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RENEWABLE RESOURCE SHOCKS AND CONFLICT IN INDIA'S MAOIST BELT

DEVESH KAPUR
Director, Center for the Advanced Study of India
Madan Lal Sobti Associate Professor for the Study of Contemporary India
University of Pennsylvania

KISHORE GAWANDE
Professor and Roy and Helen Ryu Chair of Economics and Government,
Texas A&M

SHANKER SATYANATH
Associate Professor, Department of Politics
New York University

CENTER FOR THE ADVANCED STUDY OF INDIA
University of Pennsylvania
3600 Market Street, Suite 560
Philadelphia, PA 19104
http://casi.ssc.upenn.edu/index.htm

CENTER FOR THE ADVANCED STUDY OF INDIA

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Abstract

Is there a causal relationship between shocks to renewable natural resources, such as agricultural and forest lands, and the intensity of conflict? In this paper we conduct a rigorous econometric analysis of a civil conflict that the Indian Prime Minister has called the single biggest internal security challenge ever faced by his country, the so called Maoist conflict. We focus on over- time within-district variation in the intensity of conflict in the states where this conflict is primarily located. Using a novel dataset of killings we find that adverse renewable resource shocks have a robust, significant association with the intensity of conflict. A one standard deviation decrease in our measure of renewable resources increases killings by 12.5% contemporaneously, 9.7% after a year, and 42.2% after two years. Our instrumental variables strategy allows us to interpret these findings in a causal manner.

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1. Introduction

In recent years several scholars have made the claim that there is a causal link between adverse shocks to renewable natural resources and conflict (for example Homer-Dixon 1994; Hauge and Ellingsen 1998; Homer-Dixon 1999; Kahl 2006).[1] The claim is that where people are dependent on such resources for their livelihoods, adverse shocks to these resources generate incentives to fight for survival (Mildner et al. 2011, 157). However the basis for a causal link between renewable resource shocks and conflict intensity has been strongly disputed, most powerfully by Gleditsch (1998). As Schwartz et al. (2000) summarize, "methodological issues underpin Gleditsch's critique... Gleditsch asserts that much environment-conflict research is methodologically unsound and fails to qualify as systematic research" (Schwartz et al. 2000, 78). Among his major criticisms are a failure to address reverse causality and a failure to systematically control for alternative explanations for conflict (Schwartz et al. 2000, 78). Some methodological improvements have been made in a recent study by Thiesen (2011) but fundamental concerns about endogeneity raised by Gleditsch remain unaddressed in this literature.

In this paper we attempt to advance this important debate by conducting a rigorous econometric analysis of a civil conflict that the Indian Prime Minister called "the single biggest internal security challenge ever faced by our country"[2] the so-called Maoist conflict. The Maoist conflict has largely been concentrated in a corridor of states in the East-Central part of the country, and takes the form of a Maoist insurrection with the goal

[1] This literature differs from the literature on the resource curse, in that the latter focuses on non- renewable resources such as oil and minerals.
[2] The Economist 2/25/10

of toppling the Indian government.[3] According to official Indian government data the conflict has resulted in 7862 deaths in the period 2000-2009.[4] Whereas the principal sources of politically motivated violence in India have either declined markedly (the insurgencies in Kashmir and in India's North-East) or remained unchanged at relatively low levels (communal violence) over the past decade, violence related to the Maoist movement remains the exception to this rule **[See Figure 1]**.

The Maoist conflict in India is well suited to the purpose of examining the causal links between renewable natural resource shocks and conflict, because it meets one of the central conditions under which the above link would plausibly hold: as we show later, a large proportion of the population in the Maoist belt of states is dependent on such resources for its livelihood. A growing statistical literature has sought to understand the determinants of the Maoist conflict. Several of these papers attempt to capture the cross sectional variation in conflict (Ghosh and Das 2010; Hoelscher, Miklian and Vadlamannati, 2011). Two recent papers attempt to capture within-district variation over time in these variables (Gomes 2011; Vanden Eynde 2011). However, there are several areas in which the literature currently falls short. First of all, these studies rely on data from the South Asian Terrorism Portal (SATP) and the National Counterterrorism

[3] The antecedents of the movement go back to a Maoist ideology inspired violent insurrection in Naxalbari, a village in the Eastern state of West Bengal in May 1967 (Chakravarti 2008). Violence spread over the next few years but it was violently put down by government forces and petered out by early 1970s. The movement's ideological currents, however, slowly spread across south-eastern, central and eastern part of the country and gradually gained strength from the early 1990s when the many splintered groups began coming together. The People's Liberation Guerrilla Army (PLGA) was founded on December 2, 2000, originally as the People's Guerrilla Army (PGA), by the then Communist Party of India–Marxist-Leninist (People's War). Following the merger of the PW and the Maoist Communist Centre of India (MCCI), on September 21, 2004, the PGA was renamed as the PLGA For a detailed account of the origins of the Naxalite movement see Banerjee (1980); Singh (1995) provides an empathetic account of the movement until the early 1990s from the vantage point of a senior police officer.

[4] Data collated from Annual Reports of Ministry of Home Affairs, Government of India.

Centre's Worldwide Incidents Tracking System (WITS) which measure conflict based on the study of conflict reports in the English language press. This is problematic given the limited coverage of English language newspapers, the urban bias of the English language press, and the largely rural nature of the conflict.

Second, the literature on the Maoist conflict has not convincingly addressed concerns about endogeneity. The cross sectional literature is, of course, severely subject to the problem of not controlling for non-observable differences between districts (which would be addressed by fixed effects in a panel). As for the two papers that focus on within-district over-time variation (Gomes 2011; Vanden Eynde 2011), the former includes endogenous variables in its specifications (in addition to not including district fixed effects) while the latter fails to instrument for its main explanatory variable (income), and instead relies on reduced form regressions of conflict on rainfall. We note that we do not find Vanden Eynde's reduced form results (which are based on the limited SATP violence data mentioned above) to be robust to the use of our more comprehensive database. Rather, rainfall works well as an instrument for our main measure of renewable resources, which in turn is strongly associated with conflict.

Our paper aims to explain within-district variation over time in conflict intensity. Our focus on within district variation allows us to use demanding specifications with both district and year fixed effects, which effectively control for time invariant unobservable factors that may make districts different from each other, as well as time variant shocks that may strike all districts at any given point in time. Consistent with our goal of analyzing within district over time variation our main analysis focuses on the four core states of the Maoist belt, where there is substantial year to year variation in killing (at the district level) to be explained. (The core states are Bihar, Jharkhand, Chhattisgarh, and Andhra Pradesh where 90% of Maoist related killings have occurred over 2001-2008).[5] To this end we have assembled a novel conflict dataset that is based not just on reports in the English press, but additionally on the local language (vernacular) press. As such we are able to capture a substantially larger number of casualties than the widely used South Asian Terrorist Portal or other currently available datasets **[See Figure 2]**.

Furthermore, we are able to instrument for a plausible proxy for over time variations in renewable natural resources, and can thus make causal claims relating renewable resource shocks to conflict intensity. Specifically, we use a satellite derived measure of vegetation "greenness" as a proxy for the agricultural and forest related resources on which a large proportion of residents of the Maoist belt rely for their livelihoods. Since vegetation is plausibly endogenous to conflict we instrument for vegetation with rainfall and find this to be a strong instrument.[6]

Our main finding is that adverse vegetation shocks have a robust, significant association with the intensity of conflict. The relationship is negative, rather than positive, which is consistent with adverse vegetation shocks affecting livelihoods and thereby reducing the opportunity cost of fighting.[7] A one standard deviation decrease in our favored measure of renewable resources increases killings by 12.5% contemporaneously, 9.7% after a year and 42.2% after two years. Our instrumental variables strategy allows us

[5] We also check for robustness when a fifth state – Odisha (formerly Orissa) – is added.
[6] Brown (2010) uses the same NDVI vegetation index that we use when analyzing conflict in Darfur, but does not instrument for vegetation.
[7] This is as opposed to the technological argument of denser vegetation facilitating insurgent attacks.

to interpret these findings in a causal manner and thus contribute to the debate on the causal relationship between renewable resource shocks and conflict.

In the next section of the paper we briefly summarize the current status of the literature on the relationship between renewable resource shocks and conflict and then describe the findings of the emerging literature on the Maoist conflict. In Section 3 we describe our causal story. In section 4a we describe our econometric strategy while in section 4b we describe the data that we use in our paper. In Section 5 we present our results while Section 6 concludes.

2. Literature Review

2.1. The debate over renewable resource shocks and conflict

Mildner et al. (2011) have recently provided an excellent literature review of the debate over the causal relationship between natural resources and conflict. Readers are directed to that paper for a comprehensive description of this debate. We aim here only to identify the contributions to the debate that are most relevant to the concerns of this paper.

Mildner et al. (2011) point out that the literature can be divided into two broad categories. One focuses on the effects of renewable resources on conflict, whereas the other focuses on sudden discoveries of non-renewable resources (the resource curse). While we do control for non-renewable resources our paper is most closely related to the former category of literature. Several scholars who have focused on the former concern (including Homer-Dixon 1994 and 1999 and Kahl 2006) have emphasized the threats presented by depletion of croplands, forests, water, and fish stocks to peoples' livelihoods. They have argued that such adverse resource shocks can cause conflict by endangering livelihoods and forcing people to fight for their survival. Whereas authors of this school primarily rely on case studies to justify their claims, their broad claims have also found support in some statistical studies, for instance by Hauge and Ellingsen (1998).

This school of scholars has been criticized on several grounds. For instance, Goldstone (2001) has pointed out the conceptual shortcomings in the literature, notably the failure to define variables clearly, as well as the failure to take account of alternative non-environmental explanations for conflict. Especially relevant to our paper, Gleditsch (1998) has criticized the school from a methodological perspective. He has criticized case-based scholarship as being inadequately systematic. In particular, he has pointed out failures in addressing reverse causality and in rigorously controlling for alternative explanations for conflict.

