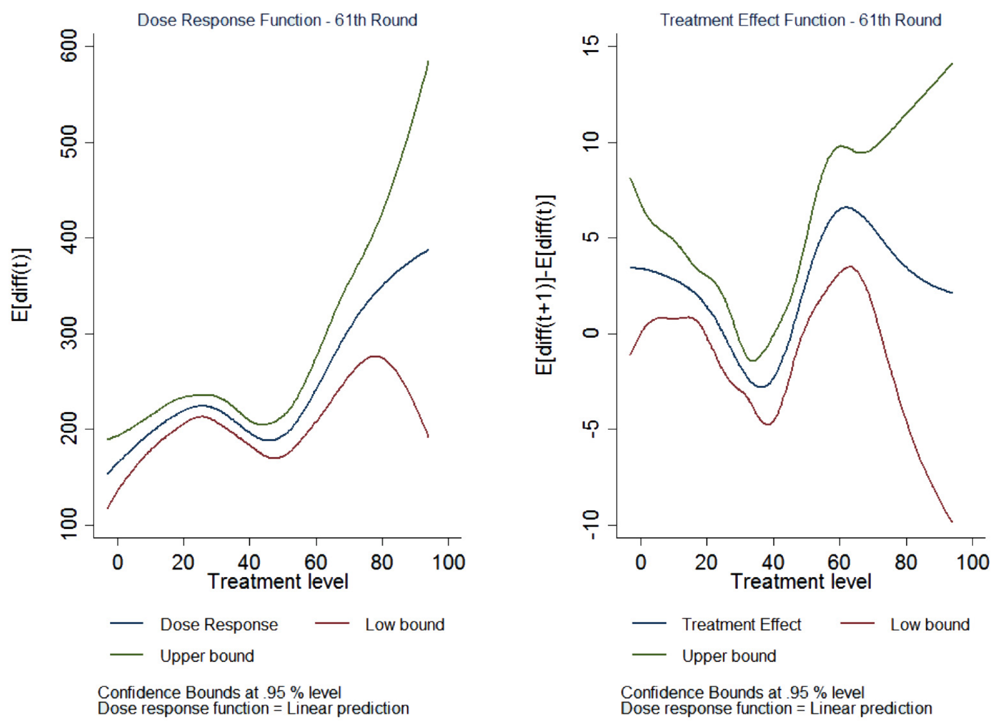

Figure 3 DRF and marginal treatment function of rural non-farm diversification on the poverty gap for sample households in the 61st survey round, 2004/05
Source Authors' estimations

