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Hit them in the Wallet! An Analysis of the Indian Demonetization as a Counter-Insurgency Policy

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An Analysis of the Indian Demonetization as a Counter-Insurgency Policy*

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Abstract

In this paper, we study empirically how a policy targeting the cash-funding system of armed groups affects criminal activities, focusing on the 2016 Indian Banknote Demonetization as a natural experiment. We take advantage of a unique dataset on daily surrenders of the Maoist insurgents in India between 2006 and 2018. In order to measure the exposure of the conflict to the policy in different districts, we use three sources of access to funding for Maoists, namely mineral resources, public works' contractors and forest products. Our results suggest that there is a positive and significant impact of the demonetization on surrenders of Maoist extremists. We find a lower increase in surrenders where insurgents have higher abilities to raise new cash through mineral resources and public works, while we find a sharper increase in districts that rely on subsistence agriculture. This paper provides evidence that policies that curb illicit cash flows have the desired impact of deterring illegal and violent activities.

Keywords: Counterinsurgency, Conflict, Demonetization
JEL classification: C23, D74, Q34, E50

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1 Introduction

Conflict and violence cost the global economy \$14 trillion a year, accounting for about 13% of the global GDP (United Nations Office for the Coordination of Humanitarian Affairs, 2018). With 385 political conflicts across the world, armed groups are a major obstacle to the economic development of several countries.[1] Understanding the underlying functioning of criminal and illegal activities is a necessity in designing key policies to counter such human and economic losses. Cash is a key element of criminal activities due to its ease of access but the difficulty of traceability. While there exist a wide variety of funding sources for illegal enterprises, such as drugs smuggling, illegal mining and extortion, they are largely based on cash rather than easily traceable means involving banks (Rogoff, 2017). There is no reliable data available on the scale and use of cash, for both legal and illegal purposes. However, irregularities tend to give reason for a large underground economy. Cash transactions, mainly used for low value payments, are estimated to account for one-third of banknotes in circulation, while the demand of high denomination notes, such as EUR 500 note, is increasing (Europol Financial Intelligence Group, 2015). Despite a global effort to fight all forms of violence, academic research focusing on the financing of criminal activities is almost inexistant. A notable exception is the recent working paper of Limodio (2018) who explores the relation between terrorist attacks and their financing through charitable donations in Pakistan. In this paper, we take a different approach and focus on the link between the cash nature of the finances of armed groups and their violent activities. Understanding the role played by cash in the funding system of illegal activities would help designing counter-policies. However, the identification of a causal impact of such policies remains a challenge, due to the inability to quantify such funding flows.

To answer this challenging question, we make use of a unique opportunity to observe the importance of cash, by studying the impact of the 2016 Indian Demonetization. On November 8, 2016, 86% of the existing circulating banknotes were suddenly and unexpectedly declared worthless by the authorities. This policy was followed by a sharp shortage of cash, affecting the entire population due to printing press constraints. While the demonetization was not directly targeted at a specific insurgency, one of the core objectives stipulated by the Indian government is *to combat corruption and crime*, our focal point in this research paper. Focusing on the Maoist insurgency, this paper provides the first study on the importance of cash in illegal activities and an ex-post evaluation of a policy countering illicit cash flows. The Maoist insurgency is a widespread and ongoing conflict which aims to overthrow the Indian Government under a communist ideology. Since 2006, the conflict is responsible for the death of about 8'000 individuals and is located in low-development areas of India, called the Red Corridor, affecting one-sixth of the overall Indian territory. The Maoists, also called Naxalites, depends on a cash funding system to support their armed insurgency. They collect rupees through levies on the local population

[1] In 2017, the Heidelberg Institute for International Conflict Research has observed in its annual Conflict Barometer that there are 385 conflicts worldwide, which can be divided between 222 violent conflicts vs. 187 non-violent crises. Violent events include 36 wars, such as Syria, Yemen and South Sudan, and 187 violent crisis (Heidelberg Institute for International Conflict Research, 2017).

and extortion of various sources, keeping cash holdings in secret locations in remote forest area. Their main cash resources come from mineral and forest resources as well as public work contractors (Ramana, 2018). Following the demonetization, the organization was badly hit. The cash reserves of funding were instantaneously worthless, preventing the procurement of firearms, ammunition, commodities for daily use and the payment of cadres. Maoists have tried to deposit old currency through sympathizers, however, the police enhanced security at banks and other financial establishments, and large bank deposits are scrutinized.[2] Such negative income shock to the organization has led to a large increase in surrenders, as documented in local newspaper. Between the announcement of the policy and the end of November, 469 Maoists and their sympathizers have surrendered before the authorities, the highest rate reported in less than a month.[3]

To study the impact of the demonetization on the Maoist conflict, we construct a novel dataset from various sources. We collect daily observations on the Maoist conflict, including the location, amount and type of incidents, casualties and surrenders from the South Asia Terrorism Portal (SATP), a source of data based newspapers' clippings since 2005. Since the cash structure of the Maoist insurgency cannot directly be observed, we collect information on their means of extortion, namely mineral resources, public work contractors and forest products. When the demonetization policy hit, Maoists had to rebuilt their cash reserves, through further extortion of their usual extortion system. We therefore use the geographical variation in the funding system as a differential exposure of the conflict to the demonetization policy. The intuition is that districts that are more exposed to the policy should experience greater growth in surrenders. Our results suggest that there is a positive and significant impact of the demonetization on surrenders of Maoist extremists. We find a lower increase in surrenders where insurgents have higher abilities to raise new cash through mineral resources and public works, while we find a sharper increase in districts that rely on forest resources. Results are stable across a series of robustness checks.

This work contributes to four distinct strands of the literature. First, we contribute to the academic research evaluating counter-insurgency policies. Despite a global effort to fight all forms of violence, the literature has mainly focused on examining the causes and consequences of conflict (Blattman and Miguel, 2010), while evaluating policies to end it remains scarce. One scarce example of such research include the recent work of Armand et al. (2017), who study the effectiveness of FM radio defection messages on the Lords Resistance Army insurgency in central Africa. Other studies have evaluated various development programs to improve economic conditions of the local population under the label of counter-insurgency policies, however with mixed evidence. Two prevalent theories predict a decrease in the violence. First, by improving local economic conditions, government programs increases the cost of opportunity to fight against authorities, decreasing participation in the insurgency and therefore related violence (Grossman, 1991). Second, development programs might increase citizen support for the government, such that the population is more likely to help authorities to fight against insurgencies

[2] The Indian Express, 13/11/2016; Times of India, 12/11/2016.
[3] Times of India, 29/11/2016

through information (Berman et al., 2011). This *winning hearts and minds* channel is tested with the implementation of US reconstruction programs in Iraq, showing a fall in violence against US forces and civilians. Similarly, Crost et al. (2016) finds a fall in conflict-related incidents in the Philippines following a conditional cash transfers program. However, development programs might as well increase violence through strategic retaliatory attacks by insurgents or by creating incentives for resources' appropriation. For instance, empirical evidence shows increased violence after the implementation of infrastructure programs in the Philippines (Crost et al., 2014), rural employment program in India (Khanna and Zimmermann, 2017)[4], US food aid in recipient countries (Nunn and Qian, 2014). Our paper differs from such literature by focusing on a counter-insurgency policy targeting directly the funding structure of conflict, rather than improving local population economic conditions.

