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Fiscal Incentives for Conflict: Evidence from India's Red Corridor

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JEL Codes: D72, D74, L23

Keywords: Counterinsurgency, Civil Conflict, Public Goods Provision



Fiscal Incentives for Conflict: Evidence from India's Red Corridor*

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Abstract

Can tax regimes shape the incentives of governments to engage in armed conflict? India's Maoist belt contains a large share of the country's most valuable mineral deposits. Indian mining royalties benefit the States, but they are set by the central government. States are largely responsible for counter-insurgency operations within their territory. Therefore, the royalty regime could shape the incentive of states to support counter-insurgency efforts. This paper exploits the introduction of a 10% ad valorem tax on iron ore that was responsible for a 10-fold increase in royalty collections by the affected State governments. In a panel of district-level violence outcomes between 2007 and 2013, we find that the royalty hike was followed by a significant intensification of violence in districts with iron ore deposits compared to other areas. We also show that the higher royalty rates are followed by an increase in illegal mining activity, suggesting that the control of mineral resources underpins the observed intensification in violence.

Keywords: COUNTERINSURGENCY, CIVIL CONFLICT, PUBLIC GOODS PROVISION

JEL Classification: D72, D74, L23

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Introduction

At the heart of any state is its ability to generate revenue from taxes. Fiscal policy could have important implications for the cost of fighting insurgencies and the prize of “winning” violent contest. However, the public finance of civil conflict has received very little attention so far. Theories of civil conflict often assume a weakly institutionalized environment, in which rebels and states fight over abstract prizes. The reality of conflict is often one in which complex institutions and policies constrain the behavior of the state and shape the prize of the contest. These constraints are particularly relevant in decentralized countries, where successful counterinsurgency requires co-ordination between and support from different levels of government. In such an environment, we study the impact of a tax regime that strongly increased the value of controlling territory for sub-national governments.

Our paper exploits the introduction of a 10% ad valorem tax on iron ore in India. This royalty regime was set by the central government, but its benefits accrued entirely to the states. Earlier, states received only 27 Rs (around \$0.5) per tonne of iron ore mined within their boundaries. The central government introduced a 10% ad valorem tax in August 2009. The introduction of this new royalty regime led to a 10-fold increase in the royalty collections of the affected states. The new iron ore royalties contributed up to 5% of the state budgets (at a value of up to 1% of the state GDP). Among the prime beneficiaries of the royalty increase were three states in India’s so-called “Red Corridor”, the broad region in the central East of the country that is severely affected by a long-standing conflict between Maoist insurgents and the Indian state. As state governments are fully responsible for managing counter-insurgency efforts within their territory, the royalty hike could have affected their incentives to allocate efforts in iron-rich districts.

The royalty change for iron ore was followed by an increase of the extent and intensity of Maoist violence in districts with iron ore deposits. There was no similar change for districts with bauxite and coal deposits - two key minerals that did not experience a comparable royalty hike. Given the economic importance of coal and bauxite for the affected states, this result constitutes a powerful placebo test. These results are consistent with the idea that an increase in tax revenue potential from con-

flict zones incentivizes lower-tier governments to increase counter-insurgency efforts. Importantly, royalty revenues are collected at the state-level and are not mechanically linked to the funding of local security operations. Because our results rely on within-state variation, the observed intensification of violence in iron ore districts must reflect a specific policy decision. The royalty hike also affected mining activity by shifting the returns for illegal mining compared to legal activity. Illegal mining activity is pervasive in India's Maoist belt, and it takes the form of mines that are larger than permitted or mines that are still in operation after their lease has expired. It is well documented that state-level officials benefit from the rents created by this illegal sector. Theoretically, the royalty hike should increase the relative profitability of illegal mining. Consistent with that expectation, measures of illegal mining activity based on satellite imagery show that the royalty hike was associated with increased illegal mining activity at iron mines, but not elsewhere.

These results speak to the large literature exploring how the presence of natural resources and variation in their value affect conflict. With respect to presence, [Lei and Michaels \(2014\)](#) find that discoveries of large oil fields increase the likelihood of conflict onset. There is conflicting evidence when it comes to value: [Bruckner and Ciccone \(2010\)](#) find that commodity price slumps increase the onset of civil war in Sub-Saharan Africa at the country level; [Berman et al. \(2017\)](#) find that price shocks boost violence in the same region using grid-cell level data; and [Bazzi and Blattman \(2014\)](#) find no relationship between commodity prices and the onset of conflict in a cross-country panel, but do observe that rising prices tend to shorten wars. Potentially reconciling these findings, theoretical work by [Dal Bó and Dal Bó \(2011\)](#) argues that the sign of the relationship between commodity price shocks and conflict depends on whether the shock hits a capital-intensive or labor-intensive industry. In an empirical test of this hypothesis, [Dube and Vargas \(2013\)](#) show how increased coffee prices reduce violence, whereas increased oil prices boost violence. They argue that the relative capital intensity of oil versus coffee explains why the so-called opportunity versus rapacity effects dominate respectively. In related work, [Fetzer and Kyburz \(2017\)](#) show how political power-sharing institutions in Nigeria mitigate resource conflict. The price shocks studied in the literature could be working either through an

increase in government revenue (because of the price increases) or through an increase in overall activity in the sector. Our contribution is to focus on the impact of a shock that directly impacts government revenue, even if the (value of the) underlying economic activity does not change.

Our results also contribute to the literature on links between taxation and conflict. [Sanchez de la Sierra \(2019\)](#), for example, links mineral booms for different types of minerals to differential patterns in the provision of public goods and taxation by rebels in the DRC. In Colombia, a setting with more established political institutions, [Ch et al. \(2018\)](#) show that the preferences of violent actors shape tax regimes at the municipal level.¹ Rather than focusing on how violent groups contribute to state formation and taxation, we highlight how the fiscal regimes that support political institutions shape the incentives of state actors to engage in conflict. In doing so, we join an emerging literature. The closest paper theoretically is [Berman and Matanock \(2015\)](#) who argue that potential tax revenues motivate governments to capture territory. They support this claim with evidence that increased private investment in the Philippines boosted both government and rebel violence. [Christensen, Nguyen and Sexton \(2019\)](#) show that Myanmar's military used more violence in areas that were rich in jade as part of a strategy of limiting the new civilian government's ability to control those resources. In the closest paper to ours empirically, [Saavedra and Romero \(2017\)](#) show that a reduction in the royalty rate flowing to local governments in Colombia boosted illegal mining, suggesting that local governments had less incentives to curb tax evasion after the change. As in our paper, they use satellite imagery to measure illegal mining. Our paper shows that tax revenues provide incentives for security operations even in a setting with no changes in the tax base.

This paper is organized as follows. First, we describe India's mining royalty regime. Second, we provide some background on the Maoist conflict. Third, we introduce the dataset. In the fourth section, we present the empirical strategy and the main results. We conclude with some additional interpretation.

¹[Dube and Vargas \(2013\)](#) also suggest that the decentralization of oil revenues could have made the relationship between oil prices and conflict stronger in the Colombian context. Their hypothesis is that it is easier for rebels to extort rents if revenues are managed by municipalities. Given the size of Indian states, the decentralization of revenues is unlikely to have boosted violence through this channel in India's Naxalite insurgency.

1 Mining royalties in India

India ranks among the world's top producers of iron ore, bauxite, and coal. In India's federal structure, the management of mineral resources is a shared responsibility between the central Government of India and the state governments, as prescribed by the Mines and Minerals Development and Regulation [MMDR] Act 1957. The national government, or "Centre" sets the royalty rates on mineral output as well as any "dead rent" (fees charged if output is too low). While the State Governments are the legal owners of all major mineral resources (with the exception of uranium), their ability to profit from mining activity is severely restricted by the fact that they cannot set royalty rates or dead rents. They do have the legal power to grant licenses, but the licenses in themselves cannot be sold.² Hence, royalties and dead rents are the main sources of direct revenue from mining activity for State Governments.

The MMDR 1957 allows the Centre to change royalty rates every three years. Occasional changes have created a complex system of royalty formulas that differ for each mineral. The 2009 round of royalty revisions is of particular interest. Most major minerals saw a limited increase in royalty rates, but iron ore royalties increased substantially. Prior to the change, iron royalties were levied per metric tonne, at a rate of 27 Rs in 2009 (approximately 0.05 USD at current prices). The August 2009 revisions introduced a 10% ad valorem tax on iron ore, which at fixed prices amounted to an immediate 5-fold increase in the per unit royalty rate. Combined with gradual price increases from early 2010 onwards, royalty collections on iron increased by a factor of more than 10 in the affected states (Table ??). By the 2010-11 budget year iron royalties accounted for more than 1% of GDP. Importantly for our analysis, iron output did not increase in 2009, and even experienced a bit of a slump before recovering in 2010, as Figure A1 shows. Bauxite by contrast experienced a small change in royalty rates in 2009. Bauxite had been subject to a royalty of 1% of the international aluminum price (at the London Metal Exchange), and saw this rate increased to 1.5%. And coal royalty rates did not increase until April 2012.

²Reconnaissance Permits, Prospect Licenses, and Mining Leases are attributed on a "first come, first serve" basis (<http://mines.nic.in/faq.html>, accessed December 2013). The application fee is negligible and set by the Centre, under the Mineral Concession Rules, 1960. However, states can still try to benefit from licenses by favoring companies that carry out complementary investments in their states.

Our empirical analysis exploits the introduction of the new royalty regime, and it is thus important to understand its specific timing. The earliest rumors of a royalty hike can be traced back to September 2007, when a study group at the Ministry of Mines formulated a recommendation to switch to such a regime. This report was a mere internal recommendation and the intention of the Government was still unclear at that point in time. The risk of inflation is cited as one of the reasons why the Government asked the Ministry of mines to delay the implementation of the proposal in June 2008 (The Economic Times, 2008). The Government's plans to change its royalty policies took clear shape in February 2009, when new and substantially higher royalties were introduced for uranium. Uranium is the only mineral that is completely controlled by the central government, but the press release for uranium royalties noted that negotiations over new royalty rates on other major minerals had started. We consider the start of these negotiations as the starting point of our treatment. The approval process was delayed by the 2009 general elections, which took place between April and May 2009, and the 10% ad valorem royalty rate was officially announced by the Ministry of Mines towards the end of June 2009 (The Economic Times, June 2009), and sent to the cabinet for final approval. The cabinet approved the royalty regime on 12 August 2009, and the implementation was effective on the same date. It is plausible that State Governments became increasingly certain of the imminent overhaul of the existing system from early 2009 onwards.

