Economics and Human Biology 39 (2020) 100900

Contents lists available at ScienceDirect

Economics and Human Biology

journal homepage: www.elsevier.com/locate/ehb

Political violence, adverse shocks and child malnutrition: Empirical evidence from Andhra Pradesh, India☆

Jean-Pierre Tranchant[a,*], Patricia Justino[b,c], Cathérine Müller[d]

[a] Independent Researcher
[b] Institute of Development Studies, University of Sussex, Library Road, Brighton BN1 9RE, UK
[c] United Nations University - World Institute for Development Economics Research (UNU-WIDER)
[d] UNICEF

ARTICLE INFO

Article history:
Received 31 March 2017
Received in revised form 2 November 2017
Accepted 16 June 2020
Available online 29 June 2020

JEL classification:
I15
I30
O12
O15

Keywords:
Malnutrition
India
Drought
Naxal
Conflict

ABSTRACT

We analyze the combined effect of political violence and adverse climatic and health shocks on child nutrition using longitudinal data from Andhra Pradesh, India. The paper shows three key results using two-stage least square (2SLS) models: (i) the presence of political violence reduces the mean height-for-age *z*-scores of children by between 0.4 and 0.9 standard deviations and reduces the mean weight-for-age *z*-scores of children by between 0.3 and 0.6 standard deviations; (ii) political violence generates such a large negative effect on the long-term nutrition of children (measured by height-for-age *z*-scores) through a reduction of the ability of households to cope with drought and illness; and (iii) drought and illness have an adverse effect on child nutrition in Andhra Pradesh only in violence-affected communities. The 2SLS results are robust to a wide range of robustness tests. Potential mechanisms explaining the strong joint welfare effect of conflict and adverse shocks are the failure of economic coping strategies in areas of violence and restricted access to public goods and services.

1. Introduction

Households in developing countries have to cope with a myriad of uncertain events, some of which may happen simultaneously. One important example is the interplay between climatic shocks and violent conflict, which has received increasing attention in the last few years. Events such as the floods in Pakistan in 2010–2011 and the 2011 drought-induced famine in east Africa have raised awareness about potential interactions between political insecurity, economic vulnerability and the impact of natural disasters (Harris et al., 2013). In the period between 2005 and 2009, more than 50% of people affected by natural disasters lived in conflict-affected countries. This number was around 80% in 2006 and 2008 (Kellett and Sparks, 2012).

Although the extent to which conflict and disasters interact differs across countries and contexts, in general, people living in fragile and conflict-affected states find it harder to cope with natural disasters given the impact of violence and instability on health, basic service provision, social cohesion, mobility opportunities and livelihoods (Buchanan-Smith and Christoplos, 2004; Eriksen and Lind, 2009; Jaspars and O'allaghan, 2010; UNDP, 2011). Existing evidence on how individuals, households and communities cope simultaneously with violence, natural disasters and other covariate and idiosyncratic shocks is, however, largely anecdotal and descriptive. This is partially due to lack of data, but also to challenges in identifying empirical causal effects when endogeneity biases may be potentially large.

☆ This research received funding from the Integrated Project MICROCON (2007–2012) funded by the European Commission under the 6th Framework Program, the European Commission's 7th Framework Program under grant agreements nos. 237156 and 300676, and the ESRC-DFID funded project 'Agency and Governance in Contexts of Civil Conflict'. We would like to thank two anonymous referees, Jean-Louis Arcand and participants at the following seminars and conferences for their helpful comments: HiCN's 7th and 9th Annual Workshops in Barcelona and Berkeley, respectively, the 'Agency and Governance in Contexts of Violent Conflict' International Conference at Northwestern University, the Conflict, Violence and Development Seminar Series at IDS and seminar presentations at the Universities of Goettingen, Nottingham and Portsmouth. Jean-Pierre Tranchant wishes to thank Sandip Sarkar, Prem Chandra and Alakh Sharma for hosting him at the Institute for Human Development in New Delhi while working on parts of the paper.
* Corresponding author.
E-mail addresses: jptranchant@gmail.com (J.-P. Tranchant), p.justino@ids.ac.uk (P. Justino), camuller@unicef.org (C. Müller).

http://dx.doi.org/10.1016/j.ehb.2020.100900
1570-677X/

The objective of this paper is to address this gap in the literature by analyzing the combined effect of exposure to political violence to a household covariate climatic shock (drought) and an idiosyncratic shock (illness) on child nutrition. The context of the analysis is the southern Indian state of Andhra Pradesh, which was for several decades affected by a left-wing (Naxal) guerrilla insurgency. Households in Andhra Pradesh face in addition cyclical climatic shocks and routine health shocks that affect the nutrition levels of their children, often quite severely (Krishna, 2006).[1]

The empirical analysis makes use of the Young Lives longitudinal survey conducted in the state of Andhra Pradesh in 2002 and in 2006–2007. We match this data to an original conflict event dataset at the sub-district (mandal) level we have compiled. Our main identification strategy is based on an instrumental variable approach that makes use of the fact that Naxal insurgents use forest cover in order to avoid detection from state troops.

We find that household exposure to drought and illness in areas of violent conflict exerts a strong long-term adverse impact on children's nutrition outcomes. We also find that political violence negatively affects short-term nutritional status of children but exposure to conflict does not affect long-term nutrition outcomes significantly on its own. Further analysis on potential mechanisms suggests that the adverse combined effect of conflict and negative shocks on child nutrition outcomes may be explained by the levels of isolation faced by households in insurgency areas, which affect the portfolio of coping strategies (use of savings, sale of productive assets, temporary migration etc) available to them and restricts access to public goods and programs during periods of drought.

These results offer a new important contribution to a well-established literature in development economics on the welfare effects of individual covariant and idiosyncratic shocks (Dercon, 2004; Dercon et al., 2005; Christiaensen et al., 2007). This paper also speaks to an emergent literature on multiple shocks (Lazzaroni and Wagner, 2016) and on the role of social protection in mitigating the effect of adverse shocks in early childhood (Gunnsteinsson et al., 2014; Adhvaryu et al., 2016; Duque et al., 2017; Garg et al., 2016). This literature has for its large part remained firmly within the economics domain, without much discussion as to how the determinants of household vulnerability and poverty, as well as the ways in which households cope with economic shocks, may depend on political constraints. Notably, political conflicts drastically change the institutional environment of contested areas (Justino, 2012; Justino et al., 2013). In this paper, we show how political violence may affect the ability of households to cope with other shocks due to isolation and fear leading to failures in common economic coping strategies and restrictions to the provision of public goods.

The paper complements also what amounts now to a substantial literature on the effects of political violence on human capital outcomes, including child nutrition. Overall, evidence shows that this impact has been largely negative (Bundervoet and Verwimp, 2005; Akresh et al., 2007; Bundervoet et al., 2009; Guerrero-Serdan, 2009; Minoiu and Shemyakina, 2014) and persistent (Alderman et al., 2006; Akbulut-Yuksel, 2014; Akresh et al., 2012; Domingues and Barre, 2013). Most of these studies have suggested that the adverse effects of violent conflict on child nutrition outcomes may be largely caused by the inability of households to cope with second-order effects of the conflict, including the imposition of economic embargoes (Bundervoet and Verwimp, 2005), famine (Alderman et al., 2006; Akresh et al., 2012), the spread of disease (Bundervoet and Verwimp, 2005) and the rise of food prices (Minoiu and Shemyakina, 2014). The precise identification of these mechanisms has remained elusive because it is usually difficult to clearly attribute the causal effects of conflict at the micro-level to precise wider institutional and economic changes that may take place simultaneously. Our paper complements this literature in that we are able to make use of original, detailed information on political violence at a very disaggregated level, and to make use of an instrumental variable strategy to illustrate the causal effect of conflict on child nutrition outcomes through its impact on the ability of households to cope with adverse shocks.

The paper is organized as follows. Section 2 provides a brief description of the Naxal insurgency in India and in Andhra Pradesh. In Section 3, we discuss the datasets and variables we use in the paper and Section 4 present the empirical strategy. The main results of the paper are presented and analyzed in Section 5. Section 6 further establishes the robustness of the instrumental variable estimates. We discuss potential mechanisms underlying our results in Section 7. In Section 8, we summarize the main findings and reflect on their theoretical and policy implications.

2. The Naxal insurgency in India and Andhra Pradesh

The Naxal movement, a left-wing Maoist-inspired insurgency, started in 1967 in the Naxalbari village in the Indian state of West Bengal. A young tribal man, who was entitled to a plot of land following post-independence land reforms in India, was attacked by a group of militiamen working for local landlords. Members of the tribal population retaliated and soon formed a widespread rebellion. The events led to the creation, in, 1969 of two parties professing armed struggle against the oppression of marginalized people. These were the Communist Party of India-Marxist-Leninist (CPIML) and the Maoist Communist Center (MCC). The movement spread to various parts of the country, but soon collapsed as many cadres lost their lives or were imprisoned (Kujur, 2008). In 1980, the People's War Group (PWG) was formed in Andhra Pradesh, and quickly became the dominant Naxal group in the state. In 2004, the PWG and the Maoist Communist Center of India (MCCI), two of the principal Naxal armed organizations, merged to form the CPI-M (Maoist).

Despite its relative anonymity outside South Asia, the Naxal armed insurgency is a protracted and violent conflict where assassinations, kidnappings, and attacks against police and property are routine. According to the Indian Ministry of Home Affairs (Government of India (Government of India, 2002, 2003, 2004, 2005, 2006)), in the period between 2002 and 2006, the yearly death toll due to the Naxal conflict ranged from 482 lives in 2002 to 678 in 2006. As in most civil war-type situations, civilians paid a heavy price. On average, they accounted for 58% of all fatalities (2470 out of the 4283 deaths) between 2003 and 2008.[2] The conflict affected 79 districts in 9 states between 2003 and 2006. Between 2008 and 2012, an estimated 200 districts in India were considered to be affected by the Naxal insurgency, creating a 'red corridor' ranging from West Bengal in the North-east to Andhra Pradesh and Karnataka in the South.

Andhra Pradesh has been the center of the Naxal insurgency since the earliest stages of the movement in the late 1960s. Andhra Pradesh used to account for a substantial amount of Naxal violence in India and its cadres were dominant within the Naxal committee.[3] According to official data, Andhra Pradesh repre-

[1] Illness and drought are the most common shocks reported by households in the Young Lives household survey that we use in the empirical section.

[2] Ministry of Home Affairs quoted by South Asian Terrorism Portal: http://www.satp.org/satporgtp/countries/india/maoist/data_sheets/fatalitiesnaxalmha.htm.

[3] According to *Times of India*, currently the CPI-M party has 17 members on its Central Committee of which 11 are from Andhra Pradesh. See http://timesofindia.indiatimes.com/city/hyderabad/AP-leaders-dominate-Maoists/articleshow/28611090.cms.

sented between 20 and 34% of all Naxal-related incidents and fatalities in India between 2002 and 2005 (Government of India 2002, 2003, 2004, 2005, 2006). The state then gradually took the upper hand and the conflict abated, even though it intensified nationwide, especially in 2009 and 2011.

It is widely believed that the Naxal insurgency is stronger in regions characterized by low levels of human development, absence of state institutions and rough terrain (Borooah, 2008; Government of India, 2008). These various dimensions are interwoven as areas of rough terrain may affect negatively the capacity of the state to deliver development, are usually populated by disenfranchised sections of the population, such as scheduled castes (SC) and scheduled tribes (ST), and constitute a safe heaven for rebels.

Despite their strong rhetoric, it is unclear how the Naxal movement has contributed to the support of vulnerable groups. Naxal groups are repeatedly accused of destroying schools, roads and other rural infrastructure much needed by the population they claim to protect, in an attempt to isolate the population from the state, facilitate recruitment and increase the distance between the rebels and state forces (Borooah, 2008; UNESCO, 2011). At the same time, the use of violence, or the threat of it, has allegedly helped agricultural laborers negotiate better wages with landlords, and led to the end of bond labor practices in the Telangana region of Andhra Pradesh during the 1970s and 1980s. The Naxal movement is also reported to help tribal populations encroach on forest and other traditional areas, protecting them against harassment by government officials, and to provide support and find shelter to tribal populations threatened by displacement (Government of India, 2008). We explore this temporal and geographical variation in the Naxal conflict further in the empirical analysis below.

3. Data sources and variables

3.1. Conflict event data

For the purpose of this study we coded and collated information contained in a diary of Naxal-related events in Andhra Pradesh between 2002 and 2006 published online by the South Asian Terrorism Portal (SATP).[4] The diary provides a description of each violent event, the place where it occurred, the parties involved and the number of casualties associated with each event. We coded this information at the lowest possible level of aggregation, which are called mandals.[5] In 11% of the cases, it was not possible to pinpoint the exact mandal because the SATP did not provide the information or because the event took place in a vaguely defined area, like a forest. In this case, we did not attribute the event to any sub-district entity: incidents were only included in the dataset if we were able to identify precisely the mandal where they took place. Although the SATP information has been used before at the district level (Borooah, 2008; Vadlamannati et al., 2017), this is the first ever attempt to code Naxal attacks in India at the mandal level.

