Lease Splitting and Dirty Entrants: The Unintended Consequences of India's Environmental Clearance Process Reform

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Abstract

Mining industries form a significant share of the industrial landscape of many poor countries. At the same time, mining activities have well-documented negative externalities: the air, land, and water pollution associated with mining has large health impacts and the destruction of forest cover can affect livelihoods. Using a comprehensive dataset on mining lease activities for India over the time period 1998 - 2013, we assess a landmark change in India's environmental clearance process, intended to increase stringency, democratic participation, and effectiveness. The reform induced strategic behavior by mining companies which, in turn, had perverse environmental impacts. First, the average mine size fell with significant bunching just below 5 hectares, a cutoff below which stringent regulatory requirements were waived. This rise in small mines was environmentally costly – after the 2006 Reform, air quality was negatively affected at villages close to new mining sites, at least over the short- to medium-term. Results regarding vegetation loss are mixed, although datasets where higher accuracy is expected indicate an increase in forest loss and the presence of barren land after the Reform.

Keywords: Environmental clearance; mining; remote sensing data; deforestation; greenhouse gas emissions.

1 Introduction

Mining is one of the oldest non-agricultural activities in human history and a crucial part of economic output in many developing countries. The World Bank categorizes 56 countries as "mining economies", where the sector plays an especially significant role in total economic output. Together over 3.9 billion people live in these countries, and over 1.5 billion live on less than 2 dollars a day (World Bank and International Finance Corporation, 2002).

Unfortunately, mining is also associated with significant environmental costs. These costs cover the gamut of air, land, and water pollution as well as ecological damage and sometimes even species loss

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(Dudka and Adriano, 1997). The Lancet Commission on Pollution and Health estimates that 9 million premature deaths in 2015 were attributable to air, water, and soil pollution globally, with a cost of USD 4.6 trillion, or more than 6 percent of the world's gross domestic product (Landrigan et al., 2017). The study cites about 2.5 million premature deaths from pollution in India alone, the most of any country. Alongside these findings in environmental health, dramatic imagery of urban air pollution in cities like Delhi and Beijing has reignited an examination of environmental policy in many rapidly industrializing countries. One key area of focus has been regulation of extractive industries, particularly in developing countries where state capacity may be limited.

In the 1970s and 1980s, India adopted a strong policy framework for controlling air and water pollution, forest clearing, and land use change. However, as India's development has accelerated in the last 25 years, enforcement capacity in its main pollution control institutions has been outpaced by the growth of polluting activities (Duflo et al., 2013). Greenstone et al. (2015) presents evidence on the magnitude of this implementation gap and the consequences for human health, finding that reducing ambient air pollution levels to those specified in current law would increase life expectancy by at least 3.2 years of life for 660 million people living in the heavily-polluted north of India. India's mining sector is one source of this pollution: while the sector comprises only a modest share of India's economic activity, it is large by global standards and widespread across the country. According to the United States Geological Survey, India ranks in the world's top six producers of iron, pig iron, aluminum, bauxite, zinc, and coal. In 2014, India's mineral mining sector was comprised of 8,355 mines producing 54 types of minerals. While mineral mining generates only about 2.5 percent of India's annual economic output, mining activity is present throughout the country: 24 of 29 states and about 45 percent of districts had active mining leases in 2014. The median mine was 4.75 hectares, or about 8 Olympic-sized football fields.

While improving the capacity of India's environmental regulatory institutions to carry out conventional monitoring and enforcement strategies requires long-term structural changes, transparency initiatives that provide public access to detailed information about industrial activities present a low cost channel for potentially improving the accountability of polluting firms. The Environmental Clearance (EC) process, which requires all major capital investment projects by the private sector or government to seek regulatory approval prior to beginning construction, is the centerpiece of environmental regulation of development in India. In 2006, India enacted a set of key reforms that sought to bring greater transparency and accountability to the EC process by subjecting larger projects to additional scrutiny from regulators, independent experts, and the public.

The reforms required projects to seek site-specific Terms of Reference (ToRs) for their environmental impact assessments, decentralized smaller projects to state-level clearance bodies, and established expert clearance bodies at both the state and central levels to review clearance applications. One key provision of the 2006 reforms was to institute a requirement that all projects hold a public hearing after undertaking the EIA and before submitting their clearance application to the ministry. Previously, only large projects had been required to hold a public hearing. Crucially, although the stringency of regulation was increased as a whole, small mines below 5 ha were exempt. One reason for this may be that it is more difficult for small mines to bear high regulatory costs.

In this paper, we first use data on the universe of legal mining leases issued by the Indian Bureau of Mines to document that the 2006 reform induced substantial strategic behavior by firms. In particular, we observe a sharp and long-lasting increase in the proportion of mines of area below 5 hectares, which were exempt of the EC process, and a simultaneous decrease in the proportion of mines of area between 5 and 25 hectares, which were subjected to stricter regulation following the 2006 reform. The visible selection in mine application trends suggests that mine proponents perceived the reforms to be substantial and costly. Two alternative scenarios could explain this distortion. On one hand, we might expect counterfactually large mines to split into sub-leases below 5 ha areas in order to avoid the stricter EC process. On the other hand, the changes introduced by the reform could have altered market conditions such that smaller scale mines – of possibly different minerals or new exploration areas – became relatively more profitable.

Given the large strategic response in mine size to the 2006 EC reform, the environmental impacts of that reform are ex ante unclear. While the reformed EC process involved additional regulatory and public oversight for large mines that still required clearance, it also created a loophole for mines under 5 ha, allowing them to evade all environmental screening. Indeed, after the 2006 reforms about 80% of all new mines had area less than 5 ha; this large majority did not receive an environmental clearance and were not required to undertake any environmental compensatory activities. Furthermore, the reform may have induced the entry of smaller mining companies that would be unable to afford environmentally-safe production technology.

Thus, we next explore the impact of the 2006 EC reform on the environmental impact of the average mine. Using records of the closest village to each lease in our data from the Indian Bureau of Mines, we link each lease granted from 1998 through 2013 with remote sensing data on nearby environmental conditions over time. In particular, we examine data on nearby ambient $PM_{2.5}$ concentrations, indices of vegetation coverage, forest loss, the extent of cropland, and the extent of barren land. We then examine the causal impact of new leases on each of these environmental outcomes, separately before and after the 2006 EC reform. We identify exogenous variation in the number of new leases in a village using instruments constructed as the product of the international price for a mineral and the distance from a village to the closest geologic reserve for that mineral; we construct these instruments for the eleven most common minerals in our lease data.

Broadly, we find that India's 2006 reform to the environmental clearance process worsened, rather than improved, the environmental impact of the average mine. We find that the execution of new mines increased $PM_{2.5}$ concentrations by more after the 2006 reform, and forest loss associated with mining increased substantially after 2006. We do find that EVI and NDVI, two measures of vegetation cover, increased with new mining after the 2006 reform, likely reflecting the imposition of additional afforestation requirements through the clearance process. However, the environmental benefits of this young vegetation growth are likely dwarfed by the costs of higher forest loss.

This paper is organized as follows. Section 2 reviews the related literature. Section 3 details the environmental clearance process and the 2006 reforms. In Section 4, we describe the various datasets used and their sources. Section 5 brings preliminary evidence on the distortion on the distribution of mine size that took place starting since the 2006 EC reform and focuses on our motivation for the analysis. Section 6.1 introduces our identification strategy. Section 6.2 and documents our analysis of the strategic behavior induced by the Reform and the associated environmental consequences. Finally, Sections 7 and 8 offer robustness checks for our findings and conclude.

2 Literature Review

Mining, the natural environment, pollution and health

Mining is associated with significant environmental costs, some of which are irreversible. These costs cover the gamut of air, land, and water pollution as well as ecological damage. Mining leads to mechanical damage of the local landscape and acid mine drainage, an outflow of acidic water from mines; mining metallic ores causes SO_2 to be released into the air, which causes acid rain; contamination of local soil and air through diversion of rivers; saltation of water; destruction of aquatic and soil habitat; mercury pollution and deforestation (Dudka and Adriano, 1997; Kitula, 2006; Li et al., 2014). Local settlements also often experience a collapse of buildings and degradation of land and livelihoods due to frequent explosions used in the extraction of ores (Kitula, 2006).

Contamination of food crops by heavy metals, such as lead, zinc or cadmium, can severely damage the nervous, skeletal, endocrine and immune system of local inhabitants (Zhang et al., 2012). Settlements near mines exhibit higher incidence of health conditions related to heavy metal toxicity, such as anemia among women and stunting among children (von der Goltz and Barnwal, 2019). The Lancet Commission on Pollution and Health estimates that 9 million premature deaths in 2015 were attributable to air, water, and soil pollution globally, with a cost of USD 4.6 trillion, or more than 6 percent of the world's gross domestic product (Landrigan et al., 2018). The study cites about 2.5 million premature deaths from pollution in India alone, the most of any country.

Local economic impacts

Villages in the vicinity of mineral deposits are smaller in size, often located in higher altitudes, and have different employment structure compared to the rest of the country, after controlling for their populations size (Asher and Novosad, 2014a). Local factor prices manifest different distribution compared to resource-poor areas (Corden, 1984), employment in the mining sector is a significant fraction of the total employment, while employment in sectors such as trade or manufacturing is significantly lower (Asher and Novosad, 2014a; De Haas and Poelhekke, 2016) in mining-intensive areas. The business environment in tradable sectors also often deteriorates (De Haas and Poelhekke, 2016).

To the contrary of long-run characteristics of resource-rich ares, by exploiting time series variation in the value of mineral deposits, Asher and Novosad (2014a) find that exogeneous increase in natural resource wealth leads to economic growth in the villages within a small radius from the mine; such an increase is found across manufacturing and service sectors. Positive spillovers can also be exhibited through infrastructure investments or transfers by local governments financed from taxes collected from mining profits (De Haas and Poelhekke, 2016).

Broader economics impacts

Excessive dependence on natural resources in many countries leads to negative consequences for the economy as a whole, such as economic volatility, real exchange rate appreciation and corruption, and consequently leads to diminished growth prospects (Van der Ploeg, 2011), particularly in countries with weak institutions (Sachs and Warner, 1995; Mehlum et al., 2006). Murphy et al. (1991) find that quality of institutions and institutional arrangements through which natural resource rents are distributed are an important determinant of whether a country is seemingly cursed by natural resources or exhibits an economic boom, through increased tax revenue generation, employment and foreign exchange.

Political effects

Mining is a government-input intensive industry. Mineral resource sectors are rent-rich and politicians often exert effort to obtain a share of the wealth (Isham et al., 2005). Corruption often increases, local elections exhibit decreased competition and local politicians are more likely to face criminal accusations (Brollo et al., 2013; Asher and Novosad, 2014b; Robinson et al., 2006). This induces several negative economic effects, such as (i) deepened inequality as the living standards of minorities decrease (Chemin, 2012); (ii) a fall in entrepreneurship as entrepreneurial talent is shifted from production-based industries to rent-seeking (Murphy et al., 1991); or (iii) deterioration in the quality of public goods, as political effort is reallocated.

3 India's Environmental Clearance Process and the 2006 Reforms

The environmental clearance (EC) process, which requires all development projects to seek regulatory approval before breaking ground, is the centerpiece of environmental regulation in India. The initial EC process, instituted in 1994, required all mines larger than 5 ha to apply for clearance at the central level. Mines would prepare an Environmental Impact Assessment (EIA) based on a standardized set of Terms of Reference (ToRs), would hold a public hearing for mines if over 25 ha in area, and would then submit the EIA and public hearing report to MoEFCC. MoEFCC would grant or deny clearance, seeking expert input where necessary.

In 2006, a notification by the Ministry of Environment and Forests dramatically overhauled this process, requiring more scrutiny of the projected environmental and social impacts of projects and greater transparency in the approval process. The reforms decentralized the EC process into a two-tiered system where larger projects (known as Category A) pass through a central process overseen by MoEFCC and smaller projects (known as Category B) pass through parallel state-level processes overseen by State Environmental Impact Assessment Authorities (SEIAAs). Within the mining sector, mines with lease areas of 50 hectares or more are considered Category A projects, while mines of area between 5 and 50 hectares are considered Category B projects. Again, mines of area less than 5 ha are not required to get environmental clearance.

As part of this decentralization, the 2006 EC reforms convened central- and state-level expert bodies to review EC applications; these review bodies, known as Central and State Expert Appraisal Committees (EACs), are comprised of representatives from industry, civil society, and academia. These committees recommend projects for clearance, rejection, or deferral, before passing them to the MoEFCC or SEIAA for a final clearance decision. The 2006 EC reforms also increased the stringency of the EC process by requiring that all Category A and B mines apply for mine-specific Terms of Reference (ToRs) before undertaking the EIA. Finally, all Category A and B mines are required to hold public hearings after completing the EIA and before submitting the application to the ministry for clearance consideration; previously, only mines of area above 25 ha were required to hold a public hearing. In sum, the reformed EC application process takes the following five steps:

1. **Application to MoEFCC or SEIAA.** The project proponent files an application with basic information about the project and proposed Terms of Reference (ToR) for the EIA.
2. **Scoping for determination of ToR.** The EAC or SEAC drafts finalized ToR based on the project characteristics
3. **EIA study and public consultation.** The project proponent undertakes and submits a draft EIA. The State Pollution Control Board then organizes a public hearing and invites written comments from the public.
4. **Project appraisal by EAC or SEAC.** Project proponent submits final EIA and clearance documents to MoEFCC or SEIAA. EAC or SEAC consider final proposal and make recommendation to MoEFCC or SEIAA to either grant or reject the clearance.
5. **Grant or reject EC.** MoEFCC or SEIAA makes a final decision to grant, defer, or reject the EC application.

When the MoEFCC or SEIAA grants clearance, it assigns cleared projects a set of specific and general conditions with which they are legally bound to comply. Project proponents must submit bi-annual reports detailing compliance with these conditions to MoEFCC or SEIAA. Figure 1 in the Appendix summarizes the provisions of the 2006 reforms across categories of mines by size and over time.

4 Data and summary statistics

Our analysis rests on a large dataset combining the universe of mining leases issued by the Indian Bureau of Mines with a village-level repository of remote-sensing data on vegetation cover and air quality.

4.1 Data on all mining leases from the Indian Bureau of Mines

We have purchased a dataset called the All India Directory of Mining Leases from the Indian Bureau of Mines (hereafter IBM). These data describe details on all mining leases (7,075) granted during the period 1990 through 2013. We hired a data team from the Jameel Abdul Latif Poverty Action Lab to digitize these data, which we initially received as 2000 hard copy pages.

Key mine characteristics in these data include the name of the mine owner (registered company or private person), the date the mining lease was granted, the date of mine execution, minerals exploited, mine area, and address. The address details include state and district where the mines are located, as well as the name of the village or villages closest to the mining site. As such, we do not have information on exact mine location and will instead focus our analysis on the changes in environmental outcomes observed around the villages closest to the mines. The results are then indicative of net impacts on the livelihood of the population residing in areas adjacent to the mines. We describe the process of geo-locating village names in Section 4.3 below.

Since remote sensing data is first available in 1998 for fine particulate matter and in 2000 for vegetation, we focus on the sample of 5,773 individual mining leases that the IBM directory records as being granted between 1998 and 2013. After lease granting, mining operations start within one year for about 90% of recorded leases. In our sample, the registry identifies 2,991 different villages to be the closest village to at least one lease, with an average of 2.03 mining leases linked to each village. We observe mining leases for 51 minerals, with quartz, limestone, feldspar, and clay accounting for a bit more than 66% of the entire sample. Tables A.2-A.1 in the Appendix capture the main summary statistics for the leases in our final dataset, divided by mineral and size category.

4.2 Satellite data on environmental outcomes

We rely on a series of satellite-based environmental outcomes to assess changes in air quality and forest cover at mine locations. First, we collect data on fine particulate matter ($PM_{2.5}$) concentrations from Van Donkelaar et al. (2016), which estimates particulate matter concentrations using geophysical-statistical models that fit satellite data with ground station measurements. The time-series estimates are available at a 0.1° x 0.1° spatial resolution and yearly frequency.

Second, we merge various satellite imagery data products to comprehensively assess changes in vegetation. Our main analysis focuses on forest cover and deforestation, for which we rely on the Landsat

Global Forest Change Data product (Hansen et al., 2013)[1]. The Landsat data provides global estimates of forest loss during the period 2000–2014 at a spatial resolution of approximately 30 meters per pixel at the equator. Here, all vegetation taller than 5m in height is classified as forest, and forest loss in a given pixel is defined as a stand-replacement disturbance, or a change from a forest to non-forest state, encoded as either 1 (loss) or 0 (no loss).

Next, we complement the forest-loss analysis with an assessment of changes in general vegetation cover using the Enhanced Vegetation Index (EVI) and the Normalized Difference Vegetation Index (NDVI) from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) satellite. The EVI and NDVI estimate land surface vegetation health and activity based on the surface reflectance of red and near-infrared (NIR) light. EVI and NDVI Values range from 0 to 1, where any value less than 0.2 indicates land that is sparse to barren. MODIS has calculated EVI and NDVI from surface-reflection data at 16-day intervals since 2000 for the entire globe at a spatial resolution of 250m. For our analysis, we collapse these data to annual maximum EVI and NDVI levels.

Finally, we distinguish among different types of vegetation using the MODIS Land Cover Type Product (MCD12Q1), which classifies land according to its primary use. The dataset is available globally at 500-meter spatial resolution for each year since 2001. We use a simplified version of the University of Maryland (UMD) land use classification, which distinguishes among different types of forests, water bodies, shrublands, savannas, wetlands, crop fields, and barren land. In particular, we aggregate these classifications to compute the percentage of land dedicated separately to (i) forests, (ii) non-forest vegetation, (iii) cropland, and (iv) barren land.

Here, we define *forested land* as land covered in proportion of at least 60% with either evergreen needleleaf forests, evergreen broadleaf forests, deciduous needleleaf forests, deciduous broadleaf forests, or mixed forests.[2] *Vegetated land* refers to land covered with vegetation that is neither forest nor crops, but instead belongs to one of the following vegetation classes: closed shrublands, open shrublands, woody savannas, savannas, grasslands, permanent wetlands, and natural vegetation mosaics.[3] We take the University of Maryland classifications for cropland and barren land as given.

Our analysis will focus in particular on the MODIS data for cropland and barren land for two reasons. First, Zeng et al. (2015) find in China that these land-use categories are most accurate. Second, the EVI/NDVI data and Hansen's Landsat forest-loss data offer alternative data sources that are specifically designed to measure vegetation and forest loss, respectively, so we will prioritize those measurements.