Theisen (2011) has attempted to respond to Gleditsch's call for more systematic research with a quantitative research design. He finds that Hauge and Ellingsen's (1998) claims of a major effect of resource shocks on conflict are likely exaggerated. Unfortunately Theisen too does not have a compelling strategy for addressing reverse causation and his study is marred by the inclusion of endogenous variables on the right hand side.

Our paper may be thought of as an effort to better address Gleditsch's critiques. By focusing on within district over time variation inside a country we are able to control for many unobservables that could affect statistical identification in a cross country (or for that matter a cross state) study. Furthermore, by developing a credible instrumental variables strategy we are able to address concerns about reverse causality.

Since resource shocks affect peoples' livelihoods our paper is also related to the cross country literature on the causal relationship between income and conflict (Collier and Hoeffler 1998, Fearon and Laitin 2003).[8] Most relevant is the paper by Miguel, Satyanath, and Sergenti (2004) which uses rainfall as an instrument for per capita GDP when studying civil conflict in Africa. The big difference is that we are focusing on a level of analysis (district level) that is bereft of income or aggregate output statistics. Furthermore, available consumption statistics are considered unreliable (as we will discuss later) and are thus not a good proxy for economic welfare. We argue below that in an environment in which a large proportion of the population earns its livelihood from agriculture or from the forest the natural resource of vegetation plausibly offers the best means of assessing economic welfare. Our paper thus offers an alternative way of addressing economic welfare at a local level in environments where citizens are reliant on agriculture/forest products for their livelihood.

2.2. The literature on the Maoist conflict

There are several ethnographic studies of the Maoist movement in India. There is also an active policy debate between those who emphasize the economic grievances of the

[8] There is also an emerging micro-economic literature on income and conflict, for example by Dube and Vargas (2010) on Colombia.

poor, and others who emphasize the weakness of the state apparatus in the states where the Maoist conflict is concentrated. For reasons of space we only summarize the statistical literature on the Maoist conflict in this section (since this is the realm of our contribution), and provide the reader with references to the most salient contributions to the ethnographic and policy literature.[9]

To begin our survey of the statistical literature on India's Maoist conflict, Barooah (2008) examines which socio-economic variables explain the existence of Maoist activity in some districts of India but not others using data from the Indian Planning Commission and South Asian Intelligence Review. The dependent variable is the likelihood of violence. The main findings are that the probability of a district being Maoist-affected rises with an increase in its poverty rate and falls with a rise in its literacy rate and that Maoist activity in a district reduced the overall level of violent crime and crimes against women. These results are from cross sectional OLS regressions at the district level, and pool across heterogeneous regions. Endogeneity is not addressed.

Iyer (2009) examines terrorist incidents in general, where terrorist activity includes separatist movements, communal violence, and the Maoist insurgency. Using data from Global Terrorism Database 2, Rand-MIPT Terrors Database, and from Planning Commission and South Asian Intelligence Review, Iyer also finds correlation between violence and poverty. Like Barooah, her findings are based on cross sectional OLS regressions at the district level. Affirming Barooah's finding makes this an interesting

[9] With regard to ethnographic studies of the Maoist movement, for Bihar see Bhatia (2005) and for Jharkhand see Shah (2010). Harriss (2010) provides a good review. For policy debates see Guha (2007) and Ajai Sahni, "India and her Maoists: A tiger crouching, a dragon curling…" *Faultlines: Wars within Borders*, November 2009.

association but once again causality is an issue.

Sen and Teitelbaum (2010) trace the history of the Maoist movement and use the World Incidents Tracking System (WITS) data on Maoist violence to examine the effects of mining. They conclude that the geographical spread of Maoist movement is simply too wide to be accounted for mainly by mining activity. However, their failure to address endogeneity militates against the robustness of their primary findings.

Hoelscher, Miklian, andVadlamannati (2011) analyze cross-sectional data from six Indian states - Chhattisgarh, Andhra Pradesh, Orissa, Jharkhand, Bihar and West Bengal from 2004 to 2010. Their data combines that from the South Asian Terrorism Portal (SATP), the National Counterterrorism Centre's Worldwide Incidents Tracking System (WITS) and the Global Terrorism Database. Using probit and negative binomial estimation techniques they find that conflict increases with forest cover, prevalence of conflict in neighboring districts, and the population share of members of scheduled castes and tribes. Once again causality is not addressed.

Gomes (2011) combines databases from different sources on Maoist incidents/violence into one comprehensive database. His paper looks at landholdings and historical land institutions, and finds a strong effect of land inequality on Maoist violence. He argues that "the significance of the Historical Land institution variable is also interesting since it shows that while the landlord districts might have indeed experienced more land reforms, the land reforms per se have not been able to address the class based antagonism and embittered social relations that these districts continue to experience." As described above this paper purports to be a district level analysis but does not include district fixed effects and also does not address endogeneity.

Vanden Eynde (2011) examines the strategic choices of targets and the intensity of violence of Maoist insurgents using data from the South Asia Terrorism Portal (SATP) between 2005 and 2010. Using variation in annual rainfall in a panel of district level casualty numbers he finds that negative labor income shocks increase violence against civilians to prevent them from being recruited as police informers. It also increases the number of rebel attacks against the government, but only if the rebels' tax base is sufficiently independent from local labor productivity (in this case access to key mineral resources). The data used in the paper has shortcomings. The casualty data is from the SATP which, as mentioned, relies primarily on the English language press. Mining data is for one year. Furthermore, claims are made about the effects of income without actually instrumenting for income or for proxies of income.

We have listed our aimed contributions to this literature at the beginning of the paper. In a more general way our paper also contributes to the statistical literature on the determinants of violence in India, for instance the work by Wilkinson (2004) on ethnic riots in India and by Jha and Wilkinson (2012) on violence during the partition of British India.

3. Causal story relating renewable resource shocks to intensity of conflict

Our causal claim is that over-time, within-district variations in the intensity of conflict in the Maoist belt of states are significantly driven by shocks to renewable natural resources.[10] In order for this claim to be plausible we must first establish that the livelihoods of people in the region are significantly reliant on renewable natural resources. We present several facts that are in line with this claim below.

The two major renewable resources on which people in the region rely for their livelihood are agricultural land and forest land. More than two-thirds of the employment in the Maoist belt is in agriculture. In 2004 (the mid-point of the time period of our analysis), 73.6% of Andhra Pradesh's, 80.1% of Bihar's, 90.9% of Chhattisgarh's, 64.4% of Jharkhand's, and 69.2% of Orissa's workforce was employed in agriculture.[11] This means that adverse shocks to agricultural land will plausibly affect economic welfare of numerous residents of the region.

Aside from agricultural land, a significant proportion of the population in the region relies on forests for its livelihood. The Maoist region includes a significant number of Scheduled Tribes.[12] In two of the four states in our analysis the share of tribals in the population exceeds 25%.[13] These tribals tend to live in or in the proximity of forests. In Chhattisgarh almost half of the land area in tribal districts consists of forest cover; in Jharkhand it is almost a third.[14] Tribals have close cultural and economic links with the forest and depend on forests for a significant part of their subsistence and cash livelihoods,

[10] As mentioned the core of this belt in our analysis is the four states listed at the outset of the paper where 90% of Maoist related killings occur, to which we add a fifth in our robustness checks.

[11] Source : Lok Sabha Unstarred Question No. 3258, dated 12.05.2006

[12] The nomenclature goes back to the 19th Century when the British expansion into the forested and hilly terrain of central India encountered culturally distinct groups living in relative geographical isolation. The first Census in 1872 categorized these communities as "Primitive Tribes." They were later termed "Backward Tribes" in the 1874 Scheduled Districts Act. The Indian Constitution in 1950 listed them in a "Schedule," granting them special protections and since then they have been known as "Scheduled Tribes."

[13] Indian Planning Commission, http://planningcommission.nic.in/data/datatable/0904/tab_119.pdf

[14] Forest Service of India. http://www.fsi.nic.in/sfr2003/forestcover.pdf 60% of the forest cover of the country and 63% of the dense forests lie in 187 tribal districts (GOI, 2008).

which they earn from fuelwood, fodder, poles, and a range of non-timber forest products, such as fruits, flowers, medicinal plants and especially *tendu* leaves (used to wrap tobacco flakes and make *beeris*, a local Indian hand-rolled cigarette).

While dozens of press and academic accounts of the tribal peoples in central and eastern India stress their dependence on forest resources for their livelihoods, a single macro-quantitative estimate of the degree of dependence is not available. We provide here the evidence that is available, which is strongly suggestive of heavy dependence. A World Bank study has found that in the state of Jharkhand fuel wood from forests supplies an average of 86 percent of energy needs while fodder from the forest provides about 55 percent of input requirements for domestic livestock for communities living proximate to forests (World Bank 2006). The FAO cites a study of tribal households in Orissa which found that an average tribal family drew about one-half of its annual income from forests, 18 percent from agriculture, 13 percent from cattle and 18 percent from other employment.[15] A study of forest fringe communities in the Jhabua district of Madhya Pradesh (which is close to the Maoist belt) measured specific components of household income and subsequent dependence on natural resources (including forests), and found this dependence to be three-fourths for those in the lowest 25% income quartile and nearly two- thirds for those in the 25-50 percent income quartile (Narain, Gupta and van't Veld 2005). Another study (in West Bengal which also neighbors the Maoist belt) found that the share of forest income in total income for tribal households ranges from 55-86% (Das 2010).

[15] http://www.fao.org/docrep/x2450e/x2450e0c.htm#joint%20forest%20management%20in%20india%20and%20the%20impact%20of%20state%20control%20over%20non%20wood%20f

None of the above is intended to suggest that the bulk of tribals rely on the forest to the exclusion of agriculture for their livelihoods. In his landmark work on the tribes of India, ethnologist von Fürer-Haimendorf (1982) has categorized tribes into three categories based on their primary economic activity: food gatherers and hunters, shifting cultivators and settled farm populations. What is clear from this categorization is that tribals are dependent on either the forest and/or agricultural resources for their livelihoods. This includes cases where tribals dependence on forest and agricultural resources is seasonal; a widespread pattern noted by von Fürer-Haimendorf is one where the tribals rely on forest products during much of the first half of the year, engage in subsistence agriculture during much of the the second half, and supplement their income with activities like basket weaving during the monsoon season.