The argument in favor of a royalty hike (in combination with a shift to an ad valorem system) focused on the need for "fair compensation" of state Governments, in the light of recent windfall revenues for miners who had benefited from the strong demand for iron ore in China. The example of other iron rich countries that rely on ad valorem taxes (e.g. Australia and Brazil) likely also played a role (Ministry of Mines, 2007). The final press release also invokes an efficiency argument: ad valorem taxes limit the need for ad hoc changes in royalty rates (Ministry of Mines, 2009). Interestingly, Government and press reports on the changing royalty regime do not focus on the Naxalite conflict. The law did not exclusively affect conflict zones either, as iron-rich districts in Goa and Karnataka have not experienced significant Maoist violence. In fact, these two states were at the centre of highly visible mining scams -

which are important for the context of this paper. In Karnataka, high-ranking members of State Government were found to have managed illegal mining businesses and became the subject of a Central Bureau of Investigation (CBI) inquiry in December 2009. The deep-rooted nature of illegal iron ore mining led the Supreme Court to establish a ban on iron ore exports in Goa and Karnataka. Illegal mining clearly enables the evasion of mining royalties, although the very low historical royalty rates served to mitigate this advantage. However, most illegal mining activity entailed a violation of environmental regulations, for instance by mining outside of the area for which a company had received environmental clearance (so-called “excess mining”), or by continued operation after the expiration of the lease.³ The measures of illegal mining we will use in our empirical analysis capture exactly these violations.

2 India’s Maoist Conflict and Mining

India’s Maoist (or Naxalite) conflict can be traced back to a peasant uprising that originated from the West-Bengali village of Naxalbari in the late 1960s. The sympathizers of the uprising founded the All India Coordination Committee of Communist Revolutionaries, which promoted “Allegiance to the armed struggle and non-participation in elections.” Between 1970 and 2000, different Naxalite groups challenged each other as much as the Indian states. However, 2004 saw a major break when the two main Naxalite outlets joined forces in the newly founded Communist Party of India (Maoist), or CPI (Maoist) (Kujur, 2009). The present-day CPI (Maoist) retains a commitment to armed struggle with the goal of overthrowing the Indian state, while opposing participation in democratic elections. The 2004 merger was followed by a marked intensification of the conflict. In 2006, the Naxalite movement was famously described by the Indian Prime Minister Manmohan Singh as “the single biggest internal security challenge ever faced by our country” (Economist, Feb 2010). From 2005-2010 the conflict claimed more than 5,000 lives. The continuing popularity and strength of the Naxalite movement is perceived to stem from chronic underdevelopment in the

³See figure A1 in the appendix.

affected communities.⁴

Many observers have pointed out the close link between the Maoist movement and the mining industry. On 20 May 2010, for example, the Maharashtra State Home Minister R. R. Patil openly accused the mining industry of funding Left Wing Extremists (LWEs).⁵ His statements reflect a widespread belief that Naxalite benefit from mining revenues through extortion and the facilitation of illegal mining activity.

Miners are reported to pay protection money to the Maoists as well as bribes to the police and other government officials in order to conduct illegal mining businesses.⁶ The simultaneous involvement of government officials and Maoists raises the possibility that Maoist activity is tolerated in order to shield illegal mines from unwanted attention. Such a Maoist-State nexus was explicitly put forward by Orissa's BJP leader in 2010.⁷ Even if there was no explicit tolerance of Maoist activities, there are good reasons to believe that State Governments did not fully internalize the economic disruption caused by the threat of Maoist violence.⁸ National government officials regularly accuse States of being "lax" in their approach towards Maoism. In 2014, for example, the outgoing chief of the Central Reserve Police Force, a centrally funded force that provides assistance to the State Police, accused "some states" of "wanting Maoists to continue" (Times of India, 28 Nov 2014).

In this context, we expect an increase in mining royalties to work through a variety of channels. First, we expect investments in security operations to be complementary to the royalty revenues from mining activity. Higher royalties raise the State Govern-

⁴Ghatak and Vanden Eynde (2017) provide an overview of the recent empirical literature on the Maoist conflict. Vanden Eynde (2018) shows that access to mining resources shapes the response of the Maoists to rural income shocks. Fetzer (2019) finds that India's rural work programme MNREGA mitigates the effect of these rural income shocks on conflict, even if Khanna and Zimmermann (2017) argue that MNREGA initially increased violence, which is consistent with attempts by the rebels to disrupt the programme.

⁵SATP 2010. See also Srivastava (2009) for similar claims.

⁶Times of India, 13 January 2013, <https://tinyurl.com/y48mo47g>. In general, the link between mining activity and political corruption is well-established. For example, Asher and Novosad (2016) show that mining booms boost the election chances of criminal politicians and increase wealth accumulation of elected politicians.

⁷Indian Express, 14 January 2010, <https://tinyurl.com/y47t9h3g>. Another example is "MLA seeks 'support' of Maoists to run mine", Hindustan Times, 24 November 2013.

⁸A large number of newspaper articles and policy briefs report such disruption, e.g. The Telegraph, 21 May 2019, <https://tinyurl.com/y4udzdsb> and Kujur (2009).

ments' returns to controlling territory. Even if the state bargains with mine owners to share rents from illegal mining activity, the boost in legal revenues will improve the state's bargaining position. Second, for mine owners, higher royalty rates increase the value of illegal mining over legal mining if illegal mining allows them to evade the royalties. However, mine owners can also collude with the state to continue illegal mining activities, which could be more profitable in state controlled versus non-controlled mining areas given the taxes the Maoists impose. While the royalty hike will unambiguously increase the State's effort to control mines, the effect on the extent of illegal mining is ambiguous. Its sign depends on whether illegal mining is more pervasive in state controlled versus non-controlled mining areas.⁹

3 Data

This paper combines data on conflict with administrative and remote-sensing derived data on mining. Our violence data comes from press reports collected by the South Asia Terrorism Portal (SATP) between 2007 and 2013.¹⁰ The SATP draws from newspaper reports in the local and national English speaking press to construct daily incident summaries. These summaries provide the district in which the incident took place, as well as the number of deaths on each side of the conflict (civilians, Maoists and security forces). In these reports, all civilian casualties are inflicted by the Maoists. However, for political reasons, the SATP data do not systematically report such incidents. As it is hard to formally identify 'Maoists', this category could include civilian victims inflicted by the Security Forces. Based on this information, we construct variables for the number of fatal attacks on Maoists by the police as well as the number of fatal Maoist attacks on the police. The conflict outcome data are collected at the district level for each half-year between 2007 and 2013. We restrict analysis to five

⁹The online appendix formalizes this argument in a simple theoretical framework that is based on a model of incentives for tax collectors by [Khan, Khwaja and Olken \(2016\)](#).

¹⁰See also [Vanden Eynde \(2018\)](#) for further discussion of this data source. The sample period starts in 2007, because the most recent information on mining activity used in the analysis was published in 2006 and because the most recent royalty change (for coal only) was introduced in the first half of 2007. In addition, the SATP data is more detailed and complete from 2007 onwards, as highlighted by [Gawande, Kapur and Satyanath \(2017\)](#).

states that are confronted with significant Naxalite activity during the period under study: Andhra Pradesh, Bihar, Chhattisgarh, Jharkhand, Maharashtra, Orissa and West Bengal.¹¹

We focus on the three most important minerals mined in the Maoist area: iron, bauxite, and coal. Data on the location and volume of mineral deposits is obtained from the Geological Survey of India.¹² The 2001 census provides a variety of control variables, and we use forest cover data from the Ministry of Environment and Forest.

We use satellite imagery to measure the size of mining areas and for evidence of truck activity at a sample of 109 iron ore, bauxite, chromite, and manganese mines.¹³ We compare these measures to administrative lease information from the India Directory of Mining Leases (collected in 2015) to identify two types of illegal mining activity: (1) truck activity in mines for which the lease has expired, and (2) mining areas that exceed the legal maximum size of a given mine.

4 Empirical strategy and results

4.1 Violent conflict

We use a difference-in-difference approach to understand the impact of the introduction of a 10% ad valorem tax on iron ore in 2009. Comparing districts with and without iron ore deposits before and after the introduction of the new tax rate allows

¹¹Only the eastern part of Maharashtra is affected by the conflict: we include Bhandara, Gondiya, Garhchiroli, and Chandrapur districts in our analysis.

¹²For iron ore: "Detailed Information Dossier on Iron Ore in India", 2006, GSI. For Bauxite: "Detailed Information Dossier on Iron Ore in India", 1994, GSI. For coal: "Indian Coal Resources", 2004, GSI). This data is complemented with data on deposit locations (that does not include estimates of the size of these deposits) for Chromite and Manganese from the "Mineral Handbook" (Geological Survey of India, 2001).

¹³Mines in our sample are drawn from those for which lease information allowed for geolocalization based on detectable mining activity and the name of the mining site. Table A13 confirms that mines included in our sample are slightly larger on average, but the size of the effect is small and not significant across specifications. Included mines also do not differ in terms of the lease expiration year. Coal is not included in the lease directory as all coal mines are state-owned. Hence, we cannot construct illegal mining measures for coal. Note that the district-level conflict results focus on bauxite and coal as placebo minerals, as economically these are the most important minerals apart from iron ore, and there is sufficient variation in their district-level deposits. For completeness, table A6 presents the main results for a broader set of minerals including manganese and chromite.

us to isolate the impact of the change. Figure A5 provides a graphical depiction of the identification strategy, plotting the interactions of the volume of iron ore deposits and dummies for each half-year, in a regression of the *asinh* transformation of the number of attacks on state-time dummies. It is clear that districts with iron ore deposits experienced a strong and sustained increase in conflict relative to other districts from 2009 onwards. This intensification weakens in later years. Districts with bauxite or coal deposits do not experience similar increases.

