Reducing Rural Poverty Through Non-farm Job Creation in India

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Abstract
Based on secondary data, this paper estimates the incidence of poverty by sectoral employment status of individuals and it explores the factors determining individual’s joint probabilities of being poor and being engaged in the non-farm sector jobs (at micro-level). It also finds the impact (at macro-level) of rural non-farm sector employment on the incidence of rural poverty, and it identifies the subsectors of the non-farm sector, which help reduce the incidence of rural poverty in India. Using bivariate probit, recursive bivariate probit regression models, it finds that individual’s human capabilities owing to better education and training and higher occupations of their head of the family significantly determine their probability of being employed in the non-farm sectors, which in turn help reduce their chance of being poor. The panel system generalized methods of moment result suggest that the provincial states of India, which have achieved higher level of non-farm sector NSDP growth along with the creation of jobs through an improved level of infrastructure (roads, railways, banking, and industries) base, have succeeded to reduce the incidence of rural poverty to substantially low levels. Based on these findings, it is argued that the incidence of rural poverty can be reduced on a sustainable basis through the development of rural manufacturing, and by promoting growth of modern service sectors like education, health, communication, real estate, and finance and insurance, along with the infrastructural development.

Keywords Non-farm employment · Income poverty · Bi-variate probit regression · India

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1 Introduction

In India, the incidence of poverty reduced substantially with a fall in absolute number of poor during 2004–2005 and 2011–2012 (Chauhan et al. 2016; Mehrotra et al. 2014; Planning Commission 2013). During this period, Indian economy had also experienced a phase of structural transformation in employment, in which both the share and number of workers in non-farm sectors increased (about 7.5 million per annum increase) with corresponding decline (about 5 million per annum decline) of jobs in the agriculture and allied sectors (Himanshu 2011; Kannan and Raveendran 2019; Mehrotra et al. 2014; Mehrotra and Parida 2019, 2021). Both the reduction in number of poor and the decline of agricultural workforce were unprecedented trends in India. Hence, it is important to know whether there exists any connectivity between growth of non-farm sector jobs and income poverty reduction in rural India. This is an important question, because not only a major share (about 65% and 0.9 billion, as per the World Bank data, 2019) of Indian population live rural areas, but also most of them (about 58%, as per 2018–2019 PLFS data) still earn their livelihood1 from agriculture and allied sectors. This is perhaps one of the main reasons, for a relatively higher incidence of poverty in rural areas as compared to the urban neighbourhoods in India (Planning Commission 2013).

Moreover, mechanization in agriculture is growing rapidly since 2004–2005, for which the landless and marginalized poor are losing their jobs in agriculture, and both educated youth unemployment (Bairagya 2018; Mitra 2019; Mehrotra and Parida 2019, 2021) and the size of discourage labour force are at the rise due to rising mean years of schooling (Mehrotra and Parida 2019, 2021); a relatively slow growth of non-farm sector jobs during the post 2011–2012 periods (Mehrotra and Parida 2021) should be a matter of great concern, because it has implications on the likely increase in the incidence and depth of rural poverty in India.

A review of cross-country studies like Nassar and Biltagy (2017) in Egypt; Awoniyi and Salman (2011) in Nigeria; Ersado (2006) in Zimbabwe; Hoang et al. (2014) and Imai et al. (2015) in Vietnam; Owusu et al (2011) and Zereyesus et al. (2017) in Ghana; Arif et al. (2000) in Pakistan; Woldehanna and Zerifu (2002) in Ethiopia; and Hossain and Al-Amin (2019) in Bangladesh has argued that development of non-farm sector has greater potential to reduce poverty in rural areas. But according to Haggblade et al. (2010), although rural non-farm employment is a potential pathway out of poverty for rural poor, it does not happen automatically. For this to happen, policy makers must stimulate buoyant rural economies, with robust non-farm income growth along with productive non-farm employment opportunities in rural areas.

In India, earlier studies like Lal (1976), Ahluwalia (1978), Omvedt (1981), Dev (1988), Ghosh (1996), Ghosh (2002), and Mehta and Shah (2003) have noted that predominance of agriculture, agricultural backwardness, and low labour

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1 This fact is clearly revealed during the COVID-19 lockdown periods, as a large number of return or reverse migrants (low skilled) are found working in agriculture and allied activities (as per PLFS, 2019–2020 data).
productivity were among the major reasons for the high incidence of poverty in India during 1980s. Hence, an increased labour productivity during the 1990s due to technological advancement in agriculture and rising agriculture wages caused a substantial reduction in the incidence of poverty in rural India (Singh and Pandey 1990; Datt and Ravallion 1998; Sundaram 2001; Sen and Himanshu 2004). But according to Unni (1998), Jayaraman and Lanjouw (1999), Lanjouw (1999), Lanjouw and Shariff (2004), Pradhan (2006), Sundaram (2007), Lanjouw and Murgai (2009a, b), Jha et al. (2009), Himanshu et al. (2013), andBinswanger-Mkhize (2013), non-farm sector could play a crucial role in the process of rural poverty reduction in India. Because the wages/earnings levels in non-agriculture activities are often higher than agriculture wages and earnings, rural non-farm sector employment growth is expected to have positive impact on both real wages and aggregate consumption in rural India (Islam 1987; Saith 1992; Papola 1992; Chadha 1993; Bhalla 1998; Mehrotra et al. 2014). But in India, there is a limited number of studies, which estimates incidence of poverty by the sectoral employment status of individuals.

Hence, the main objectives of this paper are: (1) to estimate the poverty head count ratio by sectoral employment status of individuals; (2) to explore the individual- and family-level factors that determine individual’s probabilities of being poor and being engaged in the non-farm sector jobs simultaneously; (3) to find out the impact (at macro-level) of rural non-farm sector employment on the incidence of rural poverty; and (4) to identify the subsectors of the non-farm sector which help reduce the incidence of rural poverty in India.

This paper is organized in four sections. Section two provides the sources of data and outlines the methodology of poverty estimation. It also describes the variables and explains the econometric models used in the estimation of both micro- and macro-level factors determining rural poverty in India. Section three provides the major findings of the paper. It has three subsections. While subsection one of section three provides a comparative picture of incidence and depth of poverty in rural India, the subsection two examines the impact of non-farm employment on poverty by exploring both micro- and macro-level factors determining the incidence of rural poverty. Subsection three of section three, on the other hand, identifies the subsectors of rural non-farm sector, which help reduce the incidence of rural poverty. Section four concludes the paper along with the policy suggestions.

