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Infrastructure in India's Internal War: A District-Level Analysis of the Naxalite-Maoist Conflict

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I. Introduction

A. Insurgency

The Naxalite-Maoist insurgency began over five decades ago in 1967 in Naxalbari, a rural village in West Bengal. The name "Naxalite" was derived from the name of the village from which the communist movement was born. This incident, notoriously known as the Naxalbari Uprising, occurred in March of 1967, and the revolt established the foundation of the Naxalite movement in India. The event was initially an attack on a tribal villager (Adivasi)[i] by local landlords in Naxalbari, and this soon turned into a revolt comprised of armed peasants (Vanden Eynde, 2015). The attack on the villager culminated in an insurrection because of the historical mistreatment of farmers and the socioeconomic inequality in rural India. Furthermore, the revolt was soon led by communist revolutionaries who were previously members of the Communist Party of India (Marxist)[ii], and by July of 1967, the revolt was suppressed by police forces (Chandra, 1990). Once the Government of India gained control of the conflict, Chandra (1990) discusses how the CPI (M) expelled these militant members who participated in the revolt and those who also supported this event. This act by the party soon gave way for more communists to support the militant ideology of armed struggle, and the nonviolent stance of the CPI (M) also acted as a catalyst for dissident members to abandon the party. Soon after, the communists who participated in the Naxalbari Uprising established the All India Coordination Committee of Communist Revolutionaries, which focused on armed struggle to further Maoist ideology in India (Vanden Eynde, 2015). In addition to the Naxalbari Uprising, this precursor organization became the bedrock of the current Naxalite-Maoist insurgency. Like other communist insurgencies throughout the 19th and 20th centuries, Naxalites strive to have their long-term goal of creating a Marxist state come to fruition, and the violence of the insurrection increased over the decades, but it came it became a high-intensity conflict beginning in the 2000s. The Naxals are currently most active in states such as Andhra Pradesh, Bihar, Chhattisgarh, Jharkhand, Orissa, and West Bengal. In 2006, Prime Minister Manmohan Singh stated how this insurgency is India's "single biggest internal-security challenge" (The Economist, 2010).

B. Infrastructure

While the Government of India utilized its paramilitary force, the CRPF[iii] to quash the insurgency, specific economic programs have been created to assist the most impoverished districts in the nation in terms of employment and development imbalances. One noteworthy program that deals with infrastructural goals in destitute and rural districts is the Backward

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Regions Grant Fund (BRGF). Started in 2007 by former Prime Minister Manmohan Singh, this program managed by the Ministry of Panchayati Raj and funded by the Government of India aims to address development disparities across 250 districts that are lagging economically and infrastructurally (Borthakur, 2014). Additionally, the objectives of the program are expressed in the Backward Regions Grant Fund Programme Guideline. The goal is to improve upon infrastructural and developmental gaps in these targeted districts, reinforce institutions of local governments in terms of their abilities to execute these infrastructure plans, and provide professional assistance to these institutions for organizing and enacting these development plans (Government of Jharkhand, 2007). In terms of funding, the BRGF has two sources of finances. The first source is a capacity-building fund of Rs. 250 crores[iv], which technically suggests 1 crore per district per year. The second is an untied grant of Rs. 1925 crores. This is comprised of a plan that first allocates Rs. 10 crores to each district per annum, and secondly divides the remaining funds to districts based on an equal issuance as per the population and the geographical share of each district compared to the totality of the geographical share and population of all the 250 districts (Government of Jharkhand, 2007).

C. Literature Review

India's unprecedented growth since the late 20th century has shown significant development throughout the nation in urban areas. However, the fruits of economic liberalization have not reached many agricultural and rural areas in Eastern, Southern, and Central India. Due to the lack of regional lack of growth, left-wing extremism has run rampant in many areas of the nation. The communities affected by the internal conflict are among the most disadvantaged groups in the nation due to various factors, such as occupations in low-skilled field labor and low literacy rates amongst local populations. Compelled by sheer poverty and the constant threat of communist violence, villagers continue to work in agriculture and other manual forms of labor without using any substantial infrastructure in their daily lives (Guha, 2007).

Based on current literature, there are mixed results of whether infrastructure and economic development programs tend to alleviate or exacerbate violence in conflict zones (Ali et al., 2015; Mardirosian, 2010; Mashatt et al., 2008). However, since results are not entirely conclusive on the subject, it is crucial to take a closer look at the type of civil conflict and the ideology behind its insurgents. The Naxalite-Maoist insurgency, a communist conflict in India that began in 1967, began due to rural inequality. The leaders and insurgents of the movement known as "Naxalites" soon began violent attacks on the surrounding rural population in the Red Corridor[v] to establish communist territory where the Indian state could not interfere nor administer proper governance in these regions. Narayan (2011) discusses how the ideology of Naxalism is based on repelling political corruption, decreasing poverty throughout the nation, and reforming the crippling education system. Due to these stances, a federal development program implemented in 2007 to tackle poverty and build infrastructure in the least-developed districts, the Backward Regions Grant Fund (BRGF), seemed to be the key to mitigating the extremism. Hence, this paper considers the relationship between the BRGF and the violent intensity of India's Naxalite-Maoist insurgency.

In past literature, mixed findings on infrastructure display that the region and type of conflict are significant in determining whether development programs will result in positive impacts. Ali et al. (2015) find that development does not produce the intended benefits of decreasing militia conflict in the Congo. On the contrary, Mashatt et al. (2008) discuss how in Kosovo, building infrastructure aroused support for postwar goals such as political stability.

During the insurgency, many economists have written on the subject of Naxalism and whether there are methods to decrease the violence in the affected regions of India. As mentioned earlier, this conflict is most prevalent in the rural districts of the country, particularly due to a variety of factors. These districts experience low literacy rates since there is little educational emphasis in the rural parts of the nation, low rates of infrastructure as there is little access to health facilities, electricity, and drinking water, and even lower rates of urbanization (Fetzer, 2014). Furthermore, the lack of development in these regions allows for Naxalite influence and violence, as the insurgents tend to gain legitimacy by expressing how they support the interests of the rural people. As a result, the organization can recruit villagers as insurgents and receive approval from the local population. It is crucial to understand that most of the villagers across these affected districts work in agriculture as field laborers, and Fetzer (2014) discusses how data from the National Sample Survey 2001 shows that 64.9% of households base their primary income from working in the agricultural sector. Now, since the states in the Red Corridor experience higher rates of left-wing extremism, their rates of agricultural employment are much higher, with a prime example being how 90% of the Eastern state of Chhattisgarh works in this sector (Fetzer, 2014). The rural geography, in addition to the low farming wages and lack of infrastructure, are all factors that allow the Naxalites to maintain their support base and continue violent attacks in the name of Maoist ideology.

The literature on the topic focuses on government programs, labor income shocks, and factors such as rainfall and mining rates, all of which were presumed to impact insurgent violence from Naxalite activity. Fetzer (2014) discusses how NREGA[vi], a public employment program meant for villagers at the district level, can decrease the conflict from the Naxalite-Maoist insurgency. By incorporating rainfall and district agricultural wages, Fetzer (2014), using an OLS framework, concludes that monsoon rainfall affects agricultural wages. Moreover, in a difference-in-difference analysis, Fetzer (2014) also concludes that NREGA responds to monsoon variation, which in turn drops conflict levels to around 60%. However, through the usage of a fixed-effects Poisson Quasi-Maximum Likelihood model, Vanden Eynde (2015) states that positive rainfall shocks are positively associated with crop (rice) output, but that the impact of rainfall shocks is negative for casualties from insurgent violence. In terms of data concerning mineral output, Vanden Eynde (2015) concludes that the effect of mining areas on civilian casualties is negative but far too insignificant to analyze further. Similarly, Hoelscher et al. (2012) find that by using probit and negative binomial estimations, greater mining activity and share of district GDP is unrelated to the violence caused by Naxalites.

Focusing on the BRGF led to an interesting discovery because initially, there was no direct evidence that this infrastructure program does not increase the livelihoods and productivity of rural populations in the targeted districts. In terms of agricultural wages, this factor affects Naxalite violence since a negative shock in rainfall reduces wages since agricultural output decreases. However, other than labor shocks and government employment programs, development programs such as the BRGF have not been studied to see how left-wing extremism in the Red Corridor is affected.

