Forthcoming, EPW, Jan 3, 2026
Review of Labour and Employment
Vol LXI No 1

Rise of Unpaid Family Helpers: Evidence on Distress-driven Employment Growth in India

Maitreesh Ghatak,[1] Mrinalini Jha,[2] and Jitendra Singh[3] [4]

Abstract

While the surge in India's Labour Force Participation Rate (LFPR) and Worker Population Ratio (WPR) since 2017-18 has reversed the earlier decline in female labour force participation, it raises the crucial question of whether this trend is driven by robust economic growth or underlying economic hardship. This paper addresses this debate by focusing on the rapid increase in the most vulnerable employment categories: unpaid family helpers (UFH) and own-account workers (OAW). Using two methods – residual earnings and propensity score matching (PSM) – we estimate the monetary value of the incremental productivity of UFH within household enterprises. Our findings indicate that UFH exhibit significantly lower productivity compared to any category of paid workers, with PSM estimates showing their attributable daily earnings around INR 50. The real average daily earnings for OAW, the largest employment group, dropped by around 8 percent between 2017-18 and 2023-24. Overall, the evidence strongly supports the interpretation that the recent expansion in employment reflects economic distress leading to subsistence work, rather than growth- driven better quality job creation.

Keywords: labour market, self-employment, unpaid helpers

[1] London School of Economics.

[2] Jindal School of Government and Public Policy, O.P. Jindal Global University. Corresponding Author. Email – mrinalini.jha@jgu.edu.in

[3] Thapar School of Liberal Arts and Sciences, Thapar Institute of Engineering and Technology.

[4] All authors have contributed equally.

1 Introduction

Recent rounds of the Periodic Labour Force Survey (PLFS) of India report a sharp increase in both the Labour Force Participation Rate (LFPR) and the Worker Population Ratio (WPR). The trend has been persisting since 2017-18. The rise is driven by increased employment across different demographic groups such as age, gender, sector, etc. Alongside, this has managed to push the female labour force participation rate up since 2017-18, reversing the earlier downward trend.

Are these improvements in the labour market indicators a reflection of job creation accompanying economic growth or do they reflect economic hardship faced by a large segment of the population? The positive trends in LFPR and WPR are not aligned with improved standard macroeconomic indicators of job creation, such as rise in investment rates (see, for example, Nagaraj (2023) and The Economist (2025)).[1] Indeed, a number of recent studies argue that this rise in LFPR and WPR is indicative of rising distress in the economy (Anand and Thampi, 2021; Basole et al., 2023; Ghatak et al., 2024; Ara and Shrivastav, 2025). The central claim of this argument is that the increase in employment is largely due to a surge in the categories of own-account workers (OAW) and unpaid family helpers (UFH). The unpaid family helpers – a group predominantly populated by women – do not meet the standard definition of a good job and are considered to be the most vulnerable category (ILO, 2024).

In terms of average earnings, salaried jobs are the most desirable, followed by self-employment, and then by casual work (Ghatak et al., 2024). Therefore, the rise in self-employment does not necessarily imply economic distress. Moreover, Goldar and Aggarwal (2024) estimate that the productivity of (or earnings that can be attributed to) unpaid family helpers is, in fact, comparable to that of OAW. They do so by comparing the monthly per capita expenditure (MPCE) of families with one or more unpaid female workers with the MPCE of families but

[1] The fact that India's GDP growth rate is high and yet the growth of unemployment is also high is being referred to as the "growth employment paradox" (Mundle, 2025).

with only paid workers, and do not find any statistically significant difference. If this is indeed the case, then their findings suggest that this form of employment may actually reflect individual *choices*, rather than *economic compulsion*. However, these comparisons may suffer from selection issue as it is based on the fact the households with and without unpaid family helpers are similar. In particular, the status of being an unpaid helper is likely to be driven by unobserved characteristics that may be correlated with average family income levels. Further, unpaid family helpers are bound to increase the *total* income of the household. Therefore, it is important to understand the *incremental* addition that they are making to the total income and compare it to the income that would have been added had they been involved in paid work.