In order to make sure that the SATP diary provides a fair picture of actual events, and does not introduce systematic biases, we cross-checked all events recorded by SATP against information published by Hyderabad edition of *The Hindu* newspaper.[6]

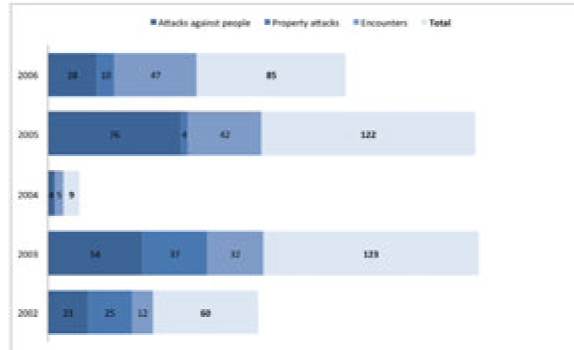

Fig. 1. Yearly number of naxal attacks against people and property, and encounters in Andhra Pradesh 2002–2006. Source: Authors' calculations based on SATP data.

When using provincial or national newspapers to count conflict events, there is a risk that we may miss many of the smaller, predominantly rural, incidents that are important in the lives of people but fail to make the headlines (Barron and Sharpe, 2005). In contrast, when using more local newspapers, it is difficult to assess the credibility and partiality of the information (especially on such a sensitive topic). Likewise, comparing events of violence across different regions require us to compare information from different local newspapers, which may be problematic. We minimized these risks by using the Hyderabad edition of *The Hindu*, which we think offers the best compromise between the need for reliability and comparability and the need to capture local-level events. We retained in our database only events for which both sources coincided.[7] For the districts that correspond to the estimation sample, we were able to locate each violent event (which appear in both SATP and *the Hindu*) at the mandal level. The fact that we were able to do so keeps at a minimum the risk of wrongly classifying a mandal as peaceful because it was affected by an event we could not precisely locate.

Fig. 1 summarizes the types of violence and other Naxal-related events in Andhra Pradesh between 2002 and 2006. The dataset shows that the Naxal movement resulted in 189 attacks against people and 86 attacks against property during that period of time. Attacks against people resulted in 200 civilians killed and 103 injured. Most civilian targets include individuals suspected to act as informers to the police, politicians and state officials. Members of political parties (53) and officials (14) represent around a third of all civilian casualties. Over the same period, government armed forces led 139 assaults (also called encounters) against the Naxal insurgents, resulting in 273 deaths and 8 injuries among the insurgents. The toll for state forces over the period is 53 deaths and 39 injuries. These fatalities figures are close to those provided by the Ministry of Home Affairs: our database includes 558 fatalities over the whole 4 years-period, whereas the corresponding government estimate is 564 (Government of India 2002, 2003, 2004, 2005, 2006).

Fig. 2 shows a map of the geographical distribution of Naxal activities at the mandal level. We coded a mandal as conflict-affected if that mandal witnessed at least one Naxal-led attack or one encounter by the police against the Naxal rebels in the period

[4] The South Asia Terrorism Portal is a project launched in 2000 by the Institute of Conflict Management, based in New Delhi. SATP collates daily news and data on terrorism. http://www.satp.org/satporgtp/icm/index.html.

[5] Mandals, which are known as *tehsils* in most of India, are the second layer of the local administration, above the gram panchayats and below the districts. Mandals in Andhra Pradesh are smaller than equivalent tehsils elsewhere in India. According to the census 2011 there are 1125 mandals in the 23 districts of Andhra Pradesh, i.e. each mandal comprises just above 75,000 people.

[6] *The Hindu* is a widely respected national publication in India with an excellent reputation for reporting on issues of violence. The Hyderabad edition covers Andhra Pradesh in depth (Hyderabad is the state capital of Andhra Pradesh.).

[7] Disagreements between the two sources are rare. Removing events that only appear in the SATP database does not affect the classification of mandals into conflict and non-conflict affected.

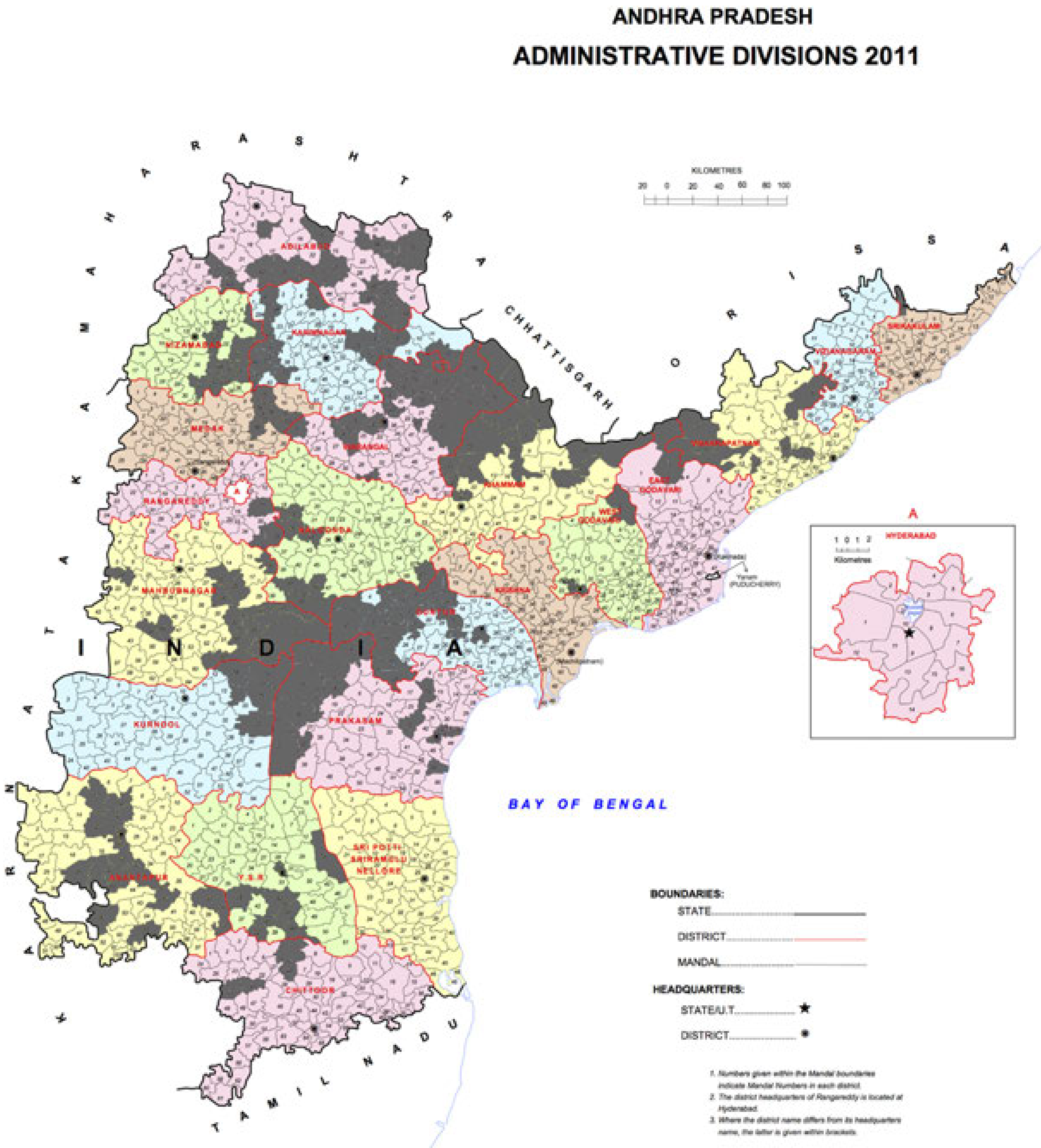

Fig. 2. Spatial distribution of mandals affected by the naxal insurgency in Andhra Pradesh, 2002–2006. Note: Affected mandals appear in grey. Source: authors' calculations based on SATP data.

between 2002 and 2006. The map reveals four main areas of Naxal presence. The first one is a circular area centered around the Karimnagar district and covering parts of Karimnagar, Adilabad, Nizamabad, Medak and Warangal districts. The second area, contiguous to the first, is located along the border of Andhra Pradesh and the states of Chhattisghar and Odisha (in the map: Orissa), and encompasses all the north-eastern mandals of the Warangal district, the north-western mandals of Khamman and the northern mandals of East Godavari and Vishakaptnam. The third area is at the confluence of Mahboobnagar, Nalgonda, Guntur, Prakasam and Kurnool districts, and roughly correspond to the Nallamala hills. The fourth area lies in the south-western part of the state, covering large parts of Anantapur and Cuddapah districts.[8]

Two important facts are revealed by the mapping exercise. First, we notice that Naxal presence is clustered geographically, a fact that coincides with journalistic accounts and lends credibility to the data. Second, the mapping exercise shows that measuring Naxal activity at the district level could be misleading as the actual

[8] Cuddapah appears as YSR on the map.

Table 1
Nutrition indicators of sampled children in 2002 and 2006.

	Height for age *z*-score (HAZ)	Weight for age *z*-score (WAZ)	% Stunted[a]	% Wasted[a]
Panel A: Statistics in 2002 (children were 1 year-old)				
Average	−0.89	−1.53	0.22	0.32
Children living in:				
Naxal-affected mandals	−0.57	−1.39	0.16	0.26
Non naxal-affected mandals	−1.00	−1.57	0.24	0.34
Drought-affected villages	−0.49	−1.43	0.16	0.28
Non drought-affected villages	−1.10	−1.57	0.25	0.33
Naxal-affected mandals &Drought-affected villages	−0.04	−1.31	0.10	0.22
Panel B: Statistics in 2006 (children were 5 year-old)				
Average	−1.70	−1.92	0.30	0.47
Children living in:				
Naxal-affected mandals	−1.67	−1.95	0.29	0.48
Non naxal-affected mandals	−1.72	−1.91	0.30	0.46
Drought-affected villages	−1.72	−1.88	0.30	0.44
Non drought-affected villages	−1.70	−1.95	0.30	0.50
Naxal-affected mandals &drought-affected villages	−1.85	−1.91	0.33	0.47

Source: authors' calculations based on the Young Lives dataset.
[a]A child is considered to be stunted if her height-for-age *z*-score is smaller than 2 standard deviations.
[a]A child is considered to be wasted if her weight-for-age *z*-score is smaller than 2 standard deviations.

areas of Naxal activity cut across district boundaries and is not homogeneous within districts. Mapping Naxal activity at the mandal level offers therefore a much better representation of the spatial dimension of the conflict.

The estimation sample that we will use in the paper is composed of 20 mandals. Our data collection exercise indicates that 5 out these 20 mandals were host to the Naxal conflict between 2002 and 2006. When we exclude the mandals that are predominantly urban (the estimations in the paper will focus on rural respondents), 3 mandals out of 18 were affected by conflict.[9]

3.2. Nutrition, drought and illness data

The data on child nutrition was collected as part of the Young Lives longitudinal survey conducted in the state of Andhra Pradesh in 2002 and in 2006–2007.[10] The surveys follow around 2000 young children, who were on average around 12 months old at the time of the first round, and 1000 older children, who were about 8 years old in 2002. The datasets contain very rich information on child development, adverse shocks (of which drought and illness are the most prevalent) and household responses to shocks. The empirical analysis in this paper focuses on the younger cohort.[11]

Our main dependent variables are the height-for-age and weight-for-age *z*-scores (HAZ and WAZ). The HAZ (WAZ) is obtained by taking the difference between the height (weight) of a given sampled child and the median of the height (weight) of a reference population of children of the same age divided by the standard deviation of height (weight)-for-age in the reference population. Height-for-age *z*-scores below −2 standard deviations are a sign of chronic malnutrition, and children are said to be stunted. Weight-for-age *z*-scores below −2 standard deviations are a sign of undernourishment. Whereas the height-for-age *z*-score is a long run indicator of child health (Hoddinott et al., 2013), the weight-for-age *z*-score indicator reacts to more short-term changes in nutrition.

Statistics on child nutrition indicators of the younger Young Lives cohort are displayed in Table 1. In the sample, children were on average 0.89 and 1.7 standard deviations shorter than the reference population in 2002 and 2006, respectively. The proportion of stunted children increased from 22% to 30% over the period, as did the proportion of undernourished children (whose WAZ is below −2 s.d.) (from 32% to 47%). The fact that malnutrition indicators have gotten worse over time is a sign that children were subject to chronic nutritional deficiencies between the ages of 1 and 5 years.[12]

The data on household exposure to climatic shocks was collected in the community survey of Young Lives. The drought variable takes the value 1 if interviewed community representatives report that a drought affected their villages between 2002 and 2006 and 0 otherwise. According to this village-level variable, droughts are very prevalent in Anantapur and Cuddapah districts (100% and 55% of drought-affected villages, respectively), and in Karimnagar and Mahboobnagar districts (100% and 76% of drought-affected villages, respectively). In Coastal Andhra Pradesh the situation is more heterogeneous: no village in West Godavari are drought-affected but 46% of the villages in Srikakulam district are affected.

The data on illness was collected as part of the YL household survey. We will use the variable of "parents' illness" which takes the value 1 if the respondent reports that either the father or the mother of the index child was ill over the last 4 years. 18% of children had their parents affected by illness between the two waves of data collection.

4. Empirical strategy: 2SLS model

We combine panel data on child anthropometrics provided by the Young Lives datasets with the violence event dataset we have constructed in order to estimate the effect of drought and illness on child nutrition outcomes in communities affected by the Naxal

[9] The total number of attacks and encounters in these three mandals is 2, 4 and 10, so the classification of these mandal into the "conflict-affected" category does not rely on a single event.

[10] Young Lives is an international study of childhood poverty, involving 12,000 children in 4 countries over 15 years. It is led by a team in the Department of International Development at the University of Oxford in association with research and policy partners in the 4 study countries: Ethiopia, India, Peru and Vietnam. More information can be found online: http://www.younglives.org.uk.