4.3 Geo-location of villages close to mine sites

Next, we combine these data sources on mining leases and environmental conditions by geolocating our sample of mining leases from the IBM directory. Unfortunately, the IBM directory does not provide

[1]The dataset is available for download at http://earthenginepartners.appspot.com/science-2013-global-forest.

[2]These forest types correspond to land use types 1-5 in the University of Maryland land use classification.

[3]These land use classes correspond to values 6-11 and 14 in the University of Maryland classification.

geographic coordinates for mines, but instead lists the closest village(s) to a lease. To match the data on mining leases to geographically-referenced data on environmental outcomes, we match village names in the IBM data (hereafter referred to as IBM village/district/state) to geo-referenced locations of villages from the 2011 Census of India (hereafter referred to as census village/district/state). This section describes the string matching procedure.

We match villages in several steps, limiting our attention to possible census villages that fall in the same district and state as those associated with the mine in the IBM directory. When we cannot match the IBM village to a census village within the same state and district, we attempt to match to census villages in nearby districts within the same state. Thus, we first fuzzy-match IBM states to census states and IBM districts to census districts before fuzzy-matching village names. Any mismatches between state and district names may arise either from (i) changes in local geopolitical structure — new states and districts were formed while other ceased to exist after the 2011 census[4] — or (ii) differences in spelling between the IBM dataset and the 2011 census. Where our threshold defined above falls short, we match strings manually.

Here, and when later matching village names, we fuzzy match strings using the Levenshtein edit distance algorithm, which computes the number of insertions, deletions and character changes required to get from one string to another (Navarro, 2001).[5] We tolerate a higher edit distance when matching very long words and compute the ratio of Levenshtein distance to the length of the corresponding string in the IBM dataset (which we will refer to as the L-ratio). We accept matches based on a "smart" threshold, accepting all matches with the L-ratio ≤ 0.16.[6] We then choose a single match among all acceptable matches as that with the lowest L-ratio.[7]

After matching district and state names between the IBM directory and the census data, we proceed to matching village names. To account for the fact that the IBM directory assigns some leases to multiple village names, we conduct the matching exercise at the level of unique state-district-village triples, while keeping track of unique lease numbers to aggregate the resulting data ex-post. Finally, we clean village names by stripping any punctuation and removing numerals. This results in a total of 3907 data points.

[4]For example, Telangana separated from Andhra Pradesh to form the 29th state of India on 2 June 2014. In a similar vein, the state of Assam had 27 districts before 2015. On 15 August 2015, CM Tarun Gogoi formed 5 additional districts, which resulted in 32 districts in total.

[5]We adjust the Levenshtein metric to account for common character substitutions in Hindi. We use `masala-merge`, a `python` script written by Paul Novosad and Sam Asher, with adjusted distance costs. For example, KS and X are often substituted in Hindi. Changing KS to X would have the Levenshtein distance equal to 2, whereas `masala-merge` assigns cost of 0.2. The authors also calibrated costs of character changes and common spelling substitutions.

[6]We determine the "smart" threshold as follows: for all $j = 1, \ldots, 15$, we draw a random sample of 10 village pairs with L-ratio in the interval $[2(j-1), 2j)$ and evaluate how closely the strings match each other. At the upper bound of 0.16, the matches begin to have a tendency to diverge from each other, while at the upper bound of 0.2, this becomes apparent. We select the L-ratio as the more conservative threshold, which still allows us to match a large amount of villages without manual input.

[7]In general, there can be multiple strings exactly matching one another or minimizing the L-ratio. Out of 1563 exact village matches (see below for how we obtained them), there is a single village with more than one exact match - there are two villages called Tulsi in Raipur district of state Chhattisgarh. It is also worth acknowledging that even an exact match should be considered uncertain if the next nearest match is very close (defined by condition 2). If there are multiple best matches, we select one randomly. Performing future adjustments requires detailed domain-specific knowledge and does not lie within the scope of our analysis. Therefore, we treat a selected match within a narrowed set of possible matches (as described below) as our "best guess".

For each mine, villages recorded in the IBM dataset are the villages closest to the mining facility. It should be noted, however, that the state and districts recorded are based on the location of the mining facility, not the assigned village. Therefore, for borderline cases, it might happen that the villages assigned fall into a bordering district. Therefore, we compute the L-ratio of each IBM village to all census villages within districts ”close to” the IBM district. We define a district Y as ”close to” district X if (i) Y is located in the same state as X; (ii) the centroid of district Y is within 100km from the centroid of district X; and (iii) the distance between centroids of X and Y is among the 8 shortest distances between the centroid of X and the rest of the districts.

We proceed in stages as follows. In the first stage, we compute the L-ratio of each IBM village to all census villages within districts close to the master district. We first accept all exact matches, giving matches for 1563 IBM villages, about 40% of our sample.[8] Among the remaining IBM village-district-states to be matched, we select the match that minimizes the L-ratio; this step results in another 1501 matched villages (approximately 38% of the total). Finally, we manually match an additional 50 villages. For each matches IBM village, we record all districts the best match is located in. Subsequently, we select the district whose centroid is closest to the centroid of the corresponding IBM district. We obtain 3114 villages matched in total, which is 79.7 % of all IBM villages.[9]

4.4 Distance to mineral reserves and international minerals and metals prices

As we describe in Section 6.1 below, we will analyze the impact of mining on environmental outcomes by instrumenting for mining leases at the village level with the product of international mineral prices and distances from each village to the closest reserve of each mineral. In particular, we collect the United States Geological Survey (USGS) mineral and material commodities prices, available at yearly frequency for 1998 through 2017, for the 11 most common minerals and metals included in the IBM directory.[10] These minerals have on average more than 100 leases and in total account for above 82% of all mining leases over the study period 1998 - 2013. The list of such minerals includes: steatite, quartz, manganese, limestone, laterite, iron, mica, feldspar, clay, silica sand, and barite. Fig. A.1 illustrates the timeseries of the number of mining leases and the USGS price for quartz, laterite, and feldspar.

Finally, we computed the distance from each village to the closest deposit of specific minerals using mineral and mineralization maps from the Geological Survey of India (GSI), which we extracted the from the Bhukosh data platform.[11] The dataset provides latitude and longitude information for all mineral reserves in India. We computed distances from each mining village to the centroid of the closest mineral reserve of the 11 most popular minerals in our dataset. The distance from each village to the centroid of

[8]Out of the 1563 matches, 34% also have another acceptable match.

[9]We further check for any district duplicates in the resulting merged data. We record 242 district duplicates, 204 out of which seem to be such pairs or triples of the same village with a slightly altered spelling. We also record 16 villages as being borderline with a potentially wrong district name. We correct them using a Geographic Information System (GIS).

[10]The time series for each mineral has been downloaded from https://www.usgs.gov/centers/nmic/historical-statistics-mineral-and-material-commodities-united-states. In a few cases, prices were constructed by dividing total value by quantity.

[11]https://bhukosh.gsi.gov.in/Bhukosh/Public

the closest mineral reserve varies in the range of 0.3 - 168 km, with a mean of 15.04km.

5 Descriptive analysis: Impacts of the 2006 reform

In this section, we provide initial descriptive evidence for the Indian mining sector's response to the 2006 EC reforms. The 2006 reforms imposed substantial new regulatory costs, like the requirement to apply for mine-specific ToRs and to hold a public hearing, but it did so differentially for mines of different sizes. In particular, the revised EC process required only that mines with area above 5 ha pass through the more stringent clearance process, while mines below 5 ha were not generally required to get any environmental clearance until a Supreme Court ruling in 2012. In other words, the 2006 EC reform may have created strong incentives for mine owners to select for small mines, escaping the regulatory and public scrutiny of the clearance process as a whole.

Indeed, we find substantial evidence that the 2006 reforms altered the distribution of mine size in India by inducing an immediate and long-lasting shift towards mines of area below 5 ha. Fig. 1 below plots the proportion of mining leases granted by area categories over time. The figure shows a striking shift in the lease size distribution after 2006. In particular, between 2005 and 2007 there was a large increase in the share of leases with area below 5 ha. At the same time, the share of mine leases of area between 5 and 15 ha fell markedly after a peak in 2005. There is little visible trend in the number of leases of area over 15 ha. These application series strongly suggest that the 2006 reform induced a shift in the distribution of mine areas from leases between 5 and 15 ha, which would have had to get clearance under the newly stringent process, to leases of less than 5 ha, which would avoid the process.

This shift towards mines of area under 5 ha persists over time. Indeed, while the number of mines in all area categories falls off precipitously after 2008, the proportion of leases that are less than 5 ha rises to over 80% in 2007 and remains there through the remainder of our sample period.

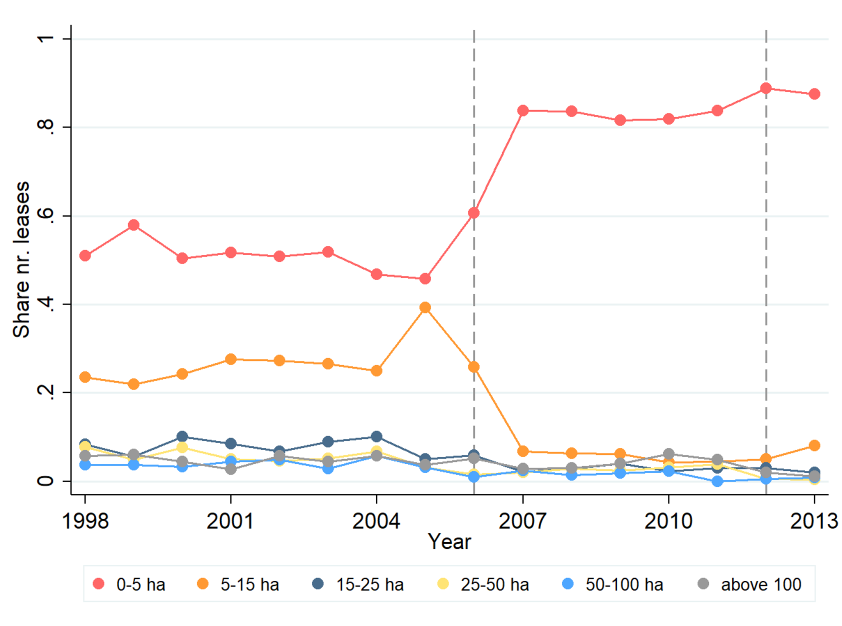


Figure 1: Share of number of new mine leases granted by area size category. Source: own illustration based on data from the Indian Bureau of Mines.

In theory, the large shift towards leases below 5 ha could reflect other market factors, like an increase in demand for minerals that are best mined in small-sized leases. However, we find that most of the new mass in leases under 5 ha falls just under the 5 ha threshold, suggesting that the shift is induced by the 2006 EC reform rather than by another market change, see Fig. 2 below. What is more, the bunching just below the regulatory cutoff is present across states and minerals (Figs. 3, A.2, and A.3). Again, these consistent patterns are suggestive of a shift in size distribution due to a national policy change.

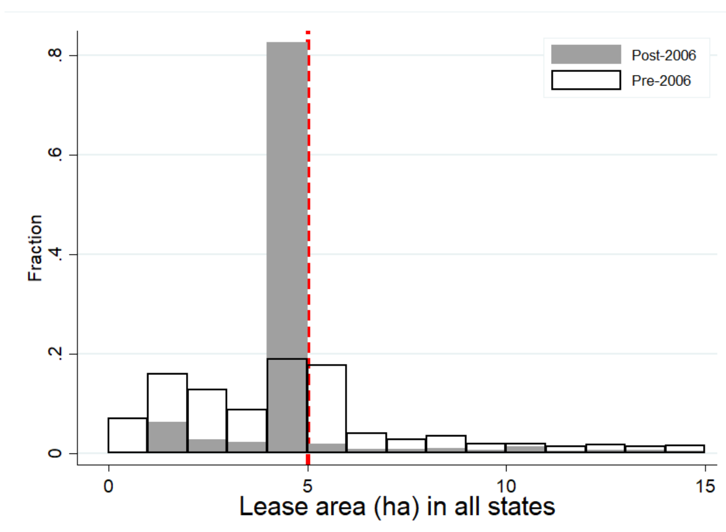


Figure 2: Area size distribution of new mine leases in all states Pre-Reform (1998-2006) and Post-Reform (2006-2013). The pre-reform period covers 1998 - 2005 and the post-reform period covers 2006 - 2013.

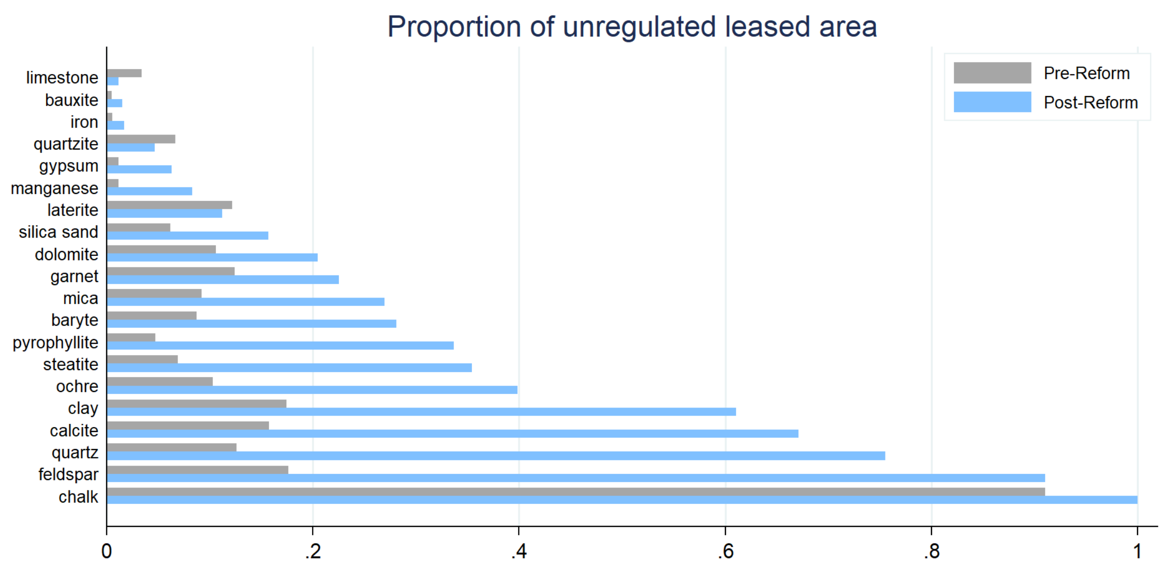


Figure 3: Proportion of leases of size 0-5ha before and after the 2006 Reform, minerals with at least 25 leases.

Along with the decrease in average lease size, Fig. 4 illustrates that we also observe changes in the portfolio of exploited minerals following the 2006 reform. A few facts are striking: while limestone and laterite dramatically reduce their presence among the newly granted leases, feldspar and quartz gain significantly in popularity. Moreover, new leases of minerals that are generally less frequent (the category ”other”) are also much less represented in the post-Reform period. These shifts in the mineral distribution of new leases could simply reflect changes in market conditions or international demand; however, since quartz and feldspar leases were small on average even before the 2006 reform, it could also reflect that leases of smaller size become more competitive following the EC Reform.

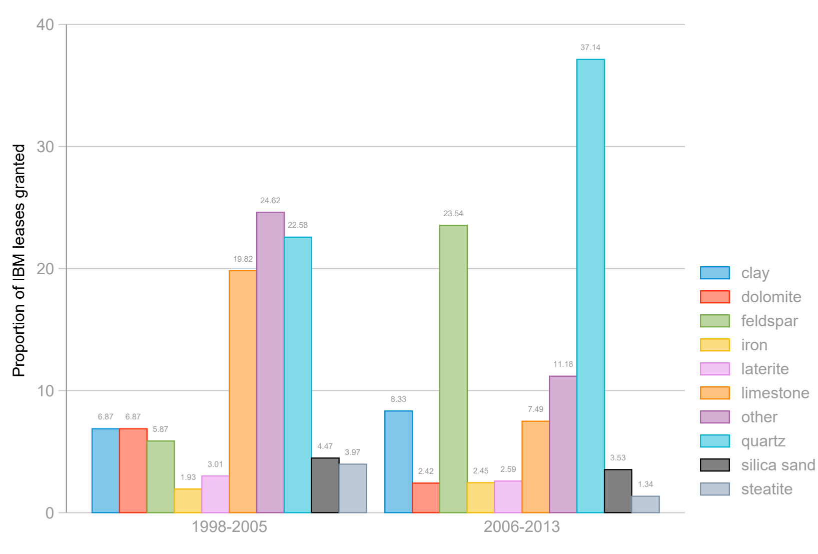


Figure 4: Mineral distribution in the years before and after the 2006 EC Reform.

6 Impacts of the 2006 reform on the environmental costs of mining

Given the large strategic response in mine size to the 2006 EC reform, the environmental impacts of that reform are ex ante unclear. While the reformed EC involved additional regulatory and public oversight for large mines that still required clearance, it also created a loophole for mines under 5 ha, allowing them to evade all environmental screening. Indeed, after the 2006 reforms about 80% of all new mines had area less than 5 ha; this large majority did not receive an environmental clearance and were not required to undertake any environmental compensatory activities.

In this section, we shed light on the impacts of the 2006 EC reform by estimating the environmental effects of an additional mine before and after the reform. Section 6.1 presents our identification strategy and Section 6.2 below will present our results.

6.1 Identification strategy

To measure the environmental impacts of a new mine, we begin with a simple fixed-effects panel specification identifying the association between air pollution or land use and the total number of executed mining leases in a village. Our specification is as follows:

$$Y_{it} = \beta N_{it} + \alpha_i + \mu_t + \epsilon_{it} \tag{1}$$

where Y_{it} is the environmental variable observed in village i at time t, α_i are village fixed effects, and μ_t are time fixed effects. Variable N_{it} denote the cumulated number of mining leases in village i at time t. Next, β is our coefficient of interest; it captures the average change in land cover or $PM_{2.5}$ associated with the execution of one additional mining lease.

To assess how the EC reform changed the environmental impacts of mining, we next modify Eq. 1 to distinguish between mining leases granted clearance before and after 2006:

$$Y_{it} = \beta_1 N_{it}^{PRE} + \beta_2 N_{it}^{POST} + \alpha_i + \mu_t + \varepsilon_{it} \tag{2}$$

where β_1 and β_2 capture the average change in environmental outcomes associated with the execution of a mine which was granted a lease either *before* or *after* the 2006 Reform, respectively. The variable N_{it}^{PRE} refers to the cumulated number of executed leases that were granted clearance before the 2006 EC Reform; thus, it is restricted to stay constant in all years after 2005. In contrast, N_{it}^{POST} captures the number of executed leases granted clearance after the Reform; it is set at 0 before 2006 and may be positive and increasing afterwards.