2 On Data and Methods

2.1 Sources of Data and Variable Descriptions

This paper is based on secondary data. The Employment and Unemployment Surveys (EUS) of the National Sample Survey Organization (NSSO) conducted during 2004–2005 (61st round) and 2011–2012 (68th round) and the annual Periodic Labour Force Survey (PLFS) conducted during 2018–2019 are used. For estimating employment status of individuals, their Usual Principal and Subsidiary Status (UPSS) is considered. To obtain the absolute number of workers, the Census
projected\footnote{Report (2020) of the Technical Group on Population Projections, National Commission on Population\textit{Ministry of Health & Family Welfare, Nirman Bhawan, New Delhi, 110011.}} population for the survey specific years are adjusted with the NSS estimates. For calculating sub-sectoral employment, the National Industrial Classification (NIC) Codes (with due concordances for the years 1998 and 2008) are used. The National Occupational Code (NCO) 2004 is used to find out the occupations in which individuals are engaged during the surveys. Individual-level information including: age, sex, level of education (within general education), type of education (general, technical, or vocational), marital status, sector of employment, occupations, and earnings, is obtained from the unit-level data of EUS and PLFS data. These surveys also provide the family-level information like: family size, social group, religion, monthly household expenditure, etc., while both individual- and family-level information is used as control variables and instruments in the micro-level estimation of determinants of poverty and non-farm employment. The percentage of people living below the poverty line (BPL) is estimated using the monthly per capita household expenditure (MPCE).

Moreover, the macro-level variables (collected at the state level from the “Handbook of Statistics on Indian States”—Reserve Bank of India (RBI)) including: Net State Domestic Product (NSDP) for the non-farm sector, Gross Fixed Capital Formation (GFCF) as a proxy for investment, dependency ratio (ratio of elderly (60 years and above) and children (below 15 years) to total population), number of factories/industries, number of branches of Scheduled Commercial Banks, length of states roads (in KMs), length of highways (in KMs), length of railways routes (in KMs), number of schools (Govt. and Private), etc., are used as control variables in the macro-level estimation.

### 2.2 On Estimating Poverty

The Poverty Head Count Ratio (PHCR) or the percentage of people living below the poverty line (BPL) is estimated using the monthly per capita household expenditure (MPCE) information using from the EUS and PLFS data, instead of the Consumption Expenditure Survey (CES). This is done because it enables us to compute PHCR by sector of employment (farm and non-farm sectors) of the individuals, which is not possible through the use of CES data. Although the recent CES survey conducted by NSSO (during 2017–2018) could have been used for the aggregate (macro-level modelling)-level analysis, had it been available in the public domain.

For estimating PHCR, the Tendulkar poverty line is used (see Table 1). The minimum threshold MPCE level as computed by the Planning Commission (for the years 2004–2005 and 2011–2012) is utilized. Moreover, the threshold poverty line for the year 2018–2019 is calculated with due adjustment of the 2011–2012 poverty line with the “Consumer Price Index (CPI) of the Rural Labour for the year 2018–2019” (see Table 1).

It is important to note that the results of PHCR calculated from EUS are either slightly over/under-estimated in some states (about 5–7 percentage points in both
| Name of the states       | Rural poverty line as per Tendulkar methodology (MPCE in Rs) | % of BPL as per based on CES data (Planning commission) | % of BPL as per the estimation based on EUS and PLFS data |
|-------------------------|---------------------------------------------------------------|-----------------------------------------------------------|----------------------------------------------------------|
|                         | 2004–2005 2011–2012 2018–2019                                 | 2004–2005 2011–2012                                     | 2004–2005 2011–2012 2018–2019 |
| Andhra Pradesh          | 433.4 860 1221.1                                              | 32.3 11.0                                               | 35.9 16.2 11.6 |
| Arunachal Pradesh       | 547.1 930 1479.3                                              | 33.6 38.9                                               | 45.2 45.1 22.6 |
| Assam                   | 478.0 828 1195.6                                              | 36.4 33.9                                               | 40.7 34.7 21.7 |
| Bihar                   | 433.4 778 1113                                               | 55.7 34.1                                               | 57.5 42.2 45.2 |
| Goa                     | 608.8 1090 1645.3                                            | 28.1 6.8                                                | 44.9 13.1 4.1 |
| Gujarat                 | 501.6 932 1316.9                                              | 39.1 21.5                                               | 40.2 33.4 37.0 |
| Haryana                 | 529.4 1015 1399.9                                             | 24.8 11.6                                               | 28.2 14.6 21.4 |
| Himachal Pradesh        | 520.4 913 1259.8                                              | 25 8.5                                                  | 27.6 16.6 19.0 |
| Jammu and Kashmir       | 522.3 891 1350.8                                              | 14.1 11.5                                               | 21.0 21.4 30.6 |
| Karnataka               | 417.8 902 1310.6                                              | 37.5 24.5                                               | 42.3 31.8 38.1 |
| Kerala                  | 537.3 1018 1524.3                                             | 20.2 9.1                                                | 24.3 15.7 13.5 |
| Madhya Pradesh          | 408.4 771 1056.3                                              | 53.6 35.7                                               | 53.8 43.6 35.5 |
| Maharashtra             | 484.9 967 1387.2                                              | 47.9 24.2                                               | 51.2 34.1 47.9 |
| Manipur                 | 578.1 1118 1889                                              | 39.3 38.8                                               | 45.6 46.5 30.6 |
| Meghalaya               | 503.3 888 1239.4                                              | 14 12.5                                                 | 11.7 12.5 16.5 |
| Mizoram                 | 659.3 1066 1491.8                                             | 23 35.4                                                 | 30.0 36.0 39.3 |
| Nagaland                | 687.3 1270 2016.4                                             | 10 19.9                                                 | 7.6 23.1 35.7 |
| Odisha                  | 407.8 695 1001.6                                              | 60.8 35.7                                               | 66.9 38.8 46.6 |
| Punjab                  | 543.5 1054 1494.6                                             | 22.1 7.7                                                | 26.9 14.7 11.6 |
| Rajasthan               | 478.0 905 1286.5                                              | 35.8 16.1                                               | 39.1 27.0 34.4 |
| Sikkim                  | 531.5 930 1397.5                                              | 31.8 9.9                                                | 36.4 17.3 52.4 |
| Tamil Nadu              | 441.7 880 1283.6                                              | 37.5 15.8                                               | 39.3 24.8 13.4 |
Source: Poverty lines and estimates (based on CES data) for the years 2004–2005 and 2011–2012 are compiled from Planning Commission reports. But, poverty lines (2018–2019) and estimates based on EUS and PLFS data are authors' estimation.