To sum up, it is reasonable to conclude that adverse shocks to the renewable resources of forests and agricultural land substantially affect the livelihoods of most residents of the Maoist belt of states. The question then is, what are our expectations about how this would result in greater intensity of conflict?

A shock to livelihoods creates incentives for people to join the Maoists as an alternative means of survival. However, we do not expect this to be immediately reflected in more intense conflict. Accounts by journalists (and there are no academic studies) stress the Maoist strategy of gradualism when inserting a new recruit into an actual combat situation (Chakravarti 2008). Recruitment is followed by training. Recruits are taken far away from their home villages and are sometimes even sent for training to other parts of India, such as the North East, before returning to fight on familiar turf. This means that the full effects of resource shock driven recruitment on intensity of conflict should not be observed contemporaneously, but with a lag.

Another reason to expect a lagged effect is that the ability of Maoists to successfully fight the government is enhanced by support from the local population. One potential source of support is goodwill resulting from some genuine service being provided by the Maoists. The immediate reaction of many to an adverse economic shock is to borrow from a moneylender. Moneylenders in the Maoist belt are well known for being ruthless in demanding collateral when repayment is not forthcoming (Guha 1999). One of the major services that Maoist cadres provide is to offer protection for villagers from confiscation of assets by moneylenders (Pandita 2011). This protection likely to be needed and provided, not when the loan is first taken, but rather when repayment is due. The goodwill of the local population should thus be at its highest not contemporaneously with the adverse economic shock, but after the passage of some time. This would generate incentives for Maoists to launch their most furious attacks at a lag from the adverse economic shock.

4. Econometric Strategy and Data

4.1 Econometric Strategy

Our first requirement is a measure of renewable resources that picks up differences between good and bad agricultural years as well as the differences between years when the forest is relatively fecund and when it is not. Both of these goals are plausibly achieved with a measure that captures the density of vegetation. Less dense vegetation is associated with poorer crops and with a less rich forest environment. A time varying measure of vegetation would thus pick up shocks to the main renewable resources which residents of the Maoist belt rely on for their livelihoods. In line with the above logic, our proxy for natural resources in the Maoist region is the degree of vegetation in a district-year. (The use of the year as the unit of observation is justified by the fact that it should both pick up greenness in the season when agricultural crops are grown and the non-agricultural season in which residents are relying on the forest for their livelihood.)

Vegetation may, of course, be endogenous to conflict. For instance the Indian government may destroy forests in places where conflict is anticipated, in order to facilitate counter insurgency operations. Thus it is necessary to instrument for vegetation. We use rainfall as our instrument for vegetation, and this critical step allows us to make causal claims about the effect of renewable resource shocks on conflict intensity.

In our tables we present results with and without instrumentation. The uninstrumented regressions have the following structure, with *i* referring to the district and *t* referring to the year:

$$\ln(\text{TotalDeaths})_{i,t} = \varphi \ln(\text{TotalDeaths})_{i,t-1} + \beta_1 \text{Vegetation}_{i,t} + \beta_2 \text{Vegetation}_{i,t-1} + \beta_3 \text{Vegetation}_{i,t-2} + \text{Year fixed-effects} + \text{District fixed-effects} + e_{i,t}, \quad (1)$$

where, after accounting for the year and district fixed effects, the error term $e_{i,t}$ is identically and independently distributed normally. (As mentioned later, we address the potential for Nickell bias from the presence of the lagged dependent variable with district dummies by conducting robustness checks with the Arellano Bond technique.) All our models are estimated with robust standard errors that are clustered at the district level. Since district dummies are included in the model, the coefficient estimates are based on the within-district variation in the data. The year- fixed effects account for macro-events that impact all districts in a given year. This is a demanding specification that takes account of observable and unobservable time invariant differences between districts. It also takes account of all common shocks affecting all districts in the sample at any point in time.

In our instrumental variables regressions we instrument for the vegetation variables above with three lags of rainfall in addition to contemporary rainfall. Given that there was a change towards a much more highly defined sensor to capture vegetation in 2001 our analysis begins with this year and runs to 2008 (the last year for which we have complete killings data.) We also conduct robustness checks using the Arellano and Bond GMM technique in which lagged levels serve as instruments for lagged first differences. More details are provided in the results section.

4.2 Data

Killings

The primary data innovation in the paper is our attempt at improving on the other sources of data that have been used in the literature: The Government of India's official data from the Ministry of Home Affairs (MHA); the RAND-MITP Terrorism Incident database; data from the Worldwide Incidents Tracking System (WITS) from National Counter Terrorism Centre and data from the South Asian Terrorism Portal (SATP). The

Ministry of Home Affairs compiles data on Maoist violence, dividing it into two categories – the number of casualties (deaths) and the number of violent incidents. While this data is available from 2001 onwards it is available only at the state level. The Rand-MIPT and the WITS data sets are world-wide but are ineffective in capturing killings reported by the non-English language press. The SATP data set has been assembled by the Institute for Conflict Management, available at their website, the South Asia Terrorism Portal. This data is also based primarily on reports in the major English press.

The dataset we have assembled, called the CASI dataset, does not draw from secondary sources. Instead for each state we examined reports from at least four distinct media sources:

i) National English press

ii) The local (or state) edition of a national English daily (if present)

iii) Local language (vernacular) dailies (at least two, except in Andhra Pradesh where we used one, Eeenadu, the largest circulation Telugu language daily in that state.)

iv) Two wire services: Press Trust of India (PTI) and India Abroad News Service (IANS).

The data sources used to construct this data base of Maoist incidents is detailed in Appendix Table A1. Further details about the dataset, including coding procedures, are provided in our online appendix (not for publication, but submitted separately for reviewers to peruse). **[See Appendix Table A1]**

Each incident is geocoded at the district level. Our core measure is one of total fatalities in incidents involving Maoists. It sums the number of civilian deaths, security personnel deaths and Maoist deaths for each year for each district in such incidents. (We also look at these separately.) The extent to which other databases underestimate the actual number of deaths is evident in Figure 2. Only the SATP data is collected at the district level, but as Figure 2 indicates, it underreports considerably compared to our CASI dataset. **[See Figure 2]**

There are two years in which our data picks up fewer killings than the aggregate data reported by the Government of India MHA numbers. Given the capacity and incentive problems of MHA data (in some cases states that reported more violence got more money to fight the Maoists), as a benchmark this data itself should be taken with caution. Is it possible that killings are over-reported by the vernacular press? This would imply that somehow the language medium would result in over-reporting. This might be if one believes that the rural press has empathy with the Maoists. But the newspapers we have used in this study – both English and vernacular – are all owned by urban capitalists, some regional capitalists and some national (none of the news sources are communist affiliated which might lead to an exaggeration of deaths). Moreover, such an argument implies that those who read/write English are less biased than those who do not, which has little basis.

We focus our attention in this paper to all districts in the four states of Andhra Pradesh, Bihar, Chhattisgarh, and Jharkhand, now known as the “red belt” for their strong association with the Maoist movement. 90% of total killings in our national data over the 2001-2008 period are from these districts.

The number of states and districts has changed over time. Chhattisgarh was carved out of Madhya Pradesh, and Jharkhand out of Bihar, in 2000. To keep the unit of observation consistent across the years, we map districts into a common set of regions using the concordance constructed by Kumar and Somanathan (2009, Tables 4-8). Specifically, we use their 1991 mapping of over 600 Indian districts into 404 regions. For the four red states that are the focus of this study, we have data on 68 regions over the 2000-2008 period. (For purposes of avoiding confusion we refer to these regions as districts everywhere else in this paper.)

Rainfall

Rainfall data are from the high resolution (1° ×1° latitude/longitude) gridded daily rainfall dataset for the Indian region, kept annually since 1951 by the India Meteorological Department (IMD). The daily rainfall data are archived at the National Data Centre, IMD Pune. Rajeevan et. al. (2006) of IMD Pune describe the collection of IMD data as follows: IMD operates about 537 observatories, which measure and report rainfall that has occurred in the past 24 h ending 0830 h Indian Standard Time (0300 UTC). In addition, most of the state governments also maintain rain gauges for real-time rainfall monitoring. IMD has the rainfall records of 6329 stations with varying periods. Out of these, 537 are IMD observatory stations, 522 are under the Hydrometeorology program and 70 are Agromet stations. The remaining are rainfall-reporting stations maintained by state governments. Rajeevan et al. (2006) show that this data correlates well both spatially and inter-temporally with the VASClimo dataset, is a global gridded rainfall dataset constructed in Germany.

We match the capital cities of (districts in) the 68 regions in the four red states to nearest rain station and ascribe that rain data to the district.[16] The daily rainfall data are aggregated into annual data.

Vegetation

Satellite imagery is now widely used in the sciences to track changes in vegetation and forest cover (e.g. Myneni et al., 1998; Tucker et al., 2001; Nemani et al.,2003).[17] We use the normalized difference vegetation index (NDVI) to measure annual change in vegetation for Indian districts. The NDVI data are derived from visible infrared and near-infrared data acquired from the MODIS sensor (Moderate Resolution Imaging Spectroradiometer) on NASA satellites. The NDVI index is computed as NDVI = (NIR – VIS) / (NIR + VIS), where NIR is the Near Infrared Band value and VIS is the visible light or the Red Band value recorded by the satellite sensor.[18] The NASA site explains the computation as follows: healthy vegetation absorbs most of the visible light that hits it and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. NDVI for a given grid ranges from -1 to +1. Scores of .above .45 are considered indicative of forest land, but we do not emphasize this cutoff since our extensive non-parametric tests fail to indicate different slopes for the vegetation-conflict relationship above and below this cutoff (not shown).[19]

[16] Where many districts map into one region, the median district mapped to the nearest rain station.

[17] In the Indian context, for example, Panigrahy et al. (2010) find dense forests denuding at 0.72% per annum in the Western Ghats, while Prabhakar et al. (2006) measure the deforestation in the Himalayas.

[18] http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_4.php

[19] D'Arrigo et al (2000) show a high correlation between NDVI and direct measures of vegetation from tree rings.

