Roles of Rural Non-Farm Employment (RNFE) in India: Why RNFE, The Conveyor of a Shock like COVID-19 is Also the Key to Recovery?

by Sunil Saroj, Mamata Pradhan, Ruchira Boss, and Devesh Roy

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Sunil Saroj[1]
Mamata Pradhan[2]
Ruchira Boss[3]
Devesh Roy[4]

Abstract

Focusing on rural labor market, we assess the role of Rural Non-Farm Employment (RNFE) in India in terms of impacts of COVID 19 shock. In India's agri-food system, the preponderance of small farmers with low endowments of human and financial capital has made rural population increasingly dependent on non-farm incomes for their livelihood. The non-farm employment has been the principal source of poverty reduction. Yet the non-farm sector is also the most adversely affected by COVID 19 and the policy measures adopted to present disease spread. The social and economic differentiation make the impacts heterogeneous across groups of workers. We uniquely utilize the recent Periodic Labor Force Survey to assess the role of non-farm in the livelihood. We then assess the potential impact of COVID 19 by using the large data to match similar workers in different states of employment. With job loss, reduction in work hours, diminished participation, movement across types of employment within RNFE that are possible by COVID 19, we estimate that through changes in RNFE, there can be significant poverty and standard of living effects on rural labor. Yet, at the same time, RNFE has the unique potential to foster recovery.

[1] Senior Research Analyst in the South Asia Regional Office of the International Food Policy Research Institute, New Delhi, India. E-mail: s.saroj@cgiar.org
[2] Research Collaborator in the South Asia Regional Office of the International Food Policy Research Institute, New Delhi, India. E-mail: pradhan.mamata@gmail.com
[3] Research Analyst in the Agriculture for Nutrition and Health, International Food Policy Research Institute, New Delhi, India. E-mail: r.boss@cgiar.org
[4] Senior Research Fellow in the Agriculture for Nutrition and Health, International Food Policy Research Institute, New Delhi, India. E-mail: d.roy@cgiar.org

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1. Introduction

In this paper we make contributions to understanding the roles of Rural Non-farm employment (RNFE) in livelihoods of India's rural population using the most recent labor force surveys. Based on Haggblade et al (2013), RNFE includes all rural economic activity outside of agriculture. It includes self-employment, wage employment, full-time, part-time, formal, informal, seasonal, and episodic nonfarm production. In rural areas of India, where landlessness is important RNFE offers important economic alternatives for the rural poor.

After assessing the roles of RNFE in livelihoods, we assess how shocks such as for example from the COVID-19 pandemic and the policy responses may affect workers in RNFE with possible changes in state of employment (SOE). The SOE comprise not having RNFE, engaged as a casual labor, being self-employed or number of hours worked.

The analysis here contributes to the broader literature on non-farm activities by quantifying the role and effect of RNFE on poverty and expenditure and showing that poor rural households in India, benefit significantly from a more diversified income portfolio. Yet there are measurable differences in outcomes based on SOE. RNFE are expected to deliver better outcomes for poor households when subject to an economic shock but it depends on SOE in relation to RNFE. Apart from SOE, with shocks, impacts on workers, in India are likely differentiated also by exogenously given characteristics such as gender and caste (Deshpande 2020). In this paper, we thus look at outcomes in different SOE (own account enterprise, casual labor, hours worked, type of contracts) across different stratifications by gender and caste in relation to RNFE.

By comparing the outcomes of workers in different SOE in RNFE, we are addressing the question, how the terms of engagement in RNFE determine and lead to variation in worker outcomes? Embedded in that question are issues such as: How much difference does it make in outcomes for workers if the nature of job in RNFE is casual labor? What are the earnings from self-employment as part of RNFE compared to being a wage earner? If the levels of earnings is significantly low (against a benchmark like wages in employment guarantee programs), is such RNFE symptomatic of distress entrepreneurship, i.e. the so called pushed entrepreneurs. Though number of regular salaried worker is quite small in case of RNFE, it may still be important to gauge the effects of formalization. How are the outcomes different for regular salaried workers compared to the rest of the employees without contract i.e., informal employment in India's RNFE?

Further, the states and type of employment may also approximate situations following a shock like COVID-19. The events surrounding COVID 19 and policy measures had profound demand as well as supply side effects on RNFE. Between March and June 2020, India witnessed a drastic reduction in the size and scope of economic activity. The first quarter figures in 2020 had economy contracting by as much as 25%, the worst print among major economies. Large sectors of the economy – comprising transportation, hospitality, and construction i.e., non-farm employment (NFE)– had essentially shut down their normal operations. The joblessness rate among youths had risen to over 27%, most of the effect in rural areas was concentrated in RNFE (Center for Monitoring Indian Economy (CMIE) 2020).

Looking at RNFE and possible effects of large shocks on the rural workers is particularly important for India. As the second most populous nation in the world, India's agriculture is characterized by extremely small landholdings. Small and marginal farmers (86% of all farmers) with average land size of 0.6 hectares own only 47% of the arable land (Bisht et al 2020). Small farmers face several constraints related to lack of credit, technology and market access and face great risks in farming.

To survive, rural households must rely on a diverse portfolio and derive their incomes not only from land (RFE) but also from their other endowments, labor, and capital i.e., RNFE. These factors imply that RNFE is an extremely important instrument for rural welfare, food security, reducing poverty, and mitigating excess dependence on farm employment (Kung & Lee, 2001; Lanjouw & Lanjouw, 2001; Ranis & Stewart, 1993). Based on PLFS 2018-19, staggering 113 million workers are engaged in RNFE in India and the number has gone up from 70 million (Foster & Rosenzweig, 2004) in the last two decades, playing an important role in non-farm income, food security and poverty reduction. Though the departure of labor from agriculture to non-agriculture sector has been sluggish in India, new opportunities have certainly emerged in non-farm economy for services sector and areas proximate to urban locations.

In this context, a shock to RNFE or performance in general can have significant welfare effects. In COVID 19, both demand and supply of labor were affected because of lockdowns, movement restrictions, social distancing, and general reduction in goods and services demand. RNFE as characterized in Ranis and Stewart (1993) with both traditional and modern employment in rural industry and services faced the brunt of COVID 19 shock in the rural labor market. Yet, RNFE remains the main source for rural employment generation, for increases in income and poverty reduction, hence is critical to recovery out of any shock to the rural labor market.

To assess the potential effects of a shock like COVID 19 on workers in RNFE, an ideal data would have been one containing both pre-and post-pandemic information on the workers combined with variation in degrees of exposure to the shock among workers. Such data however is not available. Hence, to assess the potential effects of any shock on workers, we simply look at the outcomes in different SOE in RNFE.

RNFE, apart from providing additional income to rural households, also acts as an insurance against negative shocks Oseni and Winters (2009), the extent of which depends on the incidence of the shock, whether the shocks are correlated or idiosyncratic. RNFE can smoothen consumption during a shock if it is less affected than the farm sector. Unlike some earlier studies like Imai et al (2012) using older data from 2004, who do not find RNFE to be inequality reducing in India, PLFS data clearly show that RNFE is characterized by lessened social barriers with women and lower caste having a relatively higher likelihood of employment compared with earlier years hinting at inequality reducing effects of RNFE.

Shocks can affect the workers in different ways i.e., in terms of SOE viz. having no RNFE, turning to casual labor (casualization) or self-employment (push entrepreneurship) or by reduced working hours (time rationing) each one would imply different effects of RNFE. Over time if a shock results in casualization of labor, job loss or pushed self-employment in RNFE, we can approximately gauge the extent of effects on incomes, wages, and poverty.

In looking at the effects of SOE in RNFE on worker outcomes in India, we utilize the largeness of nationally representative employment datasets. Realizing the importance of selection issue in participation in RNFE and within RNFE in different SOE, we apply a host of quasi experimental methods viz. coarsened exact matching (CEM), propensity score matching (PSM) and matching with continuous treatments (for hours of employment and number of family members engaged in RNFE). PSM estimates specifically have been buffered with Rosenbaum bounds to measure the approximate degree of possible bias owing to the inability to account for unobserved factors because of repeated cross-sectional nature of the data. The Rosenbaum bounds approach allows us to determine how strongly unobserved confounding variable must affect selection into treatment to undermine or flip conclusions about causal effects from a matching analysis. Tables A1 in the annexure provide results of propensity score matching for the same counterfactual assessment that has been done for CEM. Table A2 to A5 in the annexure provide estimates and detailed discussion on Rosenbaum bounds approach.

By matching similar laborers in RNFE with different SOE we estimate the effects of SOE, effects from not engaging in RNFE, being self-employed, employed as a casual labor to regular salaried work with contracts. These comparisons tell us, for example, how much higher income an average worker earns if engaged in RNFE or how much higher/lower wages, hours worked, or income earned are associated with casual labor in RNFE. When there is time rationing leading to slackness in the labor market, the number of family members in employment as well the number of hours worked per employee might fall. Hence, we assess the effects of number of family members engaged in RNFE and hours worked as an important SOE in RNFE on earnings and poverty. As these comparisons are based on quasi-experimental methods using repeated cross-sectional data, they do not represent true causal impact of SOE in RFNE on worker outcomes.

In comparing workers in RNFE with workers engaged only in RFE, we can heuristically assess the "impact" of job loss or less diversified earnings portfolio that might emerge also due to a shock like COVID 19. Also, to the extent that higher non-farm earning is not associated with lower farm earnings, RNFE either increases the efficiency of labor in farm activity or the labor moving into non-farm could be surplus labor reallocated to non-farm economy. All these factors matter for implications of engaging in RNFE affecting worker outcomes.

Earlier research examining labor market outcomes for RNFE in India, have only used a nationally representative quinquennial National sample survey data until 2011. That data is no longer administered, and the erstwhile labor force surveys based on long 5-year gaps are now replaced by higher frequency annual Periodic Labor Force Surveys (PLFS) since 2017 that we employ. As these data have emerged only recently, little empirical work has been done particularly to study RNFE.

With regard to the particular shock due to COVID 19, as coronavirus spreads mainly through droplet transmission that occurs when people are in close proximity, within RNFE, employment losses are likely to be heterogenous across jobs. It is expected to have been larger in jobs that involve face-to-face contact and smaller in jobs that can be done remotely. A large part of RNFE in India were directly impacted because a vast majority of jobs are contact driven and very few remotely done i.e., verified by the PLFS data.

Despite social distancing and lockdown measures, work in essential industries may not be disrupted (Montenevo et al 2020). These comprise for example specific wholesale and retail services like medicines and food. This distinction is important also for RNFE in India. As part of RNFE, we also look at specific sectoral and occupational affiliation of the labor. Further distinction that PLFS allows is to distinguish between rural posted rural non-farm employment (RPRNFE) and Urban Posted Rural Non-Farm Employment (UPRNFE), to the extent, the urban areas were comparatively adversely affected by COVID, the effects could have been relatively more pronounced for the latter type of RNFE.

Further, note that, farm sector in India has been subject to price (minimum support prices and procurement) and income support (direct benefit transfer to farmers) that were activated or brought forward during COVID. No such provisions barring the preponed public employment program (National Rural Employment Guarantee Scheme) catering to return migrants encapsulate the non-farm sector. We do look at changed subscriptions to rural employment guarantee schemes in the aftermath of COVID 19, policy measures and reverse migration.

We also summarily look at the distribution of RNFE in relation to the COVID 19 caseload in India, industry affiliation and occupational engagement. Though, initial indications seem to suggest that the historically unprecedented increase in job losses in India have largely been across-the-board in all locations, it is still important to see the work locations in relation to the disease spread. There might be relative differences in outcomes related to RFE and RNFE by COVID caseload. Location of labor would matter also due to control measures that affected both demand and supply in RNFE.

The literature on actual or potential labor market impacts of COVID-19 is only evolving. Gupta et al. (2020) for the case of United States document a massive, nationwide decline in measures of mobility outside home. Alon et al. (2020) find that the social-distancing policies had larger effect on women than men in the labor market unlike in a regular recession. In a more segregated labor market like India, separation of the outcomes not only by gender but also by groups such as caste is quite pertinent.

Hence, how employment status, wages, hours worked, and earnings vary by worker characteristics shows the vulnerability and has implications for not only the potential effect of the shock but also for recovery. Thorat and Newman (2010) show that caste affects rural and urban labor markets equally through exclusion, selective inclusion, unfavorable inclusion, and selective exclusion. In coping with downturns, inclusion and exclusion systems based on caste are likely to matter in India with lower caste facing higher probability of exclusion and a lower probability of post inclusion.

In assessing implications of RNFE for different sub-population, it is important to look at determinants of participation in the first place. We assess that RNFE comparatively require education, skills, factors that can create entry barriers, particularly for the poor. This has implications for choice between RFE and RNFE as well as type of activity within RNFE (Cherdchuchai & Otsuka,2006; Lanjouw & Murgai, 2009).

The paper is organized as follows. The next section presents details about the data used in the analysis of RFE and RNFE. Section following that provides the summary statistics that provide the contextual background including the match of RNFE with COVID 19 caseload and rural employment patterns. The next section assesses the potential impact of a shocks to RNFE by comparing the states of employment that would emerge or change because of COVID. Last section concludes with implications.