While simple, this baseline strategy is subject to obvious endogeneity concerns. Mine owners may choose their mining site out of all areas with remaining in-ground mineral reserves, and they may differentially sort to areas with certain baseilne trends in environmental conditions. For example, given the increased stringency of the EC process after 2006, owners might strategically place mines in areas with low baseline vegetation, where mining activities would have a lower impact on vegetation and thus may not be subject to costly reforestation requirements. Thus, our coefficients of interest from Eqs. 1 and 2 would capture both any location selection effects and the environmental impacts of mines themselves.

We tackle these endogeneity concerns with an instrumental variable (IV) approach. In particular, we instrument for the number of new mines in a village with a set of eleven variables, each defined as the product of the distance from the village centroid to the nearest reserve of a given mineral and the international price for that mineral. (See section 4.4 for a description of these dataseries.) We define one of these variables for each of the eleven minerals that are most common in the IBM directory between 1998 and 2013 and for which we have a full price series. We expect that higher international mineral prices will differentially increase mining in areas closest to mineral reserves. Conditional on village and year fixed effects, the variation in this scaled price index is plausibly random with respect to the unobserved factors determining mine placements. Using these instruments, our IV specification of Eq. 1 becomes:

$$N_{it} = \sum_{m=1}^{M} \gamma_m D_{mi} \times P_{mt} + \alpha_i + \mu_t + \nu_{it} \quad (3)$$

$$Y_{it} = \beta \widehat{N}_{it} + \alpha_i + \mu_t + \eta_{it} \quad (4)$$

where P_{mt} is the international price of mineral m in year t and D_{mi} is the time-invariant distance from village i to the closest reserve of mineral m. We estimate this model via two-stage least squares. When international mineral prices increase, we would expect locations that are further away from the mineral reserve to have less new mining than locations that are closer. Thus, we expect the estimated γ_m coefficients to be negative.

Finally, we modify our IV model to examine the differential impact of mining before and after the 2006 reform by estimating the following three-stage least-squares model. Here, we first separately predict the cumulated number of executed leases pre- and post-reform:

$$N_{it}^{PRE} = \sum_{m=1}^{M} D_{mi} \times P_{mt}^{PRE} + \sum_{m=1}^{M} D_{mi} \times P_{mt}^{POST} + \alpha_i + \mu_t + \gamma_{it} \quad (5)$$

$$N_{it}^{POST} = \sum_{m=1}^{M} D_{mi} \times P_{mt}^{PRE} + \sum_{m=1}^{M} D_{mi} \times P_{mt}^{POST} + \alpha_i + \mu_t + \lambda_{it} \quad (6)$$

$$Y_{it} = \beta_1 \widehat{N}_{it}^{PRE} + \beta_2 \widehat{N}_{it}^{POST} + \alpha_i + \mu_t + \zeta_{it} \quad (7)$$

Equations 5 and 6 use our price-distance indices to estimate the number of executed mining leases before and after the reform, respectively. Here, we modify these terms to reflect our two time periods of interest. Namely, $\sum_{m=1}^{M} D_{mi} \times P_{mt}^{PRE}$ is equal to $\sum_{m=1}^{M} D_{mi} \times P_{mt}$ for all years through 2005 and then is held constant at the 2005 level afterwards. In contrast, $\sum_{m=1}^{M} D_{mi} \times P_{mt}^{POST}$ is set equal to zero until and including 2005, and equal to $\sum_{m=1}^{M} D_{mi} \times P_{mt}$ thereafter.

6.2 Results

This section presents the OLS and IV estimates of the models described in Section 6.1. We primarily comment on our IV estimates for the environmental impacts of mining, sometimes contrasting them with the associations we estimate via OLS. In order to understand the consequences of the 2006 EC Reform, we aim to document both any evidence of location selection, as well as changes in the average causal impact of mines on environmental outcomes. Panel A of each table presents OLS estimates, while Panel B presents the results of the IV model described in Eq. 5-7. The results of the first stage regressions are displayed in Table B.1 in the Appendix, while we include the p-value of the Kleinbergen-Paap LM test of instrument underidentification in the main tables displaying second-stage results.

For each environmental outcome, we present estimation results where we calculate environmental outcome variables over areas around the village centroid with radii of 10, 20, and 50 km; again, we do not know the exact location of mining sites relative to the village centroids. For example, columns 1 through 3 of Table 1 define our outcome variable as log of annual average $PM_{2.5}$ across pixels within 10 km, 20 km, and 50 km of the village centroid, respectively. Our results should be interpreted as overall changes in the environmental conditions in the studied area, whether directly and indirectly related to the operation of mining activities. For example, a decrease in the share of cropland could be the result of land conversion from agriculture into mining, but also of abandonment of crop fields and their conversion into barren land when the local labor force transitions from agriculture into mining employment.

6.2.1 Fine particulate matter

Table 1 investigates the links between executed mining leases and percentage changes in fine particulate matter $PM_{2.5}$. Focusing on the IV results, we see that while a new mine actually reduced $PM_{2.5}$ concentrations by about 4% on average before the EC reform, post-reform mines increased air pollution concentrations by between 0.53% and 0.91% on average.

The negative coefficient on number of pre-reform leases is initially surprising. However, recall that these coefficients may reflect the impacts of any number of adjustments induced by a new mine being built in a village, not just the pollution impacts of the mine itself. For example, households in a village with a new mine may substitute into mining and away from agriculture that involves high-pollution activities like crop burning, or they may be wealthier and thus substitute away from burning biofuels for cooking.

While the magnitudes of our IV and OLS estimates diverge, both sets of estimates suggest that the impacts of a new mine on air pollution were substantially worse after the EC reform than before.

Table 1: Logs of annual average PM2.5 around the village closest to the mining lease and total number of mines

	(1)	(2)	(3)
		log PM2.5	
	10km	20km	50km
Panel A: OLS			
No. leases granted before 2006	-0.0004	-0.0004	-0.0006
	(0.0005)	(0.0005)	(0.0004)
No. leases granted after 2006	0.0015***	0.0017***	0.0018***
	(0.0004)	(0.0004)	(0.0004)
Village FE	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes
Observations	49,857	49,857	49,857
R^2	0.988	0.989	0.991
Panel B: IV			
No. leases granted before 2006	-0.0409***	-0.0413***	-0.0406***
	(0.0033)	(0.0032)	(0.0029)
No. leases granted after 2006	0.0053*	0.0069**	0.0091***
	(0.0029)	(0.0028)	(0.0026)
Village FE	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes
Observations	49,857	49,857	49,857
centered R^2	0.984	0.984	0.987
Kleibergen-Paap LM P-val	0.000	0.000	0.000

Note: Standard errors are clustered at the village level in the OLS models. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

6.2.2 Vegetation and land use

Next, we estimate the average effect of a new mine execution on vegetation and land use. Here, we draw from three different satellite-based data sources in order to capture changes (1) in general vegetation (using the EVI and NDVI indices), (2) in forest cover, and (3) in non-vegetation land use.

EVI and NDVI

Table 2 presents results for the vegetation indices EVI and NDVI. In Panel A, the OLS results signal no significant changes in vegetation cover after the execution of mining leases. The OLS results also provide no evidence of differential impacts before and after the 2006 EC reform.

However, the IV results paint a different picture. Overall, leases executed after the EC reform lead to a modest but positive impact on the general greenness of the sample areas, while pre-reform leases induce no impact or a negative change. When the signs of our estimates are generally consistent between the regressions using EVI vs. NDVI, they differ somewhat in magnitude and statistical significance. These differences may arise due in part to variation in how each of these two vegetation indices are computed. In particular, the EVI is known to outperform the NDVI in areas of high biomass density and to better account for meteorological factors. For example, the NDVI has been shown to asymptotically saturate in high biomass regions such as in the Amazon, while the EVI remained sensitive to canopy variations (Huete et al., 2002). Since many of the areas in our sample have high biomass density, we give more weight to the results using EVI.

In contrast to the results for particulate matter, these regressions provide some evidence that the 2006 EC reforms had positive environmental impacts; after 2006, executing a new mine in a village actually increased its vegetation cover. This counter-intuitive pattern may arise because the reformed clearance process often requires mines to engage in compensatory afforestation at and around mine sites. While this additional vegetation around mine sites might be only young-growth shrubs, it would likely show up in EVI and NDVI measurements.

Forest loss

Next, Table 3 measures the impact of a newly-executed mine on Hansen et al. (2013)'s estimated pixels of forest loss per year. A pixel of forest loss refers to a conversion from forest land to no forest, so it is a stark measure of deforestation that will not capture small-scale forest loss or forest thinning. Here, our IV estimates clearly indicate an increase in deforestation due to mining after the Reform. With a resolution of approximately 30 meters per pixel at the Equator, our results point to about 28 ha of forest loss within a 10 km radius, 94 ha within a 20 km radius, and 474.84 ha within a 50 km radius.

These magnitudes are especially striking given that average stated lease size was only about 4.64 ha during the study period. These effects may capture indirect impacts of opening a mine on land use, perhaps through increases in other forms of related development, rather than simply deforestation at the mining site. Our large estimates could also reflect that legal mining near a village is often accompanied by additional illegal mining, which our IBM mining lease data cannot capture.

It is important to note that these results are consistent with our results for EVI and NDVI in Table 2, where we find that mine execution increased vegetation coverage after 2006. Hansen et al.'s forest loss measure identifies only stark deforestation events, so it will not capture early-growth afforestation at mining sites. In contrast, EVI and NDVI will capture these forms of young vegetation growth. Thus, the combination of our results for EVI/NDVI and forest loss suggest that while mines did cause substantial forest loss after the EC reform, they successfully compensated for lost vegetation coverage.

Land use types

Finally, Table 4 estimates the impacts of new mines on the extent of cropland and barren land in a certain radius from a village centroid. Appendix Table C.1 also presents results for changes in the proportion of forested land and the proportion of non-forest vegetated land; we do not focus on those results in the main text, but rather defer to our results using EVI, NDVI, and forest loss. Instead, we focus here on our results for the impacts of new mines on cropland and barren land, the two land use types for which Zeng et al. (2015) find the MODIS land-use data to be most accurate.

Here, we see that the reform significantly increased the impact of mining on the proportion of barren land around a village. While an additional mine reduced the extent of barren land before 2006, the share of barren land increases by about 3 percentage points on average when a post-reform mine was executed.

Furthermore, in terms of general equilibrium impacts of mining on the adjacent living rural population, we find that the EC reform reversed the impacts on the share of land dedicated to crop plantation. While the share of croplands increased on average by about 10 percentage points before the Reform once a mine was executed, it slightly decreased by a bit more than 1 percentage point on average for mining leases granted after the Reform. .

Table 2: Maximum yearly EVI/NDVI and total number of mines

	(1)	(2)	(3)	(4)	(5)	(6)
		EVI			**NDVI**	
	10km	20km	50km	10km	20km	50km
Panel A: OLS						
No. leases granted before 2006	0.0004	0.0006	0.0004	0.0007	0.0008*	0.0006*
	(0.0004)	(0.0004)	(0.0003)	(0.0005)	(0.0005)	(0.0004)
No. leases granted after 2006	0.0004	0.0002	-0.0002	0.0003	0.0000	-0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,865	44,865	44,865	43,875	43,875	43,875
R^2	0.864	0.887	0.925	0.909	0.924	0.950
Panel B: IV						
No. leases granted before 2006	-0.0021	0.0007	-0.0008	-0.0085**	-0.0087***	-0.0090***
	(0.0034)	(0.0031)	(0.0024)	(0.0035)	(0.0031)	(0.0025)
No. leases granted after 2006	0.0150***	0.0162***	0.0130***	0.0054**	0.0039*	0.0019
	(0.0022)	(0.0020)	(0.0016)	(0.0023)	(0.0020)	(0.0016)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,865	44,865	44,865	43,875	43,875	43,875
centered R^2	0.850	0.868	0.911	0.906	0.922	0.948
Kleibergen-Paap LM P-val	0.000	0.000	0.000	0.000	0.000	0.000

Note: Standard errors are clustered at the village level in the OLS models. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table 3: Forest loss and number of new mines

	(1)	(2)	(3)
	Nr. pixels of forest lost		
	10km	20km	50km
Panel A: OLS			
No. new leases granted before 2006	3.2006*	11.4040**	65.6992***
	(1.7027)	(4.7909)	(24.2702)
No. new leases granted after 2006	0.1311	5.3117	19.5621
	(1.2708)	(3.9695)	(17.2994)
Village FE	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes
Observations	40,950	40,950	40,950
R^2	0.572	0.644	0.728
Panel B: IV			
No. leases granted before 2006	5.7940	-19.2017	-366.4365
	(78.5865)	(242.8677)	(1170.7660)
No. leases granted after 2006	316.9051***	1046.0510***	5276.1551***
	(71.8042)	(221.9073)	(1069.7243)
Village FE	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes
Observations	40,950	40,950	40,950
centered R^2	0.284	0.347	0.453
Kleibergen-Paap LM P-val	0.007	0.007	0.007

Note: Standard errors are clustered at the village level in the OLS models. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table 4: Annual average proportion of cropland/barren land and total number of mines

	(1)	(2)	(3)	(4)	(5)	(6)
	Proportion crops			Proportion barren land		
	10km	20km	50km	10km	20km	50km
Panel A: OLS						
No. leases granted before 2006	0.0009	0.0015*	0.0020***	-0.0004	-0.0000	0.0002
	(0.0010)	(0.0008)	(0.0006)	(0.0009)	(0.0008)	(0.0006)
No. leases granted after 2006	0.0009	0.0005	0.0002	0.0006	0.0004	0.0001
	(0.0006)	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,950	40,950	40,950	40,950	40,950	40,950
R^2	0.989	0.992	0.996	0.930	0.911	0.914
Panel B: IV						
No. leases granted before 2006	0.1164***	0.1127***	0.0959***	-0.0199***	-0.0262***	-0.0299***
	(0.0082)	(0.0075)	(0.0062)	(0.0036)	(0.0041)	(0.0041)
No. leases granted after 2006	-0.0131***	-0.0168***	-0.0180***	0.0274***	0.0305***	0.0293***
	(0.0041)	(0.0038)	(0.0031)	(0.0018)	(0.0021)	(0.0021)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,950	40,950	40,950	40,950	40,950	40,950
centered R^2	0.965	0.968	0.976	0.834	0.786	0.788
Kleibergen-Paap LM P-val	0.000	0.000	0.000	0.000	0.000	0.000

Note: Standard errors are clustered at the village level in the OLS models. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

7 Discussion

Broadly, our results suggest that India's 2006 reform to the environmental clearance process worsened, rather than improving, the environmental impact of the average mine. We find that the execution of new mines increased $PM_{2.5}$ concentrations by more after the 2006 reform, and forest loss associated with mining increased substantially after 2006. We do find that EVI and NDVI, two measures of vegetation cover, increased with new mining after the 2006 reform, likely reflecting the imposition of additional afforestation requirements through the clearance process. However, the environmental benefits of this young vegetation growth are likely dwarfed by the costs of higher forest loss.

These changes in the environmental impact of mining may arise due to the large shift towards small mines that we observed in Section 5. If the 2006 reform induced more mines to shift to slightly smaller sizes and evade the purview of the EC process, it could have reduced environmental management and monitoring for the average mine. Next, if the EC reform simply made small mines more competitive relative to large ones, it may have induced the entry of small mining companies. These companies may be less experienced, have fewer financial resources, and a weaker incentive to adopt expensive environmentally-safe production technology made feasible only by economics of scale. Indeed, Eyer (2018) find that small firms have larger per-unit environmental impacts in the fracking industry.

In the following section, we discuss these and other mechanisms through which the 2006 EC reform could have changed the environmental impact of mining in India.

7.1 Mineral heterogeneity

One salient feature of our dataset is that the portfolio of minerals being mined changes post-reform, as documented in Section 5. If mining operations associated with different minerals vary in their environmental impacts, our results in Section 6.2 might be driven by this change in mineral market shares. We investigate this hypothesis by estimating the IV models separately by mineral, whenever the sample size allows it. Namely, for each mineral, we perform the three-stage least squares estimation only on the sub-sample of villages where at least one lease of the respective mineral has been executed.

The results for all environmental outcomes are included in Appendix E in both table and figure format. All models include village and year-state fixed effects, but these coefficients are not reported. The p-value of the Kleinbergen-Paap tests allow us to reject the hypothesis of underidentification in all cases, except for the mineral-level models on the number of pixels of forest loss. Thus, we are unable to comment on mineral-specific impacts of mining on forest loss.

For each environmental variable, the results point to the existence of moderate levels of mineral heterogeneity, but no mineral alone is driving the overall results. In this sense, any changes induced by the Reform on the environmental impacts of mining can be generalized across minerals. Nevertheless, we do observe higher variability by mineral in the impact on the proportion of cropland. Interestingly, this appears to be a feature solely of the post-reform period, while impacts pre-reform are homogeneous. Finally, clay and the less popular minerals (category ”other”) seem to drive the overall results for the increase in the proportion of barren land post-Reform, and in an opposite manner to pre-reform results. Although mostly mined in leases of small area size, clay has significantly decreased its share of regulated mines and increased the share of unregulated mining post-Reform, as illustrated for example in Table A.1 in the Appendix.

7.2 Location selection

Another type of strategic behavior induced by the EC Reform could be observed in the selection of new mining locations. Such concerns are especially important when analyzing the OLS results. Due to increased stringency in environmental regulation, mine owners could have sought to obtain leases in areas with specific trends in environmental outcomes. Namely, new leases could have been strategically located, given the existence of mineral reserves, near villages where, at baseline, deforestation rates were high or air quality was low, such that any impacts of mining would be partially confounded with existing location traits.

Indeed, we find descriptive evidence of differential location sorting in Fig. 5, which simply maps the geographic distribution of mining leases before and after the 2006 reform. In this figure, it is clear that while mining leases were distributed fairly evenly across India before the 2006 reform, mines were much more geographically clustered in particular parts of the country after 2006.

