Environmental Degradation in One's Own Backyard: Who Gains and Who Loses from Sand Mining in India

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Abstract

River and beach sand, the primary raw material for modern construction, accounts for 85% of global mineral extraction. The large-scale extraction of sand from fragile riverine ecosystems is widely believed to have significant environmental consequences, especially in developing countries undergoing construction booms and operating with weak environmental oversight. However, the true magnitude of these effects, their influence on social and economic outcomes in nearby communities, and the distribution of these impacts across affected populations remain poorly understood. This project integrates novel administrative data with satellite imagery within a difference-in-differences framework to estimate the causal effects of sand mining in Bihar, India. Our findings reveal that sand mining increases both inundation rates and frequency of flood incidents by 1.5 and 2 percentage points from a baseline rate of 10% and 10%, respectively. There is a 5% decline in agricultural production as measured by vegetation index. However, despite these negative effects, sand mining leads to a $\sim$ 10-20 % increase in local income, measured by nightlight intensity in villages surrounding mines. Within villages, this income growth is distributed across both relatively wealthier and relatively poorer communities. The positive effect is concentrated among the upper

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castes and OBCs. Our results provide a partial answer to the puzzle that rampant (and often illegal) sand mining exists in India with the support of local communities despite perceived harm and government restrictions. These results underscore the need for carefully designed policies governing natural resource extraction in low- and middle-income countries and, in particular, highlight the role of local communities in the success or failure of such policies.

1 Introduction

Economic growth and urbanization have spurred a decades-long global construction boom. Revenue in the construction market quadrupled from 2001 to 2020 by one measure, and the market size is projected to increase by another 25% in the span of only four years from 2023 to 2027 (Statista, 2021; AECOM, 2023). Physically, this development is built on sand. As a primary input for concrete, asphalt, cement, and glass, sand sourced from rivers and beaches accounts for 85% of global mineral extraction, making it the second most-used natural resource after water.[1]

Unlike higher-value mined resources, sand is both costly to transport and consumed at a massive scale. Annually, up to 50 billion tonnes of sand—equivalent to 14,500 pounds per person—are extracted from fragile ecosystems near human populations and economic activity, causing significant environmental disruption (Beiser, 2018). Sand mining is most prevalent and least regulated in developing countries undergoing construction booms. This activity is estimated to have caused a 90% reduction in sediment levels in major Asian rivers, potentially triggering severe environmental and social consequences, including increased flooding, aquifer depletion, salinization, ecosystem degradation, infrastructure damage, and more (Koehnken, 2018).

[1]Desert sand is not used for these construction and industrial purposes because sand grains created by wind erosion are too rounded to bind together. River and marine sand grains, eroded by the stronger force of water, are angular and better suited to be a building material. Since marine sand requires cleaning to filter out salt, river sand is the most preferred for construction and industry.

As environmental concerns have mounted, governments have responded with regulation. However, the combination of high economic rewards of sand mining, logistical difficulties, and political incentives have led to poor enforcement of these restrictions in developing countries, with large-scale illegal sand mining existing in at least 70 countries globally (Koehnken, 2018). Thus, a key policy challenge is to identify regulations that are both welfare-improving and enforceable by being incentive-compatible within local political economies.

Currently, however, there is a vacuum of rigorous evidence that would inform such policymaking. Sand mining in developing countries is a data-poor industry due to high rates of informality and illegality. As a result, quantitative research on sand mining is scarce, and basic questions remain open: how big exactly are the environmental impacts? Given these costs, why do so many river-adjacent communities seem to participate in the mining of sand in their own backyards? What are the net economic outcomes for local communities?

In this paper, we aim to begin filling that knowledge gap by providing what is, to our knowledge, the first data-driven accounting of sand mining's causal local costs and benefits and to whom they accrue. We do so in the context of India, where the construction sector accounts for 8% of GDP and the sand mining industry thrives (Mouterde, 2022; Baijal and Awasthi, 2023). While sand mining is widespread across several states in India, we focus our analysis on Bihar, which is one of the most flood-prone states in the country and where the Sone river is known as a source of high-quality construction-grade sand. We address three key questions: (i) What are the local environmental externalities of sand mining, particularly through effects on flooding and agricultural productivity? (ii) What are the local economic benefits of sand mining? and (iii) How are these economic benefits, if any, distributed among the local population?

To answer these questions, we combine satellite imagery with newly digitized administrative data, applying a staggered difference-in-differences framework. In India, sand mining operations require environmental clearance and permitting by both district and state governments, as mandated by the National Green Tribunal. Each district is also required to

publish a District Survey Report (DSR), which lists currently permitted sand mines as well as proposed sites likely to be auctioned in the future.

We digitize these DSRs to identify the location and timing of sand mining activity. This yields a sample of 584 existing sand mines, with permit dates ranging from March 2016 to April 27, 2021, and 585 proposed sites that remain untreated during our study period. Our identification strategy assumes that, within the same district and along the same river, areas near sites permitted earlier, later, or not yet permitted would have followed similar trends in outcomes absent treatment. This allows us to use staggered difference-in-differences estimators to isolate the causal effects of sand mining on environmental and economic outcomes.

Given concerns in recent econometric literature about the traditional two-way fixed effects (TWFE) estimator under treatment heterogeneity and staggered adoption (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2020), we use the estimator proposed by Borusyak et al. (2024) as our main specification. We also show that our results are robust to alternative estimators that account for these issues.

To measure the environmental consequences of sand mining, we focus on flooding, an oft-cited outcome of the gouging of the riverbank. Matching monthly gridded satellite data on inundation to active and potential sand mines, we find that sand mining leads to a significant increase of 1.5 p.p. in inundation rate and 2.1 p.p. in flooding incidents around active mining locations after the start of mining operations, compared to locations identified as potential mining sites where operations have not yet begun. This represents a 15% increase over the baseline inundation rate of 10% in areas around active mines, or a 21% increase over the baseline flood frequency of 10.0%. Although the increase in flooding provides only a partial measure of the environmental costs of sand mining, it is already economically significant.

How does sand mining affect agriculture—by shifting land and labor, reducing productivity through flooding, or enhancing it through mechanization, irrigation, or investment? To measure its net impact, we use vegetation index as the outcome variable. Our analysis shows

that sand mining causes a 5% decline in vegetation near mining sites. Part of this decline is likely mechanical, as mining operations clear land for truck access and transportation.

On the other hand, anecdotal evidence suggests that sand mines also present economic opportunities for locals, such as employment in mining or transport of sand or collection of tolls on land that sand-transporting trucks must pass through. To measure the local net economic effects, we obtain Black Marble gridded satellite-based nightlights data (Román et al., 2018) and aggregate it to villages containing the sand mines. We find that sand mining increases nightlights in the villages containing the mines relative to not-yet-treated and never-treated villages. The positive effect begins about one year following the granting of a sand mine permit, and grows to a medium-run effect of 1.2 units after 3 years. This result is robust to removing the grid cells overlapping with the mines themselves as well as a buffer area around the mines, indicating that the nightlights increase represents income growth for local residents rather than simply economic activity directly associated with the mine.

Finally, we explore how the economic benefits are distributed within the village. In Bihar, the layout of the typical village reflects caste-based communities. Higher-caste individuals, who have higher rates of landownership, may bear the brunt of losses to agricultural productivity through flooding and land degradation, but they may be able to compensate for these losses by charging tolls or rents to sand miners. Lower-caste individuals may also lose from decreases in agricultural labor demand as well as suffer direct damages to their homes that are more likely to be built in flood-prone areas. However, they are likely to be the ones benefiting from mining jobs. Whether each group gains or loses on net is therefore an empirical question, and since wealth and political clout are concentrated among high-caste communities, the within-village distribution of net costs or benefits is potentially key to understanding the local political economy that enables sand mining.

To measure the within-village distribution of sand mining's economic effects, we begin by classifying each populated 0.25 km^2 grid cell within a village as either relatively rich

or relatively poor, according to whether its pre-treatment period (2012-2015) nightlights intensity is above or below the 80%ile at the village level. Then, we estimate staggered difference-in-differences at the grid cell level, with richer cells in all villages as one sample and poorer cells in all villages as a separate sample. We find that sand mining caused nightlights to increase in both richer and poorer cells by $\sim 12\%$ and 18% respectively. The per capita percentage increase in nightlights for both rich and poor cells is $\sim 27\%$ and 36% respectively. This indicates that sand mining generates net economic benefits broadly for the whole village. In addition to analysis along the income distribution, we compare how different caste groups were effected by sand mining using data from NFHS. Our analysis indicates that the benefits of sand mining are concentrated among the upper castes and OBCs, and scheduled castes and tribes do not see positive effects.

In summary, we combine satellite data with novel administrative records from Bihar, India, to provide the first causal, quantitative evidence on the local impacts of sand mining. Consistent with widespread narratives, we find that sand mining causes economically and statistically significant increases in flooding and reductions in agricultural production. At the same time, it also spurs local economic activity, with benefits accruing to both rich and poor households.

These distribution of economic gains help explain why sand mining persists despite its costs. However, the benefits are not evenly distributed within the poor groups. Our analysis shows that positive effects are concentrated among Other Backward Classes (OBCs) and Upper Castes, who make up roughly 79% of Bihar's population and sit higher in the social hierarchy. Dalit and Tribal communities, comprising the remaining 21%, do not experience gains in household assets. For these groups, especially if they bear the brunt of increased flooding, sand mining is likely welfare-reducing.

Rather than a simple story of outsiders exploiting local communities, our findings suggest that sand mining can represent a rational choice for many local households—benefiting the majority while harming those at the bottom. Though our study focuses on legally

permitted mines, the results may help explain why illegal mining persists and why blanket bans, common across Indian states, have largely failed.

Much work remains to understand the long term welfare implications of sand mining. For example, if flooding impacts are persistent, will benefits continue into the longer-run when the local sand supply is exhausted? Do the economic gains from sand mining induce out-migration, human capital gains, or structural transformation, and do these enable the local communities to adapt to long-term environmental changes wrought by sand mining? How do policies that regulate the supply of sand affect macroeconomic outcomes through the costs of construction and urbanization?

Related literature and contributions This paper contributes to the growing body of research at the intersection of the political economy of the environment and the resource extraction literature. Prior work on resource extraction has documented both positive and negative effects of natural resource endowments. Mines and oil production have been shown to generate short-term local labor market benefits while also increasing the likelihood of conflict in contexts with weak governance (Dube and Vargas, 2013; Berman et al., 2017). The broader welfare implications of resource extraction often depend on local policies and market infrastructure, making them difficult to generalize. However, a recurring theme in the literature is that environmental pollution and its negative consequences disproportionately affect economically disadvantaged and socially marginalized communities (Banzhaf et al., 2019).

Sand mining in India presents a unique case for bridging the resource extraction literature with studies on the political economy of the environment, particularly regarding how governments and institutions attempt—or fail—to regulate externalities (Burgess et al., 2012). While much of the existing literature on resource extraction focuses on the effects of oil and mining in higher-income countries, particularly in relation to pollution and carbon emissions, it does not typically engage with issues of weak governance and conflict (Boomhower, 2019).

More broadly, this paper contributes to the literature on the environmental impacts of economic development in low- and middle-income countries (for a review, see (Jayachandran, 2022)). To our knowledge, this is the first study to causally estimate the environmental effects of sand mining, the most extracted mineral resource globally. We show that sand mining in Bihar significantly increases flooding in mining areas. At the same time, we find that villages near mining sites experience higher incomes—an outcome that is not obvious given that mining leases are typically awarded to external contractors rather than local actors.

Finally, we add to the literature on the distributional effects of resource extraction by examining why sand mining persists despite its environmental and social costs. Our findings suggest that both wealthy and poor households derive economic benefits from sand mining, which may explain its continued prevalence despite widespread concerns over its negative consequences.

This paper is organized as follows. In Section 2, we describe the background of sand mining and the setting in detail. In Section 3, we give a description of the data we use, our identification strategy and the evidence which supports that strategy. Section 4 focuses on the results of our empirical analysis and Section 5 concludes.

