

Aggregate Impacts of Command-and-Control Environmental Policy: Evidence from Court-Ordered Mining Bans in India¹

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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 the world in settings with environmental regulations and natural resource extraction.⁵ 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

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⁵Examples include hydraulic fracturing in the US, lithium mining in Mexico, and gold mining in Brazil.

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 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 percent-

age 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 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](#)].

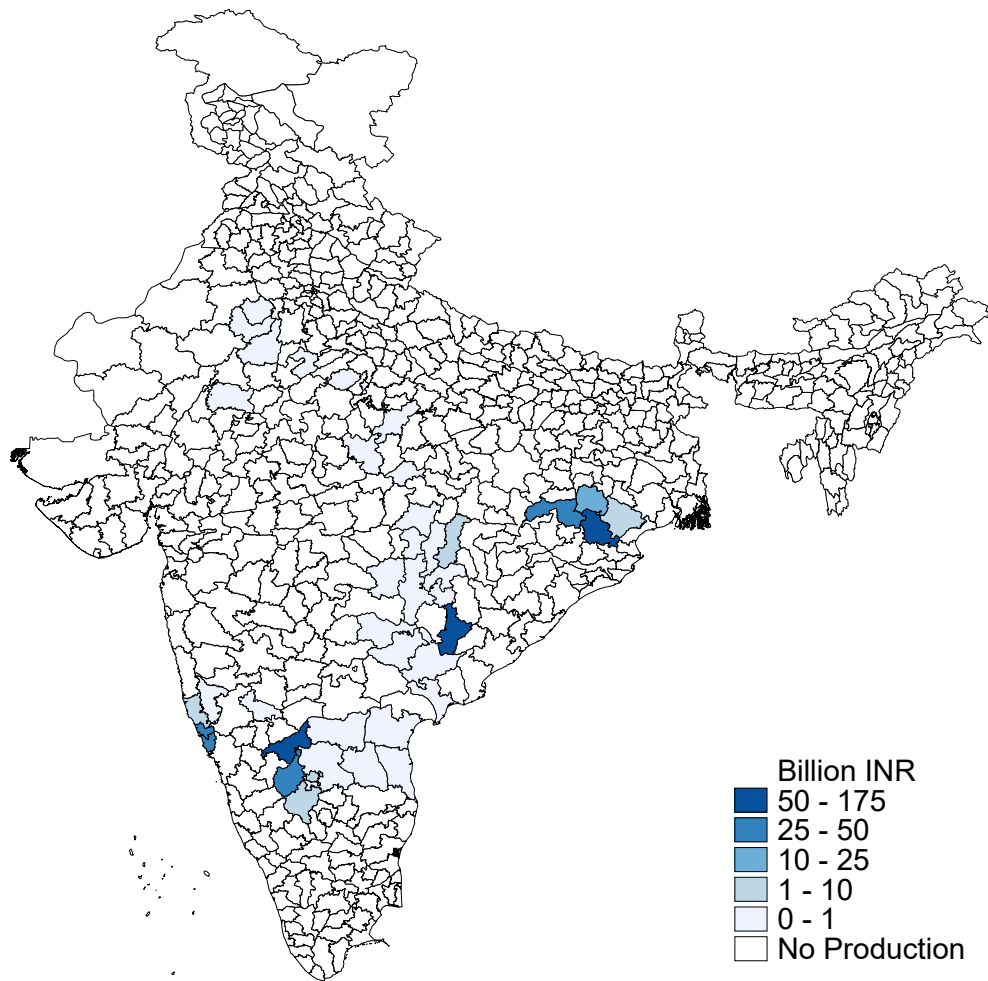
Among India’s mining states, Goa and Karnataka occupy prominent roles in both production and export. Goa’s iron ore industry, historically oriented toward the export of low-grade fines, has been instrumental in meeting international demand, particularly from China. In 2009, Goa led all Indian states 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.⁶ With high transport costs for iron ore, local iron ore prices increased despite an elastic global supply.

⁶Shares have been calculated using EPWRF State Domestic Products data on constant prices.

