Hearts and Mines:

A District-Level Analysis of the Maoist Conflict in India

Kristian Hoelscher[1]

University of Oslo, Norway
& Peace Research Institute Oslo, Norway
kristian.hoelscher@stv.uio.no

Jason Miklian

Peace Research Institute Oslo, Norway
& NORAGRIC, Ås
jason@prio.no

Krishna Chaitanya Vadlamannati

Alfred-Weber-Institute for Economics
University of Heidelberg, Germany
Krishna.vadlamannati@awi.uni-heidelberg.de

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Abstract

India's rapid economic growth over the last decade has been coupled with a Maoist insurgency that competes for the allegiances of rural populations with the state. In response to the threat, the Government of India has securitized development, using public works programs in an attempt to sway locals away from Maoist allegiance. However, these areas are also home to massive iron and coal mines that drive India's growth. This study aimed to address the lack of local-level analysis and the lack of a robust dataset by merging previous qualitative fieldwork with disparate district-level conflict data sources to explore different potential explanatory variables for the Maoist insurgency, including the relationship between development works, violence, and natural resource extraction. We find that while effective implementation of development programs like NREGA may indeed be loosely related to the immediate suppression of violent activities in districts affected by the Maoist conflict, and that under certain conditions mining activity increases the likelihood for conflict, it is the presence of scheduled caste and scheduled tribal (SC/ST) communities that is the best predictor of violence.

Keywords: Socio-economic development, Maoist conflict, insurgency, India, resource war, civil conflict, greed and grievance.

“(India’s major development employment program) NREGA is the only way forward to take on the Maoists. This is nothing about winning hearts and minds. Its only about giving people work before the rebels come in and convince them that they are a better option than the state”

–NREGA officer in West Midnapore district of West Bengal. (BBC 2010)

1. Introduction

India is often hailed as one of globalization’s success stories. Indeed, after the inception of market-economic reforms in 1991 growth has been both sustained and impressively robust in terms of national economic indicators (Bosworth, Collins and Virmani 2006). India is one of the fastest growing economies in the world, and over $40 billion USD is pumped in annually by foreign firms looking to capitalize on this powerful emerging market (Poddar and Yi 2007). Yet, large groups of citizens in rural areas of the country have missed out on the spoils of this growth, and rapidly increasing inequalities between cities and rural areas are fueling resentment (Torri 2011). High levels of poverty and the absence of basic state infrastructure (including access to drinking water, housing, sanitation, food and employment insecurity) are commonplace (Banerjee 2010). According to Oxford University’s Multidimensional Poverty Index (2010), a staggering 55% of the Indian population lives below the poverty line of US $1.25 despite a bevy of rural development programs intended to rectify the situation. These poor constitute almost 400 million people in just eight Indian states: Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh and West Bengal.

Many of these states are also facing an additional challenge: they are fighting an armed insurgency against the Communist Party of India-Maoist (or Maoists) that has taken the lives of 10,000 citizens and displaced another 150,000 as it has increased in scope and intensity since 2004 (MHA 2010). The Planning Commission of India argues that a lack of development coincides with the rise of the Maoist movement, and that the Maoists gain support primarily from impoverished rural populations that suffer from underdevelopment, social injustice, and discrimination (Planning Commission of India 2008). The report argues that the Maoists exploit the gap between social-economic promises made by the Indian government to its poorest and the government’s actual service provision in order to gain allegiance. The Planning Commission’s offered solution was to securitize development, encouraging the government to make development works and projects national security issues in themselves as a second front combined with ongoing with military actions in the fight against the Maoists. Within India, left and right disagree vociferously on how to tackle what they deem ‘the Maoist problem’, but where they unite is that India needs more of this type of ‘development’.

However, policymakers have until this point typically relied on anecdotes to support this claim, not empirics. Further, most quantitative studies of the Maoist conflict disaggregate only down to the state level when correlating India’s vast amount of available socio-economic data with Maoist conflict markers (Remøe 2010, Vadlamannati 2010, Borooah 2008, Piazza 2011). Disaggregation is essential to understanding conflict (and resolution) drivers, and rationales for disaggregation are manifold. Many of India’s 28 states are extremely large, and within the country’s 592 districts tremendous geo-spatial inequalities are hidden by state-level analyses. This is especially the case when dealing with states like Andhra Pradesh that host both wealthy mega-cities and indigenous populations suffering endemic poverty.

This study draws upon previous qualitative fieldwork and employs data from three disparate district-level conflict data sources to test theories explaining recent Maoist insurgency. Our previous research provided strong anecdotal evidence that the Maoist movement and mining industry activities are correlated (Miklian 2010; Miklian 2011; Miklian and Carney 2010). Here we empirically test the association between the mining sector and the Maoist conflict in a multivariate model. We analyze cross-sectional data from six Indian states - Chhattisgarh, Andhra Pradesh, Orissa, Jharkhand, Bihar and West Bengal. These states cover the areas where the Maoist insurgency was strongest during the 2004-2010 period, and represent 151 of India’s 592 districts. Although this reduces the total number of observations these selected districts account for 90% of total violent Maoist incidents.

Using Probit and Negative Binomial estimation techniques we find that conflict is consistently related to increased forest cover, prevalence of conflict in neighboring districts, and larger scheduled caste and tribe share of the population; while mining activity under some conditions increases likelihood of conflict.. Our conclusions suggest conflicts are more likely to occur in districts with aggrieved populations, and where conditions favor insurgency, Similarly, conflict is likely to spill across borders yet mining activity only plays a role in fueling conflict in poorer districts where existing grievances may be exploited.

2. Theoretical Background

The Maoist conflict in India dates to 1967, when an uprising over land reform in the West Bengal village of Naxalbari spurred large-scale revolts against unjust agrarian practices. Followers called themselves Naxals, professing that political violence was necessary to loosen the ruling elite's hold over rural India. The movement ebbed and flowed throughout the 1970s, reaching a nadir in the early 1980s after the government captured or killed most senior leaders. After a period of fracture and disorganization, heretofore disparate Naxal groups began to consolidate in the early 2000s, and together formed the Communist Party of India-Maoist in 2004. Since then, violence has dramatically increased, spreading to most states of east-central India.