Based on a panel of 110 districts from 2007 through 2013, I use a negative binomial framework with a series of five controls. The first model demonstrates a reverse relationship in which there is a statistically significant uptick in the number of fatal casualties when government expenditure of the BRGF increases. The second model specification includes interaction effects where I interact each control variable with the explanatory variable, BRGF funding. The results in this specification are also significant, where the interaction effects display interesting findings on how the BRGF can affect Naxalite-related fatalities.

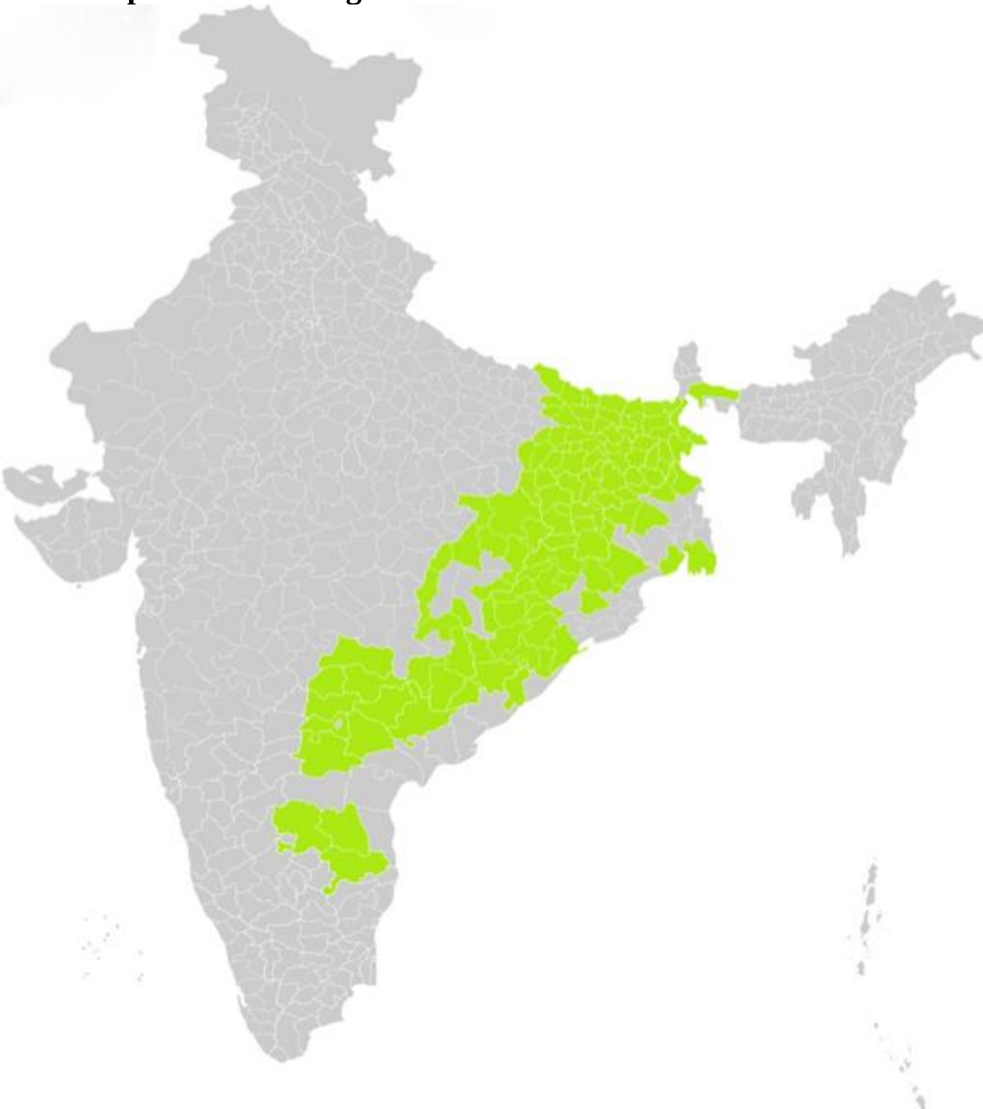
In terms of robustness checks, I use one test where the results remain consistent for each model specification. To explore whether the results remain robust, I lag one of the control variables by one year.

The paper is organized as follows: Section II discusses provides and describes the data and collection processes; Section III delineates the empirical strategy and methodology of the models; Section IV examines the results and interpretation of results; Section V concentrates on a single robustness check for the model assumptions, and Section VI concludes by summarizing the results and reflecting on future research considerations.

II. Data

The analysis on if the BRGF affects the number of fatal attacks by Naxalite activity is based on a district-by-year panel dataset from 2007 through 2013. The sample includes 110 Indian districts across six states, Andhra Pradesh, Bihar, Chhattisgarh, Jharkhand, Orissa, and West Bengal. These districts lie in the Red Corridor and receive financial resources from the BRGF. The spatial unit in this paper is an Indian district. Moreover, in the sample, there were an additional 10 districts that were given constituency status, but since they were created during the panel time frame, I merged those 10 with the original districts from which they were carved. Thus, to simplify data collection, I used a sample of 110 districts that are standardized from 2007 to 2013. This section describes the different variables I used in the model and how each dataset was compiled. Figure 1 below displays the 110 districts focused on in this paper.

Figure 1: Map of the 110 Targeted Districts



A. Response Variable – District Level Fatal Casualties

The dependent variable for the analysis of this paper is a dataset that consists of all the fatal attacks on a district-by-year panel from 2007 through 2013. This data was gathered and compiled from the South Asian Terrorism Portal (SATP), a site that contains databases on all the terrorist activities throughout South Asia. It is managed by the Institute for Conflict Management, a non-profit organization based in New Delhi, which commits to analyzing and solving internal security threats in South Asia. In terms of the Naxalite-Maoist insurgency, the SATP has detailed data on the number of fatal casualties per district over a timeline from 2000 to the current year. Additionally, it combines newspaper reports from press agencies around India into summaries that give an account of where the violent attack took place and the death count of civilians, CRPF officers, and Naxals (Vanden Eynde, 2015). Thus, the gathered data is compiled per district from 2007 through 2013 to show the total number of deaths relating to Naxalite activity. Additionally, the total fatality count is comprised of 4 categories listed below:

$$\boldsymbol{Total\ Fatality\ Count = Civilian + CRPF + Naxalites + Not\ Specified}$$

This portal contains the number of fatal casualties for each district that has been affected by left-wing extremism. However, only 110 districts were used in the analysis since the independent variable, the BRGF, had allocation funds for these specific districts that fall in the Red Corridor. Furthermore, 2007-2013 were chosen for this panel data since the BRGF began funding in 2007.

B. Independent Variable – BRGF

The independent variable for the paper is data compiled from the Backward Regions Grant Fund, and it was taken from the Open Government Data Platform[vii], a government platform that supports the Open Data initiative of the Government of India. This site allows federal government agencies to publish datasets and documents for the general public, and the data is contributed by the Ministry of Panchayati Raj, a government agency that manages matters dealing with local governance. The dataset includes all the targeted districts which the Government of India felt needed allocation funds for development purposes, but for the paper, I will be using a panel of 110 districts from 2007 through 2013 since these constituencies, as mentioned in the previous sub-section, are found within the area of the Red Corridor. The data is listed by the allocation per district per annum, and the amount of funds released to each district from that initial allocation. For this paper, I use the released funds in the analysis as these are the direct funds that each district is allowed to utilize. Additionally, the funds in rupees are calculated in crores.

C. 1st Control – Geographical Area

Based on Buhaug and Gates (2002), the scope of civil conflict is associated with geographical factors such as land area. Using ordinary least squares (OLS) and three-staged least squares (3SLS) estimation techniques, the authors found that the scope of conflict is strongly shaped by factors such as the land area of a country. As a result, I use the geographic area of each district as a control variable. Since the scope of the Naxalite-Maoist insurgency is associated with the Red Corridor, this metric seems useful to control for, as the bulk of the conflict takes place in these selected set of districts. This data was collected from the Ministry of Environment, Forest and Climate Change, where each bi-yearly State of Forest Report records the geographic area of each district. The district land area is measured in squared kilometers, where I record for the land area of each district from the years 2007 to 2013.

