Aggregate Impacts of Command-and-Control Environmental Policy: Evidence from Court-Ordered Mining Bans in India[*]

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November 5, 2024

Abstract: We estimate the aggregate impacts of court-ordered iron ore mining bans in India and consider the counterfactual welfare gains from an alternative policy to the ban. The local sectoral ban is a command-and-control (CAC) policy that is commonly applied to natural resource settings, usually when the regulator has a signal of widespread non-compliance. The Supreme Court of India imposed bans on iron ore mining and outbound iron ore trade in two states in response to reports that mines operated under fake environmental permits and underpaid mining royalties. Using firm-level industrial survey data, mine-level output data, and bilateral mine-to-firm auction data, we decompose the bans' effects into trade, production networks, and local labor demand channels. Our results indicate persistent declines in employment, capital stock, and borrowing by iron-consuming plants, despite the temporary duration of the ban. These findings highlight the economic spillovers caused by CAC policies, especially in industries that are upstream in the supply chain.

1 Introduction

Weak monitoring and enforcement are common problems that prevent governments from implementing regulations that are already on the books. Weak monitoring prevents governments from knowing which firms are in compliance, and weak enforcement prevents governments from sufficiently incentivizing compliance. In response, governments turn to command-and-control (CAC) policies to force firms to comply with regulations. A prominent form of CAC policy is the court-ordered temporary local sectoral ban: the judicial system responds to evidence of widespread regulatory non-compliance in a given region-sector by forcing all its firms to cease production so that the regulator can verify each firm's compliance status, until a future date at which firms verified to be in compliance are allowed to resume production. Court-ordered bans are prevalent around

[*]We are grateful for the helpful feedback from Abhijit Banerjee, Clare Balboni, Dave Donaldson, Sarah Gertler, Daniel O'Connor, Rob Townsend, and participants at the MIT Trade Lunch. We thank Bharat Singhal, Gabriel Hill, and Shanyiou Hu for excellent research assistance. We gratefully acknowledge financial support from the IGC, PEDL, and the Shultz Fund. Any mistakes are our own.

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the world in settings with environmental regulations and natural resource extraction.[1] However, there is little evidence on the social and economic cost that they impose.

We study a specific instance of court-ordered bans on iron ore mining in two settings in India in the 2010s: Goa and eastern Karnataka. In both settings, mines operated under fake environmental permits and underpaid mining royalties. Due to corruption and imperfect record-keeping, regulators did not know which mines were non-compliant with the permits and royalties. In response, the Supreme Court of India imposed bans on mining production and trade. Investigators determined each mine's compliance, enforced penalties as the law stipulated, and required each mine to attain compliance or permanently cease production. The court only lifted the ban when the investigation was finished, a process that took 12 months in Karnataka and 18 months in Goa. Court-ordered bans have become an increasingly common form of environmentally motivated regulatory action in India [Greenstone et al., 2017].

The courts typically only consider the value of lost output from firms facing the ban, along with the cost of unemployment for workers at those firms. In other words, courts consider the direct partial equilibrium effects. However, local sectoral bans are generally large enough to affect other sectors and locations, both through prices and through quantity rationing. In turn, with non-linear amplification through sectoral linkages, the magnitudes of these spillovers on aggregate outcomes of interest are unclear. If elasticities of substitution for trade and across inputs were close to infinite, then the general equilibrium impact would be close to zero regardless of the size of the partial equilibrium impact. Conversely, if elasticities are small, and there are frictions to labor mobility or other adjustments, the general equilibrium impact could be orders of magnitude larger than the partial equilibrium impact. We provide and estimate a framework that characterizes the general equilibrium impacts of a local sectoral ban, accounting for propagation through trade, domestic production networks, and labor markets.

In addition, the price impact of a joint ban on production and outbound trade is ambiguous. The intuition is as follows: while a production ban in location i shifts inward the supply of iron ore in i and in locations $J(i)$ whose firms previously sourced iron ore from i, an outward trade ban in i shifts inward demand in i of inventoried ore from $J(i)$, so the equilibrium price impact in i is ambiguous. Factories near the banned mines in Karnataka saw smaller increases in iron ore consumption prices than factories further away that previously sourced iron ore from Karnataka. An empirical challenge is estimating the iron ore equilibrium factory-level increase in price due to the ban. This price increase is the first stage for the domestic production network block, where we estimate how firms adjusted input allocations and output prices, key variables that enter our quantitative model. We estimate these impacts using a method based on Baqaee and Farhi [2018, 2020], with modifications based on the structure of the steel supply chain. We also consider the impacts of an alternative policy: a per-diem ad-valorem tax as long as a firm is not in compliance, where an infinite value corresponds to a ban and a zero value corresponds to the pre-ban status quo.

Using plant-level panel data and detailed trade data, together with wage and price data across space, we first illustrate the direct impacts of the ban, before estimating elasticities in our model

[1] Examples include hydraulic fracturing in the US, lithium mining in Mexico, and gold mining in Brazil.

and applying our model to estimate the general equilibrium impacts. Our difference-in-difference and event study regressions estimate the relative changes in outcomes between locations near versus far the ban, as well as between the affected sector of iron ore, closely linked sectors through the supply chain, and more distant sectors. In response to the ban, affected downstream steel sector firms reduced employment by 10 percentage points and capital stock by 15 percentage points by the second year. Affected firms increased cash holdings immediately after the ban by 12 percentage points, then decrease below the pre-ban level in all subsequent periods. Affected firms also immediately deleverage, reducing their debt by 6 percent immediately and 10 percent in the long run. These results use firm and year fixed effects, and are robust to inclusion of additional state-year and sector-year fixed effects. These regressions primarily use cross-sectional variation, and part of the effect is absorbed into the "missing intercept" through the time fixed effects, motivating our model for the general equilibrium impact.

In our counterfactuals, we reconsider the rationale to use a ban to enforce regulatory compliance. A ban provides firms with the strongest possible incentive to comply, but its total economic cost may be greater than the social benefits of faster compliance. We interpret a ban on production as an infinite tax on non-compliance. Then, our model informs how the social value of aggregate output changes as we allow taxes to vary from zero to infinity, where social value equals the sum of economic output and inferred environmental benefit. We infer a lower bound on the monetary value of environmental benefits from full compliance by taking the difference of model-implied aggregate output between the pre-ban and post-ban periods, and then scaling by the change in mining output. We reason that the government preferred the post-ban allocation to the pre-ban allocation, even though economic output was lower, because the environmental benefit was greater than the loss of output. We expect the social value to be increasing at a tax of zero, since the environmental benefits of regulatory compliance is first order while the economic costs are second-order in the absence of distortions. The social value could be decreasing as the tax goes to infinity (or the maximum finite value at which no mines continue to produce) because the marginal environmental benefit goes to zero while the marginal economic costs may or may not go to zero, depending on the local elasticity of demand, which in turn depends on the trade elasticity and the elasticity of substitution for inputs into downstream production.

Our main contribution is that we are the first to provide a comprehensive quantification of the general equilibrium impacts of a CAC method of regulatory enforcement, in a setting where we have quasi-random variation in downstream firms' exposure to enforcement. A secondary contribution is to use the decomposition into channels to inform an intermediate policy, a tax-like alternative to the CAC method. The textbook view of CAC regulation is that it is inefficient compared to market-oriented regulation due to differences in firms' costs of compliance, as Harrison et al. [2019] and Duflo et al. [2013] show empirically. Blackman et al. [2018] show that CAC regulation can be effective under limited institutional capacity. This paper focuses on the economic impacts of CAC enforcement, following a long literature studying economic impacts of other environmental policies [Greenstone, 2002, Greenstone et al., 2012, Walker, 2013, Lu and Pless, 2021]. This paper is similar to Marten et al. [2019], who show that the general equilibrium effects of single-sector environmental regulations can be large, but this paper differs by grounding the model elasticities in regression estimates.