2 Background and Institutional Setting

Urbanization driven by economic development has generated an enormous demand for sand, a key input in concrete, which is the primary material of the construction industry. In India, which has thousands of rivers traversing its diverse landscapes, the demand for sand tripled between 2000 and 2017, creating a market worth over two billion USD (Mahadevan (2019)).

This sand is predominantly sourced from rivers and, in some cases, from beaches. Sand mining can be artisanal, where workers manually extract sand using their bare hands, placing it into containers. The extraction process varies depending on the location: near the shore, the sand is typically collected and dumped into piles, while in deeper riverbeds, workers dive

into the water to excavate sand from greater depths. However, most large-scale sand mining is carried out using excavators, which extracts sand from river floodplains or artificially created islands formed by obstructing the river's flow. Figure 1 shows excavators at a sand mine in the rural areas of Patna, India.

2.1 Sand mining in India

Sand mining is done by contractors who sell their output to large firms or directly to the market through intermediaries who purchase the product at the mine, transport it to the market in towns where it is sold at a mark up. In many cases, the production process is integrated and the same firm extracts, packages and sells sand. The buyers can buy sand either from depots (which are owned by large firms) or through intermediaries which sell freshly extracted sand in trucks in markets in urban areas. The contractors and firms that mine sand do so after leasing the land from the government. Given the fact that the business is extremely lucrative, a lease is provided after a competitive bidding process and generally lasts for 5 years.

A significant portion of the sand sold in markets is extracted illegally, meaning it is sourced from areas not leased or authorized by the government. Illegal sand mining takes various forms. In some instances, firms or contractors with legitimate leases extend their operations beyond the allotted mining coordinates. In other cases, local contractors extract sand from unauthorized areas and sell it on the market. These operations are often supported by muscle power sourced from villages near the mining sites. In this paper, we shall focus on the effects of legal sand mining.

Sand extracted from riverbeds is transported either directly to markets for sale or to depots for storage. The final leg of the transportation process is typically handled by trucks, which are often owned by locals from villages near the mining sites, providing economic benefits to the local population. Additionally, local workers are frequently employed to load sand onto the trucks. Since river transport is more cost-effective, boats are commonly used

to move sand to intermediate points, from where it is subsequently transported to markets. Figure B-4 shows how boat and trucks are used to transport sand.

Sand mining can damage the environment Carefully extracting sand from riverbeds within the river's natural replenishment limits does not necessarily harm the environment. However, excessive sand mining beyond these limits can alter the riverbed's structure and dynamics. Similarly, the overuse of heavy equipment can exacerbate these effects. Furthermore, certain sand mining practices are inherently damaging. For instance, in many cases, artificial bunds are constructed to partition a section of the river from the main stream for easier mining (see Figure 2). While this simplifies operations, it significantly disrupts the river's natural flow.

Such damage to the riverbed can have far-reaching consequences, including altered river flow patterns, an increased risk of the river overflowing its banks during the monsoon season, and water inundating previously unaffected areas. Recognizing the environmental harm caused by sand mining, the National Green Tribunal (NGT)—a statutory body established by the Indian Parliament to address cases of environmental damage—has issued guidelines for state authorities to follow when granting mining licenses. These guidelines aim to minimize the environmental impact of sand mining activities.

Additionally, the NGT has enacted measures such as banning mining activities during the monsoon season to reduce the risks associated with excessive mining. However, despite these efforts, reports from news outlets indicate that violations of these regulations remain widespread.



Figure 1: Sand excavator and trucks at a sand mine in Patna

Note: Image captured in March 2023



Figure 2: Cordoning off areas in sand mining.

Note: Image captured on Google Maps in 2023.

2.2 Sand mining leases

In India, state governments have the authority to lease land for sand mining. The responsibility for identifying suitable land falls on the *District Commissioner* of each district. As mandated by the NGT, every district must prepare a District Survey Report (DSR), which documents all current mining sites and potential locations for future sand mining.

Once identified, specific tracts of land are designated as mines and leased through an auction process, typically for five years. The DSRs allow us to map existing mines across districts, including Patna. They also list potential future mining sites, which we use as the control group in our analysis.

2.3 Benefits and losses from sand mining

Anecdotal evidence and our fieldwork highlight the diverse ways in which villagers can either gain or lose from sand mining activities. In some cases, individuals within the village may act as contractors operating the mine, resulting in direct but concentrated benefits for the community. Additionally, operating a mine often necessitates the construction of an informal road connecting the mine to the main road for sand transportation. Mine owners typically lease this land or compensate villagers who own it. If mining activities can impose significant costs on the village—such as flooding or reduced agricultural productivity—mine owners may seek to appease affected villagers by providing employment opportunities to those bearing the externalities.

For instance, villagers may be employed to load sand onto trucks, creating jobs for local workers. Furthermore, the sand transported by these trucks is sold at a markup in markets, and the trucks themselves are often owned by villagers, offering additional economic benefits to the community. For these reasons, villagers may prefer to have a sand mine in the village.

The costs of sand mining can be various. Mining can weaken riverbanks, making villages more vulnerable to frequent and severe flooding, especially during the monsoon season (Padmalal and Maya (2014)). The removal of sand destroys habitats for fish, plants, and

other aquatic life, reducing biodiversity, which can affect the livelihoods of households which rely on these. Excessive sand removal can lower the water table, reducing the availability of groundwater for irrigation and drinking purposes. Additionally, dust, noise, and pollution from mining operations and truck traffic can contribute to respiratory illnesses and reduced quality of life.

To understand why sand mining persists despite its apparent negative effects, it is critical to know how large the costs and benefits actually are, how they are distributed, and how the costs may be rationalized by villagers. At least the following are possible:

1. **Sand mining is rational**: the benefits exceed the costs for a majority of households in the village.

2. **Cooptation by the powerful**: Costs exceed benefits for a majority of individuals, and benefits are concentrated among a few. The benefits are monopolized by a few with power while the costs are spread among a larger group that faces transaction costs to organizing, or among people who do not have political power within the village.

3. **Time horizon shift**: Sand mining shortens the time horizon over which the villagers care about local environmental quality, by enabling them to leave agriculture or the village altogether before the costs are fully incurred.

4. **Behavioral**: Locals are not fully internalizing the costs, due to information frictions which prevent them from observing costs or due to their inability to attribute the observable costs to sand mining. For example, even if they experience increased flooding, they may hold incorrect beliefs about how much of it is caused by sand mining.

Each of these explanations holds different implications for sand management policy and the political economy of resource extraction.

3 Data and Empirical Strategy

3.1 Data

3.1.1 Sand mine locations and permitting dates

We begin by collecting District Survey Reports for districts in the state of Bihar. From each DSR, we use optical character recognition to extract the locations of active and proposed sand mining sites, and for the active mines, their dates of lease and dates of operation. For an example of the format of the data see Appendix Figure B-1. Since the quality of the DSR PDFs varies between districts, we use manual checks to ensure that each coordinate extracted using optical character recognition is accurate. For some districts, dates of permit leases were not available from the DSRs. In these cases, we obtain dates by parsing publicly available auction documents, and use the auction call date as the date when operations started. Finally, from the bounding coordinates of each mine as listed on the DSRs, we create mine polygons, each associated with a treatment status (active or proposed sand mine) and, for active mines, a treatment date.

Of Bihar's 38 districts, 21 contain major rivers. We obtained DSRs with permit leasing dates for 16 of these districts, covering nearly all those south of the Ganga River. This region produces yellow feldspathic sand, highly valued for construction, unlike the less valuable white silica sand found in northern Bihar. As a result, our sample includes nearly all districts where large-scale sand mining is likely to occur.

To validate the location of sand mines, we randomly selected 51 out of 1,200 mine sites and manually checked them using Google Maps satellite imagery. We verified whether an active sand mine exists at the centroid of an identified mine polygon and whether no sand mine is present at the centroid of a proposed mine polygon. Table 1 summarizes the results.

For most sites listed as active mines in the DSRs, a sand mine is visible at or near the designated location—where the imagery is clear enough to confirm. Figure 3a illustrates an example. Similarly, for the majority of proposed mine sites, we do not see evidence of mining

activity, as shown in Figure 3b. However, four of the 16 proposed mine sites do show signs of mining, possibly because operations began after the DSRs were published in 2021.

Table 1: Random checks with Google Maps satellite imagery

Mining visible at centroid?	% of Existing	% of Proposed
Yes	48.6	6.2
Probably	2.9	6.2
Mining closeby	22.9	12.5
Probably not	8.6	25.0
No	0.0	37.5
Image unclear	17.1	12.5
N	35	16



(a) Example of "Yes"

(b) Example of "No"

Figure 3: Examples of Google Maps satellite imagery of locations with and without a sand mine

3.1.2 Flooding

Our flood measure comes from the JRC Monthly Water History dataset (Pekel et al. (2016)), which provides a monthly binary measure of pixel inundation. To define the area surrounding each mine for assessing flooding impacts, we begin by creating a 500-meter radius buffer around the centroid of each mine. However, when mines are located close to one another, their buffers may overlap, leading to potential double counting of affected areas. To prevent this, we merge all contiguous overlapping buffers into a single, unified observation unit. For example, if mines A, B, and C are in proximity and the buffers of A and B as well as A and C overlap, we consolidate all three into a single merged shape, ensuring that each affected area is counted only once.

We use data from 2000 onward to measure flooding in two ways. Within the truncated circle around each potential or existing sand mine, we calculate the percentage of 30m x 30m cells inundated each month. Our first measure, an area-based flooding metric, is the average inundation rate for the months from July to December, as these months are most prone to flooding.

Our second, month-based measure accounts for missing inundation data due to cloud cover, which varies by year. To establish a baseline, we calculate the long-run mean inundation rate for each month from 2004 to 2009. For each month-year combination, we classify a site as flooded if the inundation rate is at least 20% higher than its month-specific long-run mean (**?**). We then aggregate this binary measure across July-December to capture annual flooding incidents. Our empirical analysis uses panel data at the mine $\times$ year level. To prevent spillover effects from existing mines, we exclude proposed mines located within 500 meters of an active mine from our sample.

3.1.3 Nightlights data

We obtain monthly gridded nightlights data for 2012-2023 at the 15 arc-second (approximately 0.5km) resolution from NASA's Black Marble product. Black Marble is derived from the satellite imagery collected by the VIIRS instrument, but compared to previous VIIRS nightlight products, it is better-suited for tropical low and middle-income countries like India where cloud cover is persistent and many areas have low nightlight intensity. In particular, it has improved sensitivity to low-intensity lights, better accounts for seasonal variation, and employs "temporal-gap filling" to reduce persistent data gap (Román et al., 2018).

For the village-level nightlights analysis, we exclude cells with centroids inside active sand mines. We then average the remaining cells within each village to create a village $\times$ month panel of nightlights. Finally, we aggregate the data from monthly to yearly values.

For the cell-level nightlights analysis, we remove cells overlapping with active sand mines, as well as cells with estimated baseline 2015 population of less than 10. From the remaining

cells, we calculate the village-specific baseline (2012-2015) nightlights value at the 80^{th} percentile, and classify each cell as either relatively rich or relatively poor based on whether its baseline value is above or below this value.

3.1.4 Vegetation Data

To measure agricultural production, we obtain gridded data of the Enhanced Vegetation Index (EVI) at a 16-day, 250m resolution, from 2012-2024, from the MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid data product, Version 6.1 (Didan (2021)). Where granular data on agricultural production is not available, vegetation indices are a commonly used proxy (Didan et al. (2015), Burke and Lobell (2017)). Among vegetation indices, the EVI has several advantages over the Normalized Difference Vegetation Index (NDVI), including better differentiating vegetation levels in areas with either high biomass or sparse vegetation, and correcting for the influence of aerosols and haze (Huete et al. (2002)). For the 500m buffer around each mine centroid and each 16-day window, we extract the average EVI by taking the mean value of all 250m cells overlapping with the buffer. The 16-day values are then aggregated to the annual level.