In this paper we address this question by estimating the productivity of unpaid family helpers within households using two alternative estimation strategies. The unpaid family helpers assist the self-employed members of the household, and we use this to estimate productivity (in terms of the incremental earnings to total household income) for the unpaid helpers (Section 3). First, we compare earnings of workers belonging to different household compositions to deduce the earnings for the unpaid family helpers. We are calling this the residual earnings method. The method allows us to get the descriptive estimates of the productivity of unpaid family helpers. For this we simply compare the earnings of self-employed workers with and without unpaid family helpers. The difference in their earnings gets attributed to the unpaid helper. This however does not take into account the inherent differences among the two kinds of self-employed workers – with and without unpaid helpers. For this, we adopt the method of propensity score matching to get the predicted earnings for unpaid helpers based on the matched households. Our results show that unpaid helpers exhibit significantly lower productivity in comparison to any other category of paid workers. Accordingly, our estimates indicate that the expansion in the share of unpaid family helpers indeed signals distress in the labour market.

This period has also seen a rise in own-account workers combined with falling earnings. We ideally would like to get the earnings for the newly added own-account workers to establish rising prosperity or distress in the economy. However, this would require panel-data. We attempt to estimate the earnings of the new own-account workers using the cross-sectional PLFS dataset (Section 4) and find that the own-account workers are in fact earning significantly less over time. This further provides suggestive evidence towards rising distress, explained by the increasingly greater share of own-account workers in the labour force working at lower earnings.

The plan of the paper is as follows. We discuss the data and present some summary statistics on the broad labour market trends in Section 2. In sections 3 and 4, we estimate the earnings of unpaid family helpers and self-employed workers. Section 5 concludes.

2 Data

We use data from all seven available rounds of the Periodic Labour Force Survey (PLFS) spanning 2017-18 to 2023-24. The PLFS gives annual, nationally representative data for a repeated cross-section of more than 100,000 households in each round. In addition to capturing labour market indicators such as employment, earnings, industry of work, and occupation of household members, it also provides information on demographic characteristics such as age, education, caste, religion, etc.

The dataset allow us to estimate the labour market participation and type of employment for three different reference time criteria: (i) usual status (US) (ii) current weekly status (CWS) and (iii) current daily status (CDS).[2] Our analysis uses the CWS criterion for compatibility with the earnings estimates.[3] CWS classifies an individual as working if they are working for at least one hour in the previous week. An employed individual in PLFS can be classified into the following five categories: (i) own-account worker (OAW), (ii) employer, (iii) unpaid family helper (worked as helper in household enterprise), (iv) regular salaried (or wage employee) worker, and (v) casual (or daily wage) worker. Unpaid family helpers are understood as a category which attaches itself to OAW or employers within the household and contributes to the total income earned by the household-owned enterprise.

2.1 Trends in Indian Labour Market

To set the context, we begin by examining the over-time trends in some of the labour market indicators. Table 1 reports the distribution of the working-age (age 15 years and above) population across the categories of employment, unemployment, and out of the labour force. The share of the employed population (WPR) increased by approximately 10 percentage points, driven by a drop in the other two categories of unemployment and out the labour force. At a first glance, this appears to be an improvement in the state of the labour market, since it reflects a significantly sharp rise in employment within a short span of time. However, it is

[2] US, CWS and CDS classifies the household members in economic activities based on work done in the past one year, in the last week, and on the previous day, respectively. More details available here.
[3] PLFS collects earnings for the employment status which is reported as per the reference period of current weekly activity. Since we are working with earnings, we use the employment status for the same reference period.

important to examine the nature of employment that has contributed to this overall rise in the employment levels (Ghatak et al., 2024).

In Table 2, we report the composition of different types of workers over time. We observe a sharp increase in the share of unpaid family helpers between 2017-18 and 2023-24, accompanied by a decline in both casual and salaried workers. Given that overall employment also increased, the constant share of own-account workers suggests a moderate growth for workers in this category. Although the share of employers has also increased, it remained relatively small in total employment.