Second, we contribute to the literature studying the impact of the Indian demonetization, a unique episode in the history of monetary economics. To the best of our knowledge, there exists only two working papers analyzing the impact of the demonetization. Chodorow-Reich et al. (2018) provide evidence of the reduced economic activity, using nightlight data and employment surveys, while Aggarwal and Narayanan (2017) focus on domestic trade in the agricultural sector. Our paper shed light on the impact of such policy on the underground economy.

Third, we contribute to the literature investigating the effect of economic shocks on conflict. Since the pioneer work of Becker (1968), who developed a model where rational agents choose to engage in criminal activities if their expected return exceeds what they can earn from legal activities, a sizable literature has emerged on the relationship between economic resources and violence. If insurgents are not only driven by their ideology and preferences, but also by economic incentives, then there is tradeoff between legal and illegal activities. Research has widely focused on the resource curse, i.e. the role of commodity price shocks as a source of income shock (see for instance: Dube and Vargas, 2013; Berman et al., 2017; Bazzi and Blattman, 2014), however little research has focused on the cash nature of criminal finances.

Finally, we contribute to the literature investigating the Maoist Insurgency. Political scientists and historians have mainly focused on the Maoists, including economic descriptive research.[5] However, there is an emerging focus on this conflict, as shown in Vanden Eynde (2015), who examines the relationship between mining activities and maiosts' targeted attacks, or in Vanden Eynde (2017), where the impact of income shocks, through lack of rainfall, depends on the type of targets and the revenue source of the rebels: violence increases against security forces, but only in district with mineral resources. On the other hand, attacks against civilians decreases regardless of the district's profile.

The paper is organized as follows. Section 2 gives detailed information on the history of the Maoist insurgency, from its roots to its funding structure. Second, it focuses on our negative income shock,

[4]However, two similar papers find opposite results, i.e. a reduced violence, using the same rural employment program in India, the National Rural Employment Guarantee Scheme. Fetzer (2014) shows that the program mitigates adverse rainfall shocks by reducing maoist violence, whereas Dasgupta et al. (2017) uses a difference-in-differences approach with multiple local-language press data sources.

[5]See for instance: Miklian (2012) on weak institutions, Ramana (2018) on the details of the finances, Dubey (2013) on the history, Ghatak and Eynde (2017) and Gomes (2015) on the economic determinants.

the demonetization, where we detail the rules and discuss its exogeneity. Section 3 presents our data including some summary statistics, while section 4 discusses our identifying assumptions and exhibits our baseline results as well as various sensitivity checks. Finally, Section 5 offers some concluding remarks.

2 Background

2.1 The Maoist Insurgency

Responsible for decades of violence throughout India, the Maoist insurgency, in reference of the communist ideology of the Chinese revolutionary leader Mao Zedong, is an ongoing long-term and low-intensity armed conflict between Maoist organizations (also known as Naxalites) and the Government of India.[6] It originated in 1967 in a remote village called Naxalbari, located in the eastern state of West Bengal, as a land dispute between local landlords and tribal farmers. The peasant uprising quickly gained support and spread across several states of India, so-called the Red Corridor, with the common ideology to fight against the injustice and oppression of the Indian government, adopting violence and terror as the core instruments. For the first 30 years, the movement was characterized by a period of fracture and disorganization, with high level of internal conflict among various disparate sub-factions. However, in 2004, the two major organizations, the Maoist Communist Center (MCC) and the People's War Group (PWG), joined forces to form the largest operating faction, the Communist Party of India (Maoist).[7] The resulting exacerbation of violence alerted authorities, who regards the organization as a terrorist group referred as Left-Wing Extremism, and intensified direct confrontations between the insurgents and police forces.

Taking into account the features of the insurgency and the restricted amount of information disclosed by authorities, the intensity of the violence and the strength of the movement is difficult to quantify. Between 2006 and 2018, the conflict has caused the death of at least 8'000 individuals (see table 1 for the conflict-affected states) and the displacement of hundreds of thousands of people.[8] The armed wing of the insurgency, the People's Liberation Guerrilla Army (PLGA), is estimated to account for 20'000 fighters, constituting about twice the size of the FARC in Colombia (Gomes, 2015). The geographical spread of the conflict has greatly fluctuated over the past decade. In 2008, 223 districts across 20 states were under Maoist violence, whereas, in 2015, it decreased to 106 across 10 states. Following a newest expansion of the insurgency, it rose to 126 in 2017. In a recent report by the Ministry of

[6] The term *Naxalites* is derived from the place of origin of the insurgency, Naxalbari, while the term *Maoists* originates from the communist claims of the movement. We use both terms interchangeably.

[7] The MCC was operating in the eastern state of Bihar, while the PWG, created in 1976, was engaged in Andhra Pradesh. The newly-formed CPI (Maoist) is responsible for more than 80% of the violent incidents caused by left-wing extremists Ministry of Home Affairs (2015).

[8] There exists no legal framework in India to measure the extent of the affected population. Figures vary between 560'000 and 863'900 internally displaced people in the year 2015, for The Norwegian Refugee Council and the Internal Displacement Monitoring Center, respectively. The Guardian, 11/08/2016.

Home Affairs, 44 districts of the 126 were removed from the list due to negligence violence. Eight new districts were added.[9] The lasting attractiveness and power of the armed insurgency is rooted in lingering underdevelopment and poverty of the affected areas.

In order to study the impact of a policy countering the cash funding on the Maoist conflict, we are interested in knowing though which means the insurgency is funded. While this is a difficult task due to the illegal nature of such activities, the literature has found evidence of a close link between the Maoist movement and three main sources of income.

Maoists dispose of a centralized finance system, which follows their hierarchical organizational structure and allows them to reallocate their funds across conflict areas. The governing body at the country level, called Central Committee, draws the main guidelines for the collection and expenditure of funds. The lower-level committees, which are - from top to bottom - State, Regional, Zonal, Area and Village Committees, implement these guidelines (Dubey, 2013). In principle, collection and expenditures of funds are managed at the level of Zonal Committees, and then the Central and State Committees take care of reallocating excess funds where needed.

Maoists' principal source of income comes from money extortion in three main economic sectors, namely mining, public works and tendu-leaf production. Maoists have a strong presence in mineral-rich states like Jharkhand and Chhattisgarh, where they extort mining money mainly by imposing levies on buyers and contractors (Miklian, 2012). They are capable of extorting money both from legal and illegal mining, particularly coal and iron. Maoists also extort money from public-work contractors. In this case, levies are lower when public funds are used for schools and drinking-water supply, while are higher for works on exploration of minerals and transportation infrastructure. Finally, the oldest source of funding for Maoists is extorting money from contractors in the sector of tendu leaves. In India, tendu leaves are used to wrap beedi, the most common Indian cigarette (Lal, 2009). While money extorted from either mining or public works can be used by Zonal Committees to cover their budget needs, cash extorted from tendu leaves goes directly to the Central Committee. By the present guidelines, each year Zonal Committees are required to collect around three times their annual budget and store as reserves what they do not use. These reserves can be used either by platoon commanders for immediate war needs or by the Central Committee for reallocation. Committees then allocate the extorted money to finance all Maoists' activities. First, committees allocate funds to meet war needs, thus buying weapons and military supplies, such as uniforms, communications equipment, medicines and meals for the army. Second, Maoists use their funds to disseminate their ideology by financing meeting and classes, and propaganda. Third, committees allocate their budget money for indirect support to these activities, for example by providing financial assistance to the families of the cadres or legal aid to functionaries arrested by security forces (Ramana, 2018; Mahadevan, 2012).