3.1.5 Other data

Village-level polygons, Census data, and Trivedi elections data were downloaded from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (Asher et al. (2021)).

For grid cell-level population estimates, we obtain 3 arc-second resolution gridded 2015 (pre-mining) population data from GHS-POP (Schiavina et al. (2023)), a product of the Global Human Settlement Layer, which uses satellite imagery of built-up areas to downscale administrative population data. We aggregate this up to a 15 arc-second resolution to match the Black Marble nightlights data.

3.2 Identification strategy

In our analysis, focusing on the state of Bihar, causal inference is made possible by the fact that each district in India is required by the National Green Tribunal to publish a District Survey Report (DSR) listing the locations of both active, permitted sand mines and proposed potential sand mines that are likely to be auctioned for permits in the future. Our identifying assumption is that, within the same district and along the same river, there would be parallel trends in our outcome variables between areas around sites with active sand mining permits granted earlier versus later, and with areas around "potential" sand mining sites, in the absence of sand mining.

We estimate the effect of sand mining on any given outcome Y as follows. For proposed and existing sand mining sites i, on rivers r, in districts d, at year t, we estimate static and dynamic versions of

$$Y_{irdt} = \beta treat_i * post_t + \alpha_i + \delta_{rdt} + \varepsilon_{irdt} \tag{3.1}$$

where $treat_i = 1$ if the mine becomes operational and $post_t = 1$ after the mine becomes operational.[2]

Under our parallel trends assumption, β represents the ATT for sites where mining has begun. Our primary specification uses the imputation estimator proposed by Borusyak et al. (2024). This choice reflects a key feature of our setting: while the DSRs provide the date of lease or auction, the actual start of mining operations is uncertain. In some cases, mining may begin after the lease is granted; in others, it may start beforehand due to irregularities in the permitting process. Given this uncertainty, relying on the period immediately preceding the reported treatment date as a baseline is potentially unreliable. The imputation estimator addresses this by using the average of all pre-treatment periods to construct the

[2]The dynamic version is:

$$Y_{irdt} = \Sigma_{\tau=-4}^{\tau=4} \beta_\tau D_{it}^\tau * treat_i + \alpha_i + \delta_{rdt} + \varepsilon_{irdt} \tag{3.2}$$

where D_{it}^τ is a dummy variable that indicates that whether a mine i started operating τ periods earlier or will start operating τ periods after.

counterfactual, providing a more stable reference point. To ensure our findings are not sensitive to this choice, we also test robustness using alternative estimators—specifically those of Sun and Abraham (2021) and Callaway and Sant'Anna (2020)—which rely on the last pre-treatment period as the comparison baseline.

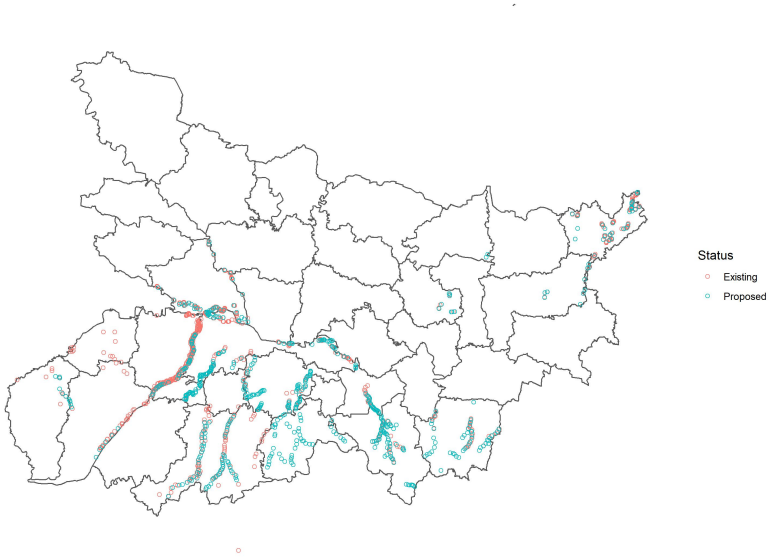
Since flooding is a physical phenomenon, our flooding analysis uses truncated circles with a 500m radius around the centroid of each mining site as the unit of analysis (i), as described in Section 3.1. This approach isolates the geographical area most likely to be affected by increased flooding, if it occurs. We apply a similar method when analyzing effects on vegetation.

For the nightlights analysis, however, we aggregate data at the village level (i= village). Since rivers rarely run through the center of villages, sand mines are often located at their edges. Aggregating at the village level allows us to capture changes in residential and commercial areas, even if they are not adjacent to a sand mine. Finally, for our analysis of distributional effects, we use grid cells as the unit of analysis (i= grid cell).

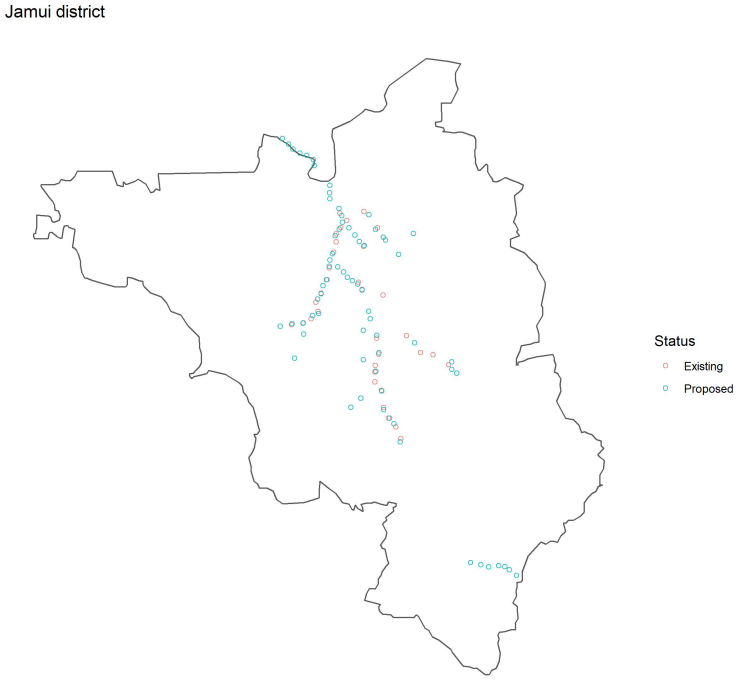
3.3 Support for parallel trends assumption

To empirically assess the plausibility of the parallel trends assumption, we begin by mapping the sites with existing and proposed leases. Figure 4a maps the centroids of existing and proposed sand mines in Bihar, and Figure 4b zooms into one district. Within any given district, the existing and proposed mines are well-interspersed, so it does not appear to be the case that timing of leases correlates with potential confounders such as being more up- or downstream along the river or distance from markets or urban areas.

Next, we check for pre-trends in economic and demographic variables in the villages around existing and proposed mines. We use the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (Asher et al. (2021)) to access village-level Population Census Abstract data from the 1991, 2001, and 2011 Censuses. For different demographic and public goods variables at the village level we perform two kinds of comparisons between



(a) Mine locations in Bihar



(b) Mine locations in Jamui district

Figure 4: Centroids of existing and proposed sand mines

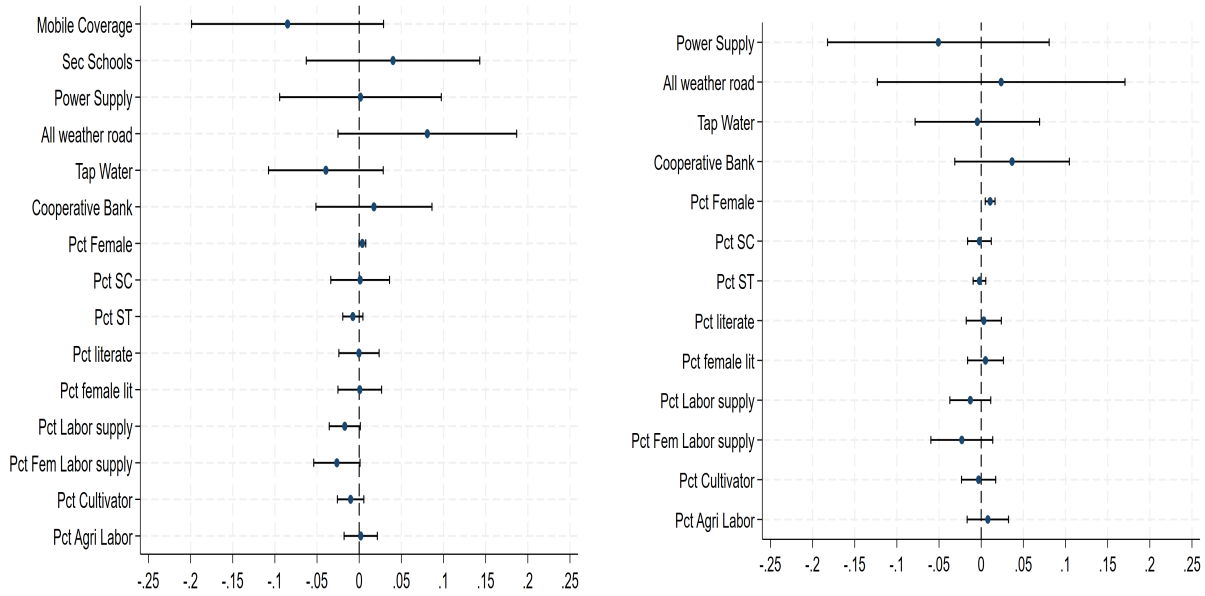
villages which had an operational mine by 2020 and those which had a potential mine. First, we compare the cross-sectional differences on these variables in 2011 (see Figure 5a). The treated and control villages are similar across most variables. Then in Figure 5b, we compare the change in these variables between 2001 and 2011 across the two types of villages. The figure clearly illustrates that the trend in change for the decade was not different between the treatment and control village.

Finally, one may be concerned that the timing of when a sand mining permit is granted in a village could be related to the village's political connections, posing a threat to the parallel trends assumption. Although we cannot test for balance in a comprehensive way - for example, we do not know of any publicly available data on district government officials' villages of origin, we can check for balance on state assembly election outcomes. Although sand mining sites are chosen and auctioned off by the district government rather than the legislative assembly, it is possible that members of the legislative assembly (MLAs) hold some informal influence over these decisions.

Bihar held state assembly elections in 2015 and 2020. In our sample of existing and proposed mines, 96% of existing mines received their permit in 2016-2020, so we check for balance based on 2015 election results. In that election, the parties winning the most assembly constituency (AC) seats were the RJD, JD(U), and BJP, in that order. The RJD, JD(U), and INC formed the ruling coalition that held a majority in the assembly. In July 2017, that coalition fell apart and a new ruling coalition formed between the JD(U), BJP, and LJP.

Appendix Table B-1a shows mine-level correlations between the party of the elected MLA and sand mine permit status. There is no significant correlation between MLA party affiliation and either the probability of having been treated (i.e. granted a permit) by 2021, when our DSR data was published, or the year in which treated mines were granted their permits. In Appendix Table B-1b, we aggregate the mines to the AC level. We find that among the 78 ACs containing any existing or proposed mines, the party of the elected MLA

Figure 5: Balance in Observable Characteristics



(a) Levels in 2011

(b) Change from 2001 to 2011

Notes: This figure studies differences between villages closest to treated and potential mines control group in an array of observable characteristics, prior to treatment. Panel A presents the coefficient obtained from a regression of each variable on a dummy that equals 1 if the village is close to a treated mine. The regression includes fixed effects for district * river. Panel B replicates the analysis but replaces the dependent variable with its first difference between 2011 and 2001.

is not significantly correlated with the total number of existing and proposed mines, the share of existing mines in that total, or the timing of existing mines' permits. Although the coefficient on RJD in Column (1) is large, this is to be expected as the RJD's support base is primarily cultivators who tend to live near rivers, where sand mining is more prominent for purely geographical reasons. As such, many of the prime locations for sand mining happen to be in RJD ACs. There is also no significant or consistent correlation between the number of sand mine permits an AC receives in a given year and whether the MLA's party is in the ruling coalition during that year.

