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Does violent conflict affect the distribution of social welfare? Evidence from India's Mahatma Gandhi National Rural Employment Guarantee Act

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Abstract

What are the contentious political dynamics of the largest workfare program in the world, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) of India? Combining quantitative analysis with a close reading of government documents and a survey of the existing literature, we suggest that the Indian government's counter-insurgency strategy against the Maoist unrest is a significant dynamic shaping the distribution of MGNREGA benefits. In our empirical analysis, we examine the effect of Maoist incidents on household income due to MGNREGA by merging a nationally representative household survey (Indian Human Development Survey-II) and a Maoist incidents dataset. Controlling for relevant household and district characteristics, we show that higher intensity of violent conflicts is associated with higher MGNREGA benefits. This result is robust to using a variety of alternative specifications and estimation methodologies.

KEYWORDS
anti-poverty program, contentious politics, India, Mahatma Gandhi National Rural Employment Guarantee Act, Maoism, social policy

1 | INTRODUCTION

Despite continuous urbanisation since its independence in 1947, India is still a predominantly rural and agricultural country. Today, two-thirds of the Indian population live in the countryside, and agriculture provides two-fifths of

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employment (World Bank, 2022). High unemployment/underemployment has been an endemic problem in the Indian countryside. In the early 1950s, the average length of employment in rural India was about 100 days (Government of India, 1955), and it was still less than 6 months in the early 2000s (Dhar, 2012, p. 109). As a result, one quarter of India's rural population is below the official poverty line (Suneja, 2015). India has also been home to a long-standing Maoist insurgency. Since mid-1960s, the armed guerrilla group known as the Naxalites has been active in the so-called Red Corridor and has been recognised as 'the single biggest internal security challenge ever faced by the country' by the Indian government in 2006 (The Times of India, 2006).

The Indian union government and state governments have implemented a series of rural workfare programs under different names since the 1960s, but the scale and duration of those programs were limited (Tiwari, 1990). In 2005, a much more comprehensive program aiming to dramatically increase the days of rural employment, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA hereafter), came into effect.[1] The act guarantees 100 days of employment in public works at the statutory minimum wage (or higher) to every rural resident at a working age who demands employment. Although it began with 21 million households in 200 districts in 2006–2007, MGNREGA became the largest workfare program in the world by covering 51 million rural households (more than a quarter of rural households) in 686 districts of India in 2017–2018 (Reddy et al., 2021,p. 4).[2]

This article aims to go beyond the structuralist understanding of anti-poverty programs as purely technical policies aiming to alleviate poverty, suggesting these programs might be motivated by contentious political factors such as targeting the containment of political unrest. We deploy quantitative methods to understand to what extent Maoist violence is associated with the MGNREGA provision. We merge a high-quality household survey with a district-level Maoist-violence dataset. Our results show that individuals in districts where Maoist violence occurs are associated with receiving higher income from MGNREGA. Taken together with our analysis of the large volume of government reports and the rich qualitative literature on the Maoist movement and MGNREGA, this empirical result suggests that MGNREGA is a part of the Indian government's repertoire of counter-insurgency instruments.

The following pages analyse the existing literature on anti-poverty programs, which emphasises demographic and economic factors and overlooks contentious political explanations. Then we explain the history of Maoist unrest and the ways in which Indian governments deployed benevolent means to contain it based on a close reading of official reports and documents. After that, we present the results of our empirical analysis, followed by a discussion of possible mechanisms through which MGNREGA is associated with Maoist violence.

2 | THE CONTENTIOUS POLITICS OF ANTI-POVERTY PROGRAMS

Over the last two decades, welfare systems around the globe have experienced important changes in their scope and content. Especially in the Global South, one of the most significant recent developments has been the creation of innovative anti-poverty programs (World Bank, 2015). This trend is led by the so-called emerging market economies (EME), which have introduced a vast number of expansive social assistance programs providing cash and in-kind support for the poor (including conditional cash transfers, free healthcare, food aid, and public works programs) (see, e.g., Dorlach, 2020; Jenson & Nagels, 2018).

What explains this contemporary expansion of anti-poverty programs in the Global South? The existing literature on this issue has been so far dominated by structural explanations that emphasise social, demographic, and economic transformations, needs, and constraints, which supposedly determine the course of welfare policies independently of the political factors and interests involved. This dominant structuralist paradigm argues that the shift in welfare systems was an almost automatic response to structural trends that characterised the post-1980 period, such as aging, labour informalisation (more in the Global South), unemployment, globalisation, de-industrialisation, the rise of poverty, and the rise of the service sector (Ansell, 2014; Gough & Wood, 2004; Hemerijck, 2012; Hong & Kongshøj, 2014; Kauppinen et al., 2014; Reininger et al., 2018; Wong et al., 2014). Scholars argue that the rise of informalisation, contingent work, aging of populations and increasing dependency ratios have

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made it difficult to cover larger segments of the population through existing social security programs, which are becoming difficult to finance, thus necessitating a social assistance expansion. In this narrative, the role played by political actors, struggles and interests in shaping social policies have been largely neglected, especially in the Global South (Mooney et al., 2009).

Political explanations, which emphasise political interests, conflicts, motivations, ideologies, processes, and strategies that mediate and translate structural trends and forces into welfare policymaking, have received much less attention. A recent systematic literature review (Yörük et al., 2022) has illustrated that only 2.5% of studies about anti-poverty programs examine political causes. While recent outstanding studies analysed the electoral dynamics of welfare programs in EMEs (Aytaç, 2014; Diaz-Cayeros et al., 2016; Garay, 2016; O, 2015; Thachil, 2014; Weitz-Shapiro, 2014; Zucco, 2013; also see Golden & Min, 2013 for a review of distributive politics literature), this systematic review illustrates that this branch of the scholarship is still only a small minority within the entire literature on contemporary welfare studies in the Global South. Furthermore, in this small volume of scholarship on the politics of social assistance, only 0.5% of studies look at contentious politics as a driving force for social assistance programs (e.g., Garay, 2016; Yörük et al., 2019; Zarate Tenorio, 2014), whereas the remaining 2% look at electoral politics. Contentious political factors here refer to a whole array of non- or extra-institutional political dynamics that remain outside of the electoral and party-political domains, including social movements, armed conflict, protest events, strikes, riots, civil disobedience, and insurrections (McAdam et al., 2001; Tilly & Tarrow, 2015). There is a separate strand of studies analysing the effect of anti-poverty programs on political conflict. These works have shown that anti-poverty programs can diminish incentives to support radicalism, as they reduce poverty and inequality, hence bringing about legitimacy for governments (Burgoon, 2006; Li & Schaub, 2003; Paxon, 2002). Hence, the literature on political dynamics of social assistance looks at political targeting and counterinsurgency as two separate factors and our study focuses on social assistance as a counterinsurgency tool.

In line with the trends in the global literature, there is little attention to the effects of social unrest in the explanations of anti-poverty programs in India including the MGNREGA. The majority of studies examine the impact of anti-poverty programs on household consumption (Bose, 2017; Deininger & Liu, 2013; Jha et al., 2011), wage levels, living standards, poverty alleviation, labour market (Breitkreuz et al., 2017; Imbert & Papp, 2015; Muralidharan et al., 2017, p. 201; National Social Watch India, 2011, p. 201), empowerment of women (Datta & Singh, 2012); the welfare of the elderly and widows (Dutta et al., 2010), and accessibility and adequacy of program benefits (Ehmke, 2016).