[9]Note that the boundaries of districts and states have greatly varied over the past twenty years in India: from 593 districts in 2001 to 712 districts in 2018, with the creation of a new state in 2014, Telangana, carved out of Andhra Pradesh. We restrict our analysis to the all districts in the 10 affected states in 2015. See table 1 for a complete list.

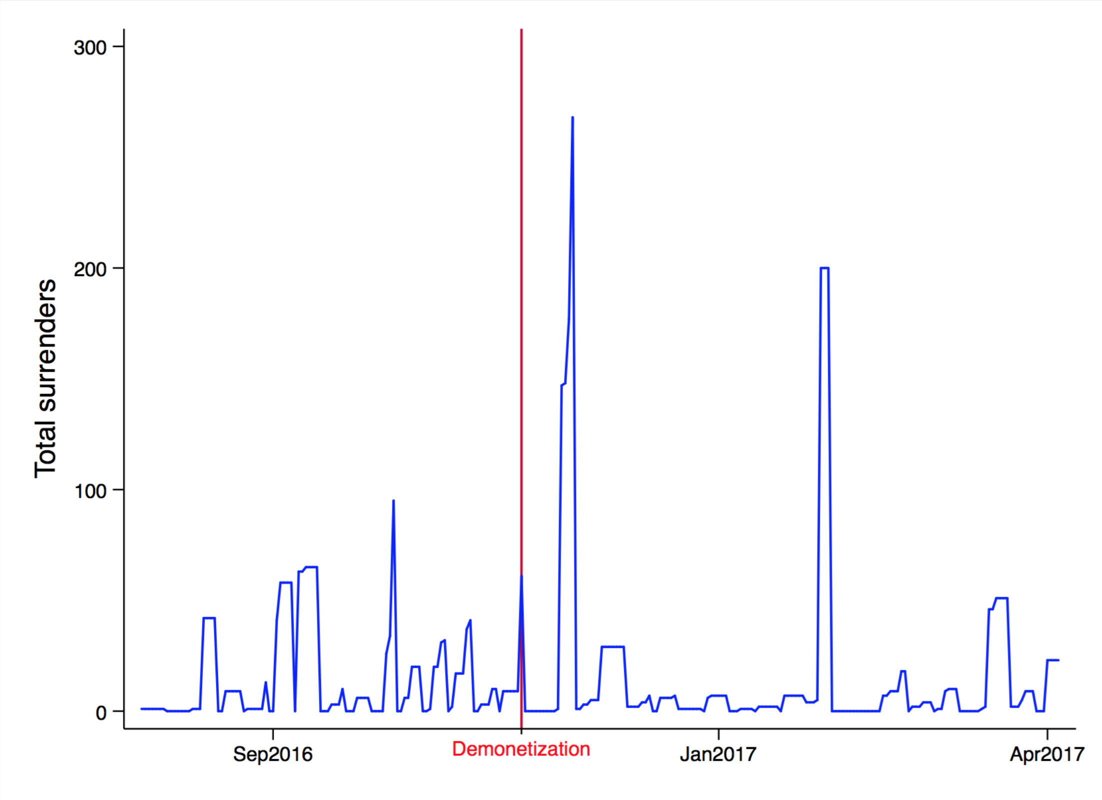
2.2 The 2016 Indian Demonetization

Until 2016, the Indian economy has relied heavily on cash. Around 68% of transactions were made in cash (Ghosh, 2017) and 86% of the currency in circulation was in form of Rs. 500 and Rs. 1000 banknotes (Chodorow-Reich et al., 2018). On November 8, 2016, President Modi announced, that, from midnight onwards, these banknotes were no longer legal tender and that new Rs. 500 and Rs. 2000 banknotes were introduced (Beyes and Bhattacharya, 2016). Mr. Modi also explained the main guidelines for the transition towards this new-denomination system. People could deposit old banknotes into bank accounts until December 30 (Banerjee et al., 2018).[10] However, people could not withdraw their money back all at once, as there were heavy constraints on withdrawals. In the months just following demonetization, cash withdrawals at banks' branches were limited to Rs. 24'000 ($340) per person per week and ATM withdrawals were limited to Rs. 2500 ($35) per card per day.[11] These early limits were necessary because, in order to maintain secrecy, the government started to print and distribute the new notes just after the announcement (Chodorow-Reich et al., 2018). All these limits on cash withdrawals were finally removed on January 30. As a result of the demonetization, the vast majority of the old notes (around 97%) were deposited back into the banking system by the end of the year (Karthikeyan and Thomas, 2017). However, the withdrawal constraints led to a huge cash shortage. On the day of the announcement, total currency in circulation dropped by 75% overnight and recovered only slowly over the following months (Chodorow-Reich et al., 2018). Concurrently, the economic sectors that rely heavily on cash registered significant economic losses. For example, daily trade in domestic agricultural markets declined by over 15% after demonetization and recovered only partially in the following ninety days (Aggarwal and Narayanan, 2017). Economic losses occurred also in the sectors of construction, local transport, community services, e-commerce, steel, refinery products, telecom and automobile (Ghosh, 2017; Karthikeyan and Thomas, 2017; Singh and Singh, 2016).The cash shortage following demonetization may have had an impact on Maoist groups, as their activity relies heavily on the availability of fund. Maoists' Zonal Committees aim to collect fundings of at least three times their annual budget, which is estimated to be around Rs. 4.2 billion ($60 million) per year for all India. Thus, when the demonetization hit, Maoists' cash reserves amounted to probably few dozens (if not hundreds) million dollars (Ramana, 2018). After the policy, reserves in old-denomination currency either were deposited and froze into bank accounts or became worthless. As a result, Maoists experienced a significant fund shortage, which led to a change in their attacks and overall related violence in the aftermath of demonetization. We aim to test this hypothesis by exploiting differences

[10] More precisely, for immediate needs people could also exchange the old-denomination banknotes over the counter at banks' branches up to a maximum of round Rs. 4000 ($60) per person per day. However, the government, after increasing this limit to Rs. 4500 on November 13, it reduced it down to Rs. 2000 on November 17, to then finally remove the option for over-the-counter exchanges from November 25 onwards (Banerjee et al., 2018).

[11] More precisely, in the days just following demonetization, people could withdraw up to Rs. 10'000 ($140) per day at banks' branches, with a maximum of Rs. 20'000 ($280) per week. From November 13, the daily limit was removed, and the weekly limit was moved from the previous Rs. 20'000 to Rs. 24'000. The limit on ATM withdrawals was set to Rs. 2000 on November 10 and changed to Rs. 2500 on November 13, to be then increased to Rs. 4500 on January 1st and to Rs.10'000 on January 16 (Banerjee et al., 2018).