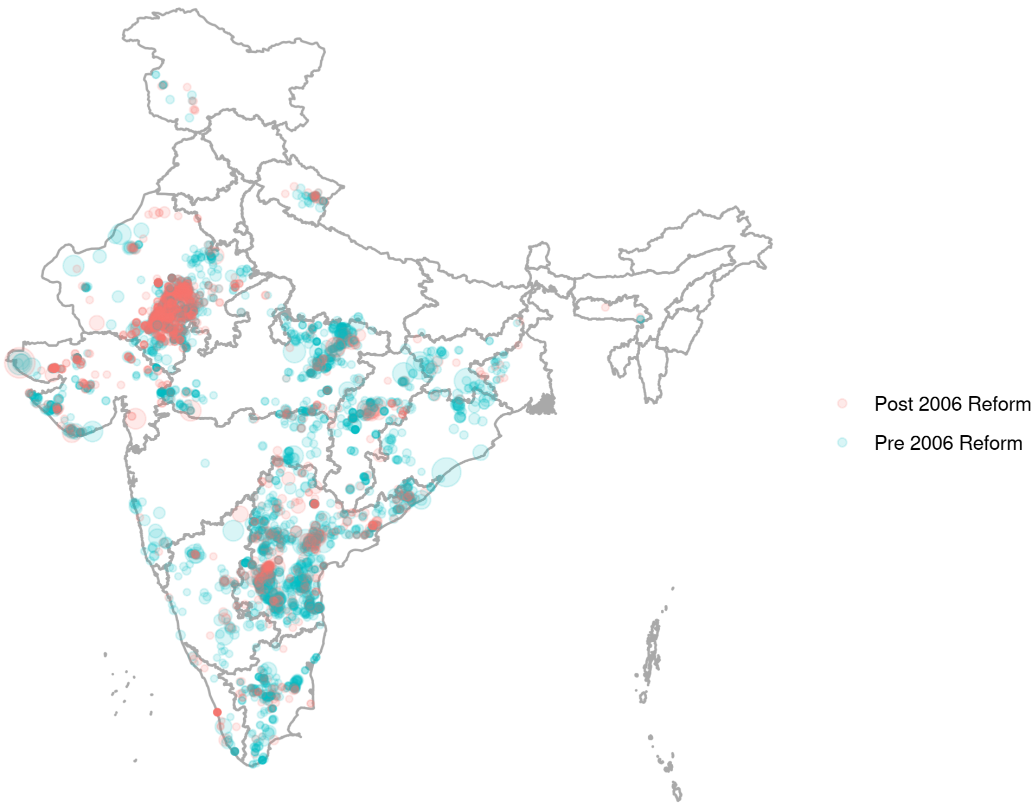


Figure 5: Spatial distribution of mining leases, granted before and after the 2006 EC Reform.

Next, we test for the presence of location selection by regressing average baseline environmental outcomes at lease locations on dummies for the year in which leases were executed. We define *baseline* values as the average over the two years preceding the execution of a mining lease and estimate the following cross-sectional model for each environmental variable:

$$\bar{Y}_l = \alpha + \sum_{1998}^{2014} \beta_y D_y + \Gamma_m + \epsilon_l \tag{8}$$

where $\bar{Y}_l$ is the baseline level of the environmental outcome in the village where lease l is executed, D are year of execution dummies, and Γ represent mineral fixed effects. In other words, this model tests whether baseline environmental conditions in villages chosen to be mine locations differed substantially by the year in which the lease was granted. We cluster standard errors by village, since villages are often the site of multiple mines.

A discontinuity in the estimated year of execution dummies would be suggestive of differential location selection before and after the Reform. We plot the estimated year of execution dummies in Section F in the Appendix. Across all environmental outcomes, the estimated year coefficients seem to follow a linear trend and no evidence of discontinuity after 2005 is observed, allowing us to conclude that no differential location selection has been incentivised by the Reform.

7.3 Lease splitting

This section aims to bring descriptive evidence related to the mechanisms behind the differential impact of mining on environmental outcomes pre- and post-Reform. In particular, one key question to answer is whether the shift in the distribution of mine size can be attributed to the splitting of counterfactually larger mines just below the regulated size threshold and/or to the entry of new small-size mining companies.

In Fig. 6, we compare the total post-Reform lease area in small mines by mineral with estimates of the area contributed from "splitting" 5-15 ha mines and "carrying over" mines that would have been under 5 ha anyways in the absence of the 2006 reform. Here we focus on the 7 most common minerals after the 2006 reforms, which are dominated by quartz, feldspar, and clay. We estimate split 5-15 ha area as the difference between the pre- and post-Reform area in 5-15 ha leases by mineral.[12] In other words, we assume that any area leased in medium-sized mines pre-reform years would also have been leased in medium-sized mines in post-reform years if not for the Reform itself; then if area in medium leases falls by X hectares, we assume that splitting of medium-size mines due to the Reform attributed X hectares to total post-Reform lease area in small mines. Next, we estimate carry-over area as the pre-Reform area in leases under 5 ha. Then, we can estimate excess post-Reform leased area in small mines as the gap between the sum of "split" and "carried-over" area and total leased area in small mines post-reform. If the 2006 Reform simply redistributed mining development between area categories, we would estimate that these two categories accounted for the total post-Reform area in small leases.

However, we find that "split" and "carryover" area only account for a small share of the post-Reform leased area in the most common minerals. Of the 2017.8 ha leased to small quartz mines in 2007 and 2008, the drop in medium-sized mines only accounts for only 0.4% and carried-over area from pre-Reform small leases accounts for only 8.8%. For quartz, we can think of the remaining 90.8% of the post-Reform lease area as *new* development.

Next, we turn to pre- and post-Reform differences in the characteristics of mine lease grantees. Broadly, the change in "environmental competence" of lease grantees after the 2006 reforms depends on whether the Reform induced the entry of a new class of small mining companies or, rather, incentivized applicants that otherwise would have produced larger mines to split counterfactually larger leases into small

[12] Note that here we measure pre-reform area totals using the 2003 and 2004 lease area distributions and measure the post-reform area totals using the 2007 and 2008 lease area distributions. We use these subsets of years to avoid conflating the impact of the reform with the large time trends in leased area both before and after the reform.

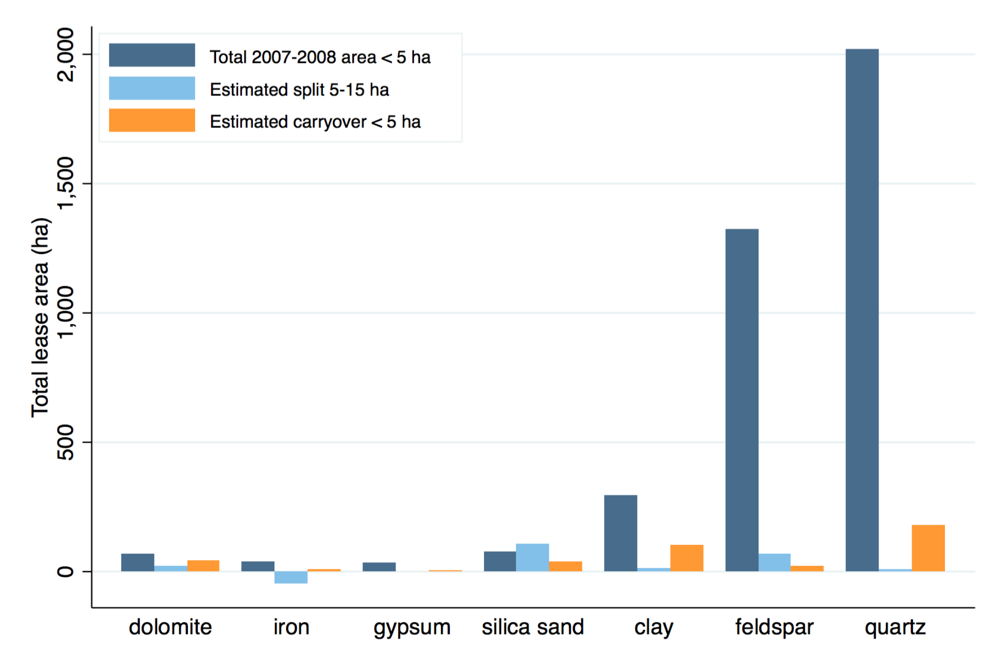


Figure 6: A decomposition of total post-2006 area leased in small mines in the most common minerals

mines. We begin exploring this question by evaluating the extent to which the spike in small leases reflects lease splitting, or the grant of multiple leases to single applicants, or the entry of small, single-lease applicants. To do so, we first identify unique grantees by fuzzy merging groups of grantee names. Consider Fig. 7, which plots series of the number of leases and number of unique grantees for small and medium mines over time. The series for unique lessees broadly tracks the number of leases over time for both area groups, suggesting that the bulk of new small leases arise from new entry of small grantees, rather than from a few large companies getting multiple small leases.

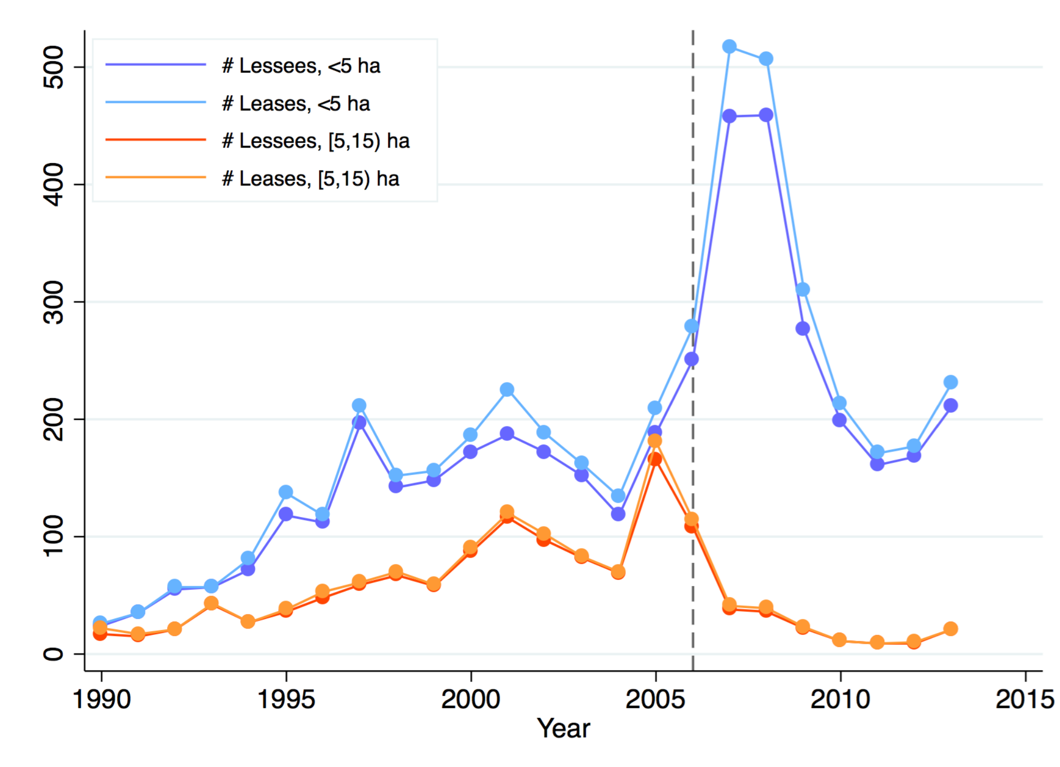


Figure 7: Number of leases and unique lessees for small and medium mines, 1990-2013

At the same time, however, we find some evidence of lease splitting, especially just below the 5 ha cutoff. Consider Fig. 8, which plots the average number of leases per unique lease grantee against lease area in the pre- and post-reform periods. Following the 2006 reform, there is a marked spike in the average number of leases per grantee among leases between 4 and 5 ha. The average number of leases per grantee rises from 1.07 leases to 1.22 leases per grantee from the pre- to post-reform period. Multiple leases from the same grantee remain a fairly small proportion of all small leases after the reform, however. Of the 2098 leases of area between 4 and 5 ha granted from 2006-2013, 30% were granted to a lessee with at least one other small lease in the same period.

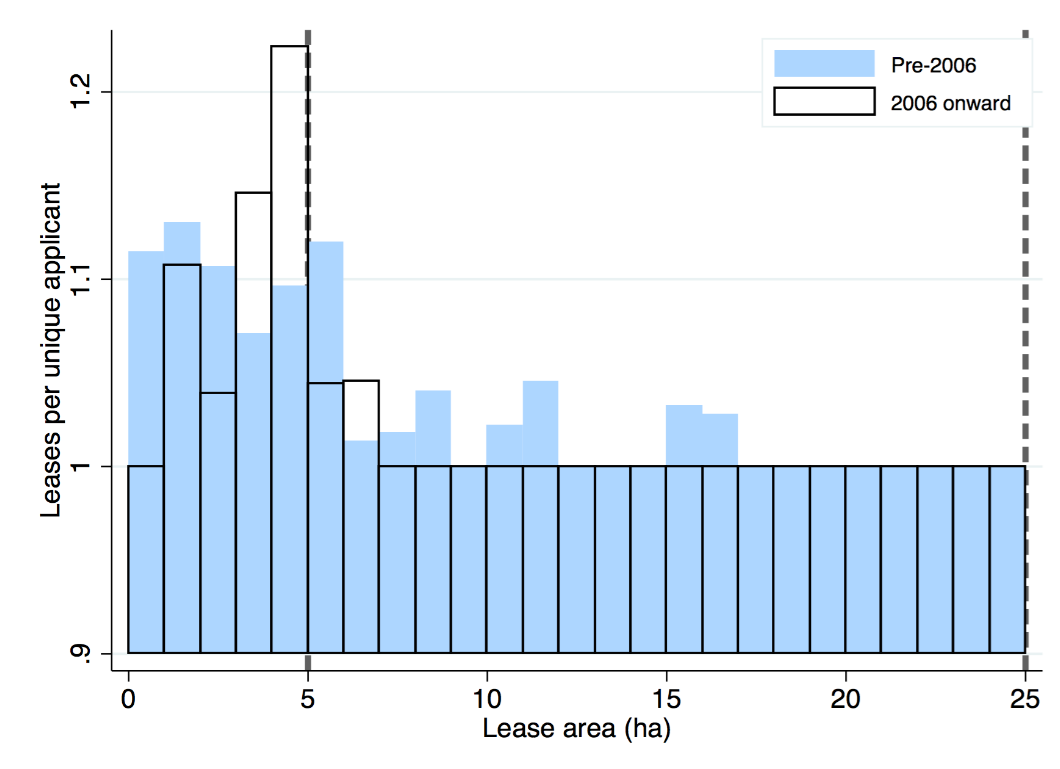


Figure 8: Average number of leases per unique grantee, against lease area (ha)

It is important to note that our measure of lease splitting so far represents a lower bound of lease-splitting behavior. While so far we have identified lease splitting by linking together leases held by unique applicants, companies could apply for leases under different names. In the same sense, lease applicants may also effectively split leases by applying for multiple leases under different names within families or other social networks. To explore this form of coordination across lease applicants, we first separate grantees into those that appear to be companies and those that appear to be individuals. We identify companies by the presence of keywords in the lessee name, like "mining," "company," "enterprise," or "cement." Within the set of leases granted to "individual" applicants, we then calculate the proportion that were granted to an individual whose surname matches that of another applicant with a lease in the same district. Figure 9 plots this proportion over time for small and medium leases. We see a visible shift in the proportion of small leases with a matching surname after 2006, while there is no such visible shift among medium leases. These trends provide additional suggestive evidence that some degree of lease splitting, rather than just entry of small, single-mine applicants, contributed to the rise in small mines after the 2006 reforms.

Figure 9: Probability of a surname match among grantees within a district over time

Even if lease splitting, rather than just an influx of individual leaseholders, accounts for some of the spike in small mines after the 2006 EC reforms, this lease splitting could be driven by new, unexperienced companies suddenly made relatively profitable by the new costs imposed on larger mines. In other words, we might expect to see larger, existing companies being forced out by the 2006 reforms and replaced by new, smaller companies. See Figure 10, which plots the number of leases granted after the 2006 reforms against area and separated by grantees who did and did not also have a lease granted in the pre-2006 period. Here, we see that while applicants that had leases both in the pre- and post-reform periods also shift heavily towards small mines in the post-reform period, most new leases in 2006 or later were granted to applicants with no pre-reform leases.

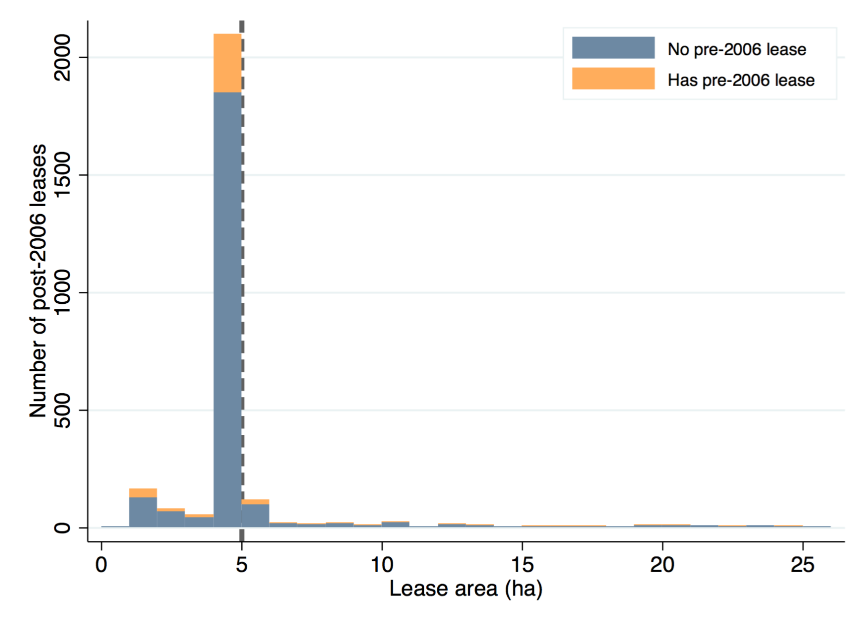


Figure 10: Proportion of leases in new mines of owners with a previous lease.

Moreover, we find that the boom in small leases around the 2006 reform was disproportionately driven by individual lessees, rather than companies. Figure 11 plots the proportion of leases that were granted to individuals over time among small and medium leases over time. While the proportion of medium-size leases granted to individuals fell precipitously after the 2006 reforms, the proportion of small leases granted to individuals rose somewhat more sharply immediately around the years of the reform.

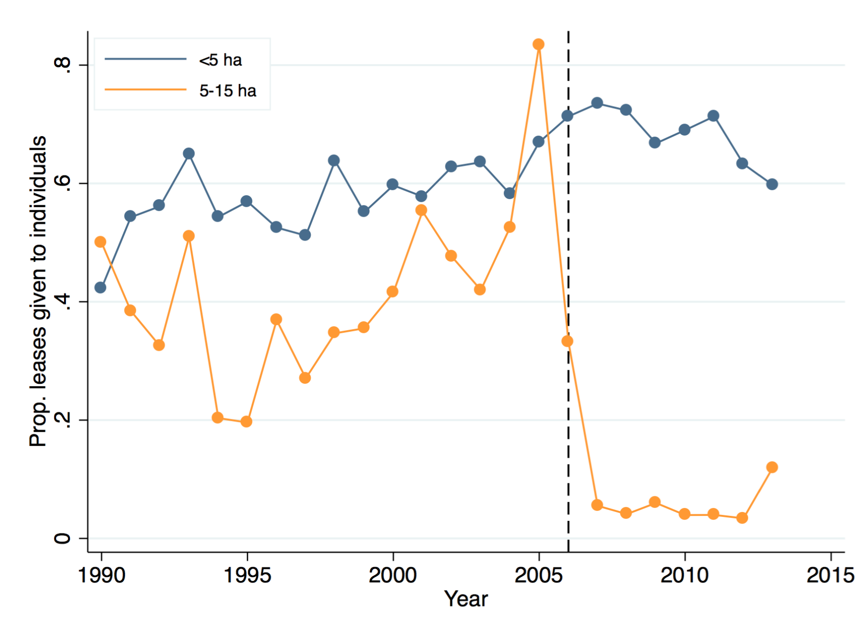


Figure 11: Proportion of individuals over time that had leases below 5 ha.