2. Data

This paper is about RNFE in India. We use the Periodic Labor Force Survey (PLFS) i.e. a nationally representative dataset conducted with two broad objectives: (i) to measure the dynamics in labor force participation in terms of worker population ratio (WPR), labor force participation rate (LFPR), unemployment rate (UR) and employment status (self-employed, regular wage/salaried and casual labor) in the short time interval of three months for urban areas in terms of Current Weekly Status(CWS).[5] (ii), for both rural and urban areas, PLFS estimates the indicators in both usual status[6] (principal status[7] and subsidiary status[8]) and CWS at annual frequency.

PLFS collects data on (i) household characteristics (household size, household type, religion, social group and monthly household expenditure), (ii) demographic profile of household members (gender, age, marital status, education level, technical education, and formal vocational training), (iii) household members characteristics at industry level (5-digit National Industrial Classification (NIC), 2008) and occupation level (3 digit National Classification of Occupations (NCO), 2004) for principal and subsidiary economic activity, and (iv) household members information on activity status, earnings and hours worked during the week at CWS level.

Moreover, COVID 19 also brought about a mass reverse migration to villages where surplus labor expanded quickly. One of the countervailing factors to labor market was utilization of the rural employment guarantees. Hence, we also obtained information on "person worked" and "person days engaged" in Mahatma Gandhi National Rural Employment Guarantee Act

[5] A person engaged in any economic activity for at least 1 hour/day in last 7 days is considered employed in current weekly status.
[6] A person engaged in any economic activity> 30 days/year is considered employed under usual status (principal status and subsidiary status)
[7] A person employed for more than 183 days in a year in any economic activity is considered the usual principal status.
[8] A person who has worked/employed for minimum 30 days are classified as usual subsidiary status.

(MGNREGA) from April to August months for the period of 2016 to 2020.[9] The new additions to MGNREGA partly reflect the job losses in RNFE, the larger part being the influx of return migrants but also the contraction in RNFE.

Further, we compiled data on number of confirmed cases of COVID-19 as on September 7, 2020 from an open source, focusing on high COVID 19 caseload states contributing to more than 80% of cases.[10] With district level COVID case load we look at density of RNFE (industry and occupation wise) in these locations to gauge vulnerability. Is it that high COVID caseload maps into high concentration of RNFE? In such cases a priori greater potential effects on RNFE can be expected. Apart from mapping location-based vulnerability as a function of disease case load, we also identify most likely affected industries due to COVID 19 from RNFE using NIC 5-digit classification. This underlies the importance of industrial affiliation where because of the nature of shock, some industries were to be more affected than others. In addition, we also look at the most vulnerable occupation groups based on NCO category drawing from International Labor Organization (ILO) identification related to COVID 19.

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[9] MGNREGA provides legal guarantee for 100 days of employment/year at minimum wage for at least one person in each rural household.

[10] https://www.covid19india.org/.

3. Contextual Background

India's case is exceptional owing to the size of the workforce. 113 million are employed in RNFE. Though the numbers are larger for farm employment, it is mainly made up of self-employed farmers. Even in one-year between the two rounds of PLFS, percentage employed in RNFE increased from 40% to 42% and farm-employment went down from 59% (158 million) to 57.8% (155 million). Overall, RNFE growth rate is nearly 5% compared to farm jobs at only 2%.

India has the youngest population in the world, and it is reflected in her workforce (average and median age 35 years) (

Table 1). Male workforce participation in RNFE has increased in 2018-2019 from 2017-2018. The female workforce has increased from 17 million in 2017-18 to 20 million in 2018-19 (

Table 1), a growth rate of 16%, while it is 4.4% in farm sector.

Overall, rural LFP has gone up by 2.2 million and urban by 4.7 million. Such massive growth in just a year does not augur well for employment during COVID crisis for India with a low manufacturing base and comparatively small footprint in global trade. Finding employment for Indian women during COVID could be a higher order task.

Apart from observable characteristics in Table 1 below, unobservable factors could also sort labor into SOE. Maloney (1999) states that casual work without contracts corresponds most closely to the overall definition of informality by Portes et al (1989) with a dualistic view of the labor market. Given the repeated cross-sectional nature of the data, we are unable to account for presorting that is a function of many unobservable factors.

Table 1: Profile of rural employment: Worker characteristics

	RNFE			RFE			Total			17-18	18-19
Variables	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**	**RNFE – RFE**	**RNFE-RFE**
Age Group (%)											
Below 25 age group	19.41	18.4	-1.01	13.47	13.05	-0.4***	15.88	15.31	-0.5***	5.94***	5.35***
	(39.5)	(38.7)		(34.1)	(33.6)		(36.5)	(36.0)			
26-35 age group	32.6	32.54	-0.06	24.56	22.36	-2.20***	27.82	26.66	-1.16**	8.04***	10.18***
	(46.8)	(46.8)		(43.0)	(41.6)		(44.8)	(44.2)			
36-45 age group	25.41	26.91	1.50	26.34	26.69	0.3*	25.96	26.78	0.8*	-0.93	0.22
	(43.5)	(44.3)		(44.0)	(44.2)		(43.8)	(44.2)			
46-55 age group	15.33	14.72	-0.61	19.95	21.09	1.14*	18.07	18.4	0.33	-4.62***	-6.37***
	(36.0)	(35.4)		(39.9)	(40.8)		(38.48)	(38.75)			
56-65 age group	6.17	6.06	-0.11	12.54	13.51	0.97***	9.96	10.37	0.41*	-6.37***	-7.45***
	(24.0)	(23.8)		(33.1)	(34.1)		(29.9)	(30.4)			
Above 65 age group	1.08	1.37	0.29	3.14	3.28	0.14	2.3	2.48	0.18	-2.06***	-1.91***
	(10.3)	(11.6)		(17.4)	(17.8)		(15.0)	(15.5)			
Male Workforce (%)	83.91	82.16	-1.7***	69.98	68.05	-1.9***	75.64	74.00	-1.6***	13.93***	14.11***
	(36.7)	(38.2)		(45.8)	(46.6)		(42.9)	(43.8)			
Social Group (%)											
Scheduled Tribes	8.88	9.42	0.54	16.9	16.49	-0.41**	13.65	13.51	-0.14	-8.02***	-7.07***
	(28.4)	(29.2)		(37.48)	(37.11)		(34.33)	(34.18)			
Scheduled Caste	24.08	25.79	1.71	20.1	19.65	-0.45	21.71	22.24	0.53	3.98***	6.14***
	(42.7)	(43.7)		(40.07)	(39.74)		(41.23)	(41.59)			
Other Backward Caste	44.07	43.14	-0.93	41.16	43.84	2.6***	42.34	43.54	1.2***	2.91***	-0.70
	(49.6)	(49.5)		(49.2)	(49.6)		(49.4)	(49.5)			
General	22.97	21.65	-1.3***	21.84	20.02	-1.82***	22.3	20.71	-1.59***	1.13***	1.63***
	(42.0)	(41.1)		(41.3)	(40.0)		(41.6)	(40.5)			
Education completed (in years)	7.63	7.76	0.13	4.9	5.07	0.17*	6.01	6.21	0.2***	2.73***	2.69***
	(5.01)	(4.92)		(4.69)	(4.73)		(5.00)	(4.99)			
Education Category (%)											
Illiterate	19.28	17.77	-1.51	39.27	37.75	-1.52	31.15	29.32	-1.83***	-19.99***	-19.98***
	(39.4)	(38.2)		(48.8)	(48.4)		(46.31)	(45.52)			
Up to Primary	19.85	20.58	0.73	21.5	22.53	1.03	20.83	21.71	0.88	-1.65***	-1.95***
	(39.8)	(40.4)		(41.0)	(41.7)		(40.61)	(41.23)			
Middle	23.86	24.49	0.63	20.2	19.73	-0.47	21.68	21.74	0.06	3.66***	4.76***
	(42.6)	(43.0)		(40.1)	(39.8)		(41.2)	(41.2)			
Secondary & above	37.02	37.16	0.14	19.02	19.98	0.96	26.33	27.23	0.90	18.00***	17.18***

	RNFE			RFE			Total			17-18	18-19
Variables	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**	**RNFE – RFE**	**RNFE-RFE**
	(48.2)	(48.3)		(39.2)	(39.9)		(44.0)	(44.5)			
Skills (%)											
Received technical / vocational training	18.97	23.82	4.85***	21.4	24.59	3.1***	20.41	24.26	3.8***	-2.43***	-0.77
	(39.2)	(42.6)		(41.0)	(43.0)		(40.3)	(42.8)			
Received technical education	3.47	3.53	0.06	0.46	0.71	0.25**	1.68	1.9	0.22	3.01***	2.82***
	(18.2)	(18.4)		(6.74)	(8.39)		(12.8)	(13.6)			

Source: PLFS 2017-18 and 2018-19
Note: A, B and C stands for Y0 (2017-18), Y1 (2018-19) and Difference (Y1-Y0), respectively

To assess the potential effects of SOE in RFNE on rural workers, it is important to understand its size and structure, particularly in terms of type of employment (self-employed, casual, or regular salaried work). Further, it is pertinent to look at employment by sector, industry, and occupation.

Table 2 gives the employment status across different subpopulations. About 31 million (65%) female and 85 million (78%) males in non-farm sector are self-employed. A generalized demand compression is likely to affect this group significantly. Outside of self-employment, 40 million workers are employed as casual labor and only 1.7 million in regular salaried employment who have any semblance of social or job security. The same kind of social pyramid holds along caste lines. Self-employed and casual labor are likely the most adversely affected from a shock like COVID 19 lacking any job protection.

Table 2: Distribution of workers by employment status (ES) across gender and caste (in Million)

	Category	ES	2017-18			2018-19		
			Farm	Non-farm	Total	Farm	Non-farm	Total
Gender	Female	SE	30.81	6.58	37.39	33.56	8.00	41.57
		RWS	0.58	6.23	6.81	0.53	7.13	7.67
		CL	16.01	4.56	20.57	15.40	5.05	20.45
		Total	47.40	17.36	64.76	49.50	20.18	69.68
	Male	SE	85.31	30.97	116.28	81.41	32.48	113.88
		RWS	1.16	26.92	28.07	1.12	27.14	28.26
		CL	24.04	32.68	56.72	22.89	33.31	56.20
		Total	110.50	90.57	201.07	105.42	92.92	198.34
Caste	ST	SE	6.40	0.34	6.74	7.09	0.59	7.68
		RWS	0.19	0.72	0.91	0.11	0.73	0.83
		CL	3.31	0.76	4.07	2.69	0.78	3.47
		Total	9.90	1.83	11.73	9.88	2.10	11.98
	SC	SE	4.45	1.25	5.70	5.14	1.52	6.65
		RWS	0.05	1.39	1.45	0.04	1.72	1.77
		CL	5.38	1.44	6.82	5.24	1.80	7.04
		Total	9.89	4.08	13.97	10.42	5.04	15.46
	OBC	SE	13.46	3.23	16.69	15.27	4.29	19.55
		RWS	0.27	2.45	2.72	0.33	2.93	3.26
		CL	5.71	1.86	7.58	6.03	2.15	8.18
		Total	19.45	7.53	26.98	21.63	9.36	30.99
	Others	SE	6.49	1.75	8.25	6.07	1.61	7.68
		RWS	0.07	1.67	1.74	0.05	1.75	1.81
		CL	1.60	0.49	2.10	1.45	0.32	1.77
		Total	8.16	3.92	12.08	7.57	3.69	11.26

Table 3 reports a simple probit model's marginal effects for determinants of employment in RNFE. Male workers and youth are more likely to partake in RNFE. Comparatively educated participate in RNFE and RNFE is associated analogously with training. The workers in RNFE being comparatively young, being slightly more educated, training helps them in getting skilled. The nature of employment in RNFE is such that there is both a greater association with casualness (conveyor of shock to workers) and regular salaried (protector against shock) where the latter follows mainly from the comparator group being farm employment.

Since job search entails utilizing personal and institutional networks, educated workers are also better able to seek and process information about job opportunities. Evidence exists from several earlier crises that less educated workers tend to take lower-paying jobs during a crisis, while more educated graduates tend to switch to better jobs more quickly. Real time surveys from other countries, i.e., the UK, US, Germany, Japan, and Canada show that the young, less educated workers, women, and minorities are more affected by COVID19.

Based on regression results, the only place where education does not seem to make a perceptible difference in earnings is casual labor. For casual labor, the biggest employer is construction followed by carpentry, trade, transport and small manufacturing enterprises and services as street vendors, hawkers, head load workers, garment makers, rag pickers and others.

Table 3: Determinants of workforce engaged in non-farm sector –Probit Model

Variables	Marginal Effect (dy/dx)
Age Category (Base-Below 25 age group)	
26-35 age group^	-0.017**
	(0.007)
36-45 age group^	-0.050***
	(0.008)
46-55 age group^	-0.090***
	(0.008)
56-65 age group^	-0.171***
	(0.010)
Above 65 age group^	-0.199***
	(0.015)
Male Workforce^	0.172***
	(0.009)
Social group (Base - OBC)	
Scheduled caste^	-0.009
	(0.008)
Scheduled tribe^	-0.090***
	(0.011)
Other/General^	-0.009
	(0.009)
Education category (Base-Illiterate)	
Up to Primary^	0.054***
	(0.012)
Middle^	0.113***
	(0.014)
Secondary & above^	0.155***
	(0.014)
Received technical / vocational training^	0.177***
	(0.016)
Received technical education^	0.015
	(0.057)
Interaction variables of education with gender	
Male workforce attained primary education	0.003
	(0.014)
Male workforce attained middle education	-0.068***
	(0.014)
Male workforce attained secondary & above education	-0.030**
	(0.015)
Male workforce received technical /vocational training	-0.116***
	(0.014)
Male workforce received technical education	-0.030
	(0.059)

Year (2018-19=1; 2017-18=0)	0.032***
	(0.007)
Constant	
District Fixed Effect	Yes
Observations	176,089

Note: ^ denotes binary variable

According to the recent data by Centre for Monitoring Indian Economy (CMIE), even salaried jobs were highly affected due to the lockdown with 19 million jobs lost during April-July 2020. In case of casual laborer/daily wagers 6.8 million people lost jobs and 0.1 million self-employed/business lost their jobs. At the beginning of the lockdown, in March and April, the informal sector (32% of workforce – involving casual laborers, small traders and street vendors were the worst hit. By occupation, a large percentage of the workforce in RNFE is in construction (13%) followed by others (Table 4).