[11] We cannot control for shocks that could have affected the development of the older cohort in the early stages (first four years) of their lives. As this might lead to serious biases in our estimations, we focus only on the younger cohort for who we have these information.

[12] For a state-level analysis of how height relates to neo-natal mortality in India, see Coffey (2015).

Table 2
Summary statistics.

Variable	Round 1					Round 2				
	Mean	SD	Min.	Max.	N	Mean	SD	Min.	Max.	N
Political violence	0	0	0	0	0	0.201	0.401	0	1	1346
Drought	0	0	0	0	1362	0.669	0.471	0	1	1346
Illness	0	0	0	0	1362	0.255	0.436	0	1	1346
Land cultivated p.c	0.584	0.694	0	5	1013	0.359	0.617	0	6.4	1341
land owned p.c	0.611	0.675	0	5.05	1013	0.367	0.546	0	5.93	1341
Draught cattle p.c	0.277	0.411	0	3	1362	0.243	0.572	0	15	1346
Sheep/pigs/goats p.c	0.399	1.812	0	25	1362	0.374	1.76	0	25	1346
Rabbit/poultry p.c	0.18	0.483	0	5	1362	0.177	0.54	0	8.199	1346
Wealth Index	0.259	0.155	0.006	0.802	1357	0.258	0.144	0	0.826	1344
Household size	5.649	2.466	2	22	1362	5.67	2.354	2	28	1346
Housing quality	0.341	0.275	0.013	1	1361	0.385	0.285	0	0.972	1345
Services Index	0.247	0.17	0	1	1359	0.279	0.169	0	1	1346
Children <5 y.o	0.243	0.517	0	6	1332	0.768	0.821	0	5	1346
MDM					1362	0.438	0.496	0	1	1346
MNREGS					1362	0.464	0.499	0	1	1346
Irrigation	0.274	0.249	0	0.987	1302	0.3	0.262	0	0.987	1267
Density CSOs	9.766	2.497	2	15	1362	9.58	2.65	2	18	1346
Access to services	6.251	2.543	1	12	1362	8.444	2.387	3	16	1346
Food prog.	3.498	0.656	1	4	1362	3.867	0.361	2	4	1346
Health prog.	1.25	0.942	0	3	1362	1.383	1.033	0	3	1346
Educ prog.	2.731	1.009	0	5	1362	3.804	0.948	0	6	1346
Infrastructure prog.	0.255	0.449	0	2	1362	0.273	0.459	0	2	1346
Other prog.	18.903	5.085	5	31	1362	16.88	5.433	5	30	1346
Educ. facilities	3.543	2.052	1	11	1362	6.978	4.222	0	26	1346
Health facilities	1.029	1.555	0	8	1362	2.051	3.161	0	17	1346
Caregiver: no school	0.74	0.439	0	1	1362					
Caregiver: prim. school	0.197	0.398	0	1	1362					
Caregiver: second. school	0.063	0.243	0	1	1362					
Mother height (cm)	151.26	6.936	47.3	175.75	1319					
HH. Head completed primary school	0.308	0.462	0	1	1362	0.307	0.461	0	1	1346
Age child (months)	11.872	3.524	5	21	1362	64.337	3.783	55	74	1346
Age mother (years)	23.560	4.395	12	48	1337					

Source: authors' calculations based on Young Lives data.

conflict in Andhra Pradesh. We start by examining the direct effects of drought, illness and conflict on the evolution of children's nutritional status.

4.1. Direct effect of conflict and shocks on the evolution of children' nutrition outcomes

We exploit the panel structure of the data to estimate the impact of shocks and violence on child nutrition. The structural equation we wish to estimate is as follows:

$$\begin{aligned} y_{ivmt+1} - y_{ivmt} \quad &= \beta_0 + \beta_1 D_{vmt} + \beta_2 I_{ivmt} + \beta_3 C_{mt} + \beta_4 (X_{ivmt+1} - X_{ivmt}) \\ &+ \beta_5 X_{ivmt} + \mu_i + u_v + v_m + \varepsilon_{ivmt}, \end{aligned} \tag{1}$$

where y_{ivmt+1} is either the height for age (HAZ) or the weight-for-age (WAZ) z-score of child i, in village v, in mandal m at time $t+1$. Only one child is followed by YL in each household so that the subscript i collects both the child and household dimensions. D_{vmt} is a binary variable indicating whether village v in mandal m was exposed to a drought over the last four years, I_{ivmt} is a binary variable indicating if someone in the household of child i went through a major illness over the last four years. C_{mt} is a binary variable taking the value 1 if mandal m witness Naxal-related political violence in the last 4 years and 0 otherwise. We described the construction of this variable in Section 3. X_{ivmt} is a vector of relevant child, household and village levels characteristics, so that β_4 measures the impact of the change over the last four years of the subset of variables in X that are time-varying; and β_5 measures the impact of initial characteristics on the subsequent evolution of nutritional status of children.

Variables describing conditions at baseline (represented by X_{ivmt}) are: the height-for-age or weight-for-age z-score of the child, the height and age of the mother, whether the head of household has completed primary education; the education level of the caregiver and the age of the child in months. The estimated effect of initial height-for-age or weight-for-age z-score on the subsequent evolution of nutrition outcomes indicates if a process of convergence, whereby children who are initially smaller grow more quickly, is at work or not.

Time-varying child and household variables (represented by $X_{ivmt+1} - X_{ivmt}$) are the amount of land cultivated and owned (per capita), the number of draft animals, sheep/pigs and goats and poultry/rabbits owned by the household (per capita), the wealth index, housing quality index and services index (all from YL), the household size, the number of children below 5 and whether household members are registered in the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) and mid-day meal scheme (a major school-feeding program).

Village variables are constructed from the community survey of YL. We have built a series of indices representing the access of villages to key services and programs. In particular, we will control for the: (1) density of civil society organizations (CSOs) (representing the breadth of presence of CSOs/NGOs in the village), (2) number of public amenities available in the village, (3) number of education facilities, (4) number of health facilities, (5) number of food programs, (6) number of health programs, (7) number of education programs, (8) number of infrastructure programs and (9) number of other programs available in the village.[13] We also control for the share of land that is irrigated in the village. All these variables are time-varying as the community survey asked about the situation in 2006 and in 2002 (through a retrospective module). These variables will then be included in the set of time-varying controls and in the set of baseline characteristics. Table 2 presents the summary statistics and Appendix A provides further detail about the construction of variables.

μ_i is a child specific effect which captures both the genetic potential of nutrition outcomes of the child and unobservable household determinants of child nutrition, u_v and v_m correspond to village and mandal specific effects, respectively, and ε_{ivmt} is the error term.

Eq. (1) is akin to the one used by Yamano et al. (2005) to estimate the impact of shocks and food aid on child growth, except that we are able to also control for the effect of time-varying covariates. Our parameters of interest are given by β_1 and β_2, which indicate whether drought and major illnesses, respectively, cause children's nutrition outcomes to subsequently lag behind that of their peers, and β_3, which indicates whether children who grew up in conflict-affected mandals have had a different nutritional outcome path over the study period than children who grew up in peaceful mandals.

We restrict the sample to households that did not move over the 2002–2006 period in order to make sure that there is a correspondence between the village-level variable of drought and the actual experience of children. Because the surveys did not register the timing of the move, we are not able to infer the actual drought experience of the children in households that moved.[14]

We cluster the standard errors at the level of the mandal, which is unit of measurement of political violence, to correct for the fact that the error terms are not i.i.d.

Finally, it is worth stressing that both the mandal- and village-specific effects u_v and v_m drop when we estimate by 2SLS equation (1). This is because there is no variation in the share of forest cover within mandals and villages.

4.2. Endogeneity and IV approach

As discussed in Section 2, it is widely believed that the Naxal conflict predominantly takes place in poor, remote areas (Borooah, 2008) and that Naxal groups purposively target marginalized (especially tribal) populations for recruitment (Government of India, 2008). In light of these facts, estimating equation (1) using ordinary least squares would not allow us to obtain a causal impact of growing up in a conflict-affected mandal on children's nutrition outcomes. These estimations would overestimate the true impact of conflict if children in conflict-affected mandals are poorer, even without being exposed to conflict.

Available data in Andhra Pradesh does not suggest that Naxal mandals were particularly deprived. According to the Young Lives data, a higher proportion of households reported accessing paved roads, drinking water and sewerage in 2002 in Naxal mandals than in non-Naxal ones. Yet, it remains plausible that the quality of public goods may be lower in conflict areas.

We propose to address this potential endogeneity bias by instrumenting the presence of conflict in a mandal with the extent of its forest cover in 1991. Instrumental variables need to fulfill two main requirements: they must be able to explain a sizable variation of the endogenous variable, and they must influence the main dependent variable (HAZ or WAZ) only through their effect on the endogenous variable (conflict). The share of forest cover variable fulfills these two requirements. First, in asymmetric conflicts such as the Naxal insurgency, insurgents tend to operate from remote hideouts in rough terrain where their superior knowledge and agility offset their numerical disadvantage (Hirshleifer, 2001; Fearon and Laitin, 2003). In India, the Naxals have historically concentrated in areas of dense forest where they can hide from the state and where the state military cannot deploy large-scale forces. The early Naxal forces, as well as the latter organizations such as the PWG and the MCCI, have used contiguous forest areas to create bases from which they could operate and expand in all affected states (Mitra, 2011).

Fig. 3 displays the map of forest cover in Andhra Pradesh. Comparing this map with Fig. 2 reveals a striking correspondence between the forested mandals of Andhra Pradesh and those where the Naxal conflict has been present between 2002 and 2006. It also shows that areas that have experienced violent events during that time are not restricted to the densest forest areas themselves but expand to adjoining areas. This is consistent with the evolution of Naxal presence in a given area as described by Mitra (2011), as well as with the Naxal tactical strategy as explained in their Strategy & Tactics document from Central Committee (Central Committee, 2004).

The first stage IV regressions shown in Tables 4 and 7 confirm the strong explanatory power of forest cover for the presence of conflict. The results show that the share of forest cover is a very strong instrument as evidenced both by the Fischer tests that the coefficient of the instrument is zero (which strongly reject the null hypothesis) and by the partial R^2 (between 19% and 27%) of the instrument. Both the F statistic and the partial R^2 are considerably above the recommendations of Stock et al. (2002). All other weak instruments tests are emphatically rejected.

In addition to being strongly related to the endogenous variable, the candidate instrument must also satisfy the exclusion restriction. In other words, the share of forest cover in a given mandal should influence children nutrition through its impact on conflict alone. Regressions will control for demographic and economic characteristics of households and villages (X_{ivmt+1}-X_{ivmt} in Eq. (1)), which might systematically differ in forest and non-forest areas (e.g. land owning, wealth, household size, exposure to shocks). Yet, it is likely that there will still be unobserved characteristics of children and villages living in densely forested mandals that make children more prone to malnutrition. In that case, the instrument would still exert an independent impact on nutrition and would not be valid.

It is possible that forest areas, which are prime areas of rebel influence, were prioritized by the state for the delivery of public goods between 2002 and 2006 in order to break the support of tribal populations toward the Naxals. The federal and state strategies against the Naxals are two-pronged and reminiscent of the "winning hearts and minds" counterinsurgency strategies combining intense repression with development efforts in the zones most likely to support the rebels (Kolas and Miklian, 2009). Hence, the state might have invested in public goods in areas of strong forest cover and therefore improved the nutrition standards of children living in forest areas. To alleviate this concern we include in the vector of time-varying controls X variables which

[13] Surprisingly, the correlations between these indices are low. An attempt to reduce the dimensionality of the village variables by using principal components analysis was also unsuccessful as the first component accounts for 23% only of the total variance; and the first three components together barely account for half (51%) of the total variance. We therefore chose to include all the indices in the estimations.

[14] 8.4% of the households moved between the two surveys. These households tend to cultivate less land, own less farm animals and are less likely to be registered with the mid-day meal school and MGNREGS programs. However, they are similar to other households in terms of initial nutrition status and wealth. We control for these variables in the regressions.