Concurrently, the ruling United Progressive Alliance (UPA hereafter) government led by the Indian National Congress party initiated several social welfare projects in an effort to stem the Maoists' allure in rural areas. The most significant such scheme is the National Rural Employment Guarantee Act (NREGA, now re-titled to MGNREGA), the government's flagship employment development program. NREGA was launched in 2006 to enhance livelihood security in rural areas beset by chronic joblessness and falling agricultural productivity by guaranteeing at least one hundred days per year of wage-employment to every rural household. Citizens register with local authorities to work, and wages are paid on a fixed daily rate (about $2.40 USD/day).

While the short-term objective of NREGA was to bolster employment, after 2008 it was also trumpeted by UPA politicians as a key policy tool to campaign for the 'hearts and minds' of local populations. Like the Planning Commission before it, UPA consensus holds that citizens join the Maoists in retribution for being chronically impoverished, and development programs that to address land, employment and inequality-based grievances highlighted by the Maoists will lead to resolution (Kolås & Miklian 2009; Verma 2011). As the opening quote illustrates, winning the ideological fight for India's rural soul is deemed essential to durable military victory, but policymakers and local implementation actors differ as to the scope, mandate, and direction that development should take. Employment generation and integration into the framework of the Indian state are the twin pillars upon which NREGA operates, and Indian policymakers often believe that more economic development (industrial growth) by definition means less conflict.

However, this grievance-based narrative of under-development as the sole cause for rebel recruitment overlooks a number of factors that while initially peripheral are now integral to the conflict. India's economic boom has heralded an explosion of both foreign direct investment (FDI) and demand for the estimated $1 trillion USD of natural resources that lie within.[2] India's mining sector has thus been eager for the past decade to rapidly ramp up operations across the country for both profit and national security reasons. Further, significant mining occurs in many of the same areas where the Maoist conflict has been the most severe. 'Push', 'pull' and 'fog of war' factors culled from our previous qualitative research suggest that this correlation is not accidental.

The mining industry has a poor reputation in India. Most of India's largest mining deposits lie within the states that are considered most corrupt, exacerbating inequality and providing vivid examples of graft. Politicians, police, and mining companies all profit from projects that either skirt or ignore laws meant to protect fragile environmental or human landscapes (Miklian 2012). Many mines are also operationalized with so little consideration for local concerns that citizens feel moved to either commit violence or support the Maoists for their anti-mining rhetoric (Navlahkan 2010, Shah 2011). In these cases, our anecdotal evidence suggested that projects 'pushed' local populations to support the anti-capitalist and anti-foreign stances of the Maoists in an attempt to save their lands.

Pull factors were also related to increased violence, as districts with heavy mining activity are tremendously attractive targets for the Maoists. These districts have common characteristics that an extensive number of studies show that insurgent groups find desirable: difficult to access terrain (Fearon and Latin 2003), a high degree of corruption in natural resource projects (Ross 2004; le Billon 2004), large amounts of explosives on mine sites that can be stolen and then used against official forces (Miklian and Carney 2010), and a ready population of citizens who feel aggrieved (Regan and Norton 2005). While literature on 'resource curses' is also extensive, it remains underpinned by what le Billon (2001:565) calls 'the socially constructed nature of resources."

Further, unending violence may actually be the desired equilibrium for all parties to the conflict. Peripheral scholars including Duffield (1998) and Keen (2008) take a more nuanced

[2] Estimated coal reserves account for approx 55% of this total, with iron at 30% and the remainder split between dozens of other minerals.

approach to the political economy of conflict, arguing that violence is not a breakdown of society but merely a different framework that empowers alternate actors financially and politically. Conflicts define material and psychological gain at both the individual and societal levels, but are fundamentally about the transfer, displacement, and acquisition of power – be it in a violent or non-violent way (Foucault 2003, Reid 2003). The Maoists have a long history of exploiting these dynamics to further their political and financial aims through both historical (Suykens 2010) and contemporary (People's March 2010) propaganda, which is couched in standard Communist 'permanent revolution' rhetoric.

Complicating matters, commercial concerns have become the third rail of conflict. Dozens of major and minor mining companies saw mining deregulation as a spectacular opportunity, and the less scrupulous united with local politicians to use the 'fog of war' as an excuse for a land grab. In the most egregious example, a civilian militia was created in southern Chhattisgarh to fight the Maoists and make the region safer for mining companies to operate (PUCL 2006). After the militia launched, over 100,000 villagers living atop resource beds were forced to flee; many were still not allowed to return years later (HRW 2008). Government mining firms paid both the militia and the Maoists for 'protection' services in order to ensure continued operations (Miklian 2009), or to clear land through proxy wars (Bahree 2010). The Maoists also contributed, extorting 3% of the profits from each of the mine owners under their areas of control to fund their war and play up their Robin Hood credentials to locals (Verma 2011). Many locals willingly joined the Maoists after hearing the government claim that their districts were 'too violent' to have schools, police, or health services for years while continuing to actively support mining activities.

There is an important distinction between insurgent recruitment and insurgent latent support (Kalyvas 2006; Weinstein 2006). In many impoverished conflict villages, local support is predicated on the belief that the Maoists can provide services that the government either fails to offer (f.ex. schools), or implements so poorly that the Maoist alternative is preferred (judicial system) (Navlakha 2010). This support is also supported by broader literature on 'hearts and minds', as citizens may choose to support a violent challenger to the state if service provision is poor (Berman et al. 2011). Support is also a function of fear, as a village that might otherwise resist a challenger often offers material or logistical aid to violent groups that represent a new status quo (Green 1994). However, recruitment remains an individual's decision, which may not reflect the grievance-based issues that drive latent support.

Individuals join rebel groups for revenge, justice, personal profit, escaping family situations, machismo, and other reasons that may have nothing to do with the conflict (Humphreys and Weinstein 2008). While latent conditions for rebel recruitment may exist throughout India, they are insufficient to explain alone the Maoists' growth.