Table 1: Labour market trends in India (2017-18 to 2023-24)

Year	Employed	Unemployed	Out of labour force
2017-18	44.14	3.48	52.38
2018-19	44.25	3.52	52.22
2019-20	46.67	3.81	49.52
2020-21	47.54	3.44	49.03
2021-22	48.31	2.91	48.78
2022-23	51.83	2.31	45.86
2023-24	53.69	2.35	43.96

Source and Notes - Authors' calculations using PLFS. The numbers indicate the share of each category in the total working age population. Each row sums to 100.

Table 2: Types of workers (2017-18 to 2023-24)

Year	Own-account worker	Employer	Unpaid family helper	Salaried	Casual
2017-18	37.59	1.96	12.41	24.21	23.84
2018-19	37.85	2.22	11.71	25.46	22.76
2019-20	37.38	2.15	14.94	23.51	22.03
2020-21	38.29	2.10	15.68	21.92	22.01
2021-22	37.89	2.62	15.18	23.29	21.02
2022-23	37.75	3.16	15.96	22.34	20.79
2023-24	37.57	3.39	17.10	23.32	18.61

Source and Notes - Authors' calculations using PLFS. The numbers indicate the share of each category in the total workers in respective years. Each row sums to 100.

Next, Table 3 reports the average daily earnings (in INR in real terms) for each category of employment.[4] We use CPI for rural and urban sector separately to convert the nominal earnings into real terms in 2016 prices. The table shows that earnings for OAW – the largest category of employment in India – dropped significantly in real terms over the seven-year

[4] This will exclude the category of unpaid account helpers for whom, by definition, earnings cannot be observed.

period. Average earnings decreased from INR 306 in 2017-18 to INR 283 in 2023-24. It also fell for salaried workers from INR 497 in 2017-18 to INR 490 in 2023-24. Earnings for casual workers increased from INR 250 to INR 297 over the period, even though the share of workers in this category fell from 24 percent to 19 percent.

We further examine the category of employment that has seen the sharpest and the most persistent increase among the overall group of employed workers, namely, unpaid family helpers. The raw figures from the PLFS do not provide information on the productivity or earnings of unpaid family helpers. In the next section we outline two approaches to estimate the productivity of this group.

Table 3: Daily earnings (in INR) for different types of workers (2017-18 to 2023-24)

Year	Own-account worker	Employer	Salaried	Casual
2017-18	305.96	665.40	497.05	250.37
2018-19	314.24	712.16	490.82	264.84
2019-20	292.34	668.60	507.09	259.90
2020-21	282.97	635.74	490.42	271.09
2021-22	297.28	653.11	503.25	301.10
2022-23	303.03	713.05	494.14	303.96
2023-24	282.61	697.37	490.15	296.92

Source and Notes - Authors' calculations using PLFS. The numbers indicate the mean earning (in INR) of different types (mentioned in Column headers) of workers in respective years.

3 Earnings of Unpaid Family Helpers

While earnings for the category of UFH cannot be observed directly in the data, these workers nevertheless contribute to the income of household enterprises operated by family members classified as either OAW or employers. For our analysis we club together the OAW and employers (as they form the group to which the UFH is attached) and refer to them as self-employed (SE)[5]. Using this SE category, we derive the earnings estimate which is attributable to UFH. Our analysis is based on the argument that the earnings of a SE worker having a UFH is necessarily at least as much as the earnings of an SE worker without a UFH, *ceteris paribus*. Our methodological contribution is towards the estimation of the counterfactual earnings of the group of SE workers with UFH in the absence of UFH. We propose two different

[5] Our results in both methods – residual earnings as well as propensity score matching – remain unchanged even if we remove the category of employers from the SE category.

estimation methods to find a range of earnings for the UFH.