D. 2nd Control – Rural Literacy Rate

The rural literacy rate is the second control I include in the model since civil conflict affects education and literacy development. According to a 2000-2004 study, of the 25 countries with the lowest adult literacy rates, 12 of those countries have conflicts or are exiting from major conflicts (Hanemann, 2005). Additionally, these nations show a strong correlation in literacy development status and their propensity towards civil conflict. During periods of civil conflict, school buildings and infrastructure are damaged or destroyed, leading to teachers being displaced and parents preventing their children from attending school due to the lack of security. Prime examples are sections of the Democratic Republic of the Congo, Somalia, and South Sudan, where chronic conflict has led to minimal access to education systems for children (Hanemann, 2005).

Furthermore, in Naxalite-prone areas, these districts also lack educational development since most of the local populace work in the agricultural sector. Guha (2007) discusses how millions of tribal villagers known as Adivasis, live in the remote regions of the Red Corridor. Since these groups live in such forested areas, they primarily work in the agricultural sector, and as a result, most have little education. Coincidentally, Naxalite forces occupy much of the same land as these Adivasi groups, and so in addition to the lack of educational attainment, these indigenous groups must live amongst insurgency violence. Moreover, since education is not prioritized in these areas, Naxalites have been known to recruit children into their ranks (Mukherjee, 2014). This variable is utilized as a control because of the apparent association between literacy and civil conflict. When collecting the data, I used the 2011 Census of India literacy data for the total rural population of each district. The censuses are conducted by the Ministry of Home Affairs every decade. Using this specific census was logical since Indian censuses are conducted once per decade, and because the time frame lies between 2007 to 2013, population numbers increase at a gradual rate. Thus, for the time frame, the rural literacy rate per district is uniform from 2007 to 2013. Literacy data is best gathered during censuses, and the 2011 Census falls near the middle of the time frame.

E. 3rd Control – Forest Cover

Forest cover is a key factor that is useful for internal civil conflicts because insurgents can continue to launch guerilla attacks and stay relatively hidden from the presence of government security forces. Fearon and Laitin (2003) explain how Maoists favor areas that are beyond state jurisdiction. Thus, they are inclined to situate themselves in forested areas. The data was collected from the Forest Survey of India, which is managed by the Ministry of Environment, Forest and Climate Change. The Forest Survey of India conducts bi-yearly geographic surveys of forest cover throughout the nation. These surveys delve into forest cover per state as well as per district. Forests are categorized into five categories: very dense forest, moderately dense forest, open forest, scrub, and total forest cover. I am using the total forest cover per district for simplicity purposes since Naxalites are known to operate in most forested terrains. Additionally, since this data is gathered biyearly, I conducted linear interpolation for the non-surveyed years of 2008, 2010, and 2012. Forest cover is measured in squared kilometers.

F. 4th Control – Annual Rainfall

Rainfall is a crucial variable to include as a control in the empirical analysis, as there is significant literature that presents evidence that in economically impoverished areas, higher conflict tends to occur when there is less rainfall (Fetzer, 2014; Guariso and Rogall, 2017; Miguel, Satyanath, and Sergenti, 2004). Thus, I utilize rainfall output as a control since this factor affects civil conflict in areas that experience rainfall shocks. The Department of Water

Resources, a subdivision of the Ministry of Jal Shakti, gathered this data. This agency is the governmental department responsible for the nation's water resources. The data is IMD[viii] gridded data at a fine spatial resolution of a 0.25-by-0.25-degree grid-cell size, which is then converted into overall yearly rainfall measured in millimeters. The high resolution allows the ministry to collect more consistent and accurate rainfall estimates. I collected this gridded data from 2007 through 2013, where I aggregated the rainfall into a yearly total output for each district.

G. 5th Control – Ruggedness

Terrain ruggedness is the last control in the model, where existing arguments about the effect of terrain on intrastate and interstate violence are much too varied than the existing data used to test such questions. As a result, Shaver et al. (2016) introduce precise geo-referenced data on terrain ruggedness and land cover globally at the national, provincial, and 1x1 kilometers grid-square levels. For the purposes of this paper, I am using the terrain ruggedness at the 1x1 kilometers grid-square level for India. Furthermore, since the Red Corridor lies in rugged and forested terrain, I aim to control this metric since Naxalites are known to occupy such areas. The data was processed in ArcGIS, where I overlaid a shapefile over the terrain map of India. The shapefile contained polygons of each district, where I then took the average ruggedness value for each district. Since the terrain is time-invariant, the ruggedness measurement per district is uniform from 2007 to 2013.

IV. Empirical Strategy

A. Model (Without Interaction)

The first proposed empirical strategy of this paper seeks to determine if the implementation of the BRGF affects the number of Naxalite-related fatal casualties per annum. I utilize a negative binomial framework to hypothesize for significance in the model. This type of model accounts for the fact that the number of fatalities from the insurgency is a count variable.[ix] The estimating model is as follows:

$$(\mathbf{1}) \qquad \boldsymbol{NAX_{d,t} = \beta_0 + \beta_1 GOV_{d,t} + \beta_2 CON_{d,t} + \varepsilon_{d,t}}$$

where $NAX_{d,t}$ the number of fatal casualties which occurred per district *d* over the time frame *t*, which is from 2007 through 2013. $GOV_{d,t}$ is the independent variable representing government expenditure through the BRGF program, where *d* stands for the district where funds were allocated in year *t*. Furthermore, $CON_{d,t}$ represents the vector of control variables per district *d* in year *t*. This vector is expanded below for further explanation. Lastly, $\varepsilon_{d,t}$ is the district and year idiosyncratic error term. Additionally, the standard errors are clustered at the district level. Due to this, they are also robust against any form of serial correlation between each district. The control vector, $CON_{d,t}$, is further explained below.

$$(2) \qquad \boldsymbol{CON_{d,t} = \theta_{d,t} + \rho_{d,t} + \phi_{d,t} + \tau_{d,t} + \omega_{d,t}}$$

Taking a closer look at the vector of district-level control variables in the overall model, I utilized a total of five. The first control, $\theta_{d,t}$, represents the geographic area in district *d* in year *t*; the second control, $\rho_{d,t}$, stands for rural literacy rate at district-level *d* in year *t*; $\phi_{d,t}$ is the third control which is forest cover over a yearly basis *t* in district *d*; the fourth control, $\tau_{d,t}$, represents rainfall output per year *t* in district *d*; and lastly, the fifth control, $\omega_{d,t}$, stands for the mean terrain ruggedness value per district *d* in year *t*.

B. Model (With Interaction)

The second empirical specification uses the negative binomial model in addition to an interaction term as in (Fetzer, 2014; Hoelscher et al., 2012). By adding interaction terms to the previous specifications between $GOV_{d,t}$ and the control vector, $CON_{d,t}$, I no longer aim to see the effects of these variables in isolation. Moreover, by interacting $GOV_{d,t}$ and $CON_{d,t}$, I aim to take the effects of both the explanatory and control variables into account and see how strong the coefficient estimate becomes. Lastly, $\nu_{d,t}$ is the district and year idiosyncratic error term. The model specification is shown below:

$$\begin{aligned}(3) \qquad \boldsymbol{NAX_{d,t}} &\boldsymbol{= \beta_0 + \beta_1 GOV_{d,t} + \beta_2 CON_{d,t} + \beta_3 (GOV * \theta)_{d,t} + \beta_4 (GOV * \rho)_{d,t}} \\ &\boldsymbol{+ \beta_5 (GOV * \phi)_{d,t} + \beta_6 (GOV * \tau)_{d,t} + \beta_7 (GOV * \omega)_{d,t} + \nu_{d,t}}\end{aligned}$$

C. Methodology

This decision of choosing a negative binomial model partially follows current literature on the insurgency; however, the model does not focus on mining rates since this factor was proven as insignificant for determining causality (Hoelscher et al., 2012). The methodology of the model revolves around the controls, as I run regressions by consistently adding one of these variables each time to strengthen the results. I include clustered standard errors throughout each regression to account for the data being gathered at the district level. Initially, I run a regression with only the independent and outcome variables to see how the results and the significance level hold without accounting for the control vector. After this first step in the process, I run a regression with the first control, geographical area. I then add the subsequent four controls gradually in the arrangement of rural literacy rate, total forest cover, rainfall output, and mean ruggedness. To test the strength of the main coefficient and whether the results are significant, I use these controls since, according to the existing literature on the Naxalite conflict, these factors are crucial in determining the fluctuation of violent attacks. By utilizing them in the series of regressions, I reduce the likelihood of omitted variable bias within the model. Lastly, I re-run my regressions in the second model specification to add the interactions between $GOV_{d,t}$ and $CON_{d,t}$. In this second specification, the first regression contains all the controls, and then each subsequent regression contains an interaction effect between BRGF expenditures and each control variable. Thus, the first interaction in the second regression will be between $GOV_{d,t}$ and

$\theta_{d,t}$, the second regression will then have $GOV_{d,t}$ interacting with $\rho_{d,t}$, and so on. The final regression includes all the individual interaction effects. In terms of robustness checks, I conduct a single test where I lag the rainfall variable since the annual rainfall metric is crucial to understanding civil conflict in rural areas. The robustness check is provided in Section VI. Table 1 below presents the summary statistics.