4 Results

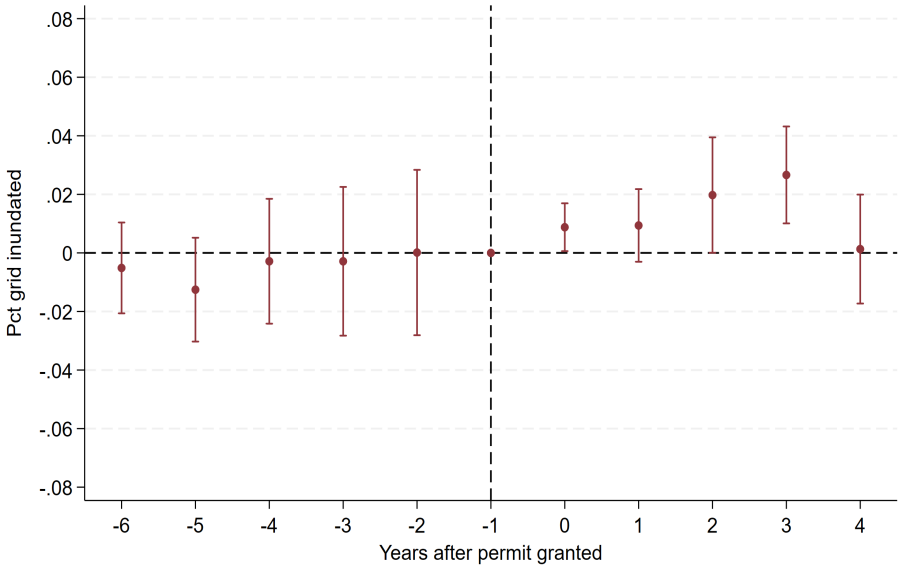
4.1 Effects on flooding

In this section we present static and dynamic difference-in-differences estimates on flooding. In Table 2, our static results indicate that within 500m of a sand mine, mining increases inundation rates by 1.5 p.p., which represents a 15 % increase over the pre-mining baseline of 10% in areas around active mines. For our second, month-based flooding measure, within 500m of sand mines, there is a 2.1 p.p. increase in the proportion of months with an incident of flooding, which represents a 21 % increase over the baseline of 10 %. Figure 6 show the event study coefficients from dynamic imputation estimator. The results from the event study are consistent with the static estimates. They show that the increase in flooding persists at least four years following the opening of a sand mine.

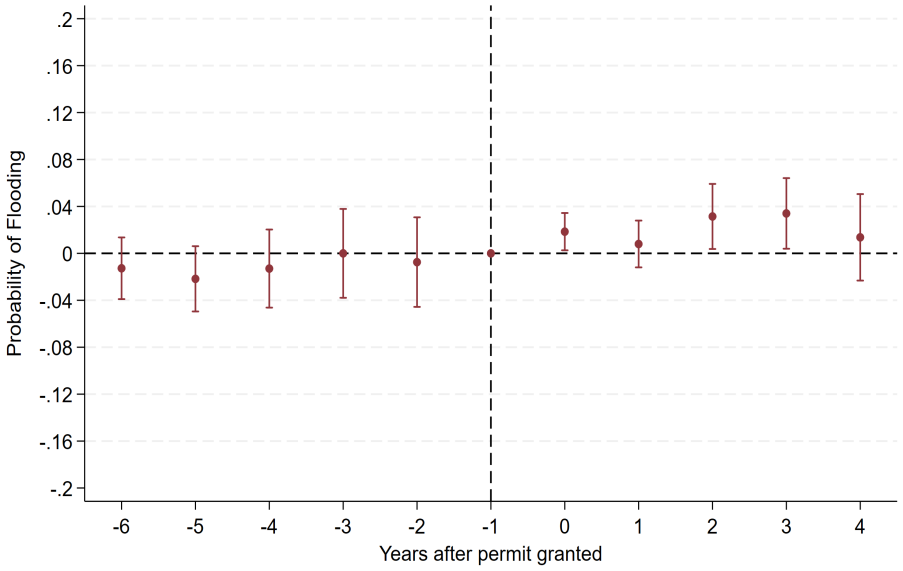
Table 2: Effect of mining on Flooding

	Percent Grid Inundated				Probability of Flooding			
Treated mines	0.015***	0.016***	0.016**	0.013**	0.021***	0.022***	0.023**	0.019**
	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.009)	(0.008)
Observations	5,725	6,196	6,101	6,310	5,725	6,196	6,101	6,310
Mean Dep variable	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Method	Imputation	Imputation	SAB	SAB	Imputation	Imputation	SAB	SAB
Fixed Effect	Dist*River	District	Dist*River	District	Dist*River	District	Dist*River	District

Notes: This table presents the impact of sand mining on flooding, as measured by mean inundation and flooding incidents in an a buffer area of 500 meter radius around the mine. Estimates are from the staggered difference-in-differences specification in Equation 3.1. The empirical analysis uses yearly panel data on inundation and includes year-by-district-by-river/year-by-district and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit. Column (1)-(4) shows estimates for mean inundation using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator. Column (5)-(8) shows estimates for flooding incidents using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator. SAB indicates that the columns shows results for the Sun and Abraham (2021) estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at mine level. * p < 0.10, ** p <0.05, *** p<0.01.



(a) Percent grid inundated with water



(b) Flooding

Figure 6: Dynamic effects of Sand mining on Flooding

Notes: This figure presents event study evidence of the effect of sand mining on flooding following Equation 3.2 estimated using the imputation procedure of Borusyak et al. (2024). Panel a) shows the estimates for mean inundation at the mine level, and panel b) shows the estimates for probability of an incident of flooding at the mine level. The empirical analysis uses yearly panel data on inundation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

4.2 Effects on village-level mean nightlights

In our main nightlights specification, we exclude towns and cities with populations over 15,000, as larger urban areas are unlikely to be affected by nearby sand mines in the same way as rural villages. We limit the sample to the four years before and after the year a mine is allotted.

Table 3 reports static estimates for villages with populations below 15,000. We find that nightlights increased by 11.2% relative to a baseline mean of 6.42 in treated villages. Figure 7 presents the dynamic effects, showing that nightlights rise steadily in mining villages compared to not-yet-treated and never-treated villages. The effect grows over time, reaching 1.2 units four years after treatment—about a 20% increase over the pre-treatment baseline.

Table 3: Effects of sand mining on village-level mean nightlights

	Nightlights			
Treated mines	0.723***	0.812**	0.760***	0.557
	(0.244)	(0.337)	(0.252)	(0.350)
Observations	4,056	4,412	4,275	4,427
Mean Dep variable	6.42	6.42	6.42	6.42
Method	Imputation	SAB	Imputation	SAB
Fixed Effect	Dist*River	Dist*River	District	District

Notes: This table presents the impact of sand mining on economic activity, as measured by nightlights in a village close to the mine. Estimates are from the staggered difference-in-differences specification in Equation 3.1. The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river/year-by-district and village fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit. Column (1)-(2) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator with year-by-district-by-river and village fixed effects. Column (3)-(4) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator with year-by-district and village fixed effects. SAB indicates that the columns shows results for the Sun and Abraham (2021) estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at village level. * p < 0.10, ** p <0.05, *** p<0.01.

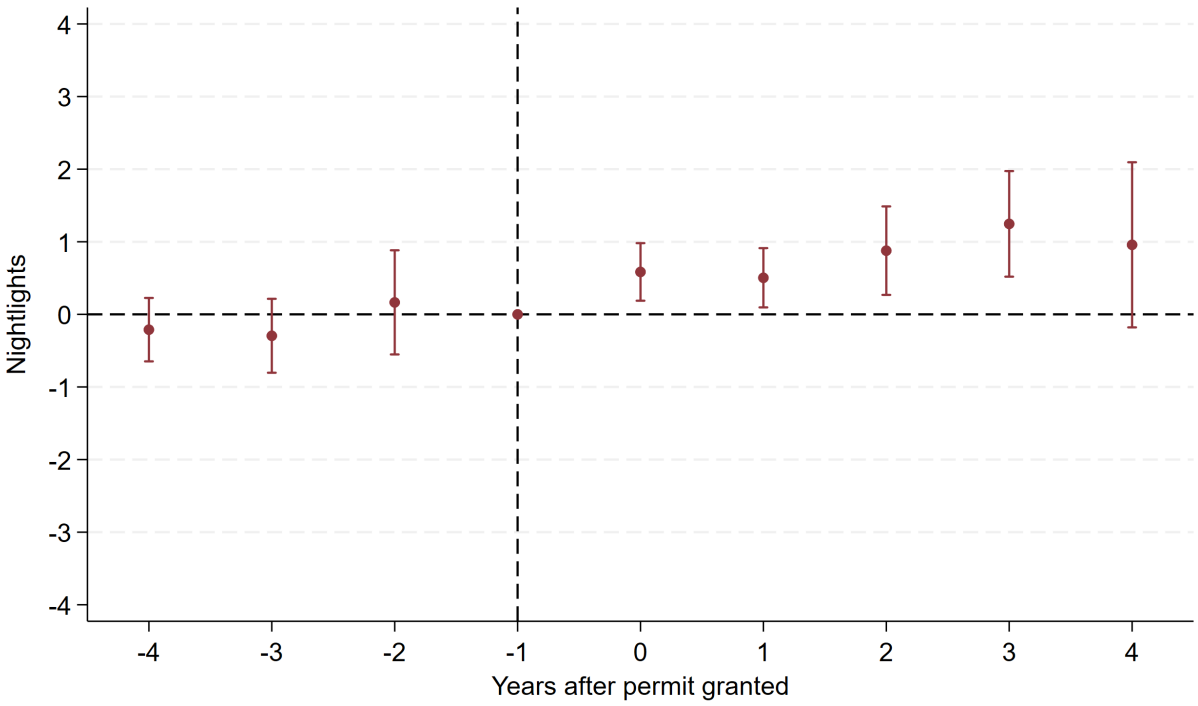


Figure 7: Village-level dynamic effects of sand mining on nightlights

Notes: This figure presents event study evidence of the effect of sand mining on nightlights following Equation 3.2 estimated using the imputation procedure of Borusyak et al. (2024). The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

4.3 Effects on Agriculture

Sand mining may affect agricultural production through several possible channels, such as substitution of land or labor from agriculture to sand mining, decreased productivity due to flooding, or increased productivity due to mechanization, irrigation, or other investments funded with sand mining-derived capital. To measure the net effect of sand mining on agricultural production, we use EVI as an outcome variable. Table 4 shows that within 500m of mine centroids, sand mining has a precise but small effect on EVI, equivalent to 2% of the pre-mining mean among treated mine areas. The magnitude is consistent across specifications. Figure 8 plots the dynamic effects using our main specification of the imputation method with district x river time dummies. The largest post-period effect occurs in the medium-run of 3-4 years, and amounts to about 5% of the pre-mining baseline. We interpret these results as indicating that there is most likely a mechanical effect of sand mining on vegetation at the mine itself.