3.1 Residual Earnings Method

In the first method, we assume that the SE with UFH (SE*w/* UFH) are similar in characteristics to the SE without UFH (SE*w/o*UFH). That is, we work with the assumption that the SE*w/* UFH are comparable to SE*w/o*UFH, and accordingly, the earnings of the two will be comparable. This then implies that the counterfactual earnings for SE*w/o* UFH (i.e., earnings for the SE worker in the absence of UFH) will be the same as earnings for SE*w/* UFH. Therefore, it follows that the earnings difference between SE*w/* UFH and SE*w/o*UFH can be attributed to the UFH. While this assumption comes with clear limitations – as we show in our second method – it nevertheless provides a reasonable estimate and a useful benchmark. The second method relaxes this assumption, yielding more robust results, but with a more nuanced interpretation.

For estimation under the first residual method, we consider the sample of households with two working members, of which one working member is necessarily SE (explained below). This forms our sample of households. We put no restrictions on the employment category of the second worker in the household. Therefore, we get four possible kinds of households depending on the employment type of the second working member.[6] Now we compare earnings of SE workers in household with UFH (SE*w/* UFH) to the earnings of SE workers in household without UFH (SE*w/o*UFH). This gives us the average earnings attributable to UFH.

The restriction of at least one self-employed member is essential for estimation since unpaid family helpers cannot directly contribute to the earnings of salaried or casual workers. Consistent with this assumption, the data show that more than 94 percent of households with unpaid family helpers also have at least one member in the household is reported to be primarily working as self-employed.[7]

Next, we restrict the sample to two working member households to allow for the possibility that an UFH is similar to any other worker and has decided to work as an unpaid helper by choice. Furthermore, data does not allow us to attribute earnings to UFH if we consider households with two or more SE and, since the link between UFH and SE is not indicated in the data.

In Table 4 we report estimates of the productivity (proxied by daily earnings) of UFH along

[6] The second worker can be SE, UFH, salaried, or casual. This gives the four combinations of SE-SE, SE-UFH, SE-Salaried, SE-Casual.

[7] In the remaining 6% of cases, it is possible that respondents reported casual or salaried work as their primary occupation in that previous week, while their secondary or part-time work was self-employment (for example, in agriculture) where they might take the help of unpaid family workers.

with the daily earnings of different types of workers in two-working-member households. We report earnings of salaried workers (Column 1), casual workers (Column 2), and SE*w/o*UFH households (Column 3). Consistent with the full sample, salaried workers earn substantially more than both casual and self-employed workers. Column 4 presents the average daily earnings of self-employed workers with one unpaid family helper (SE*w/* UFH) in the household. Since unpaid helpers contribute to the earnings reported in Column 4, we attribute the difference between Columns 4 and 3 to the productivity of unpaid family helpers. Our estimates suggest that, until 2021-22, the attributed earnings of unpaid helpers remained around INR 60 in any year. It is noteworthy that this amounts to less than 20 percent of the earnings of casual workers, who in turn earn the least among all types of remunerative work. These numbers strongly indicate that being an unpaid helper is unlikely to be a voluntary choice among all other types of employment.

Table 4: Earning estimates of unpaid family helpers (UFH) by residual earnings method

	(1)	(2)	(3)	(4)	(5)
	Daily earnings (in INR)				
Year	Salaried	Casual	SE*w/o*UFH	SE*w/* UFH	Estimated earning of UFH (4)-(3)
2017-18	418.10	254.07	281.28	332.99	51.71
2018-19	423.17	277.68	285.30	339.36	54.05
2019-20	433.72	266.15	275.00	312.85	37.85
2020-21	449.37	275.14	259.67	316.99	57.32
2021-22	442.26	305.87	274.34	335.99	61.66
2022-23	446.06	299.77	267.06	365.53	98.47
2023-24	438.04	304.02	262.20	370.35	108.15

Source and Notes - Authors' calculations using PLFS. The numbers indicate the mean earning (in INR) of different types (Column headers) of workers in respective years in the sample of two working member households. Column (1) and Column (2) indicate the mean earning (in INR) of salaried and casual workers. Column (3) indicates mean earning of SE workers with no unpaid family helper in their household and similarly, Column (4) indicates mean earning of SE worker with one unpaid family helper in their household. Column (5) is simple difference between Column (4) and Column (3).