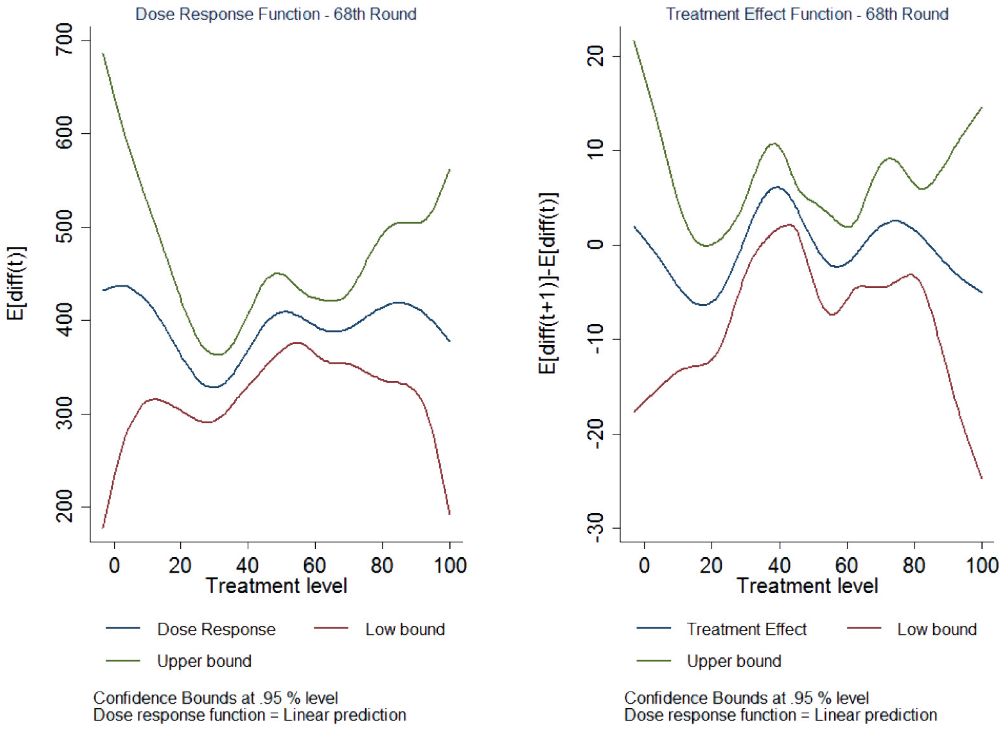

Figure 4 DRF and marginal treatment function of rural non-farm diversification on the poverty gap for sample households in 68th survey round, 2011/12
Source Authors' estimations

survey round (2011–12) illustrates a steep decline in the poverty gap (Figure 4, Table A3). Non-farm employment increased over the years and poverty levels diminished; Thus, engagement in RNFE is positively associated with reducing poverty among rural households in UP.

The normality conditions for all the three rounds are satisfied at a level less than 0.01 which is a good sign of balancing test. The treatment coefficient is positive and significant for all the three years; poverty has fallen and employment diversification improved.

Conclusion and policy recommendations

This study analysed changes in the employment profile of the rural population of UP from the mid-1990s to the early 2000s, based on the 50th, 61st, and 68th NSSO rounds on employment/unemployment conducted by Government of India. The results indicate a clear, significant shift from the farm sector to the non-farm sector.

Secondly, we modelled general employment trends on the basis of household expenditure levels and landholdings. The results indicate a distinct reduction in employment in the crop sector; substantial increases in RNFE and in employment in the livestock and other farm sectors; and a decline in employment in the crop sector across all categories of farm size. The results for the livestock and other farm sectors were mixed, while the results for the non-farm sector are positive, especially for households with only marginal landholdings.

The broad trends mark a structural shift in the economy—characterized by disengagement in agriculture and allied activities, particularly by new entrants in the workforce, in favour of employment in the non-farm sector (Parappurathu et al. 2015). The regional pattern of employment indicates that the greatest shift in RNFE occurred in southern UP (4.3%) and the least in eastern UP (3.4%). Construction had a 43% share of RNFE and manufacturing 22%.

To analyse the key determinants of non-farm diversification and its impact on household expenditure, we used a 2SLS-IV regression technique. The first stage of regression identified the determinants of non-farm diversification: age, gender, landholdings, education, and are significant and negatively impact RNFE overall, while family size and technical education have a positive effect overall. The second stage regression results indicate that RNFE has a positive impact on household-level MPCE. Households involved in regular wage and salary occupations are the most well off, followed by those engaged in casual and self-employed activities.

We used the generalized propensity score matching technique to check for the robustness of the findings of the IV regression along with examining whether RNFE diversification led to significant reduction in household poverty or not. We used the dose response function and treatment effect function to validate the results, indicating that as more households engage in RNFE, the poverty gap diminishes. The results of the dose response function shows that initially, in 1993–94, the poverty levels were increasing with increasing treatment levels, but with more awareness and literacy over the years, the poverty levels decreased with diversification of employment. It can therefore be concluded that increased participation in RNFE leads to increased rural household incomes and a reduction in rural poverty.

The non-farm sector is gaining momentum in rural UP, and policy measures are needed to support further progress. The non-farm sector is characterized by skilled labour; therefore, the rural youth need traditional education and specific vocational training. Self-employment and casual employment are less secure livelihood choices compared with salaried/wage-based employment, especially in terms of social security; social security coverage should be introduced to encourage these types of employment among rural households. Joint efforts should be made by government, educational institutions, local rural governments), and NGOs to raise awareness of RNFE opportunities among rural youth and to motivate their engagement to increase income levels and overall well-being (Ghuman 2005). A recent initiative by the Government of India to double farmers' incomes also focuses on diversifying employment to the non-farm sector.

Employment in the rural manufacturing subsector has declined over time; and steps need be taken to promote village-level manufacturing. Cottage and small-scale industries, mainly related to agro-processing, can be encouraged; these can have direct linkages to the agricultural sector. This strategy has the potential to increase employment in both the primary and secondary sectors, ultimately increasing household income levels. Promoting crop diversification—if supported by extensive infrastructure, financial and technological support, and so on—could be a socially beneficial policy for localized micro-enterprises engaged in post-harvest activities, such as packaging, processing, storing, and grading (Chakrabarti and Kundu 2009). Special assistance should be provided to organizing marketing networks to boost the non-farm and service sectors simultaneously utilizing indigenous resources.