Figure 1: Weekly Surrenders



in the ability to raise new cash among Maoist groups.

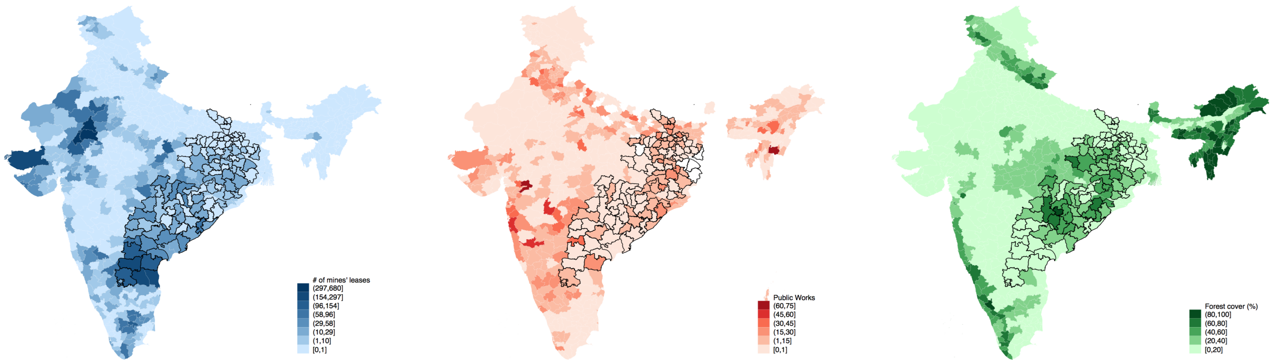
3 Data & Descriptive Statistics

Conflict data. We use the South Asia Terrorism Portal (SATP), which reports Maoists-related incidents from both local and national English-speaking newspapers in India from 2005 onwards.[12] Available data include both the location and date of the incident at various aggregation levels, as well as the number of casualties (by type: insurgents, civilians and security forces), injuries or surrenders. Using this information, we manually code these details in a daily-district level dataset. In the case of missing information, we further search for the primary source for verification. We use data from March 26, 2006 (the earliest data available on SATP) to April 15, 2018. This allows for data before and after the implementation of the policy on November 8, 2016. Figure 1 shows the number of surrenders per per week around the demonetization that took place on November 8, 2016. It is noticeable that there is an increase in the amount of surrenders after the demonetization. It is however less clear whether surrenders are more or less frequent.

Exposure Data. As discussed in the previous section, the demonetization policy was implemented for

[12]The literature on the Maoist insurgency is mostly based on data from SATP, which represents the most extensive and complete reporting of conflict-related events in South Asia (Fetzer, 2014).

Figure 2: District-level Exposure in conflict-affected areas



the entire country at the same date. Thus, our identification of the impact of this counter-insurgency policy relies on cross-sectional variation in the exposure of the different district to the policy.

- Mineral Resources.

  Data on mineral resources come from two distinct sources. First, we make use of mining leases from the Indian Bureau of mines, which collects basic data relating to major minerals except coal, petroleum and natural gas.[13] The State Governments are the owners of minerals located within their respective boundaries, and are empowered to grant individuals or companies the rights to extract minerals, in exchange of predetermined compensation, called royalties and set by the Central government.[14] Mining leases, also called mining concessions, are defined as a lease granted for the purpose of undertaking mining operations, such as winning any mineral. As of 2015, 7664 leases were in force in 23 States. The distribution per district is visible in the left-hand side panel of the maps in Figure 2. The dark border display Maoist-affected districts. While the map shows that there is a large variation of mining leases over the entire country, districts affected by the insurgency tend to by highly correlated with mining activities. Figure 1 summarizes the state-wise distribution of mining concessions in conflict-affected regions. Andhra Pradesh is leading with more than a thousand mining leases, followed by Madhya Pradesh and Telangana.

  Second, we use data on large-scale mines from the Raw Material Data (IntierraRMG, 2013).[15]. The RMD data include worldwide information on the location, production and specific minerals produced by mining companies since 1980 and are focused on large-scale mines, operated by the governments or multinational companies. Small-scale and illegal mines are not covered. However, mines extracting coal are included in the sample, in contrast to the mining leases dataset. We create a measure of large-scale mines, by identifying the number of active mines per district for

[13] Data was provided thanks to Vanden Eynde (2015).

[14] Under the Mines and Minerals Development and Regulation (MMDR) Act 1957, the State Governments may grant reconnaissance permits, prospecting and composite licenses, and mining leases by discretion. The existing MMDR Act was recently amended by the Central Government. Since January 2015, the State Governments grant the mineral concession through auctions, in order to improve transparency

[15] Data was provided thanks to Berman et al. (2017).

the year 2012, the latest observed date in the dataset. From Table 1, we can see that the number of active large-scale mines in conflict-affected states is much lower than the number of active leases. The distribution is also different: Jharkhand and Orissa show the highest number of large-scale mining companies with 69 each. A striking difference is Andhra Pradesh that displays only 3 large-scale mines, but the highest number of leases with 1293.

- Public Works.
  To measure the number of active public-work contractors at the district level, we consider the Pradhan Mantri Gram Sarak Yojana (PMGSY) program, which is a centrally-sponsored scheme for the construction of roads and other connection infrastructure (i.e. bridges) in rural areas. Within this programme, the Ministry of Rural Development allocates funds to state-level agencies (called "Executing Agencies"), which manage the tendering process to identify contractors. Winning contractors go through a thorough monitoring process and have up to 15 months to finish the job. We base on the datasets available online on the PMGSY website, specifically on the report "Physical Financial Monitoring". Among other things, such report includes, for each district and year, the project's award date, completion date, status, name of the contractor and name of the company of the contractor. We use this information to build a cross-sectional district-level measure of the number of public-work contractors from which Maoists could go extort new cash after demonetization. As demonetization was announced on November 8 2016, we focus on the number of public-work contractors that were active on the territory for at least one week in the three months following the policy (until January 31, 2017).

- Forest Resources.
  Data was collected from the Ministry of Environment and Forest, for the year 2015. The right-hand side panel of Figure 2 displays the share of forest cover per district. Conflict-affected districts, with their boundaries surrounded in dark lines, tend to be highly covered in forest resources, with a large variation between districts.

Rainfall Data. We collected monthly rainfall data by districts from the Indian Meteorological Department (IMD) for the years 2013-2017.

The sample used in the baseline analysis includes all districts in the 10 States affected by the conflict following the Ministry of Home Affairs list, limiting the sample to 102 districts out of 620.[16]

Table 1 provides summary statistics of the main variables, which all vary at the district-year level.

[16] We follow the 2015 list of 106 districts in 10 Left Wing Extremism affected States from the Ministry of Home Affairs, which is based on their violence profile and other parameters. These States are covered under the Security Related Expenditure Scheme, which allow them to receive reimbursement for counter-insurgency measures. As rainfall information is not recorded in certain districts and some of them were either split or merged between 2013 and 2017, we merged them to create a balanced panel dataset of 102 districts.