Through its setting, this paper relates to Black et al. [2005], Aragón and Rud [2013], and Allcott and Keniston [2018], studying the economic consequences of resource booms and busts. Allcott and Keniston [2018] finds that resource booms drive up local wages but can have mixed effects on long-term economic stability. In studying these dynamics, we employ a general equilibrium framework that aligns with Baqaee and Farhi [2018] in assessing the broader economic effects of local shocks, in this case induced by CAC enforcement.

We organize the remainder of the paper as follows. Section 2 describes the institutional background. Section 3 describes the data. Section 4 uses time series and event study regressions to show the impulse and impact of the ban. Section 5 introduces the model, which we calibrate using the empirical results. Section 6 derives an estimate of the aggregate impacts and considers the counterfactuals. Section 7 concludes.

2 Background

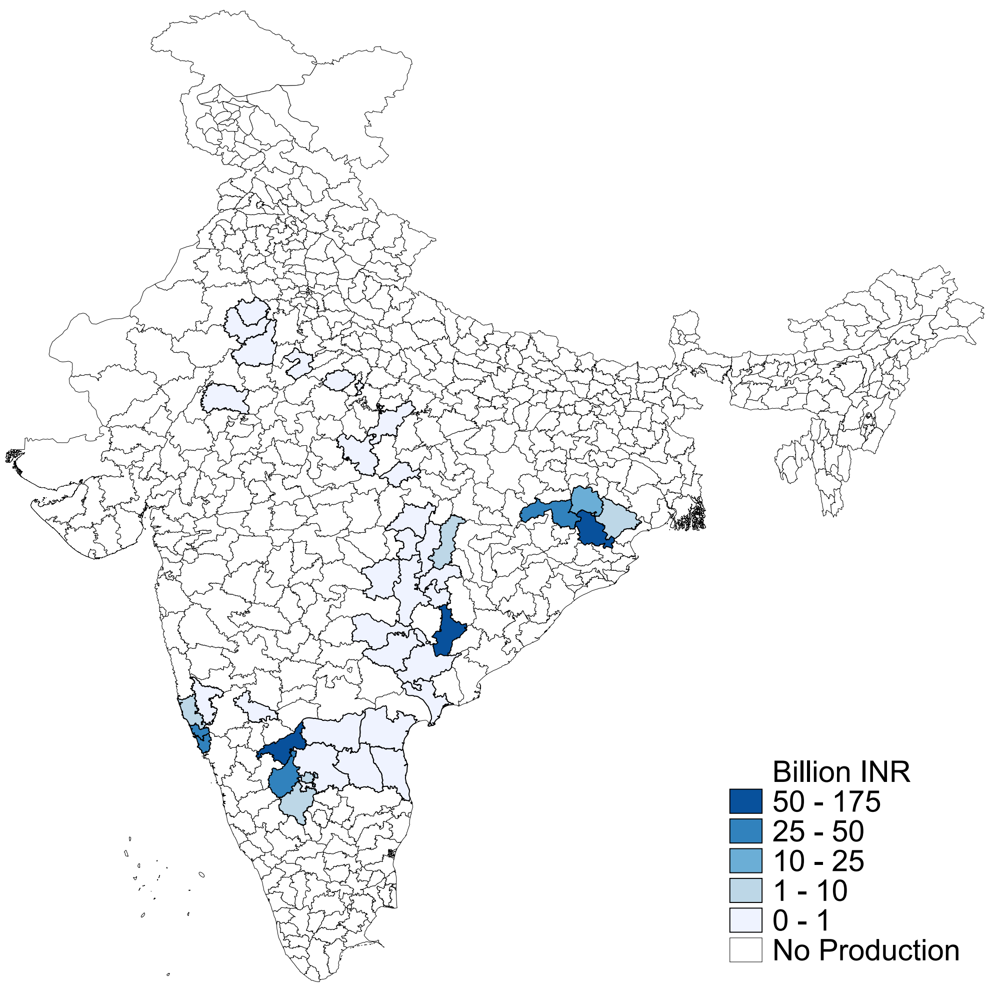
India is one of the world's largest producers of iron ore, ranking fourth globally in production volume. This sector is integral to the country's large steel sector and underpins substantial export activities. The two primary forms of iron ore found in India are hematite and magnetite, each possessing distinct geographic distributions and industrial uses. Hematite, known for its relatively higher iron content, is concentrated primarily in the eastern states of Odisha, Jharkhand, and Chhattisgarh. In contrast, magnetite, which is valuable for its high iron yield upon beneficiation, is predominantly located in southern states, with of Karnataka accounting for over 70 percent of India's total magnetite reserves [Government of India, 2022].

Among India's mining states, Goa and Karnataka occupy prominent roles in both production and export. Goa's iron ore industry, historically oriented toward the export of low-grade fines, has been instrumental in meeting international demand, particularly from China. In 2009, Goa led all Indian states in export volumes [Government of India, 2013]. Karnataka, with its vast deposits of magnetite and a significant mix of open-cast and underground mining operations, plays a central role in supporting domestic industries by providing a stable and substantial source of iron ore. Given their significance in India's mining sector, Goa and Karnataka serve as key examples for understanding the broader impacts of environmental regulation in mining.

Despite the sector's contributions to economic growth and trade, issues surrounding environmental compliance and illegal mining have posed significant regulatory challenges. Illegal mining in the form of invalid or expired permits was rampant in Goa and Karnataka in the 2000s. These permits required miners to adhere to environmental regulations and pay a stipulated share of revenue as royalties to the state government. In response to evidence of extensive regulatory violations, India's Supreme Court intervened in Goa and Karnataka through court-imposed bans on iron ore extraction. These judicial actions aimed to enforce compliance with environmental standards and to rectify revenue losses incurred by unregulated mining activities. The court-ordered bans, which temporarily halted production, had significant economic repercussions, particularly within local economies reliant on mining.

The mining bans occurred in Goa from September 2012 to April 2014, and in three districts in eastern Karnataka from July 2011 to April 2012. In 2010, Goa accounted for 17 percent of India's iron ore output and the three Karnataka districts accounted for 18.5 percent [Government of India, 2014]. In turn, India produced 8 percent of global iron ore output as the fourth largest producer [Brown et al., 2013]. In magnitude, the mining bans constituted a small (around 1 percent) share of global iron ore output, with a likewise small impact on the world price. However, iron ore mining accounted for 24 percent of GDP in Goa and 1.7 percent of GDP in Karnataka.[2] With high transport costs for iron ore, local iron ore prices increased despite an elastic global supply.

Figure 1: Spatial Distribution of Iron Ore Production in India in 2010



Notes: This map shows the value of iron ore (in billion INR) produced in Indian districts in 2010. The mining bans affected districts in Goa and Karnataka. state boundaries for these states are marked in bold and the affected districts are labeled in red.

2.1 Goa Ban

In Goa, the state government imposed a ban on iron ore mining on September 11, 2012, following the recommendation of a panel called the Shah Commission that India's Ministry of Mines convened to examine mining violations [Government of India, 2012]. The panel estimated that over the previous decades, Goa lost 349 billion INR (8.61 billion USD in 2022) of royalty revenue

[2]Shares have been calculated using EPWRF State Domestic Products data on constant prices.

due to illegal mining. The panel also presented evidence of gross environmental negligence. The state allowed trading and transportation of already mined ore. On October 5, 2012, the Supreme Court of India ruled that the Goa mining ban would remain in place, and the court suspended iron ore transport in Goa. It seems like the ban on mining itself was already carried out through the state government. On November 11, 2013, the Supreme Court reaffirmed the mining ban but allowed 11 million tonnes of unsold stockpiled iron ore to be auctioned off. It continued to allow the outbound transport of previously mined ore. On March 26, 2014, a panel set up by the court recommended lifting the ban due to satisfactory compliance plans from miners. The next month, the court allowed 20 million tonnes of iron ore mining per year to resume in Goa. While this constituted 40 percent of the pre-ban production, it was never binding, in part because miners faced higher costs under regulatory compliance.