Hypotheses

With this background, we develop several hypotheses related to conflict, socio-economic factors, mining, and development at the district level. First, we can theoretically link poverty with a decreased opportunity cost of rebellion (Collier and Hoeffler 2004). It can also, however, represent a lack of state capacity within a district (Fearon & Laitin 2003). Similarly the lack of service provision to rural communities has been cited as a grievance motivating rebellion (Borooah 2008). Maoist insurgents tend to exploit decreased state reach and local grievances in poorer areas, and support may be more easily gained and maintained where income or state reach is reduced[3]. We hypothesize that:

H1a: Lower levels of income will be related to greater Maoist violence
H1b: Lower levels of basic service provision will be related to greater Maoist violence

We also assess the role of literacy in supporting violence. Primarily, it is an indicator of human capital and a reflection of livelihood options and expected future income (Collier and Hoeffler 1998; 2004). It follows that where literacy rates are low, income and the opportunity cost to rebel is lowered. Specific to the Indian context is that the literacy rate also represents citizens' access to justice and representation in the legal system (Rukare 2006). We therefore hypothesize that:

H2: Lower literacy rates will be related to greater Maoist violence

Third, we assess the link between the presence of natural resources and conflict. The civil conflict literature gives numerous powerful examples of how rents from natural resources create and sustain civil conflicts; and that their effects on national economies prolong fighting and hinder post-conflict recoveries (e.g. Ross, 2004a, 2004b; de Soysa & Binningsbø, 2009). In several Maoist-affected states, natural resources have been expropriated to finance rebel

[3] It must be acknowledged that without undertaking a comprehensive survey of Maoist fighters it is difficult to determine which districts fighters themselves come from. For this reason, any study attempting to make claims on the relationship between district-level (or even state-level) indicators and rebel recruitment without this data will be fundamentally flawed, and the reason for our omission of regarding this important issue. We acknowledge this potential bias, but must assume that district level violence is motivated by variables of the same district.

activity (Miklian 2010). We therefore test the effect of presence and value of district level mining, and hypothesize that:

H3a: The presence of mining activity in a district will be related to greater Maoist violence
H3b: Greater value of mining activity in a district will be related to greater Maoist violence

Fourth, the Maoists claim to represent the interests and grievances of disadvantaged populations including scheduled castes and tribes (Shah & Pettigrew, 2009). If the Maoist insurgency is predicated upon an ideological platform that appeals to and requires the support of SC/ST communities, we would expect that greater SC/ST populations increase localized support for Maoists, which may then represent increased violence. Therefore:

H4: Greater SC/ST populations will be related to greater Maoist violence

Fifth, we assess the effect of policies designed to address rural poverty, most notably NREGA. We expect that where a greater percentage of households are employed under the scheme, there is a greater opportunity cost to engage in violence, leading to decreased support for the Maoists and lower rates of insurgent violence.

H5: Greater coverage of the NREGA program will be related to lower levels of Maoist violence

It is also highly likely that economic or grievance based factors do not work in isolation, and theoretical and empirical work on civil conflict has moved on considerably from a simple greed or grievance based narrative (or its newer 'opportunities vs. incentives' incarnation- see Miguel & Blattman 2010). We suggest and measure three possible ways in which motive and opportunity may coincide to increase Maoist conflict.

First, we test the possibility that mining activities are only likely to increase violence where it disenfranchises local tribal populations. Where mining occurs without creating grievances for Maoists to exploit, violence may not be ideologically or strategically possible. Second, we assess whether mining is conflict-inducing only where it occurs in the context of poor state capacity or poverty. Third, we assess whether poor provision of basic services by the state is only conflict generating where excluded populations are present. We hypothesize that:

H6: Mining activity in the context of greater SCST populations will be related to greater levels of Maoist violence.

H7: Mining activity in the context of lower levels of income will be related to greater Maoist violence.

H8: Poorer basic public services provision in the context of greater SCST populations will be related to greater levels of Maoist violence.

3. Estimation Strategy and Data

Our estimation strategy examines the correlates of Maoist violence in India. We employ a cross-sectional design at the district level, and analyze factors related to the incidence and severity of armed insurgency in six Maoist-affected states. Our sample consists of 151 districts from six Maoist affected Indian states for the period from 2004–2010 (see appendix 2). We use the count totals of Maoist-related violent events for this period to assess the aggregate levels of violence experienced in the districts of these states since the onset of the most recent phase of the insurgency. This study does not claim to measure temporal aspects that may influence the conflict but rather how structural factors have determined current levels of violence in the districts most affected by the movement.

We choose a cross sectional design for this time period for reasons both theoretical and pragmatic. We select only six states as they together represent both the historical and current loci of Maoist insurgency and the vast majority of Maoist-related incidents - over 90% of conflict events and fatalities since the CPI-Maoist was formed in 2004. Second, these states also house all of the core districts of Maoist recruitment, activity, and support in the current stage of the rebellion from 2004 onwards.[4] We thus consider that a type of 'exceptionalism' is present in these states, and therefore analyze the relationship between Maoist violence and socio-economic and structural factors for the districts in these six states alone, thus limiting our overall claims to these states.

This opens our design to criticisms of selection bias, primarily that we have non-randomly selected states that have experienced high levels of insurgent Maoist violence, thus limiting the veracity of causal inferences. This criticism of non-random selection of cases based on invariant values of the dependent variable is reasonable, and we counter with three points.

[4] Also, the UPA government came into power in 2004, providing an opportune marker for rural development policy assessment.

First, while the states we choose are hotspots of Maoist violence, our analysis is at the district rather than state level. We include all districts of the six selected states regardless of level of violence. Indeed, 30 % of the 151 districts in our study experienced no conflict events between 2004 and 2010. Further, only 57% of districts experienced more than one event over the period of analysis, with significant variation on the number of events and fatalities at this level of aggregation. Secondly, as previously stated there is an exceptionalism about these particular states. While Maoist violence occurs in some limited degree in other states, it is fundamentally less organized and more factional while also far less integrated with the movement in the Eastern states. Third, and most relevant, we do not claim to extend the findings of this paper beyond the six states in question.

Addressing the temporal aspects of the study, we forego a panel analysis as existing data is deemed to be of questionable quality or lack variation. Other recent studies have attempted pooled panel analyses that employ questionable methodologies (Gomes 2011). Given our concerns, we limit our study and inferences to what is permitted by current accessible data. Future work will employ 2011 Indian census data to analyze the mobility of the insurgency over time through a district-year panel dataset, and broaden the study to Maoist violence over each district of India to assess whether our conclusions hold.