In the main econometric specification, we rely on a fixed-effect OLS regression in which we measure outcomes either as dummy indicators, or we use an inverse hyperbolic sine (*asinh*) transformation to account for the fact that all our outcomes are count variables.¹⁴

$$y_{i,s,t} = \alpha_i + \beta Iron_{i,s} * Post_t + \gamma Iron_{i,s} * \text{Log}(\text{Iron Price})_t + \mu_{s,t} + \epsilon_{i,s,t} \quad (1)$$

The dependent variable is the number of fatal attacks inflicted by the security forces or the Maoists, for a given district *i*, in state *s*, and in half-year *t*. The indicator variable *Post_t* switches on when the negotiations for the new royalty regime are reported to have started, i.e. from the first half of 2009 onwards. In the baseline specification, *Iron* is the logarithm of the mining deposits (in million tonnes per 1000 km²).¹⁵ The coefficient β represents the difference in the extent or intensity of violence in iron ore districts compared to non-iron ore districts, before and after 2009. We control for the potential impact of international mining prices by including an interaction of *Iron* with the logarithm of the international iron ore price. India’s iron ore production is only 8.8% of the total world production (US Geological Survey, “Iron Ore Statistics”, 2010), which puts India in the “price taker” category following the rule of [Bazzi and Blattman \(2014\)](#). Moreover, the states affected by the conflict account for an even smaller percentage of the world production.

The state-specific time fixed effects $\mu_{s,t}$ account for state-level policy variables which may affect the number of attacks. As both economic policy and counterin-

¹⁴Appendix Table A7 shows the main results are robust to using a Poisson model.

¹⁵Appendix tables A6 and A8 show the results are robust to using a dummy variable for the presence of iron deposits instead.

surgency strategies are set at the state level and these policies vary widely between states, $\mu_{s,t}$ controls flexibly for a wide range of potentially relevant but unobserved determinants of violence. Importantly, the state-time-fixed effects absorb the impact of the royalty regime on the state budget, given that royalty collections are not tied to expenditures in the districts where they originate. This approach is essential to identify the impact of changed incentives for intervention (as opposed to a budgetary windfall) at the district level.

Table 1 presents the corresponding difference-in-difference estimates for the 2007-2011 period. The coefficient on our treatment variable implies that moving from a district without iron ore deposits to one with the average deposit value (conditional on positive values) increases the probability of fatal police attacks on Maoists by around 11% points and the probability of fatal Maoist attacks on the police by around 6% points. In terms of the intensity of violence, the estimates suggest that the number of attacks goes up by around 11%. Importantly, police violence is only weakly higher in months with higher prices (columns 2 and 3) and Maoist violence is uncorrelated with prices, providing evidence that the post-royalty hike increase is due to a specific policy decision and not a mechanical reflection of revenues. In table 2, we use a larger time window to test explicitly that the intensification is limited to the three years after the royalty hike.

As the main results are based on a difference-in-difference approach, the crucial identification assumption is that iron districts would have followed the same trend in the absence of the royalty change. We perform a number of placebo tests to support this assumption. Given that iron ore was the only mineral that saw an increase in royalty revenues, we can estimate the effect of bauxite and coal deposits in an analogous fashion to the effects for iron ore districts in equation 1. If β captures the causal effect of the regime change for iron ore, there should be no comparable impact for these minerals. Table 1 confirms that this is the case.¹⁶ The events studies plotting the effect of *Iron* in every year of the sample support the common trends assumption (see figure A5). Table 2 includes another important specification test in the even columns,

¹⁶The effect on bauxite is insignificant, but not significantly different from the effect on iron ore. The bauxite effect is imprecisely estimated and not consistent across time or across violence types. It is also not robust to respecification, as for example in table A9.

which include interactions of time dummies with baseline characteristics.¹⁷ These results also confirm that the intensification of violence is highest for the earlier years in our sample.

4.2 Illegal mining

We analyze the effect of the royalty change on illegal mining activity with satellite-based measures for a sample of 109 mining sites. The empirical strategy follows a similar difference-in-difference approach, comparing iron ore to non-iron ore mines, including mine fixed effects and state-year fixed effects. However, this analysis has to deal with missing measurements in multiple years for any given mine (i.e., the panel is highly unbalanced). To make sure that composition effects are not driving our findings, we complete the panel by substituting missing observations with the most recent measurements for those mines.¹⁸

Introduction of the 10% royalty was followed by an increase in the share of iron ore mines that are larger than their official size (compared to non-iron mines), as shown in table 3 (in columns 1 and 2). While iron ore mines see a reduction in measured truck activity, there is a net increase for mines of which the lease has expired (column 3). Figure 2 confirms these findings in an event study graph. Both measures of illegal mining activity point towards an increase in illegal mining. This is consistent with the idea that the royalty hike increases the willingness to pay bribes. More broadly, the observed response of the illegal mining outcomes underlines that this sector determines the value of controlling territory. And, our analysis suggests that

¹⁷The appendix tables present a range of further robustness checks. Table A3 shows the relationship between mineral measures at the district level and violence before 2009q3. Most of these mineral deposit measures are not correlated with violence outcomes. In table A6 we estimate the main results for a broader set of minerals. As we lack precise deposit estimates for chromite and manganese, we use dummy indicators for these results (which is in itself another robustness check). Again, iron ore districts experience significant increases in violence after 2009. In table A8, we show how the sensitivity of the difference-in-difference coefficient to the window of the event study. Finally, in table A12 we confirm that the ‘Integrated Action Plan’ (IAP), a development programme targeted at Maoist-affected districts and introduced in 2009, did not benefit iron-rich districts in particular. Table A11 further confirms that the main results are robust to controlling for different measures of IAP investment at the district level.

¹⁸For certain mines with no information in 2007, we use measurements from 2005-2006. This approach to completing the panel is equivalent to re-weighting observations to make sure that every mine has a similar weight in the regression.

changes in the fiscal regime can shift the incentives of governments to intervene in conflict zones.

5 Conclusion

This paper is one of the first to explore the public finance of law and order provision in an ongoing civil conflict. In the federal political structure of India, we study the introduction of a royalty regime for iron ore that strongly increased the fiscal value of iron-rich districts for state governments. As the states are responsible for the provision of law and order in their territory, they play an essential role in the management of the Naxalite conflict.

Our difference-in-difference empirical analysis shows that the introduction of this tax led to a temporary intensification of Maoist-related violence. These results are consistent with the allocation of security operations according to the value of controlling territory. Our results are part of an emerging research agenda which recognizes the institutionalized nature of conflicts, and analyses the role of the specific policies that characterize these institutions in shaping the behaviour of parties engaged in conflict.

It is important to acknowledge that we cannot determine whether incentivizing lower-level authorities to fight hard is desirable from a welfare perspective. In particular, increased counter-insurgency efforts could lead to human rights abuses. Moreover, any government action that facilitates mining activity (legal or illegal) could generate negative externalities in the form of population displacement and environmental damage. Regardless of the sign of the net benefits from government actions, the findings of this paper are important to understanding the strategic behavior of sub-national government actors. As many developing countries are decentralizing political power, understanding how fiscal decentralization shapes conflict resolution and counter-insurgency strategies has clear relevance beyond India.

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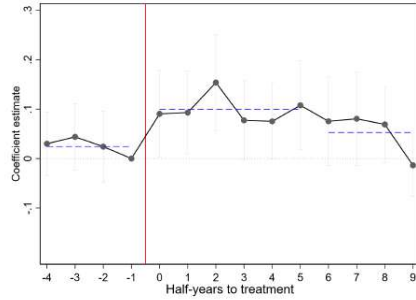
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Appendix

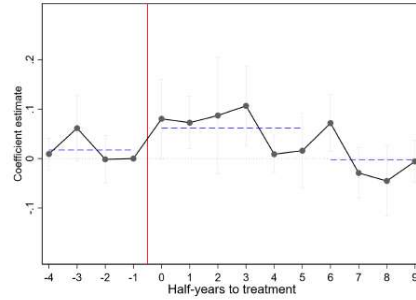
5.1 Main results

Figure 1: Event studies.

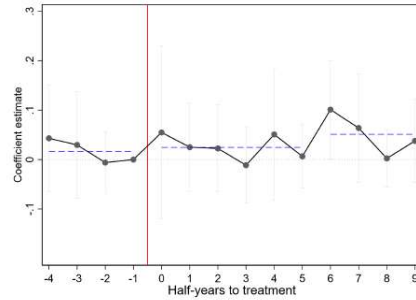
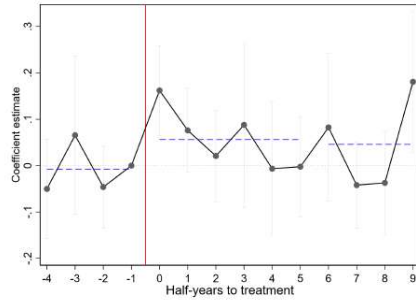
(1) Police Attacks on Maoists
Iron Ore Deposits



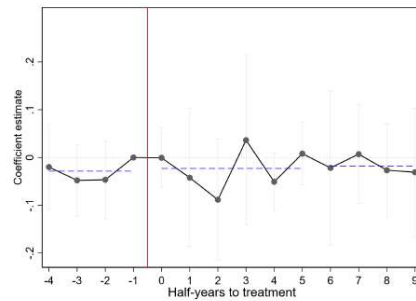
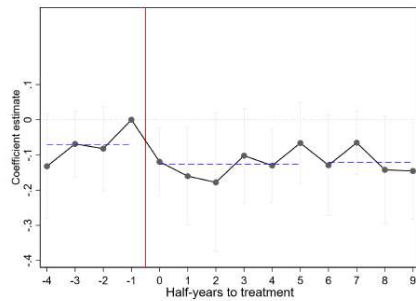
(2) Maoist Attacks on Police



Bauxite Ore Deposits



Coal Deposits



Notes: Half-yearly district-level data between 2007 and 2013. All outcomes are subject to an asinh transformation. Event studies follow the main specification (equation 1). 90% confidence intervals are shown as grey bars.