Table 1: Conflict-affected States

	Total surrenders	Total deaths	Total deaths (/100'000 inh.)	Affected districts	Affected pop. (%)	Large mines	Mines leases	Public works	Forest cover (%)
Andhra Pradesh	781	742	0.88	8/13	62.6	3	1'293	27	15.07
Bihar	193	684	0.66	22/38	56.8	1	2	292	6.60
Chhattisgarh	2'248	2'880	11.28	13/18	76.3	20	261	189	40.92
Jharkhand	165	1'566	4.75	21/24	90.1	69	65	376	28.14
Madhya Pradesh	0	5	0.01	1/50	2.3	39	588	640	23.88
Maharashtra	172	541	0.48	3/35	4.1	29	199	7	16.43
Orissa	3'155	782	1.86	19/30	62.1	69	166	758	28.58
Telangana	522	24	0.07	8/10	73.6	28	422	11	16.35
Uttar Pradesh	4	15	0.01	3/71	3.2	0	21	20	5.17
West Bengal	57	699	0.77	4/19	17.5	36	29	148	17.25
Total	7'297	7'938	0.99	102/308	28.7	294	3'046	2'904	-

4 The Impact of the Demonetization on Surrenders

The first step of the empirical strategy consists in analyzing the impact of the demonetization on insurgents' surrenders using daily observations at the district level.

4.1 Identification Strategy

The aim of our analysis is to assess whether policies that disrupt insurgents' finances are effective in reducing violence. When terrorists face a fund shortage, they cannot provide war supplies to their troops, who can either suspend the attacks until the shortage is over or surrender to security forces. We argue that the context of the Maoist conflict in India at the time of demonetization serves well to test this channel for two main reasons. First, demonetization was followed by a sudden and large cash shortage, which may trigger the channel. Second, the Indian government was successful in maintaining secrecy around the policy until the date of the announcement, so that Maoists (and anyone else) could not adjust in advance. As this policy shock was sudden and unexpected, the impact on Maoist finances may be large and the magnitude of the channel significant.

In order to identify the impact of demonetization on Maoist-related violence, we exploit cross-sectional variations in the exposure of the districts to the policy, which is proxied by the insurgents' abilities to raise new cash. As mentioned, the main resources of money extortion for Maoists are mines, public works and forest products. The intuition is that districts that are more exposed to the policy should experience greater growth in surrenders.

This identification strategy bases on two main assumptions. First, we assume that, within Maoists' organizational structure, each district is responsible for collecting the funds it needs and it does so by relying on its local resources only. We argue that the guidelines set out by the Communist Party of India on January 2007 to organize its finances bring arguments in favor of this assumption. By these guidelines, committees at all geographical level must be financially self-sustainable (Ramana, 2018). All committees are thus responsible to collect their funds, allocate them to cover their needs and save what they do not use as reserves. In addition, the basic units for collection and allocation of funds are the Zonal Committees. In order to grasp this zone-driven logic, we base our analysis at the district level. In case of fund shortages, Maoists in districts that are rich in extortion resources are more capable of rising new cash than districts with little resources. Second, we assume that, in the very aftermath of demonetization, low-resources districts did not receive funds from other districts. In principle, Maoists' centralized finance system allows the Central and State Committees to reallocate the excess funds where needed. However, we argue that this reallocation system could not work properly following the demonetization, specifically in the short term. Notably, since the policy was sudden and unexpected, Maoists could not take precautionary measures and reallocate resources in advance to low-resources districts. Furthermore, in the emergency of the fund shortage, it is likely that Maoists in high-resources districts used the new cash they could extort primarily to cover their emergency needs. It then took some time for committees of these districts to store new excess funds as reserves for reallocation purposes. Thus, low-resources districts were left with little funds after the policy and were very exposed to the consequences of the fund shortage. In the long term, the impact of demonetization on Maoists' violence may level out, as local committees would rebuild their reserves and the Central Committee would reallocate them to Maoists in districts more affected by the shock. However, Vanden Eynde (2017) suggests that Maoists capacity to share resources across local units is limited in general and therefore the impact of demonetization may also last in the long term. We use a Generalized OLS difference-in-differences (DID) specification to grasp differences in the trends of surrenders between districts after demonetization. Specifically, we test whether surrenders' increases in districts less funding resources (first difference) are larger after the demonetization (second difference). We estimate the following specification:

$$Surrender_{dt} = \beta^i (PostDem_t \times Exposure_d^i) + \lambda_d + \lambda_{st} + \varepsilon_{dt} \quad (1)$$

The level of analysis is the district $d \times$ day t. The dependant variable, $Surrender_{dt}$, represents the daily cumulative summation of surrenders since March 26, 2006. $PostDem_t$ is a binary variable taking the value 1 after the demonetization, 0 otherwise. $Exposure_d^i$ are the district-level measures of exposure to the policy, as follows: (1) the number of active leases granted to mines per district and by year; (2) the number of public work awarded to contractors; (3) forest cover relative to the district area. λ_d are the set of district fixed-effects that filter out all time-invariant characteristics affecting surrenders and the measures of exposure, e.g. local characteristics. Similarly, λ_{st} corresponds to a set of state $\times$ day fixed-effects that account for time-variant unobservables such as state-level policies that might affect surrenders of insurgents.[17] In all specifications (baseline results and robustness checks), standard

[17]Economic policy and counter-insurgency strategies are decided at the state level and vary greatly between states. For instance, different Indian states have implemented a surrender and rehabilitation policy for Maoists, which includes protection and a stipend for the insurgents who surrender before the police. State $\times$ day fixed-effects allow to control for

errors are adjusted for spatial (500 km) and serial correlation (30 days). Baseline results are based on a one-year pre- and post-policy, i.e. from 08/11/2015 to 08/11/2017, and we restrict our analysis to the 102 districts affected by the conflict in 2015.[18]

Our coefficients of interest are the β^i explaining the interaction term between the dummy for the demonetization policy and our three different exposure variables, $PostDem_t \times Exposure_d^i$. Given the fact that we include district and state × day fixed-effects in all specifications, our identification strategy relies on the exogeneity of the interaction term. While we discuss the exogeneity of the demonetization in the Section 2.2, we discuss hereafter the identification assumption concerning our cross-section variations.

- *Exogeneity of Mineral Resources.* A potential concern could arise from unobservables correlated with both each district's mining activity and its trend in surrenders. For instance, there could be a peak in the intensity of the conflict, on a specific day and in a specific district, that could trigger both an increase/decrease in surrenders and the opening/closing of mines. Similarly, a second concern could result from reverse causality from trends in surrenders to the mining activity. For instance, it can be argued that a large increase in surrenders could trigger a changer in the location of mines. To account for these issues, including state × day fixed-effects is crucial, as they partial out a common shocks at the state-level. Second, we restrict the analysis to a sample of districts that were affected by the Maoist Insurgency before and after the implementation of the demonetization policy. Furthermore, our variable of interest is the number of mines' leases per district and by year, granted the government of India in 2015, i.e. before the implementation of the policy. Last, we perform a robustness check using the number of large-scale mines per district for the year 2012, exploiting the Raw Material Data from Berman et al. (2017). Results can be found in Appendix A Table A4 and display similar patterns.