Data

While reams of data exist on the Maoist conflict in India, there is no one source that is to-date complete. Data sources are often housed within partisan think-tanks in India, making analyses based on these numbers then *a priori* either politically slanted, incomplete or misrepresentative (by underreporting civilian killings, for example). For this reason, our dataset is designed to utilize all available legitimate sources, cross-referencing the data with fieldwork, and using only total reported deaths. We do not (and can not without studying every case individually) base our assessments upon reported but often factually dubious accounts of a victim's allegiance, be it 'civilian', 'insurgent', 'army' or 'pro-government militia' member.[5] Previous academic attempts to catalogue the scale of the Maoist conflict have therefore been commendable but suffer from sizeable gaps in coverage of Maoist-related events (Iyer 2009) or overly simplify classification of districts where conflict is either present or absent that masks differences in the scale of violence (Boorah 2008). Other emerging

[5] Most sources divide deaths at roughly 1/3 civilian, 1/3 insurgent, and 1/3 government. While these figures fluctuate across districts and over time, one-sided violence is not present.

research attempts to catalogue Maoist violence over time, but sacrifices validity of measurement in order to create panel datasets (Gomes 2011).

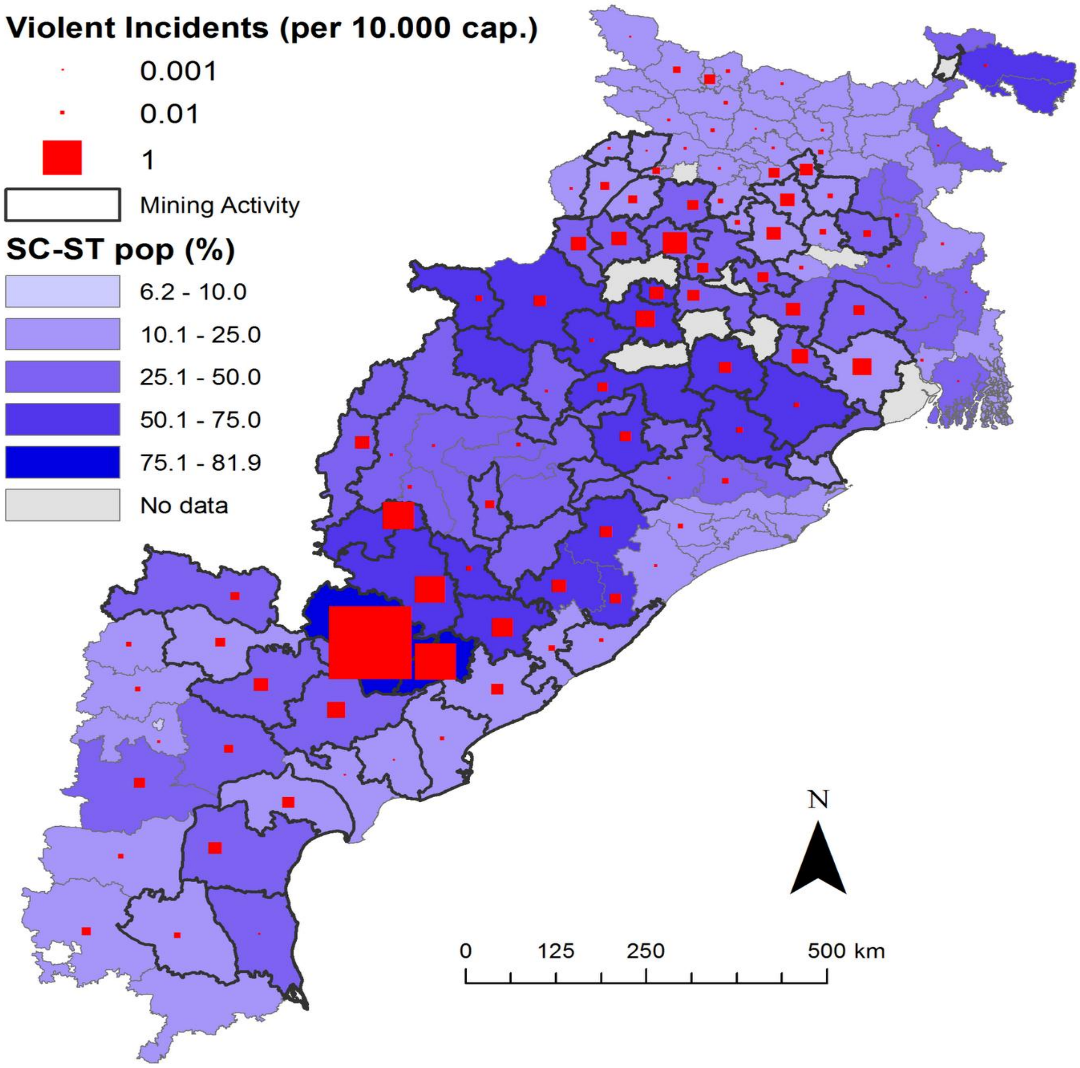
In addressing the issue of event completeness, we compiled a unique dataset on incidence and severity of conflict events at the district level using information from three separate sources. We record Maoist related events *involving at least one fatality* as reported by the South Asian Terrorism Portal (SATP), the National Counterterrorism Centre's Worldwide Incidents Tracking System (WITS) and the Global Terrorism Database. We then cross-checked between sources as well as with our previous qualitative fieldwork and the Ministry of Home Affairs in the Government of India to code all unique violent incidents. Events were geo-coded to the district level and the number of fatalities recorded Additionally, all lethal events were dummy coded, in addition to coding the total number of fatalities per event. Our dataset includes information on deaths for combatants, non-combatants, state and non-state actors for the period January 2004 to November 2010 - a total of 1827 events with 4816 fatalities. Descriptive statistics for these and other variables are shown in Appendix 1. Figure 1 shows the distribution of events and deaths by state.

While our dataset represents a significant step forward in coverage and quality, we do not claim to have compiled a complete collection of the events and fatalities of the Maoist insurgency. We rely on third party reports of conflict events from newspaper and wire agencies, and while standards of journalism in India are improving, partisan views or simple omissions most likely ensure that we have not captured all deaths or events – particularly in conflict zones. Regardless, this dataset represents the most current and complete source of Maoist related violence presently available.