We mapped the data from MODIS into 1° × 1° latitude/longitude grids for India. For each grid, monthly NDVI data are averaged to obtain the mean annual NDVI over the period 2001-2009.[20] They are then mapped into Indian regions, specifically into the 68 red districts as was done for the rainfall data.

Other Data

In an appendix we offer results using consumption data which are in line with the results using our vegetation measure. We do not choose to emphasize these results because we do not believe that the consumption measure is an accurate measure, for reasons we describe below.

The source for our consumption expenditures data is the Annual National Sample Surveys (NSS) taken over the 2000-2009 period are. Monthly per capita expenditure (MPCE) at the household level collected in these surveys are averaged using sample-proportionate-to-population weights to obtain MPCE measure for each of the 68 districts annually over the period. The accuracy of our MPCE calculations was verified by matching our figures with those in the NSS summary reports (at the state level) produced by the government of India. The Tendulkar Commission report (Tendulkar et al. 2009) expands

[20] MODIS data are a substantial improvement over its predecessor, the AVHRR sensor which provided 20 years of data going back to 1980. According to Hansen et al (2003), MODIS is a significant advance due to three reasons. First is the finer instantaneous field of view of MODIS (250 and 500 m2) as compared to AVHRR instruments (1 km2). Second, MODIS was built with seven bands specifically designed for land cover monitoring, allowing for greater mapping accuracy due to more robust spectral signatures. It also reduces background scattering from adjacent pixels as the MODIS land bands were designed to limit the impact of atmospheric scattering. Third, 500-m red and near-infrared data, two bands important for land cover mapping, are created from averaged 250-m imagery. This resampling reduces the percent contribution of adjacency effects on 500-m pixels for these bands, allowing for improved land cover estimates. The result is a dataset that reveals far more spatial detail than previous efforts.
For our purpose the great differences between the coarser-scale maps in the pre-MODIS era prevents a comparison on pre-2001 vegetation data with the MODIS data. It is a primary reason for focusing our analysis to the 2001-2008 period even though we have killings data in the pre-2000 years.

upon the difficulties of measuring poverty consistently over time from the NSS data. Translating an objective poverty baseline measure based on calorific intake into a measure based on consumption spending in rupees is fraught with problems. Changes in the price of food and measurement error in changes in the quantity and quality of food consumed lead to measurement error in measuring the poverty line, based on which other measures of poverty are calculated, such as poverty headcount. Since our econometric analysis is primarily based on within-district variation in the data, measurement error in every period generates substantial noise biasing estimates severely toward zero.

The literature has attempted to attribute the Maoist conflict to a number of sources including the extent of mining activity in this mineral-rich region of India, the predominance of underprivileged marginalized social groups, specifically tribals (Scheduled Tribe or ST) and of people of lower caste (scheduled caste or SC) in these regions, the possibility of spillover effects from neighboring regions, and the extent of inequality. We have made every attempt to incorporate these influences in our analysis. We measure mining of bauxite and iron ore in each district annually from Indiastat.com and compiled using the Indian Mineral Year Book annual district production figures published by the Indian Bureau of Mines, the proportion of each district's population that is SC and ST (from the NSS), a consumption expenditure Gini at the district level, and the number of the two closest districts that have experienced Maoist violence in the past year to capture possible spillover effects.

In sum, we have assembled a comprehensive data set for the 68 districts in the four red states of Andhra Pradesh, Bihar, Chattisgarh and Jharkhand annually over 2001-08.

Since we incorporate dynamics and use up to three lags, our results are based on 340 observations consisting of a balanced panel of the 68 districts over the period 2004-08. Table A2 in the appendix provides panel descriptive statistics for the variables we use in our analysis **[See Appendix Table A2]**.

5. Results

In Table 1 we examine the correlation between vegetation and total deaths (our core measure of the intensity of conflict). Column 1 shows that vegetation is negatively associated with total deaths and the relationship is significant at the 1% level in an OLS setting. The z statistic at the bottom of the column tests the hypothesis that the three coefficients sum to zero: $\beta1 + \beta2 + \beta3 = 0$. If vegetation and its lags are strongly correlated, their collective significance is relevant. Rejecting the hypothesis, as the z statistic implies, indicates a strong negative association of vegetation with killings. This is our first indication that vegetation is negatively associated with the intensity of conflict **[See Table 1]**.

As mentioned, the column 1 specification is an OLS specification. Since our dependent variable is a count variable it is worth checking if the result changes when we apply a negative binomial model.[21] Since the NB model encompasses the Poisson model (which assumes that the conditional mean of killings equals its conditional standard deviation) it allows a test of whether the Poisson model is appropriate. The parameter α tests for over-dispersion and rejects the Poisson process for killings. Column 2 shows the results are substantively unchanged with the NB model.

[21] The link function in the NB model is log-linear, so the OLS model in logs produces coefficients comparable to those from the NB model.

Time series scholars are concerned that panels with short T (less than 15) may be afflicted with Nickell bias when fixed effects and the lagged dependent variable are simultaneously included in the same specification (Nickell 1981). In columns 3 and 4 we thus check if the results change when the lagged dependent variable is dropped from the column 1 and 2 specifications and find that there is no substantive difference. (This is not surprising given the low serial correlation in killings; the low serial correlation is consistent with a stop-start pattern to fighting within districts reported in the press.) The Arellano Bond GMM approach offers an alternative technique to address Nickell bias. Our results are robust to the use of the Arellano-Bond technique (not shown).[22] Corresponding results with the consumption proxy are presented in the first four columns of Appendix Table A3. The results are substantively very similar and support inferences from the vegetation results. While the consumption results are in the appendix due to the concerns we have noted about measurement issues pertaining to the NSS consumption spending data, we take those results as an affirmation of our main findings from the vegetation data **[See Appendix Table A3]**.

Vegetation may be endogenous to conflict, for example if the police clear forests for ease of fighting. If shocks to killings are negatively correlated with vegetation because forests are denuded to facilitate counter-insurgency, then the negative coefficients on vegetation in Table 1 may be the result of this endogeneity bias. In order to address this concern we resort to an instrumental variables strategy, using rainfall as our instrument

[22] The Arellano-Bond results are available from the authors. They mirror the IV results we present. Even though the Arellano-Bond models are in first differences, and hence capture changes in the variables, their similar results are a strong robustness check of our core OLS-IV and NB-IV results.

for vegetation. Table 2 shows the strong relationship between rainfall and vegetation, affirming the case for rainfall as a good instrument for vegetation. Both, the first-stage *F*-statistics as well as the partial *R2* are significantly large. The Kleibergen-Paap Wald statistic of 10.19 indicates no weak instruments problem. Specifically, the K-P statistic implies the (small-sample) bias in the 2-stage estimates is less than 5% of the bias in the corresponding OLS estimates in Table 1 (Stock and Yogo 2004). As the table shows, there is generally a positive association between lagged rainfall and vegetation. The only significant negative coefficients are for forward variables – contemporaneous and once lagged rain in the twice lagged rain regression – which is explained by mean reversion because of which we see good rain years following bad rain years **[See Table 2]**.

Table 3 shows our core instrumental variables second stage results.[23] In column 1 we report the results for a linear instrumental variables regression (OLS-IV). The strong negative association between vegetation and total deaths remains even with instrumentation. The point estimates are larger, which is consistent with our instruments addressing measurement error with respect to vegetation. Essentially, the IV results exploit only exogenous variation in vegetation, which allow us to make causal statements. In column 2 we undertake the same exercise, but with a negative binomial model to better account for the count nature of our dependent variable. The results remain substantively unchanged, and are stronger in the same direction as the OLS-IV results **[See Table 3]**.

Note that once causality is addressed the significant coefficients are for lagged vegetation, which is consistent with the causal story that we presented in Section 3. It is

[23] All estimation is done using Stata 11. The 2SLS results use code due to Baum et al. (2007).

also important to test if the point estimates for twice lagged vegetation are significantly larger than those for the more contemporaneous vegetation variables since one variable being insignificant and the other being significant does not imply that the point estimate of the insignificant one is significantly lower than that of the significant one. As the p-values for the differences in point estimates show, we cannot reject the null hypothesis that contemporaneous vegetation shocks have just as large an effect on intensity of conflict as twice lagged vegetation. Our conservative interpretation of these results is that twice lagged vegetation is significantly associated with intensity of conflict, but we cannot reject the possibility that the point estimates for twice lagged vegetation are similar to those for more contemporaneous vegetation variables.[24]

As far as the substantive implications are concerned, the point estimate in column 1 for twice lagged vegetation indicates that a decrease in the vegetation measure NDVI of 0.011 (a one within-standard deviation – see table A2) increases killings by 12.5% contemporaneously, 9.7% after a year and 42.2% after two years. While the contemporaneous and the first lag effects are measured imprecisely, the second lag effect is statistically significant at 1%. The total effect of the three lags is also statistically significant at 1% (as indicated by the z statistic at the bottom of the second stage results). The total effect may be interpreted as an increase of 64% in total deaths over a three year period due to a one (within) standard deviation increase in NDVI in each of the three successive periods.[25]

[24] We indicate here one possible reason why shocks may have a relatively contemporaneous effect. Tribal livelihood depends considerably on the collection of forest produce such as tendu leaves, bamboo culms and tamarind. These are subject to taxation by Maoists. A vegetation shock is therefore an income shock to tribals and Maoists. This forces the Maoists to additionally squeeze other sources of revenues such as construction contractors and mining companies, who have deep pockets but also have better protection. This could result in a contemporaneous killing effect.

[25] Due to mean-reversion in rainfall, and therefore vegetation, this is an unlikely scenario and provides an overestimate

The estimates from the NB model in column 2 are notable as well. A one within-standard deviation decrease in NDVI increases killings by 16.5% contemporaneously, 27.7% after a one-year lag and 76.1% after a two-year lag. Columns 3 and 4 of Table 3 show that the results are substantively unchanged if we drop the lagged dependent variable from the column 1 and 2 specifications (to address Nickell bias concerns).