| Name of the states | Rural poverty line as per Tendulkar methodology (MPCE in Rs) | % of BPL as per based on CES data (Planning commission) | % of BPL as per the estimation based on EUS and PLFS data |
|-------------------|-----------------------------------------------------------|---------------------------------------------------------|---------------------------------------------------------|
|                   | 2004–2005 | 2011–2012 | 2018–2019 | 2004–2005 | 2011–2012 | 2018–2019 |
| Tripura           | 450.5     | 798       | 1207.1   | 44.5      | 16.5      | 48.8      |
| Uttar Pradesh     | 435.1     | 768       | 1065.4   | 42.7      | 30.4      | 47.8      |
| West Bengal       | 445.4     | 783       | 1138.2   | 38.2      | 22.5      | 45.0      |
| Delhi             | 541.4     | 1145      | 1615.1   | 15.6      | 12.9      | 22.7      |
| Chhattisgarh      | 398.9     | 738       | 1049.3   | 55.1      | 44.6      | 55.7      |
| Jharkhand         | 404.8     | 748       | 1090.5   | 51.6      | 40.8      | 49.4      |
| Uttarakhand       | 486.2     | 880       | 1209     | 35.1      | 11.6      | 38.0      |
| All India         | 446.7     | 816       | 1165     | 42        | 25.7      | 45.3      |
2004–2005 and 2011–2012) as compared to the estimation based on CES data (see Table 1). Hence, a similar margin of difference is expected for the poverty estimates based on PLFS (2018–2019) data. However, these margin of differences in estimation do not really matter much for our analysis as we are making comparison of the employment–unemployment surveys only.

Moreover, to measure the depth of the poverty among both farm and non-farm workers we have computed the Poverty Gap Index (PGI) using the following formula:

\[
\text{PGI} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{Z_i - X_{ij}}{Z_i} \right)
\]

(1)

where \(N\) is the number of states, \(Z_i\) is the poverty line (value of MPCE), and \(X_{ij}\) is the average (mean) MPCE of the population living below the poverty line in state “\(i\)” and in the sector “\(j\)”. As per this definition, the value of PGI lies between 0 and 1. While PGI values close to zero are always desirable, PGI values close to one imply that the depth of poverty is severe.

2.3 Econometric Methodology

To find out the factors determining poverty and non-farm sector employment simultaneously at the micro-level, both bivariate probit (BP) and recursive bivariate probit (RBP) regression models are used. These models are suitable (see Filippini et al. 2018) for modelling two jointly determined binary variables (viz. poverty and non-farm sector employment). While the BP is a system of two seemingly unrelated probit equations, in which the correlation between the binary variables under analysis is captured by the conditional tetrachoric correlation of the error terms (see Greene, 2018), the RBP is a system of two probit equations that allow the errors terms to be correlated, and the binary dependent choice in one equation is to be used as an endogenous regressor in the other equation (Filippini et al. 2018). The formal derivation of RBP is given below:

\[
Y_1^* = X_1 \beta_1 + \varepsilon_1; \quad \{ Y_1 = 1 \text{ if } Y_1^* > 0; \text{ otherwise, } Y_1 = 0 \}
\]

(2)

\[
Y_2^* = X_2 \beta_2 + \alpha Y_1 + \varepsilon_2; \quad \{ Y_2 = 1 \text{ if } Y_2^* > 0; \text{ otherwise, } Y_2 = 0 \}
\]

(3)

with \([\varepsilon_1, \varepsilon_2] \sim \Phi((0, 0), (1, 1), r), r \in [-1, 1]\)

where \(Y_1^*\) and \(Y_2^*\) are latent continuous variables for which only the binary variables \(Y_1\) and \(Y_2\) are observable; \(X_1\) and \(X_2\) are vectors of exogenous variables; and \([\varepsilon_1, \varepsilon_2]\) is a vector of error terms described by \(\Phi\) (a bivariate standard normal distribution with correlation, \(r\)).

But in the absence of recursive structure in Eqs. (2) and (3), we will end up with the following BP structure:
\[ Y_1^* = X_1 \beta_1 + \varepsilon_1; \quad \{ Y_1 = 1 \text{ if } Y_1^* > 0; \text{ otherwise, } Y_1 = 0 \} \] (4)

\[ Y_2^* = X_2 \beta_2 + u_2; \quad \{ Y_2 = 1 \text{ if } Y_2^* > 0; \text{ otherwise, } Y_2 = 0 \} \] (5)

with \([\varepsilon_1, u_2] \sim \mathcal{N}((0, 0), (1, 1), \rho), \quad \rho \in [-1, 1]\)

where \(\rho\) is the correlation between \(\varepsilon_1\) and \(u_2\).

If the BP model is estimated (by mistake) on the data generated by RBP, then the true recursive component will be absorbed by the error term \(u_2\), which implies the fact that \(\rho\) is mechanically determined by \(r\) and \(\alpha\). That means:

\[
\rho = \text{corr}(\varepsilon_1, u_2) = \text{corr}(\varepsilon_1, \alpha Y_1 + \varepsilon_2)
\]

\[
= \frac{\text{cov}(\varepsilon_1, \alpha Y_1 + \varepsilon_2)}{\sqrt{\text{Var}(\varepsilon_1) \ast \text{Var}(\alpha Y_1 + \varepsilon_2)}}
\]

\[
= \frac{\sqrt{(1) \ast \text{Var}(\alpha Y_1 + \varepsilon_2)}}{\text{cov}(\varepsilon_1, \alpha Y_1) + r}
\]

\[
= \frac{\alpha \ast \text{cov}(\varepsilon_1, Y_1) + r}{\sqrt{\text{Var}(\alpha Y_1) + \text{var}(\varepsilon_2) + 2 \text{cov}(\varepsilon_2, \alpha Y_1)}}
\]

From Eq. (5), it is clear that in the absence of recursive structure (i.e. when \(\alpha = 0\) \()\rho = r\). That means the RBP will become BP. Furthermore, it is to be noted that \(\rho\) can plausibly take value zero, depending on the signs and relative magnitude of \(r\) and \(\alpha\). That means a BP model estimated on RBP data can potentially deliver a zero correlation parameter. This may be interpreted as the evidence of independence between \(Y_1\) and \(Y_2\) by mistake. Hence, estimation of both RBP and BP regression models for comparison is highly justified in our case (see Table 2).

Moreover, to examine the impact of non-farm sector employment on poverty at the macro-level, we have estimated dynamic panel data regression models. Since we have a short panel (number of cross sections (27 states\(^3\)) greater than number of years (15 years\(^4\)), system generalized method of moments (GMM) method of estimation (see Eq. 7) developed by Arellano and Bover (1995) and Blundell and Bond (1998) is preferred to pooled ordinary least square (OLS) regression model. This method of estimation not only produces unbiased and consistent estimators in the presence of potentially endogenous regressors, but it also overcomes the possible

\(^3\) Out of 29 states of India, two states, viz., Meghalaya and Sikkim, were excluded from the dynamic panel data regression modelling because of non-availability of data on the length of railway routes in these states.