2.2 Karnataka Ban

In the three districts of Karnataka with iron ore deposits,[3] the Supreme Court of India (SCI) imposed a partial ban on mining on July 29, 2011. The ban applied to all but one miner, the publicly owned National Mineral Development Corporation (NMDC). The SCI intended for the ban to last until investigators could assess the allegations of illegal mining and excessive environmental degradation from the interim report by the Central Empowered Committee (CEC) report, released on April 15, 2011. The CEC final report was released on February 3, 2012, after investigators finished assessing the mines for noncompliance along two main dimensions: mining outside the lease area, and excessive dumping of mining waste. The 48 mines that were compliant along both dimensions were categorized as class A and allowed to reopen on April 22, 2012.[4] The 72 mines that exceeded the lease area by up to 10 percent, or dumping by up to 15 percent, were categorized as class B. Class B mines were required to submit a reclamation and rehabilitation (R&R) plan, receive approval from regulators for the plan, pay the penalties, and implement the plan. Class B mines were penalized with 120 thousand USD per hectare of illegal mining, and 25 thousand USD per hectare of illegal dumping, expressed in current USD.[5] While the first class B mines were allowed to reopen on September 28, 2012, only 23 of the mines received R&R approval by two years later, leading to a slow recovery of mining output in Karnataka. The 58 mines that exceeded guidelines by a further extent were categorized as class C.[6] The SCI canceled class C mines' leases and directed authorities to seize their ore stockpiles to cover environmental remediation costs.

[3] These districts are Bellary, Chitradurga, and Tumkur. Bellary accounts for 90 percent (verify) of Karnataka's production.

[4] 45 of these 48 mining leases had active mining at the time of the ban.

[5] The original figures in 2012 were 5 million INR and 1 million INR, respectively.

[6] 49 of the 58 mining leases had active mining at the time of the ban, which is why different sources quote different numbers for the number of closed mines.

Figure 2: Timeline of the Bans

3 Data

Annual Survey of Industries (ASI). The primary dataset for this study is the Annual Survey of Industries (ASI), which provides detailed plant-level panel data on various aspects of production and is representative of India's formal manufacturing sector. The ASI is the key source of manufacturing statistics in India and is widely used in economic research [Allcott et al., 2016, Martin et al., 2017]. It covers all plants registered under Sections 2(m)(i) and 2(m)(ii) of the Factories Act, 1948, which includes plants with more than 10 workers (or more than 20 workers if not using electricity). Large factories with over 100 workers are surveyed annually, while smaller factories are typically surveyed once every five years.

The survey collects detailed information on the products produced, input mix, labor and wages, and the assets and liabilities of manufacturing plants. ASI plants report the quantities and values of their top ten domestically sourced inputs and top five imported inputs. This plant-level input mix data enables us to identify firms that rely on inputs affected by the supply shock from the mining bans in Goa and Karnataka.

The ASI panel data do not publish information on the district in which the plant is located. This is a well-known drawback of the data. A key contribution of this study is to assemble a version of the ASI data with district identifiers for each plant. This is key to identifying which plants are located in or around the districts that were affected by the mining bans.

Indian Bureau of Mines and Karnataka Mining Auction Data. To assess the impact of the mining bans on mining activity in India, we supplement the ASI data with two additional sources. First, we digitize annual reports from the Indian Bureau of Mines for the years 2009–2019 to obtain district-level data on the quantities and prices of various iron ore varieties. Second, we use detailed data from iron ore "e-auctions" conducted in Karnataka between 2011 and 2022. These auction bid sheets were scraped from the Karnataka Department of Mines and Geology (DMG) website.[7] The DMG began conducting online "e-auctions" for iron ore in September 2011, following a mandate from the Supreme Court of India. Each auction involves multiple blocks of iron ore, where each block is characterized by its source and iron ore content. Bidders submit prices and quantities in a first-price sealed bid auction, and multiple successful bids can occur at different prices for the same block. The auction data provide information on the iron ore type, prices, and quantities, along with the names of the miners (sellers) and successful bidders (buyers). Since the winners are responsible for transporting the ore from the mine to their locations, the reported prices are mine-gate prices, consistent with the data from the Bureau of Mines.

4 The Impact of Mining Bans

We first analyze aggregate, district-level data on mining to demonstrate the impact of the Karnataka and Goa mining bans on iron ore production in these states and across India. Next, we evaluate how the resulting supply shock to iron ore affected plants that rely heavily on iron ore as a key input in their production processes.[8]

4.1 The Impact on Aggregate Mining Activity

The two panels in Figure 3 illustrate the impact of the mining bans on iron ore production in Goa, Karnataka, and the rest of India from 2009 to 2018. Panel (a) on the left shows the total quantity of iron ore mined, normalized to 2010 levels, which is the last pre-ban year. In 2010, both Karnataka and Goa were major contributors to India's total iron ore output, accounting for 20 percent and 18 percent, respectively.

Following the imposition of the mining bans in these two states, we see a sharp decline in iron ore production. Karnataka's ban was introduced in August 2011, midway through fiscal year 2011, which led to an immediate drop in output. However, the partial lifting of the ban in 2012 allowed production to recover somewhat, though it remained well below pre-ban levels. Goa's mining ban, imposed in October 2012, caused an even steeper and more sustained decline, with no recovery in output by the end of the sample period in 2018. In contrast, iron ore production in the rest of India did not decline during this period, which suggests that the drop in Karnataka and Goa was specifically due to the bans, rather than any broader sector-wide trends affecting iron ore production across the country.

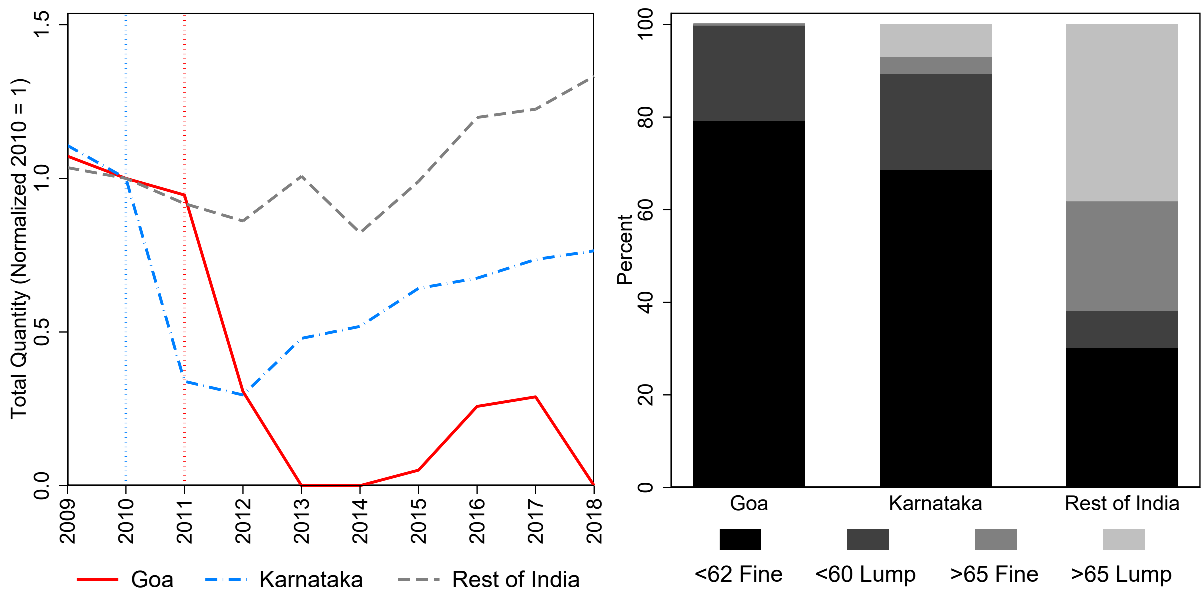
Panel (b) on the right focuses on the production of low-grade fines, a variety of iron ore with a lower iron content, which is more common in Goa and Karnataka. The data show that the production of fines declined sharply in both states after the bans were imposed. In Goa, fines production nearly disappeared, reflecting the complete halt in mining activities after 2012. In Karnataka, fines production also dropped significantly but rebounded somewhat after the partial lifting of the ban. In contrast, the production of fines in the rest of India grew steadily in this period.