Table 4: Effects of sand mining on mine-level vegetation

	Vegetation Index			
Treated mines	-0.004***	-0.004*	-0.005***	-0.003*
	(0.002)	(0.002)	(0.001)	(0.002)
Observations	6,337	7,189	7,177	7,449
Mean Dep variable	0.21	0.21	0.21	0.21
Method	Imputation	SAB	Imputation	SAB
Fixed Effect	Dist*River	Dist*River	District	District

Notes: This table presents the impact of sand mining on agricultural production, as measured by vegetation index in an a buffer area of 500 meter radius around the mine. Estimates are from the staggered difference-in-differences specification in Equation 3.1. The empirical analysis uses yearly panel data on EVI and includes year-by-district-by-river/year-by-district and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit (either district or district-by-river). Column (1)-(4) shows estimates for mean inundation using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator. Column (1)-(2) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator with year-by-district-by-river and mine fixed effects. Column (3)-(4) shows estimates for nightlights using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator with year-by-district and mine fixed effects. SAB indicates that the columns shows results for the Sun and Abraham (2021) estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at mine level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

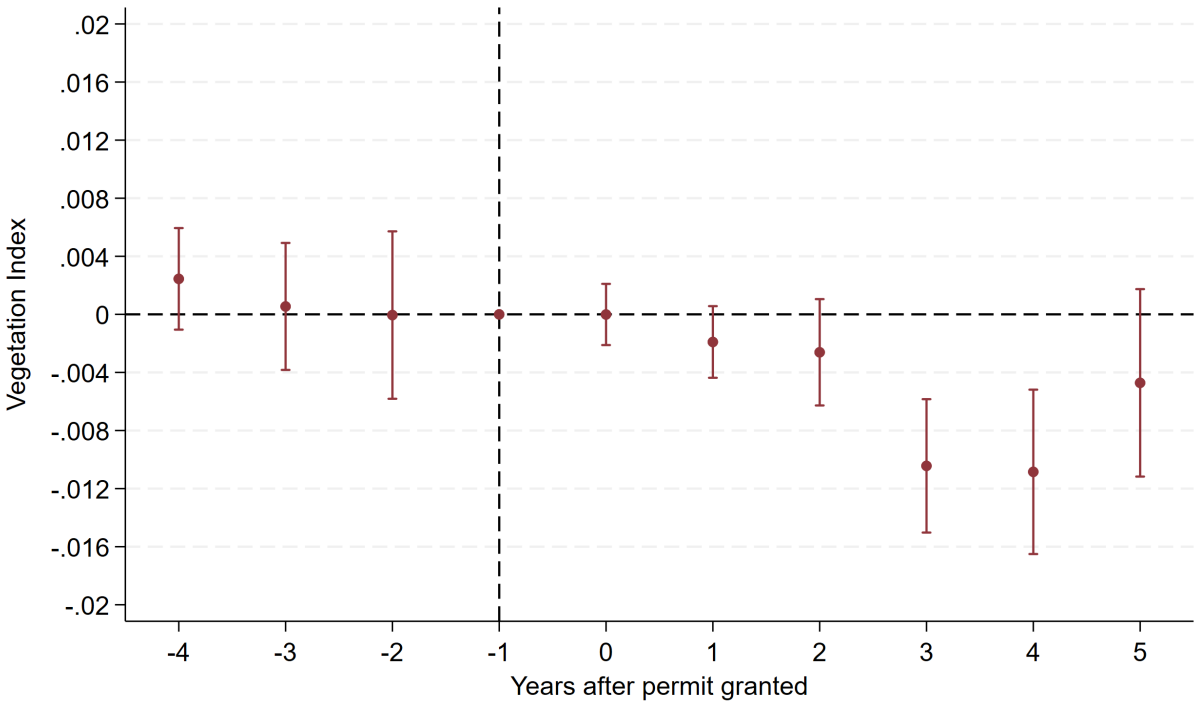


Figure 8: Dynamic effects of sand mining on vegetation

Notes: This figure presents event study evidence of the effect of sand mining on vegetation following Equation 3.2 estimated using the imputation procedure of Borusyak et al. (2024). The empirical analysis uses yearly panel data on vegetation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

4.4 How are the gains distributed?

In this subsection, we estimate the distributional effects of sand mining using two approaches: 1) Analyzing the economic impact separately for rich and poor cells, where "rich" refers to areas with nightlight values above the village median and "poor" to those at or below the median. 2) Examining the effects of sand mining on household assets in the NFHS, categorized by caste. These methods help assess how sand mining affects communities across different social and economic strata.

Impacts along the income hierarchy In our main cell-level specification, we limit the sample to cells with an estimated baseline 2015 population between 20 and 10,000, within villages with a total population of less than 15,000.

In our analysis of impacts along the income distribution (see Table 5), we find that sand mining caused nightlights in richer cells in mine-containing villages to rise by 1.6 units and nightlights in poorer cells to rise by 1.25 units on average over a period of four years after treatment. Compared to the pre-treatment of baselines of 12.71 and 6.8, this is an increase of 12.5% and 18.8% respectively (also see Figure 9a). This indicates that sand mining generates net economic benefits broadly for the whole village.

One potential concern with using baseline nightlights to identify relatively richer and poorer areas is that higher nightlights may reflect population density rather than income per capita. To address this, as a robustness check, we repeat the cell-level analysis using nightlights divided by cell-level estimated 2015 population instead of raw nightlights, both for the classification of rich and poor cells and as the outcome variable. Weidmann (2021) has shown that in African countries, inequality as measured by nightlights per capita tracks with that measured by DHS surveys. Our results shown in Table 5 and Figure 9b, indicate the nightlights per capita increased by 27% and 36% for rich and poor cells respectively.

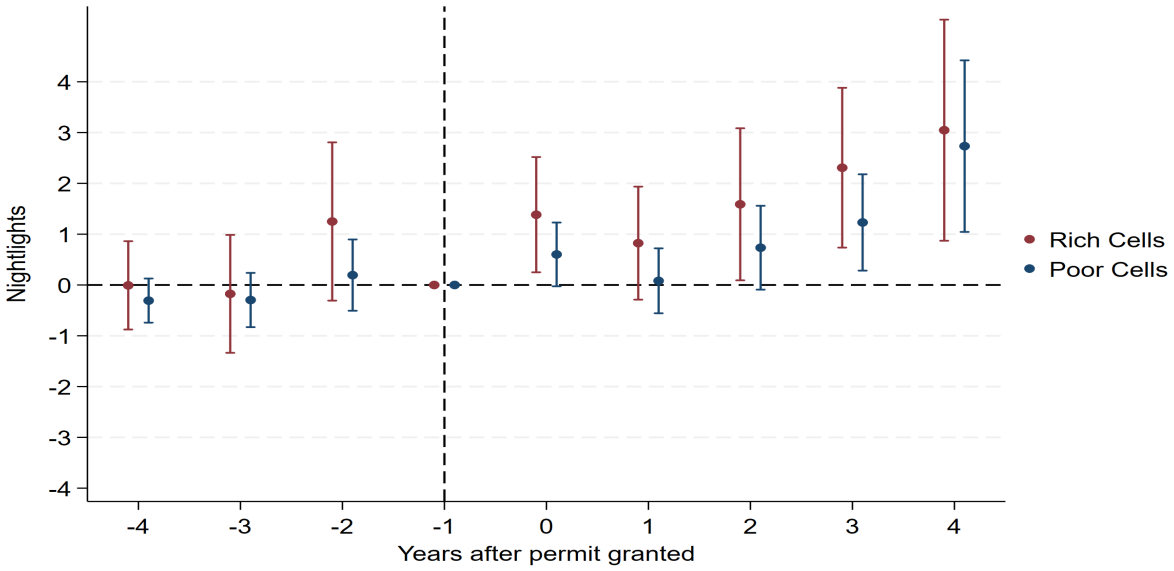
The take away from these results is that both formerly rich and poor areas benefit economically from sand mining. Percentage increase is larger for areas which were poor

at baseline, but the absolute increase, particularly in per capita values, is much larger for areas which were rich at baseline.

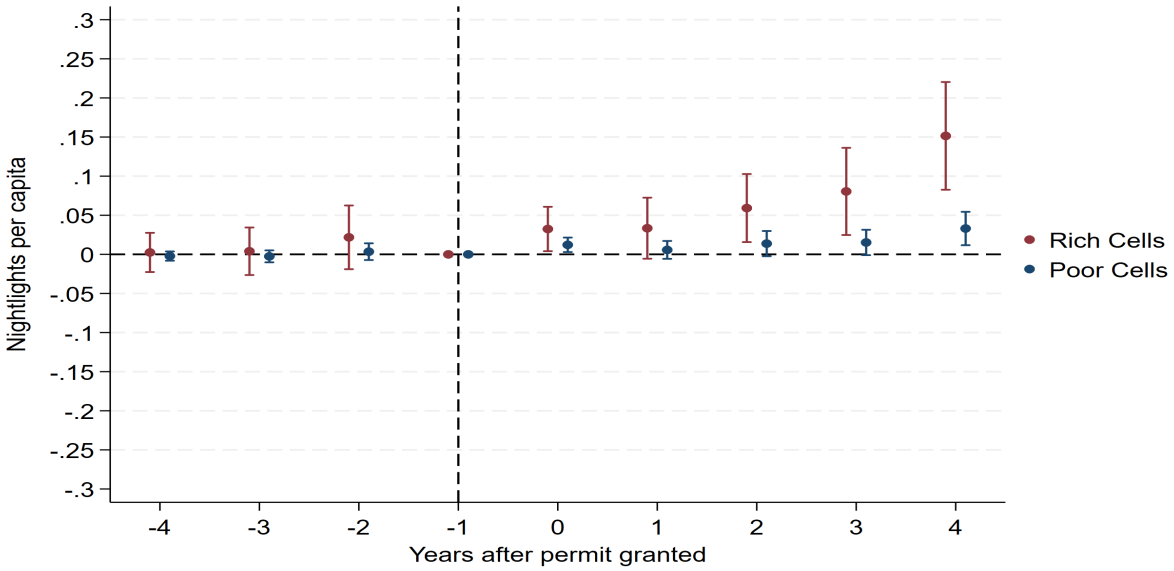
Table 5: Effects of sand mining on economic inequality

	Nighlights				Nighlights per capita			
	Rich		Poor		Rich		Poor	
Treated mines	1.603***	1.649**	1.254***	0.968***	0.065***	0.057***	0.018***	0.012**
	(0.587)	(0.655)	(0.282)	(0.344)	(0.017)	(0.018)	(0.006)	(0.005)
Observations	6,775	7,636	23,685	24,584	6,775	7,636	28,448	24,584
Mean Dep variable	12.70	12.70	6.81	6.81	0.24	0.24	0.05	0.05
Method	Imputation	SAB	Imputation	SAB	Imputation	SAB	Imputation	SAB
Fixed Effect	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River	Dist*River

Notes: This table presents the impact of sand mining on economic activity for rich and poor areas in a nearby village (defined at baseline), as measured by nightlights. Estimates are from the staggered difference-in-differences specification in Equation 3.1 estimated separately for the rich and poor sample. The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river and village fixed effects. We focus on a time window 4 years before and 4 years after a mine started operations. For each treated mine, we determine a control group which hasn't received a mine within the geographic unit. Column (1)-(4) shows estimates for nightlights for rich and poor areas using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator. Column (5)-(9) shows estimates for nightlights per capita using either the Imputation estimator (Borusyak et al. (2024)) or the Sun and Abraham (2021) estimator with year-by-district and village fixed effects. SAB indicates that the columns shows results for the Sun and Abraham (2021) estimator. The mean dependent variable is computed for ever treated in the years before treatment. Standard errors are displayed in parentheses and clustered at village level. * p < 0.10, ** p <0.05, *** p<0.01.



(a) Nighlights



(b) Nighlights per capita

Figure 9: Dynamic effects of sand mining on economic inequality

Notes: This figure presents event study evidence of the effect of sand mining on economic inequality using nightlights data. We follow Equation 3.2 which is estimated using the imputation procedure of Borusyak et al. (2024). The empirical analysis uses yearly panel data on nightlights separately for areas which were below the 80%ile of nightlights within the village between 2012-15 (poor) and those which were above (rich). Analysis includes year-by-district-by-river and mine fixed effects. Panel a) shows the estimates for nightlights at the grid level, and panel b) shows the estimates for nightlights per capita at the grid level. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

Impacts along the social hierarchy In Table 6, we analyse the effects of sand mining on household assets using data from the National Family Health Survey of 2014 and 2019. The outcome variable is a normalized value of assets at the state level. As we have data for only 2 years, we are restricted to a static analysis.