Next, we observe that the estimated earnings of unpaid helpers have approximately doubled in 2022–23 and 2023-24 when calculated using the residual method. We argue that this sharp increase reflects a limitation of the method rather than a genuine rise in productivity. Since the productivity of unpaid helpers is computed as the simple difference between Column 4 and Column 3, any factor that lowers the average earnings reported in Column 3 will mechanically raise the estimated productivity of unpaid helpers. For instance, if more workers enter self-employment in SE-SE type of households but at lower earnings, the expansion in the number of self-employed workers would reduce their average earnings, thereby inflating the residual estimate of unpaid helpers' contributions. The next method addresses this shortcoming.

3.2 Propensity Score Matching

In the residual earnings method above, we assume that SE workers with UFH are comparable to those without UFH. However, in reality, the overall group of SE*w/* UFH workers is likely to be systematically different from the group of SE*w/o*UFH workers. To relax this assumption, we use a propensity score matching (PSM) approach, which identifies comparable SE workers from both groups based on their observable characteristics. We then compare the earnings of these matched groups to estimate the contribution of unpaid helpers. For ease of exposition we call SE*w/* UFH as the "treated" and SE*w/o*UFH as the "control" group but one has to keep in mind that these categories are not randomly assigned. The PSM is used to create a "matched" comparison group from the control group that is similar in characteristics to the treatment group.[8] For every SE worker in the "treatment" sample, PSM finds a set of SE workers from the "control" sample (SE*w/o*UFH) who have an equal probability of being "treated", i.e., of having a UFH, based on the specified characteristics of the SE.

For this, we first estimate the following equation:

$$D_i = \alpha + \beta x_i + \epsilon_i \tag{1}$$

where D_i takes the value 1 if the self-employed worker i has an unpaid helper in the household, and zero otherwise. In the equation, x_i is the vector of characteristics that explains the presence or absence of unpaid helpers; ϵ_i is the error term. Table 5 reports the list of variables used for this matching exercise. Equation (1) essentially provides the coefficients or parameters that inform how each of the listed demographic variables determines the probability of treatment

[8] PSM works by matching individuals or groups who received the treatment with individuals or groups who did not, based on their "propensity score," which is the probability of receiving the treatment given a set of observed characteristics. This helps to reduce selection bias in the comparison of the two groups. See Jann, B. (2017) and Dehejia and Wahba (2002) for more details.

(i.e., SE having a UFH). The propensity score thus gives us the probability or likelihood of each SE worker having an additional UFH in the household based on the specified observable characteristics.

Table 5: List of variables used for PSM Matching

Variable	Type
Age	Numeric
Age squared	Numeric
Rural	Binary
Religion - Hindu	Binary
Religion - Muslim	Binary
Female	Binary
Married	Binary
Caste Group - SC/ST	Binary
Caste Group - OBC	Binary
Education - Below Primary	Binary
Education - Primary or Middle	Binary
Education - Secondary or Higher Secondary or Diploma	Binary
Education - Graduate and above	Binary
Zone 2 – Northeastern states	Binary
Zone 3 - Central states	Binary
Zone 4 - Eastern states	Binary
Zone 5 - Western states	Binary
Zone 6 - Southern states	Binary
10 dummies for 1-digit NIC (industry code)	Binary
10 dummies for 1-digit NCO (occupation code)	Binary

Note: The table reports the list of variables we use for the PSM. Following are the omitted categories: Other religion in religion dummies, other castes in caste dummies, illiterate in education dummies, unmarried/widowed/divorced/separated in marital status dummy, and Zone 1 (Northern states) in zone dummies. We divide the states into size administrative zones following the categorisation used for zonal council (Link- *https://www.mha.gov.in/en/page/zonal-council*). We consider geographical zones instead of states to cater to sample size issues, especially for smaller states/UTs with not enough sample size to find a worker with equal propensity score. We create 10 dummies for both NIC industry code and NCO occupation code based on their 1-digit code and keep one code as omitted category.