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Table A1 Ordinary least square (OLS) estimates

Dependent variable (log MPCE)	Ordinary Least Square (OLS) results			
	RNFE (SE)	RNFE (REG)	RNFE (CAS)	RNFE (ALL)
RNFE (SE = 1, Others = 0)	0.029***	–	–	–
	(0.007)	–	–	–
RNFE (REG = 1, Others = 0)	–	0.146***	–	–
	–	(0.011)	–	–
RNFE (CAS = 1, Others = 0)	–	–	–0.031***	–
	–	–	(0.010)	–
RNFE (ALL = 1, Others = 0)	–	–	–	0.053***
	–	–	–	(0.006)
Age	0.001	–0.001	0.001	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
Household size	–0.080***	–0.080***	–0.080***	–0.080***
	(0.007)	(0.007)	(0.007)	(0.007)
Household size squared	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Land category (base = landless)				
Marginal	0.055***	0.059***	0.048***	0.066***
	(0.014)	(0.013)	(0.014)	(0.014)
Small	0.189***	0.192***	0.176***	0.209***
	(0.016)	(0.016)	(0.016)	(0.016)
Medium	0.337***	0.341***	0.322***	0.358***
	(0.019)	(0.018)	(0.019)	(0.019)
Large	0.452***	0.458***	0.437***	0.476***
	(0.024)	(0.024)	(0.024)	(0.024)
Gender (Base = Male)				
Female	0.051***	0.049***	0.045***	0.060***
	(0.006)	(0.006)	(0.006)	(0.006)
Education (Base = Illiterate)				
Primary	0.108***	0.104***	0.109***	0.105***
	(0.007)	(0.007)	(0.007)	(0.007)
Middle	0.183***	0.176***	0.184***	0.180***
	(0.008)	(0.008)	(0.008)	(0.008)
Secondary	0.344***	0.319***	0.344***	0.337***
	(0.010)	(0.010)	(0.010)	(0.010)
Caste (Base = General and other)				
Scheduled castes or scheduled tribes	–0.131***	–0.132***	–0.131***	–0.132***
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	5.900***	5.909***	5.914***	5.882***
	(0.035)	(0.035)	(0.036)	(0.035)
Observations	46,926	46,926	46,926	46,926
R-squared	0.264	0.268	0.264	0.265

Source: Authors' estimate; Robust errors are shown in parenthesis; errors are clustered at village level; ***, **, * denote significance at the 1%, 5% and 10% levels, respectively; SE = self-employment, REG = salaried/wage-based employment, and CAS = casual employment.

Table A2 Generalised propensity score (GPS) matching estimates

Independent variables	GPS estimate
Age	0.105***
	(0.028)
Age squared	–0.001*
	(0.000)
Household size	0.580***
	(0.058)
Household size squared	–0.017***
	(0.002)
Land category (Base = Landless)	
Marginal	–9.153***
	(0.361)
Small	–17.148***
	(0.420)
Medium	–19.718***
	(0.455)
Large	–22.672***
	(0.501)
Gender (Base = Male)	
Female	–0.983***
	(0.216)
Education (Base = Illiterate)	
Primary	4.217***
	(0.253)
Middle	5.414***
	(0.284)
Secondary	8.552***
	(0.262)
Caste (Base = General)	
Schedule castes and schedule tribes	–1.984***
	(0.213)
Constant	36.626***
	(0.694)
Observations	46,926

Source: Authors' estimates, Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3 Dose Response Function (DRF) estimates of poverty level

Variables	50th round (1993 – 94)	61st round (2004 – 05)	68th round (2011 – 12)
Treatment	1.451*	4.055***	3.626*
	(0.848)	(1.212)	(3.447)
Treatment square	0.012	–0.030**	-0.034
	(0.010)	(0.015)	(0.034)
Propensity score	9,819.705***	1,417.906	-7,981.169
	(3,355.616)	(2,603.793)	(6,712.662)
Propensity score square	–112,130.831	78,376.889	355,994.270*
	(97,328.493)	(69,919.434)	(183,846.513)
Treatment × propensity score	–147.630***	–144.311***	-89.247*
	(34.884)	(24.142)	(54.205)
Constant	–58.697**	–212.191***	-436.420***
	(27.446)	(18.465)	(56.343)
Observations	18,954	16,977	11,038

Source: Authors' estimates, Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$