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

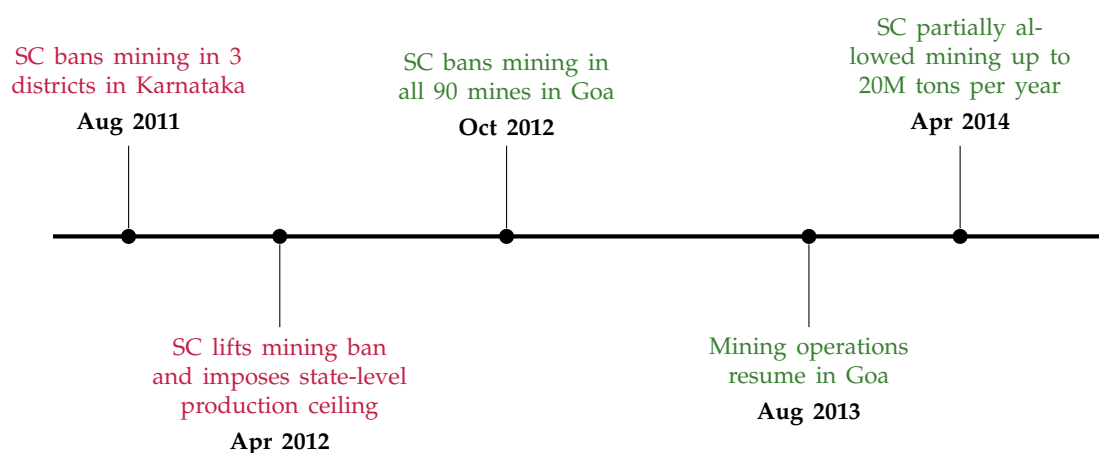
In Goa, the state government imposed a ban on iron ore mining on September 11, 2012, following the recommendation of a panel called the Shah Commission that India's Ministry of Mines convened to examine mining violations [Government of India, 2012]. The panel estimated that over the previous decades, Goa lost 349 billion INR (8.61 billion USD in 2022) of royalty revenue 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,⁷ 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, 2012.⁸ 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.⁹ 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.¹⁰ The SCI canceled class C mines' leases and directed authorities to seize their ore stockpiles to cover environmental remediation costs.

Figure 2: Timeline of the Bans



⁷These districts are Bellary, Chitradurga, and Tumkur. Bellary accounts for 90 percent (verify) of Karnataka's production.

⁸45 of these 48 mining leases had active mining at the time of the ban.

⁹The original figures in 2012 were 5 million INR and 1 million INR, respectively.

¹⁰49 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.

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.¹¹ 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

¹¹See <https://dmg.karnataka.gov.in/en> for more information. Figure ?? in Appendix ?? shows a screenshot of an example bidsheet.

a key input in their production processes.¹²

4.1 The Impact on Aggregate Mining Activity

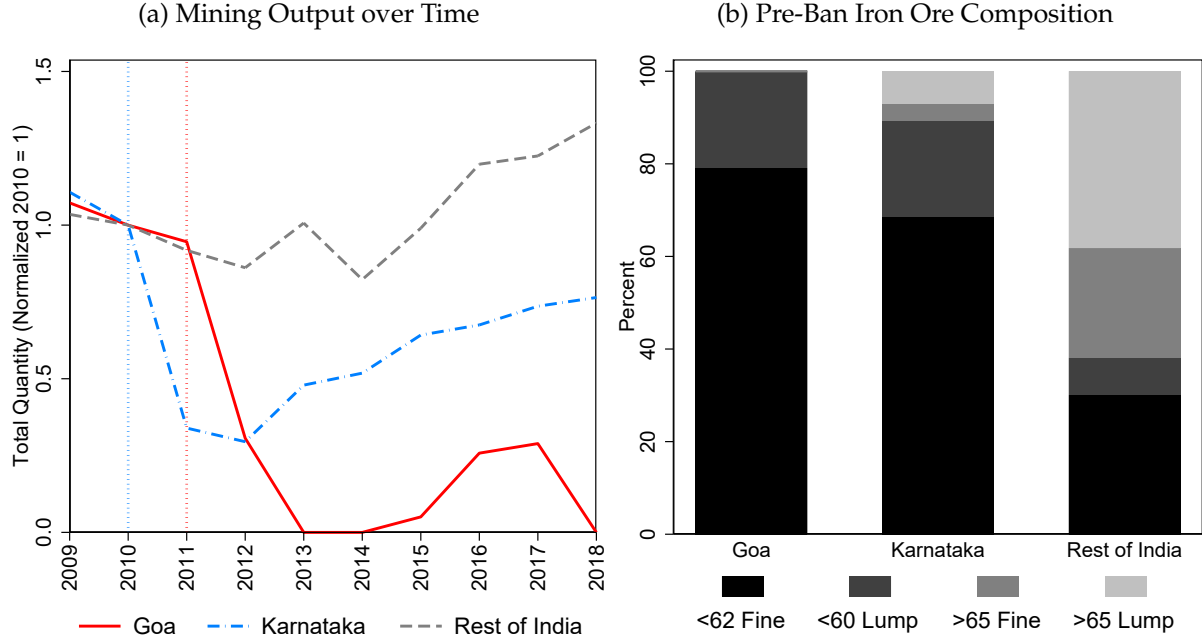
The two panels in Figure 3 illustrate the impact of the mining bans on iron ore production in Goa, Karnataka, and the rest of India from 2009 to 2018. Panel (a) on the left shows the total quantity of iron ore mined, normalized to 2010 levels, which is the last pre-ban year. In 2010, both Karnataka and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