\(^4\) From the year 2005 to 2019.
Table 2  Determinants of non-farm employment and poverty in rural India (bivariate probit regression)

| Variables                  | Bi-probit model |                      | Recursive Bi-probit model |                      |                      |
|----------------------------|-----------------|-----------------------|---------------------------|-----------------------|-----------------------|
|                            | Non-farm employment | BPL                  | Non-farm employment | BPL                  |                      |
|                            | Coefficient | Z-value  | dy/dx       | Coefficient | Z-value  | dy/dx       | Coefficient | Z-value  | dy/dx       | Coefficient | Z-value  | dy/dx       |
| Non-farm employment        | –           | –         | –           | –           | –         | –           | –           | –         | –           | –           | –         | –           |
| Age                       | 0.01        | 9.9***    | 0.005       | –0.01       | –13.4***  | –0.003      | –0.01       | 10.2***   | 0.003       | –0.0002    | –16***     | 0           |
| Age square                 | –0.00023    | –16.7***  | –0.0001     | 0.0001      | 4.8***    | 0           | –0.0002    | –16***    | 0           | –0.0002    | –16***     | 0           |
| Log daily wage predict     | 0.14        | 131***    | 0.036       | 0.07        | 69.5***   | 0.003       | 0.14       | 129.7***  | 0.03        | 0.09       | 70.6***    | 0.002       |
| Gender dummies (Reference category: male) |                  |                      |                      |                      |                      |
| Female                     | –0.57       | –97.3***  | –0.153      | –0.12       | –22.5***  | 0.014       | –0.54      | –90.1***  | –0.147      | 0.017      | 90***      | 0.013       |
| Household size             | –0.03       | –26.9***  | –0.015      | 0.08        | 106.1***  | 0.017       | –0.03      | –27.2***  | –0.016      | 0.07       | 90***      | 0.013       |
| Dependency ratio           | –            | –         | –           | –           | –         | –           | –0.03      | –2.9***   | –0.101      | 0.73       | 92.9***    | 0.146       |
| Social group dummies (Reference category: other social group) |                  |                      |                      |                      |                      |
| ST                         | –0.05       | –5.2***   | –0.08       | 0.64        | 80.6***   | 0.14        | –0.03      | –2.9***   | –0.101      | 0.73       | 92.9***    | 0.146       |
| SC                         | 0.12        | 15.4***   | –0.009      | 0.41        | 55.5***   | 0.071       | 0.14       | 17***     | –0.031      | 0.51       | 69.3***    | 0.076       |
| OBC                        | 0.13        | 19.4***   | 0.02        | 0.19        | 29.4***   | 0.025       | 0.13       | 20.3***   | 0.008       | 0.24       | 39.1***    | 0.028       |
| Religion dummies (Reference category: Hindu) |                  |                      |                      |                      |                      |
| Muslim                     | 0.19        | 16.6***   | 0.033       | 0.31        | 28.8***   | 0.041       | 0.19       | 17***     | 0.019       | 0.34       | 32.5***    | 0.037       |
| Christian                  | 0.54        | 38.7***   | 0.106       | 0.4         | 31.1***   | 0.022       | 0.55       | 39.7***   | 0.067       | 0.54       | 42.4***    | 0.03         |
| Other religion             | 0.18        | 12.2***   | 0.065       | –0.09       | –6.2***   | –0.027      | 0.17       | 11.6***   | 0.07        | 0.15       | –10.6***   | –0.033       |
| Marital status dummies (Reference category: unmarried) |                  |                      |                      |                      |                      |
| Currently married          | –0.08       | –9.8***   | –0.04       | 0.15        | 18.7***   | 0.032       | –0.09      | –10.6***  | –0.026      | –0.09      | –10.6***   | –0.026       |
| Divorced/Separated         | 0.16        | 10.5***   | 0.025       | 0.2         | 15***     | 0.025       | 0.14       | 9.7***    | 0.042       | 0.14       | 9.7***     | 0.042       |
| General level of education dummies (Reference category: illiterate) |                  |                      |                      |                      |                      |
| Primary                    | 0.22        | 34.8***   | 0.092       | –0.29       | –52.6***  | –0.066      | 0.25       | 39.8***   | 0.073       | 0.25       | 39.8***    | 0.073       |
| Secondary                  | 0.34        | 37.6***   | 0.149       | –0.44       | –51.9***  | –0.083      | 0.39       | 42.8***   | 0.118       | 0.39       | 42.8***    | 0.118       |
| Variables                                      | Bi-probit model | Recursive Bi-probit model |
|-----------------------------------------------|----------------|--------------------------|
|                                               | Non-farm employment | BPL         | Non-farm employment | BPL         |
|                                               | Coefficient | Z-value | dy/dx | Coefficient | Z-value | dy/dx | Coefficient | Z-value | dy/dx | Coefficient | Z-value | dy/dx |
| Higher secondary                             | 0.41        | 37.2*** | 0.184 | –0.54       | –49.4*** | –0.093 | 0.47        | 42.3*** | 0.146 | –          | –          | –      |
| Graduate and above                           | 0.74        | 56.9*** | 0.323 | –0.83       | –58.8*** | –0.122 | 0.82        | 62.4*** | 0.257 | –          | –          | –      |
| Technical education dummies (Reference category: no technical education) |             |         |       |             |         |       |             |         |       |             |         |       |
| TE below graduate                            | 0.19        | 7.4***  | 0.071 | –0.11       | –3.8***  | –0.031 | 0.19        | 7.5***  | 0.057 | –          | –          | –      |
| TE graduate and more                         | 0.33        | 7***    | 0.14  | –0.35       | –5.7***  | –0.068 | 0.34        | 7.3***  | 0.105 | –          | –          | –      |
| Vocational education dummies (Reference category: no vocational training or informal training) |             |         |       |             |         |       |             |         |       |             |         |       |
| Formal vocational training                   | 0.55        | 23.5*** | 0.202 | –0.21       | –8.1***  | –0.065 | 0.55        | 23.9*** | 0.173 | –          | –          | –      |
| Household head occupation dummies (Reference category: elementary occupations) |             |         |       |             |         |       |             |         |       |             |         |       |
| Administrative                                | 0.36        | 30.3*** | 0.133 | –0.17       | –13.1*** | –0.05  | 0.35        | 29.3*** | 0.132 | –0.17      | –13.1*** | –0.047 |
| Professional                                 | –0.00475    | –0.4    | 0.03  | –0.42       | –28.3*** | –0.063 | –0.03       | –2.7***  | 0.05  | –0.64      | –45.8*** | –0.071 |
| Clerical                                     | –0.05       | –1.8*   | 0.016 | –0.47       | –13.6*** | –0.066 | –0.08       | –2.5**   | 0.035 | –0.65      | –19.4*** | –0.069 |
| Sales worker                                 | 0.5         | 53.9*** | 0.177 | –0.15       | –16***   | –0.057 | 0.50        | 53.5*** | 0.171 | –0.11      | –10.8*** | –0.05  |
| Farming                                      | –1.74       | –308.5*** | –0.478 | 0.01        | 2.8***   | 0.113  | –1.73       | –308.5*** | –0.425 | –0.27      | –22.9*** | 0.086  |
| Region dummies (Reference category: north-east zone) |             |         |       |             |         |       |             |         |       |             |         |       |
| North zone                                   | 0.21        | 15.2*** | 0.091 | –0.3        | –24.9*** | –0.065 | 0.21        | 15.2*** | 0.094 | –0.27      | –22.9*** | –0.057 |
| East zone                                    | 0.24        | 16.9*** | 0.091 | –0.17       | –14.1*** | –0.045 | 0.24        | 16.8*** | 0.088 | –0.14      | –11.2*** | –0.038 |
| West zone                                    | 0.22        | 15.2*** | 0.078 | –0.09       | –7***    | –0.03  | 0.22        | 15.3*** | 0.074 | –0.06      | –4.5***  | –0.026 |
| South zone                                   | 0.17        | 11.4*** | 0.072 | –0.2        | –14.9*** | –0.043 | 0.17        | 11.5*** | 0.071 | –0.15      | –11.8*** | –0.035 |
| Central zone                                 | 0.07        | 4***    | 0.025 | –0.05       | –3.4***  | –0.013 | 0.07        | 4***    | 0.023 | –0.02      | –1.7*    | –0.009 |
| Constant                                     | –0.18       | –6.2*** | –      | –1.16       | –44.4*** | –      | –0.25       | –8.6***  | –      | –1.67      | –78.3*** | –      |
| Athrho                                       | –0.02914    | –8.2*** | –      | –      | –0      | –      | 0.278975    | 23.2***  | –      | –          | –          | –      |
| Variables          | Bi-probit model | Recursive Bi-probit model |
|--------------------|-----------------|---------------------------|
|                    | Non-farm employment | BPL                        |
|                    | Coefficient   | Z-value    | Coefficient   | Z-value    | Coefficient   | Z-value    |
| Rho                | -0.029         | 0.27       | 0.27          |            |              |            |
| Number of observation | 425,089      |            | 425,089       |            |              |            |
| Wald chi2(60)      | 201,156.2***  |            | 205,072.6***  |            |              |            |
| Log likelihood     | -364.078**    |            | -365.602      |            |              |            |
| chi2(1)            | 66.6***        |            | 555.0***      |            |              |            |