[7] See `https://dmg.karnataka.gov.in/en` for more information. Figure **??** in Appendix **??** shows a screenshot of an example bidsheet.

[8] Some of the analysis in this section draws on Saxena [2024].

Figure 3: Mining Output over Time and Pre-Ban Iron Ore Composition

(a) Mining Output over Time   (b) Pre-Ban Iron Ore Composition



Notes: Panel (a) uses data from the Indian Bureau of Mines to show the quantity of iron ore mined over time in Goa, Karnataka, and the rest of India, normalized to 2010 levels. The years correspond to fiscal years; for example, fiscal year 2010 begins on April 1, 2010, and ends on March 31, 2011. Karnataka's mining ban was imposed in August 2011, about one-third of the way through fiscal year 2011, and partially lifted at the start of fiscal year 2012. However, many mines in Karnataka did not receive immediate approval to resume operations, as discussed in Section 2.2. Goa's mining ban was implemented in October 2012, halfway through fiscal year 2012. The right panel shows the composition or iron ore in Goa, Karnataka, and the rest of India. All of the iron ore production in Goa and over 85 percent of production in Karnataka is of low-grade fines and lumps. The bans affected the production of these specific varieties of iron ore that was produced in large quantities in Goa and Karnataka, but accounted for only a small share of iron ore mined in the rest of India.

4.2 The Impact on Downstream Plants

4.2.1 Ideal Reduced-Form Regressions

The ideal experiment would be to randomly assign a temporary ban to a sector s at a given time t_0, compute the direct exposure of each firm in the economy to the ban through local labor markets, suppliers of intermediate inputs, and demand, and then regress the outcomes y_{ijst} such as output revenue, output price, and input expenditure. Define the local labor market exposure e_j^L based on the share of employees in location j who worked at firms affected by the ban, as well as the location j net migration matrix from workers of all banned firms. Define the intermediate input exposure e_{ijs}^M using the share of inputs purchased from the banned sector and location $\underline{js}$, the elasticities of substitution across locations and inputs, and the change in the price of the sector $\underline{s}$ good at location j. Define the demand exposure e_s^D based on the purchases by the banned sector and their employees of the sector s good. The regression is

$$y_{ijst} = \beta^L \text{Post}_t e_j^L + \beta^M \text{Post}_t e_{ijs}^M + \beta^C \text{Post}_t e_s^D + \alpha_i + \gamma_{jt} + \delta_{st} + \epsilon_{ijst}, \tag{1}$$

where y_{ijst} is the outcome in year t for firm i in district j and sector s, Post_t is a dummy variable indicating a time period t after the ban imposed at t_0, and ϵ_{ijst} is the error term. The parameters of interest, $\{\beta^L, \beta^M, \beta^C\}$, captures the direct partial equilibrium impacts of the ban on the outcome through each channel, comparing firms affected by the ban against unaffected firms. The establishment-fixed effects α_i, location-time fixed effects γ_{jt}, and sector-time fixed effects δ_{st} control for all other variables besides the policy change, which is at the location-sector-time jst level. The key identifying assumption is that the counterfactual values of the outcomes for the affected firms, in the absence of the ban, would be the same as those of the unaffected firms after conditioning on firm-specific characteristics, nationwide sectoral shocks, and local shocks common across sectors. Note that general equilibrium effects through the production network are absorbed by the fixed effect γ_{jt}, and general equilibrium effects through local labor markets are absorbed by the fixed effect δ_{st}. Alternative versions of regression (1) include interactions of the the $\text{Post}_t \times \text{Ban}_j$ "treatment" with firm characteristics X_{ijst}, in order to capture heterogeneous effects across sectors or the firm size distribution.

Due to pre-existing contracts in the supply chain, hedging in financial markets, labor market regulations, and other adjustment frictions, the impacts of the ban may not have been immediate. We consider the event study counterpart to the difference-in-difference regression in (1) to capture the effects over time:

$$y_{ijst} = \sum_{m=T_0}^{T_1} \left(\beta_m^L \mathbb{1}_{tm} e_j^L + \beta_m^M \mathbb{1}_{tm} e_{ijs}^M + \beta_m^C \mathbb{1}_{tm} e_s^D \right) + \alpha_i + \gamma_{jt} + \delta_{st} + \epsilon_{ijst}. \tag{2}$$

where $\mathbb{1}_{tm}$ is an indicator for whether period t corresponds to event time m, and T_0 and T_1 are the start and end dates (2005 to 2015). Here, the parameters of interest are β_τ, which capture the period τ difference in the outcome for firms in the banned sector-location, relative to all other firms, controlling for general differences between firms, general sectoral trends, and general trends by locations.

In reality, both in this setting and in most settings with CAC policy, neither the choice of sector nor the timing of the ban are completely random. For our empirical results, we focus on the Karnataka ban because it was unexpected. It was not only the first mining ban in India, but also the first ban imposed across all firms in a given sector and location in India. Also, the timing of the ban was almost immediately after the release of a report detailing the environmental non-compliance and the corruption that enabled its persistence in the iron ore sector, so downstream firms did not have time to stockpile inventories nor otherwise hedge against it.

Even with the ideal experiment, spillover effects cloud the interpretation of β. The more that the shock or policy change affects neighboring locations and sectors through indirect channels, the further the relative effect captured by β is away from the total GE impact. There are three main types of spillover effects that we believe are pertinent to this context: production network, through the higher-order terms of the Leontief inverse and adjustment of firm-to-firm links; labor market, through changes in residual local labor supply to unaffected firms from workers who worked at the affected firms; and spatial, through changes in multi-plant firms' allocation of production across plants. The labor market channel includes changes in local wages at ports and districts with major steel plants, not just the local wages in the iron ore mining areas.

4.2.2 ASI Firm Panel Regressions

Due to data limitations, we can only run (1) and (2) on manufacturing firms using the ASI dataset. To estimate the impact of the mining bans on firms in the Indian manufacturing sector, we start by defining what it means for a plant to be exposed to these bans. We consider a plant to be exposed if it operates in a sector that relies significantly on materials directly affected by the bans—specifically, magnetite, iron ore, and iron concentrates. Using data on the input-mix of ASI plants, we compute the average share of input expenditure that plants in each 5-digit sector allocate to these materials.[9]

If a plant belongs to a 5-digit sector where more than 5 percent of its input costs are spent on these affected inputs, we classify it as "treated" or exposed to the mining bans. Using this criterion, we identify 11,099 plants as exposed, which represents about 4.1 percent of the total 279,892 plants in our sample.[10]

To estimate the impact of the mining bans, we estimate the following event study specification:

$$y_{ist} = \beta_t \mathsf{MBan}_{st} + \mathbf{\Gamma X_{it}} + \theta_i + \delta_t + \epsilon_{ist}, \tag{3}$$

where i denotes a plant, s denotes a 5-digit National Industrial Classification (NIC) sector,[11] t denotes a year, and y_{ist} is the firm outcome of interest, consisting of the logs of revenue, the number of employees, and the total wage bill. MBan_{st} is an indicator variable which is equal to 1 if more than 5 percent of input costs in sector s are spent on magnetite, iron ore, and iron concentrates, materials that faced a supply shock after the mining ban. θ_i and δ_t denote firm and year fixed effects. δ_t controls for aggregate fluctuations, while θ_i removes time-invariant unobserved firm-level heterogeneity. We show below that our results are robust to including controls for state and 2-digit sector-specific trends ($\mathbf{X_{it}}$).[12] Standard errors are clustered at the 4-digit industry level to account for any serial correlation that might bias our standard errors downward.