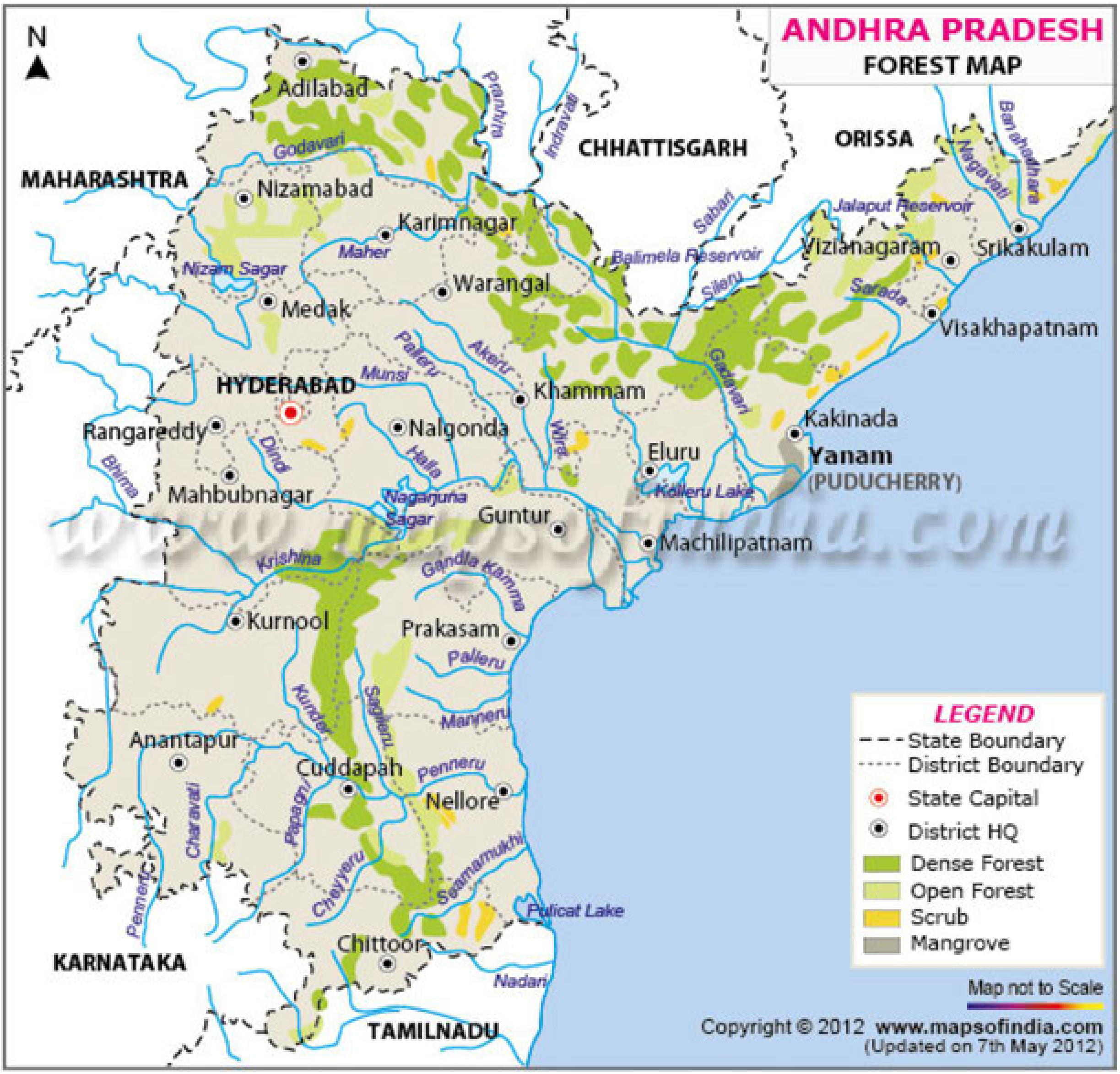

Fig. 3. Spatial distribution of forest cover in Andhra Pradesh. Source: Maps of India.

indicate whether public goods, such as irrigation of agricultural land, drinking water and sewerage facilities, and NGO and state programs have been provided between 2002 and 2006.

In addition, initial conditions might be different between forest and non-forested mandals, leading to diverging paths of children's nutrition outcomes. To address this concern, we will control for baseline characteristics of children, households and villages (through y_{ivmt} and X_{ivmt} in Eq. (1)). These include among other variables the height of the mother, education of household head, initial socio-economic conditions of the household, use of land, e.g. farm animals and the areas of cultivated land per capita, and the extent of services available in the village (recreation, agricultural, education and health facilities) as well as initial coverage of government and NGOs programs (on e.g. food, education, agriculture). We believe that by controlling for this wide array of initial conditions, the most likely pathways that potentially lead from forest cover to change in children's nutrition outcomes are explicitly included in the regression.[15]

We have also strong additional indirect evidence on the validity of forest cover as an instrument for conflict. Because the height-for-age z-score is a cumulative measure of nutrition, it reveals information about the past living conditions of children. If, in 2002, when the children were one year old, the HAZ in densely forested mandals were already significantly lower than those in non-forest

[15] Unfortunately, we do not have information regarding the types of crops grown or how farming is conducted. An exploration of the variables at our disposal do not suggest farming is systematically different in forested areas and non-forested areas. Indeed, the share of household land dedicated to agriculture, total land available to households and the number of farm animals per capita are not significantly correlated with the share of forest cover.

Table 3
Estimates of the direct effect of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006.

Dependent variable Estimator	ΔHAZ OLS (1)	ΔHAZ OLS (2)	ΔHAZ 2SLS (3)	ΔHAZ 2SLS (4)	ΔWAZ OLS (5)	ΔWAZ OLS (6)	ΔWAZ 2SLS (7)	ΔWAZ 2SLS (8)
Political violence	−1.04***	−0.37***	−0.92**	−0.84***	−0.41***	−0.26**	−0.57***	−0.64**
	(0.28)	(0.12)	(0.36)	(0.25)	(0.099)	(0.12)	(0.17)	(0.29)
Drought	−0.22	−0.066	−0.24*	−0.11	−0.0031	−0.027	−0.0085	−0.046
	(0.15)	(0.13)	(0.15)	(0.13)	(0.10)	(0.078)	(0.100)	(0.084)
Parents' Illness	−0.24*	−0.17**	−0.22*	−0.14*	−0.024	−0.037	−0.0082	−0.021
	(0.12)	(0.072)	(0.12)	(0.072)	(0.087)	(0.060)	(0.086)	(0.059)
Land cultivated p.c.	−0.051	0.021	−0.061	0.049	−0.0079	0.052	−0.0059	0.078
	(0.093)	(0.054)	(0.090)	(0.059)	(0.071)	(0.060)	(0.070)	(0.069)
Land owned p.c	−0.10	−0.097	−0.097	−0.098	−0.031	−0.100	−0.030	−0.100
	(0.12)	(0.078)	(0.12)	(0.084)	(0.077)	(0.081)	(0.079)	(0.085)
Draft cattle p.c	0.077	0.048	0.075	0.053	0.034	0.039	0.034	0.041
	(0.10)	(0.054)	(0.10)	(0.057)	(0.044)	(0.033)	(0.045)	(0.034)
Sheep, pigs, goats p.c	−0.0043	0.020	−0.0042	0.019	0.0048	0.016	0.0051	0.015
	(0.027)	(0.019)	(0.027)	(0.020)	(0.012)	(0.012)	(0.012)	(0.012)
Rabbit &poultry p.c	−0.0082	0.036	−0.012	0.026	−0.031	−0.058	−0.036	−0.068
	(0.045)	(0.051)	(0.044)	(0.053)	(0.022)	(0.040)	(0.022)	(0.040)
Wealth index	1.99	3.02***	2.10	2.57**	0.14	1.83**	0.078	1.39**
	(1.39)	(0.97)	(1.29)	(0.94)	(0.73)	(0.67)	(0.74)	(0.62)
Housing quality index	−0.34	−0.95***	−0.39	−0.85**	0.038	−0.64**	0.060	−0.52*
	(0.47)	(0.30)	(0.43)	(0.30)	(0.30)	(0.27)	(0.30)	(0.25)
Services index	−0.85	−0.88**	−0.91*	−0.59	−0.11	−0.47**	−0.068	−0.22
	(0.55)	(0.41)	(0.50)	(0.40)	(0.26)	(0.17)	(0.26)	(0.19)
Household size	0.010	−0.0065	0.0089	−0.0080	−0.0015	−0.017	−0.0012	−0.017
	(0.021)	(0.010)	(0.021)	(0.011)	(0.012)	(0.011)	(0.012)	(0.010)
Nb. of children <5	−0.040	0.0039	−0.036	0.0084	−0.033	0.040	−0.031	0.038
	(0.040)	(0.030)	(0.040)	(0.031)	(0.026)	(0.029)	(0.025)	(0.031)
MDM	0.22**	0.24***	0.21**	0.23***	0.11*	0.12***	0.11	0.11**
	(0.094)	(0.038)	(0.096)	(0.037)	(0.061)	(0.040)	(0.063)	(0.043)
MGNREGS	0.21	0.064	0.16	0.14	−0.0027	−0.040	0.053	0.027
	(0.15)	(0.093)	(0.21)	(0.10)	(0.058)	(0.065)	(0.077)	(0.10)
% Agr. land irrig.	0.16	−0.59**	0.16	−0.73***	−0.39	−0.61	−0.41	−0.71*
	(0.41)	(0.24)	(0.41)	(0.24)	(0.57)	(0.37)	(0.57)	(0.35)
Density CSOs	0.058	0.047**	0.053	0.071**	0.0079	−0.0018	0.020	0.015
	(0.041)	(0.020)	(0.044)	(0.030)	(0.019)	(0.028)	(0.027)	(0.031)
Access to services	−0.092**	0.032	−0.090**	0.031	−0.029	0.077***	−0.036	0.080**
	(0.032)	(0.032)	(0.034)	(0.033)	(0.026)	(0.025)	(0.025)	(0.029)
Food programs	−0.14**	−0.23**	−0.13**	−0.26**	0.030	0.084	0.022	0.045
	(0.049)	(0.10)	(0.049)	(0.11)	(0.058)	(0.11)	(0.063)	(0.087)
Health programs	−0.049	−0.14***	−0.056	−0.13**	0.0025	−0.090**	−0.00075	−0.091*
	(0.076)	(0.037)	(0.072)	(0.055)	(0.061)	(0.041)	(0.061)	(0.047)
Educ. programs	−0.24*	−0.14	−0.21	−0.32**	−0.095	−0.15	−0.13*	−0.30**
	(0.14)	(0.091)	(0.20)	(0.13)	(0.067)	(0.096)	(0.072)	(0.11)
Infrastructure prog.	0.068	0.010	0.079	−0.027	0.037	0.0070	0.019	−0.011
	(0.10)	(0.11)	(0.12)	(0.13)	(0.063)	(0.060)	(0.085)	(0.083)
Other programs	0.0055	0.013	0.0071	0.014	−0.014	−0.0017	−0.011	0.00033
	(0.022)	(0.018)	(0.023)	(0.020)	(0.017)	(0.017)	(0.018)	(0.017)
Educ. facilities	0.058***	0.0070	0.062***	0.0042	−0.0035	−0.0092	−0.0067	−0.012
	(0.013)	(0.012)	(0.013)	(0.015)	(0.011)	(0.012)	(0.013)	(0.017)
Health facilities	0.065**	0.055***	0.060**	0.068***	0.0085	0.017**	0.015	0.027**
	(0.026)	(0.015)	(0.027)	(0.013)	(0.010)	(0.0059)	(0.016)	(0.012)
Baseline variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	733	718	731	716	923	904	921	902
R^2	0.16	0.74	0.16	0.74	0.042	0.48	0.040	0.47

Notes: (ii) Standard errors (in parentheses) are clustered at mandal-level. (iii) "Baseline variables" refers to the inclusion of the lagged time-varying covariates plus variables for the initial. Values of HAZ (WAZ), age of the child, height of the mother, education of the caregiver and of the household head. (iv) In 2SLS estimations, violence is instrumented by the share of forest cover in 1991.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

mandals, this would cast doubt on the validity of the exclusion restriction. This is not the case. Fig. 4 depicts the scatterplot of forest cover and HAZ in 2002 and its non-parametric best fit. The relationship is positive over most of the sample and becomes negative at the very high end of the distribution of forest cover. Although the relationship is curvilinear, the mean of HAZ at high density of forest never drops below its corresponding level in non-forest mandals. A regression analysis of HAZ in 2002 on the share of forest cover and the square of the share of forest cover plus all the controls used in subsequent analyses yields coefficients of 3.95 and −5.21, respectively, and both are significant at 1%.[16] The regressions estimates predict that HAZ will be 0.4 and 0.3 standard deviations higher in mandals with 12% of forest cover

[16] The table of results is not shown to save space but is available upon request.

Table 4
First-stage results of the 2SLS estimations of the direct effect of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006.

Corresponding columns in Table 3	(3)	(4)	(7)	(8)
	Endogenous Variable:		Political violence	
% forest in Mandal in 1991	1.73***	1.82***	1.83***	1.71***
	(0.534)	(0.317)	(0.545)	(0.333)
F statistic of instruments	11.38	29.88	11.25	26.47
p-value of *F* statistic	0.00	0.00	0.005	0.00
Shea partial R^2	0.26	0.20	0.27	0.19
Kleibergen–Paap rk LM statistic	3.68	7.33	3.81	6.96
Kleibergen–Paap rk LM *p*-value	0.055	0.007	0.059	0.008
Observations	731	716	921	902

Notes: (ii) Standard errors (in parentheses) are clustered at mandal-level. The first-stage regressions feature the same list of covariates as the second-stage regressions in Table 3.
*p<0.1.
**p<0.05.
*** p<0.01.

Table 5
Lewbel estimates of the direct and indirect effects of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006.