4.1. Dependent variables

It is plausible that there are different drivers of the frequency and magnitude of attacks. Grievance-related issues may associate with the establishment of insurgency, but economic incentives can prolong conflicts and render them more violent. A greater number of attacks, or more severe violent attacks might provoke particularly harsh reactions by the respective state and central governments concerned. They also clearly represent a greater threat to the security and livelihoods of citizens in these areas. We therefore measure the Maoist conflict in three ways. We look at whether a conflict is *present* or not; how *frequently* violent events have occurred; and how *severe* these events have been.

Figure 1: Maoist Conflict, Mining districts and SC and ST population share



(Map designed by Jan Ketil Rød and Krishna Vadlamannati)
Notes:
(a) Districts with thicker border lines are the ones with the presence of some mining activities.
(b) Dark blue colour indicates SC and ST population share greater than 75%.
(c) Red spots are conflict lethal events per 10000 capita.

Conflict Incidence

We measure conflict incidence cross-sectionally by assessing whether or not a district experienced *one or more Maoist events that resulted in a fatality for the period between 2004 and 2010*. We estimate our cross-sectional regressions for conflict incidence employing the probit estimator with controlling for district effects and standard errors clustered at district level (Beck and Katz 1995). This approach assumes that the observations are non-independent within units (districts) but independent across. We estimate the following relationship:

$$Conflict_{ji} = \psi_1 N_{ji} + \psi_2 Z_{ji} + \omega_{ji} \qquad (1)$$

Where, *Conflict* $_{ji}$ represents the armed conflict incidence in a district *j* in state *i*, N_{ji} denotes key explanatory variable(s) specific to the Maoist conflict, Z_{ji} are control variables related to the outbreak of civil conflict, and ω_{ji} is an error term for district *j* in state *i*.

Conflict Intensity: frequency and severity

We estimate the intensity of conflict in two ways, generating 2 cross-sectional dependent variables. We measure *frequency* using *the sum of the total number of violent incidents* in the 2004-2010 period; and measure *severity* using the *sum of the total number of battle deaths* due to Maoist violence during the same 2004-2010 period.

For conflict intensity, we estimate the following relationship:

$$Intensity_{ji} = \psi_1 N_{ji} + \psi_2 Z_{ji} + \omega_{ji} \qquad (2)$$

Intensity $_{ji}$ is measured by counts of Maoist violent incidents or battle deaths in a district *j* in state *i*. Since the intensity of conflict is a count variable(s), we estimate our cross-sectional regressions employing the negative binomial estimator by controlling for district effects. Our data on the number of violent incidents and battle deaths are strongly skewed to the right (with an accumulation of observations at zero) and display significant over dispersion[6]. We therefore employ the Negative Binomial estimator over Poisson method (e.g. see Beck and Katz 1995; Lawless 1987: Cameron and Trivedi 1998).[7]

4.2. Explanatory variables

We test characteristics specific to the Maoist conflict in our vector N_{ji}. We construct several of our variables using data from the 2001 Indian population census and district profiles based on official data. While this data pre-dates our dependent variables measuring Maoist violence from 2004–2010 it is the most recent district-level data available. Furthermore, many socio-economic development indicators in rural areas change relatively slowly over time. Moreover,

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[6] see descriptive statistics in appendix 1

[7] This choice is supported by the results of ‘goodness-of-fit’ test indicating the appropriateness of using negative binomial methods rather than poisson estimation method.

several of these variables were constructed using the 2001 census data collected prior to the conflict data we use, partially mitigating concerns regarding reverse causality as it is unlikely that conflict between 2004 and 2010 caused the variables derived from the 2001 census[8].

We use logged district-level per capita GDP for the year 2001[9] to measure aspects of state capacity and poverty (Planning Commission of India, 2001). To measure of provision of public goods, we create a factor index from four variables, which measure the percentage of villages with access to primary health centers, education centers, water facilities and paved roads. We include the district level literacy rate to measure aspects of opportunity cost and human capital. Data for all variables above is taken from the 2001 Indian census profiles. For our mining hypotheses, we employ a measure of the relative value of mining in a district[10]. We use the per capita value of coal and iron mining and quarrying in millions of rupees for the 2006/7 fiscal year, which we then log transform.[11] This data was collated through analysis of information provided by the Ministry of Mines, Ministry of Coal, and Ministry of Steel on coal and iron production. Although we do not capture district-level information on the entirety of mining in our study, iron and coal mining represent over 90% of total mining production in our selected states.

We have two caveats with how mining is measured. First, our data does not capture changes over time, evidenced by lower than expected values of mining related GDP in some districts that have seen substantial increases in both mining and violence over the past decade. Second, there is a significant amount of illegal mining in India, which is not recorded in official revenues. This undervalues natural resource extraction in some districts. Because of issues regarding both data availability and face validity in measuring mining value in a district, we expect that our results may *underestimate* the value of mining in some districts, and thus the relationship between mining and conflict.

[8] While events in the past cannot be caused by events in the future, it is clear that there is some inertia in the levels of conflict. The current design does not allow us to test the effect of conflict in previous years, and is thus susceptible to problems of reverse causality – where previous conflict may be related to both current conflict and our explanatory variables. While our independent variables are from prior to our conflict data years, we acknowledge reverse causality as a potential problem that is not entirely solved.

[9] Measured in 1999 constant dollars.

[10] We also create a dummy variable assessing the presence or absence of any mining related revenue in a district. Substituting this variable for per capita mining revenues does not change any of our core results and we choose to omit them here.

[11] When log transforming we added a 1 to zero values before logging. We ran all analyses without log transformation without any changes to results.

To measure the effect of SCST populations, we use the percentage of the total population that is made up of members of scheduled castes and scheduled tribes at the district level taken from the Indian census district profiles (2001).[12] Finally, to address the effect of rural development programs we include a variable measuring the average percentage of households between 2004 and 2010 employed under NREGA in each district. This information is taken from NREGA's aggregated state reports at the district level.

4.3 Interaction effects

We test our three contextual hypotheses with three interaction terms. We test the effect of mining in districts with greater SC/ST populations by interacting log transformed per capita value of Coal and Iron Mining and Quarrying with the SC/ST percentage in the total population at the district level. To test the effect of mining in the context of poor state capacity or poverty we interact our logged per capita Coal and Iron Mining variable with logged per capita GDP at the district level. Finally, we test the effect of SCST populations in the context of limited service provision by interacting the share of SC/ST in the population with our index of public goods availability.