Table 1: Main Results

	Police Attacks on Maoists			Maoist Attacks on Police		
	Dummy	Asinh		Dummy	Asinh	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Iron Deposit) x Post	0.067*** (0.018)	0.066*** (0.024)	0.074*** (0.024)	0.033* (0.019)	0.054** (0.023)	0.054** (0.023)
Log(Iron Deposit) x Price (real Rs per MT)	0.051** (0.021)	0.040 (0.034)	0.034 (0.033)	-0.008 (0.020)	-0.005 (0.026)	-0.007 (0.026)
Log(Bauxite Deposit) x Post			0.032 (0.035)			-0.002 (0.035)
Log(Coal Deposit) x Post			-0.018 (0.042)			-0.017 (0.027)
Log(Bauxite Deposit) x Price (real Rs per MT)			-0.202 (0.125)			-0.072 (0.127)
Log(Coal Deposit) x Price (real Rs per MT)			0.066 (0.057)			0.052 (0.060)
Mean DV	0.137	0.172	0.172	0.113	0.133	0.133
Standard Deviation	0.344	0.480	0.480	0.317	0.413	0.413
Observations	1430	1430	1430	1430	1430	1430
Clusters	143	143	143	143	143	143

Notes: Regressions at the district-half-year level (2007-2011). Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. All regressions include district fixed effects, and state \times time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Time Patterns for Iron Ore

	Police Attacks on Maoists		Maoist Attacks on Police	
	(1)	(2)	(3)	(4)
Log(iron dep) x 2009-2011	0.066*** (0.024)	0.042* (0.023)	0.054** (0.023)	0.040* (0.023)
Log(iron dep) x 2012-2013	0.008 (0.036)	0.002 (0.034)	-0.014 (0.021)	-0.014 (0.022)
Log(Iron Deposit) x Price (real Rs per MT)	0.041 (0.034)	0.066* (0.035)	0.002 (0.026)	0.012 (0.029)
Mean DV	0.152	0.155	0.119	0.122
Standard Deviation	0.450	0.454	0.388	0.391
Observations	2002	1960	2002	1960
Clusters	143	140	143	140
Control × Time FE	No	Yes	No	Yes

Notes: Regressions at the district-half-year level (2007-2013). Outcomes are subject to an asinh transformation. Deposit values are measured as million Tonnes per 1000km², and subject to a $\log(x + 1)$ transformation. The control set includes time-effects for the rural literacy rate, the rural SC-ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state × time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

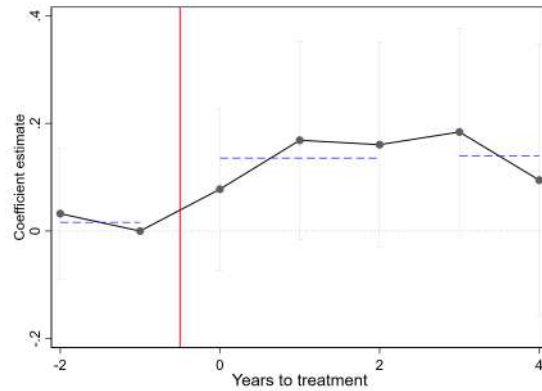
Table 3: Illegal Mining

	Excess Mining (0-1) (1)	Excess Mining 50 % threshold (0-1) (2)	Truck Activity (0-1) (3)
Iron Mine x (2009-2011)	0.110* (0.066)	0.112* (0.061)	-0.145* (0.075)
Iron Mine x (2012-2013)	0.107 (0.067)	0.110* (0.059)	-0.115 (0.112)
Iron Mine x (2009-2011) x Expired			0.231* (0.118)
Iron Mine x (2012-2013) x Expired			0.005 (0.145)
Mean DV	0.326	0.277	0.703
Standard Deviation	0.469	0.448	0.457
Observations	602	602	602
Clusters	89	89	89

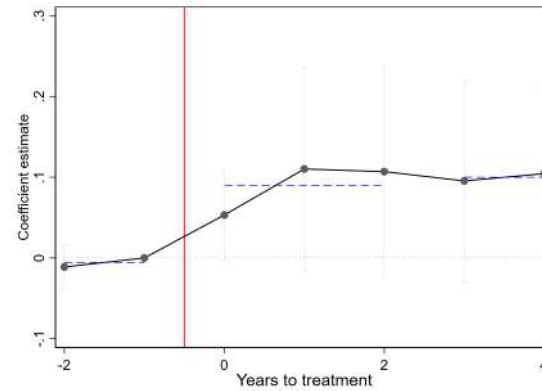
Notes: Annual mine-level data between 2007 and 2013. Truck activity and area measurements are based on satellite imagery analysed for the purpose of this study. The India Directory of Mining Leases contains the expiry data and legal maximum area of each mine. The measures are based on comparing satellite information with these administrative records. For these outcomes, we substitute missing observations with the most recent available measurement available for each mine. The excess mining indicator in column (1) is 'one' when the measured area exceeds the legal area, the indicator in column (2) switches on when the measured area exceeds the legal area by more than 50%. Control minerals include: iron ore, bauxite, manganese, chromite, and Copper. All regressions include mine fixed effects, and state \times time fixed effects. Standard errors are clustered at the mine level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2: Illegal Mining

Panel A: Truck Activity in Expired Mines (0-1)



Panel B: Excess Mining (0-1)



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Notes: Annual mine-level data between 2007 and 2013. Truck activity and area measurements are based on satellite imagery analysed for the purpose of this study. The India Directory of Mining Leases contains the expiry data and legal maximum area of each mine. The measures are based on comparing satellite information with these administrative records. For these outcomes, we substitute missing observations with the most recent available measurement available for each mine. Panel A shows coefficients on interactions of an iron ore indicator, year dummies, and a measure for whether a mine is expired before 2009. Panel B shows coefficients on interactions of an iron ore indicator and year dummies. Control minerals include: bauxite, manganese, chromite. All regressions include mine fixed effects, and state \times time fixed effects. 90% confidence intervals are shown as grey bars.

Appendix to “Fiscal Incentives for Conflict: Evidence from India’s Red Corridor”

For Online Publication

May 12, 2020

A Conceptual Framework

In this section, we develop a simple framework to describe the optimisation problem of the state and mining owners. The state government decides on the intensity of security operations against Maoists, and firms decide on the extent of illegal mining activity.¹

States invest in security operations to take control of a share s of mining regions. The costs of controlling territory that are convexly increasing, according to function $\frac{s^2}{2}$.² In the areas under the state’s control, it can allow illegal mining activity, but must bargain with the mining firms to split the rents. Firms can share their production capacity (normalized to 1) between legal and illegal mining - the share devoted to illegal mining is C . Illegal mining activity generates output θC ; legal mining generates output $1 - C$. We assume that illegal mining is more productive ($\theta > 1$) than legal mining, because it can exceed legal limits,³ and that it is associated with convexly increasing costs, according to function $\frac{C^2}{2}$.⁴ These costs could include the risk of future legal action as well as technological risks. Legal mining activity will be taxed at rate ρ . In the areas outside of the state’s control, illegal mining is taxed exogenously by the Maoists at rate μ . We assume that royalties are still paid on legal mining activity, even

¹Given that states can receive bribes from mining firms in return for facilitating illegal mining, problem (2) is similar to the tax inspection problem studied by [Khan, Khwaja and Olken \(2016\)](#). This section develops a variation on these authors’ conceptual framework.

²This functional form assumption can be relaxed; the main results hold for any convexly increasing function $g(s)$.

³There is a clear incentive to make mining pits as wide as possible, given that there are physical constraints on the steepness of mining pits.

⁴The main results hold for any convexly increasing function $f(C)$.

when the Maoists control the area around the mine, because mine owners would draw too much attention (e.g. from central inspectors) if they do not generate any royalty revenue.

In the absence of illegal mining in state-controlled mines, the state's and mining firm's pay-offs are respectively:

$$U_s^N = \rho s + \rho(1 - C)(1 - s) - \frac{s^2}{2} \quad (2)$$

$$U_m^N = s(1 - \rho) + (1 - s)[(1 - \mu)\theta C + (1 - \rho)(1 - C) - \frac{C^2}{2}] \quad (3)$$

We assumed that the state and the mining firm can collude to allow illegal mining activity in the state-controlled mines. In our model, the state and mining firm engage in Nash Bargaining (after s has been chosen). There is evidence that state governments and mine owners negotiate over the surplus from illegal mining - in Karnataka (which is not part of the Maoist belt), high-ranking members of State Government were found to have managed illegal mining businesses and became the subject of a Central Bureau of Investigation (CBI) inquiry in December 2009. The joint surplus of allowing illegal mining activity at level K in state controlled territory is:

$$s[\theta K - K - \frac{K^2}{2}] \quad (4)$$

We assume the state's bargaining power is α . After the intensity of security operations s has been chosen by the state, the mining firm then sets C and K .⁵ This yields the following pay-off for the state:

$$U_s^C = \rho s + \rho(1 - C)(1 - s) - \frac{s^2}{2} + \alpha s[\theta K - K - \frac{K^2}{2}] \quad (5)$$

⁵In this simple framework, the optimal choice of C and K does not depend on s , so there is no real strategic interaction between the state and the mining firm, and the order of play does not affect the results.