Dependent variable	ΔHAZ	ΔHAZ	ΔHAZ	ΔHAZ	ΔWAZ	ΔWAZ	ΔWAZ	ΔWAZ
Share of forest cover is included as an IV	No	Yes	No	Yes	No	Yes	No	Yes
Baseline characteristics	No	No	Yes	Yes	No	No	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second-stage regression								
Political violence	−0.87***	−0.89***	−0.059	−0.23	−0.43***	−0.44***	−0.20**	−0.28***
	(0.24)	(0.20)	(0.19)	(0.16)	(0.13)	(0.11)	(0.09)	(0.09)
First-stage regression diagnostics								
F statistic of instruments	25.10	67.77	28.25	56.06	14.49	69.03	55.92	82.44
p-value of *F* statistic	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kleibergen–Paap rk LM statistic	31.48	33.42	42.13	49.6	29.76	34.14	48.71	50.64
Kleibergen–Paap rk LM p-value	0.14	0.12	0.71	0.45	0.19	0.10	0.44	0.41
Hansen *J* Statistic	22.69	24.5	46.24	50.89	22.54	22.72	50.66	51.70
Hansen *J* *p*-value	0.48	0.43	0.50	0.36	0.49	0.54	0.44	0.33

Notes: (ii) Standard errors are clustered at the village level and not at the mandal-level to enable calculation of overidentification tests. The list of covariates is the same as in Table 3.
*p<0.1.
** p<0.05.
*** p<0.01

(corresponding to the 75th percentile) and 70% (corresponding to the most forested mandal) than in non-forested mandals, respectively. The maximum effect of forest, 0.75 s.d., is reached for mandals with 38% of forest cover. The relationship between the share of forest cover and WAZ is monotonically positive and flatter than for HAZ. These results indicate that very young children in forested mandals appear to be better-off than their peers in non-forest ones. We are therefore able to interpret any negative impact of conflict (instrumented by forest) of malnutrition in subsequent regressions as a lower bound of the true impact.[17]

Finally, one may also be concerned that forest cover is directly influenced by conflict. Ferguson et al. (2014) and Nackoney et al. (2014) recently explored the links between conflict and forest preservation in Colombia and in the Democratic Republic of Congo, respectively. Both found that conflict led to heightened forest degradation. However, in the case of Andhra Pradesh, the opposite effect is more plausible as Naxal groups have an interest in maintaining forests which act as a hideout from the police and as a way to win loyalty from the tribal populations, who themselves depend on the forest for livelihood (Government of India, 2008). The exclusion restriction does not hold when conflict is allowed to directly influence forest cover (positively or negatively). The instrument would then be correlated with past conflict (the current forest cover is determined by the cumulative impact of conflict) and since conflict in the past is often a strong predictor of contemporary conflict, there would be a direct relationship between the instrument and the dependent variable. It is to mitigate this concern that we use a measure for forest cover in 1991 and not 2001.[18]

5. Empirical results

5.1. Baseline results

The results of the 2SLS estimation of Eq. (1) are shown in Table 3. The dependent variable is ΔHAZ in the first four columns

[17] Indeed, the association we observe between the share of forest cover and higher nutrition status at baseline suggests that if the exclusion restriction were to be violated, it would introduce a bias that goes against finding a negative effect of violence (since the independent effect of forest cover would be to improve nutritional status).

[18] The estimated effect of political violence is stronger in absolute value when we use the forest cover of 1991 as an IV instead of 2001, suggesting that the presence of the Naxal conflict may directly impact on the extent of forest cover. Results when using 2001 to measure forest cover are available upon request.

Table 6
Estimates of the direct and indirect effects of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006.

Dependent variable Estimator	ΔHAZ OLS (1)	ΔHAZ OLS (2)	ΔHAZ 2SLS (3)	ΔHAZ 2SLS (4)	ΔWAZ OLS (5)	ΔWAZ OLS (6)	ΔWAZ 2SLS (7)	ΔWAZ 2SLS (8)
Political violence	−0.34	−0.13	−0.16	−0.19	−0.67***	−0.40***	−0.66***	−0.50**
	(0.23)	(0.13)	(0.20)	(0.19)	(0.10)	(0.098)	(0.18)	(0.18)
Pol. Violence × drought	−0.762**	−0.334**	−1.07***	−1.15*	0.384***	0.231	0.17	−0.27
	(0.28)	(0.13)	(0.32)	(0.56)	(0.15)	(0.16)	(0.27)	(0.47)
Pol. violence × illness	−0.44*	−0.06	−0.78***	−0.51**	−0.15	−0.05	−0.089	−0.088
	(0.21)	(0.17)	(0.25)	(0.22)	(0.13)	(0.10)	(0.20)	(0.20)
Drought	−0.073	−0.022	−0.033	0.036	−0.073	−0.056	−0.039	−0.010
	(0.16)	(0.14)	(0.15)	(0.13)	(0.11)	(0.089)	(0.13)	(0.099)
Parents' illness	−0.11	−0.14*	0.010	0.019	0.017	−0.023	0.016	0.0057
	(0.12)	(0.080)	(0.14)	(0.15)	(0.11)	(0.071)	(0.080)	(0.094)
Land cultivated p.c	−0.054	0.019	−0.051	0.068	−0.0039	0.056	−0.0042	0.080
	(0.089)	(0.051)	(0.090)	(0.059)	(0.072)	(0.059)	(0.072)	(0.071)
Land owned p.c	−0.11	−0.098	−0.12	−0.11	−0.031	−0.10	−0.030	−0.098
	(0.12)	(0.077)	(0.13)	(0.084)	(0.078)	(0.081)	(0.079)	(0.085)
Draft cattle p.c	0.066	0.047	0.061	0.049	0.037	0.039	0.035	0.041
	(0.096)	(0.052)	(0.093)	(0.051)	(0.044)	(0.033)	(0.045)	(0.034)
Sheep, pigs, goats p.c	−0.0056	0.020	−0.0061	0.017	0.0043	0.016	0.0048	0.014
	(0.026)	(0.020)	(0.026)	(0.021)	(0.012)	(0.012)	(0.012)	(0.013)
Rabbit &poultry p.c.	−0.00042	0.036	−0.0087	0.019	−0.035	−0.058	−0.037	−0.069
	(0.046)	(0.050)	(0.047)	(0.055)	(0.022)	(0.040)	(0.022)	(0.041)
Wealth Index	1.87	3.07***	1.77	2.57**	0.24	1.83**	0.13	1.35*
	(1.40)	(0.97)	(1.38)	(0.97)	(0.72)	(0.66)	(0.71)	(0.63)
Housing quality index	−0.28	−0.97***	−0.23	−0.88**	0.0054	−0.63**	0.043	−0.52*
	(0.48)	(0.30)	(0.48)	(0.30)	(0.30)	(0.27)	(0.29)	(0.25)
Services index	−0.76	−0.89**	−0.67	−0.49	−0.16	−0.47**	−0.092	−0.20
	(0.57)	(0.40)	(0.57)	(0.43)	(0.25)	(0.17)	(0.25)	(0.22)
Household size	0.013	−0.0065	0.014	−0.0076	−0.0027	−0.017	−0.0018	−0.017
	(0.021)	(0.010)	(0.021)	(0.011)	(0.012)	(0.010)	(0.012)	(0.011)
Nb. of children <5	−0.031	0.0040	−0.022	0.011	−0.034	0.040	−0.031	0.040
	(0.037)	(0.030)	(0.037)	(0.033)	(0.025)	(0.029)	(0.026)	(0.031)
MDM	0.23**	0.24***	0.22**	0.22***	0.11*	0.13***	0.10	0.11**
	(0.091)	(0.037)	(0.089)	(0.044)	(0.060)	(0.040)	(0.062)	(0.048)
MGNREGS	0.16	0.048	0.19	0.13	0.013	−0.031	0.055	0.024
	(0.16)	(0.098)	(0.17)	(0.13)	(0.053)	(0.063)	(0.074)	(0.11)
% Agr. land irrig.	0.21	−0.59**	0.20	−0.80**	−0.42	−0.61	−0.42	−0.72*
	(0.47)	(0.24)	(0.51)	(0.32)	(0.53)	(0.36)	(0.56)	(0.37)
Density CSOs	0.077*	0.054**	0.096**	0.11**	−0.0034	−0.0069	0.014	0.023
	(0.039)	(0.020)	(0.043)	(0.045)	(0.019)	(0.030)	(0.031)	(0.036)
Access to services	−0.083**	0.041	−0.086**	0.069*	−0.032	0.072**	−0.037	0.089***
	(0.033)	(0.031)	(0.033)	(0.036)	(0.026)	(0.025)	(0.025)	(0.028)
Food programs	−0.17***	−0.21**	−0.19***	−0.25**	0.043	0.069	0.028	0.053
	(0.052)	(0.095)	(0.055)	(0.11)	(0.060)	(0.10)	(0.068)	(0.082)
Health programs	−0.010	−0.11***	−0.0017	−0.033	−0.020	−0.11**	−0.010	−0.067
	(0.073)	(0.037)	(0.076)	(0.098)	(0.065)	(0.051)	(0.069)	(0.072)
Educ. programs	−0.21	−0.14	−0.23	−0.42**	−0.099	−0.15	−0.13*	−0.33**
	(0.14)	(0.093)	(0.17)	(0.18)	(0.064)	(0.095)	(0.071)	(0.14)
Infrastructure prog.	0.023	−0.011	−0.015	−0.11	0.057	0.023	0.028	−0.030
	(0.12)	(0.11)	(0.13)	(0.19)	(0.056)	(0.054)	(0.086)	(0.12)
Other programs	0.0023	0.011	0.0047	0.0086	−0.013	−0.00051	−0.011	−0.00090
	(0.020)	(0.018)	(0.020)	(0.022)	(0.017)	(0.017)	(0.017)	(0.018)
Educ. facilities	0.051***	0.0078	0.044**	0.0054	−0.0012	−0.0096	−0.0054	−0.012
	(0.014)	(0.012)	(0.016)	(0.022)	(0.011)	(0.012)	(0.012)	(0.019)
Health facilities	0.052*	0.050***	0.051*	0.052***	0.015	0.021**	0.017	0.023
	(0.027)	(0.015)	(0.026)	(0.014)	(0.012)	(0.0075)	(0.016)	(0.014)
Baseline variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	733	718	731	716	923	904	921	902
R^2	0.17	0.74	0.17	0.72	0.046	0.48	0.043	0.46

Notes: (ii) Standard errors (in parentheses) are clustered at mandal-level. (iii) "Baseline variables" refers to the inclusion of the lagged time-varying covariates plus variables for the initial. values of HAZ (WAZ), age of the child, height of the mother, education of the caregiver and of the household head. (iv) In 2SLS estimations, violence is instrumented by the share of forest cover in 1991.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

and ΔWAZ in the last four columns. For each dependent variable, we first show the results of OLS estimations that will serve as a benchmark for the 2SLS estimations. For each pair of dependent variable and estimator, we show the results of two specifications: the first one only includes time-varying variables and corresponds to a child fixed effects estimation (columns 1, 3, 5 and 7). The second specification adds baseline child, household and villages characteristics to help alleviating endogeneity concerns (columns

Table 7
First-stage results of the 2SLS estimations of the direct and indirect effects of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006.

Corresponding column in Table 6	(3)	(4)	(7)	(8)
Endogenous variable:	Political violence			
% forest in Mandal in 1991	2.90***	3.44***	2.86***	3.32***
	(0.72)	(0.60)	(0.76)	(0.63)
% forest in Mandal in 1991 × drought	−1.32**	−2.16***	−1.25*	−2.03***
	(0.62)	(0.71)	(0.67)	(0.73)
% forest in Mandal in 1991 × illness	−0.13	−0.17	−0.11	−0.16
	(0.18)	(0.13)	(0.15)	(0.13)
F Statistic of instruments	7.4	26.87	5.71	20.36
p-value of F statistic	0.003	0.00	0.01	0.00
Shea partial R^2	0.66	0.40	0.63	0.63
Endogenous variable:	Political violence × drought			
% forest in Mandal in 1991	−0.58	−0.20	−0.53	−0.24
	(0.45)	(0.39)	(0.43)	(0.39)
% forest in Mandal in 1991 × drought	2.13***	1.42**	2.12***	1.45***
	(0.63)	(0.56)	(0.63)	(0.56)
% forest in Mandal in 1991 × illness	−0.15	−0.18	−0.14	−0.16
	(0.18)	(0.13)	(0.16)	(0.12)
F statistic of instruments	5.47	26.14	4.5	16.46
p-value of F statistic	0.01	0.00	0.02	0.00
Shea partial R^2	0.46	0.18	0.45	0.28
Endogenous variable:	Political violence × illness			
% forest in Mandal in 1991	−0.01	0.19	0.03	0.12
	(0.12)	(0.13)	(0.12)	(0.13)
% forest in Mandal in 1991 × drought	−0.19	−0.39**	−0.24*	−0.34**
	(0.15)	(0.17)	(0.13)	(0.13)
% forest in Mandal in 1991 × illness	1.97***	1.96***	2.07***	2.05***
	(0.40)	(0.38)	(0.33)	(0.33)
F statistic of instruments	9.13	12.83	16.34	18.94
p-value of F statistic	0.001	0.00	0.00	0.00
Shea partial R^2	0.27	0.26	0.32	0.29
Kleibergen–Paap rk LM statistic	2.38	5.30	2.63	5.05
Kleibergen–Paap rk LM p-value	0.12	0.02	0.10	0.025
Observations	731	716	921	902

Notes:(ii) Standard errors (in parentheses) are clustered at mandal-level. The first-stage regressions feature the same list of covariates as the second-stage regressions in Table 3.
* p<0.1.
** p<0.05.
*** p<0.01.

2, 4, 6 and 8).[19] The number of observations slightly differs between specifications with and without baseline covariates (due to some variables being missing). There is no meaningful change in the results when we run these estimations on the same (smaller) sample. Likewise, results of the specifications without baseline covariates do not change much when we restrict the list of included variables to increase the sample size. We tend to favor specifications with baseline variables as their introduction strengthens our claim that the instrument is valid.