To estimate the impact of the ban on mining of iron ore on downstream sectors, we estimate the event study (3). Figures 4, 5, and 6 show the impact of the mining ban on plants in iron-using sectors relative to plants in sectors that do not consume iron ore.[13]

[9]For instance, plants in NIC 17023 (manufacture of cardboard boxes) and NIC 27310 (manufacture of fibre optic cables for data transmission or live transmission of images) allocate less than 0.1 percent of their input costs to the affected materials, while plants in NIC 24101 (manufacture of pig iron and spiegeleisen in pigs, blocks or other primary forms) and NIC 24102 (manufacture of direct reduction of iron (sponge iron) and other spongy ferrous products) allocate over 30 percent of their input expenditure on magnetite, iron ore, and iron concentrates.

[10]Defining treatment at the 5-digit sector level helps minimize the impact of measurement error in the input-mix data of individual plants. For instance, a plant might misreport its product codes or fail to provide a complete account of its inputs in a given year. If treatment were determined at the plant level, these inaccuracies could lead to errors in the treatment classification. However, by averaging input shares across many firms within a sector, the likelihood of such errors is reduced.

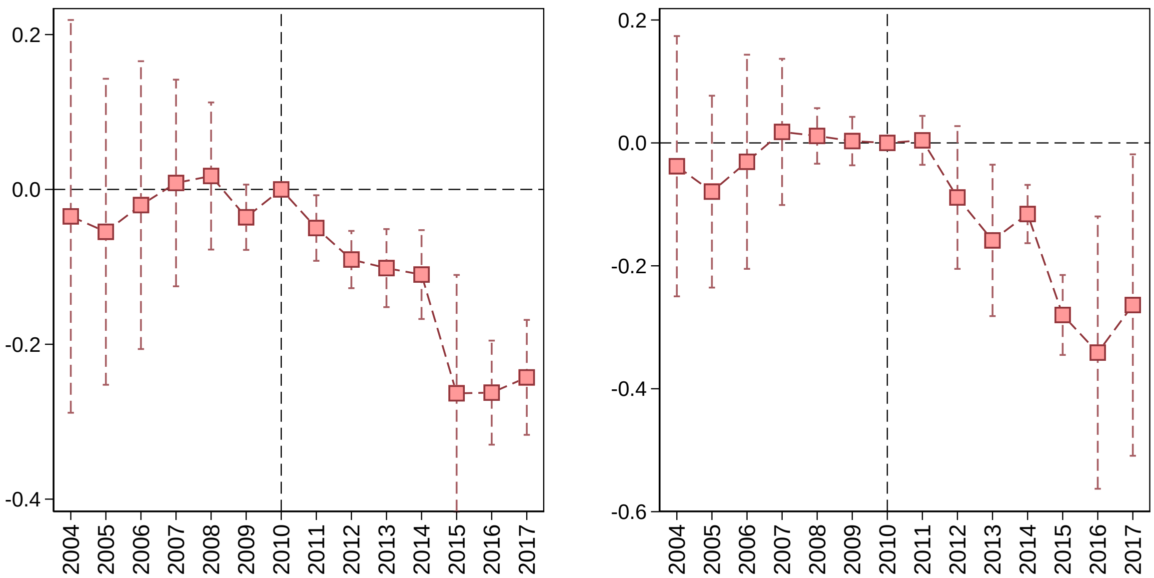
[11]The specificity of a 5-digit National Industrial Classification (NIC) sector is similar to that of the 6-digit Harmonized Standards (HS) code.

[12]We are able to include 2-digit sector $\times$ year fixed effects as the mining ban is defined at a narrower 5-digit level. There are 706 5-digit industries in the ASI whereas there are only 22 industries at the broader 2-digit level.

[13]In the appendix, we show that these results are robust to controlling for state-year and 2-digit industry-year fixed

Figure 4: Impact of Mining Ban on Log Employment and Total Wage Bill

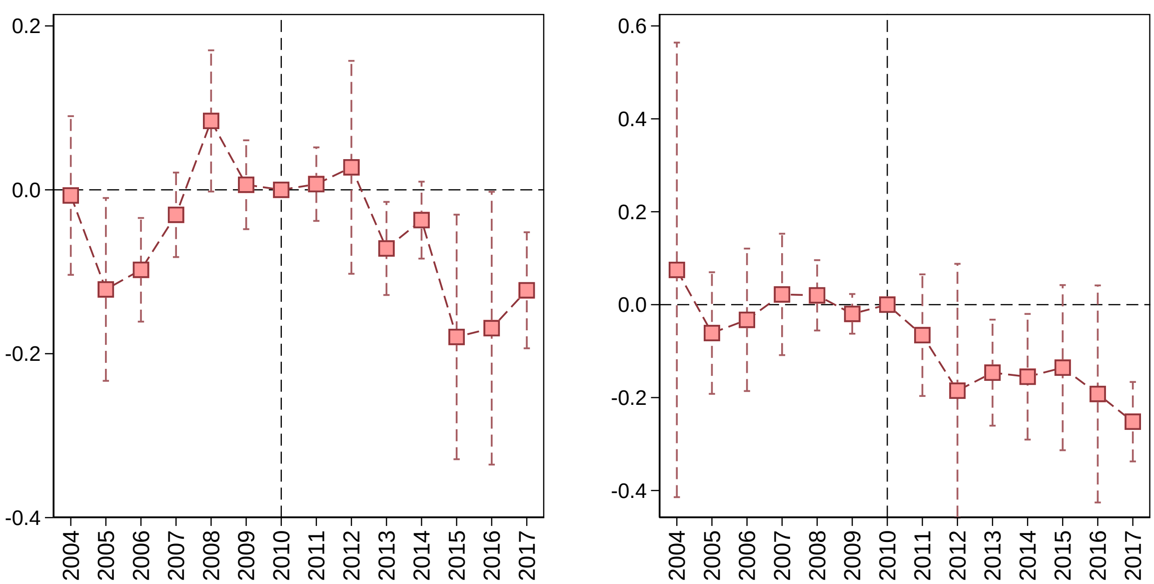
(a) Log Employment (b) Log Wage Bill



Notes: This figure plots the estimated β_t coefficients from event study (3) with firm and year fixed effects, along with 95 percent confidence intervals. The dependent variable is log employment (left panel) and log wage bill (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, so the coefficient β_{2010} is normalized to zero.

Figure 5: Impact of Mining Ban on Log Revenue and Capital Stock

(a) Log Revenue (b) Log Capital Stock



Notes: This figure plots the estimated β_t coefficients from event study (3) with firm and year fixed effects, along with 95 percent confidence intervals. The dependent variable is log revenue (left panel) and log capital stock (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, so the coefficient β_{2010} is normalized to zero.