The Hansen *J*-statistic cannot reject the joint null hypothesis that (i) the instruments are uncorrelated with the error term, and (ii) the instruments (rainfall) are correctly excluded from the estimated equation. The Anderson-Rubin (A-R) statistic tests the significance of the endogenous regressors. The statistic rejects the joint null hypothesis that the coefficients of the endogenous regressors in the structural equation (the three vegetation measures) are jointly equal to zero.[26] This statistic is important in assessing the results when instruments are weak. The rejection of the null is perhaps not surprising in this case since rainfall instruments vegetation well.

In line with measurement error concerns described above, consumption only instruments weakly with rainfall. While not emphasizing these results by any means we can show that statistics that take account of the degree of weakness of the instrument (effectively penalizing weakness) yield results that are broadly similar to those reported

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of the total effect.

[26] The AR statistic actually tests the *joint* null hypothesis that (i) the coefficients of the endogenous regressors in the structural equation are each equal to zero, and that (ii) the overidentifying restrictions are valid. Thus, the AR statistic can reject either because the endogenous regressors are significant (here $\beta 1=0$, $\beta 2=0$, and $\beta 3=0$) or because the instrument orthogonality (with the error) conditions fail. A variety of tests have been proposed (Kleibergen 2002; Moreira 2003) that maintain the hypothesis that the instruments are valid. Moreira shows that the AR test is optimal when the equation is just identified (number of excluded instruments equals the number of endogenous variables), which is the case here. A caveat is that with extremely weak instruments and strong endogeneity of the regressors, the power of the A-R test (its ability to not falsely reject) may be poor.

above. We refer in particular to the Anderson Rubin weak instrument robust p-value. Results with consumption replacing vegetation are presented in the final two columns of Table A3. The individual coefficients on consumption and its two lags are statistically insignificant. However, their insignificance may be driven by the inability of rainfall to instrument consumption adequately, not because consumption is irrelevant. The A-R statistic of 3.55 rejects the null hypothesis that the coefficients on the three consumption variables are jointly zero, at the 1% level.[27]

What is the effect of successive years of vegetation depletion on violence in Maoist areas? We investigate the impact of vegetation depletion by interacting the three lagged vegetation variables Vegetation_t, Vegetation_{t-1}, and Vegetation_{t-2}. The interactions are highly correlated with the individual lagged measures, and including a full set of variables produces collinear models whose coefficient estimates are not individually informative.[28] In the last three columns of Table 3 we present results from the set of interactions that are informative. The vegetation interactions are instrumented with the three rainfall lags and their interactions.

If the interactions have negative coefficients, it implies that successive years of depletion only worsen violence. The first column shows that Vegetation_{t-2} and its interaction with Vegetation_t and Vegetation_{t-1}have negative coefficients, although none of

[27] The small Kleibergen-Paap statistics in Table A3 indicate that rainfall is a weak instrument for consumption. The problem of weak instruments has deservedly attracted much attention, for strong instruments are hard to find. A set of "weak-instrument robust" tests, beginning with Anderson and Rubin (1949, A-R), seek to produce valid inference about endogenous regressors and confidence intervals for their coefficients despite the weakness of instruments. Kleibergen (2002) and Moriera (2003) are two prime examples of such "conditional" tests. We turn to the traditional A-R statistic to test of the significance of the consumption regressors.

[28] The partial correlation (after partialing out district and year fixed effects) of Vegetationt and the interaction (Vegetationt-1, ×Vegetationt-1), for example, is over 0.75. Including all possible interactions and the linear terms leads to large coefficients and standard errors, with opposite signs.

them are statistically significant. This is likely due to the collinearity among the three variables.[29] Dropping the linear term Vegetation$_{t\text{-}2}$, in the next columns yields negative signs on both interaction terms and a statistically significant estimate on Vegetation$_{t\text{-}2}$ × Vegetation$_{t\text{-}1}$. This implies that the marginal effect of an increase in 2-period lagged vegetation, or ∂ Total Deaths / ∂ Vegetation$_{t\text{-}2}$, equals (-36.89 × Vegetation$_t$) – (84.83 × Vegetation$_{t\text{-}1}$). Evaluated at their means, the marginal effect is -49.94, implying that a one-sd increase (of 0.011) in 2-period lagged vegetation decreases total killings by 55%.

The last column shows results from one-lag interactions of Vegetation$_{t\text{-}2}$ with Vegetation$_{t\text{-}1}$ and Vegetation$_{t\text{-}1}$ with Vegetation$_t$. The negative and statistically significant coefficient on Vegetationt-2 × Vegetationt-1 indicates that the impact on killings due to the denuding of vegetation two periods ago (t-2) is strongly exacerbated if the vegetation is not renewed in the following year (t-1). The marginal effect ∂ Total Deaths / ∂ Vegetation$_{t\text{-}2}$, equals -45.92 and is precisely measured. It affirms the finding above.

We now disaggregate total deaths into civilian casualties, Maoist (militants) casualties, and security (police) casualties. Table 4 presents instrumental variables results for these categories using the same IV strategy as for the first two columns of Table 3. The negative relationship between vegetation and casualties is in evidence for all three types of casualties. We also do not see a robust difference in the responses to vegetation of different types of casualties. (The slight difference in timing in the OLS-IV does not carry over into the negative binomial IV regressions.) Our first-hand experience with gathering killings data indicates civilian victims are sometimes classified as Maoists (especially when

[29] They are, however, informative about the marginal effect (see below).

the incident is reported by the security forces). Combining the two categories yields very similar results.[30] **[See Table 4]**

One potential concern is whether the vegetation results reflect aspects of the technology of fighting. Less vegetation could change the balance of power between security forces and rebels by making it harder for rebels to conduct insurgency operations from the forest because it is harder for them to remain hidden as they attack or retreat, and therefore in conducting guerilla operations. In addition, thinner vegetation should make it easier for security forces to conduct counterinsurgency operations and kill rebels because the latter will find it harder to hide. If either of these mechanisms is driving the results, vegetation should be *positively* associated with security deaths minus rebel deaths. The OLS-IV results in the column labeled “ln(Sec) – ln(Mao)” in Table 4 show that this is not the case and this increases our confidence that our vegetation results are likely not picking aspects of the technology of fighting.[31] The other reason to believe that our results are not driven by such technological concerns is the fact that contemporaneous vegetation is not robustly associated with any type of casualty (and there is no good purely technological reason why vegetation two years ago should have an effect on conflict now).

We now consider the influence of several key control variables on our core regressions. These variables have appeared in other studies and in popular stories and reports of the conflict. Mining contracts sold by the state to firms for bauxite and iron ore mining that rampantly denude forest lands and displaces its denizens, have been blamed as a source of conflict. Tribals and the lower caste population have been especially

[30] These results are available from the authors.
[31] An NB specification is not justified here because there is no truncation at 0 of this variable.

affected by such actions, and districts with greater proportion of SC and ST populations are likely to experience greater displacement and therefore propensity to violence as they are recruited into the Maoist fold. Income inequality may be a uniting force among insurgents and districts with greater inequality have been shown to experience greater intensity of conflict in Nepal's Maoist insurgency (Nepal, Bohara and Gawande 2011). Finally, the incidence of conflict in neighboring districts may spill over into conflict in the present district **[See Table 5]**.

Table 5 examines the robustness of our primary results to the inclusion of these influences as control variables. The first five columns include each of these controls, one variable at a time in the OLS-IV models. The spillover effect is statistically significant and indicates that if one of the closest two neighboring districts experiences Maoist violence, then killings increase 26.4%. While there is evidence that SC, inequality and mining all increase killings, that evidence is weak since the coefficients are statistically not significant. The sixth column pools these controls into one specification. Two results are notable. The first is that core results are unchanged with the addition of these controls. Second, the proportion of the ST population is positively associated with more deaths. An increase of .01 in the tribal population (on account of migration, for example), results in a 1.606% increase in killings.

Could our results be driven by states in which Scheduled Tribes have not achieved representation in the set of parties that are competing in state politics? The states where there is such representation are Jharkhand and Chhattisgarh, which were carved out as separate states in 2000 precisely to ensure greater representation of tribals. Ironically the

Maoist insurgency surged in these areas after the new states were created and the tribals got more political representation. In Table 6 we interact the vegetation variables and state dummies, with Andhra Pradesh as the baseline (excluded) state. The z statistics at the bottom summarize the results by summing the coefficients for each state across the three coefficients for each state (contemporaneous plus two lags). These coefficients test the hypothesis that the state's "total effect," that is, the sum of its coefficients relative to the Andhra Pradesh sum, equals zero. The *z*-statistics for the OLS_IV regression indicates that the total effect of vegetation is *negative* in all states. The only state for which the total effect of vegetation is insignificant in the OLS-IV regression is Chhattisgarh. (The *z*-statistic in the Negative Binomial regression is positive, albeit insignificant.) We verified that the effect for Chhattisgarh is significantly lower than for Jharkhand where representation of Scheduled Tribes is highest. This suggests that lack of political representation is likely not the reason for the differences across states. It also suggests that the results are not driven by differences in state capacity (since both Chhattisgarh and Jharkhand are considered to have exceptionally weak states).

There are two logical explanations for the lack of a vegetation effect in Chhattisgarh. One stems from the security strategy, unique to Chhattisgarh, of sequestering large numbers of tribals in camps that are close to main roads and are separated from their traditional agricultural and forest lands (Boyini 2010).[32] This would logically render their livelihoods less sensitive to vegetation shocks and thus dampen the vegetation-conflict link. A second possible explanation stems from the fact that Chattisgarh differs from the

[32] Guha (2007) points to tribals being herded "in roadside camps controlled by the Salwa Judum. As many as fifty thousand people have been displaced from their homes." Sundar (2007: 279) cites a wireless message from a senior police official, "The janjagaran people are telling very clearly to villagers "you come with us first time, or second time. If you do not come third time, we will burn your village…"

other states in having a state sponsored private militia (Salwa Judum) whose strategy is to deter collaboration of civilians with Maoists by a policy of randomized terror (which by virtue of its random targeting would dampen the correlation between vegetation and deaths).[33] **[See Table 6]**

While not affecting our claims with respect to the hard core Maoist belt states it interesting to assess the effects of slightly expanding the definition of the Maoist belt. The most logical expansion is to Orissa because, while not traditionally considered to be part of the Maoist belt, parts of Orissa were subject to Maoist conflict. We coded killings in Orissa and checked if our core Table 3 results were affected by the inclusion of Orissa. We found that our core results were unchanged.[34]

Finally, could the results be driven by violations of the exclusion restriction? One possible violation highlighted by Sarsons (2011) in the context of riots all over India lies in the need to account for the building of large dams in our analysis. This may be a relevant consideration for an analysis which includes western India (where over two thirds of India's large dams are present and where most of India's dam building occurs). However, it is not a serious consideration for our analysis because there is no time variation for our region of analysis in the building of large dams. (Using the standard definition of 50 meters, no new large dams were built in our region after 2000.)