- *Exogeneity of Public Work.* Turning to public works, it could be similarly argued that low economic development might codetermine the awarding of public works by the state authorities and the location of the conflict, hence of the surrenders. However, our district fixed-effects account for this potential unobserved confounding factor, as well as other initial local conditions. On the other hand, a reverse causality issue seem unlikely. While public works are an instrument to foster development by the construction of road for instance, it is doubtful that the trends in Maoist surrenders are a determinant of the number of public work contractors. From Figure 2, we can see that the distribution of public works is quite widespread, and that Maoist-affected districts are not specific targets for the spending in public funds. However, to account for the potential bias in the estimate, we use the number of public work awarded to contractors before

such unobserved heterogeneity (Vanden Eynde, 2017).

[18] As discussed, we follow the 2015 list of 106 districts in 10 Left Wing Extremism affected States from the Ministry of Home Affairs, which is based on their violence profile and other parameters. However, due to missing information and the variation of district boundaries over time, we create a balanced panel dataset of 102 districts. The list of districts used can be found in Appendix C Table C6.

the implementation of the policy.

- *Exogeneity of Forest Resources.* The underlying determinants of forest cover are rooted in the ecosystem of the districts, such as climate conditions and topography. While forest resources play an important role in the source of income for Maoist, we believe that the trends in surrenders do not impact forest cover directly.

4.2 Baseline Results

Baseline results are displayed in Table 2. In columns (1), (2) and (3) we test each measure of exposure separately, while in column (4) all three measures are included. Despite the loss of significance of the mines' leases as exposure measure, coefficients remain stable and significance for our two other measures of exposure. Overall, we find a lower increase in surrenders where insurgents have higher abilities to raise new cash through mineral resources and public works, while we find a sharper increase in districts that rely on forest resources. The intuition is that funding resources based on public works and mining activities are a direct cash source, while forest resources are tangible assets, that take more time to be converted into a worthy capital. Thus, in districts with a high share of forest resources, when the cash shortage hit, insurgents tend to surrender more than in districts with less forest resources. The hypothesis is that in low forest share districts the insurgents rely on a different cash-funding system, such as mineral resources and public works. We test further this hypothesis in Appendix A (see table A5), where we estimate a triple DID to exclude districts that rely on mineral resources and public works.

In terms of magnitude, after the policy, the difference in cumulative surrenders between districts at the 75^{th} and 25^{th} percentiles (of the observed distribution of the exposure measure) decreases by one surrender for mines' leases, by 18 surrenders for public works, and increases by 21 surrenders for forest resources.[19]

4.3 Robustness Checks

Studying the impact of counter-insurgency policies, our identification strategy relies on the various measures of exposure of the different districts to the demonetization policy and their relative impact on the surrenders of rebels. The difference-in-difference specification provides evidence that the counter-insurgency policy has had an unexpected and welcomed negative impact on insurgents who are less capable of raising new cash. However, it could be argued that there are other characteristics at the district-level that correlate with the exposure variables and affect rebel activity.

[19]With regards to mineral resources, there are 12.7 leases at the 75^{th} percentile of the distribution and 0 at the 25^{th}. There are 19.25 public works awarded at the 75^{th} percentile of the distribution and 1 at the 25^{th}. Forest cover varies between 38.15% and 11.8%, for the 75^{th} and the 25^{th} percentile of the distribution respectively. Thus, the growth differential is calculated as follows: $\beta^i \times (exposure^i_{75th} - exposure^i_{25th})$.

Table 2: Baseline Results

	Cumulative Surrenders			
	(1)	(2)	(3)	(4)
Post Dem $_t$ × Mines $_{dy}$	-0.078***			-0.011
	(0.0196)			(0.0141)
Post Dem $_t$ × Public Works $_d$		-1.002***		-1.082***
		(0.333)		(0.338)
Post Dem $_t$ × Forest $_d$			0.791***	0.875***
			(0.0872)	(0.105)
Growth Differential *Mines*	-0.99			-0.13
Growth Differential *Public Works*		-18.03		-19.47
Growth Differential *Forest*			20.61	22.81
Fixed Effect	d,st	d,st	d,st	d,st
Observations	74,664	74,664	74,664	74,664
R-squared	0.946	0.947	0.946	0.947

The dependent variable is the cumulative of daily surrenders starting on March 26, 2006.
Standard errors adjusted for spatial (500 km) and serial correlation (30 days) in parentheses following Colella et al. (2018).
Growth differential figures calculate the difference between the 75th percentile and the 25th percentile distribution of the exposure variable.
*** p<0.01, ** p<0.05, * p<0.1

In this section, we show that the baseline results are robust to various sensitivity checks, by extending the previous results and exploring a number of potential alternative factors. Column (1) of Table 3 replicated the baseline results of Table 2 column (4) including all measures of exposure to the policy. The following columns are detailed hereafter.

Weighted Regression. We start by replicating our baseline results weighted by each districts' total surrenders the day before our regression's timeframe, i.e. on November 7, 2015.[20] Our weighted regression allows for a higher emphasis on districts with larger variance in the distribution of surrenders. Results are displayed in Table 3 column (2). We further performed a two-step calculation of the implied impact of the demonetization policy that takes into account the weights across the distribution of the measures of exposure, following Pierce and Schott (2016).[21] As reported under the *Growth Differential* rows, the weighted specification implies a relative decline in surrenders of 10 insurgents for mineral resources, 240 for public works and 2.5 for forest between high resources vs. low resources districts. However, results for the forest resources are not significant.

Rainfall Shock. A first threat to our identification strategy is the possibility that the relationship between insurgents' surrender and district-level characteristics changes in the post-policy period. For instance, it could be argued that a confounding contemporaneous income shock could explain insurgents' surrender. For instance, Vanden Eynde (2017) finds that lack of rainfall increases Maoist violence against the security forces but only in districts where mining activity is sufficiently important, whereas it increases violence against civilians regardless of the location of mining activities. To address this concern, we replicate our baseline Table 2 column (4) controlling for district-level monthly rainfall shocks, which proxy for labor-income shocks, as follows:

$$Surrender_{dt} = \beta^i(PostDem_t \times Exposure^i_d) + \beta^i(PostDem_t \times X_{dm}) + \lambda_d + \lambda_{st} + \varepsilon_{dt} \qquad (2)$$

Our rainfall shock, X_{dm}, is built similarly to Miguel et al. (2004) as the proportional change in rainfall from the same month previous year, $(R_{dm} - R_{d,m-12})/R_{d,m-12}$, where d stands for district and m for month. It is strongly correlated with income growth. Results are displayed in table 3 column (3). Our coefficients of interests, the β^i, remain stable, with the newly significant level at 10% for the mineral resources exposure, whereas the rainfall shock does not show any significant impact. The loss of observations is due to the missing rainfall data for some of the months or districts in our sample.

Timeframe. We further test alternative timeframe for our baseline regressions. We first restrain the timeframe of our sample to 6-month pre- and post-policy. Results, presented in column (4), remain stable in term of sign, but the magnitude of the implied impact is slightly lower. Similarly, we expand

[20] Our baseline specification is based on a one-year pre- and post-policy, i.e. from 08/11/2015 to 08/11/2017. Thus our weight is the total number of surrender per district between the beginning of our sample, i.e. 26/03/2006, to 07/11/2015.