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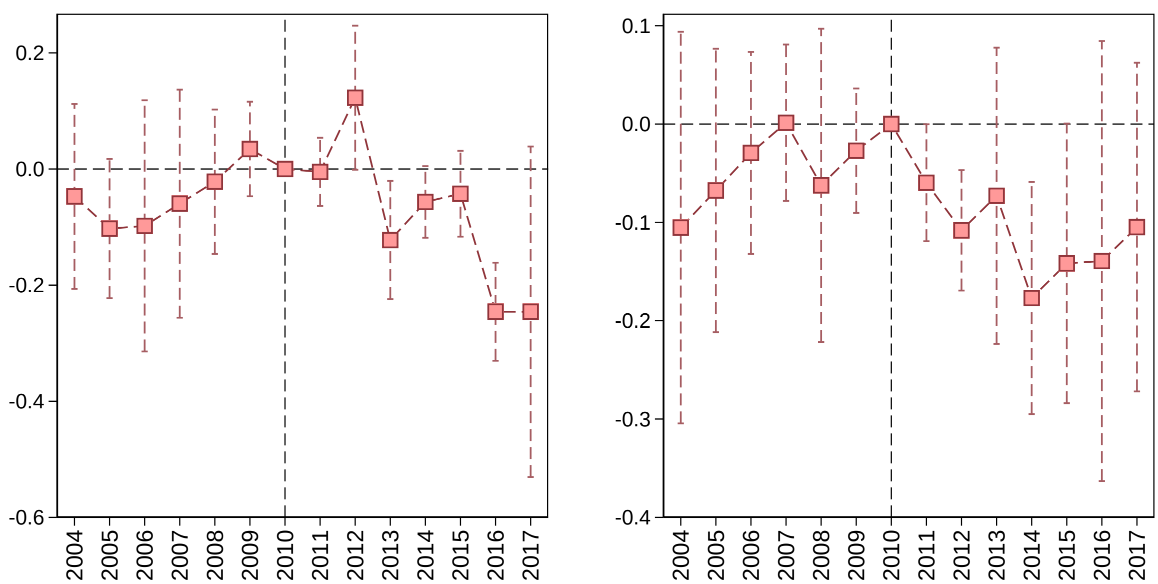
effects, i.e. comparing firms within the same state and the same broad 2-digit industry.

In Figure 4, we show the impacts on labor market outcomes. Figure 4a shows that affected downstream steel sector firms reduced employment by 10 percentage points by the second year after the ban was imposed, and continued to decrease as the mines slowly reopened and iron ore prices remained elevated for affected firms. Figure 4b shows that the decrease in the wage bill was of similar magnitude to employment.

In Figure 5, we show the impact on revenue and capital stock. Capital stock by 15 percentage points by the second year after the ban was imposed. Finally, we consider financial outcomes in Figure 4. Affected firms increased cash holdings immediately after the ban by 12 percentage points, then decrease below the pre-ban level in all subsequent periods. We explain this through firms' expectations of tighter credit conditions, due to spillover effects of non-performing loans on local banks, as well as precautionary savings. Compared to a free market benchmark, firms reduced input demand by more in reality because iron ore is Leontief with other inputs in the steel production function in the short run, and iron ore was quantity rationed. Iron ore is expensive to transport as a share of value, India's railways are notoriously subject to congestion [Firth, 2017], and India had high tariffs on iron ore. Affected firms also immediately deleverage, reducing their debt by 6 percent immediately and 10 percent in the long run.

Figure 6: Impact of Mining Ban on Log Cash Holdings and Log Debt Outstanding

(a) Log Cash Holdings (b) Log Debt Outstanding



Notes: This figure plots the estimated β_t coefficients from event study (3) with firm and year fixed effects, along with 95 percent confidence intervals. The dependent variable is log cash holdings (left panel) and log debt outstanding (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, so the coefficient β_{2010} is normalized to zero.

4.2.3 Shift-Share Regressions

To obtain a precise measurement of the impulse of the mining ban shock on downstream plants, and to potentially use finer-grained sector-time fixed effects, we consider a shift-share design. The "shift" comes from the sudden closure of Karnataka's mines; as Figure 3b shows, the distribution of iron ore varieties from Karnataka's mines was rather different from the distribution of iron ore varieties from the other mining clusters in India, primarily in Odisha and Chhattisgarh, over a thousand kilometers to the northeast.[14] Each downstream plant i in location j and sector s faces a different inward shift in the supply curve of each iron ore variety based on its location, relative to Karnataka versus to other mining clusters, with larger inward shifts for plants relatively closer to Karnataka.

The "shares" are the iron ore consumption profiles of the plants at the time of the ban, i.e. the share of total iron ore consumption in each iron ore variety. We argue that the shares are difficult and costly to adjust because the machinery and production process are specialized by feedstock.[15] Since the ban was unexpected and shares are costly to adjust, we argue that the shares are as good as random relative to the shift as well as relative to the treatment effect on firms' outcomes. In other words, firms did not select in response to the ban along the dimension of the shares.

Then, the shift-share treatment variable is the sum across varieties of the products of the shifts and the shares, and we run regressions on this continuous treatment variable.

5 Model

To estimate the aggregate effect of the bans and assess the counterfactual regulatory enforcement policy, we build a quantitative macroeconomic model that focuses on the role of iron ore in the steel supply chain, with heterogeneity between sectors and locations. We calibrate our model using the regression results from (3) as well as moments from the firm-level ASI data and the transaction-level mining auction microdata.

The economy has a production block and a household block. The production block features manufacturing firms in an input-output network, distributed unevenly across locations according to the ASI data, as well as an informal sector in each location. Specific locations also have a representative iron ore mining firm that consumes a composite input good from the manufacturing sector and sells to a subset of manufacturers. The household block features a representative household in each location. We assume that labor is immobile across locations.[16]

[14] Iron ore trade within India was mostly by rail, and rail transport prices generally scaled linearly with distance. The cost to transport ore between Karnataka's mines and Odisha's mines at the time of the ban was 42 USD per tonne in 2024 dollars, compared to domestic prices that varied from 100 to 200 USD per tonne, based on variety.

[15] In practice, we use the data from the Bureau of Mines on major downstream plants' feedstock profiles, supplemented with auction data aggregated to the purchaser (plant) level for the many plants that are not in the Bureau of Mines data. Auction data are only available from September 2011 onwards, so we must assume that the shares do not change from early 2011 to late 2011.

[16] We will use the 2011 Census migration data to relax this assumption in a future version of this paper

5.1 Production Block

Let j index the set of locations J, and let s index the set of sectors S.

5.1.1 Manufacturing

In each sector s, there is a subset of locations $j \in J_s \subseteq J$ that feature a representative competitive manufacturer that produces output y_{js} using a Cobb-Douglas bundle of two factors, labor ℓ_{js} and capital k_{js}, as well as an intermediate input bundle X_{js}:

$$y_{js} = z_{js} L_{js}^{\alpha_s^L} K_{js}^{\alpha_s^K} X_{js}^{\alpha_s^X}, \tag{4}$$

where z_{js} is a productivity shifter. Assume that each manufacturing sector's good is perfectly substitutable across locations, with zero domestic trade costs, so there is a single sectoral price p_s. Let $\underline{s}$ denote the sector for the subset of manufacturers in the steel supply chain that were directly affected by the mining ban through their purchases of iron ore. We assume that the production function of $\underline{s}$ is Leontief in iron ore and a composite input good; iron ore is a crucial input whose share in the composition of steel products is fixed by chemistry. We model the ban as a decrease in $z_{j\underline{s}}$ proportional to the magnitude of the change in log wages, the difference between Figures 4b and 4a. Let σ be the elasticity of substitution:

$$X_{jk} = \left(\omega_{\underline{s},s} x_{j\underline{s}s}^{\frac{\sigma-1}{\sigma}} + \omega_s x_{js}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where $x_{j\underline{s}s}$ is the amount of the sector $\underline{s}$ good that the sector s firm in location j purchases, and x_{js} is its demand for the composite good. We assume that the steel sector $\underline{s}$ is an upstream sector whose output is only used by other manufacturers (e.g. automobiles, industrial machinery, consumer durables), not directly consumed by households. Each manufacturer's cost minimization problem gives the demand functions for factors and intermediate inputs.

5.1.2 Aggregation

For all of the other sectors $s' \in S \setminus S_{\underline{s}}$, assume that there is a competitive aggregation sector that produces a composite good Q with constant elasticity of substitution σ across sectors:

$$Q = \left(\sum_{s' \neq \underline{s}} \omega_{Qs'} q_{s'}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

Similarly to each manufactured good, we assume that there are zero domestic trade costs, so we normalize the price of the composite good to be 1.