The summary statistics presented here make it clear that there likely are going to be large disparities in effect of shocks. While there is a certain transition over the long run from RFE to RNFE of which the two-year data is merely symptomatic, many rural workers continue to be engaged in both farming and non-farming activities (20% men and 29% women). In case of women, percentage engaged only in non-farm activities is higher. While there can be several reasons behind this, one possibility is that the differential wage rate for women as also their number of hours worked is lower in both farm and non-farm sector. Comparatively it seems women are more likely to be moonlighting i.e., doing more than one job.

Taking the SOE in RFNE to look at possible worker outcomes relates to effects over the short run. Literature has established that in large shocks to labor markets, there are deeper structural damage what Rothstein (2019) calls the scarring effects and early career setbacks to youth entering the labor force. Such assessment of potential long-term effects is not possible given the data.

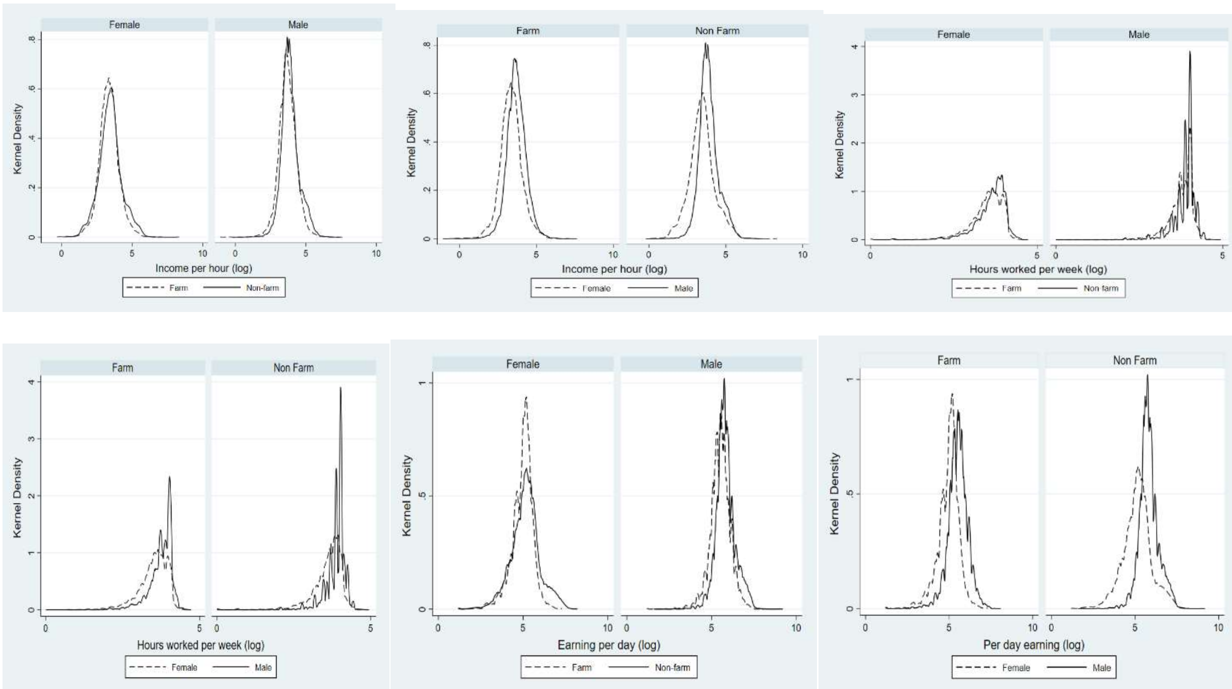
Table 4: Percentage of Workforce Employed in Farm and Rural Non-Farm Sector (in percentage)

	2017-18	**2018-19**
Agriculture	59.4	57.8
Mining and quarrying	0.39	0.36
Manufacturing	7.78	7.75
Electricity & water supply	0.36	0.34
Construction	12.27	13
Trade	6.68	7.23
Transport	3.75	3.87
Accommodation & food services	1.22	1.16
Other services	8.16	8.48

Source: PLFS data 2017-18 & 2018-19

Figure 1 plots the density of several labor market outcomes in RNFE in terms of wages, hours worked and earnings. There is significant variation by gender and sector of employment. A definite pecking order exists in the outcomes by gender and by employment in non-farm. Not presented for brevity but such an ordering is present by caste as well. Given the preexisting differences, impact of any shock on the rural labor market in India would be differentiated by these attributes viz. gender, caste, sector of employment and occupation.

Figure 1 Kernel density-earning/day, hours worked/week and income/hour by gender and sector



In 2018-19, the average income earned per day in the non-farm sector was INR 305 ($4.15), much higher than the average income of INR 174 ($2.37) per day in the farm sector. Women fare worse than men in both categories, i.e., farm and non-farm. On average, nearly 17% of workforce in farm sector fall below poverty line (BPL) in comparison to 12% for non-farm.

RNFE can be broadly divided into two groups of occupations: high-income /high productivity activities and low-income/ low productivity activities. The latter largely serves as the residual source of employment – a “last-resort “source of income (Dang and Lanjouw, 2015). In India, a large proportion of the workforce engaged in the low income RNFE where an average worker is precariously close to falling into poverty. Any sizable shock by changing SOE such as disengagement in RNFE and casualization of the workforce in RNFE would likely translate into rising poverty of the rural labor force in India.

Coming to the context of COVID 19, according the PLFS 2018-19, for the workers employed in vulnerable occupations (like street vendors, domestic helpers, cleaners; manufacturing laborer) the average earning per day for rural located non-farm activities was merely INR 233 ($3.1), whereas for urban-based non- farm activities it was approximately INR 280 ($3.8).

3.1. Vulnerability in farm and non-farm employment due to COVID-19: Possible location-based heterogeneity

Figure 2, Figure 3 and Figure 4 show the disease case load as of September 7, 2020 and distribution of employment in different groups of non-farm activities. There are many areas of high caseload based on reported cases which also have high share of non-farm employment and employment in COVID 19 affected industry or occupation. The similar kind of congruence is obtained if the case load is measured in terms of COVID 19 positivity rate.

Figure 2: RNFE distribution and COVID caseload across space

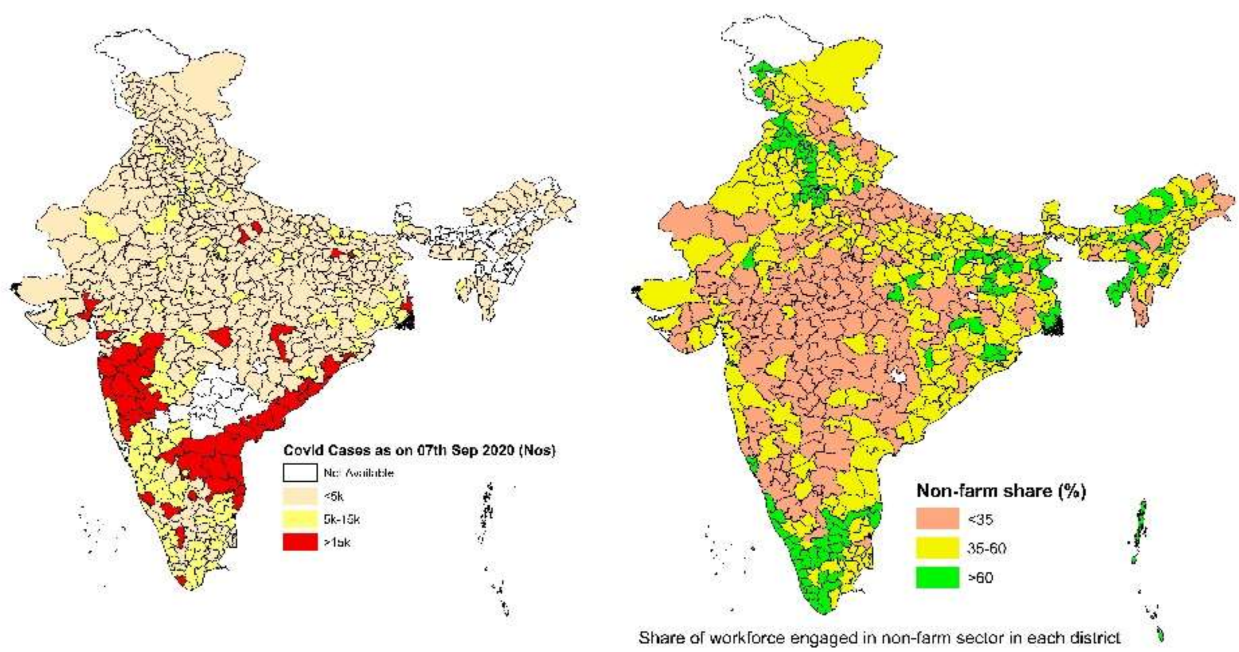


Figure 3: COVID caseload and non-farm employment in vulnerable industries

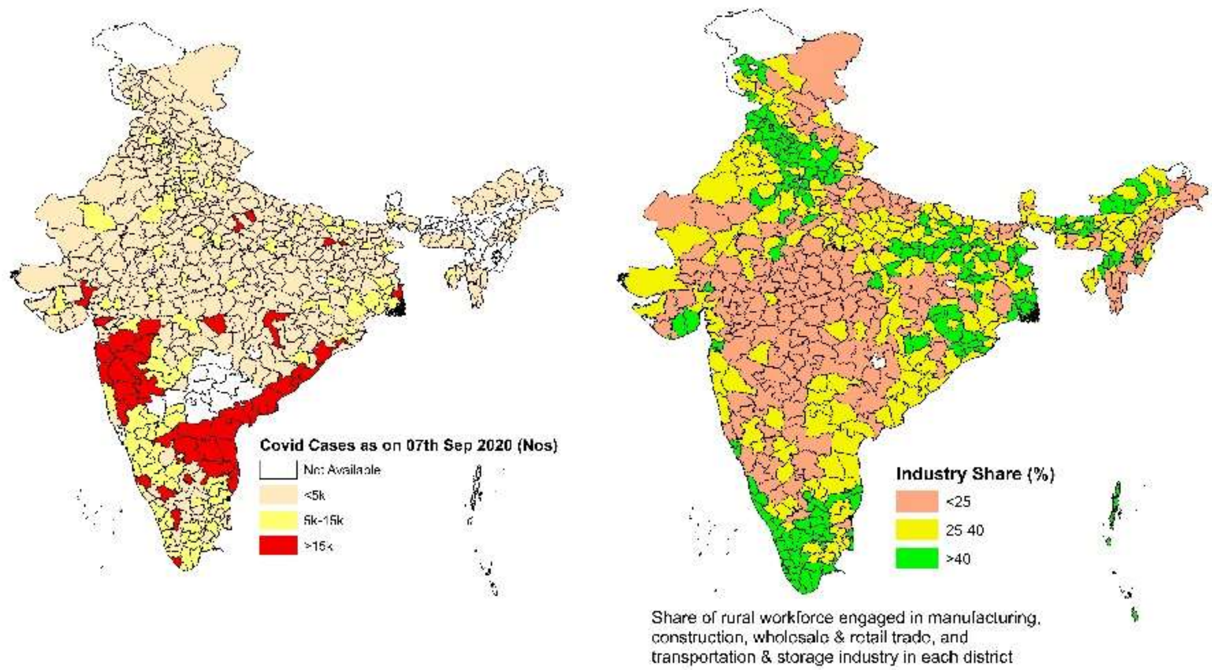
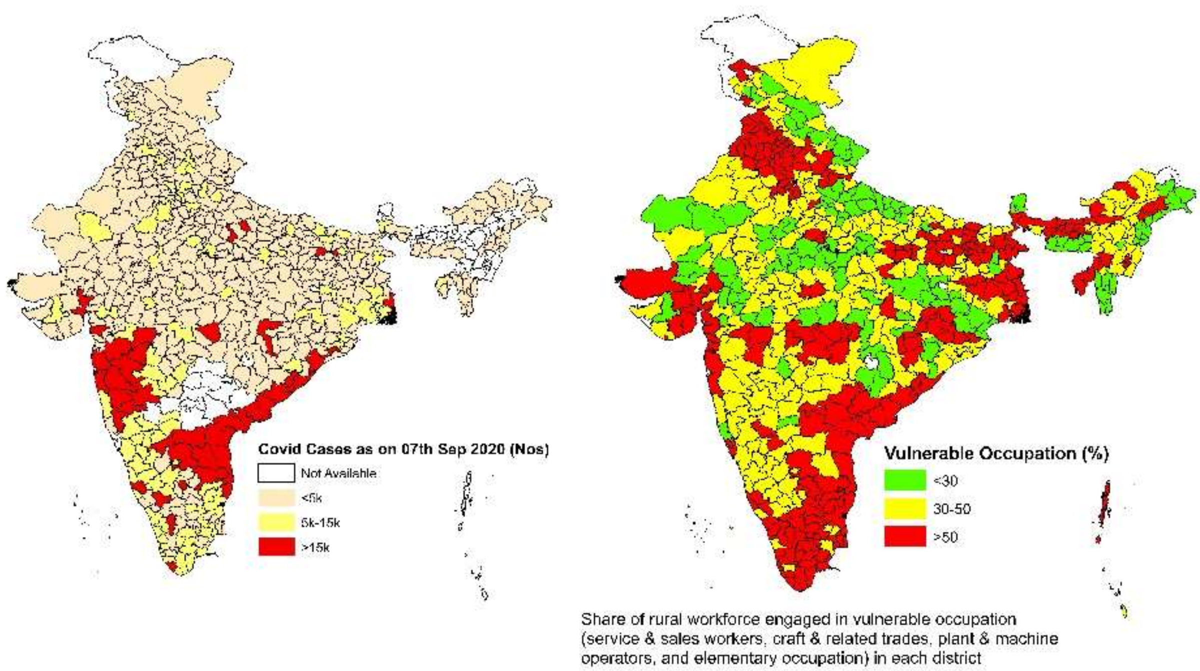
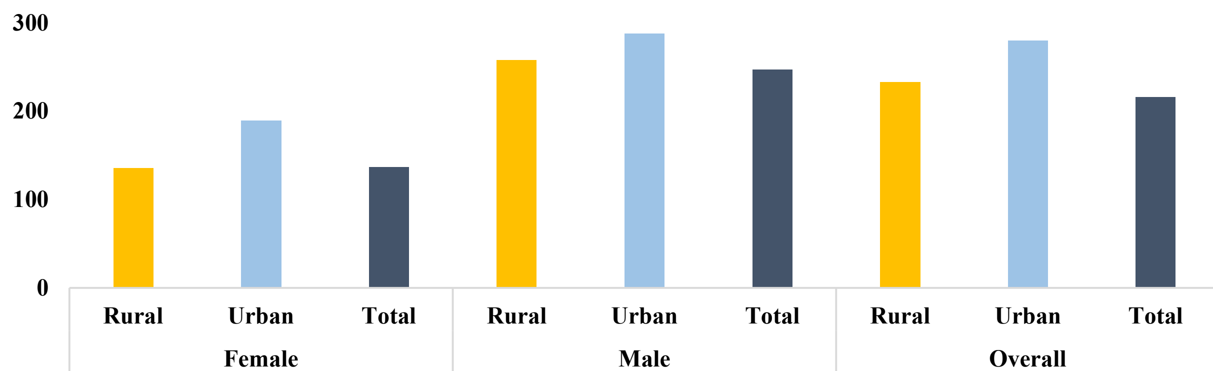