Next, we match SE workers with a UFH in the household to SE workers without a UFH but having similar propensity scores. We use the nearest-neighbour technique to match each worker in the treatment group with a counterpart from the control group who has the closest propensity score. The matching is done using three nearest neighbours and a caliper size (the allowed maximum distance between neighbours to ensure that the matches are relatively close) of 0.02 standard deviation. Our results are robust to different thresholds defining a "neighbourhood". The estimates give us the average treated effect on the treated (ATT) - the increase in earnings of SE workers on account of the treatment (presence of UFH).

Table 6 presents the results from propensity score matching (PSM). Columns 1 and 2 report mean earnings for the two groups of SE across years. From Column 3 onwards, the table shows estimated earnings of UFH under different specifications. In Specification 1, we use demography predicting variables such as age, age squared, gender, caste, religion, and education dummies. Specification 2 brings in geographic zones. This ensures that comparisons are made among workers within the same geographical zone. We do not use states as the unit of geographical unit since small sample sizes in several states make it difficult to find suitable matches with similar propensity scores. Specification 3 additionally includes 1-digit industry dummies, as some industries can be more conducive to having UFH as additional workers as compared to others. Finally, as a robustness check, Specification 4 replaces industry codes with 1-digit occupation codes to test the consistency of results. Our preferred specification is Specification 2. Specifications 3 and 4 may suffer from endogeneity as SE workers may choose to enter specific industries or occupations precisely because they can rely on UFH for assistance. In such cases, the presence of an unpaid helper influences the choice of industry or occupation, rather than the other way around.

We find that in almost all the specifications across years, the estimates of unpaid family helpers remain below INR 50 per day – significantly low in comparison to any other type of workers. This is consistent with the results from the previous subsection using the residual approach. We now turn to a more detailed discussion of these two approaches.

3.3 Comparison between Residual Earnings Estimates and PSM Estimates

The PSM estimates remain broadly consistent and in the same range across the seven years and align with estimates from the residual earnings method up to 2021-22. It suggests that on an average the SE are more or less comparable irrespective of whether they have an additional UFH in the household. However, unlike the residual earnings method (which shows higher earnings for UFH in 2022–23 and 2023–24), the PSM estimates remain in the

Table 6: Earning estimates of unpaid family helpers (UFH) by propensity score matching

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean Earning of SE		Estimates earning of UFH			
	SE*w/o*UFH	SE*w/* UFH	Specification 1	Specification 2	Specification 3	Specification 4
2017-18	281.28	332.99	37.98***	49.87***	53.65***	60.81***
			(6.593)	(6.389)	(6.609)	(6.584)
2018-19	285.30	339.36	38.70***	38.85***	52.08***	49.98***
			(6.452)	(7.832)	(6.479)	(7.779)
2019-20	275.00	312.85	27.94***	37.43***	46.88***	45.96***
			(6.094)	(6.235)	(6.357)	(6.477)
2020-21	259.67	316.99	25.93***	37.85***	41.33***	43.92***
			(5.440)	(5.321)	(6.814)	(5.917)
2021-22	274.34	335.99	27.33***	27.93***	44.57***	40.92***
			(5.839)	(6.011)	(6.245)	(6.911)
2022-23	267.06	365.53	45.57***	51.25***	61.33***	60.29***
			(6.293)	(6.328)	(6.470)	(6.802)
2023-24	262.20	370.35	39.81***	34.20***	47.62***	50.66***
			(7.007)	(10.76)	(6.855)	(7.055)
Matching variables						
Demographic			Yes	Yes	Yes	Yes
Administrative zones				Yes	Yes	Yes
Industry group					Yes	Yes
Occupation group						Yes

Source and Notes - Authors' calculations using PLFS. The sample consist of two working member households. Column (1) indicates mean earning of SE workers with no unpaid family helper in their household and similarly, Column (2) indicates mean earning of SE worker with one unpaid family helper in their household. Column (3) to Column (6) reports PSM estimates of earnings for unpaid family helpers (UFH). Specification 1 use matching variables: age, age squared, dummies for rural, female, Hindu, Muslim, OBC, SC-ST and education levels. Specification 2 includes dummies for 6 state regions in addition to Specification 1. Specification 3 includes dummies for 10 1-digit industry groups in addition to Specification 2. Specification 4 includes dummies for 10 1-digit occupation groups in addition to Specification 3.