Our analyis is at the NFHS cluster level, and a cluster which is within 2 km of a mine which became operational between 2016 and 2018 is considered as treated, and a cluster which lies between 2 to 5 km of a mine treated in that period is control. Additionally, we consider clusters within 0 to 5 km of a potential mine as control.

In Columns 1 to 3, we compare overall assets and by caste at baseline in 2014. We find that assets in 2014 are similar across caste groups and on average. In 2019, after mines become operational, the assets in treated areas are higher than in control areas. Importantly, these positive effects are concentrated among the Upper castes and the other backwards castes (OBCs), and Scheduled Castes and Tribes do not see any positive effects on assets. It is worth keeping in mind that backward castes is a term used for caste groups which are heterogeneous. Around 40% of these groups consists of the Yadavs, Kurmis and Koeris, who are the dominant OBCs, and parties which have Kurmis and Yadavs as their base have won power in Bihar for the last 35 years. Thus, even though we do not observe assets by sub castes in the NFHS data, this analysis suggests that benefits are concentrated among the dominant caste groups.

The effects of sand mining differ notably when analyzed through the lens of income versus caste. In terms of income, both rich and poor areas benefit economically, but the nature of these benefits varies. In absolute terms richer areas gain more, reinforcing pre-existing economic advantages. When analyzed along caste lines, the distributional effects show a different pattern. Unlike the income-based analysis, where all groups benefit but to different extents, the caste-based analysis reveals a stark divide in who gains and who does not. Asset growth is concentrated among Upper Castes and dominant Other Backward Castes (OBCs), while Scheduled Castes and Scheduled Tribes see no measurable benefits. This suggests

Table 6: Effect of Sand Mining on Household Assets

	Assets in 2014			Assets in 2019					
	All	UC + OBC	SC/ST	All		UC + OBC		SC/ST	
Treated HH	-0.074	-0.115	0.045	0.227**	0.212**	0.300**	0.292**	0.059	-0.059
	(0.150)	(0.171)	(0.146)	(0.106)	(0.100)	(0.131)	(0.116)	(0.152)	(0.158)
Observations	2,945	2,134	807	2,923	2,923	2,005	2,005	905	904
Control group mean	.11	.283	-.369	.145	.145	.313	.313	-.222	-.222
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
River FE	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes

Notes: This table presents the impact of sand mining on household assets in mining areas disaggregated by caste groups. The dependent variable is a normalized index of (rural) household assets for the state of Bihar and is taken from NFHS-IV and V. The sample includes households which were within 5 kilometers of a mine which was operational by 2018 or a potential mine. Within this sample, if a household lies within 2 km of a treated mine then it is considered to be treated and otherwise it is considered to be part of the control sample. We use data from districts which have both a treated and control mine. We control for distance to mine in all specifications. Standard errors are clustered at the NFHS cluster level. * p < 0.10, ** p <0.05, *** p<0.01.

that historical social hierarchies shape economic outcomes, with dominant groups better positioned to capitalize on new opportunities.

5 Conclusion

Economic growth and urbanization have fueled a global construction boom, sharply increasing demand for sand—a key input in construction materials. This surge has driven widespread sand mining, especially in developing countries where regulation tends to be weak or poorly enforced. While sand mining creates economic opportunities, it also brings serious environmental risks, including flooding, aquifer depletion, and ecosystem damage. Understanding the local tradeoffs is essential for designing effective and enforceable policy.

This study provides the first causal, quantitative evidence of sand mining's local effects, using Bihar, India as a case study. We find that sand mining leads to a significant rise in flooding: inundation rates increase by 1.5 percentage points, or about 15% over baseline levels. Agricultural production falls by 5%, likely due to physical disruptions from mining.

These results highlight the environmental costs of extraction, especially in a flood-prone region like Bihar.

At the same time, we find that sand mining generates net economic benefits for nearby villages. Using satellite-based nightlights as a proxy for income, we observe a sustained rise in economic activity beginning about a year after mining starts. These gains are not confined to a single income group—both relatively rich and poor households experience improvements. This broad distribution of benefits likely contributes to the persistence of mining despite the environmental harms we document. However, disaggregating by social group reveals that the economic gains are concentrated among castes higher in the social hierarchy. Dalit and tribal households, who are fewer in number and have less political and economic influence, do not share in these benefits. Given their exposure to increased flooding, their overall welfare is likely negative.

Overall, our findings suggest that sand mining brings gains to local households and cannot be dismissed as purely exploitative. But the unequal distribution of benefits at the social group level and environmental costs points to the need for more targeted regulation. Policymakers should consider measures to mitigate flooding, promote sustainable mining, and compensate communities—especially socially marginalized groups—for environmental harm.

Future research should examine the long-term impacts of sand mining on migration, structural transformation, and human capital. Understanding how communities perceive and adapt to mining-related environmental change will be critical for crafting policies that are both effective and politically viable. Additional work should also evaluate how sand mining regulations affect broader economic outcomes, including construction costs and urban development.

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Part I

Online Appendix

A Additional Results and Checks

A.1 Descriptive data

अरवल जिलान्तर्गत पर्यावरणीय स्वीकृति प्राप्त बालूघाटों की विवरणी

क्र0सं 0	बालूघाट का नाम	पूरा पता	नदी का नाम	रकवा (हे0 में)	GPS Coordomates(Latgitide &Longitude) (Latgitide &Longitude)			EC का पत्रांक एवं दिनांक	EC की वैधता की तिथि
1	मुरादपुर हुजरा	मुरादपुर हुजरा थाना– अरवल	सोन नदी	5	A	25° 14' 28.2397" N	84° 37' 55.5743" E	116 dt 16.03.2018	15.03.2024
					B	25° 14' 29.8595" N	84° 38' 1.3338" E		
					C	25° 14' 21.5127" N	84° 38' 3.6433" E		
					D	25° 14' 18.9588" N	84° 37' 57.1714" E		
				5	A	25° 14' 29.9815" N	84° 38' 2.8154" E		
					B	25° 14' 31.5059" N	84° 38' 7.4365" E		
					C	25° 14' 25.6215" N	84° 38' 13.9054" E		
					D	25° 14' 21.7375" N	84° 38' 5.7228" E		
				5	A	25° 14' 20.9216" N	84° 38' 7.9650" E		
					B	25° 14' 24.7778" N	84° 38' 14.7047" E		
					C	25° 14' 19.8157" N	84° 38' 19.7828" E		
					D	25° 14' 15.0806" N	84° 38' 13.5446" E		

Figure B-1: Example of mine details in a District Survey Report

Notes: This figure shows an example of a District Survey Report (DSR) from which mines' locations and treatment dates were extracted. This example is taken from the DSR of Arwal district. It contains the following important information: a) the third column is the river name, b) the fifth column contains the coordinates of the mine, separated into latitude and longitude, c) the sixth column is the date the mine received Environmental Clearance (EC), which is required to operate the mine—we take the date of EC as the treatment date, and d) the seventh column is the expiry date of the EC. While the expiry date is redundant in this case, we can, in theory, subtract five years from the expiry date to calculate the treatment date.



Figure B-2: Defining flooding area around a mine

Notes: This figure shows examples of mine polygons and the Area of Interest (AOI) for measuring floods. The orange rectangles represent mine polygons, each with two concentric circles centered at the mine centroid. We exclude the area corresponding to the smaller circle from our measurement to avoid capturing mechanical inundation caused by digging. When the larger circles overlap, as shown in this figure, we merge the contiguously overlapping circles into a single area and treat it as one unit of observation.

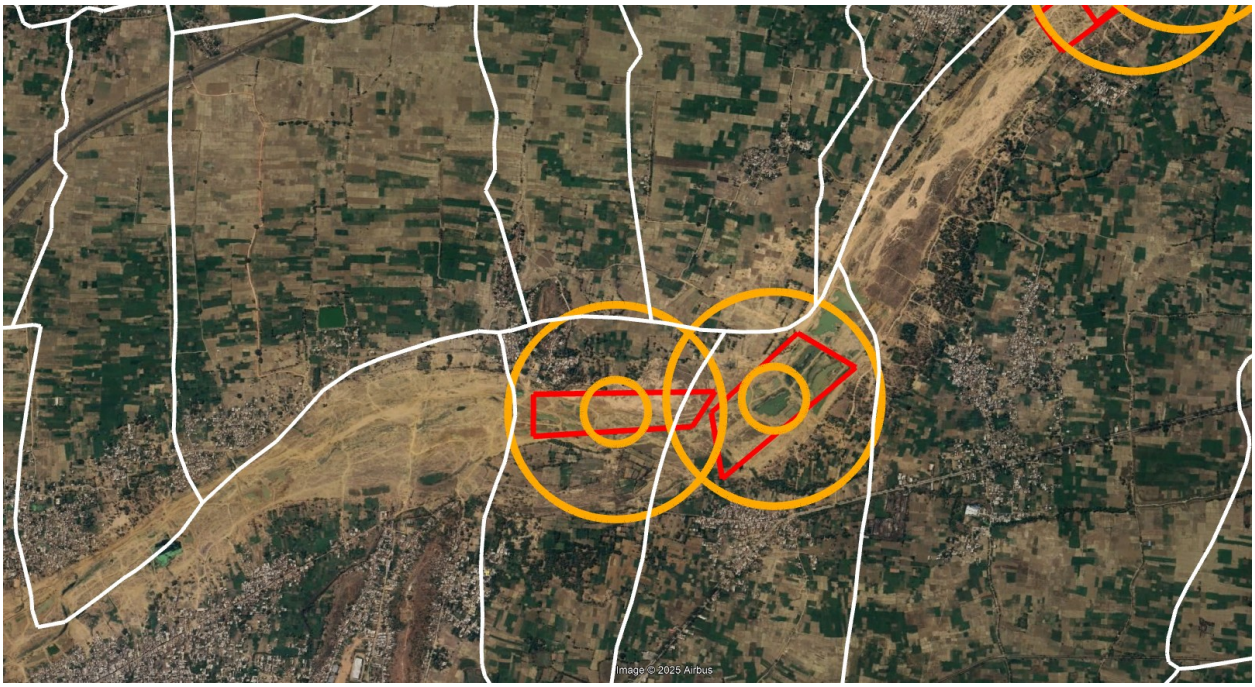


Figure B-3: Defining flooding area around a mine

Notes:This figure is a zoomed-out version of Figure B2 and displays village (shrid) boundaries, represented by white lines. As shown, villages vary significantly in size and may contain one or multiple clusters of settlements.