8 Conclusion

This paper documents the strategic behavior adopted by mines in response to changes in environmental regulation in India. We find evidence of a strong distortion in the distribution of mine size towards smaller areas that were waived of the regulatory burden. We observe a sharp and long-lasting increase in the proportion of mines of area below 5 hectares, which were exempt of the EC process, and a simultaneous decrease in the proportion of mines of area between 5 and 25 hectares, which got subjected to stricter regulation starting with the 2006 Reform. The visible selection in mine application trends suggests that mine proponents perceived the reforms to be substantial and costly.

The distortion of the size distribution of mines could also have environmental impacts both because small mines are not subject to the formal regulatory environmental protection process, and because smaller mines may be less able to afford environmentally safe production technology. We find that this is indeed the case - after the Reform, the average executed mine seems to have stronger negative impacts on air quality and result in more forest loss than before the Reform. Our analysis focuses on changes in environmental outcomes around the villages closest to the mining lease and, thus, speaks of final net outcomes, which could be both directly and indirectly related to the mine opening.

The documented change in environmental impacts between pre- and post-Reform could be related to differences in the mining process itself, where due to losses in economies of scale mines become *dirtier* on average. Alternatively, as more mines stayed outside the regulatory purview after 2006, the change in impacts could be related to the absence of compensatory activities (such as afforestation) that would have been imposed on counterfactually larger mines. We find suggestive evidence that the large shift to small-scale mining can be attributed to both the splitting of counterfactually larger mines but also to the entry of new small mining companies.

Our analysis assesses the impact of mining on the livelihoods of village communities living in close proximity to mining leases. Although this is important as it allows us to draw conclusions regarding the impacted population and not only an environmental setting, our analysis only captures final outcomes and is limited in understanding the concrete channels through which changes take place. For example, we observe changes in the proportion of land dedicated to crops or left barren due to the execution of a mine, but we are not able to assess how exactly these changes took place. Next, we cannot assess the full range of impacts related to the Reform. While we can assess its impact on environmental outcomes, we might expect that the increase in stricter environmental regulation, including the forced public consultation imposed on regulated mines, to increase mines' other benefits to nearby communities, like increasing local employment or investments in local schools or health centers, for example.

Our results reaffirm that ensuring that new policies work as intended requires not just establishing them, but also implementing them well. Our analysis has revealed the value of using low-cost tools like remote-sensing data to monitor compliance. India's regulatory environment has relatively low capacity for site monitoring; satellite monitoring may provide a useful complement to traditional, higher-cost forms of monitoring in this context.

Appendix

A Summary statistics

Table A.1: Proportion of unregulated mining in Pre- and Post-Reform periods, minerals ordered by unregulated area proportion in Post-Period.

	Proportion of unregulated mining (Area)		(Nr. leases)		Median lease size		Nr. leases (Unregulated)		(Regulated)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Amethyst	1	1	1	1	0.89	4.94	3	1	0	0
Chalk	0.9103	1	0.9804	1	2.02	2.03	50	9	1	0
Kyanite	0.1123	1	0.375	1	5	3.445	3	2	5	0
Limeshell	0.0086	1	0.3333	1	22.255	4.85	2	1	4	0
Magnesite	1	1	1	1	1.995	3.63	6	2	0	0
Marl	0	1	0	1	0	4.9	0	1	0	0
Feldspar	0.1767	0.9102	0.3598	0.9529	5	4.38	59	668	105	33
Quartz	0.1263	0.7556	0.5246	0.9153	4.85	4.4	331	1005	300	93
Calcite	0.1578	0.6711	0.5833	0.8824	4.82	4.5	14	15	10	2
Clay	0.1748	0.6106	0.6492	0.9156	4.13	4.52	124	217	67	20
Vermiculite	0.0518	0.5789	0.3333	0.6667	23.71	3.84	1	2	2	1
Ochre	0.1029	0.3988	0.36	0.7778	5.615	4.795	18	28	32	8
Steatite	0.0693	0.3545	0.5766	0.875	4.58	4.36	64	35	47	5
Pyrophyllite	0.0474	0.337	0.3182	0.6667	6.305	4.75	7	6	15	3
Baryte	0.0871	0.2809	0.619	0.7222	3.255	4.355	52	13	32	5
Mica	0.0919	0.2695	0.28	0.5185	5	4.99	28	14	72	13
Corundum	1	0.2652	1	0.75	1.5	3.34	1	3	0	1
Garnet	0.1246	0.2255	0.7895	0.8333	3.38	3.465	45	15	12	3
White Shale	0.2984	0.2098	0.8889	0.3333	1.53	5.71	8	1	1	2
Dolomite	0.1059	0.2048	0.5	0.6111	4.99	4.605	96	44	96	28
Wollastonite	0	0.2011	0	0.5	16.7	12.205	0	1	4	1
Silica Sand	0.0619	0.1571	0.336	0.6961	8.09	4.24	42	71	83	31
Laterite	0.1216	0.1123	0.4048	0.4416	7.02	5.26	34	34	50	43
Manganese	0.0115	0.083	0.1622	0.4478	19.78	5.73	6	30	31	37
Gypsum	0.0116	0.0628	0.5	0.7188	9.99	4.75	8	23	8	9
Quartzite	0.0667	0.0468	0.3214	0.1538	7.485	13.36	9	2	19	11
Sillimanite	0	0.0323	0	0.5	1265.525	53.785	0	2	2	2
Tin	0.0539	0.0175	0.1667	0.1111	12.415	16.4	1	1	5	8
Iron	0.0054	0.0169	0.2222	0.2877	23.625	19	12	21	42	52
Bauxite	0.0051	0.0151	0.2143	0.3077	30.795	16.735	12	8	44	18
Limestone	0.0338	0.0116	0.6155	0.4529	4.25	7.27	341	101	213	122
Agate	0	0	0	0	27.49	0	0	0	2	0
Apatite	0	0	0	0	16.12	0	0	0	1	0
Borax	0	0	0	0	0	159	0	0	0	1
Chromite	0	0	0	0	116.76	0	0	0	5	0
Copper	0	0	0	0	215.94	0	0	0	4	0
Diaspore	0.196	0	0.5714	0	3.2	6.17	4	0	3	1
Felsite	0	0	0	0	20.23	0	0	0	1	0
Fluorite	0	0	0	0	0	31.6	0	0	0	2
Gold	0	0	0	0	38.04	433.1	0	0	1	5
Graphite	0.0034	0	0.0833	0	30.21	12.89	1	0	11	1
Iolite	0.083	0	0.4286	0	9.5	0	3	0	4	0
Jasper	0	0	0	0	5	0	0	0	1	0
Lead/Zinc	0.0017	0	0.25	0	340.145	52	1	0	3	3
Lime Kankar	0.2753	0	0.5	0	4.755	5.44	2	0	2	2
Phosphorite	0.01	0	0.2	0	24.84	13.47	1	0	4	1
Pyroxenite	0.053	0	0.25	0	11.475	0	1	0	3	0
Ruby	1	0	1	0	2.565	0	2	0	0	0
Sand	0.0131	0	0.1053	0	16.05	212.4	2	0	17	4
Shale	0.256	0	0.7	0	3.625	10.28	14	0	6	1
Slate	0	0	0	0	18.25	5.7	0	0	9	1

Table A.2: Changes in area proportion by size category between Pre- and Post-Reform periods.

	Change in area proportion by size category					Nr. leases	
	<5ha	5-15ha	15-25ha	25-50ha	≥50ha	Pre	Post
Limeshell	0.991	-0.008	0	-0.073	-0.911	6	1
Kyanite	0.888	-0.532	-0.355	0	0	8	2
Feldspar	0.734	-0.278	-0.065	-0.154	-0.236	164	701
Quartz	0.629	-0.142	-0.15	-0.162	-0.176	631	1098
Vermiculite	0.527	0.421	-0.948	0	0	3	3
Calcite	0.513	-0.149	0.274	-0.124	-0.515	24	17
Clay	0.436	-0.115	-0.009	-0.083	-0.228	191	237
Ochre	0.296	-0.134	-0.272	0.11	0	50	36
Pyrophyllite	0.29	0.119	0.305	-0.244	-0.469	22	9
Steatite	0.285	-0.057	0.061	0.022	-0.312	111	40
Wollastonite	0.201	-0.114	0.799	-0.886	0	4	2
Baryte	0.194	0.096	0.042	-0.215	-0.117	84	18
Mica	0.178	-0.003	0.162	0.154	-0.491	100	27
Garnet	0.101	-0.034	0	0.174	-0.241	57	18
Dolomite	0.099	-0.082	0.06	0.073	-0.149	192	72
Silica Sand	0.095	-0.157	0.008	0.034	0.019	125	102
Chalk	0.09	-0.09	0	0	0	51	9
Manganese	0.072	0.046	-0.04	0.078	-0.156	37	67
Gypsum	0.051	0	-0.016	0	-0.035	16	32
Sillimanite	0.032	0	0	0	-0.032	2	4
Iron	0.012	0.013	0.03	0.043	-0.097	54	73
Bauxite	0.01	0.006	-0.006	0.023	-0.034	56	26
Agate	0	0	0	0	0	2	0
Amethyst	0	0	0	0	0	3	1
Apatite	0	0	0	0	0	1	0
Borax	0	0	0	0	0	0	1
Chromite	0	0	0	0	0	5	0
Copper	0	0	0	0	0	4	0
Felsite	0	0	0	0	0	1	0
Fluorite	0	0	0	0	0	0	2
Gold	0	0.002	0.008	-1	0.989	1	5
Iolite	0	0	0	0	0	7	0
Jasper	0	0	0	0	0	1	0
Magnesite	0	0	0	0	0	6	2
Marl	0	0	0	0	0	0	1
Pyroxenite	0	0	0	0	0	4	0
Ruby	0	0	0	0	0	2	0
Slate	0	0.85	-0.484	-0.366	0	9	1
Lead/Zinc	-0.002	0.007	0	0	-0.005	4	3
Graphite	-0.003	0.964	-0.069	-0.532	-0.36	12	1
Laterite	-0.009	-0.287	0.071	-0.114	0.339	84	77
Phosphorite	-0.01	0.96	-0.109	-0.152	-0.689	5	1
Sand	-0.013	-0.097	-0.096	-0.105	0.311	19	4
Quartzite	-0.02	0.217	0.223	-0.088	-0.332	28	13
Limestone	-0.022	-0.017	-0.016	-0.023	0.078	554	223
Tin	-0.036	0.01	-0.336	0.047	0.315	6	9
White Shale	-0.089	0.79	0	-0.702	0	9	3
Diaspore	-0.196	0.701	-0.505	0	0	7	1
Shale	-0.256	0.662	0	0	-0.406	20	1
Lime Kankar	-0.275	0.275	0	0	0	4	2
Corundum	-0.735	0	0.735	0	0	1	4
Mean	0.099	0.075	-0.014	-0.084	-0.077	Total 2787	2949

Table A.3: Changes in number of leases proportion by size category between Pre- and Post-Reform periods.

	Change in nr. leases proportion by size category					Nr. leases	
	<5ha	5-15ha	15-25ha	25-50ha	≥50ha	Pre	Post
Limeshell	0.667	-0.167	0	-0.333	-0.167	6	1
Kyanite	0.625	-0.5	-0.125	0	0	8	2
Feldspar	0.593	-0.506	-0.029	-0.035	-0.023	164	701
Sillimanite	0.5	0	0	0	-0.5	2	4
Wollastonite	0.5	-0.5	0.5	-0.5	0	4	2
Ochre	0.418	-0.249	-0.172	0.003	0	50	36
Quartz	0.391	-0.236	-0.084	-0.046	-0.024	631	1098
Silica Sand	0.36	-0.304	-0.041	-0.001	-0.015	125	102
Pyrophyllite	0.348	-0.187	0.066	-0.136	-0.091	22	9
Vermiculite	0.333	0.333	-0.667	0	0	3	3
Calcite	0.299	-0.275	0.059	-0.042	-0.042	24	17
Steatite	0.298	-0.218	-0.004	-0.011	-0.065	111	40
Manganese	0.286	0.025	-0.193	-0.019	-0.1	37	67
Clay	0.266	-0.188	-0.021	-0.027	-0.03	191	237
Mica	0.239	-0.25	0.044	0.007	-0.04	100	27
Gypsum	0.219	0	-0.125	0	-0.094	16	32
Dolomite	0.111	-0.156	0.038	0.023	-0.016	192	72
Baryte	0.103	0.024	-0.016	-0.095	-0.016	84	18
Bauxite	0.093	0.032	-0.069	0.026	-0.082	56	26
Iron	0.065	0.007	0.058	0.058	-0.188	54	73
Garnet	0.044	-0.12	0	0.056	0.02	57	18
Laterite	0.037	-0.124	0.082	-0.035	0.04	84	77
Chalk	0.02	-0.02	0	0	0	51	9
Agate	0	0	0	0	0	2	0
Amethyst	0	0	0	0	0	3	1
Apatite	0	0	0	0	0	1	0
Borax	0	0	0	0	0	0	1
Chromite	0	0	0	0	0	5	0
Copper	0	0	0	0	0	4	0
Felsite	0	0	0	0	0	1	0
Fluorite	0	0	0	0	0	0	2
Gold	0	0.2	0.2	-1	0.6	1	5
Iolite	0	0	0	0	0	7	0
Jasper	0	0	0	0	0	1	0
Magnesite	0	0	0	0	0	6	2
Marl	0	0	0	0	0	0	1
Pyroxenite	0	0	0	0	0	4	0
Ruby	0	0	0	0	0	2	0
Slate	0	0.667	-0.444	-0.222	0	9	1
Tin	-0.056	0	-0.222	0.167	0.111	6	9
Graphite	-0.083	0.833	-0.083	-0.5	-0.167	12	1
Sand	-0.105	-0.316	-0.211	-0.105	0.737	19	4
Limestone	-0.163	-0.023	-0.009	0.012	0.183	554	223
Quartzite	-0.168	0.176	0.093	-0.03	-0.071	28	13
Phosphorite	-0.2	0.8	-0.2	-0.2	-0.2	5	1
Corundum	-0.25	0	0.25	0	0	1	4
Lead/Zinc	-0.25	0.333	0	0	-0.083	4	3
Lime Kankar	-0.5	0.5	0	0	0	4	2
White Shale	-0.556	0.667	0	-0.111	0	9	3
Diaspore	-0.571	0.714	-0.143	0	0	7	1
Shale	-0.7	0.75	0	0	-0.05	20	1
Mean	0.063	0.034	-0.029	-0.061	-0.007	Total 2787	2949

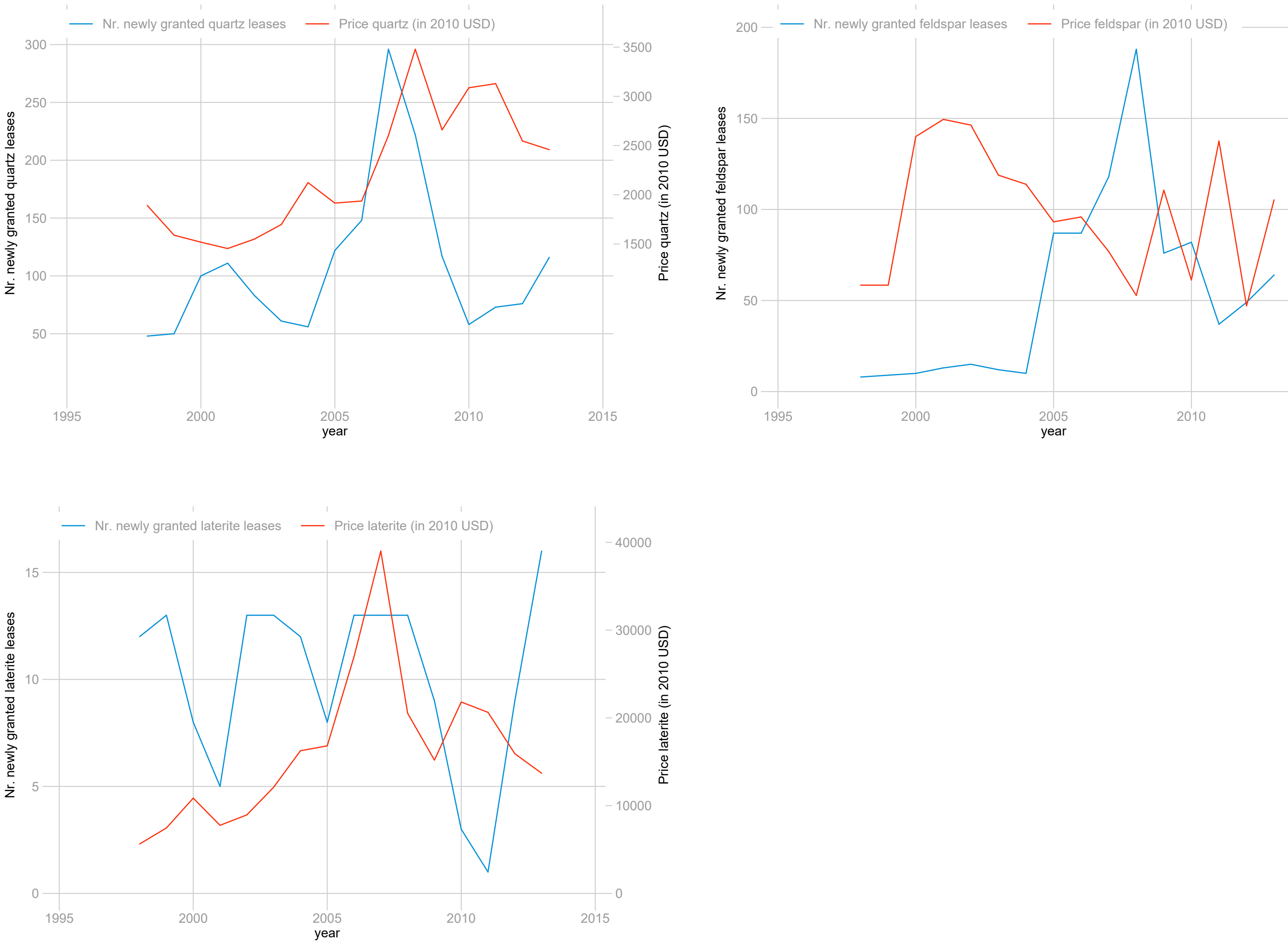


Figure A.1: Timeseries of Indian mining leases and the USGS price for the corresponding mineral, 1998 - 2013.