[21] The two-step calculation of the implied impact of the policy consists in taking into account the trends in surrenders between districts before the implementation of the policy across the different measures of exposure. First, for each district d, we multiply the coefficients β^i with the districts' measures of exposure i. Second, we take the average of the implied relative effects for all districts, using the initial cumulative surrenders as weights.

the timeframe to a longer period of study, from 2015 to April 2018. Column (5) shows the results, which are also stable. In an opposite fashion to the shorter timeframe, the implied effects are larger.

Geographical Coverage. Next, we test an alternative geographical scope, by including all districts in India. Results, as shown in Table 3 column (6), retain the same sign, but exhibit lower implied effects. This is expected since this specification includes districts that are not affected by the Maoist insurgency, and thus, where there are no surrenders.

Outliers. We further check whether results are driven by outliers. From Figure B3 in Appendix B, it is noticeable that there is a peak of surrenders on November 8, date of the implementation of the policy. However, as the policy was announced in the evening, it is unlikely that this peak drives the results. From the local newspaper, we know that

> [...] 52 milita members have surrendered before Malkangiri police. [...] the surrenders have taken place close on the heels of the killing of at least 28 rebels in a fierce encounter with police on October 24.[22]

Second, a large peak is apparent post-policy, on January 29, 2017. The Indian Express reveals that

> 195 Maoist cadres surrendered before senior police officials during a programme at Narayanpur district headquarters.[23]

As we cannot control for day × district specific events that would have a direct impact on surrenders, we removed both peaks from our baseline regressions. Results are displayed in Table 3 column (7), showing similar significant coefficients.

Logarithm. We finally check whether results are sensitive to the definition of our dependent variable. Using the logarithm of the daily cumulative surrenders as our explained variable allows to smooth the trend in surrenders and further taking into account issues of common support across highly and less exposed districts. However, due to the inclusion of all districts in conflict-affected states, we lose our counterfactual, i.e. the 28 districts in which they were no surrenders over the entire period. Table 3 column (8) displays the results. Our mineral resources exposure variable turns out to be significant, however, with a very low coefficient leading to little growth differential between exposed and non-exposed districts. On the other hand, our two other measures of exposure, public works and forest cover, show similar results to our baseline specification, with a growth differential measured in percentage points rather than in levels.

[22] The Indian Express, 09/11/2016
[23] The Indian Express, 29/01/2017

Table 3: Robustness Checks

	Cumulative Surrenders							Log Cumulative Surrenders
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Dem $_t$ × Mines $_{dy}$	-0.011	-0.685***	-0.026**	-0.006	-0.032*	-0.003**	-0.029**	0.0003***
	(0.0141)	(0.169)	(0.0131)	(0.0105)	(0.0183)	(0.00117)	(0.0124)	(8.69e-05)
Post Dem $_t$ × Public Works $_d$	-1.082***	-7.729***	-1.026***	-0.607***	-1.430***	-0.330**	-0.923***	-0.002***
	(0.338)	(1.471)	(0.333)	(0.183)	(0.360)	(0.151)	(0.341)	(0.001)
Post Dem $_t$ × Forest $_d$	0.875***	-0.079	0.701***	0.526***	1.193***	0.176***	0.762***	0.005***
	(0.105)	(0.474)	(0.102)	(0.0813)	(0.112)	(0.0229)	(0.103)	(0.000537)
Post Dem $_t$ × Rainfall Shock $_{dm}$			-0.020					
			(0.0181)					
Growth Differential *Mines*	-0.13	-10	-0.33	-0.08	-0.41	-0.01	-0.37	0.004
Growth Differential *Public Works*	-19.47	-240	-18.47	-10.92	-25.74	-2.64	-16.62	-0.04
Growth Differential *Forest*	22.81	-2.48	18.27	13.72	31.56	5.68	19.86	0.13
Fixed Effect	d,st	d,st	d,st	d,st	d,st	d,st	d,st	d,st
Districts	102	66	102	102	102	627	102	74
Month pre/post-policy	12	12	12	6	2015-18	12	12	12
Weighted	no	yes	no	no	no	no	no	no
Peaks	yes	yes	yes	yes	yes	yes	no	yes
Observations	74,664	48,312	61,443	37,332	122,502	458,964	74,664	51,968
R-squared	0.947	0.985	0.957	0.990	0.904	0.948	0.953	0.989

The dependent variable is the cumulative of daily surrenders starting on March 26, 2006.
Standard errors adjusted for spatial (500 km) and serial correlation (30 days) in parentheses following Colella et al. (2018).
*** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

This paper uses the 2016 Indian Banknote Demonetization to study the impact of counter-insurgency policies. Using different measures of exposure to the policy, the demonetization has had an unexpected and welcomed negative impact on insurgents who are less capable of raising new cash. Maoists have been hit, but whether the policy will weaken the insurgency in the long term is not clear. The welfare costs of the policy still need to be investigated.

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Appendix A Additional Tables

In table A4, we use a second measure of the mining activity per district: large-scale mines. The measure is fixed to the number of active mines in 2012. Results are similar to our baseline measure, mines' leases, displayed in columns (1) and (3). However, large-scale mines tend to show larger coefficients, which increases (in absolute value) the growth differential effects between districts at the 25^{th} and 75^{th} percentile of the distribution.

Table A4: Mines' Leases vs. Large-scale Mines

	Cumulative Surrenders			
	(1)	(2)	(3)	(4)
Post Dem $_t$ × Mines' Leases $_{dy}$	-0.0780***		-0.0106	
	(0.0207)		(0.0148)	
Post Dem $_t$ × Large-scale Mines $_d$		-1.341***		-0.988***
		(0.415)		(0.307)
Post Dem $_t$ × Public Works $_d$			-1.082***	-1.047***
			(0.355)	(0.347)
Post Dem $_t$ × Forest $_d$			0.875***	0.880***
			(0.110)	(0.111)
Growth Differential *Mines' Leases*	-0.99		-0.13	
Growth Differential *Large-scale Mines*		-2.68		-1.98
Growth Differential *Public Works*			-19.47	-18.84
Growth Differential *Forest*			22.81	22.94
Fixed Effect	d,st	d,st	d,st	d,st
Observations	74,664	74,664	74,664	74,664
R-squared	0.946	0.946	0.947	0.948

The dependent variable is the cumulative of daily surrenders starting on March 26, 2006.
Standard errors adjusted for spatial (500 km) and serial correlation (30 days) in parentheses following Colella et al. (2018).
Growth differential figures calculate the difference between the 75^{th} percentile and the 25^{th} percentile distribution of the exposure variable.
*** p<0.01, ** p<0.05, * p<0.1

In Table A5, we further explain the positive coefficient of the forest resources exposure. In our baseline specification, we find a lower increase in surrenders where insurgents have higher abilities to raise new cash through mineral resources and public works, while we find a sharper increase in districts that rely on forest resources. The intuition is that funding resources based on public works and mining activities are a direct cash source, while forest resources are tangible assets, that take more time to be converted into a worthy capital. Thus, in districts with a high share of forest resources, when the cash shortage hit, insurgents tend to surrender more than in districts with less forest resources. The hypothesis is that in low forest share districts the insurgents rely on a different cash-funding system, such as mineral resources and public works. We test this hypothesis by estimating a triple DID specification as follows:

$$\begin{aligned} Surrender_{dt} =& \beta(PostDem_t \times Forest_d) \\ & + \alpha(PostDem_t \times Forest_d \times OtherSources_d) \\ & + \lambda_d + \lambda_{st} + \varepsilon_{dt} \end{aligned}$$