5.1.3 Mining

A small subset $J_m \subseteq J$ of locations have mines. Each location $j \in J_m$ has a mine m that uses labor L_m and the composite manufactured good X_m to produce iron ore with Cobb-Douglas labor share

α^M:

$$y_m = z_m L_m^{\alpha^M} X_m^{1-\alpha^M}.$$

Following the geography of ore deposits, assume that only several locations j have mines, and each mining location produces a differentiated variety of iron ore.[17] Assume that only iron ore is mined, and iron ore is only used in the production of steel $\underline{s}$, not in any other sector nor as a final consumption good.[18]

5.1.4 Pollution

Each mine faces a pollution limit $\bar{\pi}_m$. Pollution $\pi_m = \phi_m y_m$ is produced linearly in output y_m, and the cost C_m^{ω} of handling waste is concave in the waste rate ϕ_m, meaning that as ϕ_m decreases, there is increasing marginal cost of decreasing ϕ_m further: $C_m^{\pi} := \frac{C^{\pi}}{\phi_m}$.

The regulator is capacity constrained; it can only audit a fraction ρ of mines, observing waste perfectly after auditing, and otherwise observes no signal of π_m. The regulator assess a statutory penalty P^{π} per unit of non-compliance audited above the waste limit.

5.1.5 Informal Sector

Each location j has an informal sector that produces a non-tradable good $x_j^I = z_j^I L_j^I$ under perfect competition with labor L_j^I and no other inputs. Its price is P_j^I.

5.2 Household

Each location j has a representative household. The household has log preferences over a Cobb-Douglas bundle over consumption $\tilde{c}_j$ of the local informal sector good, as well as consumption of the composite manufactured good c_j, with exponential disutility over a CES bunde ℓ_j between "skilled" manufacturing ℓ_{Sj} and "unskilled" mining and informal sector labor ℓ_{Uj}:

$$U_j = \beta \log c_j + (1-\beta) \log \tilde{c}_j - \frac{\ell_j^{1+\gamma}}{1+\gamma}, \tag{5}$$

$$\ell_j = \left(\omega_S \ell_{Sj}^{\frac{\varsigma-1}{\varsigma}} + \omega_U \ell_{Uj}^{\frac{\varsigma-1}{\varsigma}} \right)^{\frac{\varsigma}{\varsigma-1}}. \tag{6}$$

In each location, there are two wages: w_{Uj} in the informal sector, as well as mining if there is any mining activity, and w_{Sj} in the manufacturing sector.

[17] In practice, transport costs as a share of value are substantial for iron ore, because transport costs scale with weight and iron ore has low value per weight compared to most other goods. The transport costs are implicitly captured in a lower elasticity of substitution across varieties of iron ore.

[18] In India, the steel sector comprises 97% of manufacturing demand for iron ore.

5.2.1 Equilibrium

Given the productivity shifters $\{z_m\}$, $\{z_{js}\}$, and $\{z_j^I\}$, CES shares $\{\omega_s\}$, and other parameters $\{\phi_m\}$, $\{\alpha_s^L, \alpha_s^K, \alpha_s^X\}$, α^M, and β, an equilibrium consists of

- Prices p_s and wages $\{w_{Uj}, w_{Sj}\}$,
- Allocations of inputs $\{L_{js}, K_{js}, X_{js}\}$, and $\{L_m, X_m\}$
- Output $\{y_{js}\}$ and Q,
- Pollution $\{\pi_m\}$,

such that the household maximizes utility (5) subject to the budget constraint

$$c_j + P_j^I \tilde{c}_j = w_{Sj} L_{Sj} + w_{Uj} L_{Uj}, \tag{7}$$

firms minimize costs subject to their production functions, and markets clear:

- The sum of household demand and intermediate demand for the composite good equals the production of the composite good

$$\sum_{j \in J} c_j + \sum_{s \in S} \sum_{j \in J_s} x_{js} + \sum_m X_m = \left(\sum_{s' \neq \underline{s}} \omega_{Qs'} q_{s'}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

  the production in the steel sector equals supply

$$\sum_{j \in J_{\underline{s}}} y_{j\underline{s}} = \sum_{s' \in S} \sum_{j \in J_{s'}} x_{j\underline{s}s'},$$

  and the production in the other manufacturing sectors equals supply

$$\sum_{j \in J_s} y_{js} = q_s, \ \forall s \neq \underline{s}.$$

- Labor demand equals labor supply for each type of labor in each location:

$$\sum_{s \in S} L_{js} = \ell_{Sj},$$
$$L_j^I + \mathbb{1}\{j \in J_m\} L_m = \ell_{Uj}.$$

5.3 Calibration

We calibrate the Cobb-Douglas shares using expenditure shares in the ASI data, and we calibrate the input elasticity of substitution σ using the substitution patterns in response to the shock to the steel sector $\underline{s}$.

5.4 Counterfactuals

- The firm can choose environmental productivity ζ with cost $\kappa(\zeta)$ cet. par.
- The enforcer faces enforcement cost $\varepsilon(\tilde{\tau})$ with $\varepsilon(0) = 0$ and $\varepsilon(\tilde{\tau}) > \varepsilon(\infty)$ for large enough non-compliance penalty $\tilde{\tau}$
- The pollution generates an externality $\psi(\pi)$

How should the enforcer choose the non-compliance penalty $\tilde{\tau}$? Under reasonable assumptions for the functions and parameters, what is $\tilde{\tau}$ in this setting?

6 Conclusion

This paper provides a novel assessment of the aggregate impacts of command-and-control (CAC) environmental policies by examining the court-ordered mining bans in India. Using event study regressions and a structural model, we quantify the economic costs incurred by sectors closely linked to the banned mines, particularly the downstream steel industry. We show that the ban caused substantial decreases in employment, capital investment, and borrowing among downstream firms, suggesting that the economic repercussions of CAC policies can extend well beyond the sectors directly subject to regulatory action. Furthermore, our findings emphasize that sectoral banscan cause large economic spillovers through production networks and labor markets, potentially amplifying the aggregate impact.

Our counterfactual analysis suggests that a less extreme regulatory measure, such as a variable ad-valorem tax on non-compliant firms, could achieve compliance while reducing aggregate economic losses. By modeling the impact of a hypothetical tax on mining firms' compliance costs, we observe that an intermediate tax level would likely generate greater social value than an outright ban, balancing the environmental benefits with economic costs. This paper contributes to the broader literature on environmental policy by illustrating the importance of considering general equilibrium effects in regulatory design. We also contribute to the literature on CAC policies in developing economies, where limited institutional capacity often necessitates such interventions. Future research could explore similar frameworks in other regulatory settings to assess whether intermediate policies could yield optimal outcomes in terms of social welfare.

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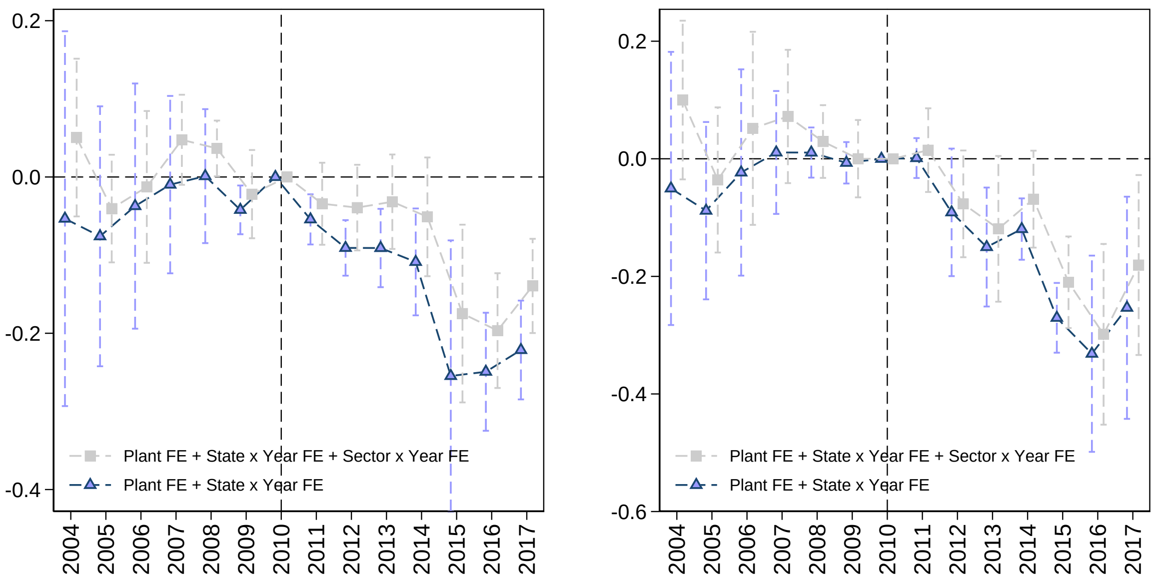
A Appendix - Regressions

To estimate the impact of the ban on mining of iron ore on downstream sectors, we estimate the event study (3). Figures 7, 8, and 9 show the impact of the mining ban on plants in iron-using sectors relative to plants in sectors that do not consume iron ore, with additional fixed effects beyond what we show in Section 4.2.2.