Figure 4: COVID case load and non-farm employment in vulnerable occupations



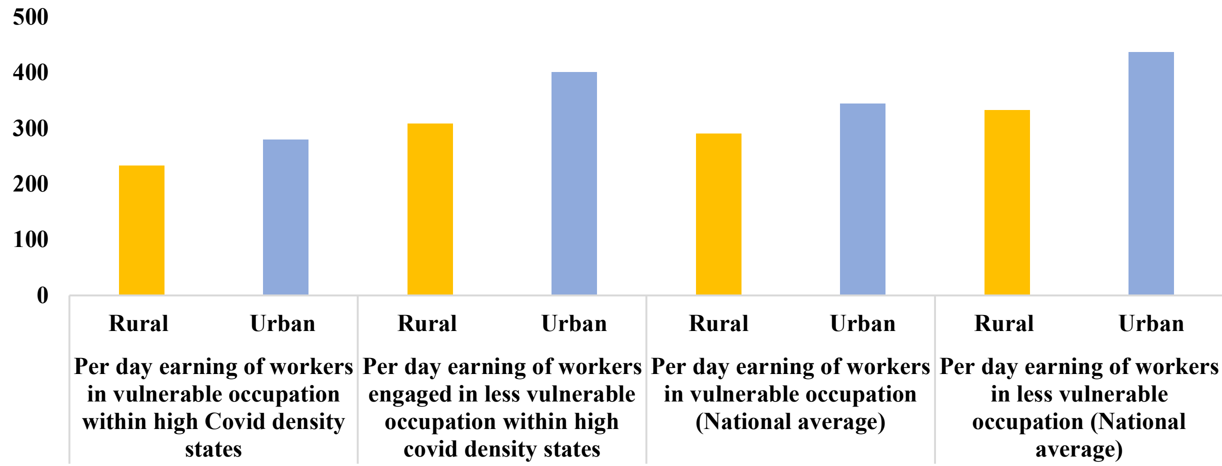
As of August 2020, the states with high density of COVID-19 cases in India include Maharashtra, Andhra Pradesh, Tamil Nadu, Karnataka, Uttar Pradesh, New Delhi, West Bengal, Bihar, Telangana, and Assam. About 60% of the total workforce in RNFE is concentrated in these 10 high COVID caseload states of which about 67% of the workforce is engaged in vulnerable occupations like street vendors, domestic helpers, laborers engaged in manufacturing and construction sector. About 58% of the total women workforce is in 10 highly COVID-19 affected states, 70% are engaged in vulnerable occupations (including street vendors, agricultural laborers, transport laborers and other personnel workers) without any social security benefits (Figure 5 and Figure 6).

Figure 5: Average income/day of women and men employed in rural and urban non- farm sector in states with high COVID density (in INR)



Source: PLFS data and authors' compilation

Figure 6: Per day earning of workers engaged in rural and urban non-farm sector based on vulnerability in the occupations (in INR)



3.2. Assessment of the potential impact of SOE or shocks like COVID 19 on RNFE

To assess how the RNFE or type of employment or SOE impacts wages and hours and ultimately earnings and poverty status, in non-experimental settings, an ideal case would be longitudinal data where workers would switch from one type of employment to another and outcomes in different states could be recorded. In absence of such data, we use within sample matching methods to assess the implications of different SOE in RNFE on outcomes. Casual labor and self-employed in the sample of rural labor have the highest incidence of poverty. We match comparable workers based on observable characteristics. The outcomes are (i) wages/day (ii) hours/week (iii) per capita consumption expenditure (iv) poverty status based on the two different poverty line.

The comparison of states that we use to derive the counterfactual scenarios possible due to labor market shock comprise the following:

(i) Changes in engagement in non-farm employment– As a COVID fallout for example, the non-farm job may be lost. The outcomes from RNFE participation on poverty, per capita expenditure would capture on average the outcomes from job loss in RNFE.

(ii) Changes in employment status- Owing to a shock like COVID, impact on being self-employed if pushed into micro-entrepreneurship due to stress.

(iii) Changes in employment status (casualization) – Because of shocks like COVID, being turned into casual labour.

(iv) Changes in the hours worked due to scaling down of employment following a shock.

(v) Changes in share of family members engaged in RNFE.

The outcomes that we assess are poverty based on national poverty estimates (based on Tendulkar poverty line), per day income, income per hour (in INR), hours worked per week, per capita expenditure (in INR/day), percentage of people living below international poverty line ($1.90/day) and, percentage of people earning less than Rs 375/day ($5) i.e., the amount judged by government's expert panel for a basic living wage.

As a first assessment, Table 5 presents the results of ''Coarsened Exact Matching'' (CEM), where the treatment is engagement in RNFE. For robustness, assessment has also been done using propensity score matching. CEM is a matching technique belonging to the ''Monotonic Imbalance Bounding'' (MIB), introduced by Iacus et al (2011). Compared to PSM, CEM reduces imbalance in means of the covariates between treated and control units as well as imbalances in higher moments of the empirical distributions and other non-linearities and interactions due to better overlapping. The basic idea of CEM is to coarsen each variable by recoding so that substantively indistinguishable values are grouped and assigned the same numerical value (groups may be the same size or different sizes depending on the substance of the problem). King et al. (2011) show that CEM dominates commonly used existing matching methods in its ability to reduce imbalance, model dependence, estimation error, bias, variance, mean square error, and other criteria.

In this comparison, we match up SOE in RNFE within the dataset to try and forge an adequate counterfactual. Results show the effects of employment in RNFE, is significantly associated with lower poverty-based on national as well as international poverty lines. Since measurement based on poverty lines is criticized (Deaton 2005, Ravallion 2003) for its arbitrariness, we also look at per capita expenditure.

Table 5: "Impact" of Non-farm employment on outcomes –Coarsened Exact Matching Model

Outcome Variables	**2017-18**	**2018-19**
Poverty Tendulkar	-0.027***	-0.022***
	(0.004)	(0.003)
Per day income (In INR)	115.35***	114.070***
	(2.241)	(2.303)
Hours worked per week	7.530***	6.904***
	(0.207)	(0.201)
Per capita expenditure (In INR)	4.857***	4.258***
	(0.298)	(0.292)
Income earned per hour (In INR)	10.960***	12.944***
	(0.425)	(0.485)
Poverty at IPL <$1.90	-0.052***	-0.042***
	(0.004)	(0.003)
Poverty at Rs 375/day	-0.117***	-0.122***
	(0.004)	(0.004)
Explanatory Variables		
District fixed effect	Yes	Yes
Year fixed effect	No	No
Clustering at FSU level	Yes	Yes

4. What does type of employment imply for rural labor outcomes?

If a shock like COVID 19 were to result in casualization of labor, what is the potential average outcome from casualization i.e., being a casual labor, relative to other SOE from the point of view of earnings, hours worked and standard of living in terms of income and likelihood of being poor? As part of COVID 19 shock, there could be movement of labor towards casual labor as well as self-employment as distress entrepreneurship particularly when reentering the labor market. We are not in position to identify the type of entrepreneurship but relative to salaried and even casual labor, the premium or discount in earnings would be symptomatic of pushed entrepreneurship as a fallout of COVID like shock and the resulting policy response.

Borowczyk-Martins and Lale (2019) show that the share of workers employed part-time increases substantially in economic downturns. One reason is that casual or part time jobs are more prevalent in sectors that are less sensitive to the business cycle. In stressed labor markets during crisis, there always have been reductions in working hours in jobs and that may be one part of adjustment to COVID shock beyond the proliferation of casual labor.

Hence, in RNFE we do find that being a casual labor or being self-employed significantly "impacts" the probability of being poor (Table 6) and varies by gender and caste. Hence, relative to alternatives if a shock leads to casualization and/or self-employment the difference in earnings for similar workers would assess the potential impact of the shock.

Further, one of the impacts expected of labor market shock from COVID would be shrinkage in the possible number of hours available to work and extent of participation of family members at the household level. Hence, we also assess the impact of hours worked and the share of family members engaged in RNFE by applying a Generalized Propensity Score Matching and estimating dose response functions (DRF) following Hirano and Imbens (2004). Matching for working hours and share of family members employed in non-farm on incomes earned conjectures that there can be reduced availability of work as an aftermath of COVID type shock.

Occupationally, there are several employments that faced COVID 19 related labor market disruptions comprising elementary occupations, characterized by low skills hence replaceable, delivering products or services that are deferrable (non-essential category) and involving activities that are impeded with social distancing.[6] These occupations where most casual laborers in RNFE are employed have been most adversely impacted during COVID lockdowns and restrictions.

Table 6: Impact of employment status on outcome indicators in rural non-farm sector– using Coarsened Exact Matching Model

Treatment variable	**1= Engaged in Casual labor; 0=Otherwise**		**1=Engaged in Self-employment, 0 = Otherwise**		**1=Engaged in regular / salaried; 0=Otherwise**	
Outcome Variables	**2017-18**	**2018-19**	**2017-18**	**2018-19**	**2017-18**	**2018-19**
Poverty Tendulkar	0.049***	0.042***	-0.01***	-0.009**	-0.019***	-0.013***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
Per day income (In INR)	-23.03***	-16.27***	-75.6***	-83.6***	119.033***	112.328***
	(3.501)	(3.172)	(3.253)	(3.535)	(4.759)	(3.980)
Hours worked per week	-13.295***	-10.501***	2.088***	3.129***	6.207***	2.294***
	(0.338)	(0.310)	(0.227)	(0.225)	(0.243)	(0.232)
Per capita expenditure (In INR)	-6.054***	-5.598***	-2.285***	-1.956***	7.849***	6.560***
	(0.451)	(0.457)	(0.420)	(0.401)	(0.571)	(0.495)
Income earned per hour (In INR)	16.439***	16.689***	-15.578***	-21.583***	7.712***	14.758***
	(0.821)	(0.824)	(0.573)	(0.944)	(1.741)	(0.858)
Poverty at IPL <$1.90	-0.066***	-0.061***	0.033***	0.041***	-0.001	-0.009**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Poverty at Rs 375	0.042***	0.042***	0.033***	0.038***	-0.084***	-0.069***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
District fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	No	No	No	No	No	No
Clustering at FSU level	Yes	Yes	Yes	Yes	Yes	Yes
Explanatory Variables	Age, gender, Caste, Education, Technical training, Technical education, engaged in elementary occupation					

Source: Authors' estimates

4.1. Impact of hours worked and level of participation in RNFE: Estimates from Generalized Propensity Score Matching

We estimate the relationship between hours worked and share of family members in RNFE and outcomes such as wages and earnings (per capita daily expenditure) and likelihood of being poor. Obviously, answer to this question would vary by type of employment —a stratification that we maintain in our analysis. The Dose Response Function (DRF) establish the ranges in which hours worked in RNFE is effective in influencing earnings and hence poverty.