Another exclusion-restriction-related consideration is that fighters may not want to fight when it is raining, so rainfall may be directly affecting conflict via this mechanism.

[33] See Guha (2007), Chakaravarti (2008), and Sundar (2007, 78).
[34] Results with the 13 additional districts of Orissa included are available from the authors.

This violation is hard to measure. Whether or not this biases against our results and whether the bias is large enough to kill our result thus remains an unknown. However, we do note that this is not likely to be a serious factor affecting our analysis because our dataset indicates that the most killings occur outside of the rainfall season in good and bad rainfall years alike.

6. Conclusion

We have demonstrated that even after addressing endogeneity concerns and subjecting our findings to multiple robustness checks there is a strong and substantively large relationship between adverse renewable resource shocks and the intensity of conflict in the Maoist belt of India. Aside from contributing to a central debate in the civil conflict literature, this paper offers some policy implications. One approach would be to help citizens deal with adverse income shocks that result from adverse renewable resource shocks. This could be done in several ways. The creation of the National Rural Employment Guarantee Act (NREGA) could offer promise as an insurance against income shocks. (NREGA only came into effect midway through our period of analysis, so we cannot offer any firm statistical results along this line.) Another option might be to implement a catastrophic insurance scheme. While this does not seem feasible now since these communities are far from any financial inclusion, after the roll-out of the Unique ID scheme to these communities, it could become feasible. However, to the extent that these options rely on the same government machinery that has, through acts of commission, exacerbated the plight of tribals, their prospects may be questionable.

Our paper however suggests an alternative path that relies less heavily on the government's technical capability. Giving tribals greater access to forests and a range of forest products, whose consumption is the only available option during times of distress, can provide them with a critical self-insurance mechanism. Tribals have been denied this access for many years, especially after passage of the Forest Conservation Act of 1980. Reversing this situation was the goal of the Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act 2006, which came into force on 1st January 2008. Our paper suggests that rigorous implementation of the government withdrawal called upon by this act may offer promise.

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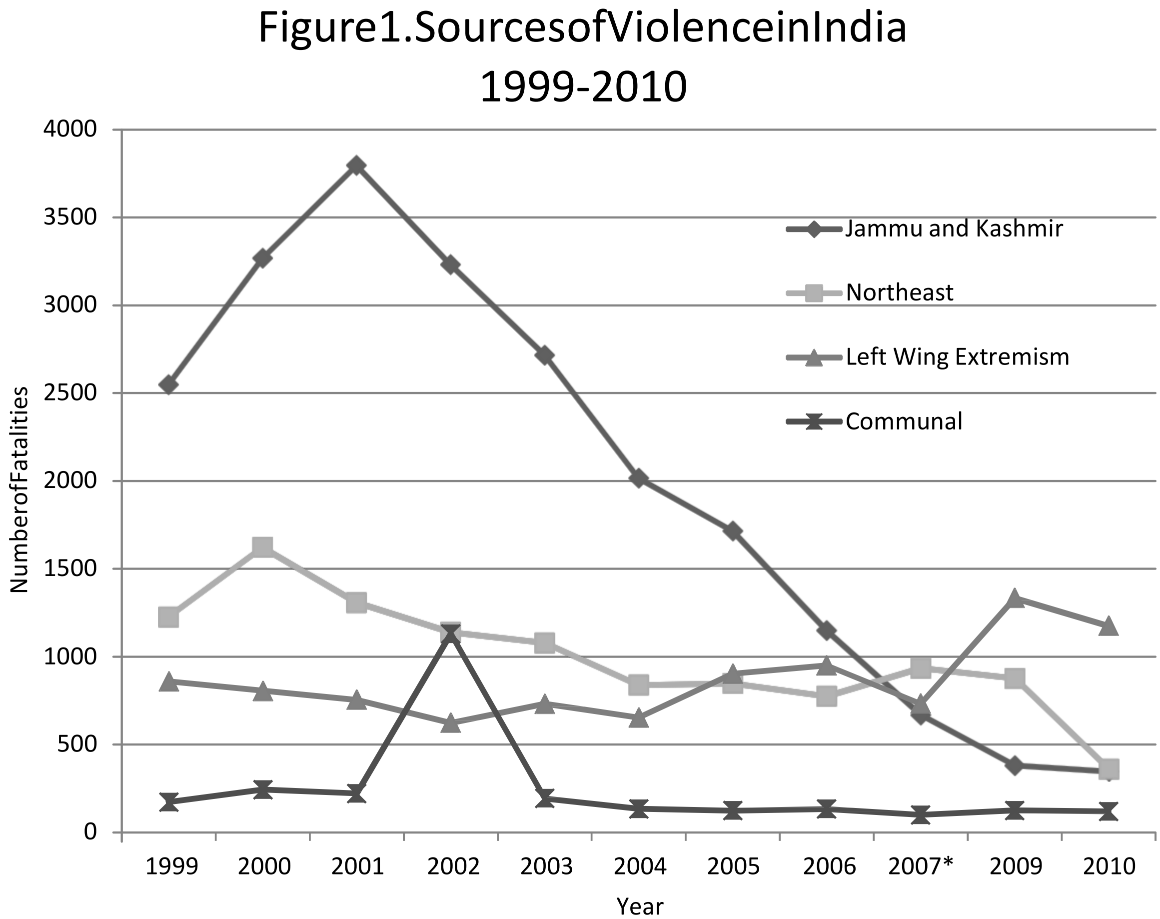

Source:(i) Ministry of Home Affairs Annual Reports (various years), (ii) Indiastat

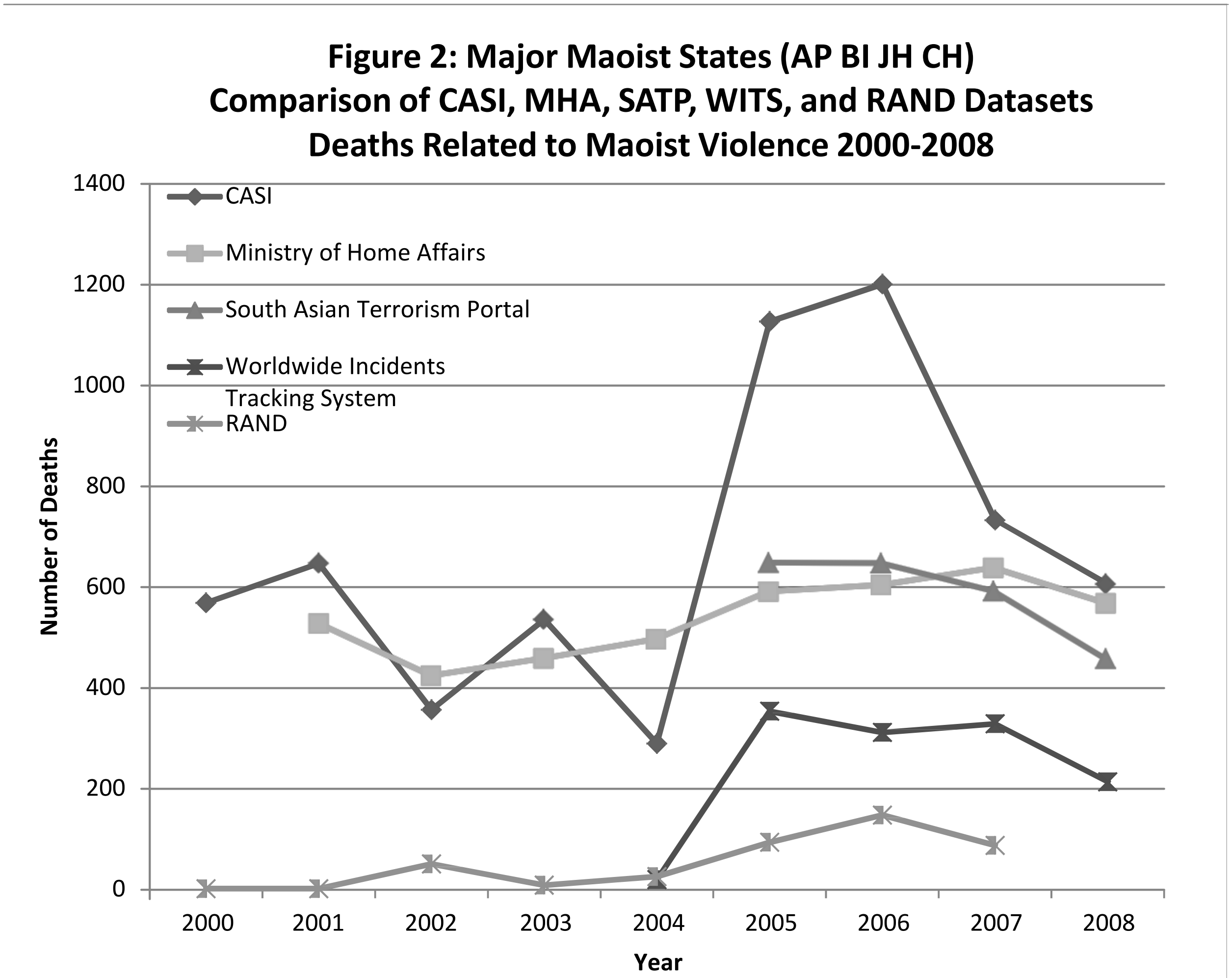
Figure 2: Major Maoist States (AP BI JH CH)
Comparison of CASI, MHA, SATP, WITS, and RAND Datasets
Deaths Related to Maoist Violence 2000-2008
CASI
Ministry of Home Affairs
South Asian Terrorism Portal
Worldwide Incidents Tracking System
RAND
Number of Deaths
1400
1200
1000
800
600
400
200
0
2000
2001
2002
2003
2004
2005
2006
2007
2008
Year