4.4. Control variables

We test a vector of control variables (Z_{ji}), which are drawn from the previous literature on cross-country studies of civil violence (Fearon and Laitin, 2003; Collier et al., 2009; Fearon, 2004; de Soysa, 2002; Do & Iyer, 2007; Bohara, Mitchell & Nepal, 2006). First, we include a variable measuring the total population at the district level, which we then log transform to adjust for a non-normal distribution. This variable captures some effects of both the pressures on renewable natural resources (e.g. Homer-Dixon, 1999; Homer-Dixon & Blitt, 1998); and controls for that, all things equal, more populous districts should experience more violent incidents and a greater number of battle deaths.

Second, insurgent actors often favor areas that lie beyond the state’s reach (Fearon & Laitin, 2003), and in India, the Maoists indeed favor densely forested areas. We measure the effect of remoteness and lack of state reach by using the percentage share of a district that is covered in forested area; and ‘ruralness’ as a percentage of the district population living in urban areas to control for this effect. Population, urbanization and forest area variables are from the

[12] We also consider that it may be only tribal populations which respond to Maoist calls for rebellion. We have run separate models including only scheduled tribal populations with no differences in results.

government of India's census district profiles (2001).Third, we test the claim that land rights based grievances may create cleavages and horizontal inequalities that may motivate rebellion, whereby the design of colonial institutions created path dependencies affecting inequalities over access to land.[13] We dummy code with a 1 if a district was under the British direct rule and 0 otherwise using data from Somanathan and Banerjee (2005). Essentially, where British-created landlord institutions have persisted (Iyer 2010), collective action is weakened, enabling unfairly compensated land claims by public and private interest groups. Violence may be greater in such districts as land-related grievances may support Maoist recruitment, especially given the movement's initial foundations in land grievances a generation before. Finally, many conflicts expand beyond where they originated (Hegre et al. 2009). Pertinently, the Maoists are highly mobile given the lack of 'territoriality' in their demands (they are not separatist, for example). We therefore include the count of lethal conflict incidents in immediately neighboring districts to capture possible spillover effects

5. Empirical Results

We present three estimations in our results, each summed at the district level for the period 2004 and 2010. In table 1, the first column analyses the *presence* of lethal Maoist events; and columns 2 – 5 analyses the *frequency* of lethal Maoist events. Table 2 presents conflict *intensity* measured by the total number of casualties from Maoist related violence. For conflict presence in column 1 in table 1 we use probit estimation technique, while for frequency of lethal events and battle deaths use negative binomial regressions. Baseline Models for conflict incidence and frequency are presented in the first and second columns of Table 1; and for severity in the first column of Table 2, with marginal effects at the mean for explanatory variables are reported in all tables. [14]

Our main results are generally consistent across models, with several variables standing out as consistent and robust correlates of presence, frequency and severity of Maoist activity. Our results support previous theories of civil conflict and insurgency, while extending understanding of conflict drivers in Maoist affected states. Intriguingly, they indicate that

[13] See also, for example, Banerjee & Iyer (2005) and Banerjee et al (2005) regarding path dependencies affecting patterns of investment and public goods availability in India, also factors which may foster grievances.

[14] We use Stata 11.0's margins command to calculate marginal effects.

conflict is most likely in districts where local grievances coincide with economic conditions that make organization of rebellion more feasible.

We find support for a hypothesis 1a between lower district level GDP and greater frequency and severity of Maoist violence (Column 2, table 1 & Column 1 Table 2). District per capita GDP is associated with fewer conflict events and battle deaths, with, for example, a standard deviation increase in per capita GDP (log) is associated with decline in roughly one or more battle deaths. We do not, however, find support that lower availability of public goods is related to Maoist violence, with our baseline models remaining insignificant despite their negative sign. Hypothesis 2 largely unsupported, with only our baseline model for conflict incidence being weakly correlated with literacy rates. All baseline and interactive models for frequency and severity of conflict while negative, were insignificant, suggesting that human capital measured this way is not strongly related to conflict. Our third hypothesis that mining GDP would co-vary with Maoist violence is not supported here. We find that greater of mining share of district GDP is unrelated to the presence, frequency and severity of Maoist violence (columns 1 and 2 in table 1, and column 1 in table 2, respectively), with mining share variables taking a positive sign but remaining not significantly different from zero[15].

Our results strongly support our fourth hypothesis, with greater shares of SCST in the population related to greater incidence frequency and severity of violence in all model specifications. This suggests the presence of excluded populations may provide insurgents with a source of support or a pool to recruit from. We also see a strong relationship between greater numbers of households covered by the NREGA program and lower incidence, frequency and severity of violence. This implies that there may be peaceful returns to the programs the Indian state has employed in its attempts to securitize development. We are though cautious about this interpretation as we are unable to assess the causal direction of the relationship. It is possible that in districts less threatened by insurgent violence, programs designed to win the 'hearts and minds' of rural populations are more easily able to be rolled out; or that in more violent districts it is more difficult to reach the programs target population.

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[15] This is in line with the findings of Brunnschweiler and Bulte (2009) who find no effect of natural resources on outbreak of violent conflict after controlling for institutions and treating natural resources variables as endogenous.

Our controls generally show support for structural factors related to violence and insurgency that emerge from the quantitative literature. For nearly all specifications, districts with larger populations experience greater levels of violence. This is consistent with previous findings at the district (Borooah, 2008; Do and Iyer, 2007; Bohrah et al., 2006) and state level in India (Urdal, 2008). For our measures of geographic remoteness, we find districts with large forest shares are repeatedly correlated with the presence of Maoist activity, emphasizing how lack of state reach and poor infrastructure supports conditions for insurgency. However, we find no strong support that the level of urbanization in districts is significantly related to Maoist violence. While results are not robust, this insignificant effect might stem from insurgency favoring rural areas and migration to urban areas easing pressure on rural resources.[16]

No evidence is found that districts with landlord colonial institutions are related to Maoist conflicts in any of our specifications, yet we do find consistent support that violence is greater in districts sharing borders with other districts themselves experiencing Maoist attacks. Tables 1 and 2 indicate that the incidence, frequency and severity of Maoist violence is positively and significantly related to the number of lethal events in neighboring districts. This finding is robust to all model specifications for our three dependent variables, and indicates that cross-border spillover effects are occurring in these six Indian states, supporting similar previous at the national and sub-national level (Hegre et al., 2009). Furthermore, the mobility of Maoists and their propensity to cross borders to evade the reach of Indian forces is at least partially driving the association between violence in neighboring districts.