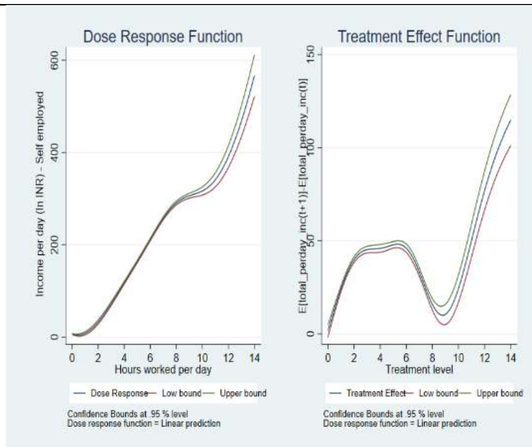
The first measure enables us to consider the participation of household members in RNFE over the previous twelve months. However, if the household size is large, they would be more likely to engage more of their members to work in RNFE. Therefore, the second measure of non-farm activity allows us to consider the relative prevalence of non-farm employment in the household. Admittedly, the two measures do not distinguish the time periods that households spend in non-farm activities. For example, some households might work for more time in a year. This concern is mitigated to an extent by the hours spent in nonfarm activities at an individual level.

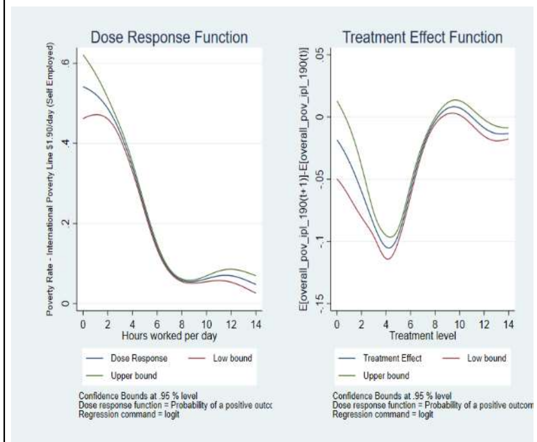
Based on the estimated DRFs for different ranges of hours worked and participation in RNFE at the household level, casual labor and self-employed have the highest returns to hours worked in terms of per capita daily expenditure after a threshold (Figure 7). Hours worked for them are quite important for maintaining a standard of living. Any reduction in hours worked can have significant negative effects due to COVID 19 related downturn. Other salient features of DRFs are: (i) these are estimated comparatively precisely with thin confidence intervals (ii) At high level of hours of work DRFs are with wider intervals because of fewer observations.

Figure 7: Dose response functions for hours worked

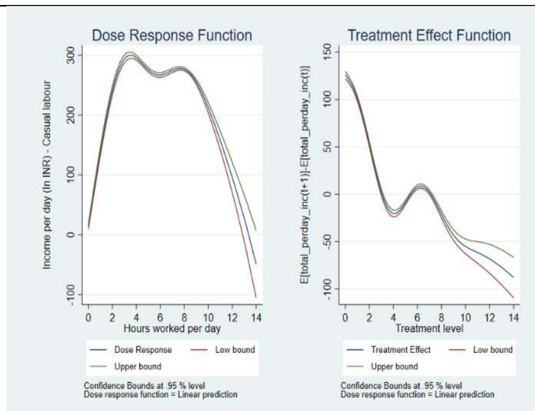
Outcome Variables →	Income per day (in INR)	Poverty Rate

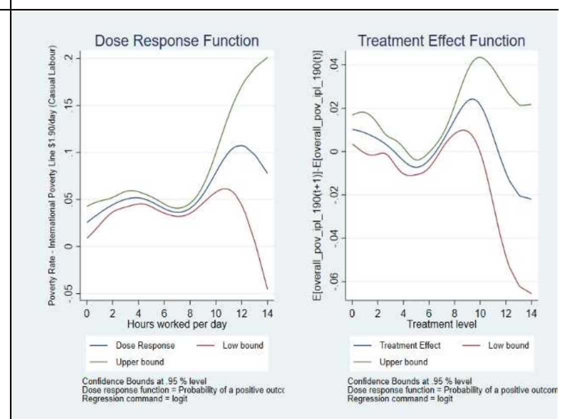
Self-employed



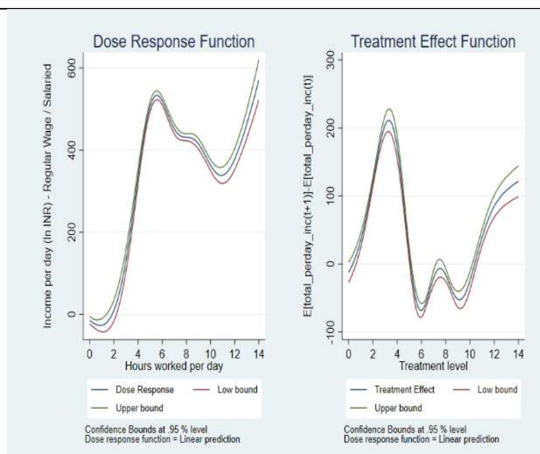


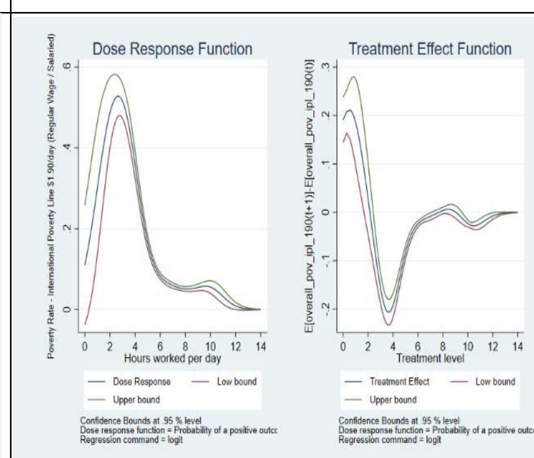
Casual labour





Regular wage / salaried

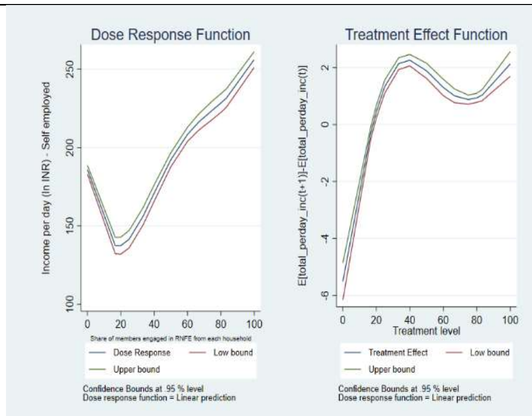
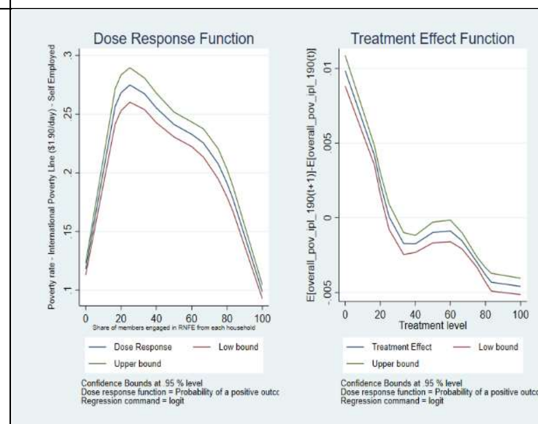
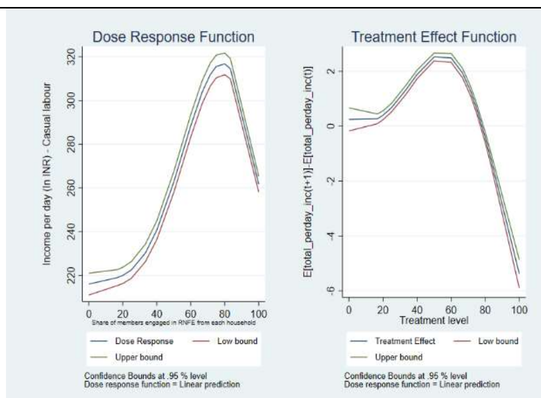
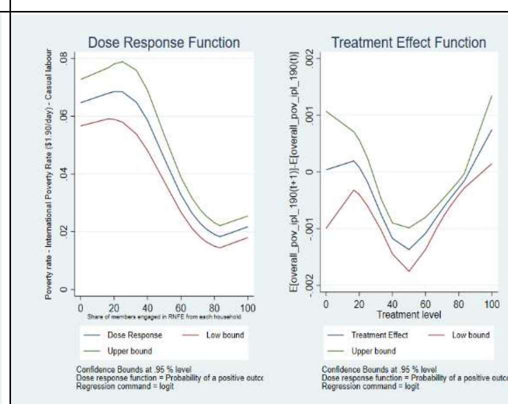




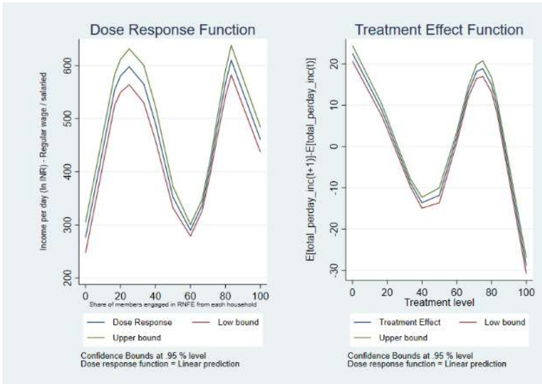
Source: Authors' estimates

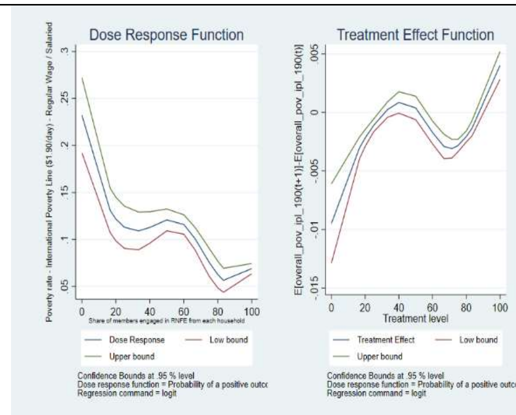
Alternatively, we also obtain the dose response function for the level of engagement in RNFE at the household level. If less RNFE were to be available, this would not only be reflected in terms of reduced hours at the individual level but also scaled down participation of the members in RNFE at the household level. The DRFs are estimated imprecisely at high levels of hours worked because there are few observations at that level.

Figure 8: DRF for level of participation in RNFE at household level

Outcome Variables →	**Income per day (in INR)**	**Poverty Rate**
Self-employed		
Casual labour		

Regular wage / salaried





Source: Authors' estimates

Both

Figure *7* and Figure 8 show the potential for shrinkage in availability of work for RNFE due to a shock like COVID 19. Reduced working hours or curtailed participation of the household members in RNFE would increase poverty significantly. Extreme poverty also is associated with greater engagement in RNFE possibly as distress employment. After a level, greater participation brings down poverty just like greater intensity of participation at the individual level.

4.2. Uptake of rural employment guarantee

How much joblessness may have occurred in rural areas because of COVID is still not clear and difficult to say. One marker for the job losses due to COVID 19 is the uptick in the job card usage in rural areas. MGNREGA which guarantees non-farm employment for 100 days in a year had a surge in applications post COVID (

Table 7). That the workers had increased the uptake of MGNREGA is due to a mix of two factors. Certainly, it is emblematic of return migration but may also capture the shrinkage in RNFE. Compared year-on year and covering the harvest period for winter (rabi) crop when person days worked remained same as earlier years, post-harvest it escalated depicting that RNFE was probably shrinking, paying lower or even not operational (

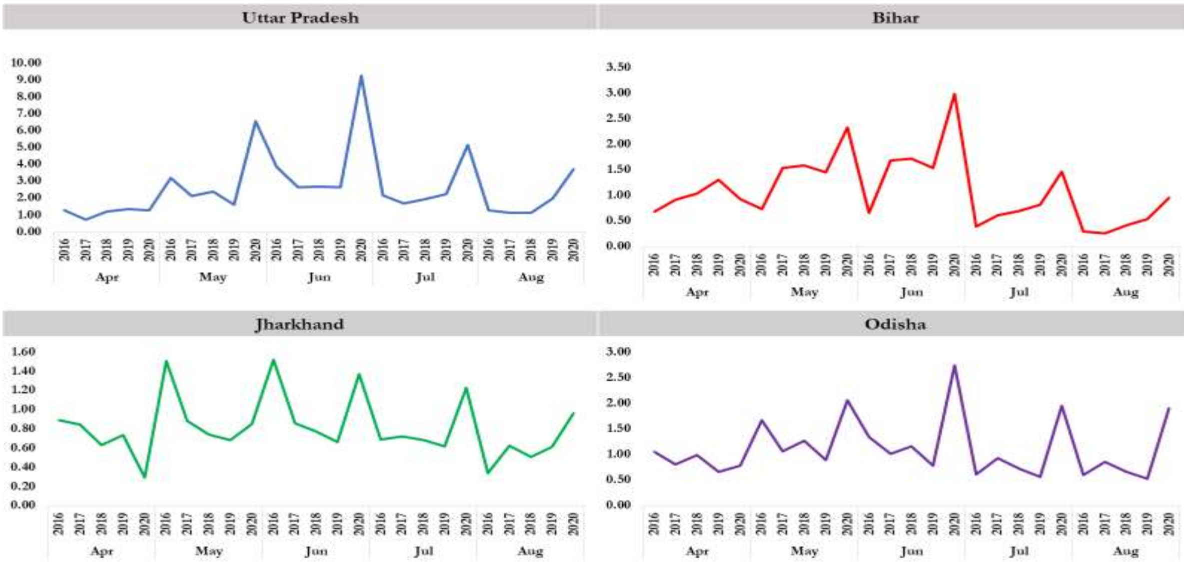
aand 9b).