Table 1: Vegetation and Total Deaths from Maoist incidents
OLS and Negative Binomial (NB) models (Uninstrumented)

Dependent Variable : Total Deaths. (logged for OLS)

	OLS	NB	OLS	NB
ln(Total Deaths)$_{t-1}$	0.0802	0.0944		
	[0.0693]	[0.106]		
Vegetation$_t$	−13.99***	−21.87***	−13.87***	−21.75***
	[4.732]	[7.215]	[4.789]	[7.257]
Vegetation$_{t-1}$	−7.857*	−16.48**	−8.234*	−17.20**
	[4.565]	[7.399]	[4.569]	[7.287]
Vegetation$_{t-2}$	−7.827	−14.33*	−8.398	−15.10*
	[5.567]	[8.287]	[5.701]	[8.362]
N	340	340	340	340
R^2	0.13	0.205	0.125	0.205
k	77	77	76	76
α		1.098***		1.105***
z_{VEG}	−2.964***	−4.133***	−2.98***	−4.232***

Note:

1. Robust standard errors in brackets. Clustered (by disctrict) in OLS models.
   *** p<0.01, ** p<0.05, * p<0.1
2. All models include district fixed effects and year dummies. NB models estimated with true fixed-effects (in the model).
3. Dependent variable in NB models is Total Deaths, but coefficients interpreted as log-linear. Pseudo R2 repotrted in NB models
4. α is the overdispersion parameter in NB model. α > 0 indicates overdispersion; α = 0 indicates Poisson is appropriate.
5. All coefficients are to be interpreted as in a log-linear model.
6. z_{VEG} tests the hypothesis: Vegetation$_t$ + Vegetation$_{t-1}$ + Vegetation$_{t-2}$ = 0.
7. Models without lagged dependent variables are reported to check for Nickell bias (Nickell 1981).

Table 2: First stage for IV results

Dependent variable: Lags of Vegetation Index (NDVI)

	Vegetation_t	$\text{Vegetation}_{t\,-1}$	$\text{Vegetation}_{t\,-2}$	Vegetation_t	$\text{Vegetation}_{t\,-1}$	$\text{Vegetation}_{t\,-2}$
$\ln(\text{Total Deaths})_{t-1}$	0.0002	−0.001	−0.001			
	[0.001]	[0.001]	[0.001]			
Rain_t	−0.104	−0.0144	−0.652***	−0.108	−0.0017	−0.639***
	[0.243]	[0.247]	[0.247]	[0.243]	[0.246]	[0.246]
Rain_{t-1}	1.393***	0.0828	−0.369*	1.396***	0.0709	−0.381*
	[0.211]	[0.238]	[0.216]	[0.211]	[0.239]	[0.217]
Rain_{t-2}	0.272	1.585***	0.0688	0.271	1.590***	0.0733
	[0.225]	[0.223]	[0.254]	[0.224]	[0.225]	[0.253]
Rain_{t-3}	1.189***	0.419	1.349***	1.181***	0.446*	1.376***
	[0.254]	[0.256]	[0.253]	[0.254]	[0.253]	[0.253]
District fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	340	340	340	340	340	340
R^2	0.218	0.222	0.206	0.217	0.219	0.202
k	78	78	78	77	77	77
Weak Instrument Diagnosis:						
Partial R^2	0.14	0.134	0.158	0.14	0.135	0.162
First-stage F	12.86	13.61	14.55	12,89	13.42	15
Kleibergen-Paap (WI)		10.19			10.25	

Note:

1. Robust standard errors clustered (by district). *** p<0.01, ** p<0.05, * p<0.1
2. Models include 68 district fixed effects and 5 year dummies.

Table 3: Vegetation and Total Deaths from Maoist incidents
IV models. *Dependent Variable* : Total Deaths (logged for OLS-IV)

	Vegetation				Vegetation Interactions		
	OLS-IV	**NB-IV**	**OLS-IV**	**NB-IV**	**NB-IV**	**NB-IV**	**NB-IV**
SECOND STAGE:							
ln(Total Deaths)$_{t-1}$	0.0398	0.104			0.070	0.0729	0.0793
	[0.0780]	[0.102]			[0.101]	[0.101]	[0.101]
Vegetation$_t$	−11.54	−15.05	−11.35	−14.75			
	[14.28]	[20.08]	[14.20]	[19.99]			
Vegetation$_{t-1}$	−8.831	−25.17	−8.905	−24.54			
	[13.31]	[22.47]	[13.31]	[22.24]			
Vegetation$_{t-2}$	−38.45***	−69.15***	−39.16***	−70.97***	−27.79		
	[14.49]	[23.60]	[14.38]	[23.76]	[39.76]		
Vegetation$_{t-2}$ × Veg$_t$					−22.29	−36.89	
					[35.33]	[33.27]	
Vegetation$_{t-2}$ × Veg$_{t-1}$					−66.71	−84.83**	−101.8***
					[43.23]	[33.70]	[37.00]
Vegetation$_t$ × Veg$_{t-1}$							−10.76
							[32.33]
N	340	340	340	340	340	340	340
k	77	77	76	76	80	79	80
α		1.107***		1.115***	1.094***	1.099***	1.103***
$z_{(\Sigma\ VEGt)}$	−3.276***	−3.647***	−3.335***	−3.629***			
p-val$_{(\Sigma\ VEGt)}$	0.001	0.0003	0.001	0.0003			
p-val$_{(VEGt - VEGt\text{-}1)}$	0.896	0.761	0.906	0.763			
p-val$_{(VEGt - VEGt\text{-}2)}$	0.251	0.081	0.230	0.071			
p-val$_{(VEGt\text{-}1 - VEGt\text{-}2)}$	0.173	0.245	0.167	0.219			
∂ ln(Total Deaths) /∂ Veg$_{t-2}$					−64.3***	−49.94***	−45.92***
					[25.46]	[11.80]	[11.12]
∂ ln(Total Deaths) /∂ Veg$_t$							−4.413
							[13.25]
FIRST STAGE:							
#Instruments	4		4				
Kleibergen-Paap (WI)	10.19		10.25				
Hansen's *J*	0.060		0.084				
Hansen's *J* (*p*- value)	0.807		0.772				
Anderson-Rubin (A-R)	3.547		3.752				
Anderson-Rubin (*p* val)	0.008		0.005				

Note:

1. Robust standard errors in brackets. Clustered (by district) in OLS models.*** p<0.01, ** p<0.05, * p<0.1
2. See Notes to Table 1
3. NB-IV models: Predicted endogenous variables in first stage used as regressors in the second stage.
4. ∂ ln(Deaths) /∂ Vegetation$_{t-2}$ reported at the means of other interactions.
5. p-val$_{(VEGt - VEGt\text{-}1)}$ is the p-value for the hypothesis test Vegetation$_t$ = Vegetation$_{t\text{-}1}$

Table 4: Robustness: Killings disaggregated by:
(1) # Civilians killed, (2) # Maoists killed, and (3) # Security Personnel killed

	OLS - IV				NB - IV		
	ln(Civilian)	ln(Maoist)	ln(Security)	ln(Sec)−ln(Mao)	Civilian	Maoist	Security
Vegetation_{t}	−14.83	−1.648	−17.84**	−16.63	−31.51	8.53	−54.78
	[10.65]	[12.06]	[8.655]	[14.05]	[26.19]	[25.52]	[38.51]
Vegetation_{t-1}	−14.25	−1.927	2.287	4.174	−53.31*	15.87	−25.39
	[11.02]	[11.01]	[8.497]	[11.36]	[29.61]	[27.58]	[34.42]
Vegetation_{t-2}	−22.79**	−22.65*	−12.77	9.682	−54.46**	−72.94**	−75.83**
	[9.868]	[12.45]	[8.758]	[14.39]	[26.88]	[30.62]	[36.74]
$\text{ln(Civilian Deaths)}_{t-1}$	−0.008				0.036		
	[0.094]				[0.150]		
$\text{ln(Maoist Deaths)}_{t-1}$		−0.016				−0.082	
		[0.075]				[0.122]	
$\text{ln(Security Deaths)}_{t-1}$			0.044				−0.128
			[0.103]				[0.198]
$\text{ln(Total Deaths)}_{t-1}$				−0.0177			
				[0.074]			
$z_{(\Sigma \text{ VEG}t)}$	−3.652***	−1.712*	−2.494**	−0.147	−3.518***	−1.272	−3.301***
$p\text{-val}_{(\Sigma \text{ VEG}t)}$	0.0003	0.088	0.013	0.883	0.0004	0.203	0.001
$p\text{-val}_{(\text{VEG}t - \text{VEG}t\text{-2})}$	0.642	0.288	0.713	0.230	0.565	0.048	0.744
N	340	340	340	340	340	340	340
k	77	77	77	77	77	77	77
α					1.252***	1.332***	1.76***
#Instruments	4	4	4	4			
Kleibergen-Paap	10.4	10.12	10.22	10.19			
Hansen's *J*	5.475	1.451	1.628	0.127			
Hansen (*p*- val)	0.019	0.228	0.202	0.722			
Anderson-Rubin	4.575	1.632	2.881	0.485			
A-R (*p*-val)	0.001	0.167	0.023	0.746			

Note:

1. Robust standard errors in brackets. Clustered (by district) in OLS models. *** p<0.01, ** p<0.05, * p<0.1
2. See Notes to Table 3.