Taken together, our baseline results provide an interesting picture about Maoist violence in India. It appears that poorer districts with larger tribal and caste populations are more likely to experience violence, and that development programs to address grievances may reduce violence. Similarly, the insurgency appears likely to be mobile and spill across borders, and benefit from operational advantages in remote or rough terrain. While our previous work suggested that the Maoists are operating primarily in a loot-seeking enterprise, violence appears unrelated to mining operations exist. While mines (both legal and illegal) provide opportunities and incentives for actors on all sides to loot resources to finance their operations, our results do not support the anecdotal evidence in previous fieldwork that this is the core factor driving the conflict.

[16] Seemingly though, the 'rural' dimensions this variable measures may have been better captured in other measures, such as basic service provision or percentage forest share.

Table 1: Conflict Incidence and Frequency

Variables	(1) Conflict Incidence Probit	(2) Conflict Events Nbreg	(3) Conflict Events Nbreg	(4) Conflict Events Nbreg	(5) Conflict Events Nbreg
District Per capita GDP (log)	-0.623	-0.713*	-0.510	-0.505	-0.840**
	(1.58)	(1.84)	(1.33)	(1.30)	(2.10)
Access to Public Basic Goods	0.133	-0.229	-0.333*	-0.230	0.411
	(0.68)	(1.25)	(1.86)	(1.32)	(1.22)
Total Literacy Rate	-0.020*	-0.015	-0.011	-0.013	-0.006
	(1.66)	(1.11)	(0.81)	(0.96)	(0.39)
Per capita Iron & Coal value (log)	0.135	0.016	-0.792***	9.035***	0.028
	(0.69)	(0.10)	(2.91)	(2.61)	(0.18)
SC & ST Population share	0.019*	0.048***	0.036***	0.045***	0.040***
	(1.89)	(4.87)	(3.39)	(4.36)	(4.22)
Households Employed under NREGA per capita	-0.007	-0.092***	-0.081**	-0.092***	-0.082**
	(0.32)	(2.66)	(2.52)	(2.78)	(2.47)
Total Population (log)	0.631**	1.050***	1.015***	0.977***	1.130***
	(2.39)	(3.50)	(3.52)	(3.26)	(3.88)
Share of Forest Area in Sqkms	0.049***	0.030**	0.031***	0.027***	0.033**
	(2.63)	(2.38)	(2.67)	(2.70)	(2.09)
Urbanization Rate	0.002	0.007	0,007	0,006	0,006
	(0.14)	(0.42)	(0.48)	(0.36)	(0.38)
British Direct Rule dummy	-0.138	-0.025	-0.144	-0.023	-0.076
	(0.42)	(0.07)	(0.45)	(0.07)	(0.23)
Conflicts in Neighboring Districts	0.010	0.008***	0.009***	0.007***	0.008***
	(1.46)	(2.68)	(2.97)	(2.68)	(2.81)
Per capita Iron & Coal value (log) × SC & ST Population share			0.015***		
			(3.22)		
Per capita Iron & Coal value (log) × District Per capita GDP (log)				-0.949***	
				(2.66)	
SC & ST population share × Access to Basic Public Goods					-0.022**
					(2.49)
Total Observations	140	140	140	140	140

a. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
b. Reports average marginal effects holding covariates at mean.

Table 2: Conflict Severity

Variables	(1) Battle deaths Nbreg	(2) Battle deaths Nbreg	(3) Battle deaths Nbreg	(4) Battle deaths Nbreg
District Per capita GDP (log)	-1.283***	-1.123***	-1.004**	-1.429***
	(2.94)	(2.73)	(2.32)	(3.23)
Access to Public Basic Goods	-0.250	-0.370**	-0,264	0.482
	(1.37)	(2.06)	(1.48)	(1.40)
Total Literacy Rate	-0.003	0.002	-0.002	0,009
	(0.22)	(0.14)	(0.13)	(0.56)
Per capita Iron & Coal value (log)	0.141	-0.943***	13.045***	0.148
	(0.72)	(3.18)	(2.73)	(0.75)
SC & ST Population share	0.048***	0.034***	0.042***	0.037***
	(4.54)	(3.21)	(3.62)	(3.72)
Households Employed under NREGA per capita	-0.129***	-0.115***	-0.126***	-0.119***
	(3.51)	(3.47)	(3.60)	(3.35)
Total Population (log)	0.747**	0.733**	0.673**	0.843***
	(2.31)	(2.38)	(2.15)	(2.68)
Share of Forest Area in Sqkms	0.031**	0.031***	0.027***	0.035**
	(2.39)	(2.74)	(2.68)	(2.07)
Urbanization Rate	-0.002	0.002	-0.004	-0.003
	(0.12)	(0.14)	(0.26)	(0.20)
British Direct Rule dummy	0.184	0.045	0.179	0.099
	(0.50)	(0.13)	(0.50)	(0.28)
Conflicts in Neighboring Districts	0.009**	0.010***	0.008**	0.009***
	(2.42)	(2.79)	(2.45)	(2.70)
Per capita Iron & Coal value (log) × SC & ST Population share		0.019***		
		(3.71)		
Per capita Iron & Coal value (log) × District Per capita GDP (log)			-1.356***	
			(2.76)	
SC & ST population share × Access to Basic Public Goods				-0.026***
				(2.72)
Number of Observations	140	140	140	140

a. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
b. Reports average marginal effects holding covariates at mean.

The inclusion of additional interaction terms reiterate that the relationship between motive and opportunity in the Maoist insurgency is nuanced. Given we find only minimal support that mining GDP is related to conflict, our sixth hypothesis interacts logged per capita mining revenues with SC/ST population share, assessing whether rebels are more active in engaging in violence where local grievances coincide with feasibility to organize costly conflict - namely where the probability for material and financial gain is higher. The results in column 3 in table 1 and column 2 in table 2, show positive relationship between the interaction term and conflict frequency and severity, suggesting that conflict is higher in places where mining activities coincide with higher levels of grievances. These results are highlighted in figure 2, showing the significant overlap between SC/ST populations, mining activities, and violence.