Table 1: Descriptive Statistics

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
Total Fatalities	770	5.31039	23.36015	0	365
BRGF Funds	770	15.35864	8.108196	0	67.65
Geographical Area (km^2)	770	5893.127	4466.159	572	19130
Rural Literacy Rate	770	0.5165153	0.0802354	0.2941148	0.7221895
Total Forest Cover (km^2)	770	1514.942	1942.861	0	11350
Annual Rainfall (mm)	770	1382.104	616.8331	504.8	4602.86
Mean Ruggedness	770	64.00092	62.38993	3.254561	321.5186
Lagged Annual Rainfall (mm)	769	1381.348	616.8777	504.8	4602.86

V. Empirical Results

The results are provided in the same sequence as shown in the empirical strategies section. I first begin by establishing the relationships between the fatality count and government expenditure, along with the vector of controls. Then, in the following specification, I display the results with the interaction effects between BRGF expenditure and each of the controls.

A. Results – Prior to Interaction Effects

Given the model I am using, I interpret the negative binomial regression coefficients as follows: for a one-unit change in the independent variable, the difference in the logs of expected counts of the response variable is expected to change by the specified regression coefficient. Since the response variable is a count variable that is over-dispersed, this model focuses on modeling the

log of the expected count as a function of the explanatory variables. This first set of results show the relationship between fatality numbers and BRGF funds, along with my vector of controls. The regression results are presented in Table 2. First, I add each control in subsequent order from the geographical area, rural literacy rate, total forest cover, actual rainfall in millimeters, and finally mean ruggedness. When looking at the table, after adding the entire vector of controls to the regression, I see a slight significance at the 10% level for my explanatory variable of released BRGF funds. For each 1 crore increase in**Table 2: Prior to Interaction Effects**
 BRGF spending, the difference in the logs of expected counts would be expected to increase by 0.0285 fatalities. After adding the vector of controls, I still see that the BRGF program does lead Naxalite-related deaths to increase. The baseline results from the first specification provide an interesting display about the Naxalite-Maoist Insurgency, where districts that receive greater funding experience a higher number of fatalities. These results are further interpreted in the two subsections below.

B. Interpretation of Results (Table 2) – Funding and Productivity

Variables	(1) Total Fatalities	(2) Total Fatalities	(3) Total Fatalities	(4) Total Fatalities	(5) Total Fatalities	(6) Total Fatalities
BRGF Funds	0.0521**	0.00300	0.0131	0.0217	0.0250	0.0285*
	(0.0163)	(0.0142)	(0.0140)	(0.0132)	(0.0133)	(0.0128)
Geographical Area (km^2)		0.000207***	0.000194***	0.0000497	0.00000994	0.00000988
		(0.0000415)	(0.0000417)	(0.0000850)	(0.0000759)	(0.0000742)
Rural Literacy Rate			-2.383	-0.590	-1.053	0.330
			(1.668)	(2.092)	(2.003)	(2.134)
Total Forest Cover (km^2)				0.000335*	0.000308*	0.000219
				(0.000160)	(0.000136)	(0.000135)
Annual Rainfall (mm)					0.000441	0.000359
					(0.000249)	(0.000251)
Mean Ruggedness						0.00536
						(0.00384)
Constant	0.718**	-0.0911	1.043	0.282	0.108	-0.777
	(0.268)	(0.291)	(0.931)	(1.068)	(1.036)	(1.164)
Log-Transformed Over-Dispersion Parameter	1.959***	1.765***	1.752***	1.719***	1.697***	1.684***
	(0.145)	(0.124)	(0.124)	(0.122)	(0.122)	(0.121)
Observations	770	770	770	770	770	770

Standard errors in parentheses
Notes: In all regressions, the response variable is total fatalities by Naxalite activity, and the estimation techniques are negative binomial regressions.
Column (1) is the only column without controls. Column (2) controls for geographical area, Column (3) controls for rural literacy rate, Column (4) controls for total forest cover, Column (5) controls for total yearly rainfall, and Column (6) controls for the mean ruggedness per district.
Negative binomial regressions display standards errors clustered at the district level.
The stars represent:
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In concern to the BRGF, I found the results particularly intriguing because due to the rural and underdeveloped nature of these districts, it would seem that infrastructure development would decrease the number of fatal attacks. While Naxalites believe the federal government to be responsible for immense poverty throughout India and specifically in the areas in which they operate, the increase in their number of attacks draws attention to this topic. The mission of the Backward Regions Grant Fund is to address district imbalances in infrastructure and economic development. However, Naxalites seem to be provoked by the government involving itself to assist these lagging regions. From existing literature, Crost, Felter, and Johnston (2014) discuss how through a regression discontinuity design, they found that economically lagging municipalities in the Philippines tend to experience a surge in insurgent attacks when the government introduced a development program to target these regions. The KALAHI-CIDSS[x] development program in the Philippines caused an increase in conflict from insurgent groups such as the New People's Army and the Moro-Islamic Liberation Front (Crost, Felter, and Johnston, 2014). According to this study, it seems that Naxalites, due to their anti-government stance, became more aggressive as the federal government began operational plans of the BRGF in these selected districts.

Additionally, because this is an infrastructure program, building paved roads, health facilities, and sanitation buildings all require a prolonged time frame since these districts already have very little infrastructure. Literature on the BRGF also highlights the flaws of the program. Districts in the state of Assam had to deal with management problems, fund utilization issues, the lack of technical support in building, and the poor structure of the District Planning Committees (Borthakur, 2014). These crucial flaws in the productivity of the program affect its ability to bridge development gaps between districts. Moreover, the World Bank review (2010) scrutinizes the program and suggests that the government increase the number of funds and allocate them to districts on a speedy basis; the National Advisory Council report (2010) also emphasizes the importance of government oversight on the program and the capacity to sustain constant development. These inadequacies in the program may be the reasons why Naxalites continue and escalate attacks.

C. Interpretation of Results (Table 2) – Geography

While funding and efficacy appear to be significant issues within the program, Naxalites might also increase their violence due to how the BRGF interprets geography for development interventions. Specifically, the government does not take terrain ruggedness into account when considering the geographic landscapes of the targeted districts (Yumnam, 2007). Thus, by failing to account for terrain ruggedness, districts with uneven terrain and numerous rivers are negatively affected since they may not receive the necessary funds. Furthermore, specific geographical landscapes such as the Chhota Nagpur Plateau in Eastern India and the Eastern Ghats mountain range in South India cover much of the area in the Red Corridor. If specific districts receive less assistance because their terrain ruggedness is not accounted for, there is a high possibility that Naxalite violence increases because the government decides the allocation of development funds based on a narrow definition of geography (Yumnam, 2007).