Few studies that offer political explanations look at electoral dynamics of the MGNREGA. Jha et al. (2009) argue that local politicians use MGNREGA 'as an opportunity for advancement for their followers and encourage capture' (p. 463); Chowdhury (2014) examines how electoral outcomes affected the placement and implementation of MGNREGA; Gulzar and Pasquale (2017) show that MGNREGA performance is higher in locations where bureaucrats answer to a single politician; Gupta and Mukhopadhyay (2016) illustrate how political competition affects allocation of MGNREGA funds; and Jha et al. (2011) draw attention to the manipulation of anti-poverty programs for mobilising electoral support. Jenkins and Manor (2017) illustrate how political competition shape the provision of MGNREGA, which in turn impact the political capacities of poor people.

Those who build a relationship between welfare and contentious politics in India usually align themselves in the conflict studies tradition and look at whether or how social welfare provision diminishes social unrest (Banerjee & Saha, 2010; Bendfeldt, 2011; Kennedy & Purushotham, 2012; Shapiro et al., 2017; Sundar, 2012). Using state level data, Justino (2015) shows that redistributive transfers have significantly reduced civil unrest in India and 'are both a more successful and cost-effective means' than policing (Justino, 2015, p. 3). While Khanna and Zimmermann (2017) find a short-term increase in violence after the introduction of MGNREGA, Dasgupta et al. (2017, p. 605) illustrate that 'the rollout of India's National Rural Employment Guarantee Scheme caused a large long-run reduction in Maoist conflict violence.' Using different datasets, Fetzer (2014) and Hoelscher et al. (2012) have reached similar results. The opposite causal direction, that is, the way in which contentious politics shapes anti-poverty programs, is almost an empty field of analysis. A small number of case studies point out how poor people's demands and movements

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have shaped the expansion and distribution of anti-poverty programs in India (Jenkins & Manor, 2017; Nayak, 2015; Roy, 2014; Shah, 2008, p. 200). Most recently, Fischer and Ali (2019) observe that village protests by different caste groups affect their respective level of MGNREGA employment in Jamui district in Bihar. These studies provide important insights but they do not offer a comprehensive and representative picture of the contentious politics of welfare. As Jenkins and Manor (2017, p. 214) point out, MGNREGA is 'a central component of the strategy to expand India's counter-insurgency efforts'. Our objective in this article is to explore to what extent this strategy has shaped the provision of MGNREGA.

3 | THE MAOIST MOVEMENT AND SOCIAL POLICY IN INDIA

Manmohan Singh (the Prime Minister of India from 2004 to 2014) described the Maoist insurgency as 'the single biggest internal security challenge ever faced by' India (The Times of India, 2006). Maoist insurgency has gone through three waves over the last 70 years. The first wave came immediately after Indian independence. During the Telangana Rebellion in the princely state of Hyderabad—consisting of today's Telangana and Andhra Pradesh states—between 1948 and 1951, the local branch of the Communist Party of India (CPI) formally adopted the Maoist strategy of 'prolonged civil war in the form of agrarian revolution' (Kennedy & Purushotham, 2012, p. 835). Tribal people living in the hilly and forest areas—known as 'Adivasis' and officially called as 'Scheduled Tribes', ST—who carried out a series of revolts against British colonialism since the nineteenth century provided mass support to CPI-led insurgency.

The second wave of Maoist insurgency started in 1967, when a local conflict between big landowners and poor peasants in the Naxalbari village in the Darjeeling district of West Bengal quickly transformed into an armed uprising. Dalits (Scheduled Castes, SC) and Adivasis, the poorest and most excluded social groups within the class and caste hierarchy, massively participated in the uprising. The initial phase of the uprising was led by the local representatives of the radical faction of the Communist Party of India (Marxist). This faction splintered from the CPI (M) and founded the Communist Party of India (Marxist-Leninist) in 1969. Beyond West Bengal, the insurgency affected Andhra Pradesh, Bihar, Kerala, Madhya Pradesh, Orissa, and Uttar Pradesh. Indian government suppressed the Naxalbari uprising in 1971 but failed to eradicate Maoist insurgency entirely. Maoist guerrillas were still operating in Telangana even after the suppression of the uprising (Kennedy & Purushotham, 2012, pp. 848–849). Following this second wave, Maoists came to be called 'Naxalites', a term referring to the Naxalbari uprising.

The third—and continuing—wave of Maoist insurgency started in the early 1980s (Kennedy & Purushotham, 2012, p. 833). This wave peaked following the reunification of the two of the strongest Maoist factions—People's War Group and Maoist Communist Center—under the roof of the Communist Party of India (Maoist) that was founded in 2004. In the mid-2000s, the Indian and foreign media and scholars explicitly reported that the 'Red Corridor' where the CPI (Maoist) is active encompasses vast areas stretching from the southern state of Andhra Pradesh to the India-Nepal border. In September 2009, the Indian government declared that Maoist guerrillas 'were calling the shots in nearly 40,000 square kilometre area' (The Times of India, 2009).

Successive governments have acknowledged the close connection between socio-economic grievances and mass support for Maoists since the earlier phases of the insurgency. In 1950, the special commissioner of the Hyderabad proposed welfare-oriented measures including the 'provision of medical aid, opening of schools, distribution of food and other essential commodities, and, most importantly, agrarian reform legislation' (Kennedy & Purushotham, 2012, p. 842). In 1980, the Research and Policy Division of the Ministry of Home Affairs recognised that the official approach of dealing with the Maoist insurgency 'clearly backfired' and concluded that 'if there is no effective governmental intervention on behalf of the rural poor against the rural rich, a further radicalisation of the rural poor is inevitable' (Chakrabarty, 2014, p. 299). According to Manoj Srivastava (former Chief Secretary of the Government of Bihar), successive governments have used rural employment schemes to keep 'India's dangerous (or 'surplus') classes' at bay. Srivastava stresses that the Employment Assurance Scheme, which came into effect in

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1993 and inspired the design of the MGNREGA, was one of 'the principal means of protecting the poor people […] against the temptations of organized left-wing politics' in East-Central India (Corbridge & Srivastava, 2013, p. 457). In 2005, Planning Commission identified 55 districts as 'Naxalite affected' recommending them to be prioritised for the Backward Districts Grant Fund, arguing that in these districts 'disaffection with low developmental levels has driven people to violent forms of protest and opposition' (Government of India, 2008). The Planning Commission's report entitled *Development Challenges in Extremist Affected Areas* argues that the problem of Maoist insurgency 'has to be tackled in a multipronged approach' including the 'ameliorative measures' like the MGNREGA (Government of India, 2008).

4 | EMPIRICAL ANALYSIS

4.1 | Data

In our analysis, we combine three types of data: Maoist conflict data at the district level, household survey data, and administrative/geographical data on district characteristics from various sources. The first two data establish our main explanatory and outcome variables, respectively, and the third is used for control and robustness purposes. While the districts constitute the smallest administrative units in India with reliable data, they also exhibit significant variation in terms of violence even in the same state. Therefore, combining district-level data with a rich household survey allows us to analyse the link between Maoist violence and the household benefits from MNREGA quantitatively while considering the heterogeneities of both dimensions.