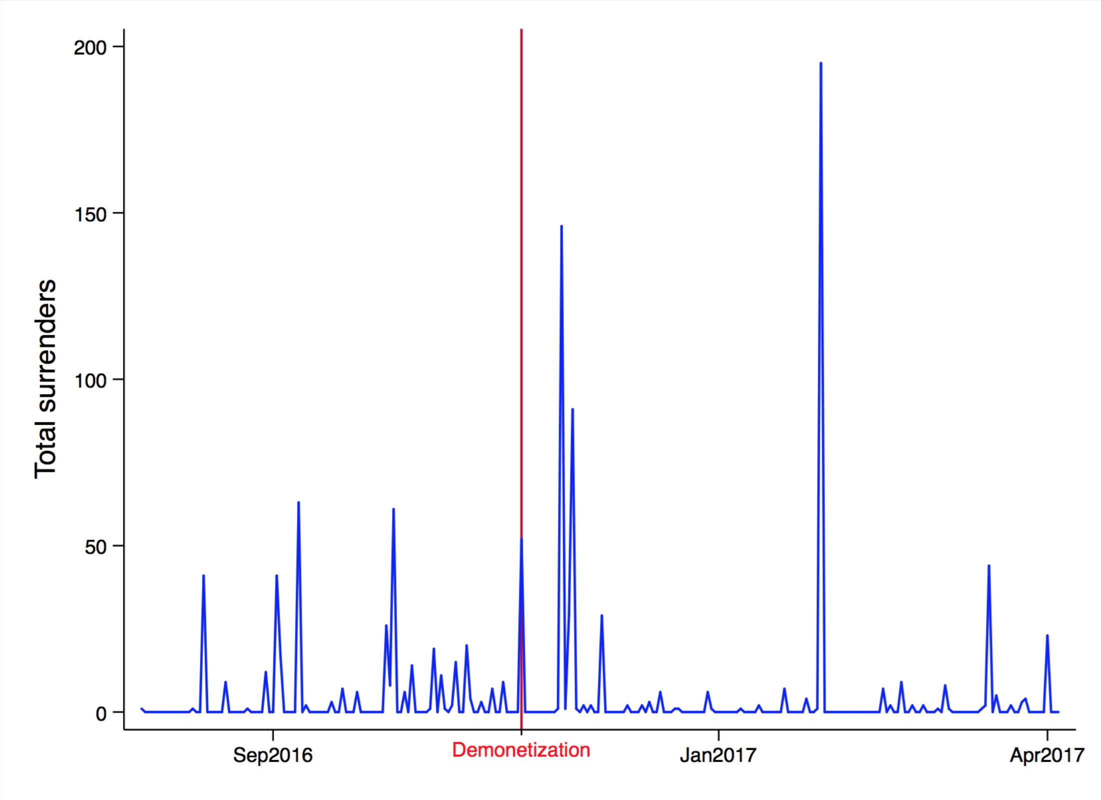
Where $OtherSources_d$ is a binary variable, indicating whether mines or public work contractors are located in the district. The specification allows for a comparison of the trends in surrenders in districts with versus without other sources of income and tests the idea that forest resources drive the differential in surrenders in districts without alternative source of funding. Results are expected to be negative for the triple interaction term, which is the case for exclusion of public works and of both public works and mines. Column (1) display a counter-intuitive results, with a positive coefficient.

Table A5: Forest Resources

	Cumulative Surrenders		
	(1)	(2)	(3)
Post Dem $_t$ × Forest $_d$	0.458***	5.153***	0.972***
	(0.101)	(1.086)	(0.149)
Post Dem $_t$ × Forest $_d$ × Mines $_d$	0.760***		
	(0.162)		
Post Dem $_t$ × Forest $_d$ × Public Works $_d$		-4.595***	
		(1.088)	
Post Dem $_t$ × Forest $_d$ × Exposure $_d$			-0.451**
			(0.197)
Fixed Effect	d,st	d,st	d,st
Observations	74,664	74,664	74,664
R-squared	0.947	0.953	0.947

The dependent variable is the cumulative of daily surrenders starting on March 26, 2006.
Standard errors adjusted for spatial (500 km) and serial correlation (30 days) in parentheses following Colella et al. (2018).
*** p<0.01, ** p<0.05, * p<0.1

Figure B3: Daily Surrenders



Appendix B Additional Figures

Appendix C List of Districts affected by the Conflict

In our analysis, we follow the 2015 list of 106 districts in 10 Left Wing Extremism affected States from the Ministry of Home Affairs, which is based on their violence profile and other parameters. These States are covered under the Security Related Expenditure Scheme, which allow them to receive reimbursement for counter-insurgency measures. Table C6 gives the exhaustive list. Furthermore, districts colored in blue are considered as severely affected districts. As rainfall information is not recorded in certain districts and some of them were either split or merged between 2013 and 2017, we merged them to create a balanced panel dataset of 102 districts.

Table C6: Conflict-affected Districts

States	Districts
Andhra Pradesh	Anantapur,East Godavari, Guntur, Kurnool, Prakasam, Srikakulam, Visakhapatnam, Vizianagaram
Bihar	Arwal, Aurangabad, Banka, Begusarai, Bhojpur, Gaya, Jamui, Jehanabad, Kaimur Bhabua, Khagaria, Lakhisarai, Munger, Muzaffarpur, Nalanda, Nawada, Pashchim Champaran, Patna, Purba Champaran, Rohtas, Sheohar, Sitamarhi, Vaishali
Chhattisgarh	Bastar, Bijapur, Dakshin Bastar Dantewada, Dhamtari, Durg, Jashpur, Koriya, Mahasamund, Narayanpur, Raipur, Rajnandgaon, Surguja, Uttar Bastar Kanker
Jharkhand	Bokaro, Chatra, Deoghar, Dhanbad, Dumka, Garhwa, Giridih, Gumla, Hazaribagh, Khunti, Kodarma, Latehar, Lohardaga, Pakur, Palamu, Pashchimi Singhbhum, Purbi Singhbhum, Ramgarh, Ranchi, Saraikela-Kharsawan, Simdega
Madhya Pradesh	Balaghat
Maharashtra	Chandrapur, Gadchiroli, Gondiya
Orissa	Balangir, Bargarh, Debagarh, Dhenkanal, Gajapati, Ganjam, Jajapur, Kalahandi, Kandhamal, Kendujhar, Koraput, Malkangiri, Mayurbhanj, Nabarangapur, Nayagarh, Nuapada, Rayagada, Sambalpur, Sundargarh
Telangana	Adilabad, Karimnagar, Khammam, Mahabubnagar, Medak, Nalgonda, Nizamabad, Warangal
Uttar Pradesh	Chandauli, Mirzapur, Sonbhadra
West Bengal	Bankura, Birbhum, Paschim Medinipur, Puruliya