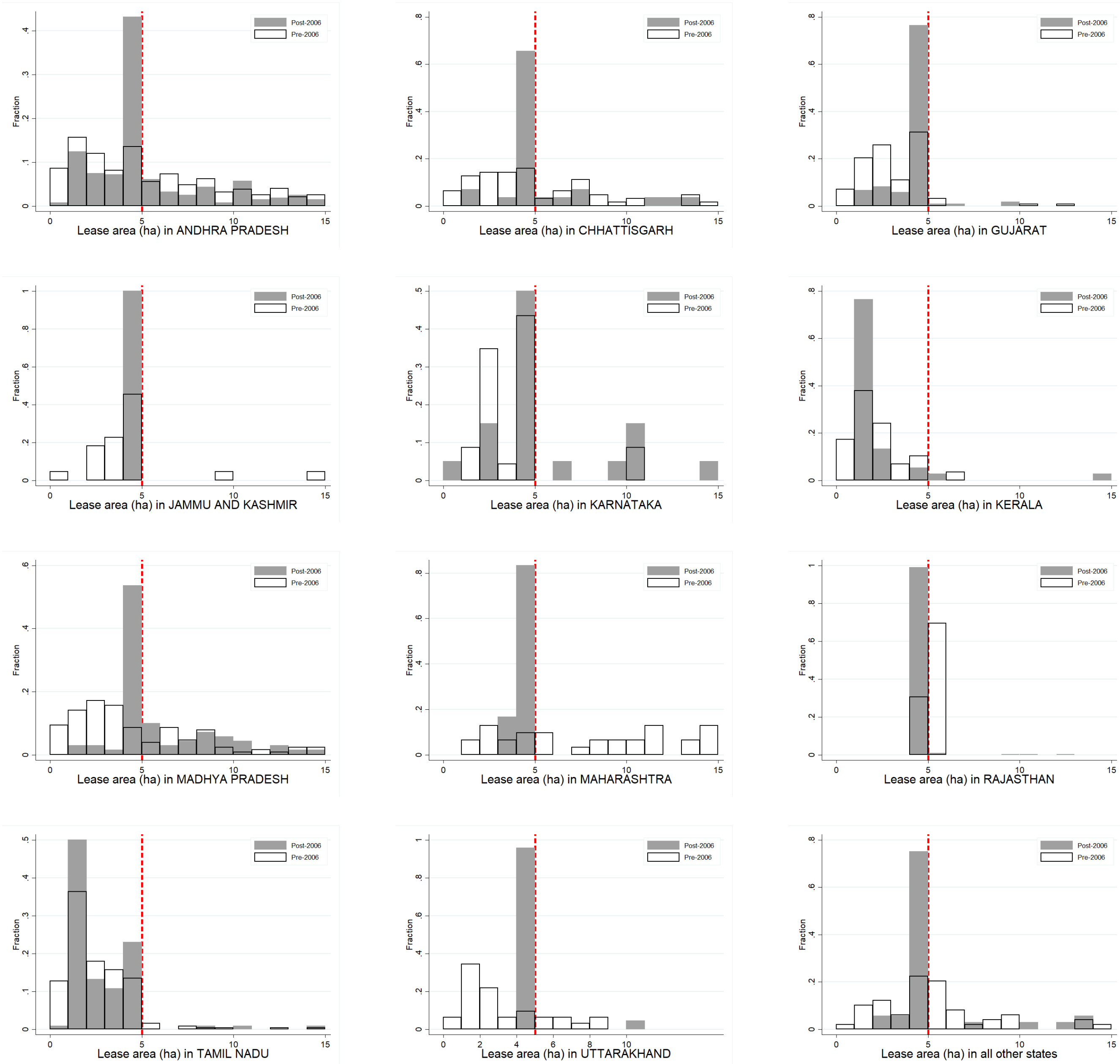


Figure A.2: Area size distribution of new mine leases, by STATE.

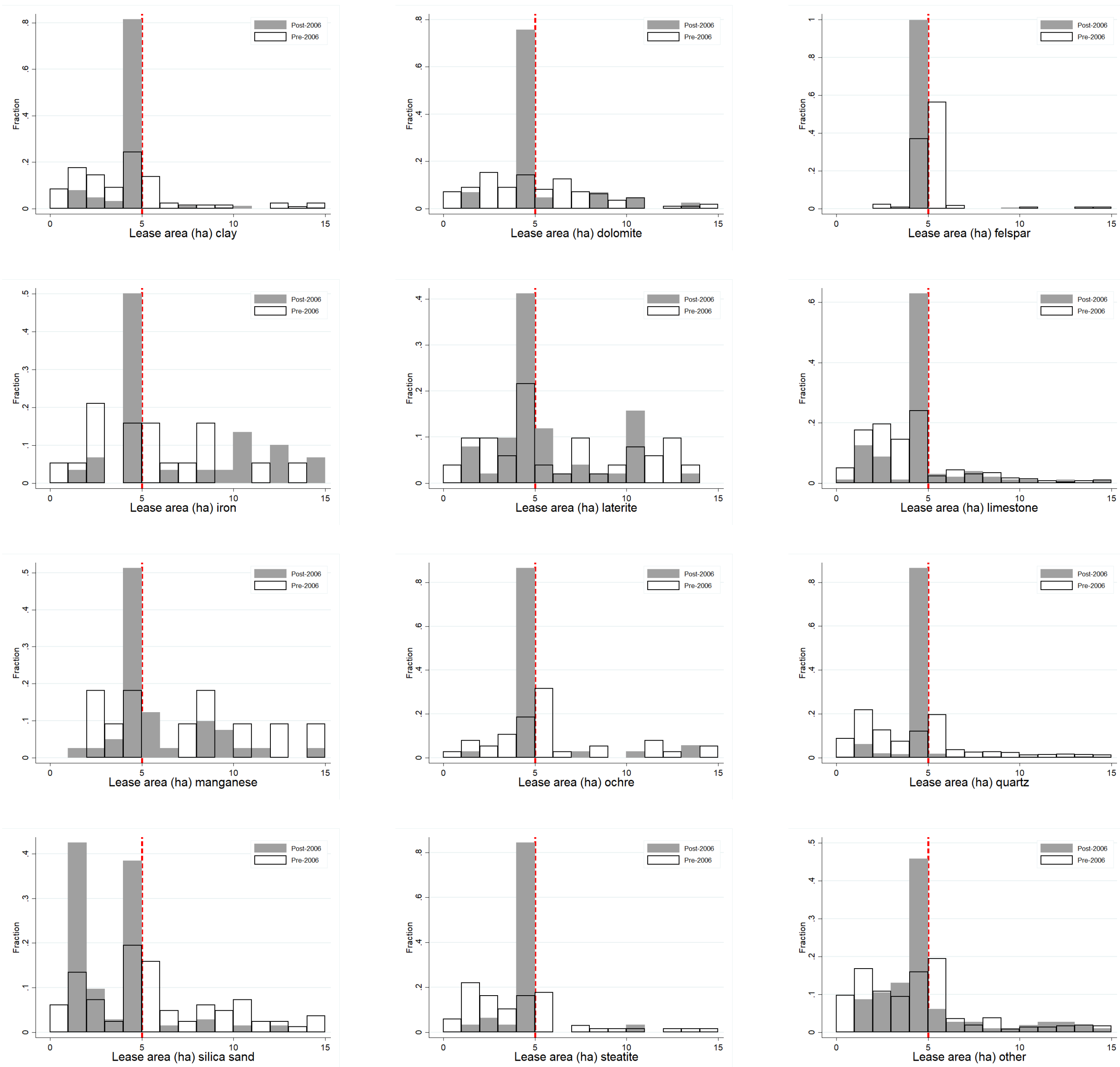


Figure A.3: Area size distribution of new mine leases, by MINERAL.

B IV First-stage results

Table B.1: Cumulated number of mines in PRE- and POST-Reform period and value of minerals

	(1) No. leases granted before 2006	(2) No. leases granted after 2006
PRE Steatite price x distance	0.01179**	-0.00033
	(0.00)	(0.01)
PRE Quartz price x distance	-0.05045***	-0.00011
	(0.01)	(0.01)
PRE Manganese price x distance	0.18475***	-0.09348***
	(0.02)	(0.02)
PRE Limestone price x distance	-0.29830***	0.02281
	(0.02)	(0.03)
PRE Laterite price x distance	0.06418***	0.00736
	(0.00)	(0.01)
PRE Iron price x distance	-0.08250***	0.08780***
	(0.02)	(0.02)
PRE Mica price x distance	-0.00191	0.00286
	(0.00)	(0.00)
PRE Feldspar price x distance	-0.00492	0.00379
	(0.00)	(0.00)
PRE Clay price x distance	0.01205	0.00511
	(0.01)	(0.01)
PRE Silica sand price x distance	-0.10256***	-0.02473
	(0.02)	(0.03)
PRE barite price x distance	-0.03028	-0.05292*
	(0.02)	(0.03)
POST Steatite price x distance	-0.00159	-0.00646**
	(0.00)	(0.00)
POST Quartz price x distance	-0.01134***	0.02426***
	(0.00)	(0.00)
POST Manganese price x distance	-0.00104	-0.00377
	(0.00)	(0.00)
POST Limestone price x distance	-0.01661*	0.00858
	(0.01)	(0.01)
POST Laterite price x distance	0.00006	-0.00252
	(0.00)	(0.00)
POST Iron price x distance	0.00213	0.01638**
	(0.01)	(0.01)
POST Mica price x distance	-0.00260	0.07305***
	(0.01)	(0.01)
POST Feldspar price x distance	0.00060	0.00133
	(0.00)	(0.00)
POST Clay price x distance	-0.00242	-0.02606***
	(0.01)	(0.01)
POST silica sand price x distance	-0.00238	0.03015***
	(0.00)	(0.00)
POST barite price x distance	-0.00538	-0.03350***
	(0.00)	(0.00)
Village FE	Yes	Yes
Year-state FE	Yes	Yes
Observations	50,888	50,888
R^2	0.882	0.741

Note: Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1. Standardized prices are in 2010 USD, distace is measured in 100km.

C MODIS IV results for forest and vegetated land

Table C.1: Annual average proportion of forested/vegetated land and total number of mines

	(1)	(2)	(3)	(4)	(5)	(6)
	Proportion forested land			**Proportion vegetated land**		
	10km	20km	50km	10km	20km	50km
Panel A: OLS						
No. leases granted before 2006	-0.0001	-0.0003	-0.0002	-0.0003	-0.0012	-0.0019**
	(0.0002)	(0.0002)	(0.0002)	(0.0014)	(0.0011)	(0.0008)
No. leases granted after 2006	-0.0000	-0.0000	-0.0000	-0.0014**	-0.0009	-0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0007)	(0.0006)	(0.0005)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,950	40,950	40,950	40,950	40,950	40,950
R^2	0.990	0.991	0.994	0.980	0.981	0.982
Panel B: IV						
No. leases granted before 2006	-0.0164***	-0.0220***	-0.0221***	-0.0779***	-0.0644***	-0.0474***
	(0.0014)	(0.0017)	(0.0015)	(0.0071)	(0.0061)	(0.0048)
No. leases granted after 2006	-0.0020***	-0.0020**	-0.0013*	-0.0115***	-0.0109***	-0.0104***
	(0.0007)	(0.0008)	(0.0008)	(0.0036)	(0.0030)	(0.0024)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,950	40,950	40,950	40,950	40,950	40,950
centered R^2	0.980	0.974	0.975	0.963	0.967	0.970
Kleibergen-Paap LM P-val	0.000	0.000	0.000	0.000	0.000	0.000

Note: Standard errors are clustered at the village level in the OLS models. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

D McCrary tests for discontinuities in the distribution of area size

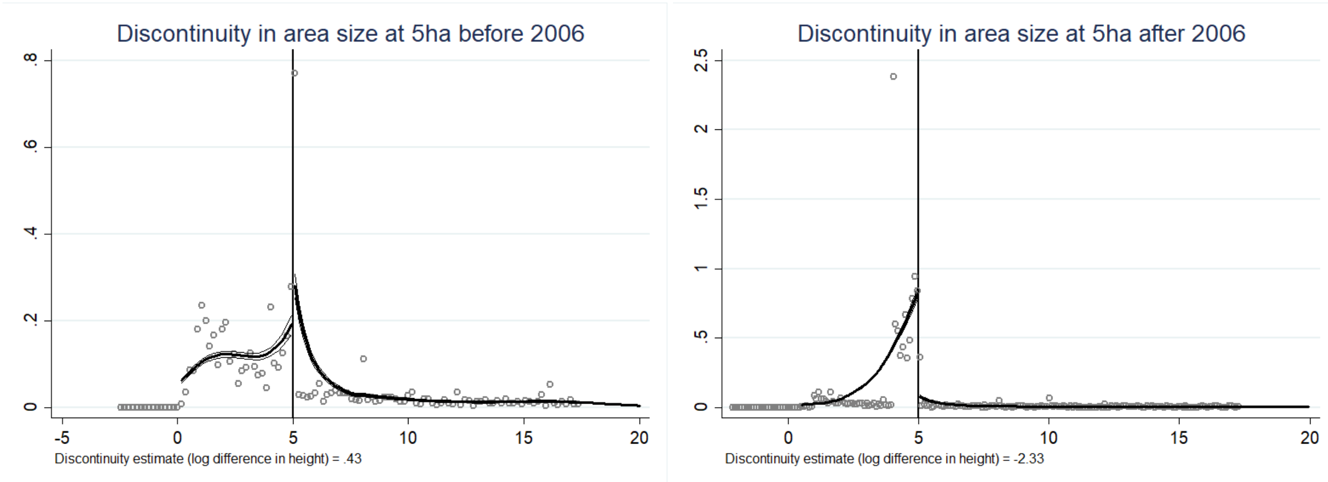


Figure D.1: McCrary tests of density discontinuity at the 5 ha cutoff before and after the 2006 EC Reform.

E Estimated impact of mining: mineral heterogeneity

E.A IV Results by mineral: Figures

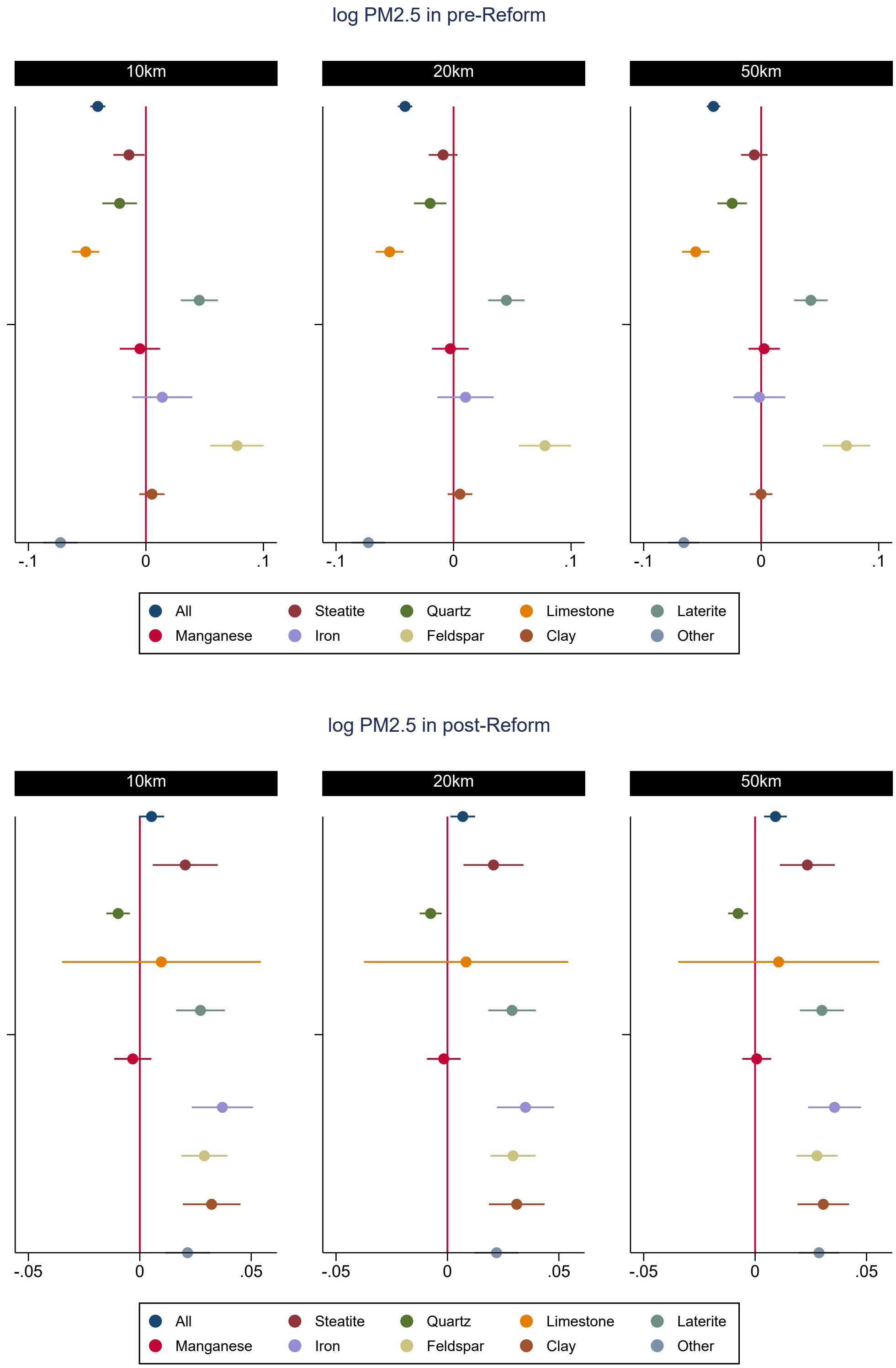


Figure E.1: IV estimates of the impact of a mine execution on log PM2.5 before and after the 2006 Reform, by mineral.