For the Maoist conflict-related violence, we use a recent and novel dataset constructed by Dasgupta et al. (2017). Using both English and local-language press sources, they collected geo-coded data on all incidents related to the Maoist insurgency in the 'Red Corridor' states for the 1999–2009 period. This dataset is superior to the widely used Global Terrorism Database (GTD), which only covers English-language news sources and went through a significant methodological change during the period under analysis.[3] The dataset covers 144 districts[4] in six states—Andhra Pradesh, Bihar, Chhattisgarh, Jharkhand, Odisha, and West Bengal– that make up the Red Corridor. Over 90% of Maoist insurgency-related deaths occur in this region. The data set geo-codes attacks and deaths to districts on a quarter-yearly basis, which we aggregate over the 7 years before the MGNREGA program is implemented, that is, between 1999 and 2005, to create our main explanatory variables. Figure 1 shows that the death and incidents counts are highly correlated. Figure 2 exhibits the variation in average annual deaths across districts.

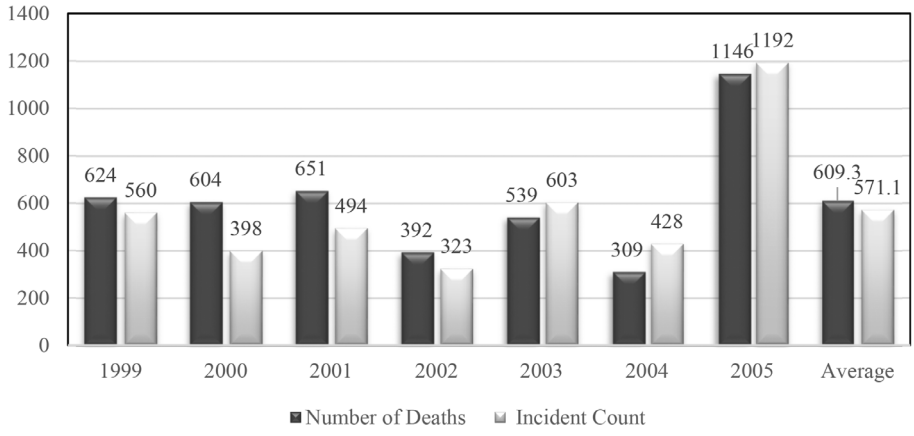


FIGURE 1 The number of incidents and deaths related to the Maoist insurgency, 1999–2005. Authors' calculations using Dasgupta et al. (2017).

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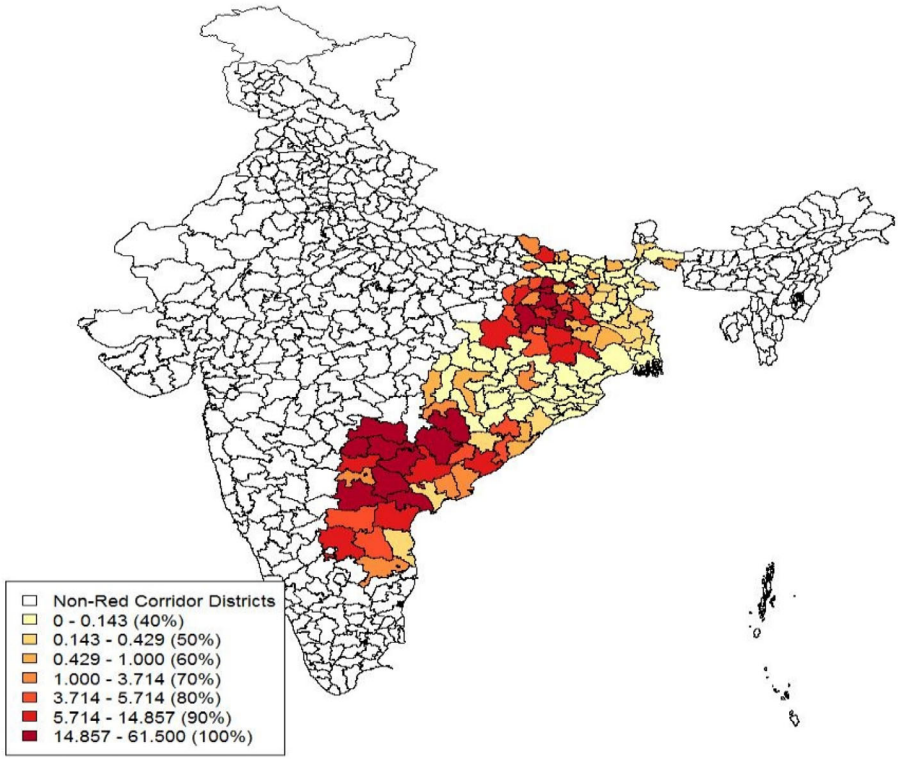


FIGURE 2 Average annual deaths due to Maoist insurgency by districts, 1999–2005. Authors' calculations using Dasgupta et al., 2017. Cumulative shares in parenthesis. [Colour figure can be viewed at wileyonlinelibrary.com]

We use the India Human Development Survey-II (IHDS-II) (Desai & Vanneman, 2018) for the data regarding the MGNREGA benefits and other characteristics of rural households. This is a nationally representative, multi-topic survey of 42,152 households, 27,236 of which are in rural areas. Survey period is 2011–2012. Households provide information on a variety of topics, from health to gender relations. As such, the survey brings together information on income, MGNREGA participation, and other household characteristics, all critical for our purposes. We use the household income from MGNREGA as our main dependent variable, and MGNREGA card ownership and MGNREGA working days as alternative dependent variables. For the first two, information is directly available in the survey. We calculate the number of days the household members have worked at MGNREGA projects by dividing their MGNREGA income to the official MGNREGA wage for their respective states.

We use many other dimensions of household characteristics available in the data as control variables: highest adult education, household head's age, household size, total household assets (an index between 0 and 33, constructed by summing household items such as TVs, cars, etc. possessed by the household), if they own/cultivate any land, if they own any non-farm businesses, number of household members who work at part-time or full-time jobs other than MGNREGA-related jobs, if they have any village council members in or close to their households, and finally, their religions and castes. We restrict the data to the respondents who reside in rural districts and do not report an implausibly high number of working days (greater than 150 days) in the program.

Finally, we use administrative and geographical data for our district-level control variables: First is a district-level local state capacity variable à la Acemoglu et al. (2015) that we construct to control for the variations in district administrations' ability to implement policies. It is an average of a district's rank across essential state services as

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measured in the 2001 Census, and therefore it is independent of the MGNREGA program implementation. Following the previous literature, we use the following basic state services: (i) a paved road; (ii) a primary school; (iii) a primary health centre; and (iv) an agricultural credit cooperative (the lowest tier of the government-run agricultural credit network) (Dasgupta et al., 2017). We calculate the share of villages in each district that owns each of these and rank them accordingly on each dimension. Then we average those ranks to arrive at our final measure of local state capacity.

We also use some demographic and geographical variables that could potentially correlate with the variation of MNREGA benefit distribution across the districts. These are the population and land size of the district, average consumption expenditure in the district, shares of literate, SC and ST populations as a percentage, very dense forest coverage as a percentage of the district land, and the percentage deviation of the rainfall in the district in 2010 and 2011 from its long-run averages.[5] While the demographic variables are from the Census data and provided by Asher and Novosad (2019), the latter two are provided by the Forest Survey of India and the India Meteorological Department, respectively. Table 1 contains the summary statistics for all variables used in the study.