(a) Sand being transported on boats

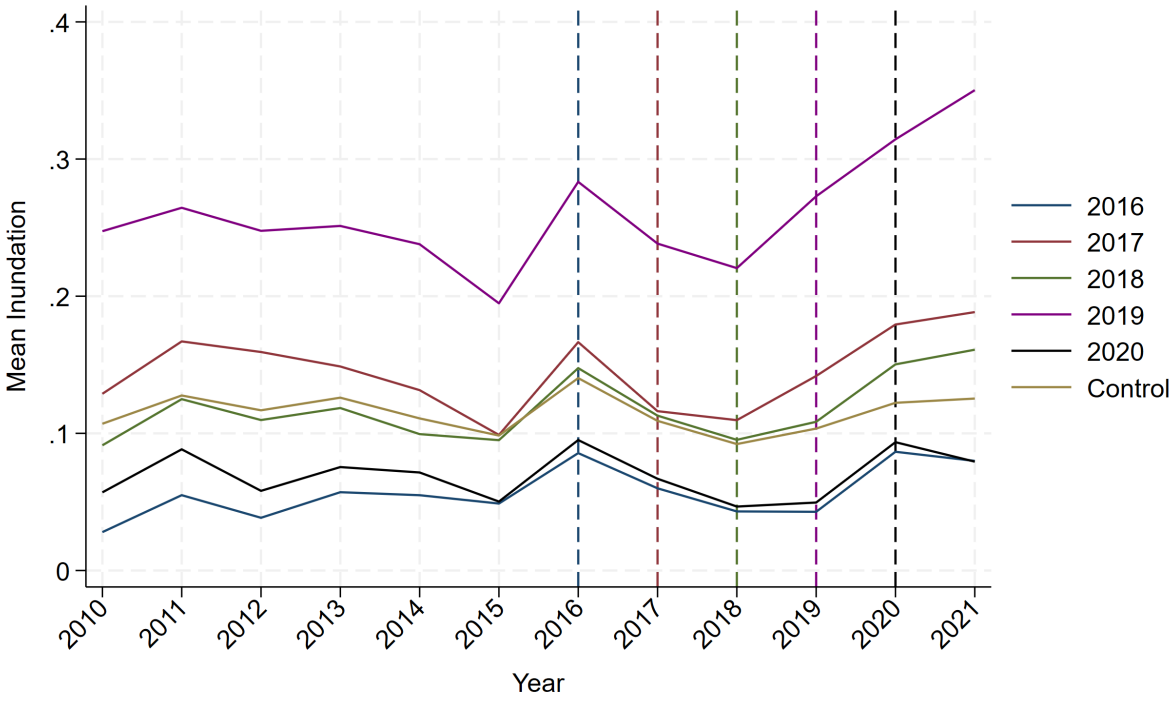


(b) Trucks lining up to transport sand at mine

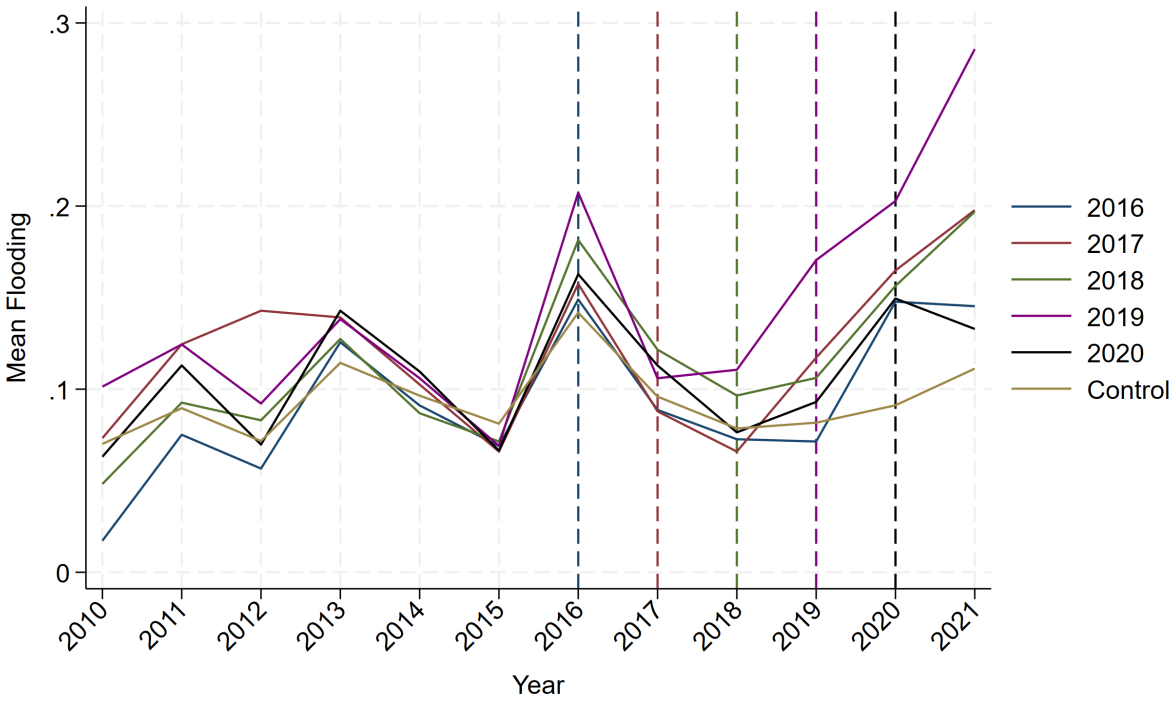
Figure B-4: Sand Transportation

Note: Panel a image was captured in March 2023. Panel b image is taken from Google Maps.

A.2 Raw Data



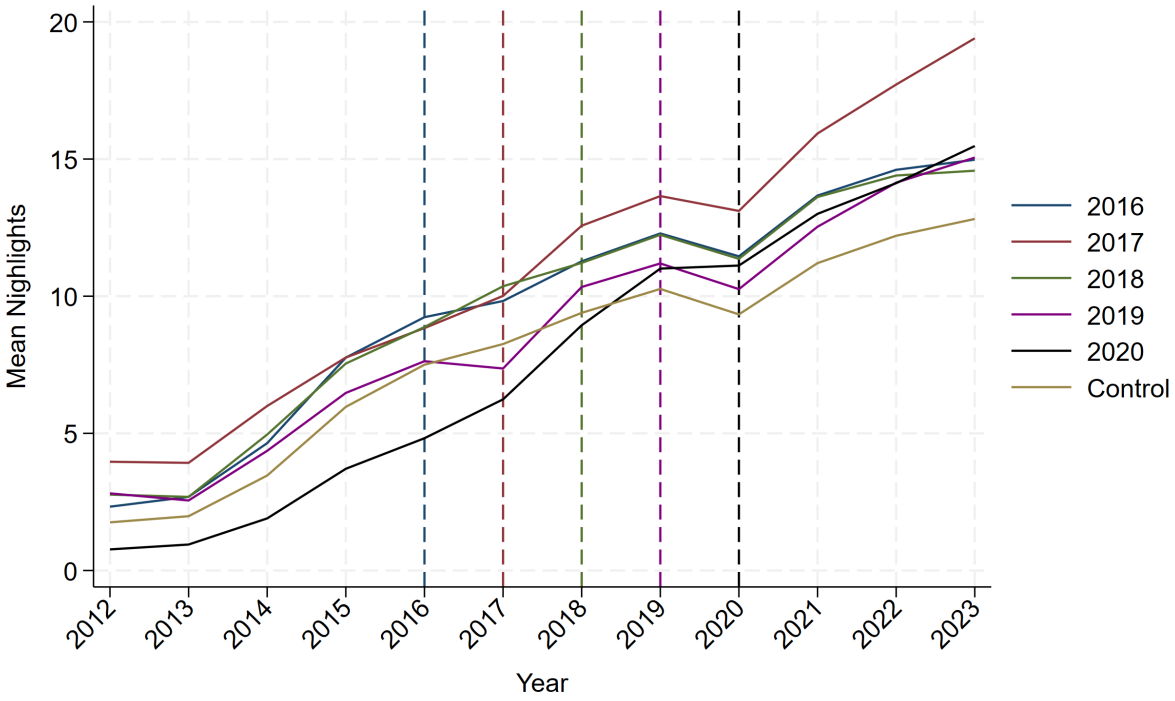
(a) Inundation



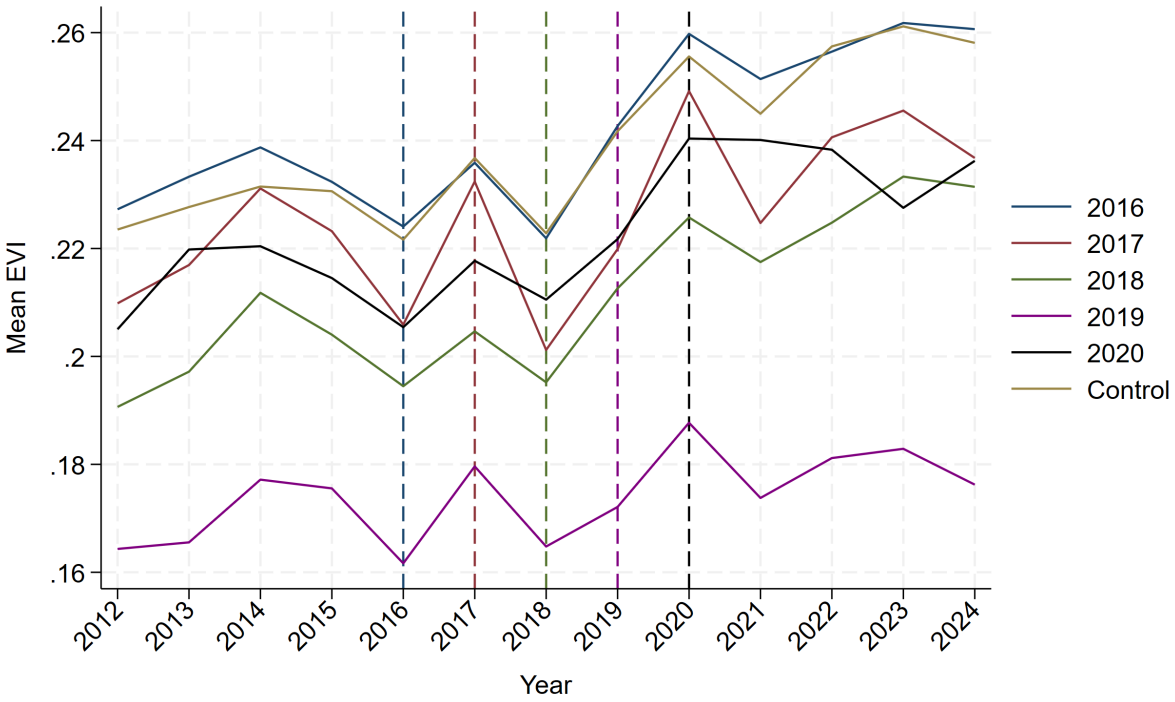
(b) Flood

Figure B-5: Mean Inundation over time

Notes: This figure plots mean of Inundation (Panel a) and Probability of Flooding (Panel b) for each year grouped by the year of treatment.



(a) Nighlights



(b) EVI

Figure B-6: Mean Nighlights and EVI over time

Notes: This figure plots mean of nightlights (Panel a) and Enhanced Vegetation Index (Panel b) for each year grouped by the year of treatment.

A.3 Balance Checks

Table B-1: Correlations between treatment status or timing and assembly election outcomes

(a) Mine-level correlations

	(1) Treated (permit)	(2) Treated (permit)	(3) Treated (permit)	(4) Permit year	(5) Permit year	(6) Permit year
RJD	-0.0481	0.00753	0.0531	0.0449	0.0875	0.210
	(0.104)	(0.0494)	(0.0448)	(0.469)	(0.240)	(0.305)
JD(U)	-0.185	-0.110	-0.00654	0.000497	0.203	1.011*
	(0.115)	(0.0696)	(0.0706)	(0.465)	(0.362)	(0.549)
BJP	-0.0593	0.0619	0.0577	0.623	0.262	0.503
	(0.0974)	(0.0529)	(0.0712)	(0.446)	(0.295)	(0.501)
Constant	0.664**	0.602**	0.560**	2018.7**	2018.7**	2018.4**
	(0.0870)	(0.0406)	(0.0415)	(0.394)	(0.225)	(0.320)
Observations	1421	1421	1383	727	727	715
District FE		Yes			Yes	
District x river FE			Yes			Yes

$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
In Columns (1)-(3), the dependent variable is a binary indicator for whether the mine is existing, i.e. has a permit, rather than proposed. In Columns (4)-(6), the sample is restricted to existing mines, and the dependent variable is the year in which the mine's permit was granted. Standard errors in parentheses, clustered by AC.