Source: Author's estimation using NSS unit level and Periodical Labour Force Survey (PLFS) data
***, **, and * imply statistical significance at 1%, 5%, and 10% levels, respectively.
heteroscedasticity and autocorrelation problems in the data. The formal derivation of system GMM equation can be shown through the OLS Eq. (6):

\[ Y_{st} = \alpha + \beta Y_{s,t-1} + \gamma X_{s,t} + \delta Z_{s,t} + \varepsilon_{s,t} \]  

where \( Y_{st} \) is the dependent variable (PHCR), \( Y_{s,t-1} \) is the first lag of the dependent variable, \( X_{s,t} \) is the set of exogenous, and \( Z_{s,t} \) is the set of endogenous variables. The subscripts \( s \) and \( t \) indicate the cross section (state) and time period, respectively. The stochastic disturbance term, \( \varepsilon_{st} = \theta_s + \theta_{st} \), has two important components, viz. fixed effects component (\( \theta_s \)) and the idiosyncratic shocks (\( \theta_{st} \)), which satisfies the following statistical conditions:

\[
E(\theta_s) = 0; \quad E(\theta_{st}) = 0; \quad E(\theta_s \theta_{st}) = 0;
\]

\[
E(\theta_{st} \theta_{sk}) = 0; \quad E(Y_{s1} \theta_{st}) = 0; \quad E(\theta_s \Delta Y_{s2}) = 0
\]

Rewriting Eq. (7) in the first difference form will produce this:

\[
\Delta Y_{st} = \beta \Delta Y_{s,t-1} + \gamma \Delta X_{s,t} + \delta \Delta Z_{s,t} + \Delta \varepsilon_{s,t}
\]  

To obtain the system GMM formulation, a further modification based on Eqs. (7) and (8) is necessary:

\[
E(Y_{s,t-k} \Delta \varepsilon_{st}) = 0 \text{ for } t \geq 3 \text{ and } k \geq 2 \quad (9a)
\]

\[
E(\varepsilon_{st} \Delta Y_{s,t-1}) = 0 \text{ for } t \geq 3 \quad (9b)
\]

According to Roodman (2009), the system GMM is an augmented version of the difference GMM (developed by Arellano and Bond 1991) with an additional assumption that first differences of instrumental variables are uncorrelated with the fixed effects (see Eq. 9a, 9b), which allows the introduction of additional instruments that can improve the level of efficiency considerably. The estimated system GMM results based on one-step and two-step methods are given in Table 3.

3 Results and Discussion

3.1 Incidence and Depth of Poverty by Sector of Employment

Though, due to growth of mechanization, people are leaving agriculture since 2004–2005, still a large proportion of rural population (about 58%) earns their livelihood from this sector. As a matter of fact, both the incidence (based on PHCR) and depth (based on PGI) of poverty are relatively high among the people engaged in agriculture and allied sectors. This is because agriculture and allied sectors offer a relatively low level of earning as compared to the rural non-farm sector activities (Lanjouw and Shariff, 2004). About 44% of the workforce engaged in agriculture and allied sectors were poor during 2004–2005, while incidence of poverty (percentage of BPL based on PHCR) was relatively lower (36.4%) among those, who
were engaged in non-farm sector activities (Fig. 1A). Although incidence of poverty declined among both farm and non-farm sectors workers, the inter-sectoral differences still persist during 2018–2019 with 35.5% poor in agriculture and allied sectors vis-à-vis 26.3% poor among the non-farm sector workforce.