In all specifications, violence is found to exert a strong and statistically significant adverse effect on the evolution of children's nutrition outcomes. Children living in Naxal-affected mandals have grown by 0.37 to a full 1 standard deviation less than their peers. The magnitude of the effect of political violence on ΔHAZ is

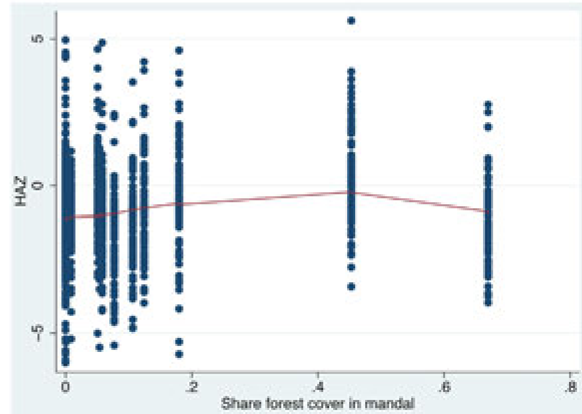

Fig. 4. Relationship between share of forest cover and HAZ in 2002. Source: Authors' calculations based on YL data.

very similar across OLS and 2SLS estimations in columns 1 and 3 (−1.04 and −0.92, respectively). In column 4, when baseline characteristics are included, the 2SLS estimate becomes larger in absolute value than the OLS estimate in column 2 (−0.84 and −0.37, respectively) but it remains similar in magnitude to the one previously obtained without baseline characteristics in column 3.

The effect of violence on ΔWAZ is also strong and robust and ranges from −0.26 to −0.64 standard deviation, depending on the specification. This suggests that there is a direct effect of living in a conflict-affected area on child nutrition.[20] As above, the difference between OLS and 2SLS estimates of political violence is limited in the first specification (−0.41 and −0.57, respectively) but it substantially increases when baseline characteristics are included, with the 2SLS estimate (−0.64) larger in absolute value than the OLS estimate (−0.26).

We take reassurance from the robustness of the results in Table 3. The fact that the estimated effect of political violence is very stable across different specifications when the 2SLS method is used and is negative and statistically significant with both OLS and 2SLS estimations (although the magnitude differs when baseline characteristics are included) shows that these results are not dependent on a particular specification.

Drought does not seem to exert a statistically significant impact on child growth in any specification but parents' illness lowers children's growth – by 0.14–0.24 standard deviation – in all specifications, although this effect is statistically significant at the 10% level only in columns 1, 3 and 4. However, parents' illness does not exert a statistically significant impact on ΔWAZ.

Other covariates display the expected signs. The index of wealth is strongly associated with progress in nutritional status (but only when baseline characteristics are included), as is access to the Mid-day Meal School program (MDM) and to educational and health facilities. The density of CSOs in the village is associated with positive evolution of children's nutrition outcomes once baseline characteristics are introduced. Surprisingly the index of services accessed by the household is negatively associated with ΔHAZ (but positively so for ΔWAZ) and the higher the share of agricultural land in the village, the lower the subsequent evolution of HAZ and

[19] In Appendix B, we show the results of an additional specification that only include baseline characteristics.

[20] Given that WAZ is a short-term nutritional indicator, we assume that these effects are being driven by violent events that occurred towards the end of the period 2002–2006. The years 2005/2006 correspond to a period of intense police crackdown on the rebels that would eventually virtually eradicate the Naxals from Andhra Pradesh after 2006. In 2006, we coded 38 instances of Maoist attacks on people and/or property and 47 encounters led by the police against the rebels. In 2005, we observed 81 attacks and 42 encounters.

WAZ. There is a negative relationship between presence of food and health programs in the village and the evolution of nutritional status, which may partly be due to selection of such programs in areas most exposed to shocks. Finally, there is a convergence process at work as the baseline value of HAZ and WAZ are negatively related to the subsequent evolution of nutritional status.[21] This may also explain why children living in households with more services display lower growth of HAZ and WAZ than other children.

5.2. Allowing for a modest violation of the exclusion restriction

When discussing the validity of the instrument, we have argued that children living in heavily forested mandals were not worse-off than children living in sparsely forest mandals at the beginning of the study period. In other words, we contend that if the share of forest cover was to exert an independent impact on nutritional status in the structural equation; this effect would most likely be positive and so the estimated impact of conflict would be a lower bound of the true impact.

But what if there was nonetheless a negative relationship between density of forest cover and changes in HAZ or WAZ that we failed to capture? Sensitivity tests suggest that the results would still hold even in this unlikely case, especially for ΔWAZ. Conley et al. (2012) propose a procedure for generating confidence intervals of the estimated effect of the (plausibly exogenous) explanatory variable under the assumption of a modest violation of the exclusion restriction. When we implement this procedure (the Union of Confidence Intervals, UCI) on our data[22], we find that the estimated effect of violence on ΔHAZ (ΔWAZ) remains significantly negative at the 5% level when we allow for the share of forest cover to exert a negative impact of up to 0.6 (0.4) standard deviation on the dependent variable and when the forest cover of 1991 is used as an instrument. The inclusion of baseline covariates does not change these thresholds. Overall, these results suggest that even if the share of forest cover had an independent adverse impact on nutrition outcomes (and we have good reason to think this is unlikely), then our main finding would hold.[23]

5.3. Heteroskedasticity-based instruments

To provide further reassurance that our instrument (share of forest cover) is valid, we generate heteroskedasticity-based instruments according to the method proposed by Lewbel (2012). This method considers a system of equations where equation (i) describes the structural equation to be estimated (in our case, Eq. (1)) and equation (ii) is the auxiliary equation describing the process generating the endogenous variable. Lewbel (2012) shows that as long as the covariance between the exogenous regressors and the squared error term in the auxiliary equation is non-null (i.e. there is some heteroskedasticity) and that the covariance between the regressors and the product of the error terms in the main and auxiliary equations is null (which is always the case under the standard assumption that the error terms have a mean of zero and are conditionally independent of each others), then a set of valid internal instruments can be generated. The instruments take the form $[Z - E(Z)].\varepsilon$ where Z are the exogenous regressors and ε is the residual of the auxiliary regression.

This method allows us to check whether our results hold using the heteroskedasticity-based instruments and to run over-identification tests. Indeed, the presence of the generated instruments means that we have more instruments than endogenous variables. A rejection of the over-identification test (we will report the Hansen test as we use clustered standard errors) would call into question the validity of the instruments.

Table 5 replicates the 2SLS specifications of columns 3–4 and 7–8 in Table 3. For each specification, we report results obtained when we only use the generated instruments and when we use both the generated instruments and the share of forest cover. When baseline covariates are not included (columns 1–2), results for ΔHAZ as they appear in Table 5 are very similar to those obtained in Table 3. The coefficient associated with political violence is estimated at around -0.9 standard deviation with the Lewbel method (irrespective of whether the share of forest cover is used as an instrument or not) while it was estimated to be between -0.9 and -0.8 standard deviation in Table 3. For ΔWAZ, the results of the Lewbel specifications shown in columns 5–6 are also close to the corresponding results in Table 3 although the magnitude of the effect of political violence decreases in absolute value with the Lewbel method (from -0.6 in Table 3 to -0.4 standard deviations in Table 5). Yet, the coefficient remains statistically different from zero at the 1% level.

When the baseline characteristics are introduced in columns 3–4 and 7–8, however, the effect of political violence strongly decreases in absolute value with respect to the estimations of Table 3. This does not impact the precision of the estimates for ΔWAZ but the effect of political violence is no longer statistically significant for ΔHAZ. It is not clear why the introduction of baseline variables causes such a change in the estimated effect of political violence on ΔHAZ. Without downplaying the relevance of this result, it is worth stressing that since heteroskedasticity-based instruments are valid by construction, the specification displayed in column 1 (which does not include baseline variables) and which confirms the negative impact of political violence on *HAZ* should not be given a lower value than that of column 3, in contrast to estimations using the share of forest cover as an IV.

The first-stage diagnostics reveal that the generated instruments are strongly correlated with political violence and that the p-value of the Hansen test never drops below 30%, meaning we cannot reject the null hypothesis that the instruments are valid.

Overall, the Lewbel estimations confirm the main 2SLS results: i.e. that political violence negatively affects ΔHAZ and ΔWAZ, although the former is only true when baseline characteristics are not introduced. The associated over-identification tests also provide further reassurance as to the validity of our instrument. Importantly, we established that most of the main results of Table 3 are not dependent on the use of the share of forest cover as an instrument.

5.4. Joint exposure to conflict and adverse shocks

In this section, we estimate the following equation in order to capture the joint effect of conflict and shocks:

$$\begin{aligned} y_{ivmt+1} - y_{ivmt} = {} & \beta_0 + \beta_1 D_{vmt} + \beta_2 I_{ivmt} + \beta_3 C_{mt} \\ & + \beta_4 (X_{ivmt+1} - X_{ivmt}) \quad + \beta_5 X_{ivmt} + \beta_6 D_{vmt} \times C_{mt} \\ & + \beta_7 I_{ivmt} \times C_{mt} + \mu_i + u_v + v_m + \varepsilon_{ivmt} \end{aligned} \qquad (2)$$

The full impact of conflict is given by the sum of the direct effect (β_3) and the two interactions between conflict and economic shocks (β_6 and β_7). β_3 indicates by how much ΔHAZ and ΔWAZ

[21] The effect of this variable, along with all baseline covariates, is not shown in the table of results to save space, but is available upon request. It is worth noting, however, that catch-up growth of initially disadvantaged children does not explain our results. Instead, children in conflict-affected areas, who tended to be better-off initially, have subsequently grown so much slower than their counterparts in non-affected mandals than their initial height advantage has entirely dissipated over the study period. We are thankful for an anonymous reviewer for this observation.

[22] We used the user-written package *plausexog* in Stata.

[23] The results for all specifications are available upon request.

differ in mandals affected by conflict and in peaceful mandals. The interaction terms should be interpreted as the differentiated impacts of shocks in conflict-affected mandals with respect to peaceful mandals. The full impact of conflict is given by the sum of the direct effect and the indirect effects that operate through drought and illness.

The instrumentation remains unchanged with respect to the previous analysis except that there are now three endogenous variables (violence and the interaction of violence with drought and illness each) and three instruments (the share of forest cover and the interaction of the share of forest cover with drought and illness each). The three instruments are distinct but collinear (because all are based on the same excluded variable) which is why in Table 7, which shows the first stage regression results, two of the interactions are sometimes jointly significant in explaining one endogenous variable. Nevertheless, it is the interaction between forest and drought that explains most of the variation in the interaction between conflict and drought while the other instruments are at best weakly associated with the latter. This is true for all three endogenous variables.

Results for ΔHAZ are displayed in columns (1–4) of Table 6. The standalone effect of political violence is no longer statistically distinguishable from zero in all the specifications. However, both the interactions of violence with drought and illness exert a statistically significant impact on children's growth. The magnitude of the effect of the interaction between political violence and drought is very large in absolute value at about -1.1 standard deviation with 2SLS estimations. The point estimate of the interaction is virtually the same irrespective of whether baseline characteristics are included or not but the precision of the estimation is lower when baseline characteristics are included (column 4) although the effect remains statistically significant at the 10% level. OLS estimates of the interaction term between political violence and drought are smaller in absolute value than the corresponding 2SLS estimates but so are the standard errors meaning that the statistical significance of the estimated effect of the interaction is unchanged.

The interaction between political violence and parents' illness also exerts a negative and statistically significant impact on ΔHAZ. There is only one specification (OLS with baseline characteristics, column 2) in which the effect of this interaction is indistinguishable from zero. The magnitude of the effect and the precision of the estimations are also larger in absolute value with 2SLS estimations (-0.78 and -0.51 standard deviation in column 3 and 4, respectively) than with OLS estimations (-0.44 and -0.006 standard deviation in columns 1 and 2, respectively). The standalone coefficients of drought and illness are not statistically different from zero.

Results for ΔWAZ are shown in columns 5–8 of Table 6. The effects of the two newly introduced interaction terms are not significantly different from zero except in column 5 where the coefficient associated with the combination of violence and drought is surprisingly positive. The estimated direct impact of violence is mostly unchanged from that of Table 3, when interactions were not included in the regressions. There are only limited differences between OLS and 2SLS estimates.

Overall, these results show that political violence exerts a direct, short-term adverse impact on children's nutrition (measured by ΔWAZ). Political violence is also found to adversely impact long-term growth's trajectories of children (captured by ΔHAZ), but such an impact only arises when children have additionally been exposed to severe climatic and health shocks. In the absence of other negative shocks, political violence does not seem to impact the long-term nutritional status of children. Likewise, in the absence of violence, health and climatic shocks do not exert a lasting impact on child nutrition outcomes.[24]

6. Robustness tests

To demonstrate that the results are not driven by a particular specification, we have so far considered 3 estimators (OLS, 2SLS and 2SLS with Lewbel instruments), two regression specifications (one without and one with baseline variables) and two dependent variables (ΔHAZ and ΔWAZ). In this section, we present further tests of the robustness of the results.

First, we have assumed so far that drought and illness were exogenous in Eqs. (1) and (2). Yet it is possible that the presence of conflict increases the odds that people suffer from shocks as external help is less likely to reach on time (in the case of drought) and households have access to a narrower range of coping strategies (if, for instance, health facilities become understaffed or if people fear traveling to another village to visit a doctor). In the absence of credible external instrumental variables, we have instrumented drought and illness with the Lewbel procedure. Unfortunately, these instruments proved weak (F-statistics were routinely below 10 for drought and below 5 for illness and under-identification tests did not pass). However, Hausman tests of exogeneity based on such instruments could not reject the assumption that drought and illness are exogenous, which lends credibility to the approaches of Tables 3 and 6 .[25]

Second, we present in Table 10 in the appendix estimations results when variables of drought and illness are excluded from Eq. (1). We had included these variables in our regressions because of their strong correlation with political violence. Yet, if drought and illness are outcomes of political violence, including them in the regression would alter the meaning of the coefficient associated with political violence. When we remove drought and illness from the regression in Table 10, we can see that the magnitude of the effect of political violence remains very similar to those in Table 3 in all specifications, while the precision of the estimates increases.