In our estimations, we use a number of controls at the district and household levels while minimising the possibility that there are unobserved omitted variables. To ensure this as much as possible, we relied on the literature on violent conflict to consider what such possible omitted variables might be: what predicts insurgencies and violence, and are these same variables likely to be correlated with the implementation of MNREGA? In the scope of the vast literature on the dynamics and determinants of the Naxalite conflict in India, scholars have converged on the main predictors of Naxalite violence: Scheduled Caste, Scheduled Tribe, water deficit/rainfall shocks/monsoon rainfall, literacy rate, income, urbanisation, consumption, inequality (Dasgupta et al., 2017; Fetzer, 2014; Gawande et al., 2017; Hoelscher et al., 2012). In our models, we controlled for these variables or their correlates to ensure that the risk of omitted variable bias is minimal.

4.2 | Empirical strategy and results

To investigate the effects of Naxalite violence on the intensity and distribution of MGNREGA program benefits, we combine the district-level violence data from the period before the program implementation (1999–2005) with the household survey data that was conducted 3 years after the program was implemented nationwide (2011–2012). Using the household data has the obvious advantage of controlling for household characteristics that could potentially explain the variation of MNREGA benefit distribution. As a workfare program targeting the poorest segments, MGNREGA would attract the demand of households that are poorer in income and assets, unemployed, less educated and larger in size relative to the average. We control for all of these and more. Our main independent variable is not affected by the MGNREGA program in any way since it captures the Maoist violence before the initial program implementation in 2005.[6] We summarise this temporal difference, which guarantees that our estimations do not suffer from any simultaneity bias, in Figure 3.

Our regression model is given by Equation (1) below.

$$(MGNREGA\ Benefits)_{i,j} = \alpha\,(Violence)_j + \beta \boldsymbol{X}_{i,j} + \gamma \boldsymbol{Z}_j + \delta_s + \varepsilon_{i,j} \tag{1}$$

We use IHDS data on self-reported household income due to MGNREGA as our main dependent variable, $(MGNREGA\ Benefits)_{i,j}$ where i represents the household and j is the district. $(Violence)_j$ is the average number of Naxalite-related violent incidents per year from 1999 to 2005 in district j and will be our primary explanatory variable in the baseline regressions. $\boldsymbol{X}_{i,j}$ represents the control variables related to the household characteristics: highest level of adult education, household head's age, household size, number of members with part-time and full-time jobs (has worked more than 240 h in a job), land ownership, non-farm business ownership, total household assets, district committee member in/close to the household, and caste and religion of the households. Note that all of these

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TABLE 1 Summary statistics of variables.

Variables	Obs	Mean	SD	Min	Max
MGNREGA income (Annual)	26,401	1136	2804	0	20,000
MGNREGA days	26,401	9.102	22.42	0	150
MGNREGA card ownership	26,401	0.411	0.492	0	1
Incidents per year	26,401	0.960	4.993	0	59.29
Deaths per year	26,401	0.925	4.438	0	52.43
Highest adult education	26,401	7.173	4.966	0	16
Household head's age	26,401	49.51	13.93	11	99
Household size	26,401	4.899	2.380	1	33
Number of working members of the household (except MGNREGA)	26,401	1.873	1.295	0	13
Land owned or cultivated (0–1)	26,401	0.626	0.484	0	1
Non-farm business ownership (0–1)	26,401	0.157	0.364	0	1
Total household assets (0–33)	26,401	13.11	6.044	0	31
District committee member in/close to the household	26,401	0.333	0.471	0	1
Hindu	26,401	0.838	0.369	0	1
Muslim	26,401	0.098	0.298	0	1
Christian	26,401	0.022	0.145	0	1
Sikh	26,401	0.028	0.163	0	1
Buddhist	26,401	0.006	0.079	0	1
Jain	26,401	0.001	0.030	0	1
Tribal	26,401	0.007	0.083	0	1
Others	26,401	0.001	0.032	0	1
None	26,401	0.0002	0.014	0	1
Brahmins	26,401	0.042	0.201	0	1
Forward/general (except Brahmin)	26,401	0.204	0.403	0	1
Other Backward Castes	26,401	0.400	0.490	0	1
Scheduled Castes (SC)	26,401	0.231	0.421	0	1
Scheduled Tribes (ST)	26,401	0.111	0.315	0	1
Other	26,401	0.012	0.108	0	1
State capacity (District ranking—Higher the better)	26,401	306.9	129.5	30.25	561
District population (Rural, 2011, $\times$1000)	26,401	1686	1049	80.14	5703
Very dense forest coverage	26,401	0.074	1.158	0	24.33
Deviation of rainfall from its long run average, 2010	26,401	5.249	38.50	−75.25	213.8
Deviation of rainfall from its long run average, 2011	26,401	14.74	33.12	−60.25	146
Annual consumption expenditure per capita (Rs)	26,401	18653.9	4011.7	12165.6	32182.6
Share of literate population	26,401	0.637	0.093	0.385	0.887
Share of Scheduled Caste population	26,401	0.176	0.079	0	0.425
Share of Scheduled Tribes population	26,401	0.106	0.163	0	0.933
District size (Hectares)	26,401	63.65	45.79	0.03	456.5

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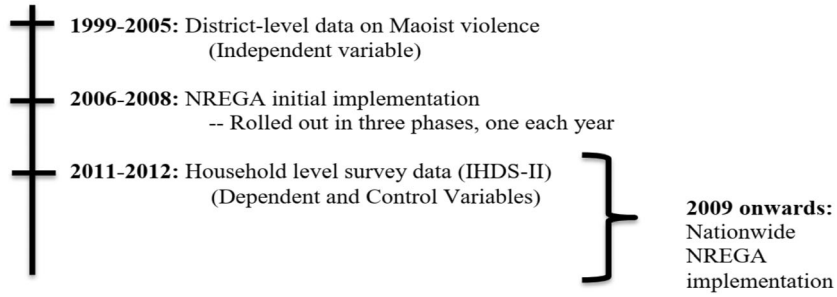


FIGURE 3 Timeline of the independent and dependent variables in our estimation.

household characteristics would be useful in controlling for household's poverty level and the resulting demand for a workfare program like MGNREGA. $\boldsymbol{Z}_j$ is the vector of control variables composed of district characteristics: state capacity, district population and size, district-level quartile rankings of average consumption expenditure level, shares of literate, SC and ST populations as a percentage of district population, forest coverage, and deviation of rainfall from its long-run average. Finally, δ_s constitutes the state dummy.

Table 2 presents our baseline regression results where the dependent variable is the annual income of the household from MGNREGA. All SEs are clustered at the district level. We first present the model with only household control variables and state fixed effects in column (1), then we add the religion and the caste of the head of the household as control variables in model (2). In column (3), we also include district-level controls. The coefficient of the *Incidents* variable represents the effect of a one-unit increase in yearly Maoist violence in the district on the MGNREGA income of the household.[7] The size of the effect remains stable and significant in all our specifications both here and in the Supporting Information,[8] confirming our main hypothesis that the higher MGNREGA income is associated with higher Maoist violence.

Household characteristics are mostly significant, and they have the expected signs except for the land ownership/cultivation dummy. While the per person income, highest adult education, head's age, number of members with part-time and full-time jobs (has worked more than 240 h in a job), non-farm business ownership, and the amount of assets the household has are negatively correlated with MGNREGA income, household size is negatively associated with it. The positive sign of the land cultivation coefficient is due to the fact that most rural households, including some of the poorest, either own or rent marginal amounts of land. According to the Government of India (2014), only 7.41% of rural households are landless, and 75.42% hold a marginal (less than 1 hectare) amount of land in 2013. However, the survey does not differentiate between owners and renters and does not allow us to measure the size of their holdings.