And for the mining firm:

$$U_m^C = s(1 - \rho) + (1 - s)[(1 - \mu)\theta C + (1 - \rho)(1 - C) - \frac{C^2}{2}] + (1 - \alpha)s[\theta K - K - \frac{K^2}{2}] \quad (6)$$

The optimal degree of illegal mining in government and Maoist controlled mines, respectively, is given by:

$$K^* = \theta - 1 \quad (7)$$

$$C^* = \rho + (1 - \mu)\theta - 1 \quad (8)$$

The optimal intensity of security operations s^* is derived by maximizing the state's pay-off:

$$s^* = \rho C^* + \alpha[\theta K^* - K^* - \frac{K^{*2}}{2}] \quad (9)$$

The increase in royalties on legal mining output (ρ) now has the following effect on the intensity of security efforts:

$$\frac{ds^*}{d\rho} = C^* + \rho > 0 \quad (10)$$

The intensity of security efforts by the state increases unambiguously through two channels. First, the higher royalty rate improves the bargaining position of the state and investments in security are complementarity. Second, the increase in the royalty rate boosts illegal mining in the non-controlled mines and therefore the benefit of bringing these mines under control increases from the state's perspective. We now examine how total illegal mining responds to the increase in the royalty:

$$\frac{d[s^*K^* + (1 - s^*)C^*]}{d\rho} = (C^* + \rho)[K^* - C^*] + (1 - s^*) \quad (11)$$

The total effect runs through 2 mechanisms. First, the higher royalties incentivize firms to mine illegally, so illegal mining will expand in non-controlled mines. Second,

the increased security force efforts bring more mines under the state’s control. Depending on whether illegal mining is higher or lower in state controlled mines than in non-controlled mines, this second effect can increase or decrease the extent of illegal mining. Hence, the second channel allows us to formulate a sufficient condition under which the effect of the royalty hike on illegal mining is positive:⁶

$$K^* > C^* \Leftrightarrow \theta > \frac{\rho}{\mu} \tag{12}$$

In other words, if the benefits of illegal mining θ and the tax rate of the Maoists μ are high relative to the state’s tax ρ , then illegal mining will expand in response to the rise in iron ore royalties.⁷

B Additional Tables and Figures

Table A1: State-wise Royalty Collection of Iron Ore in India (Million \$)

States	2008-09	2009-10	2010-11	% of GDP 2010-11	% of Budget 2010-11
Andhra Pradesh	3.3	5.9	2.1		
Chhattisgarh	11.9	70.0	201.1	1.1	6.1
Goa	5.3	55.6	187.0		
Gujarat	-	0.0	-		
Jharkhand	6.9	30.1	74.0	0.5	4.2
Karnataka	20.8	62.4	111.3		
Madhya Pradesh	0.1	0.4	1.6		
Maharashtra	0.1	0.3	3.9		
Odisha	29.1	130.4	361.1	1.1	5.6
Rajasthan	0.0	0.1	0.1		

Source: Royalty figures from the Ministry of Mines. GDP data from the Ministry of statistics and Program Implementation. State Budget (2010-2011) for Jharkhand, Chhattisgarh, and Orissa from the Ministry of Finance.

⁶If we relax the functional form assumption for the costs of illegal mining, the same condition holds as long as C and K follow the same convex and monotonically increasing cost function f .

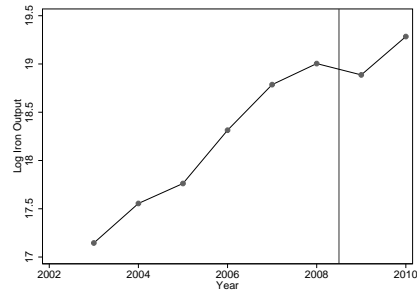
⁷This condition fails if ρ becomes too high, because of the increased incentives mine owners have to evade the royalty. Even in this parameter range, the total effect of the royalty change on illegal mining is given by equation 11 and can remain positive.

Table A2: Summary Statistics

	Number of Observations (1)	Mean (2)	Standard Deviation (3)
<i>Time-varying measures</i>			
Attacks on Maoists	2002	.2402597	.9675998
Attacks on Police	2002	.1798202	.7926653
PMGSY Roads	2002	9.746254	13.70028
RGVY Projects	2002	60.8956	169.4411
Bauxite Deposit x Price (real Rs per MT)	2002	1.267279	3.451556
Coal Deposit x Price (real Rs per MT)	2002	.8230203	1.749419
Iron Deposit x Price (real Rs per MT)	2002	.9519671	1.933516
<i>District-level measures</i>			
Log(Iron Deposit)	143	.3412573	1.022886
Log(Bauxite Deposit)	143	.2172061	.726655
Log(Coal Deposit)	143	.1531209	.4376067
Iron Deposits (0-1)	143	.1958042	.3982133
bauxitedepdum	143	.1188811	.3247862
Coal Deposits (0-1)	143	.1818182	.3870503
Percentage Literates, Rural	143	.4423532	.1175795
ST/SC rate, Rural	143	.3408698	.1763016
Forest Cover (percentage of area)	140	19.87052	18.41067
Villages with road (percent), 2001	143	.4487715	.2057755
Population density (100 per sq km)	143	5.328224	4.347078
Log(Iron Deposit), positive	28	1.74285	1.723224
Log(Bauxite Deposit), positive	17	1.827087	1.249406
Log(Coal Deposit), positive	26	.842165	.6958575

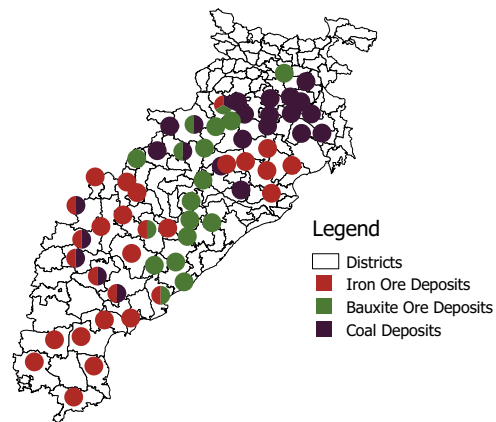
Notes: Observations at the district-level. The states of Andhra Pradesh, Bihar, Chhattisgarh, Jharkhand, Maharashtra (4 districts), Orissa, and West-Bengal are included in the sample. ‘ST/SC’ refers to the scheduled tribe/scheduled caste population. Time-varying measures are half-yearly and cover 2007-2013. District-level baseline measures are from the 2001 census, with the exception of forest cover (“District-Wise Forest Cover in 2007” from the Ministry of Environment and Forest, Government of India). The text provides a detailed description of our mineral measures, which are mostly based on the Geological Survey of India.

Figure A1: Iron ore output



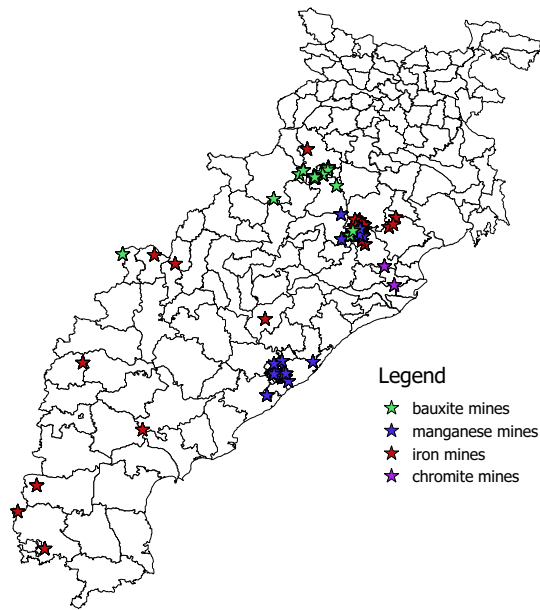
Notes: Aggregate output of iron ore (logarithmic) in India between 2003 and 2010.

Figure A2: Mineral deposits (Iron ore, bauxite, and coal)



Notes: District-level mineral deposits (dummy indicators) for our main sample.

Figure A3: Satellite measurements of mines

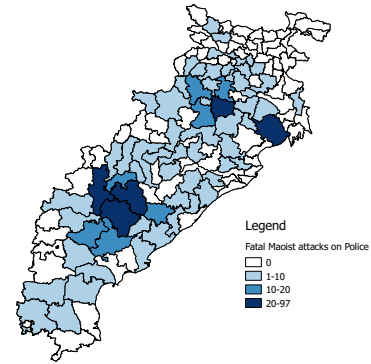
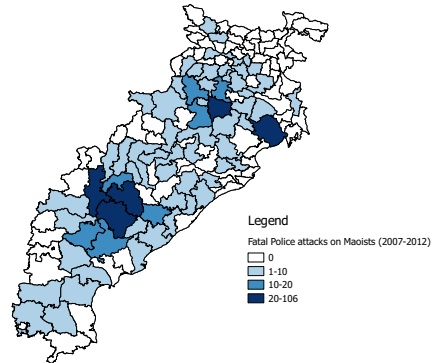


Notes: Coordinates of mines for which satellite measurements are available.