Table 5: Controls: Spatial Effects, SC/ST, Mining, Inequality
Dependent Variable : Total Deaths (logged for OLS-IV)

	OLS-IV						NB-IV					
ln(Total Deaths)$_t$	0.0377	0.041	0.05	0.031	0.015	0.020	0.085	0.112	0.113	0.101	0.094	0.091
	[0.0765]	[0.078]	[0.078]	[0.078]	[0.080]	[0.078]	[0.099]	[0.103]	[0.101]	[0.103]	[0.100]	[0.097]
Vegetation$_t$	−8.955	−10.09	−12.74	−10.33	−11.11	−7.445	−9.682	−13.29	−17.54	−13.88	−15.21	−8.313
	[14.51]	[14.45]	[14.28]	[14.28]	[14.56]	[14.72]	[20.31]	[20.25]	[20.45]	[20.23]	[20.08]	[21.02]
Vegetation$_{t-1}$	−6.765	−7.461	−7.973	−8.333	−10.09	−3.724	−18.99	−22.04	−21.23	−24.58	−26.06	−4.906
	[13.13]	[13.64]	[13.35]	[13.46]	[13.10]	[13.28]	[22.24]	[22.95]	[23.02]	[22.95]	[22.27]	[23.55]
Vegetation$_{t-2}$	−35.49**	−39.57***	−37.45**	−40.60***	−41.86***	−40.65***	−67.13***	−70.01***	−69.17***	−71.51***	−73.11***	−74.03***
	[13.93]	[14.66]	[14.51]	[14.49]	[15.81]	[15.27]	[22.53]	[23.69]	[23.98]	[23.59]	[24.43]	[23.65]
Neighborhood2	0.264**					0.324**	0.326*					0.514***
	[0.125]					[0.131]	[0.167]					[0.178]
Proportion SC		0.916				1.022		1.443				2.338*
		[0.704]				[0.710]		[1.301]				[1.345]
Proportion ST			0.841			1.606**			2.101			3.333***
			[0.832]			[0.796]			[1.320]			[1.286]
Consumption GINI				1.076		1.409				0.952		1.412
				[1.162]		[1.181]				[1.467]		[1.476]
Value of Mining Output					0.059	0.069					0.082	0.105
					[0.048]	[0.048]					[0.087]	[0.097]
z_{VEG}	−2.74***	−3.17***	−3.25***	−3.29***	−3.35***	−2.69***	−3.10***	−3.50***	−3.58***	−3.67***	−3.73***	−2.73***
N	340	340	340	335	340	335	340	340	340	335	340	335
k	81	81	81	81	81	85	81	81	81	81	81	85
α							1.067	1.101	1.106	1.122	1.103	1.027
#Instruments	4	4	4	4	4	4	4	4	4	4	4	4
Kleibergen-Paap	10.26	9.76	10	10.35	9.684	9.409						
Hansen's *J*	0.019	0.037	0.056	0.075	0.016	0.003						
Hansen (*p*- val)	0.889	0.847	0.812	0.784	0.898	0.957						
Anderson-Rubin	2.743	3.519	3.453	3.789	3.576	2.845						
A-R (*p* -val)	0.029	0.008	0.009	0.005	0.007	0.025						

Note:
1. Robust standard errors in brackets. Clustered (by district) in OLS models. *** p<0.01, ** p<0.05, * p<0.1
2. See Notes to Table 3.

Table 6: Robustness: By State

Dependent Variable : Total Deaths (logged for OLS-IV)

	OLS-IV	NB-IV
ln(Total Deaths)$_{t-1}$	0.054	0.069
	[0.061]	[0.095]
Vegetation$_t$	−3.059	5.124
	[13.57]	[20.75]
Vegetation$_{t-1}$	−19.87	−42.60*
	[13.28]	[23.96]
Vegetation$_{t-2}$	−39.13**	−74.16***
	[14.98]	[25.84]
BIHAR × Vegetation$_t$	−7.416	−24.24
	[8.841]	[15.65]
BIHAR × Vegetation$_{t-1}$	9.27	16.77
	[7.699]	[15.99]
BIHAR × Vegetation$_{t-2}$	−7.709	−4.382
	[12.42]	[21.60]
CHATTIS × Vegetation$_t$	10.09	21.25
	[25.02]	[31.57]
CHATTIS × Vegetation$_{t-1}$	−4.477	28.92
	[18.77]	[24.02]
CHATTIS × Vegetation$_{t-2}$	44.87***	95.39***
	[8.697]	[19.31]
JHAR × Vegetation$_t$	−36.51**	−83.11***
	[17.77]	[28.72]
JHAR × Vegetation$_{t-1}$	−2.222	−2.885
	[12.36]	[23.21]
JHAR × Vegetation$_{t-2}$	6.546	−6.761
	[17.08]	[28.45]
$z_{\text{VEG (Andhra Pradesh)}}$	−3.641***	−3.497***
$z_{\text{VEG (BIHAR)}}$	−2.564***	−3.271***
$z_{\text{VEG (CHATTISGARH)}}$	−0.244	0.568
$z_{\text{VEG (JHARKHAND)}}$	−2.775***	−3.969***
N	340	340
α		0.98***

Note:

1. $z_{\text{VEG (Andhra Pradesh)}}$ is the z-statistic for the hypothesis of the *total effect* for AP: Vegetation$_t$ + Vegetation$_{t-1}$ + Vegetation$_{t-2}$ = 0.

   $z_{\text{VEG (JHARKHAND)}}$ is the z-statistic for the total effect for Jharkhand:
   (Vegetation$_t$ + Vegetation$_{t-1}$ + Vegetation$_{t-2}$)
   + (JHAR×Vegetation$_t$ + JHAR×Vegetation$_{t-1}$ + JHAR×Vegetation$_{t-2}$) = 0

Table A1. Media Sources for Data Base on Maoist Incidents

	State	**Media Source**
1	Andhra Pradesh	(E) Indian Express; The Hindu (V) Eenadu (WS) PTI; IANS
2	Bihar	(E) Indian Express; The Hindu; Times of India (Patna ed.) ; Telegraph (V) Hindustan; Prabhat Khabar (WS) PTI; IANS
3	Chhattisgarh	(E) Indian Express; The Hindu (V) Deshbandhu; Harit Pradesh; Navbharat; Hindustan (WS) PTI; IANS
6	Jharkhand	(E) Indian Express; The Hindu; Times of India(Patna ed.); Telegraph (V) Hindustan; Prabhat Khabar (WS) PTI; IANS

(E): English Language Daily
(V): Vernacular/Local Language Daily
(WS): Wire Services. PTI: Press Trust of India; IANS: India Abroad News Service (2000-2009).

Table A2: Descriptive Statistics

		Mean	sd	*N*
Total Deaths (#)	overall	11.51	45.44	340
	within		28.20	
Civilian Deaths (#)	overall	4.506	23.78	340
	within		17.72	
Maoist Deaths (#)	overall	4.353	13.27	340
	within		8.790	
Security Deaths (#)	overall	2.649	14.71	340
	within		9.828	
ln(Total Deaths)	overall	1.205	1.401	340
	within		0.844	
ln(Civilian Deaths)	overall	0.686	1.054	340
	within		0.711	
ln(Maoist Deaths)	overall	0.719	1.122	340
	within		0.701	
ln(Security Deaths)	overall	0.430	0.888	340
	within		0.605	
Vegetation (NDVI measure, range [−1, +1])	overall	0.411	0.310	340
	within		0.011	
Vegetation (Predicted)	overall	0.411	0.310	340
	within		0.005	
Consumption ('000 Rupees per month)	overall	0.640	0.243	340
	within		0.136	
Consumption (Predicted)	overall	0.640	0.223	340
	within		0.095	
Neighborhood2 (number of closest two districts with killings)	overall	0.903	0.802	340
	within		0.478	
Proportion Scheduled Caste (SC)	overall	0.187	0.118	340
	within		0.075	
Proportion Scheduled Tribe (ST)	overall	0.117	0.187	340
	within		0.059	
Consumption Gini	overall	0.257	0.068	335
	within		0.044	
Consumption 90 percentile / 10 percentile	overall	0.427	0.110	335
	within		0.076	
Value of Iron Ore Output (Rupees Billion)	overall	0.443	2.942	340
	within		1.532	
Value of Bauxite Output (Rupees Billion)	overall	0.013	0.060	340
	within		0.032	
Value of Mining Output (sum of iron ore and bauxite)	overall	0.455	2.950	340
	within		1.542	

Note: 2004-2008 for 68 districts in AP, BI, CH, JH.

Table A3: Total Deaths from Maoist incidents and its association with Consumption Spending

Dependent Variable : ln(Total Deaths)

	Uninstrumented			
	OLS	NB	OLS	NB
ln(Total Deaths)$_{t-1}$	0.0897	0.103		
	[0.0627]	[0.105]		
Consumption$_t$	−0.613	−1.143	−0.635	−1.172
	[0.572]	[0.783]	[0.568]	[0.783]
Consumption$_{t-1}$	−0.917**	−2.160***	−0.947**	−2.213***
	[0.442]	[0.719]	[0.448]	[0.716]
Consumption$_{t-2}$	−0.00175	0.25	−0.0335	0.242
	[0.467]	[0.865]	[0.475]	[0.887]
N	340	340	340	340
k	77	77	76	76
α		1.143***		1.152***
z_{CONSUMP}	−1.556	−2.003**	−1.584	−2.047**

	Instrumented	
	OLS-IV	NB-IV
ln(Total Deaths)$_{t-1}$	0.0465	0.104
	[0.109]	[0.102]
Consumption$_t$	−7.831	−12.45*
	[7.013]	[6.941]
Consumption$_{t-1}$	2.244	1.099
	[7.888]	[8.041]
Consumption$_{t-2}$	−8.859	−15.52**
	[6.419]	[6.839]
N	340	340
k	77	77
α		1.11***
z_{CONSUMP}	−2.023**	−3.771***
FIRST STAGE:		
#Instruments	4	
Kleibergen-Paap (WI)	0.496	
Hansen's *J*	0.054	
Hansen's *J* (*p*- value)	0.816	
Anderson-Rubin (A-R)	3.547	
Anderson-Rubin (*p* -val)	0.008	

Note:

1. Robust standard errors in brackets. Clustered (by district) in OLS models. *** p<0.01, ** p<0.05, * p<0.1
2. See Notes to Table 1 and Table 3