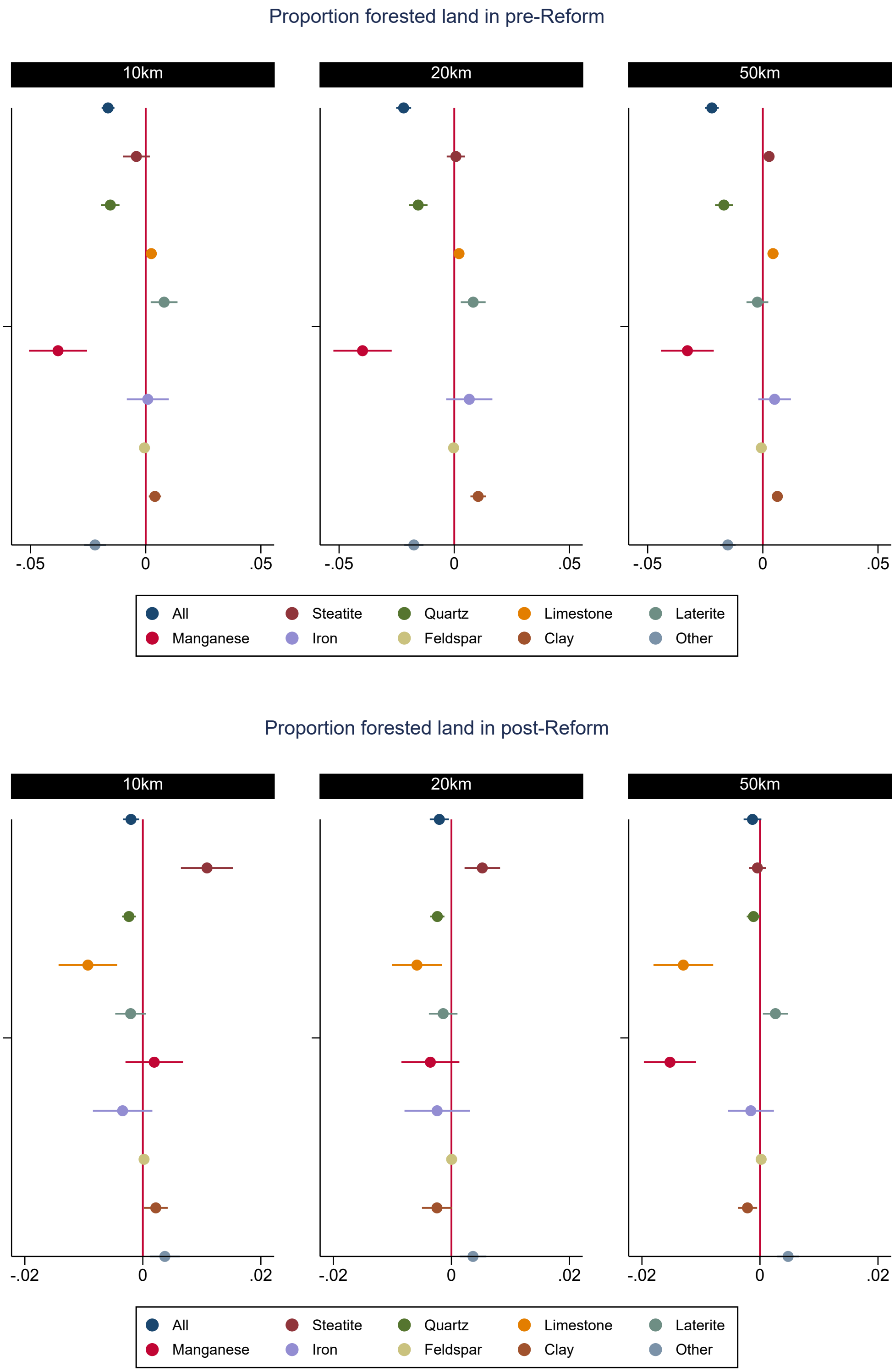


Figure E.2: IV estimates of the impact of a mine execution on proportion of forested land before and after the 2006 Reform, by mineral.

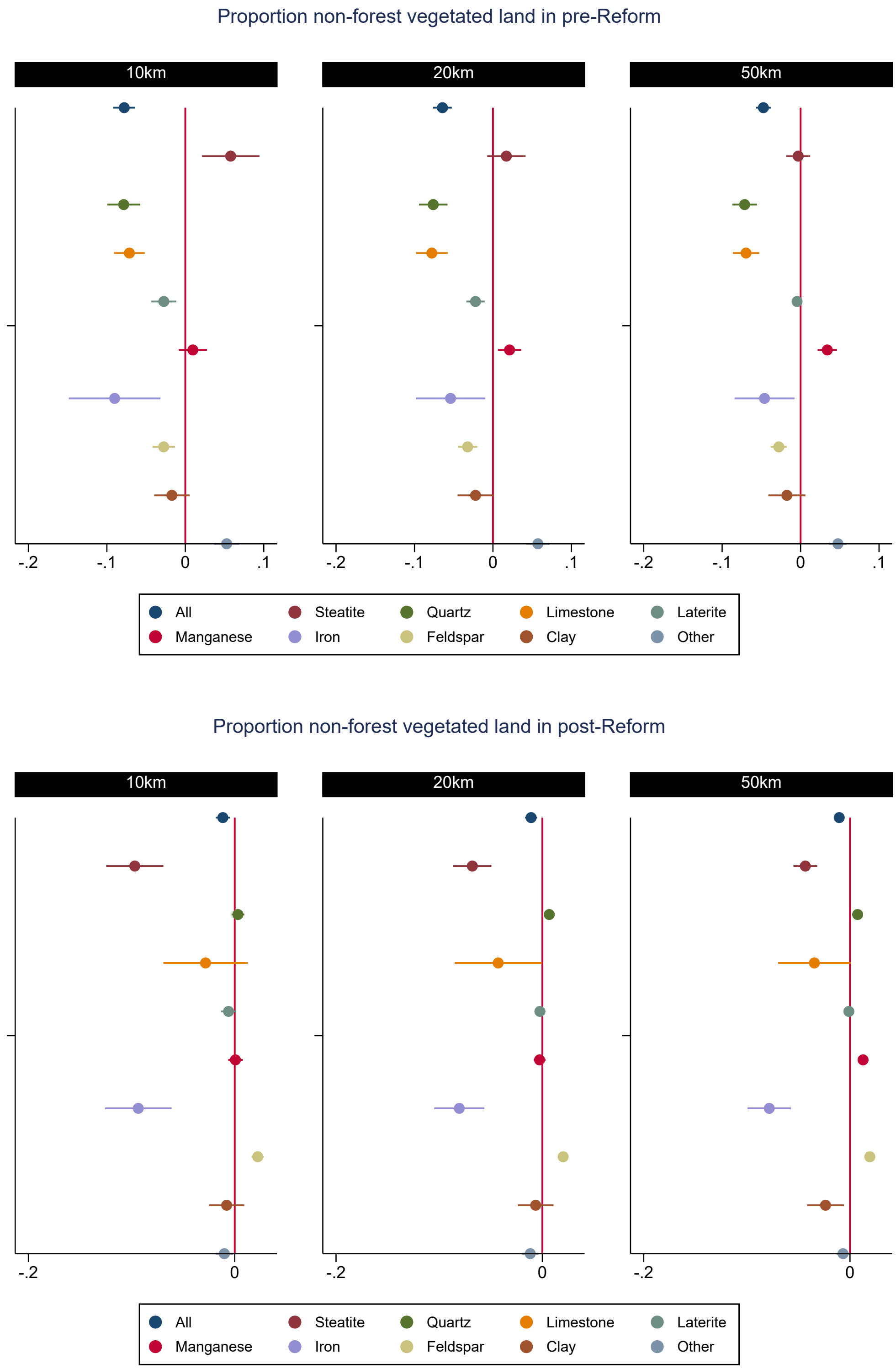


Figure E.3: IV estimates of the impact of a mine execution on proportion of non-forest vegetated land before and after the 2006 Reform, by mineral.

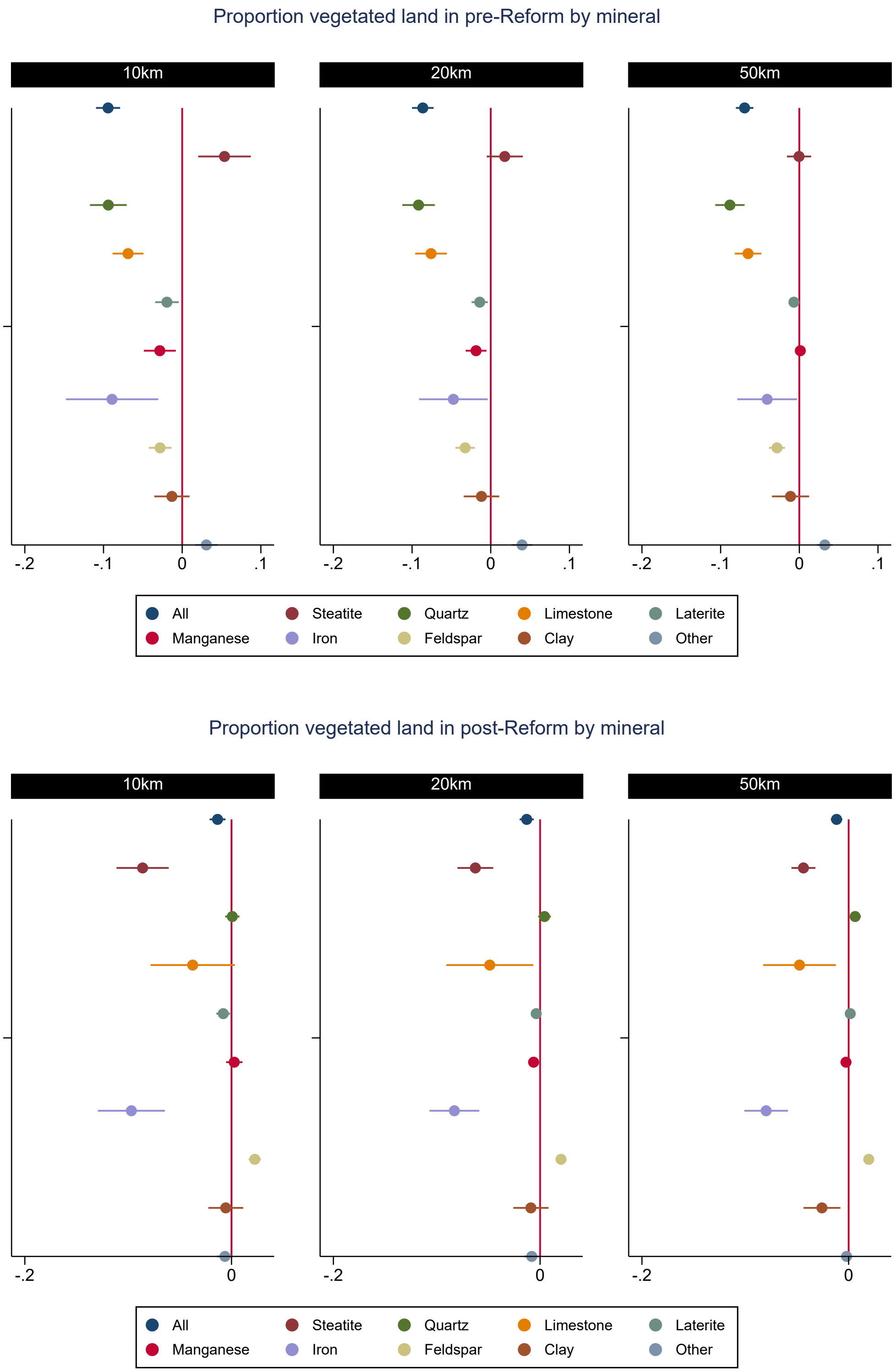


Figure E.4: IV estimates of the impact of a mine execution on proportion of forested and vegetated land before and after the 2006 Reform, by mineral.

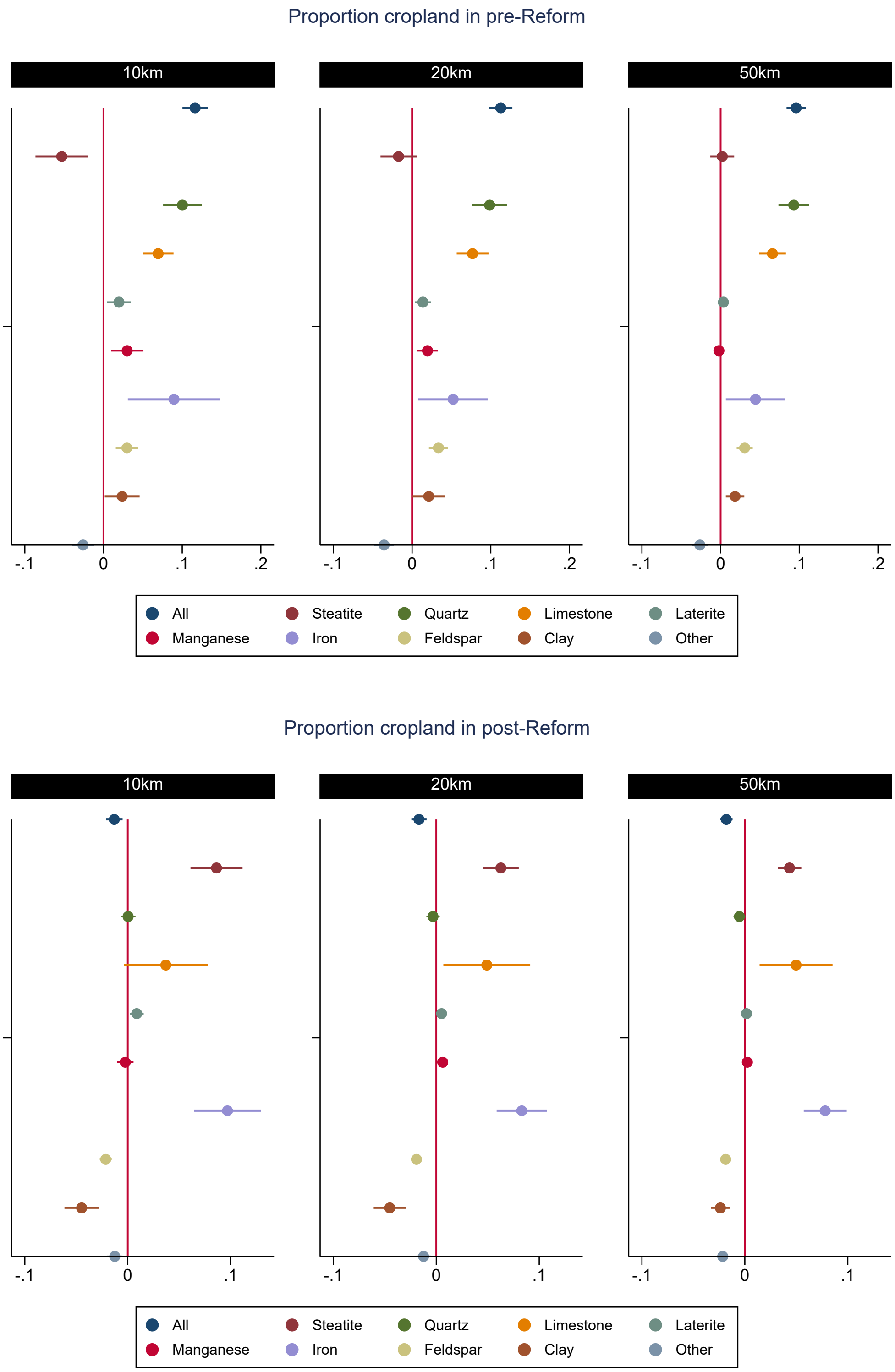


Figure E.5: IV estimates of the impact of a mine execution on proportion of cropland before and after the 2006 Reform, by mineral.

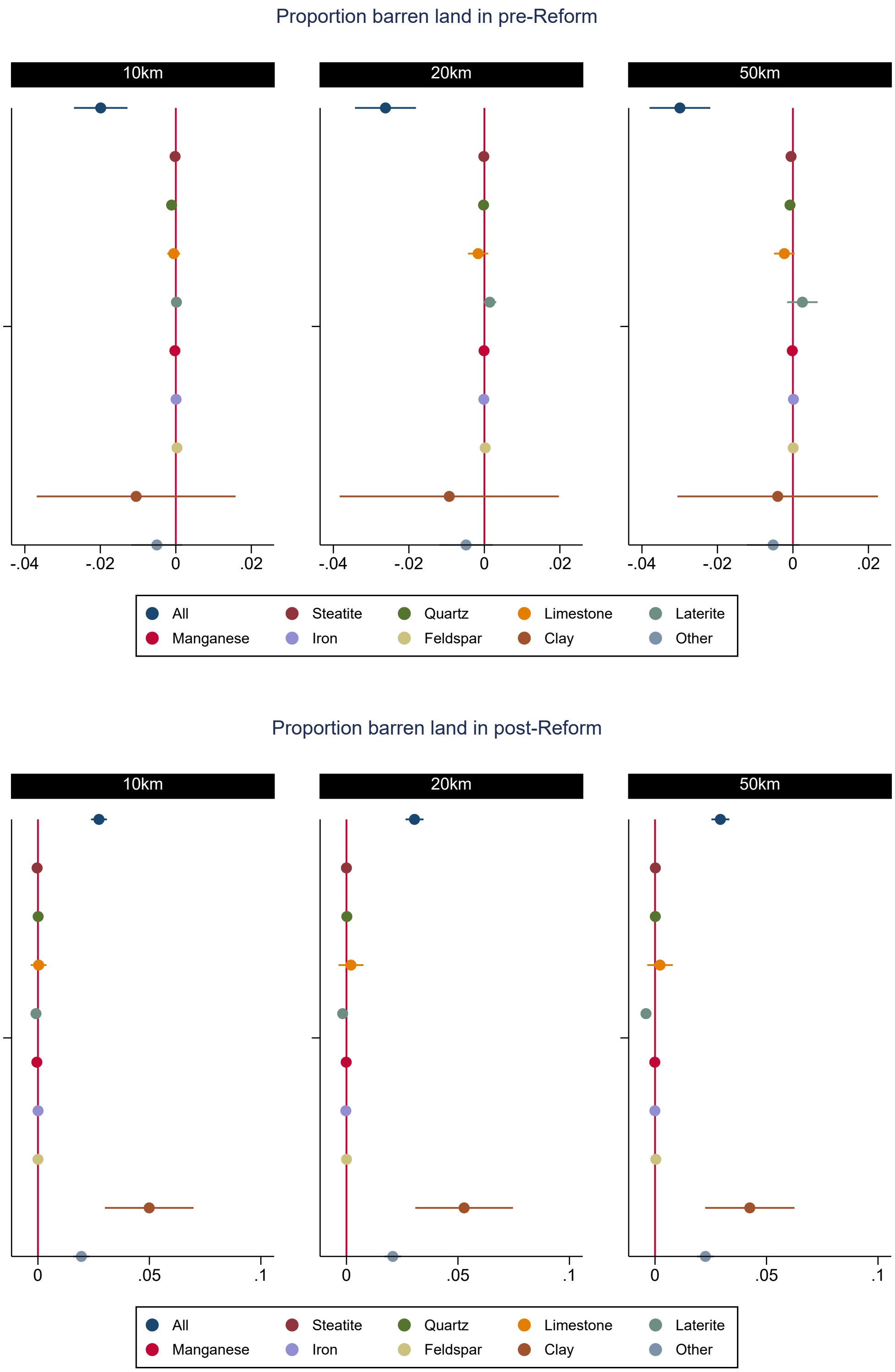


Figure E.6: IV estimates of the impact of a mine execution on proportion of barren land before and after the 2006 Reform, by mineral.