Table 7: State wise MGNREGA job card issued (In Million)

State Name	2018-19	2019-20	2020-21	April 2020 to 25th Aug 2020	YoY (2017 to 2018)	YoY (2018 to 2019)	YoY (2019 to 25th Aug 2020)	Change from April 2020 to Aug 2020
Andhra Pradesh	8.82	8.96	9.33	9.33	2.03	1.65	4.11	0.00
Arunachal Pradesh	0.23	0.24	0.25	0.25	4.10	5.89	4.78	3.14
Assam	4.65	4.88	4.89	5.32	5.15	4.78	9.08	8.79
Bihar	15.86	16.92	17.51	19.36	6.95	6.64	14.46	10.61
Chhattisgarh	3.80	3.88	3.98	4.17	2.62	2.09	7.39	4.62
Goa	0.03	0.03	0.03	0.04	0.75	0.27	10.63	10.60
Gujarat	3.73	3.90	4.03	4.18	5.50	4.65	7.08	3.65
Haryana	0.93	0.98	1.04	1.05	4.80	5.98	6.23	0.09
Himachal Pradesh	1.24	1.28	1.30	1.33	2.74	2.53	4.43	2.74
Jammu And Kashmir	1.22	1.25	1.24	1.34	3.31	2.01	6.93	7.57
Jharkhand	4.40	4.64	4.83	5.35	6.75	5.48	15.25	10.69
Karnataka	5.96	6.35	6.73	6.73	7.88	6.45	6.09	0.08
Kerala	3.51	3.64	3.70	3.72	5.28	3.56	2.23	0.47
Madhya Pradesh	6.98	7.10	7.22	7.43	4.17	1.76	4.63	2.98
Maharashtra	8.51	8.68	8.70	9.47	1.06	2.06	9.12	8.88
Manipur	0.57	0.57	0.57	0.58	3.41	0.75	1.02	0.71
Meghalaya	0.56	0.59	0.59	0.61	5.56	4.14	3.67	2.48
Mizoram	0.19	0.20	0.20	0.20	1.37	3.21	0.92	0.51
Nagaland	0.43	0.44	0.44	0.44	1.26	0.61	0.72	0.15
Odisha	6.48	6.80	6.98	7.22	2.39	4.95	6.17	3.39
Punjab	1.59	1.71	1.76	1.89	8.52	7.46	10.57	7.40
Rajasthan	10.13	10.52	10.92	11.31	3.84	3.91	7.46	3.60
Sikkim	0.08	0.08	0.08	0.09	1.71	1.12	2.20	1.50
Tamil Nadu	8.17	8.38	8.45	8.70	2.62	2.48	3.92	2.96
Tripura	0.63	0.63	0.63	0.64	2.38	0.70	1.31	0.77
Uttar Pradesh	16.19	17.06	18.65	19.80	4.66	5.38	16.06	6.17
Uttarakhand	1.06	1.09	1.12	1.17	2.22	2.68	6.92	4.16
West Bengal	11.98	12.48	12.74	13.39	2.28	4.12	7.31	5.08
All India	**128.07**	**133.39**	**138.05**	**145.22**	**2.52**	**4.16**	**8.87**	**5.20**

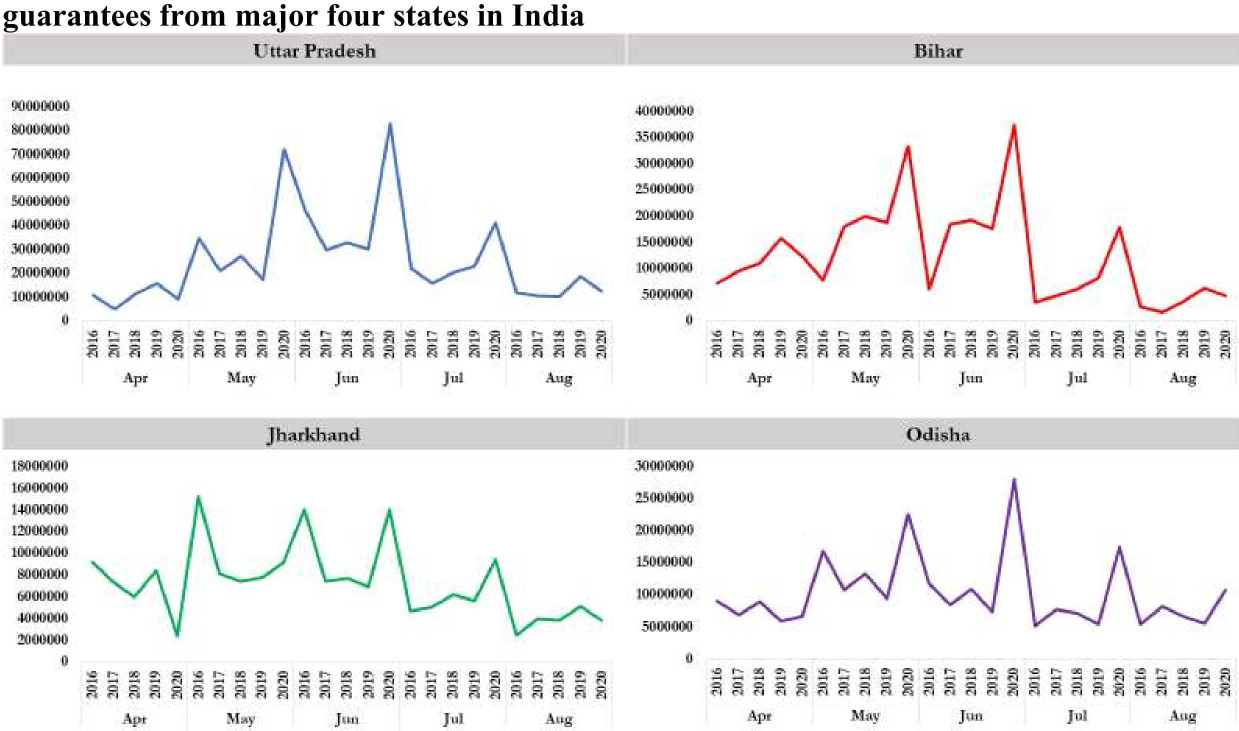
Source: MGNREGA Public Portal Data; https://nregarep2.nic.in/netnrega/dynamic2/dynamicreport_new4.aspx; YoY- year on year change

Figure 9a: Month on Month comparison in person worked (in Million) under employment guarantees from major four states in India



Source: MGNREGA Public Portal Data; https://nregarep2.nic.in/netnrega/dynamic2/dynamicreport_new4.aspx

Figure 10b: Month on Month comparison in person days engaged under employment guarantees from major four states in India



Source: MGNREGA Public Portal Data; https://nregarep2.nic.in/netnrega/dynamic2/dynamicreport_new4.aspx

5. Conclusions and Policy Options

The objective of this paper was to evaluate the roles of RNFE in livelihoods and assess possible effects of labor market shocks in general or the COVID 19 crisis in particular on India's rural labor market. Our results show the significant role of RNFE in household incomes and poverty reduction. Women are engaging in RNFE at a greater rate than men. RNFE is also marked by participation of other disadvantaged groups though their wages and working hours are lower. In spite of the lower wages and working hours for some groups, RNFE is significantly associated with poverty reduction. Hence, a shock to RNFE can potentially have effects on household wellbeing and overall poverty. Owing to this, COVID 19 can have significant developmental impacts as rural non-farm employment has been the most affected with the pandemic.

By creating counterfactuals based on workers in different states of employment we estimate the potential impacts on different labor market outcomes. Heterogeneity of workers by education, training, caste, and gender is to be associated with differentiated adjustments in labor markets hit by COVID shock. Sharp increases in unemployment and enterprise closures happened as a fallout of COVID 19. We do find significant likelihood of transient poverty owing to labor market shocks affecting RNFE. The effects are also gendered with women wage earnings characterized by a discount. Such differentiation is also there based on caste.

In the discussion we pointed out the distinct worker, work and location characteristics that lead to vulnerability of India's vast rural workforce from the labor market shocks. This crisis for India's rural labor market is unprecedented, unmatched in severity and is likely to affect disproportionately those who are least able to respond, such as casual labor and self-employed micro entrepreneurs. In both the farm and non-farm sector there is very little presence of regular salaried work that could provide job or social security.

There are several policy options that can follow for meeting the challenges in the rural labor market. The government could focus on the most affected as the results show significant heterogeneity across workers. The same considerations would apply for reengaging and reentry into the RNFE accordingly. We do see several entry barriers in RNFE that government could ease as part of COVID recovery. Understanding the importance of skill for resilience in the labor market, large scale skilling in rural non-farm sector might be needed as part of recovery package.

While we do not claim to provide fully causal estimates, our identification strategies generate relatively consistent and mutually supportive results, an outcome that provides confidence that our non-farm participation and state of employment impact estimates broadly capture the potential fallout of a labor market shock like COVID 19. One may conclude that non-farm activities are equally important for men and women. However, non-farm activities are differentially important to women's welfare as evidenced by women's greater and faster growing participation in non-farm activities in India.

Access to social security benefits which is a marker of vulnerability includes benefits like paid leaves, job contracts and pensions, among others. The RNFE seems to fare better though marginally than farm sector in providing these benefits to its workforce. However, different sectors within RNFE fare differently in providing these benefits. About 71 million workers in rural based non-farm sector do not have any benefits compared to about 13 million workers in the urban-based non-farm sector (Nearly 84 million in total in RNFE do not receive any social security benefits (Not only an overwhelming number of people employed in rural located non-farm sector are without any social benefits, but it is also characterized by low level of earnings in comparison to urban-based non-farm sector).

Strikingly less than 7% have a job contract and 86% have no benefits associated with job, the perfect recipe for vulnerability to labor market disruptions. Disadvantaged workers typically have a low reservation wage, with no social security and job protection. With large shocks like COVID 19, these workers may be pushed to take any job that allows for some cash.

Our findings also emphasize rural diversification as an important tool for alleviating poverty, for increasing expenditure, absorbing the surplus agricultural labor and as a coping mechanism to deal with shocks. However, notwithstanding the opportunities and effectiveness of the non-farm economy, in times of shock like COVID and for recovery, it may not benefit all rural households equally; in particular, the poorest may be left behind, given their lack of certain endowments, such as education and training. Our results, taken together, also suggest that while the RFNE is the conveyor of shock of COVID 19 to the rural labor market, it uniquely can be the savior given India's endowments, its level of industrialization and place in global trade.

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Annexure

Table A1: Impact of employment status on outcome indicators in rural non-farm sector– using PSM Model (2017-18)