D. Results - With Interaction Effects

Regarding the second model specification, this set of regressions includes the interaction effects between BRGF expenditures and each control variable. The results are provided in Table 3. I begin by displaying the last regression in Column (6) from Table 2, and then start adding each of the interaction effects. Lastly, Column (7) includes all of the individual interactions. The results in Table 3 are more significant compared to those of Table 2, where Columns (3), (5), (6), and (7) are particularly interesting. Column (3) contains the interaction between $GOV_{d,t}$ and $\rho_{d,t}$, where I find significance at the 1% level. The result shows a positive relationship between the interaction term and the number of fatalities, suggesting that the fatalities increase in districts where funding coincides with greater rural literacy rates. Looking at the main effect, I find that at the 1% significance level, for every 1 crore increase in BRGF spending, the difference in the logs of expected counts would be expected to decrease by 0.194 fatalities. In Column (5), at the 5% significance level, the result displays a positive relationship between the interaction of $GOV_{d,t}$ and $\tau_{d,t}$, and the number of fatalities. This suggests that for districts that receive more BRGF funding and have greater annual rainfall, the number of fatalities increases. Looking at the main effect, I see slight significance where for every 1 crore increase in spending, the difference in the logs of expected counts would be expected to decrease by 0.0662 fatalities. Moving onto Column (6), the results show a negative relationship between the interaction of $GOV_{d,t}$ and $\omega_{d,t}$, and the number of fatalities. This negative coefficient at the 5% level of significance suggests that districts that receive greater funding are likely to have a decreased number of fatalities for districts with a greater mean value of terrain ruggedness. I also find that the main effect displays significance at the 1% level, where the difference in the logs of expected counts would be expected to increase by 0.0655 fatalities. Lastly, Column (7) includes all individual interaction terms, where the coefficient on my main explanatory variable of BRGF released funds displays significance at the 10% level. This finding is particularly interesting since after including all interaction terms, I see that for every 1 crore increase in spending, the difference in the logs of expected counts would be expected to decrease by 0.187 fatalities. Thus, after including all interactions, I witness that districts with more BRGF funding lead to a decrease in fatalities. These results are further interpreted in the four subsections below.

Table 3: With Interaction Effects

Variables	(1) Total Fatalities	(2) Total Fatalities	(3) Total Fatalities	(4) Total Fatalities	(5) Total Fatalities	(6) Total Fatalities	(7) Total Fatalities
BRGF Funds	0.0285*	0.0130	-0.194***	0.0370*	-0.0662*	0.0655***	-0.187*
	(0.0128)	(0.0276)	(0.0522)	(0.0181)	(0.0327)	(0.0191)	(0.0870)
Geographical Area (km^2)	0.00000988	-0.0000218	-0.0000242	0.00000637	0.0000277	-0.0000290	0.000309*
	(0.0000742)	(0.0000827)	(0.0000545)	(0.0000760)	(0.0000637)	(0.0000660)	(0.000134)
Rural Literacy Rate	0.330	0.270	-6.615*	0.237	0.290	-0.187	-6.398
	(2.134)	(2.137)	(2.691)	(2.157)	(2.093)	(2.035)	(3.511)
Total Forest Cover (km^2)	0.000219	0.000220	0.000326**	0.000297	0.000182	0.000318*	-0.0000907
	(0.000135)	(0.000136)	(0.000114)	(0.000211)	(0.000121)	(0.000127)	(0.000315)
Annual Rainfall (mm)	0.000359	0.000335	0.000284	0.000376	-0.000506	0.000335	-0.000779
	(0.000251)	(0.000251)	(0.000226)	(0.000255)	(0.000369)	(0.000233)	(0.000411)
Mean Ruggedness	0.00536	0.00569	0.00498	0.00505	0.00645	0.0140**	0.0124
	(0.00384)	(0.00394)	(0.00372)	(0.00389)	(0.00392)	(0.00498)	(0.00664)
BRGF Funds x Geographical Area (km^2)		0.00000170					-0.0000146**
		(0.00000305)					(0.00000498)
BRGF Funds x Rural Literacy Rate			0.390***				0.379*
			(0.0884)				(0.158)
BRGF Funds x Total Forest Cover (km^2)				-0.00000379			0.0000166
				(0.00000585)			(0.0000122)
BRGF Funds x Annual Rainfall (mm)					0.0000484**		0.0000593***
					(0.0000159)		(0.0000172)
BRGF Funds x Mean Ruggedness						-0.000593**	-0.000444
						(0.000214)	(0.000291)
Constant	-0.777	-0.496	3.207*	-0.855	0.709	-0.957	3.001
	(1.164)	(1.190)	(1.471)	(1.154)	(1.211)	(1.129)	(1.825)
Log-Transformed Over-Dispersion Parameter	1.684***	1.682***	1.635***	1.683***	1.648***	1.658***	1.592***
	(0.121)	(0.121)	(0.123)	(0.122)	(0.120)	(0.121)	(0.121)
Observations	770	770	770	770	770	770	770

Standard errors in parentheses

Notes: In all regressions, the response variable is total fatalities by Naxalite activity, and the estimation techniques are negative binomial regressions. Column (1) is the only column without interaction effects. Column (2) interacts with geographical area, Column (3) interacts with rural literacy rate, Column (4) interacts with total forest cover, Column (5) interacts with total yearly rainfall, Column (6) interacts with mean ruggedness per district, and Column (7) includes all individual interactions. Negative binomial regressions display standards errors clustered at the district level. The stars represent:

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E. Interpretation of Results (Table 3) – Funding and Productivity

Looking at the main effects from Table 3 for the main explanatory variable, I find interesting results compared to those of Table 2. Columns (3), (5), and (7) are particularly intriguing as they differ entirely from my main results in Column (6) from Table 2. Similar results are found in the literature. In Hoelscher et al. (2012), they find that development programs to address Scheduled Castes and Scheduled Tribes[xi] may reduce violence. Moreover, Hoelscher et al. (2012) also find a strong relationship between greater households covered by the NREGA program and lower frequency of violence. This finding implies that either districts with less violence have more accessibility to the NREGA program or that this program has difficulty reaching the targeted population in more violent districts.

Furthermore, in Fetzer (2014), the key finding in this paper suggests that the introduction of the NREGA program eliminates the link between monsoon shocks and civil conflict. Thus, the monsoon shocks cease to lead to conflict as a result of the NREGA program. Fetzer (2014) concludes that removing the link between productivity shocks in terms of rainfall and conflict can lead to lower levels of insurgent violence. The findings from Table 3 show that by interacting the main explanatory variable with some of the controls, the main effect changes its sign entirely. Due to the complicated nature of interaction terms, these main findings must be interpreted to consider the interaction effects. Thus, while the main effects show that an increase in BRGF funding can lead to fewer fatalities, it is best to interpret these results while considering the interactions. In the three subsections below, I interpret the interaction effects.

F. Interpretation of Results (Interaction with Rural Literacy Rate)

For the interaction between BRGF funding and rural literacy rates, a possible reason for why districts with greater literacy experience more fatalities can be due to Naxalite recruitment patterns. To explain further, Naxalites are known to recruit in a particular manner, where they target individuals with intellectual and cognitive skills (Mukherjee, 2014). Moreover, people with a set of technical skills are also highly sought after, so there may be a potential association with districts with greater rural literacy rates and the number of people recruited into the Naxalite cause. In terms of violence, districts with a greater share of technically-minded, literate individuals may experience a higher rate of fatalities. As a result, greater funding in districts with higher rural literacy rates may mean that Naxalites focus their efforts to recruit talented people into their ranks. Since Naxalites already operate in rural areas, they may be more incited to cause violence if they recruit intellectual and capable individuals in select districts where they want to remove government interference of any sort.

G. Interpretation of Results (Interaction with Annual Rainfall)

While Fetzer (2014) displays a negative relationship between monsoon rainfall and civil conflict, the relationship is weak and statistically insignificant. Moreover, Fetzer (2014) shows that highly positive rainfalls can induce civil conflict as well. Regarding this paper, many of the districts in the sample fall into tropical and subtropical moist broadleaf forests. As a result, this bioregion naturally has high levels of rainfall due to the monsoons of South Asia. This interaction term shows that the number of fatalities increases for districts with more funding and greater annual rainfall. This would mean that districts with monsoon issues may deal with more violence if these areas require the funding for necessary infrastructure such as paved roads and electrical grids, both of which can be severely damaged during the monsoons. A district with such issues may be a prime location for Naxalite activity since the area would be rural and underdeveloped.

H. Interpretation of Results (Interaction with Terrain Ruggedness)

While it seems that highly rough terrain may be beneficial for insurgents, I see otherwise in this study. To understand better, I look at the geography of these districts and find that since the Chhota Nagpur Plateau in Eastern India and the Eastern Ghats mountain range in South India cover much of the area in the Red Corridor, rugged terrain seems to be present in Naxalite territory. For example, Kalyvas (2006) finds that in order for insurgents to cooperate to maintain their organization and avoid state armed forces, they have to emphasize the need for support from the local people. As a result, many local populations do not live in the most rugged terrain, which means that rebel groups such as the Naxalites cannot use the such rugged terrain to their advantage. Moreover, Carter et al. (2019) explain that insurgent groups cannot stay in extremely rugged areas for long-term situations since it may be challenging to launch ground operations. Long-term settlement in these areas may also be a challenge because, in terms of supplies, rebel groups will have difficulties bringing in a constant supply of recruits, weapons, and provisions. Regarding the Naxalite-Maoist insurgency, I believe the extreme ruggedness is more of a challenge than an advantage since this group needs access to supplies so that they can continue their operations against state police forces.