One interesting result concerns the link between the caste of the household and MGNREGA benefits. Inclusion of the caste of the household head variable in models (2–3) shows that the Scheduled Castes and Scheduled Tribes receive significantly higher MGNREGA income. At first sight, this result might be seen as a natural consequence of the high poverty incidence of these groups.[9] However, noting that we control for the household characteristics in these regressions, these results may potentially reflect a positive bias towards these groups.

In models (2–3) we include a dummy to control for the possible bias in MGNREGA benefit distribution due to close ties with village committee members. Households which have a village committee member in or close to them seem to benefit from this relationship as the related coefficient is positive and significant. However, the addition of this variable does not create a major effect on the size or the significance of the Violence variable, suggesting that higher MGNREGA benefits due to local clientelistic networks and the higher MGNREGA benefits due to violence work through two separate channels. When we introduce an interaction term between violence and Panchayat Member proximity, that is, *Panchayat Member* × *Violence*, its coefficient is relatively small, negative, and insignificant, confirming our inference.

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TABLE 2 Regression estimates of the association between Maoist violence and MGNREGA income.

	Dependent variable: MGNREGA income		
	(1)	(2)	(3)
Incidents	**38.39*** **	**37.04*** **	**34.25*** **
	(8.231)	**(7.969)**	**(6.825)**
Highest adult education	−17.54***	−17.70***	−17.11***
	(6.077)	(5.993)	(5.821)
Household head's age	−3.592***	−2.701**	−2.438**
	(1.291)	(1.253)	(1.227)
Household size	208.8***	209.8***	210.0***
	(18.66)	(17.97)	(17.59)
Number of working members	−388.2***	−409.8***	−411.1***
	(33.27)	(33.12)	(33.02)
Land owned or cultivated (0–1)	329.7***	391.3***	373.7***
	(57.31)	(55.34)	(54.41)
Non-farm business ownership (0–1)	−185.9***	−138.6**	−145.7***
	(54.10)	(53.62)	(53.78)
Total household assets (0–33)	−53.31***	−42.87***	−42.26***
	(6.753)	(6.430)	(6.611)
Village comm. member in/close HH (0–1)		195.3***	196.5***
		(70.38)	(68.86)
State capacity			0.0200
			(0.675)
District population (/1000)			−0.182**
			(0.0734)
Very dense forest (%)			83.39***
			(7.828)
Caste dummies—Relative to Brahmins			
Forward/General (except Brahmin)		169.5	183.2
		(151.3)	(144.6)
Other Backward Castes		311.5**	315.1**
		(139.5)	(135.8)
Scheduled Castes (SC)		803.0***	796.8***
		(154.3)	(151.0)
Scheduled Tribes (ST)		648.2***	569.3***
		(174.8)	(164.5)
Other		331.7	333.9
		(280.4)	(267.2)
Observations[15]	26,401	26,401	26,401
R^2	0.194	0.204	0.209
State FE	Y	Y	Y
Religion and caste	N	Y	Y
District controls	N	N	Y

Note: Robust SEs in parentheses are clustered at the district level. State dummies, religion dummies (except for Muslims), some district controls and constant are omitted.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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Finally, in our full specification model (3), we introduce several district-level variables to control for any variation in MGNREGA benefit distribution due to district characteristics. Most important of those controls is the state capacity of the district, a variable that could potentially explain the higher incidence of MGNREGA benefits in districts with better administrative capacity. We observe that the state capacity has no significant relation to the MGNREGA income level and most geographical variables are also insignificant. Nevertheless, the *Violence* variable stays highly significant and sizeable, lending support to our hypothesis that the intensity of the Maoist conflict is an important factor in MGNREGA benefit distribution.

4.3 | Extending the analysis to alternative outcomes and discussion of empirical results

In this part, we aim to take a first step towards explaining the mechanisms behind this result by looking at the association between Maoist violence and two alternative outcome variables, namely, how many working days the household has been allocated under the MGNREGA program and the MGNREGA card ownership. Card ownership is a necessary first step for receiving MGNREGA benefits. Households have to apply through their local governments (*Gram Panchayats*, GPs) to receive the card. Once the application is accepted the households are also supposed to demand work from the GPs according to the MGNREGA rules. As such, both of these steps could work as a mechanism of benefit allocation towards favoured districts for the government.

For the dependent variable, we utilise two different pieces of information on MGNREGA benefits: (i) days worked at MGNREGA-related jobs (calculated by dividing the MGNREGA income by the government-determined minimum MGNREGA wage level in the respective state) and (ii) MGNREGA card ownership in the household (0 for no cards and 1 for having at least 1 card). Using the full specification in model (3) above, we empirically estimate the relationship between the Maoist violence variable and MGNREGA working days and card ownership of the households, in models (4) and (5) below, respectively. All results include full set of control variables and state fixed effects. We employ logit regressions when we use the MGNREGA card ownership as our dependent variable in model (5).

Our results in Table 3 indicate that both of these alternative outcome variables have significant relationships with the Maoist violence; a result that supports our results in the main specification overall. Moreover, it indicates that the MGNREGA benefit distribution towards more violent districts might be working through both more abundant distribution of the MGNREGA cards and the larger availability of MGNREGA projects in certain districts, but relatively smaller size of the coefficient in (5) might indicate that this is a less important channel compared to the working days.

In the next part, we discuss in detail why this strong positive association between the level of Maoist violence and MGNREGA benefits is most likely to be due to supply-side decisions; in particular, we argue that it indicates that this workfare program is part of Indian government's containment strategy against the Maoist unrest. However, one alternative explanation is that the households in non-violent districts show a relatively lower level of demand for the program, in other words a demand channel that could create similar effects. As expected, we cannot perfectly distinguish between these two channels using our household level data, but we control for all possible correlates of demand for such workfare programs with our household level controls. Moreover, we can insulate the supply channel by excluding those households from our analysis that do not demand to work under the MGNREGA program.[10] There are two types of such households in our dataset that do not want MGNREGA work. First is those that did not apply for an MGNREGA card at all and the second is those with an MGNREGA card but has not worked in the program because they were not interested in it. In the Appendix, we show that our results are robust to the exclusion of both types of households. Moreover, we also show that controlling for the possible selection bias via a Heckman (1979) selection model approach also leads to similar results.

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TABLE 3 Regression estimates of the association between Maoist violence and MGNREGA outcomes.