(b) AC-level correlations

	(1) Total mines	(2) % Existing	(3) Permit year	(4) Permits 2016-17	(5) Permits 2018-20
RJD	3.949	0.0396	-0.381		
	(5.599)	(0.105)	(0.709)		
JD(U)	-0.0162	-0.0114	-0.928		
	(6.070)	(0.114)	(0.742)		
BJP	-3.322	-0.0283	0.263		
	(6.297)	(0.118)	(0.762)		
Ruling coalition 2016-17				3.386	
				(4.358)	
Ruling coalition 2018-20					-4.282
					(3.809)
Constant	17.38**	0.577**	2019.1**	15.70**	20.14**
	(4.677)	(0.0878)	(0.606)	(3.758)	(2.552)
Observations	78	78	52	78	78

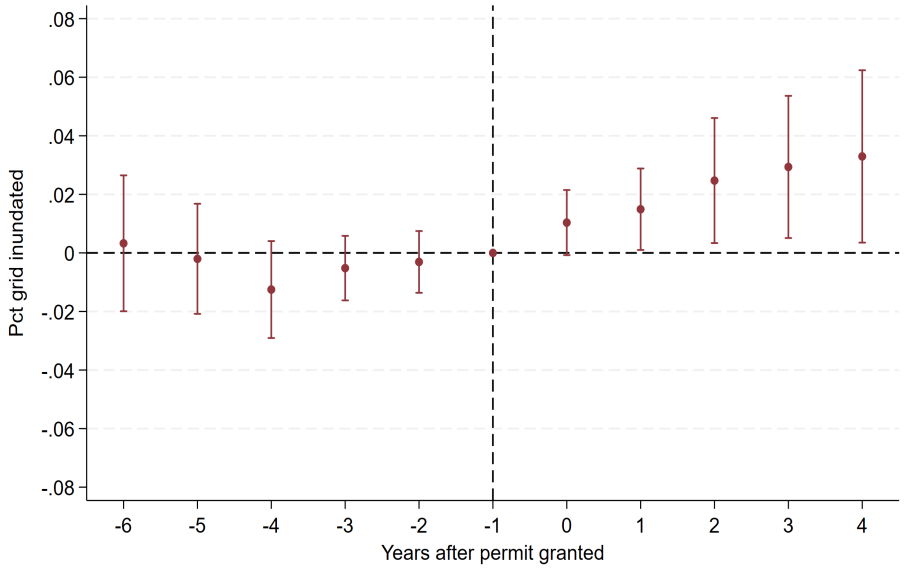
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
In Column (1), the dependent variable is the total number of existing and proposed mines. In Column (2), the dependent variable is the share of existing mines in the total. In Column (3), the sample is restricted to ACs with any existing mine, and permit year is the average of the years in which the existing mines received their permits. Column (4) shows the correlation between electing an MLA in the 2016-2017 ruling coalition (RJD, JD(U), INC) and the number of sand mine permits received during those two years. Column (5) shows the correlation between electing an MLA in the 2018-2020 ruling coalition (JD(U), BJP, LJP) and the number of sand mine permits received during those three years. Standard errors in parentheses.

A.4 Robustness

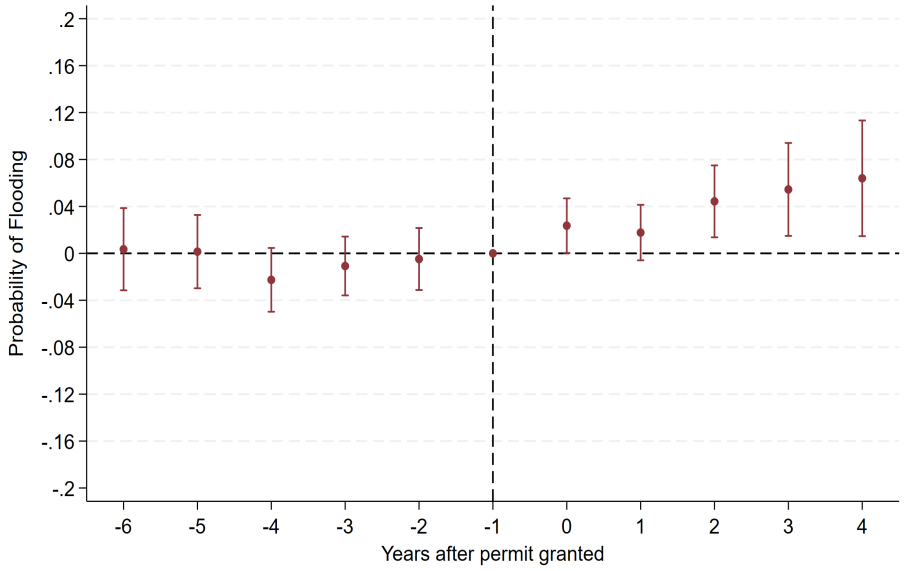
Table B-2: Effect of Sand Mining on Household Assets

	Assets in 2014			Assets in 2019					
	All	UC + OBC	SC/ST	All		UC + OBC		SC/ST	
Treated HH	-0.004	-0.135	0.098	0.314	0.472*	0.405	0.399	0.188	0.304
	(0.245)	(0.278)	(0.197)	(0.246)	(0.240)	(0.301)	(0.258)	(0.273)	(0.245)
Observations	1,054	756	297	851	851	571	571	275	275
Control group mean	-.43	-.27	-.83	-.34	-.34	-.23	-.23	-.57	-.57
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
River FE	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes

The dependent variable is a normalized index of (rural) household assets for the state of Bihar and is taken from NFHS-IV and V. The sample includes households which were within 2 kilometers of a mine which was operational by 2018 or within 5 km of a potential mine. We use data from districts which have both a treated and control mine. We control for distance to mine in all specifications.Standard errors are clustered at the NFHS cluster level. * p < 0.10, ** p <0.05, *** p<0.01.



(a) Percent grid inundated with water



(b) Flooding

Figure B-7: Effect of Sand mining on Flooding - Using Sun and Abraham (2021)

Notes: This figure presents event study evidence of the effect of sand mining on flooding following Equation 3.2 estimated using the procedure of Sun and Abraham (2021). Panel a) shows the estimates for mean inundation at the mine level, and panel b) shows the estimates for probability of an incident of flooding at the mine level. The empirical analysis uses yearly panel data on inundation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

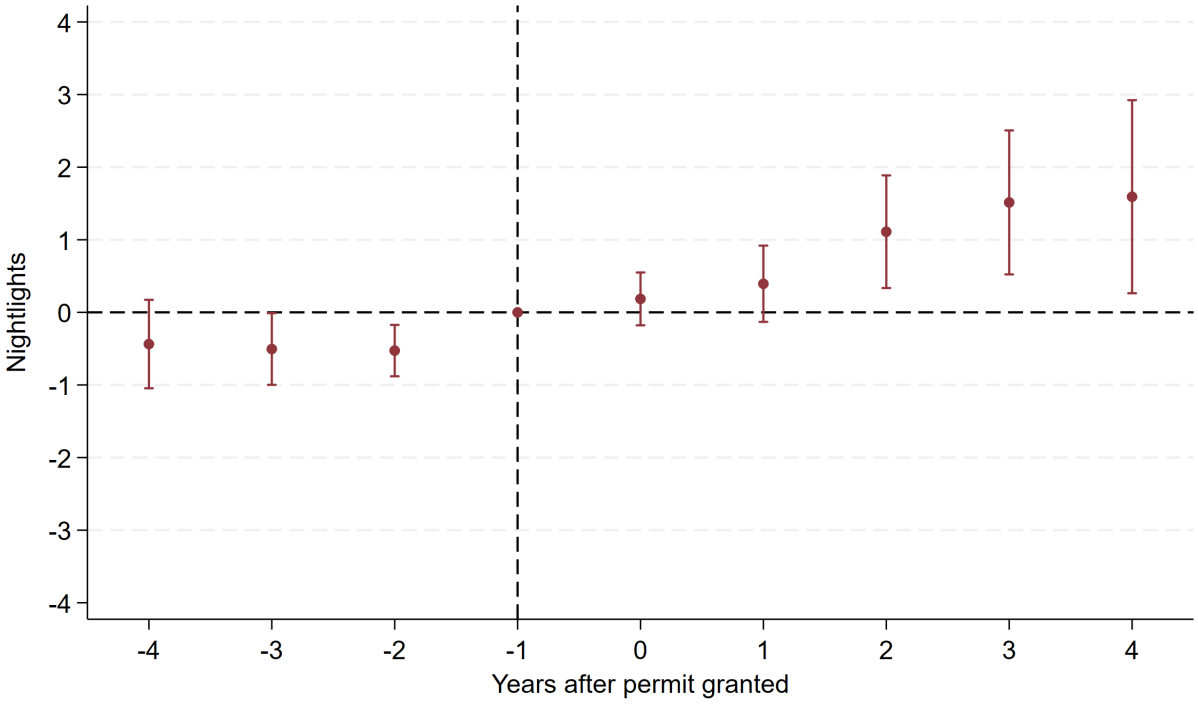


Figure B-8: Village-level effects of sand mining on nightlights - Using Sun and Abraham (2021)

Notes: This figure presents event study evidence of the effect of sand mining on nightlights following Equation 3.2 estimated using the procedure of Sun and Abraham (2021). The empirical analysis uses yearly panel data on nightlights and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.

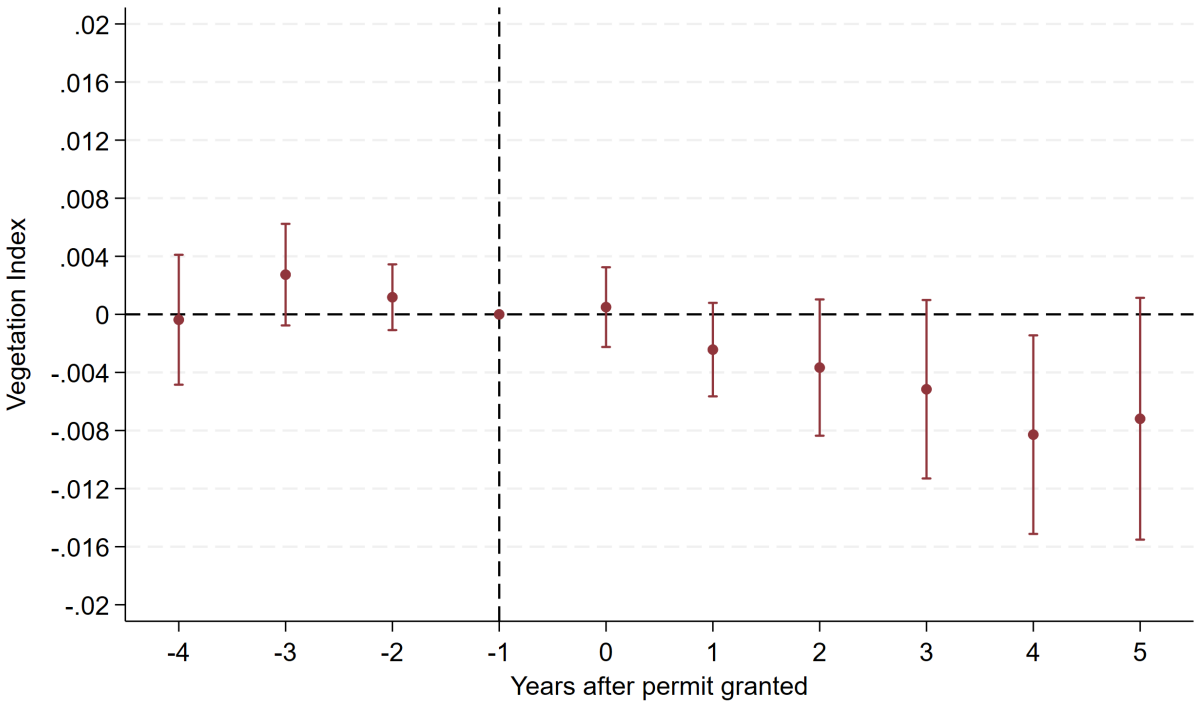


Figure B-9: Mine level effects of sand mining on vegetation - Using Sun and Abraham (2021)

Notes: This figure presents event study evidence of the effect of sand mining on vegetation following Equation 3.2 estimated using the procedure of Borusyak et al. (2024). The empirical analysis uses yearly panel data on vegetation and includes year-by-district-by-river and mine fixed effects, as well as controls for temperature and precipitation in the year. We focus on a time window 4 years before and 4 years after a mine started operations. Each dot corresponds to an estimated coefficient, and vertical lines indicate the corresponding 95% confidence intervals. The dashed line represents the omitted coefficient. Standard errors are clustered at mine level.