However, over the years comparison reveals that the incidence of poverty among both farm and non-farm workers has declined more rapidly and massively during

| Table 3 | Determinants of poverty in rural India (system GMM results) |
|---------|----------------------------------------------------------|
| | (Model 1) | (Model 2) |
| L.BPL | One-step SGMM | Two-step SGMM |
| | 1.08*** | 1.09*** |
| | (41.34) | (32.83) |
| Growth of non-farm NSDP | − 6.73 | − 6.19** |
| | (− 0.49) | (− 2.33) |
| Log of non-farm employment | − 1.30*** | − 1.49*** |
| | (− 2.97) | (− 3.68) |
| Log of GFCF | − 0.70*** | − 0.68*** |
| | (− 4.33) | (− 3.42) |
| Dependency ratio | 0.55*** | 0.48*** |
| | (5.41) | (4.37) |
| Growth of number of industries | − 0.22*** | − 0.26*** |
| | (− 6.54) | (− 8.15) |
| Growth of banks | − 4.24 | − 4.74* |
| | (− 1.01) | (− 1.92) |
| Growth of roads | − 2.67** | − 2.29*** |
| | (− 2.37) | (− 4.84) |
| Growth of highway | − 0.58 | − 1.06** |
| | (− 0.74) | (− 2.37) |
| Growth of railway routs | − 0.65*** | − 0.71*** |
| | (− 2.84) | (− 8.25) |
| Growth of schools | − 2.78* | − 2.65*** |
| | (− 1.87) | (− 3.41) |
| Constant | 6.48* | 11.4** |
| | (1.84) | (2.59) |
| Observations | 378 | 378 |
| No. of instruments | 26 | 26 |
| Arellano-Bond AR1 (p-value) | 0.023 | 0.028 |
| Arellano-Bond AR2 (p-value) | 0.81 | 0.56 |
| Sargan (p-value) | 0.00 | 0.00 |
| Hansen-J (p-value) | 0.15 | |
| F statistic | 2761.8 | 19,831.2 |

*Source: Authors estimation using macro-level data
Calculated t-statistics are given in parentheses, *p < 0.10; **p < 0.05, ***p < 0.010
the period 2004–2005 and 2011–2012. This is also confirmed by estimates of Planning Commission (2013) and Chauhan et al. (2016). But during the 2011–2012 and 2018–2019, the incidence of poverty has increased (even during pre-COVID-19 periods), a retrogressive and an unwelcome trend that set to begin due to the stagnation in real wages (Das and Usami 2017; Chakraborty 2018) and falling job opportunities for educated rural youth (Mehrotra and Parida 2021). This is an alarming situation. It needs immediate policy attention.

Furthermore, it is noted that the depth and severity of poverty (based on PGI) among both farm and non-farm workers increased over the period 2005–2019. While the absolute value of PGI increased from 0.194 to 0.237 for the workers engaged in agriculture and allied sectors, it increased from 0.204 to 0.228 for non-farm workforce (Fig. 1B). That means even though a segment of the rural population were moved above the poverty line, their standard of living did not increase much. They are still highly vulnerable to economic shocks like that of COVID-19 pandemic.

Fig. 1 Incidence and depth of poverty by sectoral employment in rural India. Source: Author’s estimation using NSS unit level and Periodical Labour Force Survey (PLFS) data
3.2 Impact of Non-farm Sector Employment on Poverty

In rural India, individuals often participate in a wide range of non-agricultural activities, such as wage and self-employment in commerce, manufacturing, and services, along with their traditional rural activities of farming (Lanjouw and Shariff 2004). However, in this context, we have segregated them into two mutually exclusive groups based on their usual (principal and subsidiary) activity status and the industry of employment (NIC codes) to find out the impact of non-farm sector employment on the incidence of poverty.

First, we have explored the micro-level (both individual- and family-level characteristics) factors simultaneously determining the probability of being a non-farm sector worker (including employers, self-employed and employees) and the probability of being poor (living below the poverty line). As discussed previously in the data and method section, both binary probit (BP) and recursive binary probit (RBP) regression models are estimated (see Table 2). The correlation parameter of BP model reflects the correlation of two binary dependent variables. That means a zero or close to zero BP correlation coefficient suggests that these binary variables can be modelled as independent of each other (Humphreys et al. 2014), but this may not always imply independence of the binary dependent variables (Filippini et al. 2018). In our case, correlation coefficient (rho) of BP model is significantly different from zero (−0.029). To check the consistency of this result (possible independency of poverty and non-farm employment), the estimated coefficient of the endogenous binary variable (non-farm employment) of the RBP model needs to be verified. In this case, it is negative (−0.55) and statistically highly (1% level) significant (Table 2: row one-tenth column entry). This implies probability of non-farm sector employment has a likely negative impact on the likelihood of being poor. Moreover, we have explored that the control variables which have positive impacts on the probability of individuals decision to take up or enable them to join the non-farm sector jobs simultaneously have negative impacts on their probability of being poor.

The coefficients of all education and training dummies are positive in case of non-farm sector employment in both BP and RBP regression models, while these coefficients are significantly negative in case of poverty equation. The positive and relatively higher coefficients values of general education dummies (reference category: not literate) as we move from lower to higher level of education reflect the fact that individual’s probability of being employed in the non-farm sector increases with their increased level of general education. But, the converse is true in case of the chance of being a poor. Individuals with better level of general education have relatively lower probability of falling below the poverty line. The dummy coefficients of technical educations and formal vocational training are also revealed the same story. That means as rightly said by Sen (1990, 2001) expansion of “human capability” and “functioning” has poverty-reducing impacts.

The second important factor that affects the probability of being employed in the non-farm sector jobs and the likelihood of being fall below the poverty line is the occupation of family’s head. It is found that in families whose head are engaged in high paid occupations (including administrative, professional, clerical, sales and services in the non-farm sectors), their children are more likely to be employed in
the non-farm sectors and hence their chance of being poor is relatively lesser. On the other hand, whose head of the family are engaged in low-paid informal sector occupations including farming are less likely to be hired by the non-farm sector employers and their chance of being poor is relatively higher. This is mainly because of the fact that the families whose head are engaged in high paid occupations are capable of buying better and quality education or training for their children, which has positive implications on their human capability. But in the case of the disadvantaged families, the vicious circle of poverty and low human capability is still working in rural India.

Other important family characteristics like family size and dependency ratio (number of non-working to working members with a family) have also positive impacts on the family members’ probability of being a poor. Moreover, the estimated social group dummy coefficients reflect that individuals belonging to socially disadvantage groups (including Scheduled Caste (SCs) and Scheduled Tribes (STs)) are less likely to be engaged in the non-farm sector jobs. On the other hand, individuals belonging to these socially disadvantage groups are more likely to be poor in rural India. The religion dummy coefficients indicate that although all the religious minor groups (including Muslims, Christian, and Others) are more likely to be engaged in the non-farm sector jobs as compared to Hindus, the probability of being poor is less only in the case of religion minor group classified as “Other Religion”.

Although individual characteristics like age and age square (proxies for job market experience) and the log mean wage/earning (predicted) reflect the true labour market features, and they produce expected signs in the case of non-farm employment equation, the coefficient of log mean wage/earning (predicted) in poverty equation contrasts the theoretical expectation (in both BP and RBP models). This contrasting results may be due to the fact that even within the rural non-farm sector workers, a considerable proportion of workers are still living below the poverty line (Fig. 1A).

Moreover, the coefficients of region dummies (reference category is North-East Indian states) reflect that individual living in North-East and Central regions of India is less likely to be engaged in non-farm sectors as compared to those who live in either Northern, Southern, or Western regions. But the converse is true, in the case of their probability of being poor.