E.B IV Results by mineral: Tables

Table E.1: Log PM2.5 and total number of mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.041***	-0.014**	-0.022***	-0.051***	0.045***	-0.005	0.014	0.078***	0.005	-0.073***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N post	0.005*	0.020***	-0.010***	0.010	0.027***	-0.003	0.037***	0.029***	0.032***	0.021***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Obs	49,857	1,853	16,374	7,832	1,666	1,292	1,480	6,876	2,987	17,019
R^2	0.984	0.990	0.988	0.972	0.987	0.994	0.990	0.915	0.967	0.980
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.060	0.000	0.000	0.000

Table E.2: Log PM2.5 and total number of mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.041***	-0.009	-0.020***	-0.054***	0.045***	-0.003	0.010	0.078***	0.005	-0.072***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N post	0.007**	0.021***	-0.008***	0.008	0.029***	-0.002	0.035***	0.029***	0.031***	0.022***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Obs	49,857	1,853	16,374	7,832	1,666	1,292	1,480	6,876	2,987	17,019
R^2	0.984	0.991	0.990	0.970	0.987	0.995	0.991	0.918	0.970	0.981
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.060	0.000	0.000	0.000

Table E.3: Log PM2.5 and total number of mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.041***	-0.006	-0.025***	-0.056***	0.042***	0.003	-0.001	0.073***	-0.000	-0.066***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
N post	0.009***	0.023***	-0.008***	0.011	0.030***	0.001	0.036***	0.028***	0.031***	0.029***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Obs	49,857	1,853	16,374	7,832	1,666	1,292	1,480	6,876	2,987	17,019
R^2	0.987	0.993	0.992	0.971	0.989	0.996	0.992	0.932	0.975	0.984
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.060	0.000	0.000	0.000

Table E.4: Nr pixels forest loss and number of new mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	5.794	30.440	-57.821	0.935	-189.068	109.951	38.817	21.418	85.193	-38.641
	(78.59)	(25.59)	(86.40)	(72.59)	(228.11)	(111.11)	(118.04)	(35.18)	(68.27)	(60.92)
N post	316.905***	45.230**	275.455***	263.547	406.360	20.131	-257.954*	-21.774	54.582	162.773*
	(71.80)	(22.97)	(71.71)	(184.96)	(308.08)	(61.75)	(156.64)	(27.08)	(40.72)	(87.34)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.284	0.727	0.157	0.619	0.471	0.670	0.475	0.593	0.561	0.461
K-Paap	0.007	0.983	0.083	0.683	0.999	0.101	0.087	0.001	0.834	0.364

Table E.5: Nr pixels forest loss and number of new mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-19.202	115.189	-277.222	266.590	-469.035	23.972	-30.084	62.446	372.304*	-313.780*
	(242.87)	(73.70)	(316.06)	(178.41)	(558.88)	(327.58)	(303.43)	(95.59)	(225.11)	(183.05)
N post	1046.051***	122.325*	1040.462***	827.767*	707.786	-238.654	-521.408	-44.290	165.974	509.175*
	(221.91)	(66.15)	(262.32)	(454.59)	(754.82)	(182.06)	(402.63)	(73.56)	(134.26)	(262.46)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.347	0.833	0.193	0.683	0.641	0.601	0.630	0.653	0.614	0.588
K-Paap	0.007	0.983	0.083	0.683	0.999	0.101	0.087	0.001	0.834	0.364

Table E.6: Nr pixels forest loss and number of new mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-366.436	1279.340*	-465.691	2749.432***	-2108.776	1720.901	-1107.376	167.412	4152.493**	-1099.911
	(1170.77)	(725.36)	(1358.18)	(798.72)	(3462.08)	(1291.22)	(1183.96)	(357.45)	(1620.50)	(908.99)
N post	5276.155***	-848.263	4251.900***	4407.977**	8431.392*	-725.089	-763.236	-190.255	1012.755	2699.095**
	(1069.72)	(651.15)	(1127.25)	(2035.13)	(4675.83)	(717.63)	(1571.03)	(275.08)	(966.54)	(1303.31)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.453	0.816	0.429	0.676	0.347	0.765	0.754	0.745	0.625	0.714
K-Paap	0.007	0.983	0.083	0.683	0.999	0.101	0.087	0.001	0.834	0.364

Table E.7: Proportion forest and total number of mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.016***	-0.004	-0.015***	0.002**	0.008***	-0.038***	0.001	-0.001***	0.004***	-0.022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
N post	-0.002***	0.011***	-0.002***	-0.009***	-0.002	0.002	-0.003	0.000***	0.002**	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.980	0.991	0.958	0.990	0.998	0.982	0.994	0.992	0.977	0.969
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.8: Proportion forest and total number of mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.022***	0.001	-0.016***	0.002**	0.008***	-0.040***	0.007	-0.000	0.010***	-0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
N post	-0.002**	0.005***	-0.002***	-0.006***	-0.001	-0.004	-0.002	0.000	-0.002*	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.974	0.996	0.972	0.992	0.998	0.985	0.994	0.994	0.965	0.979
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.9: Proportion forest and total number of mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.022***	0.003***	-0.017***	0.004***	-0.002	-0.033***	0.005	-0.001***	0.006***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
N post	-0.001*	-0.000	-0.001*	-0.013***	0.003**	-0.015***	-0.002	0.000**	-0.002**	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.975	0.999	0.976	0.988	0.997	0.988	0.996	0.997	0.980	0.985
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.10: Proportion non-forest vegetated land and total number of mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.078***	0.058***	-0.079***	-0.071***	-0.027***	0.010	-0.090***	-0.027***	-0.017	0.053***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
N post	-0.011***	-0.097***	0.003	-0.028	-0.006	0.001	-0.093***	0.022***	-0.008	-0.010**
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.963	0.975	0.949	0.959	0.995	0.991	0.949	0.873	0.957	0.977
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.11: Proportion non-forest vegetated land and total number of mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.064***	0.017	-0.076***	-0.078***	-0.022***	0.021***	-0.054**	-0.032***	-0.022*	0.057***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
N post	-0.011***	-0.068***	0.007**	-0.043**	-0.002	-0.003	-0.081***	0.020***	-0.006	-0.012***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.967	0.988	0.951	0.943	0.996	0.991	0.958	0.901	0.945	0.976
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.12: Proportion non-forest vegetated land and total number of mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.047***	-0.003	-0.071***	-0.070***	-0.004	0.034***	-0.046**	-0.028***	-0.017	0.048***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
N post	-0.010***	-0.043***	0.007***	-0.035*	-0.001	0.013***	-0.078***	0.019***	-0.024***	-0.007**
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.970	0.994	0.953	0.929	0.997	0.992	0.942	0.886	0.903	0.980
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.13: Proportion vegetated land and total number of mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.094***	0.054***	-0.094***	-0.069***	-0.019**	-0.028***	-0.089***	-0.028***	-0.013	0.031***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
N post	-0.014***	-0.086***	0.001	-0.038*	-0.008**	0.003	-0.097***	0.023***	-0.006	-0.006
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.963	0.985	0.947	0.964	0.997	0.993	0.963	0.881	0.959	0.985
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.14: Proportion vegetated land and total number of mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.086***	0.018	-0.092***	-0.076***	-0.014***	-0.019***	-0.047**	-0.032***	-0.012	0.040***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
N post	-0.013***	-0.063***	0.004	-0.049**	-0.004	-0.006**	-0.083***	0.020***	-0.009	-0.008**
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.966	0.993	0.952	0.952	0.998	0.996	0.974	0.915	0.948	0.985
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.15: Proportion vegetated land and total number of mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.069***	-0.000	-0.088***	-0.065***	-0.007**	0.001	-0.041**	-0.028***	-0.011	0.032***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)
N post	-0.012***	-0.044***	0.006**	-0.048***	0.002	-0.003**	-0.080***	0.019***	-0.026***	-0.002
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.971	0.996	0.956	0.949	0.999	0.999	0.966	0.908	0.908	0.989
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.16: Proportion crops (min 0.6) and total number of mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	0.116***	-0.053***	0.100***	0.069***	0.020**	0.030***	0.090***	0.030***	0.024**	-0.026***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
N post	-0.013***	0.086***	0.000	0.037*	0.009**	-0.002	0.097***	-0.021***	-0.045***	-0.013***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.965	0.985	0.946	0.966	0.997	0.993	0.966	0.908	0.968	0.989
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.17: Proportion crops (min 0.6) and total number of mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	0.113***	-0.017	0.099***	0.077***	0.014***	0.020***	0.052**	0.034***	0.021**	-0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
N post	-0.017***	0.063***	-0.003	0.049**	0.005**	0.006**	0.083***	-0.019***	-0.045***	-0.012***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.968	0.993	0.950	0.958	0.998	0.996	0.977	0.924	0.970	0.990
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.18: Proportion crops (min 0.6) and total number of mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	0.096***	0.002	0.093***	0.066***	0.004	-0.002	0.044**	0.031***	0.018***	-0.026***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)
N post	-0.018***	0.043***	-0.005*	0.050***	0.002	0.002*	0.078***	-0.019***	-0.024***	-0.021***
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.976	0.997	0.957	0.963	1.000	0.999	0.974	0.921	0.990	0.992
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.19: Proportion barren land and total number of mines, 10km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.020***	-0.000**	-0.001***	-0.001	0.000	-0.000	0.000	0.000***	-0.011	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N post	0.027***	-0.000***	0.000**	0.000	-0.001***	-0.000**	0.000*	0.000	0.050***	0.020***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.834	0.584	0.895	0.922	0.998	0.937	0.958	0.960	0.775	0.953
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.20: Proportion barren land and total number of mines, 20km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.026***	-0.000*	-0.000***	-0.002	0.001	-0.000	-0.000	0.000***	-0.009	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N post	0.031***	-0.000	0.000***	0.002	-0.002***	-0.000**	-0.000***	0.000	0.053***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.786	0.963	0.970	0.868	0.998	0.943	0.915	0.966	0.726	0.946
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

Table E.21: Proportion barren land and total number of mines, 50km radius

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N pre	-0.030***	-0.001	-0.001***	-0.002	0.003	-0.000**	0.000	0.000	-0.004	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N post	0.029***	0.000	0.000***	0.002	-0.004***	-0.000***	-0.000	0.000***	0.043***	0.023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Obs	40,950	1,526	13,468	6,440	1,372	1,064	1,204	5,656	2,450	13,958
R^2	0.788	0.999	0.943	0.939	0.992	0.965	0.980	0.944	0.764	0.940
K-Paap	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000

F Location selection

Figure F.1: Average PM2.5 and EVI outcomes in years $t-1$ and $t-2$

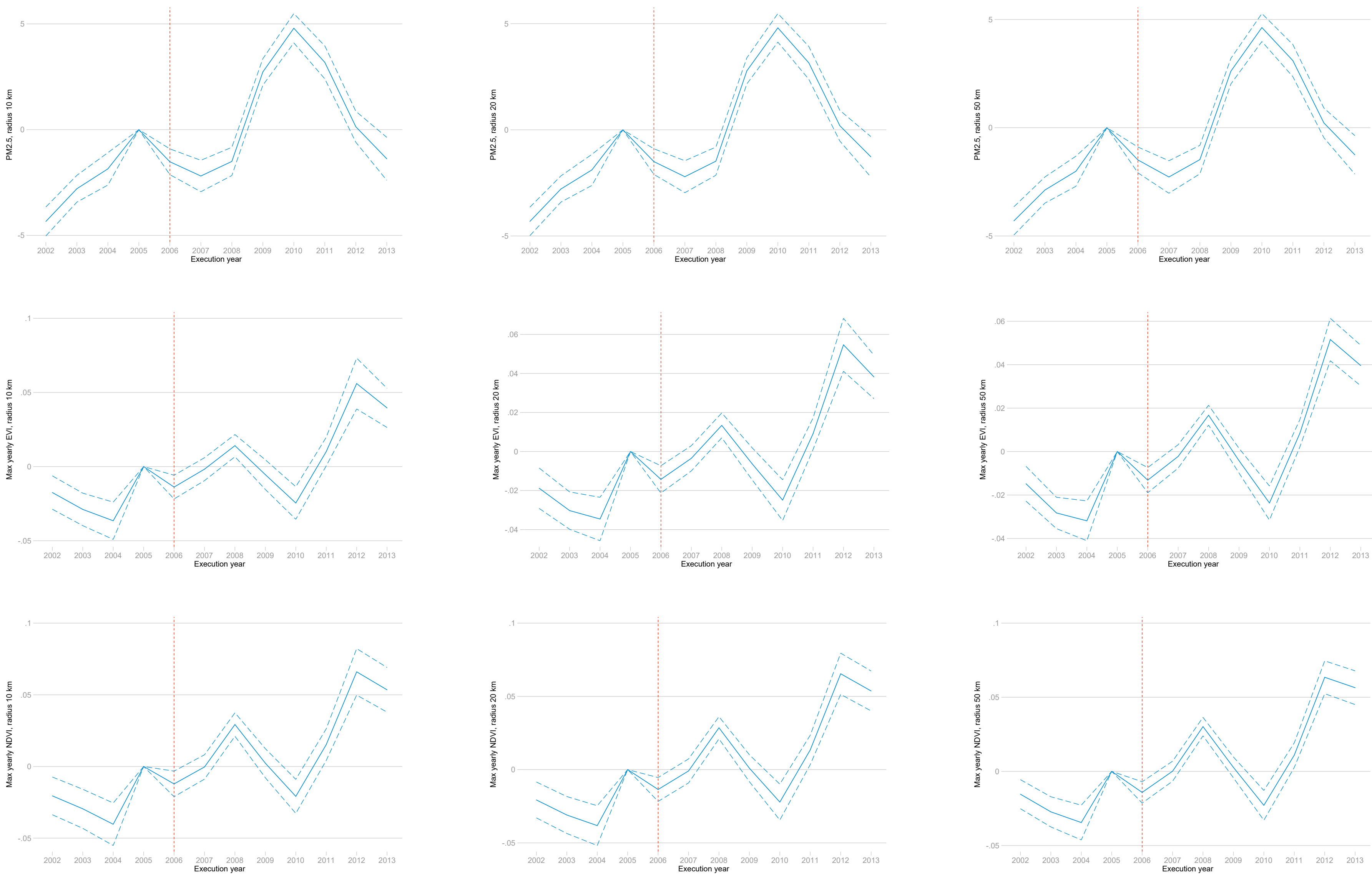
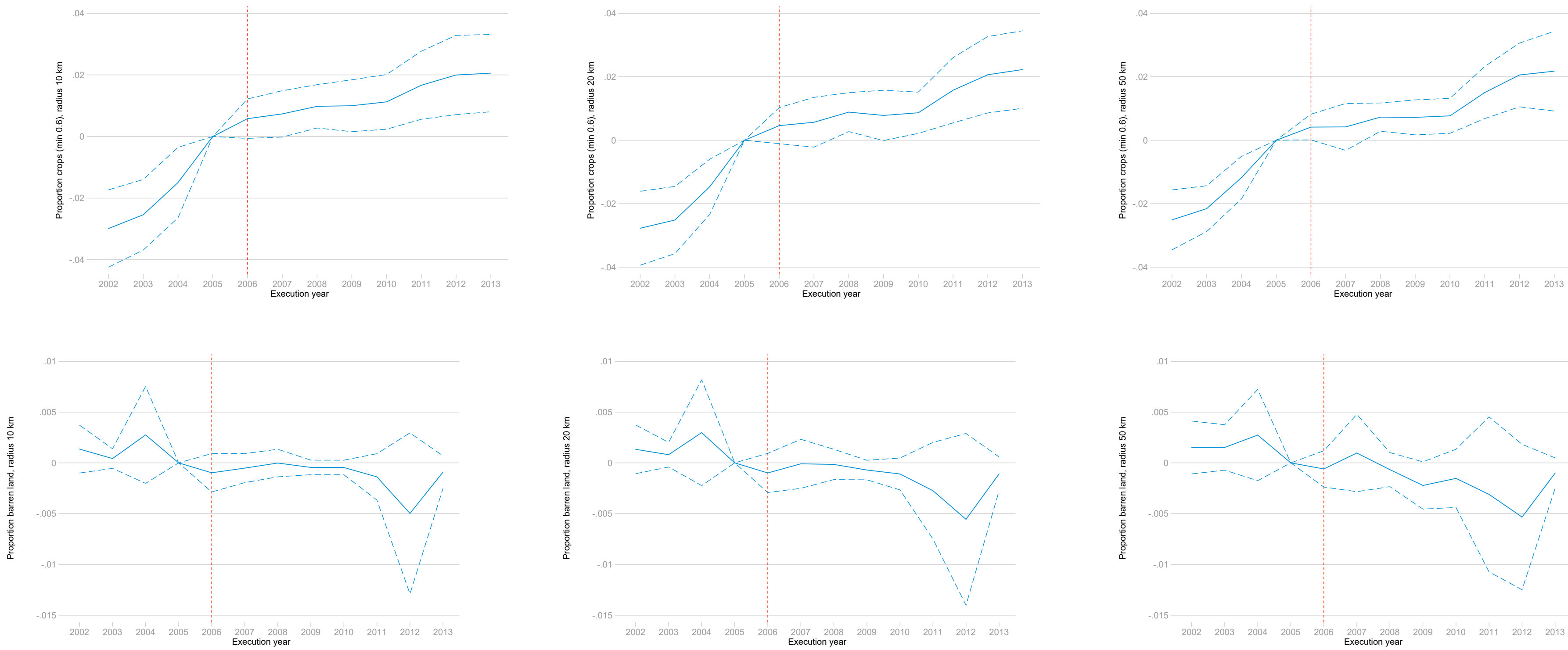


Figure F.2: Average forest loss, prop forests, and prop vegetated in years $t-1$ and $t-2$

Figure F.3: Average prop cropland and barren in years $t-1$ and $t-2$



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