	Dependent variable		
	(3) MGNREGA income	(4) MGNREGA days	(5) MGNREGA card
Incidents	**34.25*** **	**0.286*** **	**0.020*** **
	(6.825)	**(0.056)**	**(0.004)**
Village comm. member in/close HH (0–1)	196.5***	1.553***	0.243***
	(68.86)	(0.536)	(0.056)
State capacity	0.0200	−0.0001	−0.0002
	(0.675)	(0.005)	(0.0008)
Muslim dummy (relative to Hindus)	−232.6***	−1.872***	−0.275***
	(85.40)	(0.674)	(0.099)
Other Backward Castes (relative to Brahmins)	315.1**	2.341**	0.393***
	(135.8)	(1.076)	(0.128)
Scheduled Castes (SC) (relative to Brahmins)	796.8***	6.146***	0.962***
	(151.0)	(1.184)	(0.136)
Scheduled Tribes (ST) (relative to Brahmins)	569.3***	4.454***	0.600***
	(164.5)	(1.321)	(0.145)
Observations	26,401	26,401	26,401
R^2	0.209	0.216	0.231
State FE	Y	Y	Y
Religion and caste	Y	Y	Y
District controls	Y	Y	Y

Note: Same as Table 2.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

5 | MECHANISMS OF CONTAINING THE MAOIST UNREST BASED ON MGNREGA

Our empirical analysis has shown that the level of income an individual generates from the MGNREGA program is strongly associated with the level of Maoist incidents in the district where the individual resides. We demonstrate that although MGNREGA is an anti-poverty program, the factors that shape the amount individuals receive under MGNREGA are not only about how poor they are, but also related to the political characteristics of the districts they live in. Even among the people at similar levels of poverty, those who are more affected by Maoist incidents are more likely to benefit from MGNREGA. We also found that Scheduled Castes and Scheduled Tribes generate higher incomes from MGNREGA. These findings resonate with the findings of an earlier generation of theories (Isaac & Kelly, 1981; Piven & Cloward, 1971) that explain social assistance as a containment strategy and suggests that these theories may have validity in the Indian case. We now turn to the mechanisms through which MGNREGA benefits are associated with Maoist incidents.

First, it is likely that higher MGNREGA provision is related to higher budget allocations in Maoist affected regions in the Red Corridor. In February 2011, Prime Minister Singh made it clear that 'priority is given to Left-Wing extremism affected districts' (The Hindu Business Line, 2011). Indeed, according to our calculations based on Census data and Lok Sabha Unstarred Question No. 4944 (2013), average MGNREGA funds utilised per rural person are

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higher in the Red Corridor states (2085.5 Rs) than in non-Red Corridor states (1885.33 Rs) between 2007 and 2012. The prioritisation of the Maoist-affected districts in the implementation of the MGNREGA is also apparent in the training and dispatching of development personnel. The graduates of the Prime Minister Rural Development Fellows program are sent to the Red Corridor 'to help identify areas of improvement' including the MGNREGA implementation 'as a way of dealing with the "Maoist problem"'. (Veeraraghavan, 2017, p. 209).

For an effective geographical and community-based political targeting strategy, governments must have adequate capacity to collect such information and distribute the resources accordingly. The Indian government has been working to collect sufficiently granular data on Maoist insurgency, allowing the implementation of welfare programs from a counter-insurgency perspective. For example, founded in October 2006, the Naxal Management Division of the Ministry of Home Affairs (renamed as the 'Left-Wing Extremism Division' in 2015) regularly collects and publishes district-level data regarding the number, casualties, and material costs of Maoist incidents (Government of India, n.d.).[11] The Division also collects data on the unarmed activities of the Maoists, such as propaganda and recruitment across the country, including the districts where Maoists do not carry out armed attacks (Verghese & Teitelbaum, 2019). The Ministry of Home Affairs publicly updates the list of Naxal-affected districts every year. The union government is using this list to devise new welfare schemes and coordinate the existing ones for counter-insurgency purposes. In fact, one of the declared tasks of the Left-Wing Extremism Division is to coordinate 'the implementation of various development schemes in LWE (Left Wing Extremism) affected States' (Government of India, n.d.).

Moreover, the Integrated Action Plan (IAP), which was approved on 25 November 2010, aims to coordinate a variety of welfare and development schemes including the MGNREGA to better support the counter-insurgency efforts of the security apparatuses. Left-wing Extremism Division oversees this program in cooperation with the Ministry of Rural Development and various administrative branches of the IAP districts.[12] The Ministry of Rural Development for 2011–12 explains the IAP as the culmination of the 'development initiatives' to combat Maoist insurgency (Ministry of Rural Development, 2012). Moreover, 'special relaxations in the criteria and special provisions have also been made under certain programmes' (Ministry of Rural Development, 2012) including the MGNREGA for the IAP districts. For example, although the program focuses on infrastructure construction, construction of playgrounds is approved as a permissible MGNREGA activity in the IAP districts (The Indian Express, 2011). In October 2011, the Ministry of Rural Development disclosed a new IAP-related policy according to which the central government will bear 75% of the costs 'required to overhaul the administrative capacity' in 72 districts most affected by Maoist insurgency in order to implement the MGNREGA successfully, while covering only 6% of such costs of the districts that are not affected by the insurgency (The Economic Times, 2011).[13] The significance of the IAP for counter-insurgency was confirmed again in 2013, when the Ministry of Home Affairs refused the Finance Ministry's proposal to merge the IAP funds (that are used exclusively for countering Naxalism) with the Backward Region Grant Fund, which does not exclusively target Naxal-affected regions. By keeping the IAP funds separate, the government 'put to rest concerns that a change in definition of backward districts will reduce the number of districts eligible for a special development scheme launched to curb Left-wing extremism' (Sharma & Goswami, 2013).

The popular base of the Maoists seems aware of this strategy. For instance, in 2010 a villager from the Midnapore district of West Bengal told a BBC reporter that 'if the Maoists were not at our door, this development [MGNREGA] wouldn't have happened' (Biswas, 2010). In her pilot surveys, Sen found that over 80% of the people who expressed sympathy for the Maoists 'also admitted that there is a good side of the state, particularly visible in state-welfare schemes like rural employment guarantee scheme'. For Sen, this relatively positive outlook must also be considered to understand why some Maoist rebels quit the insurgency (Sen, 2021:18). One could argue that the Maoists would fight against the MGNREGA. Studies on this topic, however, show that this is not true. Banerjee and Saha's (2010) analysis of the Maoists' response to the MGNREGA in Chhattisgarh, Jharkhand, and Odisha suggests that except for road construction, which potentially eases the access of the security forces to insurgent-controlled areas, Maoists do not sabotage the MGNREGA-related work, because they are unable to provide better economic opportunities and therefore must act carefully to avoid alienating their popular base. Eynde et al.'s study of the

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implementation of the central government's infrastructure programs in the Red Corridor demonstrates that guerrillas attack road and telecommunications projects but do not attack others (Eynde et al., 2015, pp. 7–11).[14]

6 | CONCLUSION

This study examined the contentious political determinants of the largest workfare program in the world, the MGNREGA. Our paper is based on a multivariate regression analysis, in which we examine the effect of Maoist violence on our dependent variable, household level income generated from MGNREGA participation. Our regression estimates show that the level of district level Maoist violence is positively related to the MGNREGA income when we control for several program-related factors and state level fixed effects. The robustness of the relationship between MGNREGA program and Maoist violence is also evidenced by the fact that different models with similar dependent variables (MGNREGA card ownership status or days worked at MGNREGA-related jobs) and independent variable (average casualties in Naxalite events) yield similar results as we document in the Appendix. We also show that Scheduled Castes and Scheduled Tribes constituting the main popular base of Maoists are positively discriminated in MGNREGA provision. We interpreted these associations to suggest that MGNREGA is part of Indian government's repertoire of counter-insurgency instruments.

This finding is an important contribution to the growing literature on anti-poverty programs in India and elsewhere. As we outlined in our article, this literature suffers from a predominance of structuralism, materialised by an overemphasis on demographic and economic explanations, and by an under-exploration of contentious political factors (except for electoral dynamics). Alternatively, some scholars analyse contentious politics, such as terrorism or radicalism, as dependent variables, which can be reduced by expanded anti-poverty programs. This article is one of few studies which illustrate the reverse relationship, that is, how contentious politics affect anti-poverty programs.