The capacity of the state may explain why some districts with the presence of mining activity have escaped Maoist violence. Our seventh hypothesis interacts per capita GDP, a proxy for state capacity, with per capita mining revenues. As seen from column 4 in table 1 and column 3 in table 2 the interaction term is negative and significantly different from zero at 5% level, suggesting that in pooerer areas where state capacity is weaker, the conflict inducing effects of mining increase. This may partly explain why some regions where there is significant presence of mining activities have escaped from Maoist violence.

Finally our eighth hypothesis further explores grievances as motivation by interacting the SC/ST share in population with availability of public goods. We do find that the effect of SC/ST populated areas on conflict events and battle deaths turns negative when access to public goods provisioning is higher (see column 5 in table 1 and column 4 in table 2). This infers that where districts have a greater share of SC/ST population and receive comparatively higher standards of services, there risk of Maoist violence is significantly *lower*. This suggests that there may be pacifying returns to extending the reach of the state's services to aggrieved populations.

5.1. Checks on Robustness

We examine the robustness of the main findings in the following ways. Following Brandt et al. (2000) and King (1988), we estimate all the results reported here using alternative estimate technique namely, zero-inflated negative binomial method. Although it is true that there is over dispersion in the conflict data, the possibility of two types of zero-values for the both lethal events and battle deaths is relatively absent. Despite that, it would provide a good test for robustness of our findings with alternative estimation technique (Vadlamannati 2011). The results from zero-inflated negative binomial estimations do support our earlier baseline findings.

Conclusions and Considerations for Future Research

We have three primary findings. First, the strongest correlates of Maoist violence are those districts where SC/ST populations form the highest percentages of population. Second, most socio-economic and government capacity factors only find marginal support in our model. Third, the relationship between mining and violence in our model is positive, but weak. Slightly stronger results are found with both violent border districts (mobility), forest cover (access) and government development (NREGA). Taken together, the results show that neither the 'grievance-based' arguments presented by the Maoists (hearts) nor the 'greed-driven' factors (mines) are supported by our results as a fundamental explanation for the insurgency - even though both carry substantial anecdotal power in the conflict zone.

As the initial phases of the conflict, rhetoric on all sides, and our interviews with both current and ex-combatants paint a different picture, these findings require further explanation. Due to the mobility of the Maoists, and their lack of ties to one particular 'homeland' or other essential territory (as a separatist movement would), strategic decisions about *where* to fight may outweigh localized rationales for *why* people fight. Further research is needed to determine if justice-based demands drive recruitment, but our research shows they are not driving the conflict's locational aspects. In support of this assessment is the conflict's shift away from more 'traditional' theatres of conflict in its nascent stages (primarily West Bengal and Andhra Pradesh) to the resource-rich states of Jharkhand, Orissa and Chhattisgarh – which also is supported by our 'border districts' correlation. In this way, rebel incentives and opportunities may be symbiotically intertwined, feeding off of each other to increase conflict.

This assessment should temper the popular view both in India and abroad that 'development' of poor districts is the solution to the Maoist conflict, particularly when no distinction is made for the specific needs of SC/ST communities, or when development in practice takes the form of industrial expansion instead of social service provision. Driven to maximize mining output, Delhi has been under tremendous industrial and political pressures since 1991 to not only maintain existing mining projects, but rapidly expand into mineral-rich SC/ST populated lands. To wit, the states of Chhattisgarh and Jharkhand were specifically created in 2000 in order to be 'safe zones' for the tribal populations residing within. Instead, they became the focal point of the conflict zone while remaining mining havens – suggesting that elements of horizontal inequality may be fueling conflict, not the vertical inequality measures that dominate headlines and qualitative narratives. And while most government scholars and policymakers continue to believe that military success is ‘just around the corner’ (e.g Routray 2010), our data which indicates conflict events and deaths are increasing year-on-year suggests otherwise.

With reflection on the fact that mining production has more than doubled since 2006 (MOSPI 2010), future research will reassess the relationship between mining, SC/ST communities and conflict to assess whether these ties are either more nuanced than our initial results have shown, or whether changes over time have stronger explanatory value. Future research will employ more updated data, as some of the most significant districts of post-2005 industrial expansion have also been the most violent (including areas of southern Chhattisgarh, southern Jharkhand, and southeastern Orissa). This may suggest that it is not a lack of development that triggers conflict, but the inverse–a ramping up of industrial development without safeguards to prevent against corruption or other abuses draws conflict actors as they transit from opportunity- to incentive-based decisionmaking. Or put another way, this may illustrate a “grievance then greed” model that can be seen anecdotally in many rebel group conflict timelines throughout the world. We are currently collecting sources for a follow-up paper combining 2011 census and mining information with informal mining data (illegal mining accounts for up to 50% of total mining in many conflict-affected districts, particularly in Jharkhand) to test related hypotheses in a time-series format. Perhaps not least, we will explore these findings in the context of Indian narratives and counter-narratives on the Maoist conflict, researching how our qualitative assessments to a point ‘got it wrong’, how rhetoric can lead research (and researchers) astray when repeated to the point of doctrine, and how the belief in false narratives can lead policymakers and conflict actors down unintended paths.

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Appendix 1: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Obs
Dependent					
Conflict Incidence	0.708	0.456	0.00	1.00	151
Conflict Lethal Events (count)	12.099	33.600	0.00	320.00	151
Battle Deaths (count)	31.894	118.053	0.00	1314.00	151
Independent					
District Per capita GDP (log)	9.302	0.52	8.25	10.73	148
Basic Public Goods Access	0.000	1.000	-2.13	2.35	140
Total Literacy Rate	56.356	12.888	30.17	80.86	142
Per capita Iron & Coal Mining revenue (log)	0.290	0.790	0.00	3.77	142
SC and ST Population share	31.210	16.875	6.22	81.88	142
Households share under NREGA	15.457	6.367	1.87	58.78	140
Control					
Total Population (log)	14.418	0.697	12.52	16.08	142
Forest Area Share	11.614	14.395	0.00	98.84	142
Urbanization Rate	16.947	15.678	3.24	100.00	142
British Direct rule dummy	0.437	0.50	0.00	1.00	151
Conflict Events in Neighboring Districts	49.894	66.854	0.00	368.00	151