This regional difference in the non-farm sector employment opportunities and its implication on regional poverty incidences can be better understood through the interpretation of our macro-level panel data regression results below.

To substantiate our arguments further, we have estimated panel data regression models (using system GMM methods) considering poverty (PHCR) as the dependent variable. Apart from non-farm sector employment, we have used non-farm sector output (NSDP), investment (GFCF), dependency ratio (as a demographic indicator), and other infrastructure indicators (including: number of factories/industries, number of branches of Scheduled Commercial Banks, length of states roads (in KMs), length of highways (in KMs), length of railways routes (in KMs), number of schools (Govt. and Private), etc.) as other control variables. Since the system GMM method of estimation also requires a set of instrumental variables, we have used population growth, Youth Labour Force Participation...
Rate (LFPR), and the Mean Years of Schooling (MYS) as additional instrumental variables along with our control variables. During estimation, we have used both one-step and two-step methods using *xtabond2* command in Stata. While one-step GMM sometime produces inconsistent estimates due to either inclusion of wrong moment conditions (too many instruments) or model misspecification, GMM estimates based on two-step method are asymptotically efficient and robust. The robustness checking based on *F*-statistics, Hansen-*J* test statistics (over identification of restrictions), and Arellano–Bond test for second-order serial correlation (AR-2) is comfortably passed (see Table 3).

The system GMM estimates also suggest that the effects of non-farm sector employment opportunities on the incidence of rural poverty are negative. Furthermore, the impact of non-farm sector out (a proxy for income) is also negative (−6.19) and statistically highly significant (Table 3). This implies the fact that a 1% increase in the growth of overall non-farm sector NSDP is likely to bring the incidence of poverty down by about 6.2 percentage points in rural India. Similarly, a 1% increase in the overall investment (GFCF) in India states is about to reduce rural poverty (PHCR) incidences by about 0.7 percentage points. Moreover, the growth of number of industries has also negative impact on the incidence of poverty. These results are as expected. On the basis of these results, it is argued that growth and promotion of the non-farm sector should be the top most priority of the policy makers as it has dynamic and long-term poverty-reducing impacts.

This result also suggests that development of infrastructure plays a key role in the process of rural poverty reduction in Indian states. A 1% growth of number of branches of the Scheduled Commercial Banks is about to reduce rural poverty by 4.7 percentage points (Table 3), through its interlinkage with growth of non-farm sector employment. The growth of number of branches of the Scheduled Commercial Banks has also implication on the process of financial inclusion-led poverty reduction (see Nanda and Kaur 2017; Inoue 2018). Similarly, growth of number of schools has poverty-reducing impacts (2.65%) immediately (in the short and medium run) through creation of additional non-farm sector jobs. In the long run, it has also positive impact on the process of human capital accumulation, and thereby on the process of improvement of rural income and the standard of livings of the rural folks.

It is also noted that growth of road (both state roads and highway lengths) and railway infrastructures has poverty-reducing impacts. The growth of road infrastructure not only has short- and long-term effects on the employment creation, and thereby poverty reduction; but also it has multiplier impacts on the growth of non-farm sector output and income, which has positive impacts on rural poverty reduction in India.

However, it is noted that growth of dependency population is likely to exacerbate the poverty situations further as it reflects a statistically significant positive (0.48) estimated coefficient (Table 3). The context in which rural folks are losing jobs due to mechanization in agriculture and educated youth unemployment is rising due to unavailability of adequate number of jobs (Mehrotra and Parida 2021), and the dependency ratio in rural areas is going to increase. Hence, unless and otherwise, an adequate number of non-farm sector jobs are created; in the due course of time, rural
poverty conditions are going to be worsen further because of the dynamic impacts of rising dependency ratio.

3.3 Identifying Non-farm Subsectors that Helped Reduce Poverty in Rural India

Although the process of structural transformation got momentum during the post 2004–2005 periods in India, in which the share farm employment has come down more rapidly than ever with absolute decline of the workforce, the share of employment in rural manufacturing sector remained almost constant at around 8%. But, on the other hand, the share of employment in construction (from about 3 to about 14%) and service (mostly in traditional and informal services) sectors (from about 10 to about 21%) continued to increase during last two and half decades (see Fig. 2). This might be the main reason for decline in the incidence of mass rural poverty in India. But this decline may not be sustainable over long run because of the following reasons: First, the construction sector itself may not provide a sustainable source of employment to the rural poor; second, the rural manufacturing sector has not yet developed to boost the structural transformation process; and third, labour-intensive informal services might not provide adequate level of earning (that help reduce poverty) though it could accommodate the low-skilled workers leaving agriculture. Given the importance of rural non-farm sector employment in process of rural poverty reduction, we next focus on exploring the sub-sectoral employment and poverty scenario in rural India.

To begin with the manufacturing sector, it is noted that its labour-intensive subsectors like food, beverages, tobacco products, textile, wearing apparel wood products, and non-metallic products are the leading employment generating sectors in rural India. But the incidence of poverty among the workers engaged in these sectors is also very high (see Table 4). The incidence of poverty is quite low among workers engaged in other subsectors like leather products (9.7%), paper products (10.4%), rubber, plastic and coke products (12.1%), basic metals products (12.6%), electronic

![Fig. 2 Trends of sectoral employment shares in rural India, 1983–2019. Source: Author’s estimation using NSS unit level and Periodical Labour Force Survey (PLFS) data](image-url)
Table 4  Sub-sectoral employment and poverty incidence in rural non-farm sectors, 2005–2019