same range for these two years too. This raises the question of why the residual earnings estimates come out to be much higher in 2022-23 and 2023–24 as compared to estimates from PSM. We explain this difference through the composition of SE workers in these latter years. If many new workers with very low or zero earnings report themselves as SE, this will automatically pull down the group average of SE workers. Consequently, the estimated earnings of UFH increases on account of the design of the residual earnings method (explained in Section 3.1). Accordingly, matching workers based on characteristics becomes important as the newly added SE workers in 2022-23 and 2023-24 with lower earnings are likely to be systematically different from the older pool of SE workers. Thus, newly added SE workers are unlikely to be considered suitable matches under PSM. We thus claim that our second method of PSM gives us more accurate estimates of productivity for UFH.

In the next section, we provide strong suggestive evidence that the earnings of the newly added SE in 2022-23 and 2023-24 are indeed significantly lower than those of earlier pool in the category of SE. The evidence remains suggestive since PLFS gives a repeated cross-sectional data which does not allow us to track the same individual over time.

4 Earnings of self-employed workers

Menon and Jha (2025) show that the recent rise in household earnings is driven by an increase in workforce participation rate within households, i.e., on account of more working members within the household. In the absence of longitudinal data, we are not able to identify households with *new* SE workers. However, since we know that households increasingly have a greater number of working individuals, we compare earning for SE workers in two-working-member households with SE workers in one-working-member households. We want to test if the new SE entrants have lower productivity. This comparison thus allows us to use the SE in one-working-member households as a proxy for households *before* the entry of low productive SE, and the SE in two-working-member households as a proxy for the households *after* the entry of low productivity SE.

Table 7 reports earnings of SE workers in households with one SE worker, and in households with two SE workers. We exclude households with any UFH, since their inclusion would over-estimate the productivity/earning of SE workers. No restrictions are applied to the number of casual or salaried workers in the household, as their earnings are reported separately in the data. We find that the share of SE workers from two–self-employed-worker households rose substantially from 19 percent to 39 percent. Combined with the overall increase in self-employment between 2017–18 and 2023–24, this suggests that the growth in self-employment is primarily driven by households with two SE members. However, their average earnings are lower and have declined significantly in recent years, suggesting that newly added workers are less productive than the existing ones. The results show that the gap in earnings between the two cohorts is increasing over time, reinforcing the argument that the newly added SE workers have lower earnings as compared to their earlier counterparts.

Table 7: Self-employed (SE) workers in various types of households

	(1)	(2)	(3)	(4)
Year	One SE worker in HH		2 SE workers in HH	
	daily earning	share	daily earning	share
2017-18	342.57	81.24	290.92	18.76
2018-19	344.24	81.07	288.8	18.93
2019-20	334.32	77.54	279.03	22.46
2020-21	329.46	75.5	258.35	24.5
2021-22	362.05	71.63	277.39	28.37
2022-23	405.98	68.33	268.09	31.67
2023-24	382.30	61.05	268.28	38.95

Source and Notes - Authors' calculations using PLFS. The sample comprises SE workers from households with either one or two such workers and exclude the households with any unpaid family helper. Column (1) indicates mean earning of SE workers in households with one SE worker and similarly, Column (3) indicates mean earning of SE workers in households with two SE workers. Column (2) reports the share of SE workers from households with a single SE member, and Column (4) reports the share from households with two SE members. The two shares sum to 100.

5 Discussion and Conclusion

The recent period, spanning 2017-18 to 2023-24, has been characterized by a notable increase in India's Labour Force Participation Rate (LFPR) and Worker Population Ratio (WPR), reversing a previous downward trend in female labour force participation. While this secular reversal is a welcome change, it introduces significant concern regarding the quality of the employment being created. This paper aimed to resolve the debate on whether these improved labour market indicators reflect job creation due to economic growth or economic hardship faced by a large portion of the population. Our findings pro- vide support for the latter argument, indicating that the surge in employment is plausibly explained by economic distress rather than growth-driven voluntary participation.