Third, we are considering alternative variables of drought. So far, we have defined drought based on answers from the community respondents. Directly using rainfall data to identify drought would be a better alternative but the historical data provided by the Indian Meteorological Department are not available at the required administrative units for our analysis, i.e. villages and mandals. We present then further robustness checks to establish the validity of our community-measure of drought.

In Table 11, we replicate the analysis of Table 3 by replacing the drought indicator with a measure of "severe drought". We operationalize drought severity by the proportion of people in the village affected by droughts. The number of affected people is compiled from the community survey which asked village respondents to estimate the number of people affected by drought. The proportion of affected people ranges from 3% to 25%. We consider a drought to be severe when the proportion of affected people is equal to or higher than the median value of severity (15.5%). The rationale for looking at severe droughts is that droughts at the low and high end of this severity metric may be very different phenomena. This is especially problematic as households do not equally benefit from informal coping mechanisms depending on whether the shock is idiosyncratic or

[24] Unlike for the baseline results, we do not present the results of a Lewbel estimation of equation 2. This is because the introduction of 3 endogenous regressors in the model causes a proliferation of generated instruments, preventing us from estimating the first-stage regressions with clustered standard errors.

[25] The results are available upon request.

Table 8
Proportion of households using selected coping strategies in response to drought in peaceful and conflict-affected mandals.

Coping strategy	Non-naxal mandals	Naxal mandals	Difference (*p*-value)
Used credit	0.238	0.257	−0.0196 (0.644)
Migrated	0.174	0.146	0.0274 (0.451)
Worked more	0.143	0.105	0.0381 (0.246)
Bought less	0.023	0.053	−0.030* (0.094)
Nothing	0.158	0.047	0.112*** (0.000)
Aid from government/NGO	0.023	0.094	−0.0709*** (0.001)
Insurance paid	0.042	0.070	−0.0287 (0.192)
Ate less	0.004	0.058	−0.0547*** (0.000)
Aid from community	0.030	0.047	−0.0166 (0.369)
Aid from friends & family	0.091	0.053	0.0379 (0.144)
Used savings	0.049	0.035	0.014 (0.487)
Observations	265	171	436

Source: Authors' calculations based on Young Lives data.
*p<0.1.
**p<0.05.
***p<0.01.

covariant. Another concern is related to the possibility that the definition of drought followed by community representatives may not be consistent across all communities. Restricting the analysis to severe droughts is therefore useful to check that our previous analyses were not affected by these potential measurement errors. However, it results in a drastic reduction of the sample size as observations affected by non-severe droughts are set to missing. The lower statistical power that ensues is seen in higher standard errors. Yet, results of Table 11 show that the interaction term between violence and drought remains negative and statistically significant in columns 1–4 (although the magnitude of the coefficient is reduced by two in column 4 with respect to Table 6). The estimated effect of violence on ΔWAZ remains negative, but the inflation of the standard errors caused by the smaller sample size causes this effect to stop being statistically significant when the 2SLS estimator is used. Unsurprisingly, the standalone coefficient associated with severe drought tends to be larger in absolute value than the one associated with all droughts, but the effect of severe drought is still not significantly negative. Overall, looking at severe droughts alone tends to corroborate our previous findings.[26]

In addition, we also considered another drought variable based on self-reported information from the household survey. This new variable takes the value 1 if at least 50% of the respondents in a given village report a drought and 0 otherwise. Estimating Eqs. (1) and (2) with this new variable yields similar results than those displayed in Table 6, as can be seen in Table 12. The main changes are that the interaction between drought and political violence is only statistically significant in columns (1–2), i.e. without baseline covariates, and that the standalone effect of drought (i.e. the effect of drought in peace) is now larger and more precisely estimated (it is negative and strongly statistically significant when ΔWAZ is the dependent variable and baseline covariates are introduced, in columns 6 and 8).

Finally, we also ran the regressions with the growth of the child in centimeters (ΔHAD) instead of the change in z-score of the height-for-age (ΔHAZ) as the dependent variable. Leroy et al. (2014, 2015) have argued that growth faltering is better captured by the former construct. The results are qualitatively similar when we use ΔHAD instead of ΔHAZ. These results are available upon request.

7. Potential mechanisms and discussion

There are several plausible reasons why the Naxal insurgency may have had such dramatic adverse on short-term and long-term nutritional status of children. The available data does not allow us to provide precise quantitative evidence on the mechanisms that may explain these strong effects; however, the information we have allows us to discuss below what we believe is very compelling evidence suggesting that the Naxal insurgency may have considerably affected two key mechanisms which mediate how households are negatively or positively affected by shocks: household access to economic coping strategies and household access to government-provided goods and services.

7.1. Coping strategies during the conflict

Violent conflicts tend to have substantial effects on local social relations and informal support networks, due to increased mistrust and lower levels of cooperation between community members (Kalyvas, 2006), and the isolation of communities by armed groups seeking to control territories and populations (Gafaro et al., 2014). As a result, important coping strategies such as risk-sharing arrangements at the level of the extended family, villages or ethnic networks may be severely disrupted. One of the strongest channels reported in the media and in more qualitative literature on the

[26] An alternative approach suggested by an anonymous reviewer consists in coding non-severe droughts as "no droughts" instead of being set to missing. This preserves the sample size but by blurring the distinction between "drought" and "no drought", it causes the standard errors associated with the interaction between political violence and drought to substantially increase so that the coefficient is no longer distinguishable from zero statistically.

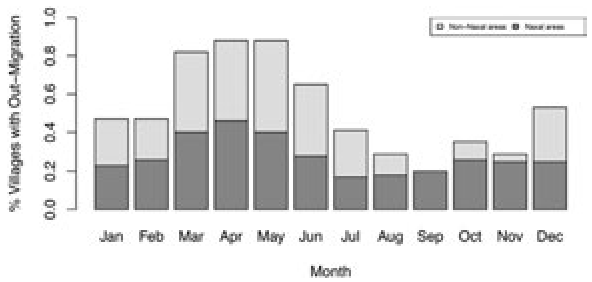

Fig. 5. Overlaid graph of monthly rates of village out-migration in peaceful and conflict-affected mandals. Source: authors' calculations based on the Young Lives data.

Naxal insurgency in India is the fact that the presence of the Naxals in contested areas may lead to an increase in isolation of communities by making travel and outside relations unsafe and by explicitly restricting people's freedom of movement (Chakravarti, 2009; Pandita, 2011; Sharma, 2012). Isolation and fear could, in turn, undermine social interactions that underpin informal risk-pooling mechanisms, as well as hindering coping strategies that involve access to markets and public goods (Christiaensen et al., 2007)e.g.. Such an isolation - especially from food markets – has been shown to expose children from the effects of climate change in Nepal (Mulmi et al., 2016). Shah (2009) and Shneiderman (2009) describe, respectively, the rise of levels in uncertainty and ambivalence in local social relations in areas of conflict in Jharkhand (where the Naxal movement operates strongly) and Nepal (where similar groups fought government troops for several years).

In Andhra Pradesh, we have some evidence suggesting that coping strategies based on local social interactions may have been affected by the Naxal conflict. Table 8 lists the most common coping strategies reported by households affected by drought in Andhra Pradesh. The table compares households in Naxal-affected communities with those in communities not affected by the conflict. The results show that community and family-based strategies are not widely used by households affected by drought. This may be due to the covariant nature of the shock. However, the table shows some substantial differences in the type of coping strategies used by households in conflict and non-conflict areas. Notably, households living in areas affected by the Naxal insurgency tend to reduce their expenditure, are more dependent on government and NGO transfers and reduce significantly the amount of meals consumed. These results suggest a large degree of distress among households trying to cope with drought in Naxal-affected mandals.

Seasonal migration is often reported as an important coping strategy adopted by vulnerable populations in Andhra Pradesh (Jones et al., 2007). Table 8 shows no statistically significant difference in the number of households reporting having migrated for work as a coping strategy when we compare Naxal-affected and non-Naxal affected areas. However, differences in seasonal migration patterns are visible in Fig. 5, where we report data from the community survey of Young Lives on annual migration in violence-affected and non-affected areas in 2006: during the lean season (especially from March to May) many people leave their villages to seek work. The pattern is similar in both areas but in violence-affected areas the magnitude of out-migration is noticeably lower.

7.2. Access to public goods and services

Government-provided services usually cease to operate in conflict-affected areas (if they existed at all in place in the first place) (Mampilly, 2011). This is often caused by concerns with the security of government officials, or the destruction of roads and other infrastructure that prevents services from reaching violence-affected areas. Both mechanisms could be at play in our case study. First, in their study on linkages between women's empowerment and childhood poverty, Jones et al. (2007) hint to this situation in one of our sampled mandals: "[t]he area is also affected by the presence of Naxalite forces, which makes government officials reluctant to implement programs and prevents local people from gaining access to authorities and information" (p. 11). Second, as discussed in section 2, Naxal groups in Andhra Pradesh have been reported to destroy infrastructure and attack government officials as tactics to isolate populations and territories from government access, create safe heavens for themselves and ensure population compliance.

Making use of the information provided in the Young Lives panel dataset, we have investigated whether restricted access to public programs in conflict areas may explain our results. The dataset contains information on household participation in several programs. The main program in place is the Public Distribution System (PDS). Table 9 gives an overview on some of the variables indicating distribution levels, scope and satisfaction with this

Table 9
Proportion of households accessing and satisfied by food aid and sanitation services and selected health indicators in peaceful and conflict-affected mandals.

	Non-naxal mandals	Naxal mandals	Difference (*p*-value)
Recipient of food aid	0.890	0.863	0.027 (0.022)
Food aid money goes directly to the child	0.357	0.249	0.108*** (0.002)
Satisfied with food aid	0.657	0.557	0.101*** (0.004)
Access to sanitation services	0.367	0.103	0.264*** (0.000)
YL child has a vaccination card	0.499	0.245	0.254*** (0.000)
YL child is immunized against meningitis	0.383	0.304	0.079** (0.018)
YL child had severe disease	0.319	0.384	−0.065** (0.043)

Source: Authors' calculations based on the Young Lives data.
*p<0.1.
** p<0.05.
*** p<0.01.

service. During the 12 months prior to the second wave of the Young Lives survey (in 2006), about 88% of households report having received food aid through the Public Distribution System. The extent of access to the food distribution system was 86.3% in conflict areas and 89% in non-affected areas. When asked whether recipients were satisfied with the service, 55.7% of respondents living in conflict-affected answered positively, while a higher percentage (65.7%) reported being satisfied with the service in non-affected areas (differences are significant at the 1% level). Also, only 24.9% of respondents in conflict areas (versus 35.7% in non-affected areas) declared that at least some of this aid went directly to the child followed by the Young Lives dataset (significant at 1%). These results suggest that food aid in 2006 may have been less efficient in conflict-affected areas, in comparison to non-affected areas.

But adequate food supply is not the only driver of stunted growth. Health and sanitation also play significant parts in child growth and development (e.g. World, 2013). As alluded to earlier in the paper, available data on access to services does not suggest that Naxal mandals were worse off than non-Naxal mandals in either 2002 or 2006. However, looking specifically at sanitation, we find a much lower proportion of households accessing relevant services in 2006 in Naxal mandals (10.3%) than in non-Naxal mandals (36.7%). The difference is significant at the 1% level.

Furthermore, some health indicators suggest significant differences across the areas. For example, 447 respondents in the second round of the Young Lives survey reported that the child followed in the Young Lives survey had a serious injury or illness (where the caretaker/respondent thought it might die, mostly from malaria or high fever) in the four years prior to the survey. This corresponds to 38.4% of respondents in conflict areas, and 31.9% in areas not affected by the insurgency. The data shows in addition that households in conflict areas are significantly less likely to have vaccination cards for their children (24.5 versus 49.9%) and that children living in violence-affected areas are less likely to have been immunized against meningitis (38.3 versus 30.4%).

8. Conclusion

Sustaining economic development in areas characterized by longstanding political tensions where actors persistently resort to violence to resolve social conflicts is an enormous challenge. This paper shows that this challenge is significantly exacerbated by the complex effects of political violence on the ability of households to cope with common covariant and idiosyncratic shocks.

The paper shows three important results. First, drought and illness exert a strong impact on long-term malnutrition, but only when it occurs in a violent environment. Second, we found that political violence exerts a long-term impact on child malnutrition only indirectly, when the combination of conflict with drought and illness prevents households to appropriately protect their children against adverse nutritional shocks. Third, conflict adversely impacts short-term malnutrition. Although existing data does not allow us to show irrefutable evidence for the mechanisms at play, our analysis strongly suggests that the adverse combined welfare impact of conflict and adverse shocks is explained by a failure of economic coping strategies and restricted access to public services and aid in conflict-affected communities, possibly due to fear, insecurity and isolation.

This result has several theoretical and policy implications. First, the analysis discussed in the paper provides a strong sense of how people cope with multiple (economic and political) shocks. 1.5 billion people live in conflict-affected countries (World, 2010), where they have to cope with a myriad of risks, in addition to violence and instability. An important feature of these political shocks is the fact that they lead to significant changes in the institutional environments under which people make decisions (Gafaro et al., 2014), and to people's social preferences (Voors et al., 2012). This paper provides a first attempt at documenting how violent conflict may affect the ability of households to cope with periods of drought and illness, two shocks commonly experienced by many other low-income countries affected by civil wars and other forms of political instability.