Figure A4: Violence and Iron Ore

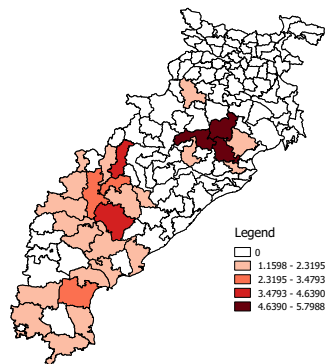
Panel A: Police Attacks on Maoists

Panel B: Maoist Attacks on Police



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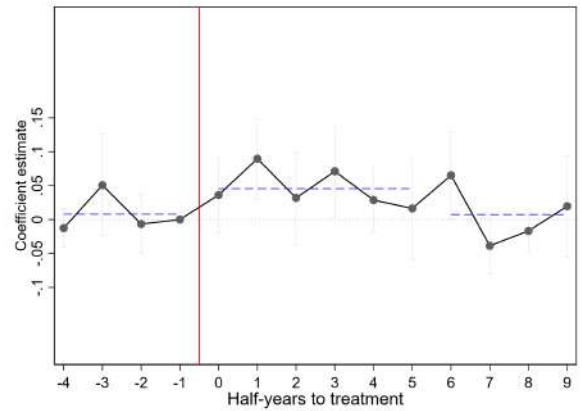
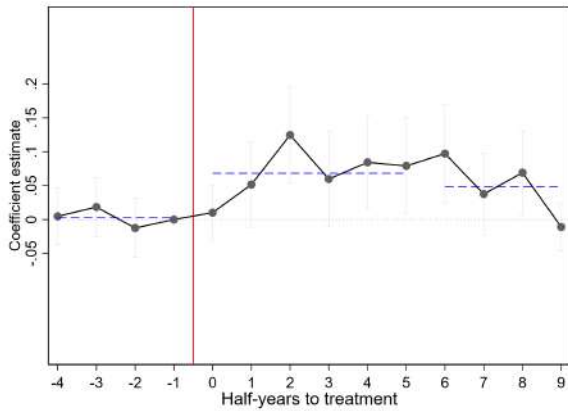
Panel C: Iron Ore Deposits



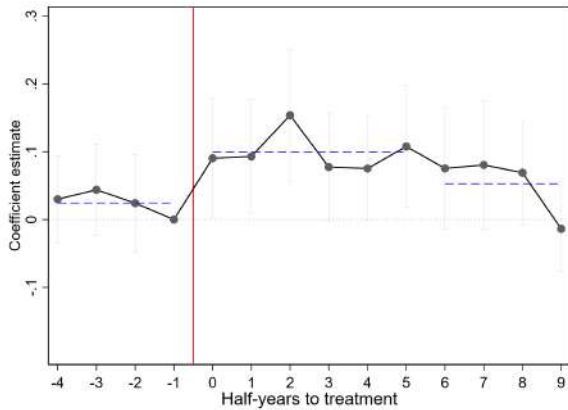
Notes: District-level totals between 2007 and 2013.

Figure A5: Event studies for Iron Ore Deposits.

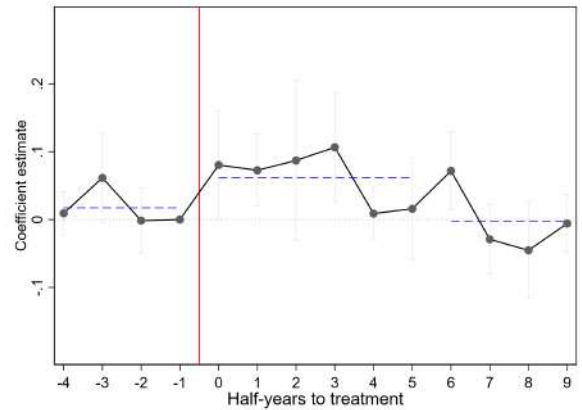
Panel A: Police Attacks on Maoists (dummy) Panel B: Maoist Attacks on Police (dummy)



Panel C: Police Attacks on Maoists



Panel D: Maoist Attacks on Police



Notes: Half-yearly district-level data between 2007 and 2013. Outcomes in panels C-D are subject to an asinh transformation. Event studies follow the main specification (equation 1). 90% confidence intervals are shown as grey bars.

Table A3: Correlations

	Police Attacks on Maoists (1)	Maoist Attacks on Police (2)	Log(Iron Ore Deposits) (3)
Log(Iron Deposit)	0.761 (0.659)	0.311 (0.261)	
Log(Bauxite Deposit)	0.213* (0.126)	0.041 (0.041)	
Log(Coal Deposit)	-0.058 (0.150)	-0.031 (0.067)	
Villages with road (percent), 2001			0.979 (0.632)
Percentage Literates, Rural			0.580 (0.991)
ST/SC rate, Rural			2.592** (1.031)
Forest Cover (percentage of area)			0.004 (0.005)
Population density (100 per sq km)			0.001 (0.021)
Mean DV	0.382	0.166	0.349
Standard Deviation	2.386	0.998	1.033
Observations	143	143	140

Notes: Regressions at the district-level. Outcomes in columns 1-2 are measured per capita. The deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. All regressions include state fixed effects. Robust standard errors are presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Main Results with Control \times Time Effects

	Police Attacks on Maoists			Maoist Attacks on Police		
	Dummy	Asinh		Dummy	Asinh	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Iron Deposit) \times Post	0.050*** (0.018)	0.040* (0.022)	0.050** (0.023)	0.020 (0.019)	0.039* (0.023)	0.037 (0.024)
Log(Iron Deposit) \times Price (real Rs per MT)	0.051** (0.021)	0.040 (0.034)	0.034 (0.033)	-0.008 (0.020)	-0.005 (0.026)	-0.007 (0.026)
Log(Bauxite Deposit) \times Post			0.013 (0.039)			-0.020 (0.034)
Log(Coal Deposit) \times Post			-0.014 (0.041)			-0.018 (0.029)
Log(Bauxite Deposit) \times Price (real Rs per MT)			-0.202 (0.126)			-0.072 (0.127)
Log(Coal Deposit) \times Price (real Rs per MT)			0.067 (0.057)			0.052 (0.060)
Mean DV	0.140	0.175	0.175	0.116	0.136	0.136
Standard Deviation	0.347	0.484	0.484	0.320	0.417	0.417
Observations	1400	1400	1400	1400	1400	1400
Clusters	140	140	140	140	140	140
Control \times Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regressions at the district-half-year level (2007-2011). Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. The control set includes time-effects for the rural literacy rate, the rural SC/ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state \times time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

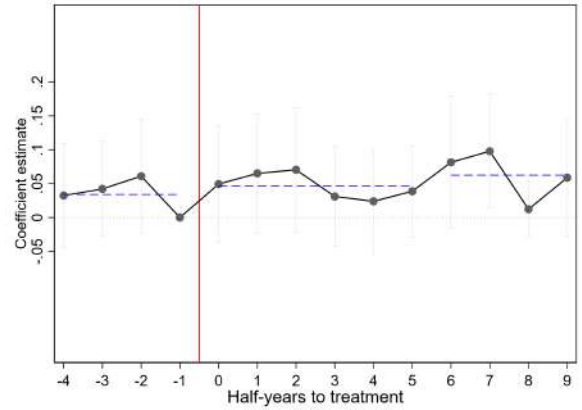
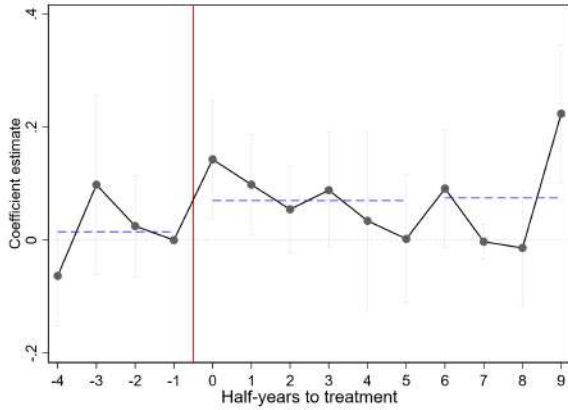
Table A5: Main Results with Conley standard errors

	Police Attacks on Maoists			Maoist Attacks on Police		
	Dummy	Asinh		Dummy	Asinh	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Iron Deposit) x Post	0.067*** (0.017)	0.066*** (0.022)	0.074*** (0.022)	0.033** (0.017)	0.054*** (0.019)	0.054*** (0.019)
Log(Iron Deposit) x Price (real Rs per MT)	0.051** (0.024)	0.040 (0.036)	0.034 (0.036)	-0.008 (0.019)	-0.005 (0.024)	-0.007 (0.024)
Log(Bauxite Deposit) x Post			0.032 (0.030)			-0.002 (0.028)
Log(Coal Deposit) x Post			-0.018 (0.036)			-0.017 (0.021)
Log(Bauxite Deposit) x Price (real Rs per MT)			-0.202* (0.107)			-0.072 (0.098)
Log(Coal Deposit) x Price (real Rs per MT)			0.066 (0.052)			0.052 (0.047)
Mean DV	0.137	0.172	0.172	0.113	0.133	0.133
Standard Deviation	0.344	0.480	0.480	0.317	0.413	0.413
Observations	1430	1430	1430	1430	1430	1430

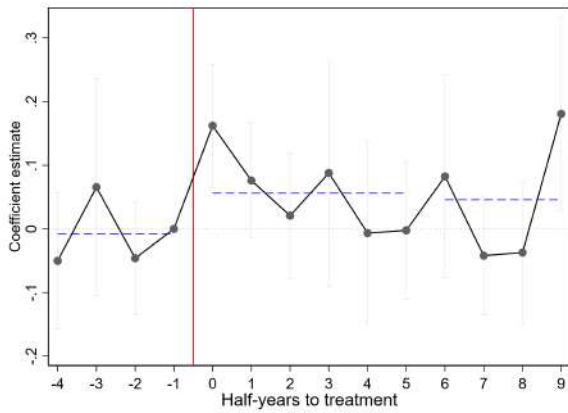
Notes: Regressions at the district-half-year level (2007-2011). Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. All regressions include district fixed effects, and state \times time fixed effects. Standard errors are corrected for geospatial correlation using Conley's method for a 200km cut-off; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A6: Event studies for Bauxite Ore Deposits.