VI. Robustness Checks

I organize the robustness of the main findings in one manner. This check inquires as to whether the initial results hold. To begin, this robustness check utilizes lagged rainfall where the measures are lagged by one year. I first include lagged annual rainfall for the first model specification by controlling for this variable. Similar to how I conducted these regressions earlier, I control for lagged annual rainfall after controlling for the original annual rainfall variable.

Regarding the second model specification, I interact lagged annual rainfall with the main explanatory variable of BRGF spending. I begin by first including the final regression from the first robustness check, and then gradually include each interaction as done before in Table 3. I then include the lagged interaction along with the others in the final regression.

This robustness check investigates if lagging rainfall is significant to the outcome of the results. From existing literature, rainfall is widely known as a crucial factor in the fluctuations in insurgency activity through negative wage shocks. However, since the Red Corridor only has a specific number of BRGF-targeted districts, I focus on a particular set of districts in the region that receive infrastructure funds. I explore the robustness of the results by lagging rainfall by one year to see if this variable as a lagged control does alter the overall results.

A. Lagged Annual Rainfall (Prior to Interaction Effects)

The results for the first robustness check are displayed below in Table 4. Looking at Column (7), I see that my results remain robust with the addition of lagged rainfall as a control. For every 1 crore increase in BRGF spending per district, the difference in the logs of expected counts would be expected to increase by 0.0263 fatalities. Thus, by including lagged rainfall, I see that this variable does not alter the results significantly, where the main result in Column (7) still displays significance at the 10% level. Lagged rainfall proves to show that rainfall luctuations in these districts do not significantly alter the relationship between BRGF funding and the number of fatalities due to Naxalite-related activity. Table 4 is presented below.

Table 4: With Lagged Annual Rainfall Control

Variables	(1) Total Fatalities	(2) Total Fatalities	(3) Total Fatalities	(4) Total Fatalities	(5) Total Fatalities	(6) Total Fatalities	(7) Total Fatalities
BRGF Funds	0.0521**	0.00300	0.0131	0.0217	0.0250	0.0227	0.0263*
	(0.0163)	(0.0142)	(0.0140)	(0.0132)	(0.0133)	(0.0126)	(0.0123)
Geographical Area (km^2)		0.000207***	0.000194***	0.0000497	0.00000994	0.000000658	0.00000272
		(0.0000415)	(0.0000417)	(0.0000850)	(0.0000759)	(0.0000727)	(0.0000721)
Rural Literacy Rate			-2.383	-0.590	-1.053	-1.254	-0.0383
			(1.668)	(2.092)	(2.003)	(1.983)	(2.134)
Total Forest Cover (km^2)				0.000335*	0.000308*	0.000308*	0.000229
				(0.000160)	(0.000136)	(0.000131)	(0.000133)
Annual Rainfall (mm)					0.000441	0.000202	0.000171
					(0.000249)	(0.000186)	(0.000189)
Lagged Annual Rainfall (mm)						0.000374*	0.000312
						(0.000167)	(0.000171)
Mean Ruggedness							0.00473
							(0.00379)
Constant	0.718**	-0.0911	1.043	0.282	0.108	0.103	-0.664
	(0.268)	(0.291)	(0.931)	(1.068)	(1.036)	(1.022)	(1.150)
Log-Transformed Over-Dispersion Parameter	1.959***	1.765***	1.752***	1.719***	1.697***	1.683***	1.673***
	(0.145)	(0.124)	(0.124)	(0.122)	(0.122)	(0.122)	(0.122)
Observations	770	770	770	770	770	769	769

Standard errors in parentheses
Notes: In all regressions, the response variable is total fatalities by Naxalite activity, and the estimation techniques are negative binomial regressions.
Column (1) is the only column without controls. Column (2) controls for geographical area, Column (3) controls for rural literacy rate, Column (4) controls for total forest cover, Column (5) controls for total yearly rainfall, Column (6) controls for lagged total yearly rainfall, and Column (7) controls for the mean ruggedness per district.
Negative binomial regressions display standards errors clustered at the district level.
The stars represent:
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B. Lagged Annual Rainfall (With Interaction Effects)

In regards to the second model specification, I notice slight changes in the results. Table 5 provides the findings below. The main effect of Column (8) becomes insignificant when I include the interaction term between BRGF spending and lagged annual rainfall. Additionally, from Table 3, there was only slight significance at the 10% level, so the change in the value of the coefficient alters only slightly after the inclusion of lagged rainfall. Nonetheless, the main effect from Column (8) loses significance with the inclusion of this interaction. The interaction term in Column (6) is highly significant at the 1% level, where lagging rainfall remains robust in my findings. The interaction in Column (5) is significant at the 5% level, so lagging rainfall actually increases significance for that specific interaction term in Column (6) as well as the main effect in the column. For the main explanatory variable coefficient, the significance is at the 5% level, where it remains more robust compared to the main coefficient in Column (5). Thus, after including a lagged variable in these regressions, it is interesting that the results remain robust and become more significant, as shown in Columns (5) and (6).

Table 5: With Lagged Annual Rainfall Interaction Effects

Variables	(1) Total Fatalities	(2) Total Fatalities	(3) Total Fatalities	(4) Total Fatalities	(5) Total Fatalities	(6) Total Fatalities	(7) Total Fatalities	(8) Total Fatalities
BRGF Funds	0.0263*	0.0150	-0.186***	0.0335	-0.0641*	-0.0717**	0.0622***	-0.128
	(0.0123)	(0.0271)	(0.0516)	(0.0178)	(0.0321)	(0.0258)	(0.0183)	(0.0870)
Geographical Area (km^2)	0.00000272	-0.0000199	-0.0000249	-0.000000389	0.0000240	0.00000760	-0.0000320	0.000337*
	(0.0000721)	(0.0000790)	(0.0000547)	(0.0000740)	(0.0000637)	(0.0000599)	(0.0000648)	(0.000135)
Rural Literacy Rate	-0.0383	-0.0632	-6.517*	-0.123	0.0581	-0.491	-0.514	-4.486
	(2.134)	(2.141)	(2.670)	(2.154)	(2.113)	(2.123)	(2.051)	(3.546)
Total Forest Cover (km^2)	0.000229	0.000229	0.000329**	0.000297	0.000186	0.000234*	0.000326**	-0.0000964
	(0.000133)	(0.000134)	(0.000114)	(0.000213)	(0.000120)	(0.000116)	(0.000126)	(0.000315)
Annual Rainfall (mm)	0.000171	0.000161	0.000199	0.000188	-0.000608	0.0000898	0.000183	-0.000613
	(0.000189)	(0.000191)	(0.000180)	(0.000197)	(0.000327)	(0.000190)	(0.000184)	(0.000405)
Lagged Annual Rainfall (mm)	0.000312	0.000298	0.000139	0.000308	0.000222	-0.000554*	0.000252	-0.000496
	(0.000171)	(0.000165)	(0.000153)	(0.000173)	(0.000166)	(0.000261)	(0.000156)	(0.000295)
Mean Ruggedness	0.00473	0.00499	0.00461	0.00445	0.00593	0.00552	0.0131**	0.0140*
	(0.00379)	(0.00389)	(0.00375)	(0.00384)	(0.00392)	(0.00389)	(0.00487)	(0.00648)
BRGF Funds x Geographical Area (km^2)		0.00000124						-0.0000161**
		(0.00000294)						(0.00000507)
BRGF Funds x Rural Literacy Rate			0.373***					0.222
			(0.0874)					(0.164)
BRGF Funds x Total Forest Cover (km^2)				-0.00000320				0.0000174
				(0.00000589)				(0.0000120)
BRGF Funds x Annual Rainfall (mm)					0.0000464**			0.0000397*
					(0.0000155)			(0.0000180)
BRGF Funds x Lagged Annual Rainfall (mm)						0.0000499***		0.0000447**
						(0.0000121)		(0.0000161)
BRGF Funds x Mean Ruggedness							-0.000574**	-0.000595*
							(0.000206)	(0.000285)
Constant	-0.664	-0.464	3.111*	-0.727	0.719	1.182	-0.837	2.298
	(1.150)	(1.179)	(1.463)	(1.141)	(1.205)	(1.212)	(1.117)	(1.810)
Log-Transformed Over-Dispersion Parameter	1.673***	1.672***	1.630***	1.672***	1.641***	1.628***	1.649***	1.573***
	(0.122)	(0.121)	(0.124)	(0.122)	(0.121)	(0.120)	(0.121)	(0.120)
Observations	769	769	769	769	769	769	769	769