Our results show that the recent rise in employment is largely driven by a category of highly vulnerable workers (UFH), who contribute very little to household income, alongside falling mean real earnings for workers in the largest employment category (OAW). Taken together, the evidence strongly supports the interpretation that the reported increase in employment since 2017-18 reflects a distress-driven search for making ends meet rather than taking advantage of remunerative economic opportunities.

Even with these two estimates of earnings for unpaid helpers, the paper suffers from some limitations. First, in terms of comparability of SEw/oUFH and SEw/UFH, the PSM method improves over residual earnings method by accounting for the observable differences between the two groups. However, the difference in unobservable characteristics between the two groups remain a concern in PSM. The PSM estimator assumes conditional independence, i.e., it is assumed that the assigned treatment (in this case the presence of UFH) is unconfounded given the observables – but the decision to employ UFH may be driven by unobserved household characteristics such as economic distress, family structure, gender norms, and other cultural factors which can also directly affect earnings. Second, it should be noted that the low earnings for UFH may be driven by them not working for as many hours as any other kind of worker. This however reinforces our argument that being a UFH does not appear to be a choice which workers are making despite having other options. The low earnings for UFH could be coming from fewer working hours or lower productivity. In both cases, this does not appear to be a preferred form of employment.

The findings of the paper also highlight the pressing concern of underemployment amongst individuals identified as employed in the labour market. Traditionally identified as a phenomenon persisting in rural agriculture, it is now spreading in the urban landscape too. Taking note of the widely reported problems of youth unemployment (ILO, 2024), without a rise in productivity in the self-employment sector (Afridi, 2025), our results buttress the need to focus on creation of quality jobs not only for better livelihood but also for being the catalyst for higher economic growth through the channel of improved productivity and demographic dividend. Mere higher employment numbers - either through self-creation of jobs or through the wage and salaried kind - falls short of both the above.

References

Afridi, F. (2025). The landscape of self-employment in India: Trends, constraints, and policy prescriptions. *The Indian Journal of Labour Economics*, pages 1–22.

Anand, I. and Thampi, A. (2021). Growing distress and a falling unemployment rate: What is going on in the labour market? In *The India Forum*.

Ara, S. and Shrivastav, P. K. (2025). Decoding rising female labour force participation in india. *Economic and Political Weekly*, 60(26-27).

Basole, A., Abraham, R., Rakshit, A., Vijayamba, R., Shrivastava, A., and Halder, T. (2023). State of working india 2023: Social identities and labour market outcomes.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics*, *84*(1), 151-161.

Ghatak, M., Jha, M., and Singh, J. (2024). Quantity vs quality: Long-term trends in job creation in the Indian labour market. In *The India Forum*.

Goldar, B. and Aggarwal, S. C. (2024). Explaining the significant hikes in female workforce participation rate in India in recent years and some thoughts on how to raise it further. Technical report, Institute of Economic Growth.

ILO (2024). India employment report 2024: Youth employment, education and skills.

Jann, B. (2017). KMATCH: Stata module for multivariate-distance and propensity-score matching, including entropy balancing, inverse probability weighting, (coarsened) exact matching, and regression adjustment. https://ideas.repec.org/c/boc/bocode/s458346.html

Menon, R. and Jha, M. (2025). Household income trends in India: Earnings versus participation. *The Indian Journal of Labour Economics*, 68(1):163–182.

Mundle, S. (2025). The growth employment paradox and how to address it. *Journal of Quantitative Economics*, pages 1–13.

Nagaraj, R. (2023). India derailed: A falling investment rate and deindustrialisation. In *The India Forum*.

The Economist (2025). India has a chance to cure its investment malaise. *The Economist*, (https://www.proquest.com/magazines/india-has-chance-cure-investment-malaise/docview/3213200525/se-2).