Figure 7: Impact of Mining Ban on Log Employment and Total Wage Bill

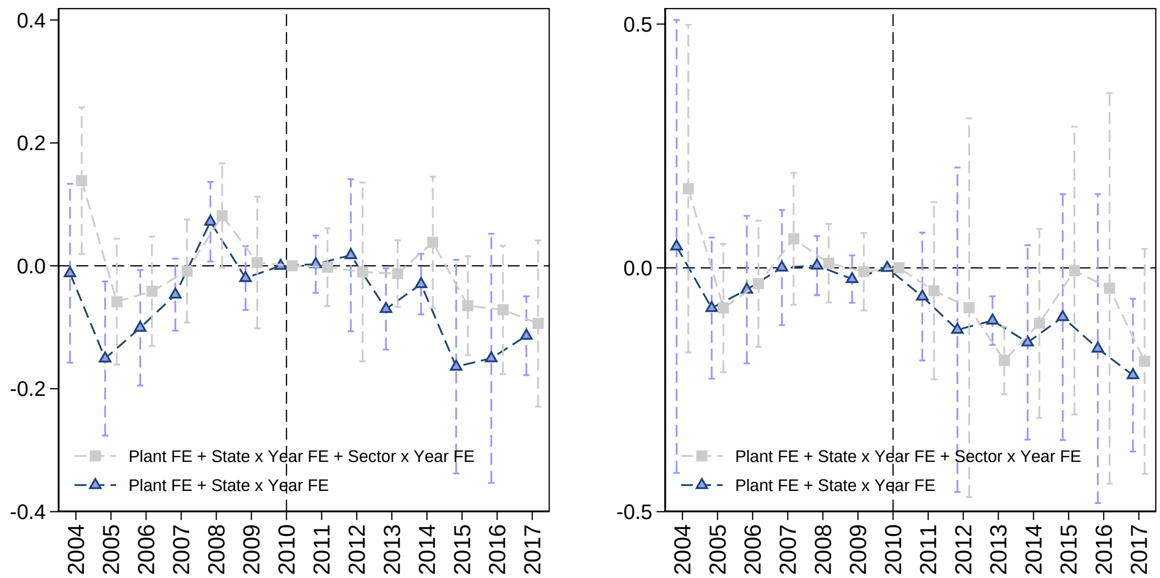
(a) Log Employment (b) Log Wage Bill



Notes: This figure plots the estimated β_t coefficients from event study (3), with 95 percent confidence intervals. The dependent variable is log employment (left panel) and log wage bill (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, so the coefficient β_{2010} is normalized to zero.

Figure 8: Impact of Mining Ban on Log Revenue and Capital Stock

(a) Log Revenue (b) Log Capital Stock

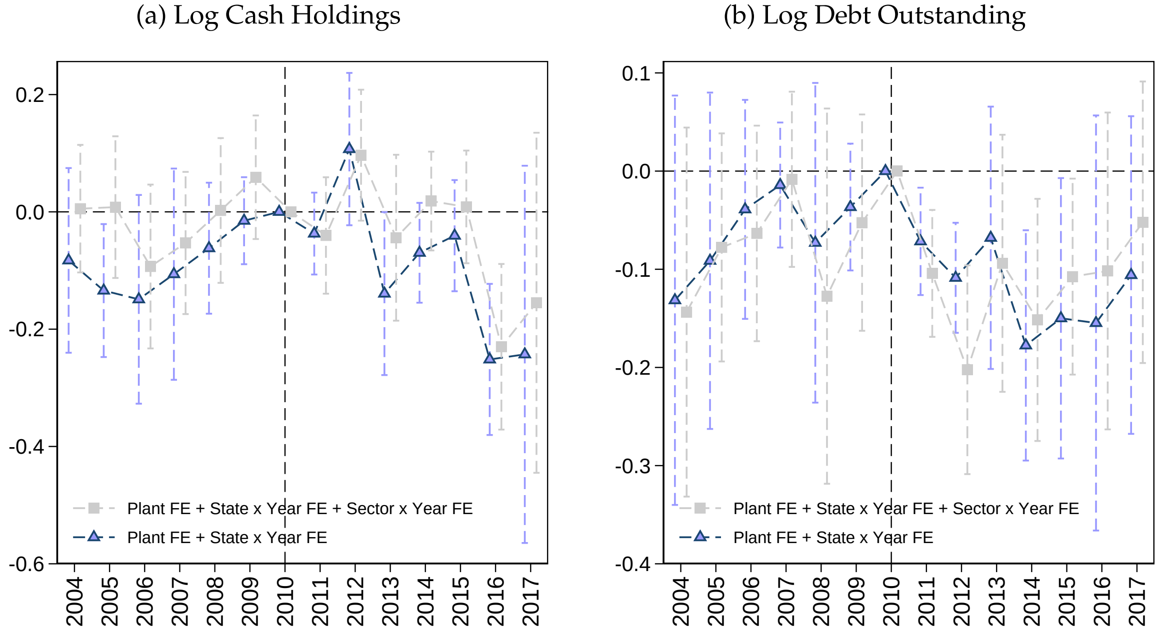


Notes: This figure plots the estimated β_t coefficients from event study (3), with 95 percent confidence intervals. The dependent variable is log revenue (left panel) and log capital stock (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, so the coefficient β_{2010} is normalized to zero.

In Figure 7, we show the impacts on labor market outcomes. Figure 7a shows that affected downstream steel sector firms reduced employment by 10 percentage points by the second year after the ban was imposed, and continued to decrease as the mines slowly reopened and iron ore prices remained elevated for affected firms. Figure 4b shows that the decrease in the wage bill was of similar magnitude to employment.

In Figure 8, we show the impact on revenue and capital stock. Capital stock by 15 percentage points by the second year after the ban was imposed. Finally, we consider financial outcomes in Figure 7. Affected firms increased cash holdings immediately after the ban by 12 percentage points, then decrease below the pre-ban level in all subsequent periods. We explain this through firms' expectations of tighter credit conditions, due to spillover effects of non-performing loans on local banks, as well as precautionary savings. Compared to a free market benchmark, firms reduced input demand by more in reality because iron ore is Leontief with other inputs in the steel production function in the short run, and iron ore was quantity rationed. Iron ore is expensive to transport as a share of value, India's railways are notoriously subject to congestion [Firth, 2017], and India had high tariffs on iron ore. Affected firms also immediately deleverage, reducing their debt by 6 percent immediately and 10 percent in the long run.

Figure 9: Impact of Mining Ban on Log Cash Holdings and Log Debt Outstanding



Notes: This figure plots the estimated β_t coefficients from event study (3), with 95 percent confidence intervals. The dependent variable is log cash holdings (left panel) and log debt outstanding (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, so the coefficient β_{2010} is normalized to zero.