| Sub sectors of manufacturing sectors (in million) | Employment (million) | Poverty (per cent) |
|--------------------------------------------------|----------------------|-------------------|
|                                                  | 2004–2005 | 2011–2012 | 2018–2019 | 2004–2005 | 2011–2012 | 2018–2019 |
| Agriculture and allied sectors                   | 259.8   | 223.5    | 191.7    | 44       | 32       | 35.46     |
| Manufacturing subsectors                         |          |          |          |          |          |           |
| Food, beverages and tobacco products             | 7.21    | 7.33     | 5.18     | 43.2     | 30       | 27.3      |
| Textiles and wearing apparel                     | 8.12    | 8.08     | 7.39     | 35.4     | 21.4     | 20.98     |
| Leather products                                 | 0.3     | 0.31     | 0.30     | 35.9     | 15.1     | 9.69      |
| Wood products                                    | 4.14    | 2.91     | 1.78     | 52.4     | 36.1     | 30.29     |
| Paper products and printing media                | 0.36    | 0.33     | 0.47     | 21.2     | 17.3     | 10.36     |
| Rubber and plastics, coke and petroleum products | 0.26    | 0.45     | 0.47     | 22.5     | 17.4     | 12.08     |
| Chemical products                                | 0.81    | 0.72     | 0.85     | 34       | 18       | 18.37     |
| Non-metallic products                            | 3.59    | 3.75     | 2.80     | 51.8     | 32.1     | 29.13     |
| Basic metals                                     | 0.36    | 0.77     | 0.66     | 16.8     | 27.5     | 12.62     |
| Fabricated metals                                | 1.04    | 1.23     | 1.21     | 32.8     | 14.7     | 16.33     |
| Machinery and equipment’s                       | 0       | 0.23     | 0.52     | 0        | 6.2      | 27.96     |
| Electronics and electrical machinery and medical instruments | 0.24 | 0.46 | 0.58 | 21.6 | 4.2 | 14.49 |
| Motor vehicles and other transports              | 0.3     | 0.52     | 0.42     | 23.5     | 2.8      | 21.57     |
| Others (furniture, jewellery, sports and recycling) | 1.74 | 3.03 | 3.09 | 28.4 | 21.5 | 18.72 |
| Manufacturing total                              | 28.47   | 30.11    | 25.73    | 40.6     | 25.2     | 22.51     |
| Non-manufacturing subsectors                     |          |          |          |          |          |           |
| Mining and queries                               | 1.83    | 1.63     | 1.2      | 23.23    | 21.43    | 27.6      |
| Electricity and gas                              | 0.44    | 0.49     | 0.6      | 14.4     | 10.9     | 10.0      |
| Distribution of water                            | 0.11    | 0.33     | 0.5      | 15.7     | 20.4     | 26.1      |
| Construction                                     | 17.42   | 38.54    | 43.0     | 48.3     | 37.5     | 37.4      |
| Non-manufacturing total                          | 19.8    | 40.98    | 45.3     | 47.2     | 36.8     | 36.6      |
Table 4 (continued)

| Sub sectors of manufacturing sectors (in million) | Employment (million) | Poverty (per cent) |
|--------------------------------------------------|----------------------|-------------------|
|                                                  | 2004–2005 | 2011–2012 | 2018–2019 | 2004–2005 | 2011–2012 | 2018–2019 |
| Service subsectors                                |           |           |           |           |           |           |
| Wholesale trade                                  | 2.66      | 2.58      | 3.5       | 26        | 12.6      | 14.22     |
| Retail trade                                     | 16.81     | 16.99     | 20.4      | 31.3      | 19.8      | 23.44     |
| Hotels and restaurants                           | 2.56      | 3.04      | 3.8       | 32.8      | 20.9      | 26.67     |
| Land transport                                   | 7.9       | 9.3       | 11.8      | 35.6      | 21.3      | 25.41     |
| Water transport                                  | 0.04      | 0.04      | 0.1       | 7.7       | 35.2      | 15.68     |
| Air transport                                    | 0.01      | 0         | 0.0       | 37.1      | 0         | 7.29      |
| Incidental, storage and warehousing              | 0.1       | 0.36      | 0.9       | 42.4      | 29.7      | 21.1      |
| Communications                                   | 0.76      | 0.73      | 0.6       | 13.5      | 9.6       | 11.79     |
| Finance and insurance                            | 0.77      | 1.16      | 1.4       | 11        | 7         | 14.66     |
| Real estate and business activities              | 0.95      | 1.6       | 3.0       | 15.9      | 9.8       | 18.75     |
| Public administration and defence                | 2.96      | 2.75      | 3.6       | 16        | 10.4      | 11.71     |
| Education                                        | 5.77      | 7.22      | 10.0      | 14.2      | 10.3      | 14.28     |
| Health and social work                           | 1.58      | 1.31      | 1.8       | 16.2      | 13.5      | 9.85      |
| Other social service                             | 6.21      | 7.02      | 7.7       | 48.3      | 30.6      | 25.01     |
| Services total                                   | 49.09     | 54.09     | 68.7      | 29.6      | 18.6      | 20.82     |

Source: Author’s estimation using NSS unit level and Periodical Labour Force Survey (PLFS) data
and electrical machineries (14.5%), etc. Hence, promotion of these subsectors may significantly help to reduce the volume of rural poverty on a sustainable basis.

Although construction sector (within non-manufacturing utilities) helped initiating the structural transformation of rural labour force by providing ample job opportunities during 2004–2005 and 2011–2012, its labour absorption capacity has come down during the post 2011–2012 periods. More importantly, it is argued that this sector does help reduce the incidence of rural poverty as the percentage of poor is very high (37%) among the construction workforce. The only other subsector of the non-manufacturing sector which could help reduce incidence of rural poverty is the “Electricity and gas distribution” in which only about 10% of the people live below the poverty line (see Table 4).

It is noted that workers engaged in traditional service subsectors are relatively poorer as compared to those who are engaged in the modern services. The incidence of poverty is high among workers engaged in retail trade (23.5%), hotels and restaurants (26.7%), land transports (25.4%), storage (21.1%), and other social services (25%). The subsectors which have poverty-reducing impacts include: health and social work, education, communication, finance and insurance, and real estate business (to some extent).

4 Conclusion and Policy Suggestions

The main objective of this paper is to examine the impact of rural non-farm sector employment on the incidence of rural poverty. Based on NSS and PLFS unit-level employment data, it estimates the incidence and depth of rural poverty and explores the factors determining the individual’s probabilities of being poor and being engaged in the non-farm sector jobs simultaneously. It also finds the impact (at macro-level) of rural non-farm sector employment growth on the incidence of rural poverty and identifies the subsectors of the non-farm sector which help reduce the incidence of rural poverty in India.

The major findings of the study suggest that incidence of poverty is relatively high among the workers engaged in farming as compared to non-farm sector workers. However, the depth of poverty is relatively high and it increased among non-farm sector workers in rural India. The regression result based on micro-level data suggests that individual’s human capabilities owing to better education and training and higher occupations of their head of the family significantly determine their probability of being employed in the non-farm sectors. On the other hand, the probability of non-farm sector employment reduces their likelihood of being poor in rural areas. Based on panel data regression, it is also found that the provincial states which have achieved a relatively higher level of non-farm sector NSDP growth along with creation of non-farm jobs through an improved level of infrastructure (roads, railways, banking, and industries) base have succeeded in reducing the incidence of rural poverty substantially.

Moreover, it is found that transition from farm to either construction or traditional services like retail trade, hotels and restaurants, land transports, and storage is not going to help much in reducing the incidence of poverty. But, the incidence of
rural poverty can be reduced on a sustainable basis through the development of rural manufacturing, and by promoting growth of modern service sectors like education, health, communication, real estate, and finance and insurance.

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**Conflict of interest**  On behalf of all my co-author, I declare that we do not have any conflict of interest with any person or any institution.

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