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CONFLICT OF INTEREST STATEMENT

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

DATA AVAILABILITY STATEMENT

Data derived from public domain resources.

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ENDNOTES

[1] The Lok Sabha, the lower house of India's bicameral national parliament, passed the National Rural Employment Guarantee Act on 23 August 2004. The President of India signed the act on 5 September 2005. The act was renamed as the Mahatma Gandhi National Rural Employment Guarantee Act on 2 October 2009.

[2] On the other hand, the program has so far failed to provide 100 days of employment per year. The proportion of households with 100 days of employment was 13.5% in 2009–2010 and 5.8% in 2017–2018 (Reddy et al., 2021, p. 7).

[3] Dasgupta et al. (2017) show that using local-language data sources provides significantly better coverage than using English-language data sources, especially in high-violence, rural districts.

[4] As India's district and state boundaries change over the period under consideration, we use the boundaries at the time of the 2001 Census.

[5] Since the survey period is from October 2011 to October 2012, it covers the main harvest seasons of both 2011 and 2012. Harvests in these years will be directly affected by the previous year's rainfall. That is why we deem it necessary to include both 2010 and 2011 rainfall data. Note that using only one of those years or actual rainfall data instead of the deviations gives very similar results.

[6] The nationwide implementation of the MGNREGA program took 3 years: In its first phase, 200 districts received the program in 2006. One hundred thirty more districts were added in 2007. It became available to all districts by mid-2008. The time gap between the nationwide implementation of MGNREGA (2008) and the survey period (2011–2012) provides ample time for the standardisation of the program across all districts, especially from an administrative perspective. The local bureaucrats that implemented the program later would have caught up with those in the previous phases by the time the survey was conducted.

[7] Using a back-of-the-envelope calculation that does not take the general equilibrium effects into account, we calculate that this coefficient represents a 6.8% boost to the average yearly MGNREGA income for the average household in the district with average violence relative to a no-violence district household. In our sample, the highest number of incidents in a year is 115, translating into over 4400 Rs. extra, or nearly doubling the average MGNREGA income, in the most violent district.

[8] In the Appendix, we check the robustness of our results with several alternative specifications, dependent/independent variables, and methodologies including instrumental variables and propensity score matching.

[9] Scheduled Castes and Scheduled Tribes make up 29% and 22% of the rural poor in our sample, respectively.

[10] We would like to note that exercise leads to a conservative estimate of the supply channel as some of the households who do not demand the program might have been discouraged due to the rationing of the program. Narayanan et al. (2017) show that such previous rationing of the work is a significant factor in why households show less demand for the MGNREGA later on. See also Fraser (2015) for an overview of claims on rationing and corruption in MGNREGA.

[11] We should note that the South Asia Terrorism Portal, a website maintained by the Institute for Conflict Management, a non-governmental agency set up and presided by a retired Director General of Police, regularly updates district-level data on Maoist insurgency that trace back to the year 2000 (South Asia Terrorism Portal, n.d.).

[12] Sixty-two thousand nine hundred nineteen IAP projects were completed in 88 districts of 10 Maoist-affected states between April 2013 and July 2016 (Government of India, 2016). The IAP was rebranded as the 'Special Central Assistance for 30 most LWE Affected Districts' in 2017 and is still under implementation (Government of India, n.d.).

[13] This financial assistance aimed to cover the cost of appointing one Panchayat development officer and one junior engineer in each gram Panchayat within the IAP districts for increasing the effectiveness of the implementation of the MGNREGA (Mohan, 2012).

[14] There is even some anthropological work that suggests Maoists have tried to mobilise the locals to demand MGNREGA 'to deliver 365 days of employment, not just 100' (Shah, 2019, p. 183).

[15] In order to ensure comparability of results across models, we use the same sample in all regressions: the one that has the observations necessary to run the most rigorous empirical model with both household level and district level control variables. In Online Appendix OD, we show that our results are robust using different subsamples in each regression.

[16] We also do the following checks in the Online Appendix: (i) use propensity score matching techniques where the Naxalite violence acts as a treatment on rural households as an alternative estimation method to check the robustness of our estimations, (ii) rerun the main specifications at the district level and (iii) estimate a falsification model where our main explanatory variable Violence is replaced with an alternative, Relative Poverty Level of the Districts. In (i) and (ii), these estimations yield highly significant, positive, and hence, robust results. In (iii), we show that poverty of the district has no explanatory power on MGNREGA benefits by itself.

[17] James J. Heckman (1979), p. 153, https://doi.org/10.2307/1912352.

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[18] There are two reasons that complicate the issue in our case: (1) It is possible that some of the households who do not have a card did not participate because of Maoist violence. (2) It is possible that the households with the MGNREGA card (i.e., the ones that have chosen to participate in the program) may not be able to work due to the rationing of the available work, again due to contentious politics. In those cases, our sample bias correction methods will take away some of the variation that is actually due to Maoist violence.

[19] Heckman, 'Sample Selection Bias as a Specification Error'.

[20] See the details in Wooldridge (2010, pp. 802–808).

[21] Interestingly, Das (2015, pp. 202–217) explored the effect of political activity (in the sense of being affiliated to a legal political party and related activism) in MGNREGA work and benefit allocation in two blocks of West Bengal using a Heckman-selection model, and concluded that there was not enough evidence in favour of a sample bias.

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SUPPORTING INFORMATION

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APPENDIX

ROBUSTNESS OF ESTIMATION RESULTS

In this appendix, we check the robustness of our results[16] with several alternative specifications, independent variables, and methodologies.

Alternative dependent and explanatory variables

First, we run the full specification regression with alternative explanatory variables and compare them with results in column (3) of Table 2 (reproduced in Table A1 for ease of comparison). We adopt the following alternative explanatory variable: average number of deaths in Naxalite-related incidents per year from 1999 to 2005 in the districts. We report the results with the number of deaths in Table A1. All results include the full set of control variables and state fixed effects. We employ logit regressions when using the MGNREGA card ownership as our dependent variable in models (6) and (9).

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TABLE A1 Regression estimates of the association between Maoist violence and MGNREGA outcomes with alternative *Violence* variable: Number of deaths per year due to Maoist violence.

	Dependent variable		
	(6) MGNREGA income	(7) MGNREGA days	(8) MGNREGA card
Deaths	**24.88***	**0.211***	**0.018*****
	(13.20)	**(0.107)**	**(0.006)**
Village comm. member in/close HH (0–1)	199.4***	1.578***	0.245***
	(68.64)	(0.535)	(0.056)
State capacity	−0.002	−0.001	−0.001
	(0.678)	(0.005)	(0.001)
Muslim dummy (relative to Hindus)	−228.8***	−1.839***	−0.271***
	(85.76)	(0.677)	(0.099)
Other Backward Castes (relative to Brahmins)	317.0**	2.356**	0.394***
	(136.0)	(1.077)	(0.128)
Scheduled Castes (SC) (relative to Brahmins)	798.5***	6.162***	0.963***
	(151.1)	(1.186)	(0.136)
Scheduled Tribes (ST) (relative to Brahmins)	570.4***	4.464***	0.601***
	(164.7)	(1.323)	(0.145)
Observations	26,401	26,401	26,401
R^2	0.208	0.215	0.231
State FE	Y	Y	Y
Religion and caste	Y	Y	Y
District controls	Y	Y	Y

Note: Same as Table 2.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Overall, results in Table A1 show that the estimates in the baseline specification are robust to alternative specifications. Both explanatory variables are significant in all models. Alternative explanatory variable Deaths shows slightly smaller effects. However, this is expected as the average number of casualties per incident is larger than one, 1.16. Signs and magnitudes of control variables remain stable across specifications.