Although the Naxal insurgency has been brutal, it is by no means comparable to civil wars such as those in Burundi, Rwanda, DRC or South Sudan, where hundreds of thousands of civilians have died, either directly or indirectly due to food shortages and diseases. However, the ongoing armed Naxal insurgency in India and the extreme brutality of some of the attacks has created an environment hostile to poverty alleviations strategies, common to many other countries affected by violent conflict in Asia, Africa and Latin America. Interestingly, low levels of child nutrition have been shown to be of particular concern in India, where malnutrition has remained high despite considerable levels of economic growth (Deaton and Dreze, 2009). Our result suggests that at least in some parts of India this may be partially due by unusual high levels of violence, fear and uncertainty. This could provide an interesting area of future research.

Appendix A. Definition and sources of key variables

Height-for-age *z*-score (HAZ) and **Weight-for-age *z*-score (WAZ)**. The nutrition scores of “Height for age”, “Weight for age” and “BMI for age” were calculated using an SPSS Macro for the growth standards that were downloaded from the WHO website.

Source: YL household survey.

Drought: takes the value if respondent of the YL community survey reports a drought in the village between 2002 and 2006.

Source: YL community survey

Severe drought: takes the value if respondent of the YL community survey reports a drought in the village between 2002 and 2006 AND if the reported proportion of affected people in the village exceeds 15.5%.

Source: authors' calculations from YL community survey.

Alternative drought variable: takes the value 1 if 50% of respondents in a village report a drought.

Source: authors' calculations from YL household survey.

Illness: takes the value 1 if either the father or mother of the YL child or another member of the household was ill between 2002 and 2006.

Source: authors' calculations from YL household survey.

Draught cattle p.c.: Number of draught cattle owned by the household; divided by household size.

Source: authors' calculations from YL household survey.

Sheeps, pigs, goats p.c: Number of sheep, pigs and goats owned by the household; divided by household size.

Source: authors' calculations from YL household survey.

Rabbit, poultry p.c: Number of rabbits and poultry owned by the household; divided by household size.

Source: authors' calculations from YL household survey. **Housing Quality Index**:This value is based on the number of rooms per person in the household and the main materials used for the walls, roof and floor. The number of rooms is divided by the size of the household. This result is divided by 1.5 to allow for rooms such as kitchens and bathrooms not used for general living. If the result of this calculation is greater than 1, it is set to 1. If the walls are made of brick or concrete then 1 is added to the index. If the roof is made of iron, concrete, tiles or slate then 1 is added to the index. If the floor is made of cement or is tiled or laminated then 1 is added to the index. This gives a value between 0 and 4 which is then divided by 4 to give a housing quality index of between 0 and 1.

Source: YL household survey.

Services Index: This value is based on whether or not the dwelling has electricity, the source of drinking water, type of toilet facility and the main type of fuel used for cooking. If the dwelling has electricity then 1 is added to the index. If drinking water is piped into the dwelling or the yard then 1 is added. If the household has their own toilet facility (not shared with other households) then 1 is added and if paraffin, kerosene, gas or electricity is used for cooking another 1 is added. The result is then divided by 4 to give a value between 0 and 1.

Source: YL household survey.

Wealth Index: This value is calculated as the average of the Housing Quality Index, the Consumer Durables Index and the Services Index.

Source: YL household survey.

Household size.

Source: YL household survey.

Nb. of children below 5 y.o. Corresponds to infkind variable in YL survey.

Source: YL household survey.

MDM: takes the value 1 if the household is registered with Mid-day Meal School Programme (MDM). Corresponds to inmdmreg in YL survey.

Source: YL household survey. **MNREGS**: takes the value 1 if the household is registered with MNREGS programme. Corresponds to inregegs in YL survey.

Source: YL household survey.

Irrigation: Share of agricultural land that is irrigated.

Source: authors' calculations from YL community survey.

Density of CSOs: Number of CSOs present in the village. Variables of CSOs in YL are: LBRUNION COMMKITC MTHRCLUB APAFA POLTGRP RELGGRP SVGSCOOP HOUSCOOP LENDCOOP SPRTASSC CRMASSC PSNTASSC NTVASSC AGRIASSC PRDCRS CASTEGRP WEAVASSC LOOMASSC SHEEPASC VSSASSC SHGASSC MAHILA BUAASSC WATRASSC NGOGRP EDUCOMM KDGTNGRP VOCTRGRP YTHGRP TRADPAN FACTION HEALCOMM SERVCOOP IDDIR BUSGRP BHAJAGRP OTHERS1 OTHERS2 OTHERS3

Source: authors' calculations from YL community survey.

Access to services: Number of services present in the village. Variables of services in YL (in 2006) are: PBLTELE PRVTELE PBLINRNT ELCTRCTY DRNKWATR SEWAGER PLCSTTN NONJUDG PROFJUDG NTLBANK LCLGOVRN AGRICOOP OTHSERV1 ANGANWAD REGMARK PDSSHOP VETHOSP. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Food programmes: Number of food programmes present in the village. Variables of food programmes in YL (in 2006) are: PDSPROG AAYPROG ANNAPROG MEALPROG OTFDPROG. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Health programmes: Number of health programmes present in the village. Variables of health programmes in YL (in 2006) are: HLTHPROG CRSPPROG SWAJPROG OTHEPROG. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Education programmes: Number of health programmes present in the village. Variables of health programmes in YL (in 2006) are: PRVNR4YR PRNOE4YR PRVPR4YR PBPRY4YR PRVPRM4Y PBSEC4YR PRVTSC4Y PSTTCH4Y PRVTCH4Y GOVJU4YR PRVJU4YR UNVTY4YR CEO4YR OTED4YR. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Infrastructure programmes: Number of health programmes present in the village. Variables of infrastructure programmes in YL (in 2006) are: SOILPROG OTINFRA. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Other programmes: Number of other programmes present in the village. Variables of other programmes in YL (in 2006) are: FFWPROG WIDOPROG NFBSPROG NMBSPROG GGPSPROG IAYPROG CCSSPROG NOAPPROG SGRYPROG SGSYPROG PMRYPROG JGSYPROG DWACPROG JFMPROG FARMPROG WDWPROG DPAPPROG WTSDPROG DDPPROG WLDPPROG NREGPROG BIOGPROG IREPPROG ICDPPROG IDDPPROG FFDPPROG CROPPROG AGRIPROG DPADPROG LANDPROG ADARPROG SUBSPROG CLABPROG FVCPROG CHEYPROG CMEYPROG SWADPROG SCCOPROG STCOPROG BCCOPROG MINOPROG KGBVPROG NCLPPROG APSPPROG APRLPROG. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Education facilities: Number of education facilities present in the village. Variables of education facilities in YL (in 2006) are: PRVTNRSY PRONOEI GOVPRPRE PRVTPRE PUBPRMRY PRVTPRMY PUBSEC PRVTSCND POSTTECH PRIVTECH GOVJUCOL PRVJUCOL UNVRSTY CEOS OTEDINST. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Health facilities: Number of health facilities present in the village. Variables of health programmes in YL (in 2006) are: PBHSPCUR PVHSPCUR STHLTCUR PVDSPCUR PBDSPCUR HTLCRCUR PHARMCUR PBFRTCUR PVFRTCUR OTFACCUR. Corresponding variables are used to generate the index in 2002.

Source: authors' calculations from YL community survey.

Education of caregiver: takes the value 1 if the caregiver has not completed any formal education; takes the value 2 of the caregiver completed primary school and takes the value 3 if the caregiver completed secondary school.

Source: authors' calculations from YL household survey.

Mother height: height of the mother of the YL child in centimetre.

Source: YL household survey.

Education of the household head: takes the value 1 if the household head completed primary school and 0 otherwise.

Source: authors' calculations from YL household survey.

Age of the YL child: In months.

Source: YL household survey.

Age of the mother: In years.

Source: YL household survey.

Share of forest cover: Proportion of land in the mandal that corresponds to forest. We first computed the total forested area in mandals by adding up the forested land surface of all villages, and then we divided this figure by the total land area of the mandal.

Source: authors' calculations from Andhra Pradesh Village Directory, Census of India.

Appendix B. Robustness tests

Table 10
Estimates of the direct effect of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006. Drought and illness are excluded from estimations.

Dependent variable Estimator	ΔHAZ OLS (1)	ΔHAZ OLS (2)	ΔHAZ 2SLS (3)	ΔHAZ 2SLS (4)	ΔWAZ OLS (5)	ΔWAZ OLS (6)	ΔWAZ 2SLS (7)	ΔWAZ 2SLS (8)
Political violence	−1.06*	−0.37***	−1.04**	−0.88***	−0.41***	−0.26*	−0.57***	−0.66**
	(0.33)	(0.12)	(0.40)	(0.27)	(0.099)	(0.12)	(0.10)	(0.30)
Baseline variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	733	718	731	716	923	904	921	902
R^2	0.15	0.74	0.15	0.74	0.04	0.48	0.039	0.47

Notes: (ii) Standard errors (in parentheses) are clustered at mandal-level. (iii) "Baseline variables" refers to the inclusion of the lagged time-varying covariates plus variables for the initial. values of HAZ (WAZ), age of the child, height of the mother, education of the caregiver and of the household head. (iv) In 2SLS estimations, violence is instrumented by the share of forest cover in 1991. (iv) The list of covariates included (but not shown) is the same as in Table 3.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 11
2SLS estimates of the direct and indirect effects of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) z-scores of children between 2002 and 2006 with alternative drought variable, I.

Dependent variable Estimator	ΔHAZ OLS (1)	ΔHAZ OLS (2)	ΔHAZ 2SLS (3)	ΔHAZ 2SLS (4)	ΔWAZ OLS (5)	ΔWAZ OLS (6)	ΔWAZ 2SLS (7)	ΔWAZ 2SLS (8)
Political violence	−0.17	0.001	0.12	0.15	−0.39***	−0.40**	−0.26	−0.29
	(0.21)	(0.15)	(0.29)	(0.22)	(0.13)	(0.16)	(0.21)	(0.27)
Pol. violence × severe drought	−0.94**	−0.50***	−1.32**	−0.48*	0.12	0.18	−0.02	0.38
	(0.33)	(0.16)	(0.47)	(0.23)	(0.20)	(0.24)	(0.34)	(0.44)
Pol. violence × illness	−0.35**	−0.04	−0.30	−0.48	−0.19	−0.05	0.11	−0.08
	(0.16)	(0.19)	(0.37)	(0.29)	(0.18)	(0.16)	(0.30)	(0.26)
Severe drought	−0.24	−0.19	−0.18	−0.22	−0.14	−0.19	−0.12	−0.23
	(0.18)	(0.12)	(0.17)	(0.13)	(0.14)	(0.12)	(0.15)	(0.14)
Illness	0.04	−0.06	0.07	0.09	0.16	0.04	0.08	0.06
	(0.14)	(0.09)	(0.16)	(0.13)	(0.14)	(0.09)	(0.12)	(0.11)
Baseline variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	445	435	443	433	565	553	563	551
R^2	0.18	0.76	0.19	0.76	0.06	0.49	0.05	0.49

Notes: (ii) Standard errors (in parentheses) are clustered at village-level. (iii) "Baseline variables" refers to the inclusion of the lagged time-varying covariates plus variables for the initial. values of HAZ (WAZ), age of the child, height of the mother, education of the caregiver and of the household head. (iv) A drought is considered severe if at least 15.5% of households in the village were affected by it. (iv) Non-severe droughts are set to missing. (iv) In 2SLS estimations, violence is instrumented by the share of forest cover in 1991.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 12
2SLS estimates of the direct and indirect effects of political (Naxal-related) violence on change in height-for-age (ΔHAZ) and weight-for-age (ΔWAZ) *z*-scores of children between 2002 and 2006 with alternative drought variable, II.

Dependent variable Violence is instrumented by mandal forest cover in:	ΔHAZ 2001 (1)	ΔHAZ 2001 (2)	ΔHAZ 1991 (3)	ΔHAZ 1991 (4)	ΔWAZ 2001 (5)	ΔWAZ 2001 (6)	ΔWAZ 1991 (7)	ΔWAZ 1991 (8)
Endogenous variables								
Political violence	−0.26	−0.14	0.03	−0.48	−0.61***	−0.43***	−0.38	−0.45*
	(0.23)	(0.21)	(0.42)	(0.34)	(0.14)	(0.16)	(0.25)	(0.23)
Pol. violence × drought	−1.93*	−0.93	−2.04**	−0.47	0.07	−0.28	−0.24	−0.17
	(1.06)	(0.65)	(0.94)	(0.63)	(0.46)	(0.50)	(0.44)	(0.44)
Pol. violence × illness	−0.19	−0.50***	−0.28	−0.45**	−0.29	−0.45*	−0.09	−0.27
	(0.34)	(0.16)	(0.39)	(0.20)	(0.28)	(0.27)	(0.30)	(0.25)
Exogenous variables								
Drought*	0.11	−0.09	0.11	−0.14	−0.16	−0.30***	−0.11	−0.30***
	(0.29)	(0.12)	(0.24)	(0.13)	(0.17)	(0.11)	(0.15)	(0.11)
Illness	−0.11	0.09	−0.09	0.08	0.01	0.13	−0.04	0.08
	(0.16)	(0.08)	(0.15)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)
Baseline variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	731	716	731	716	921	902	921	902
R^2	0.15	0.74	0.16	0.74	0.04	0.47	0.04	0.48

Notes: (ii) Standard errors (in parentheses) are clustered at village-level. (iii) "Baseline variables" refers to the inclusion of the lagged time-varying covariates plus variables for the initial values of HAZ, age of the child, height of the mother, education of the caregiver and of the household head. (iv) A village is considered drought-affected if 50% of household respondents report a drought affected them.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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