		Nonfarm and Farm			Within Non-farm sample								
		1=RNFE;0=Otherwise			1=CL;0=Otherwise			1=SE;0=Otherwise			1=RWS;0=Otherwise		
Outcome Indicators	**Methods**	**ATT**	**SE**	**P-val**	**ATT**	**SE**	**P-val**	**ATT**	**SE**	**P-val**	**ATT**	**SE**	**P-val**
Poverty Tendulkar	Kernel - BW(.01)	**-0.064**	0.003	-22.5	**0.089**	0.006	15.7	**-0.015**	0.004	-3.8	**-0.036**	0.005	-7.6
	Kernel - BW(.05)	**-0.064**	0.003	-22.8	**0.089**	0.006	15.96	**-0.016**	0.004	-3.95	**-0.035**	0.005	-7.76
	NNM=1	**-0.029**	0.024	-1.22	**0.119**	0.022	5.48	**-0.014**	0.024	-0.58	**-0.037**	0.026	-1.45
	NNM=3	**-0.035**	0.014	-2.50	**0.111**	0.013	8.53	**-0.003**	0.014	-0.22	**-0.034**	0.014	-2.36
	NNM=5	**-0.049**	0.011	-4.44	**0.105**	0.010	10.09	**-0.007**	0.011	-0.61	**-0.027**	0.012	-2.36
	Radius Caliper (0.01)	**-0.065**	0.003	-22.89	**0.089**	0.006	15.75	**-0.015**	0.004	-3.67	**-0.036**	0.005	-7.72
	Radius Caliper (0.05)	**-0.064**	0.003	-23.01	**0.089**	0.006	15.92	**-0.015**	0.004	-3.92	**-0.036**	0.004	-7.97
	Local Linear BW (0.05)	**-0.065**	0.024	-2.73	**0.089**	0.022	4.11	**-0.017**	0.024	-0.68	**-0.035**	0.026	-1.38
	Bootstrap (R=1000)	**-0.029**	0.024	-1.23	**0.119**	0.024	4.98	**-0.014**	0.024	-0.60	**-0.037**	0.022	-1.65
Per Day Income (In INR)	Kernel - BW(.01)	**146.28**	1.81	80.91	**-14.70**	4.70	-3.13	**-75.38**	3.27	-23.07	**129.93**	3.93	33.09
	Kernel - BW(.05)	**146.80**	1.80	81.61	**-16.02**	4.63	-3.46	**-80.04**	3.24	-24.73	**129.08**	3.88	33.25
	NNM=1	**120.20**	13.88	8.66	**-46.03**	18.87	-2.44	**-130.28**	24.19	-5.39	**108.92**	16.91	6.44
	NNM=3	**121.31**	7.50	16.18	**-37.97**	11.04	-3.44	**-94.05**	14.22	-6.61	**102.21**	10.17	10.05
	NNM=5	**133.36**	5.73	23.29	**-33.81**	8.76	-3.86	**-91.10**	11.4	-7.9	**110.44**	7.72	14.31
	Radius Caliper (0.01)	**146.21**	1.81	80.77	**-14.55**	4.70	-3.09	**-80.42**	3.26	-24.64	**130.31**	3.93	33.17
	Radius Caliper (0.05)	**146.97**	1.79	81.88	**-17.35**	4.63	-3.75	**-81.06**	3.23	-25.12	**131.36**	3.86	33.99
	Local Linear BW (0.05)	**146.93**	13.88	10.58	**-19.91**	18.87	-1.06	**-78.69**	24.19	-3.25	**126.50**	16.91	7.48
	Bootstrap (R=1000)	**120.22**	11.33	10.61	**-46.03**	12.18	-3.78	**-130.29**	18.57	-7.01	**108.92**	17.44	6.24
Income per hour (In INR)	Kernel - BW(.01)	**16.29**	0.34	47.30	**17.44**	0.80	21.67	**-16.25**	0.54	-30.17	**10.21**	0.66	15.45
	Kernel - BW(.05)	**16.43**	0.34	48.09	**17.16**	0.80	21.52	**-16.56**	0.53	-31.02	**10.13**	0.65	15.68
	NNM=1	**13.42**	2.87	4.67	**12.47**	2.48	5.03	**-20.94**	3.56	-5.87	**9.09**	2.65	3.43
	NNM=3	**13.08**	1.99	6.56	**13.29**	1.58	8.43	**-16.63**	2.14	-7.79	**8.59**	2.09	4.12
	NNM=5	**15.38**	1.42	10.85	**14.01**	1.28	10.97	**-16.78**	1.96	-8.56	**10.50**	1.52	6.91
	Radius Caliper (0.01)	**16.31**	0.35	47.26	**17.43**	0.81	21.57	**-16.28**	0.54	-30.21	**10.01**	0.66	15.14
	Radius Caliper (0.05)	**16.45**	0.34	48.29	**16.96**	0.80	21.25	**-16.65**	0.53	-31.30	**10.53**	0.64	16.46
	Local Linear BW (0.05)	**16.30**	2.87	5.67	**16.56**	2.48	6.68	**-16.53**	3.56	-4.64	**9.64**	2.65	3.64
	Bootstrap (R=1000)	**13.42**	2.24	5.99	**12.47**	1.68	7.43	**-20.94**	3.26	-6.43	**9.09**	3.38	2.69
Hours worked per week	Kernel - BW(.01)	**7.96**	0.13	59.21	**-12.89**	0.27	-47.76	**2.21**	0.20	10.95	**5.32**	0.23	23.07
	Kernel - BW(.05)	**7.96**	0.13	59.73	**-12.86**	0.27	-48.05	**2.13**	0.20	10.65	**5.32**	0.22	23.96
	NNM=1	**10.75**	1.14	9.43	**-12.97**	1.02	-12.70	**1.98**	1.17	1.69	**5.51**	1.33	4.14
	NNM=3	**10.27**	0.66	15.66	**-13.01**	0.63	-20.60	**1.89**	0.72	2.64	**4.38**	0.78	5.59
	NNM=5	**9.48**	0.51	18.76	**-12.78**	0.50	-25.34	**1.95**	0.56	3.45	**3.72**	0.61	6.08
	Radius Caliper (0.01)	**7.98**	0.13	59.22	**-12.85**	0.27	-47.55	**2.15**	0.20	10.65	**5.35**	0.23	23.20
	Radius Caliper (0.05)	**7.96**	0.13	59.98	**-12.87**	0.27	-48.09	**2.08**	0.20	10.41	**5.34**	0.22	24.38
	Local Linear BW (0.05)	**8.02**	1.14	7.04	**-12.79**	1.02	-12.52	**2.29**	1.17	1.95	**5.42**	1.33	4.07
	Bootstrap (R=1000)	**10.75**	1.07	10.09	**-12.97**	0.98	-13.23	**1.98**	1.15	1.72	**5.51**	1.20	4.60

		Nonfarm and Farm			Within Non-farm sample								
		1=RNFE;0=Otherwise			1=CL;0=Otherwise			1=SE;0=Otherwise			1=RWS;0=Otherwise		
Outcome Indicators	**Methods**	**ATT**	**SE**	**P-val**	**ATT**	**SE**	**P-val**	**ATT**	**SE**	**P-val**	**ATT**	**SE**	**P-val**
Per capita exp (In INR)	Kernel - BW(.01)	**9.51**	0.24	39.79	**-8.60**	0.60	-14.36	**-3.53**	0.43	-8.24	**11.58**	0.51	22.69
	Kernel - BW(.05)	**9.54**	0.24	40.15	**-8.74**	0.59	-14.77	**-3.86**	0.42	-9.09	**11.53**	0.50	23.00
	NNM=1	**2.13**	2.75	0.77	**-7.77**	2.29	-3.39	**-3.29**	2.99	-1.10	**9.45**	2.49	3.80
	NNM=3	**5.51**	1.26	4.39	**-8.27**	1.43	-5.78	**-3.75**	1.77	-2.12	**8.75**	1.44	6.06
	NNM=5	**6.85**	0.96	7.15	**-8.32**	1.15	-7.27	**-3.76**	1.41	-2.66	**10.29**	1.10	9.34
	Radius Caliper (0.01)	**9.55**	0.24	39.92	**-8.69**	0.60	-14.49	**-3.97**	0.43	-9.26	**11.63**	0.51	22.77
	Radius Caliper (0.05)	**9.57**	0.24	40.39	**-8.89**	0.59	-15.03	**-3.98**	0.42	-9.39	**11.72**	0.50	23.50
	Local Linear BW (0.05)	**9.57**	2.75	3.47	**-9.04**	2.29	-3.94	**-3.71**	2.99	-1.24	**11.15**	2.49	4.48
	Bootstrap (R=1000)	**2.14**	1.61	1.32	**-7.77**	1.83	-4.26	**-3.29**	2.33	-1.41	**9.45**	2.36	4.00
Pov $1.90	Kernel - BW(.01)	**-0.059**	0.003	-19.81	**-0.095**	0.005	-21.01	**0.040**	0.004	11.26	**0.012**	0.004	3.14
	Kernel - BW(.05)	**-0.059**	0.003	-20.25	**-0.092**	0.004	-20.66	**0.041**	0.004	11.46	**0.010**	0.004	2.74
	NNM=1	**-0.127**	0.022	-5.67	**-0.095**	0.021	-4.50	**0.043**	0.020	2.09	**0.025**	0.018	1.38
	NNM=3	**-0.102**	0.013	-7.90	**-0.080**	0.013	-6.17	**0.021**	0.012	1.75	**0.012**	0.012	0.99
	NNM=5	**-0.102**	0.010	-10.16	**-0.091**	0.010	-8.95	**0.023**	0.009	2.60	**0.005**	0.010	0.57
	Radius Caliper (0.01)	**-0.058**	0.003	-19.77	**-0.094**	0.005	-20.79	**0.040**	0.004	11.30	**0.012**	0.004	3.21
	Radius Caliper (0.05)	**-0.059**	0.003	-20.42	**-0.091**	0.004	-20.49	**0.041**	0.004	11.60	**0.011**	0.004	3.00
	Local Linear BW (0.05)	**-0.059**	0.022	-2.63	**-0.095**	0.021	-4.49	**0.040**	0.020	1.97	**0.011**	0.018	0.59
	Bootstrap (R=1000)	**-0.127**	0.020	-6.27	**-0.095**	0.022	-4.31	**0.043**	0.019	2.26	**0.025**	0.017	1.52
Rec Rs 375	Kernel - BW(.01)	**-0.166**	0.003	-56.81	**0.027**	0.007	3.60	**0.041**	0.005	7.53	**-0.100**	0.006	-15.95
	Kernel - BW(.05)	**-0.167**	0.003	-57.28	**0.029**	0.007	3.91	**0.045**	0.005	8.29	**-0.100**	0.006	-16.34
	NNM=1	**-0.110**	0.022	-4.99	**0.130**	0.032	4.05	**0.127**	0.035	3.65	**-0.033**	0.033	-1.01
	NNM=3	**-0.116**	0.012	-9.36	**0.080**	0.018	4.39	**0.072**	0.020	3.64	**-0.044**	0.018	-2.41
	NNM=5	**-0.132**	0.010	-13.74	**0.068**	0.015	4.65	**0.052**	0.016	3.32	**-0.055**	0.014	-3.78
	Radius Caliper (0.01)	**-0.167**	0.003	-56.95	**0.026**	0.007	3.52	**0.045**	0.005	8.23	**-0.101**	0.006	-16.00
	Radius Caliper (0.05)	**-0.167**	0.003	-57.45	**0.030**	0.007	4.12	**0.046**	0.005	8.45	**-0.104**	0.006	-17.03
	Local Linear BW (0.05)	**-0.168**	0.022	-7.61	**0.032**	0.032	1.01	**0.043**	0.035	1.23	**-0.097**	0.033	-2.99
	Bootstrap (R=1000)	**-0.110**	0.020	-5.58	**0.130**	0.025	5.12	**0.127**	0.032	3.91	**-0.033**	0.032	-1.03

Note: CL=Casual labour, SE=self-employed and RWS=regular / wage salaried

Rosenbaum bounds for PSM estimates.

In general, the conjecture of randomization is not valid with observational data. Hence without randomization of a treatment, one cannot assume that the data points are exchangeable due to the probability of treatment being equal across treated and control groups. Matching methods are thus not robust against "hidden bias" arising from the existence of unobserved variables that simultaneously affect assignment to treatment and the outcome variable (Di Prete and Gangl 2004). One strategy for addressing this problem is the Rosenbaum bounds approach, which allows to determine how strongly an unmeasured confounding variable must affect selection into treatment in order to undermine the implications of a matching analysis.

In the Rosenbaum bounds approach, the starting point is estimating the Average Treatment Effect on the treated (ATT) using matching methods based on standard ignorability assumption. In the second step, as analyst, one postulates the existence of a confounding variable W, which is associated with the odds of being assigned to the treatment (D=1), conditional on covariates. With the potential impact of W on D (in terms of odds ratios) becomes stronger, the confidence interval on the estimated effect becomes wider. Alternatively, the significance level of the test of null hypothesis of no effect of treatment on outcomes (i.e., the p-value goes up). For each assumed level of association between W and D, there are associated end points on the bounds for significance level of the test of the null hypothesis for the case where W's effect on the outcome is so strong that knowledge of W would perfectly predict which of a pair of matched cases would have the higher response regardless of which case received the treatment (Di Prete and Gangl 2004).

Estimation of Rosenbaum bounds

Rosenbaum's method of sensitivity analysis relies on the sensitivity parameter γ (gamma) that measures the degree of departure from random assignment of treatment. This implies that two known distributions with the same observed characteristics may differ in the odds of receiving the treatment by at most a factor of γ. In a randomized experiment, randomization of the treatment ensures that $\gamma = 1$. In an observational study, if $\gamma = 2$, and two known distributions are identical on matched covariates then one might be twice as likely as the other to receive the treatment because they differ in terms of an unobserved covariate (Rosenbaum 2005).

While values of γ are unknown, we try several values of γ and see if the conclusions change. The hidden bias estimates are provided in tables below. The unobserved heterogeneity has varied for all five outcome indicators of three different set of treatment variables. We compare Rosenbaum bounds on treatment effects at different level of γ and compare Rosenbaum bounds on treatment effects at different level of γ values in the steps of 0.10, starting from 1. Hence, in all three treatment equations for all seven outcome variables, the γ values ranging from 1.0 to 3.90 in the case of casual labour treatment function (Table A3). The critical level of γ at which we would have to question our conclusion of a positive effect of RNFE is between 1.90 and 2.0 (income per day) i.e., is attained if an unobserved covariate caused the odds ratio of treatment assignment to differ between treatment and control cases by a factor of about 2.60. For self-employed and regular wage / salaried, γ values range from 1.0 to 3.0 (Table A4 and A5).

However, we have provided values of lower bound, but this is not significant since it is always lower than the observed p-value. Hence, for instance $\gamma = 3.0$ in self-employed case, this means that self-employed worker in the matched pair may be 3.0 times likely to earn more income per hour as the other due to different values on an unobserved covariate and the effect we observe here would still be significant at $(\gamma - 0.10)$ level. This implies that to attribute a higher income per hour in self-employed cases due to an unobserved covariate the effect on odds ratio will have to be 2.40 times. This is a high value of γ and higher value greater than one implies that the hidden bias is increasing the likelihood of the being assigned to one group compared to being assigned to the other group.

Table A2: Rosenbaum Bounds for rural non-farm sector treatment effects.