Alternative methodologies: Instrumental variables and Heckman selection models

In the second set of robustness exercises, we address the potential 'sample selection bias'.[17] Since the MGNREGA program requires the households to obtain an MGNREGA Card first in order to work and receive the benefits of the program, the households who do not have this card might have opted out due to various reasons. If those reasons are unobserved, our estimation results will be biased. Since we control for a wide array of household and district characteristics, an important part of this bias is likely to have been removed. Nevertheless, we use two standard techniques to address the sample bias issue[18] and prove the robustness of our results against it.

First method we use is to include MGNREGA participation as a control variable in our main estimation. Since the participation itself is endogenous, that is, determined by factors which also affect the MGNREGA benefits, we use an instrumental variable strategy. We use district-level variables that have relatively little explanatory power in

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TABLE A2 Instrumental variable regression estimates of the effects of Maoist violence on MGNREGA income controlling for participation (district characteristics used as IV for participation).

	Dependent variable: MGNREGA income		
	(IV1)	(IV2)	(IV3)
Incidents	28.68***	30.32***	28.95***
	(7.780)	(7.767)	(6.611)
MGNREGA participation (*instrumented*)	2035.93***	1550.78*	1340.05*
	(702.410)	(807.216)	(807.2)
Highest adult education	−14.21**	−15.11***	−13.42**
	(5.629)	(5.790)	(5.849)
Household head's age	−1.01	−1.07	−1.08
	(1.283)	(1.249)	(1.290)
Household size	171.05***	180.70***	184.29***
	(21.182)	(22.120)	(22.78)
Number of working household members	−418.64***	−427.43***	−419.02***
(Non-MGNREGA jobs)	(30.905)	(31.134)	(31.67)
Land owned or cultivated (0–1)	245.78***	315.64***	292.29***
	(61.001)	(75.538)	(72.15)
Non-farm business ownership (0–1)	−121.42**	−104.66**	−113.67**
	(53.195)	(51.477)	(51.89)
Total household assets (0–33)	−16.07	−18.33	−21.95
	(13.382)	(13.665)	(13.70)
Village comm. member in/close HH (0–1)		120.09*	141.72*
		(72.320)	(73.95)
State capacity			0.018
			(0.573)
District population (/1000)			−0.184***
			(0.064)
Very dense forest (%)			86.74***
			(7.070)
Relevant test statistics			
Underidentification test	24.66	19.41	18.91
(Kleibergen–Paap rk LM statistic)	[0.000]	[0.004]	[0.004]
Weak identification test (Kleibergen–Paap rk Wald *F* statistic)	8.797	6.601	5.698
Stock–Yogo critical values for maximal IV relative bias at 10%	11.12	11.12	11.12
Overidentification test of all instruments	4.758	3.904	2.827
(Hansen *J* statistic)	[0.446]	[0. 563]	[0.727]
Endogeneity test of MGNREGA participation:	0.158	0.992	1.541
	[0.691]	[0.319]	[0.214]
R^2	0.326	0.316	0.312

Note: Robust SEs in parentheses are clustered at the district level. All regressions have 26,401 observations and include state dummies, religion and caste dummies, further district controls and a constant. Terms in brackets are *p* values of the relevant tests. All test statistics are produced by partialling out the State dummies.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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TABLE A3 Heckman-selection model estimates of the effects of Maoist violence on MGNREGA income.

	Dependent variable: MGNREGA income			
	(Heckman 1) Excluded = District controls	(Heckman 2) Excluded = HH controls	(Heckman 3) Excluded = Both controls	(Selection)
Incidents	26.09***	26.23***	26.267***	0.012***
	(7.253)	(7.227)	(7.14)	(0.002)
Highest adult education	−14.04*	−13.33	−15.32*	−0.010***
	(8.147)	(8.363)	(8.026)	(0.002)
Household head's age	4.73*			−0.003***
	(2.619)			(0.001)
Household size	360.05***	357.78***	363.26***	0.067***
	(20.45)	(18.59)	(18.00)	(0.005)
Number of working household members	−887.83***	−880.80***	−880.60***	0.016**
(Non-MGNREGA jobs)	(29.40)	(29.04)	(29.03)	(0.008)
Land owned or cultivated (0–1)	348.34***	363.47***	374.20***	0.193***
	(83.26)	(77.29)	(76.84)	(0.020)
Non-farm business ownership (0–1)	−265.68***	−249.85**	−269.07***	−0.070***
	(99.48)	(100.49)	(99.45)	(0.025)
Total household assets (0–33)	1.265			−0.053***
	(13.10)			(0.002)
Village comm. member in/close HH (0–1)	190.50**	181.96**	198.80***	0.138***
	(79.17)	(77.64)	(76.75)	(0.020)
State capacity	−1.085**	−1.118**	−1.079**	−0.000
	(0.494)	(0.494)	(0.492)	(0.000)
District population (/1000)	−0.326***	−0.351***	−0.330***	−0.000
	(0.057)	(0.059)	(0.057)	(0.000)
Very dense forest (%)	126.37***	129.23***	125.85***	−0.010
	(25.58)	(25.61)	(25.52)	(0.010)
Inverse Mill's ratio	−57.02	−129.84	29.46	
	(310.55)	(235.48)	(202.10)	

Note: Robust SEs in parentheses are clustered at the district level. All regressions have 26,401 observations and include state dummies, religion and caste dummies, further district controls and a constant.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

determining the level of MGNREGA benefits to construct the instruments for MGNREGA participation. These are the literacy rate, SC&ST population shares in the district and district's relative poverty ranking as quartiles. We then repeat the analyses in Table 2 with Instrumental Variable regressions and report the results below.

Results in Table A2 show that, first of all, the IVs we constructed pass the under-identification, weak IV and over-identification tests that account for clustering and non-i.i.d. SEs (except for the IV1, for which the weak IV hypothesis cannot be rejected). Second, there is no strong evidence that the NREGA participation itself is endogenous as the endogeneity test consistently fails in all three IV regressions. Finally, although the coefficient of the

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violence variable declines a bit, it is still significantly and positively related to the dependent variable, MGNREGA income.

Second method we use, called the Heckman selection model, is developed specifically for correcting the selection bias.[19] This method estimates a selection equation first (much like the first stage of an IV regression) then uses one parameter—Inverse Mill's ratio—from that regression in the outcome regression to account for possible sample bias.[20] However, this method also requires some variables to be excluded from the outcome regression, or in other words, there has to be at least one variable that can explain selection into the program but is not related to the outcome of the program. We use some of the district controls such as the literacy rate, SC&ST population shares in the district and district's relative poverty ranking as quartiles in (Heckman 1), two of the household controls, household's age and total assets, which could explain the selection into the program (Heckman 2), and then all of them together (Heckman 3) in our Heckman-correction regressions. The table below presents the outcome equations in three models in line with the IV models above and the common selection equation that includes all variables in our original estimations (Table A3):

The results are very similar to the IV-regression results: Our main explanatory variable stays significant with a smaller coefficient and the insignificance of the Inverse Mill's Ratio suggests that there is no selection bias[21] in our sample.

Overall, IV and Heckman selection estimations show that, even after overly controlling for possible selection bias, our original results are still valid. Moreover, there is not enough evidence towards a significant selection problem.

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