Standard errors in parentheses

Notes: In all regressions, the response variable is total fatalities by Naxalite activity, and the estimation techniques are negative binomial regressions. Column (1) is the only column without interaction effects. Column (2) interacts with geographical area, Column (3) interacts with rural literacy rate, Column (4) interacts with total forest cover, Column (5) interacts with total yearly rainfall, Column (6) interacts with lagged total yearly rainfall, Column (7) interacts with mean ruggedness per district, and Column (8) includes all individual interactions. Negative binomial regressions display standards errors clustered at the district level. The stars represent: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

VII. Conclusions and Considerations for Future Studies

This research provides insight into how the effects of public development programs on internal conflicts are mixed. The existing conflict literature has utilized different empirical methodologies to study the relationship between development programs and the frequency of violence. The findings of this study have shown that while the results are significant, they are dependent on various of factors.

The key findings of the first model specification suggest that the Backward Regions Grant Fund has an adverse effect on the Naxalite-Maoist insurgency. An increase in district funding leads to an uptick in fatalities, where further research is needed to determine the exact reasoning behind why these insurgents wish to remove government assistance in the poorest of districts.

Nevertheless, after including the vector of controls, the results remain significant and show that public development programs may not always lead to less violence in rural areas. The success of such programs is dependent on how insurgents react to government assistance. Moreover, the ideology of rebel groups is crucial in determining whether development programs are beneficial in reducing violence.

In regards to the second model specification, the key results are especially interesting. Since this model includes interaction `effects, I see how the interactions between a few of the controls and my main explanatory variable display vastly different results to those of the first specification. The interactions with rural literacy rate, annual rainfall, and terrain ruggedness all show highly significant results. However, further research must be done to understand how each variable interacts with the Backward Regions Grant Fund. Additionally, it is imperative to apprehend the relationship between these three controls and how they affect Naxalite activity and ideology.

From this assessment, I believe that for the BRGF to succeed in limiting Naxalite-related fatalities, the overall program must become more productive and efficient as mentioned by the World Bank review (2010) and the National Advisory Council report (2010). Furthermore, Borthakur (2014) discusses how there is a striking level of negligence among District Planning Committees and a lack of technical support for executing infrastructure plans. A potential solution may be direct management by the Ministry of Panchayati Raj rather than allowing these districts to decide the processes and implementations of infrastructure goals. More federal government oversight can perhaps standardize such goals. If districts remain in charge of infrastructure development, infrastructure may not be developed on time due to the lax nature of these committees.

In terms of future research, rather than just focusing on these six states, it would be prudent to include districts on the outer edges of the Red Corridor, such as those in the states of Karnataka, Madhya Pradesh, and Maharashtra. By including these districts, I would be accounting for left-wing extremism outside of the Naxalite-Maoist insurgency. This would allow the results to account for all left-wing violence as opposed to conflict from only one insurgent group. Thus, by accounting for all left-wing extremism, the results can display how the BRGF affects civil conflict in various regions of India outside of the Red Corridor.

VIII. Appendix

The following appendices contain the data gathering process in detail as well as the original sources of the data. The datasets involved in the analysis were publicized by the Government of India and its supporting Ministries, with the exception of the terrain ruggedness data, which was calculated by Shaver et al. (2016). The datasets were compiled in Python using Jupyter Notebook, and the regressions were conducted in STATA. All data described in the article and the necessary programming scripts to replicate the regression results are available at https://drive.google.com/drive/folders/105vhjg_jgQ9KCIgFgXOHpa4x25B6rQf9?usp=sharing.

A. Response Variable Data – District Level Fatal Casualties

The response variable data was collected from the South Asian Terrorism Portal (SATP), which is affiliated under the Institute for Conflict Management, a non-profit organization based in New Delhi. The source of the data can be found at https://satp.org/datasheet/district/india-maoistinsurgency.

B. Independent Variable Data – BRGF

The independent variable data was compiled from the Backward Regions Grant Fund, where the original data is located on the Open Government Data Platform, a government platform that provides the Open Data initiative of the Indian federal government. The data can be collected at https://data.gov.in/catalog/allocation-and-fund-release-under-brgf-0?filters%5Bfield_catalog_reference%5D=158890&format=json&offset=0&limit=6&sort%5Bcreated%5D=desc.

C. 1st Control Data – Geographical Area

This data was collected from the Ministry of Environment, Forest and Climate Change, where each bi-yearly State of Forest Report records the geographic area and forest coverage in square kilometers of each district. The following data is recorded at https://fsi.nic.in/forest-report-2019.

D. 2nd Control Data – Rural Literacy Rate

The rural literacy district reports were collected from the 2011 Census of India Population Enumeration Data. The literacy data is under the title of "C-08 Educational Level By Age And Sex For Population Age 7 And Above (Total, SC/ST) (India & States/UTs-District Level)", and can be downloaded at https://censusindia.gov.in/2011census/population_enumeration.html.

E. 3rd Control Data – Forest Cover

The forest cover data was collected from the Forest Survey of India, a department under the Ministry of Environment, Forest and Climate Change. The department conducts a bi-yearly State of Forest Report, where geographic surveys of forest cover throughout the nation are recorded. The data can be gathered at https://fsi.nic.in/forest-report-2019.

F. 4th Control Data – Annual Rainfall

Annual rainfall data is reported by The Department of Water Resources, a subdivision of the Ministry of Jal Shakti. This agency is the governmental department responsible for India's water resources. The data is gridded at a fine spatial resolution of a 0.25-by-0.25-degree grid-cell size, where the unit is in millimeters. The GIS figure below displays the nation's summed annual rainfall in millimeters, from the time period of 2007 to 2013. The rainfall data can be collected at https://indiawris.gov.in/wris/#/rainfall.

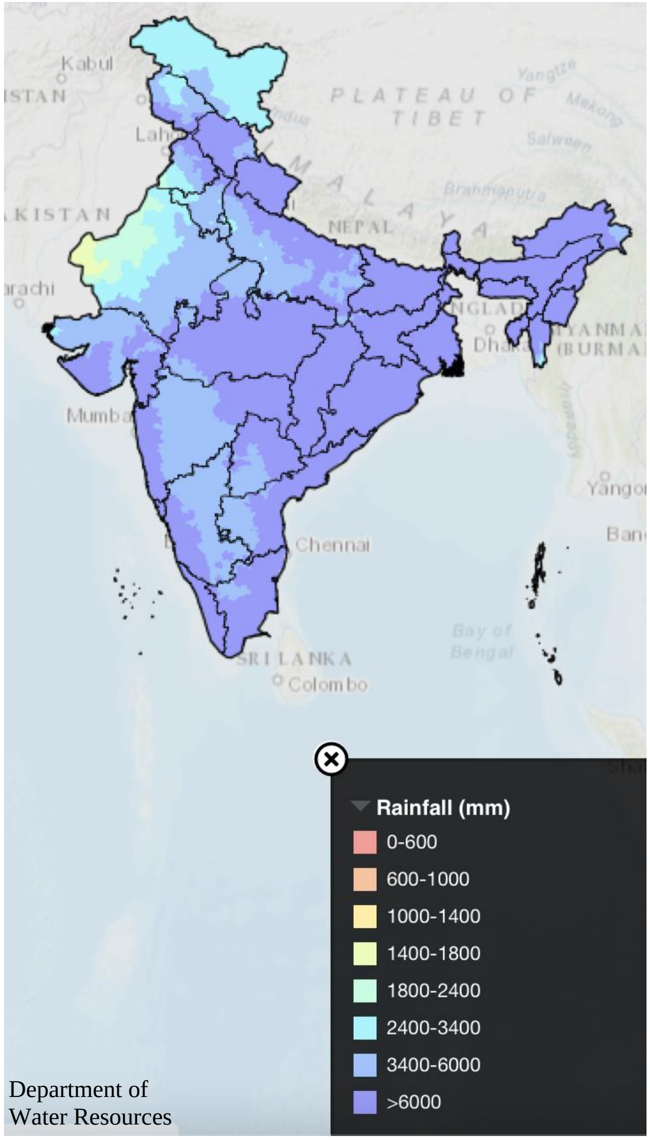


Figure 2: Annual Rainfall (mm) from 2007-2013

G. 5th Control Data – Ruggedness

Terrain ruggedness levels were gathered using the ArcGIS datasets compiled by Shaver et al. (2016), where precise geo-referenced data on ruggedness is calculate at the 1x1 kilometers grid-square levels. In order to fully process the data, I relied on creating a Python script using the geomapping package, ArcPy, which is relevant for raw GIS data analysis and management. Average ruggedness levels were created using the Spatial Analyst extension in ArcGIS Pro. To access the gridded data, the ArcPy script is written below to simplify the ruggedness aggregation process. Figure 3 illustrates the varied elevation of the Indian Subcontinent. The following data is publicly available through Harvard Dataverse at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/WXUZBN.