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	2.1/2.6 /3.3/4. 0
Poverty Tendulkar	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.98
	Hidden Bias	U	0.00	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Confidence Interval	U	0.00	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Income per day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Hidden Bias	U	100.00	88.89	79.94	71.43	63.49	55.56	49.50	42.86	36.88	31.29	26.11	-0.20
		L	100.00	110.00	119.44	128.33	136.83	144.44	152.38	159.17	166.51	172.22	178.06	211.11
	Confidence Interval	U	97.22	86.90	77.78	69.44	61.11	53.93	47.22	40.95	34.92	29.29	23.93	-2.78
		L	101.59	111.91	122.22	130.56	138.89	147.22	154.82	161.11	168.33	175.00	180.56	213.61
Income per hour	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.73	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	10.43	8.84	7.40	6.09	4.86	3.73	2.68	1.68	0.75	-0.12	-0.96	
		L	10.43	12.04	13.51	14.88	16.16	17.36	18.50	19.58	20.61	21.59	22.53	
	Confidence Interval	U	10.10	8.51	7.08	5.75	4.54	3.40	2.34	1.35	0.41	-0.46	-1.30	
		L	10.76	12.37	13.85	15.22	16.51	17.71	18.86	19.95	20.98	21.97	22.92	
Hours worked per week	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Hidden Bias	U	11.00	10.17	9.33	8.67	8.00	7.33	6.67	6.17	5.67	5.17	4.67	-0.17
		L	11.00	11.83	12.67	13.50	14.00	14.67	15.33	15.83	16.33	16.83	17.33	21.50
	Confidence Interval	U	10.83	10.00	9.17	8.50	7.83	7.17	6.50	6.00	5.50	5.00	4.50	-0.33
		L	11.17	12.17	12.83	13.67	14.33	14.83	15.50	16.00	16.50	17.00	17.50	21.83
Per capita expenditure	Critical Value	U	0.00	0.00	0.03	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	2.1/2.6/3.3/4.0
	Hidden Bias	U	2.76	1.46	0.29	-0.77	-1.74	-2.64	-3.48	-4.26	-4.98	-5.67	-6.31	
		L	2.76	4.06	5.28	6.42	7.47	8.48	9.42	10.32	11.17	11.98	12.76	
	Confidence Interval	U	2.49	1.20	0.03	-1.02	-2.00	-2.90	-3.74	-4.51	-5.24	-5.93	-6.58	
		L	3.02	4.34	5.56	6.70	7.76	8.77	9.71	10.61	11.47	12.30	13.08	
Poverty rate below $1.90/day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14
	Hidden Bias	U	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.33
		L	-0.17	-0.17	-0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Confidence Interval	U	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.33
		L	-0.17	-0.17	-0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Poverty rate below INR 375/day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.00	0.00	0.00	0.00	0.00	0.77	1.00	1.00	1.00	1.00	1.00	
	Hidden Bias	U	0.00	0.00	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.33	-0.33	-0.33	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Confidence Interval	U	0.00	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.33	-0.33	-0.33	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

Note: U-Upper limit, L-Lower Limit and highlighted column cell means p-value is not significant beyond that Gamma values and hidden bias (upper and lower limit) has reached close to zero value. The maximum gamma values for poverty Tendulkar, income per day, hours worked per week, and poverty rate below $1.90/day are 2.10, 2.60, 3.30 and 4.00, respectively.

Table A3: Rosenbaum Bounds for casual labour from rural non-farm sector treatment effects

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	2.3/2.4 /3.9
Poverty Tendulkar	Critical Value	U	0.00	0.00	0.00	0.30	0.98	1.00	1.00	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	
		L	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.17	0.17	0.33	
	Confidence Interval	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	
		L	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.17	0.17	0.17	0.33	
Income per day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.00	0.00	0.00	0.00	0.07	0.95	1.00	1.00	1.00	1.00	1.00	
	Hidden Bias	U	-30.56	-38.89	-46.03	-52.78	-58.89	-64.91	-70.52	-75.56	-80.56	-85.56	-89.50	
		L	-30.56	-22.22	-15.19	-8.33	-2.78	2.78	8.33	13.16	17.34	21.98	25.56	
	Confidence Interval	U	-33.33	-41.67	-49.17	-55.56	-62.11	-68.17	-73.79	-78.89	-83.61	-88.89	-92.94	
		L	-27.78	-19.44	-12.22	-5.56	0.00	5.56	11.11	16.11	20.27	25.00	28.50	
Income per hour	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.55	0.99	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	7.48	6.22	5.08	4.05	3.11	2.23	1.42	0.67	-0.04	-0.71	-1.34	
		L	7.48	8.75	9.94	11.04	12.07	13.04	13.97	14.85	15.69	16.49	17.27	
	Confidence Interval	U	6.97	5.72	4.59	3.56	2.62	1.75	0.93	0.18	-0.53	-1.20	-1.83	
		L	7.98	9.27	10.46	11.57	12.61	13.60	14.53	15.42	16.28	17.10	17.89	
Hours worked per week	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.46
	Hidden Bias	U	-11.50	-12.50	-13.33	-14.17	-15.00	-15.83	-16.50	-17.17	-17.83	-18.33	-19.00	-26.17
		L	-11.50	-10.67	-9.67	-9.00	-8.33	-7.67	-7.00	-6.50	-6.00	-5.67	-5.17	0.00
	Confidence Interval	U	-11.83	-12.83	-13.83	-14.67	-15.33	-16.17	-16.83	-17.50	-18.17	-18.83	-19.33	-26.67
		L	-11.17	-10.33	-9.33	-8.67	-8.00	-7.33	-6.83	-6.17	-5.67	-5.33	-4.83	0.33
Per capita expenditure	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95
	Hidden	U	-9.25	-10.26	-11.18	-12.02	-12.80	-13.51	-14.18	-14.80	-15.39	-15.93	-16.46	-18.28

Outcome Indicators		**Gamma Values →**	**1.00**	**1.10**	**1.20**	**1.30**	**1.40**	**1.50**	**1.60**	**1.70**	**1.80**	**1.90**	**2.00**	**2.3/2.4 /3.9**
	Bias	L	-9.25	-8.21	-7.28	-6.41	-5.60	-4.83	-4.12	-3.45	-2.80	-2.19	-1.62	0.45
	Confidence Interval	U	-9.62	-10.64	-11.56	-12.40	-13.17	-13.89	-14.56	-15.19	-15.76	-16.32	-16.84	-18.68
		L	-8.86	-7.83	-6.89	-6.01	-5.20	-4.43	-3.71	-3.03	-2.39	-1.78	-1.19	0.89
Poverty rate below $1.90/day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	-0.01	-0.01	-0.01	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	
		L	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Confidence Interval	U	-0.01	-0.01	-0.01	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	
		L	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Poverty rate below INR 375/day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Hidden Bias	U	0.17	0.17	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
	Confidence Interval	U	0.17	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.33

Same as Table A2. The maximum gamma values for hours worked per week, per capita expenditure and poverty rate below INR 375/day are 3.90, 2.40 and 2.30, respectively.

Table A4: Rosenbaum Bounds for self-employed from rural non-farm sector treatment effects

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	2.4/3.0
Poverty Tendulkar	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.59	
	Hidden Bias	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	
		L	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	
	Confidence Interval	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	
		L	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	
Income per day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96
	Hidden Bias	U	-91.48	-101.72	-111.11	-120.00	-127.94	-136.11	-143.24	-150.00	-155.97	-162.22	-167.94	-188.89
		L	-91.48	-80.56	-71.13	-62.22	-54.17	-46.85	-39.44	-33.33	-27.06	-21.11	-15.61	3.89
	Confidence Interval	U	-94.44	-105.56	-114.94	-123.74	-132.00	-139.44	-147.22	-153.57	-160.24	-166.59	-172.22	-192.22
		L	-87.59	-77.22	-67.25	-58.33	-50.28	-42.98	-36.11	-29.44	-23.15	-17.22	-11.67	8.02
Income per hour	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31
	Hidden Bias	U	-16.44	-17.92	-19.27	-20.52	-21.69	-22.78	-23.80	-24.77	-25.68	-26.54	-27.35	-33.86
		L	-16.44	-14.99	-13.66	-12.45	-11.34	-10.30	-9.33	-8.43	-7.59	-6.78	-6.03	-0.16
	Confidence Interval	U	-16.95	-18.43	-19.79	-21.04	-22.22	-23.31	-24.34	-25.32	-26.23	-27.09	-27.92	-34.48
		L	-15.94	-14.48	-13.16	-11.95	-10.83	-9.79	-8.83	-7.93	-7.07	-6.27	-5.51	0.38
Hours worked per week	Critical Value	U	0.00	0.00	0.00	0.00	0.02	0.91	1.00	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	2.83	2.17	1.50	0.83	0.33	-0.17	-0.67	-1.17	-1.67	-2.17	-2.50	
		L	2.83	3.50	4.17	4.83	5.33	5.83	6.33	6.83	7.17	7.50	8.00	
	Confidence Interval	U	2.67	2.00	1.17	0.67	0.00	-0.50	-1.00	-1.50	-2.00	-2.33	-2.83	
		L	3.17	3.83	4.50	5.00	5.67	6.00	6.67	7.00	7.33	7.83	8.17	
Per capita expenditure	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.00	0.00	0.00	0.00	0.22	1.00	1.00	1.00	1.00	1.00	1.00	
	Hidden	U	-4.75	-6.01	-7.16	-8.22	-9.19	-10.10	-10.94	-11.73	-12.47	-13.17	-13.84	

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	2.4/3.0
	Bias	L	-4.75	-3.48	-2.31	-1.22	-0.21	0.73	1.62	2.47	3.26	4.02	4.74	
	Confidence Interval	U	-5.19	-6.45	-7.60	-8.65	-9.63	-10.54	-11.37	-12.18	-12.91	-13.62	-14.29	
		L	-4.31	-3.04	-1.86	-0.77	0.24	1.20	2.09	2.94	3.74	4.50	5.23	
Poverty rate below $1.90/day	Critical Value	U	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		L	1.00	1.00	1.00	1.00	1.00	1.00	0.96	0.46	0.03	0.00	0.00	
	Hidden Bias	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.17	-0.17	
		L	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	
	Confidence Interval	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.17	-0.17	-0.17	
		L	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	
Poverty rate below INR 375/day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.02	0.81	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	
	Confidence Interval	U	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
		L	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.33	

Same as Table A2. The maximum gamma values for income per day and income per hour are 2.40 and 3.00, respectively.

Table A5: Rosenbaum Bounds for regular wage / salaried from rural non-farm sector treatment effects

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	3.0
Poverty Tendulkar	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99
	Hidden Bias	U	0.00	0.00	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Confidence Interval	U	0.00	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Income per day	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.50	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	61.18	48.52	36.67	26.19	16.67	8.33	0.00	-7.54	-13.89	-20.83	-26.98	
		L	61.18	75.00	88.33	100.00	111.11	122.22	133.33	142.47	152.48	161.11	169.72	
	Confidence Interval	U	57.22	44.44	32.78	22.22	12.46	3.89	-4.19	-11.11	-18.52	-25.00	-30.56	
		L	66.67	80.56	92.78	105.56	116.67	127.78	138.65	148.25	158.33	166.67	175.93	
Income per hour	Critical Value	U	0.00	0.00	0.40	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	3.50	1.69	0.09	-1.34	-2.64	-3.82	-4.91	-5.93	-6.86	-7.74	-8.56	
		L	3.50	5.36	7.12	8.79	10.38	11.89	13.35	14.74	16.09	17.38	18.62	
	Confidence Interval	U	2.87	1.08	-0.50	-1.93	-3.21	-4.39	-5.48	-6.49	-7.42	-8.30	-9.12	
		L	4.13	6.02	7.80	9.50	11.11	12.64	14.12	15.54	16.91	18.22	19.48	
Hours worked per week	Critical Value	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.92	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden Bias	U	4.50	3.83	3.17	2.67	2.17	1.67	1.17	0.83	0.50	0.17	-0.17	
		L	4.50	5.00	5.67	6.17	6.67	7.17	7.67	8.00	8.50	8.83	9.17	
	Confidence Interval	U	4.17	3.50	3.00	2.50	2.00	1.50	1.00	0.67	0.33	0.00	-0.33	
		L	4.67	5.33	5.83	6.33	6.83	7.33	7.83	8.33	8.67	9.00	9.33	
Per capita expenditure	Critical Value	U	0.00	0.00	0.00	0.08	0.99	1.00	1.00	1.00	1.00	1.00	1.00	
		L	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Hidden	U	4.74	3.17	1.74	0.45	-0.73	-1.81	-2.82	-3.74	-4.62	-5.44	-6.21	

Outcome Indicators		Gamma Values →	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00	3.0
	Bias	L	4.74	6.35	7.85	9.25	10.56	11.80	12.99	14.10	15.16	16.19	17.15	
	Confidence	U	4.20	2.62	1.22	-0.08	-1.25	-2.34	-3.33	-4.26	-5.14	-5.96	-6.73	
	Interval	L	5.28	6.90	8.42	9.83	11.16	12.41	13.60	14.73	15.81	16.84	17.83	
	Critical	U	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	Value	L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.71	0.19	
Poverty rate below $1.90/day	Hidden	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	
	Bias	L	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	
	Confidence	U	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	
	Interval	L	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	
	Critical	U	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Value	L	0.00	0.01	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
Poverty rate below INR 375/day	Hidden	U	-0.01	-0.01	0.00	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	
	Bias	L	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.17	0.17	0.17	0.17	
	Confidence	U	-0.01	-0.01	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	-0.17	
	Interval	L	-0.01	-0.01	0.00	0.00	0.00	0.00	0.17	0.17	0.17	0.17	0.17	

Same as Table A2.