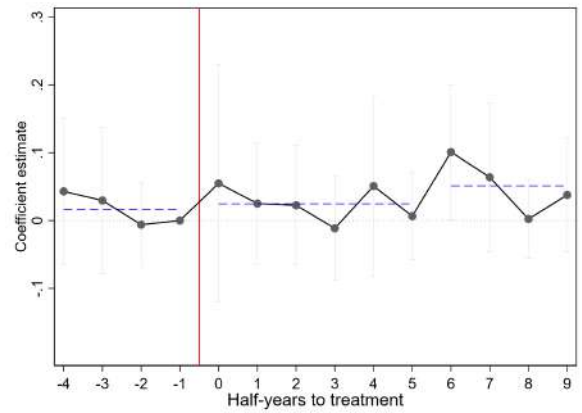
Panel A: Police Attacks on Maoists (dummy) Panel B: Maoist Attacks on Police (dummy)



Panel C: Police Attacks on Maoists



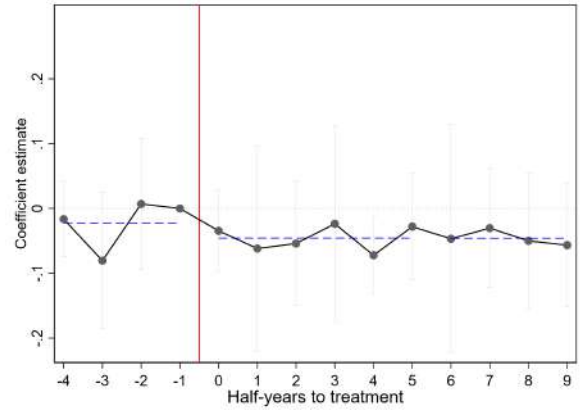
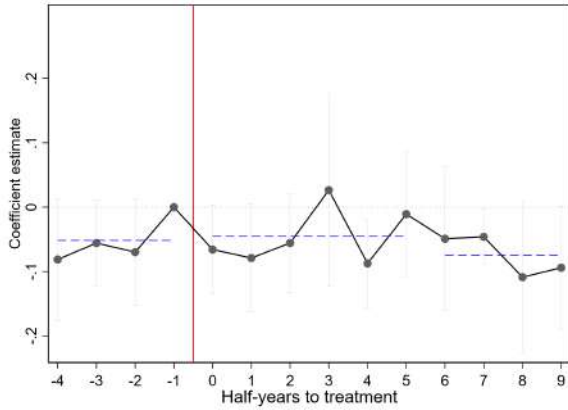
Panel D: Maoist Attacks on Police



Notes: Half-yearly district-level data between 2007 and 2013. Outcomes in panels C-D are subject to an asinh transformation. Event studies follow the main specification (equation 1), including mineral-time dummies for the three main minerals: baux ore, bauxite, and coal. 90% confidence intervals are shown as grey bars.

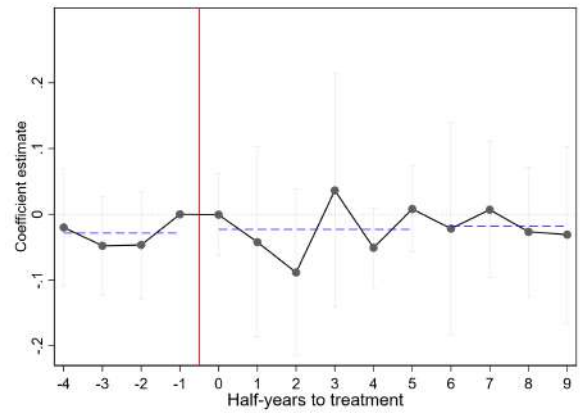
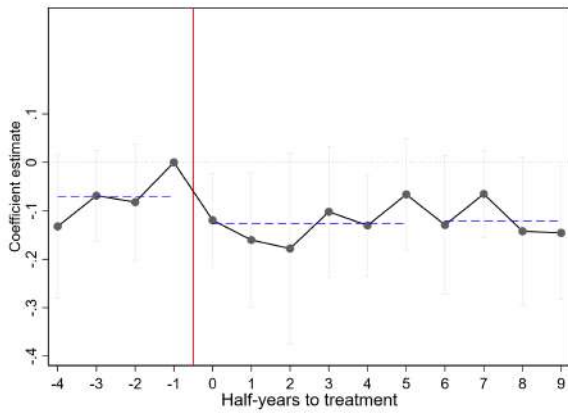
Figure A7: Event studies for Coal Deposits.

Panel A: Police Attacks on Maoists (dummy) Panel B: Maoist Attacks on Police (dummy)



Panel C: Police Attacks on Maoists

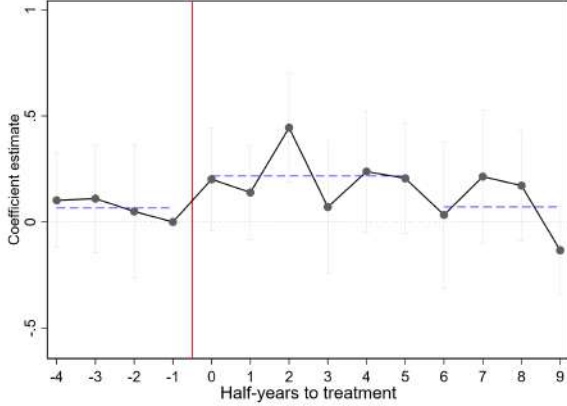
Panel D: Maoist Attacks on Police



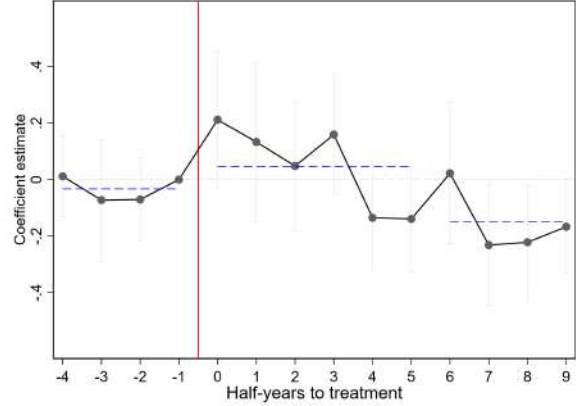
Notes: Half-yearly district-level data between 2007 and 2013. Outcomes in panels C-D are subject to an asinh transformation. Event studies follow the main specification (equation 1), including mineral-time dummies for the three main minerals: coal ore, bauxite, and coal. 90% confidence intervals are shown as grey bars.

Figure A8: Event studies for Iron Ore Deposits (dummy mining measure).

Panel A: Police Attacks on Maoists



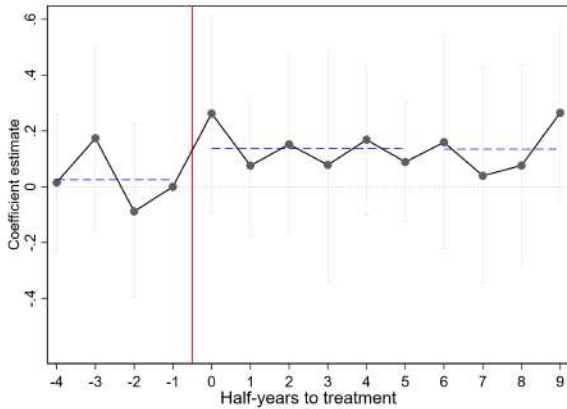
Panel B: Maoist Attacks on Police



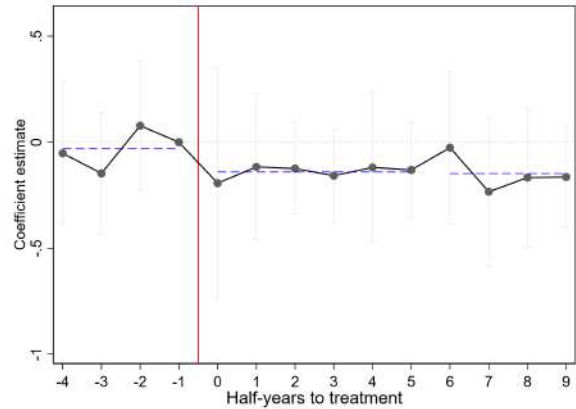
Notes: Half-yearly district-level data between 2007 and 2013. All outcomes are subject to an asinh transformation. Event studies follow the main specification (equation 1). 90% confidence intervals are shown as grey bars.

Figure A9: Event studies for Bauxite Ore Deposits (dummy mining measure).

Panel A: Police Attacks on Maoists



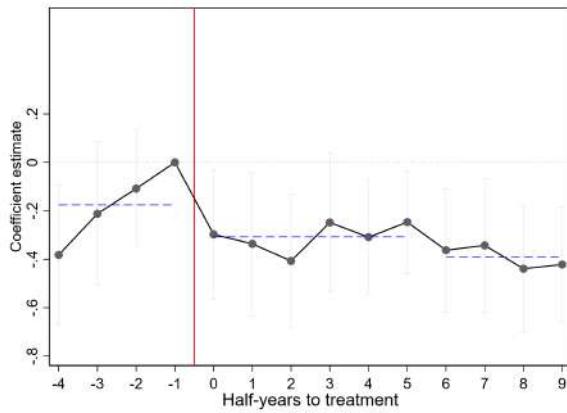
Panel B: Maoist Attacks on Police



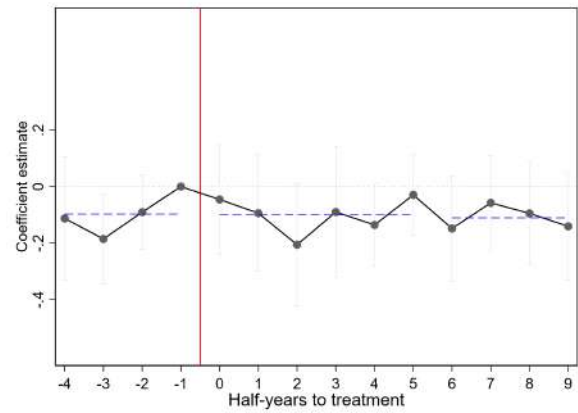
Notes: Half-yearly district-level data between 2007 and 2013. All outcomes are subject to an asinh transformation. Event studies follow the main specification (equation 1). 90% confidence intervals are shown as grey bars.

Figure A10: Event studies for Coal Deposits (dummy mining measure).

Panel A: Police Attacks on Maoists



Panel B: Maoist Attacks on Police



Notes: Half-yearly district-level data between 2007 and 2013. All outcomes are subject to an asinh transformation. Event studies follow the main specification (equation 1). 90% confidence intervals are shown as grey bars.