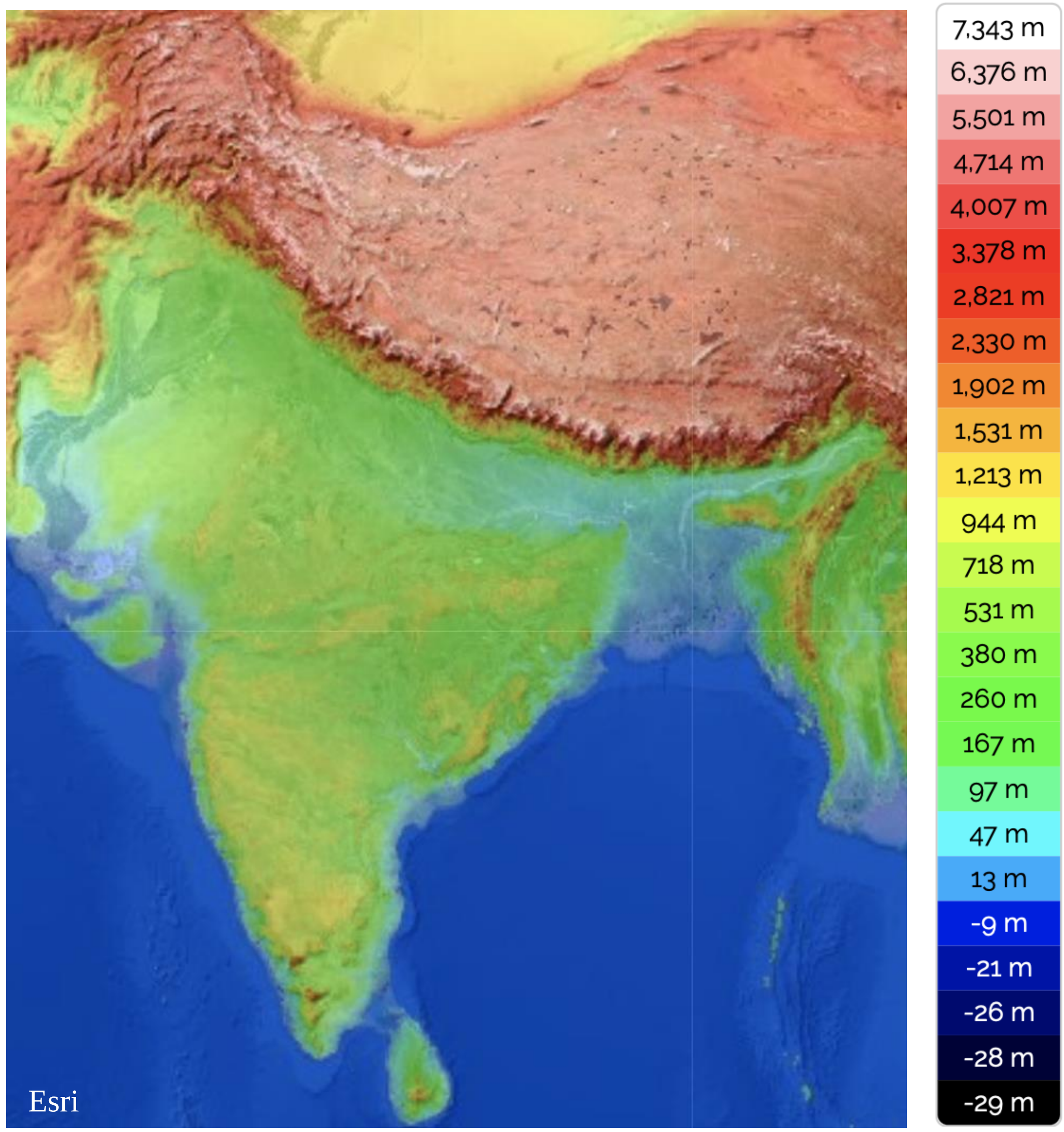


Figure 3: Elevation Map of Indian Subcontinent

Firstly, to access the ruggedness data, the user must have ArcGIS Pro installed on their computer. Shaver et al (2016) provides the ArcPy script for aggregating ruggedness data.

1. The script below allows for a calculation of ruggedness factors based on 1x1 kilometer grid-levels. Furthermore, the data can be focused on the administrative, country, or other specified boundaries.
2. Import ArcPy, a GIS scripting package that in this case, allows for terrain and land cover measurements.

3. Set the workspace *(env.workspace)* for where the data is located.
4. Replace *AdminData* with the name of the specified boundaries data, and then change *"NAME"* to a unique identifier.
5. Use the *ruggedness.tif* dataset for measurement calculations.
6. The table, *ruggednessTable.dbf* is the table that creates terrain ruggedness measures. Within the *ZonalStatisticsAsTable* function, allow *"DATA"* and *"ALL"* to remain as they are.
7. Once the user has run the script, it shall generate a series of terrain ruggedness variables, such as the minimum, maximum, range, mean, standard deviation, and sum measures for each unit.

```
import arcpy
from arcpy import env
from arcpy.sa import*
env.workspace = "C : /datalocation"
arcpy.gp.ZonalStatisticsAsTable_sa("AdminData",
"NAME", "ruggedness.tif", "ruggednessTable.dbf", "DATA", "ALL")
```

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IX. Endnotes

[i] This is an indigenous person of the Indian subcontinent, where most are rural villagers who work in agriculture and manual labor.

[ii] It is a communist political party formed in 1964 which adheres to Marxist-Leninist ideology.

[iii] The Central Reserve Police Force is an armed police force under the authority of the Ministry of Home Affairs of the Government of India. Their tasks are to maintain law and counter insurgency efforts in States and Union Territories.

[iv] One crore is worth equivalent to ten million Indian rupees.

[v] This is the region in Eastern, Southern, and Central India that experiences the most violence from the Naxalite-Maoist Insurgency.

[vi] The National Rural Employment Guarantee Act 2005 is an Indian labor law that also acts as a social safety net program.

[vii] A public platform that supports the Open Data Initiative of the Government India. Data is published by government ministries and departments for public use.

[viii] This is the India Meteorological Department, an agency of the Ministry of Earth Sciences. This department is responsible for meteorological observations and weather forecasting.

[ix] Rather than using a Pseudo Maximum Likelihood Poisson (PPML) estimator as in Fetzer (2014), I use a negative binomial model due to the presence of over-dispersion in the fatalities data. For a Poisson distribution, if the variance equates to the mean, the model is a better fit for the data. However, in the case of this paper, the variance is greater than the mean of fatality count, and thus, a negative binomial distribution is more suited for the data. As seen in (Beck and Katz, 1995; Lawless, 1987; Cameron and Trivedi, 1998), I am employing the negative binomial estimator over a Poisson model since my data on the number of fatalities displays significant over-dispersion.

[x] Starting in 2003, this is a poverty alleviation program under the Department of Social Welfare and Development in the Philippines. This program aims to develop impoverished areas and utilize resources to implement development initiatives for local communities.

[xi] The Scheduled Caste (SCs) and Scheduled Tribes are the designated groups of people in India that are either of lower-caste background or of indigenous origin. These groups are given reservation status, which grants them political representation in the form of affirmative action.