Table A6: Main Results: Extra Minerals

	Police Attacks on Maoists		Maoist Attacks on Police	
	Dummy (1)	Asinh (2)	Dummy (3)	Asinh (4)
Iron Deposit x Post	0.096 (0.059)	0.136** (0.068)	0.086 (0.057)	0.121 (0.086)
Bauxite Deposit x Post	0.052 (0.088)	0.088 (0.085)	-0.007 (0.068)	-0.061 (0.091)
Coal Deposit x Post	-0.058 (0.059)	-0.121 (0.081)	-0.024 (0.042)	-0.036 (0.051)
Chromite Deposit x Post	-0.039 (0.149)	-0.182 (0.200)	0.044 (0.115)	0.037 (0.161)
Manganese Deposit x Post	0.087 (0.145)	0.095 (0.163)	0.117* (0.065)	0.092 (0.080)
Iron Deposit x Price (real Rs per MT)	0.076 (0.074)	0.030 (0.097)	-0.051 (0.066)	-0.165 (0.100)
Bauxite Deposit x Price (real Rs per MT)	-0.355* (0.214)	-0.387* (0.224)	-0.057 (0.179)	-0.291 (0.263)
Coal Deposit x Price (real Rs per MT)	0.162* (0.083)	0.180* (0.100)	0.048 (0.078)	0.065 (0.077)
Chromite Deposit x Price (real Rs per MT)	0.301 (0.256)	0.395 (0.242)	-0.281* (0.154)	-0.290 (0.213)
Manganese Deposit x Price (real Rs per MT)	0.038 (0.167)	0.058 (0.177)	0.014 (0.027)	0.016 (0.026)
Mean DV	0.137	0.172	0.113	0.133
Standard Deviation	0.344	0.480	0.317	0.413
Observations	1430	1430	1430	1430
Clusters	143	143	143	143

Notes: Regressions at the district-half-year level (2007-2011). Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. The control set includes time-effects for the rural literacy rate, the rural SC/ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state \times time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Main Results in Poisson Model

	Police Attacks on Maoists (1)	Maoist Attacks on Police (2)
Log(Iron Deposit) x Post	0.251* (0.135)	0.284*** (0.094)
Log(Bauxite Deposit) x Post	0.220 (0.180)	0.291 (0.319)
Log(Coal Deposit) x Post	0.137 (0.528)	-0.134 (0.495)
Log(Iron Deposit) x Price (real Rs per MT)	0.081 (0.139)	0.187** (0.094)
Log(Bauxite Deposit) x Price (real Rs per MT)	-0.837* (0.440)	-0.658 (0.630)
Log(Coal Deposit) x Price (real Rs per MT)	1.736** (0.861)	0.694 (0.852)
Mean DV	0.623	0.535
Standard Deviation	1.555	1.358
Observations	640	550

Notes: Poisson regressions at the district-half-year level (2007-2011). Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. The control set includes time-effects for the rural literacy rate, the rural SC/ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state \times time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Varying time windows

	Police Attacks on Maoists				
Log(Iron Deposit) x Post	0.095 (0.062)	0.138*** (0.048)	0.077** (0.031)	0.072*** (0.025)	0.066*** (0.024)
Log(Iron Deposit) x Price (real Rs per MT)	0.070 (0.070)	0.137** (0.054)	0.056 (0.035)	0.048 (0.033)	0.040 (0.034)
Mean DV	0.179	0.175	0.176	0.176	0.172
Standard Deviation	0.501	0.498	0.494	0.490	0.480
Observations	572	858	1144	1287	1430
Clusters	143	143	143	143	143
Sample	2008h1 - 2010h2	2007h2 - 2011h1	2007h1 - 2011h2	2007h1 - 2012h1	2007h1 - 2012h2

Notes: Poisson regressions at the district-half-year level (2007-2011). Outcomes are subject to an asinh transformation. Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. The control set includes time-effects for the rural literacy rate, the rural SC/ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state \times time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Time Patterns for Bauxite Ore

	Police Attacks on Maoists		Maoist Attacks on Police	
	(1)	(2)	(3)	(4)
Log(baux dep) × 2009-2011	0.012 (0.033)	-0.009 (0.041)	-0.013 (0.033)	-0.028 (0.033)
Log(baux dep) × 2012-2013	-0.009 (0.050)	0.003 (0.058)	-0.003 (0.025)	0.008 (0.026)
Log(Bauxite Deposit) × Price (real Rs per MT)	-0.222* (0.114)	-0.225* (0.121)	-0.063 (0.123)	-0.043 (0.116)
Mean DV	0.152	0.155	0.119	0.122
Standard Deviation	0.450	0.454	0.388	0.391
Observations	2002	1960	2002	1960
Clusters	143	140	143	140
Control × Time FE	No	Yes	No	Yes

Notes: Regressions at the district-half-year level (2007-2013). Outcomes are subject to an asinh transformation. Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a log(x+1) transformation. The control set includes time-effects for the rural literacy rate, the rural SC/ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state × time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Time Patterns for Coal

	Police Attacks on Maoists		Maoist Attacks on Police	
	(1)	(2)	(3)	(4)
Log(coal dep) × 2009-2011	-0.056 (0.045)	-0.037 (0.042)	-0.037 (0.030)	-0.027 (0.030)
Log(coal dep) × 2012-2013	-0.043 (0.043)	-0.042 (0.044)	-0.009 (0.036)	-0.016 (0.037)
Log(Coal Deposit) × Price (real Rs per MT)	0.072 (0.058)	0.068 (0.056)	0.056 (0.055)	0.058 (0.051)
Mean DV	0.152	0.155	0.119	0.122
Standard Deviation	0.450	0.454	0.388	0.391
Observations	2002	1960	2002	1960
Clusters	143	140	143	140
Control × Time FE	No	Yes	No	Yes

Notes: Regressions at the district-half-year level (2007-2013). Outcomes are subject to an asinh transformation. Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a log(x+1) transformation. The control set includes time-effects for the rural literacy rate, the rural SC/ST population, the percentage forest cover, the percentage of villages connected by road in 2001, and the population density. All regressions include district fixed effects, and state × time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Main results with IAP controls

	Police Attacks on Maoists				Maoist Attacks on Police			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Iron Deposit) x Post	0.094*** (0.028)	0.092*** (0.027)	0.093*** (0.028)	0.092*** (0.028)	0.086*** (0.023)	0.083*** (0.022)	0.085*** (0.023)	0.083*** (0.026)
Log(Bauxite Deposit) x Post	0.044 (0.045)	0.047 (0.045)	0.045 (0.045)	0.053 (0.045)	0.000 (0.042)	-0.006 (0.042)	-0.001 (0.042)	0.002 (0.041)
Log(Coal Deposit) x Post	-0.593* (0.312)	-0.605* (0.314)	-0.595* (0.312)	-0.631** (0.309)	-0.311 (0.186)	-0.320* (0.187)	-0.313* (0.185)	-0.328* (0.171)
Log(Iron Deposit) x Price (real Rs per MT)	0.042 (0.042)	0.041 (0.042)	0.041 (0.042)	0.038 (0.041)	-0.012 (0.041)	-0.014 (0.041)	-0.013 (0.041)	-0.018 (0.042)
Log(Bauxite Deposit) x Price (real Rs per MT)	-0.214 (0.155)	-0.228 (0.161)	-0.212 (0.155)	-0.238 (0.161)	-0.105 (0.166)	-0.106 (0.169)	-0.107 (0.166)	-0.124 (0.165)
Log(Coal Deposit) x Price (real Rs per MT)	0.633*** (0.212)	0.631*** (0.207)	0.633*** (0.213)	0.547*** (0.197)	0.476** (0.187)	0.468** (0.194)	0.472** (0.189)	0.442** (0.194)
Mean DV	0.373	0.373	0.373	0.373	0.299	0.299	0.299	0.299
Standard Deviation	0.685	0.685	0.685	0.685	0.607	0.607	0.607	0.607
Observations	510	510	510	510	510	510	510	510
Clusters	51	51	51	51	51	51	51	51
<i>IAP Controls:</i>								
Projects Sanctioned x Time FE	Yes				Yes			
Projects Taken Up x Time FE		Yes				Yes		
Projects Completed x Time FE			Yes				Yes	
Expenditures x Time FE				Yes				Yes

Notes: Regressions at the district-half-year level (2007-2013). Outcomes are subject to an asinh transformation. Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a log(x+1) transformation. Integrated Action Plan data are based on cumulative performance data for 2011-2012. IAP variables are expressed per 100,000 of the population and subject to a and subject to a log(x+1) transformation. All regressions include district fixed effects, and state x time fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Integrated action plan

	Projects Sanctioned		Projects Taken Up		Projects Completed		Expenditures (Rs)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Iron Deposit)	-0.070 (0.075)	-0.055 (0.084)	-0.065 (0.075)	-0.046 (0.085)	-0.053 (0.099)	-0.000 (0.114)	-0.020 (0.072)	0.020 (0.097)
Log(Bauxite Deposit)		0.089 (0.124)		0.104 (0.125)		0.241 (0.147)		0.238 (0.195)
Log(Coal Deposit)		-0.277 (0.535)		-0.247 (0.522)		-0.116 (0.597)		-0.705 (0.717)
Mean DV	4.117	4.117	4.084	4.084	3.623	3.623	5.307	5.307
Standard Deviation	1.236	1.236	1.259	1.259	1.515	1.515	1.738	1.738
Observations	51	51	51	51	51	51	51	51
Clusters	51	51	51	51	51	51	51	51

Notes: Regressions at the district level. All outcomes are based on Integrated Action Plan cumulative performance data in 2011-2012. Outcomes are expressed per 100,000 of the population and subject to a and subject to a $\log(x+1)$ transformation. Deposit values are measured as million tonnes (billion tonnes for coal) per 1000 squared km, and subject to a $\log(x+1)$ transformation. All regressions include state fixed effects. Standard errors are clustered at the district level and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Sample of mines with satellite measurements

	Included in Mine Sample (0-1)	
	(1)	(2)
Legal lease area (log)	0.027** (0.011)	0.019 (0.013)
Year of lease expiration	0.001 (0.000)	-0.001 (0.002)
Mean DV	0.196	0.150
Observations	459	266
Minerals included	All	Iron Ore

Notes: Observations at the level of mines included in the India Directory of Mining Leases. The outcome measures if mines are included in our sample with satellite measurements. Minerals include: iron ore, bauxite, manganese and chromite. Standard errors are clustered at the mine level, and presented in parentheses; stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.