¹²Some of the analysis in this section draws on [Saxena \[2024\]](#).

Figure 3: Mining Output over Time and 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 of 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 $y_{i,j,s,t}$ 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 $e_{i,j,s}^M$ using the share of inputs purchased from the banned sector and location j, s , the elasticities of substitution across locations and inputs, and the change in the price of the sector 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

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

where $y_{i,j,s,t}$ 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 $\epsilon_{i,j,s,t}$ 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 $\gamma_{j,t}$, and sector-time fixed effects $\delta_{s,t}$ control for all other variables besides the policy change, which is at the location-sector-time j, s, t 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 $\gamma_{j,t}$, and general equilibrium effects through local labor markets are absorbed by the fixed effect $\delta_{s,t}$. Alternative versions of regression (1) include interactions of the $\text{Post}_t \times \text{Ban}_{j,t}$ “treatment” with firm characteristics $X_{i,j,s,t}$, 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:

$$y_{i,j,s,t} = \sum_{m=T_0}^{T_1} \left(\beta_m^L \mathbb{1}_{t,m} e_{j,t}^L + \beta_m^M \mathbb{1}_{t,m} e_{i,j,s}^M + \beta_m^C \mathbb{1}_{t,m} e_s^D \right) + \alpha_i + \gamma_{j,t} + \delta_{s,t} + \epsilon_{i,j,s,t}. \quad (2)$$

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.¹³ 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.¹⁴

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

$$y_{i,t} = \sum_{k=\underline{C}}^{\bar{C}} \beta_k \cdot (MBan_{j,t} \cdot \mathbb{1}[t = 2010 + k]) + \Gamma X_{i,t} + \theta_i + \delta_t + \epsilon_{i,t}, \quad (3)$$

where i denotes a plant, j denotes a 5-digit industry, and t denotes a year. The variable y_{it} represents the outcome of interest, i.e., log revenue, log number of employees, and log total wage bill. $MBan_{j,t}$ is an indicator variable, which takes value 1 if industry j devotes more than 5 percent of its input expenditure to magnetite, ores of iron, and iron ore and magnetic concentrates in the pre-ban period. $k \in [\underline{C}, \bar{C}]$, where we set $\underline{C} = -5$ and $\bar{C} = +7$ and normalize $\beta_{2010} = 0$. $\mathbb{1}[\cdot]$ is the indicator function and ϵ_{it} is an error term. The terms θ_i and δ_t represent plant and year fixed effects, respectively. Year fixed effects control for aggregate fluctuations, while plant fixed effects control for time-invariant, unobserved firm-level heterogeneity. X_{it} is a vector of controls that includes state-time and 2-digit industry-by-year fixed effects. We show below that our results are robust to including controls for state and 2-digit sector-specific trends (X_{it}).¹⁵ Standard errors are clustered at the 5-digit industry level to account for any serial correlation that might bias our standard errors downward.

Figures 4, 5, and 6 show the results from (3) on the impact of the mining ban on plants in iron-using sectors relative to plants in sectors that do not consume iron ore.¹⁶

¹³For 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.

¹⁴Defining 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.

¹⁵We 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.

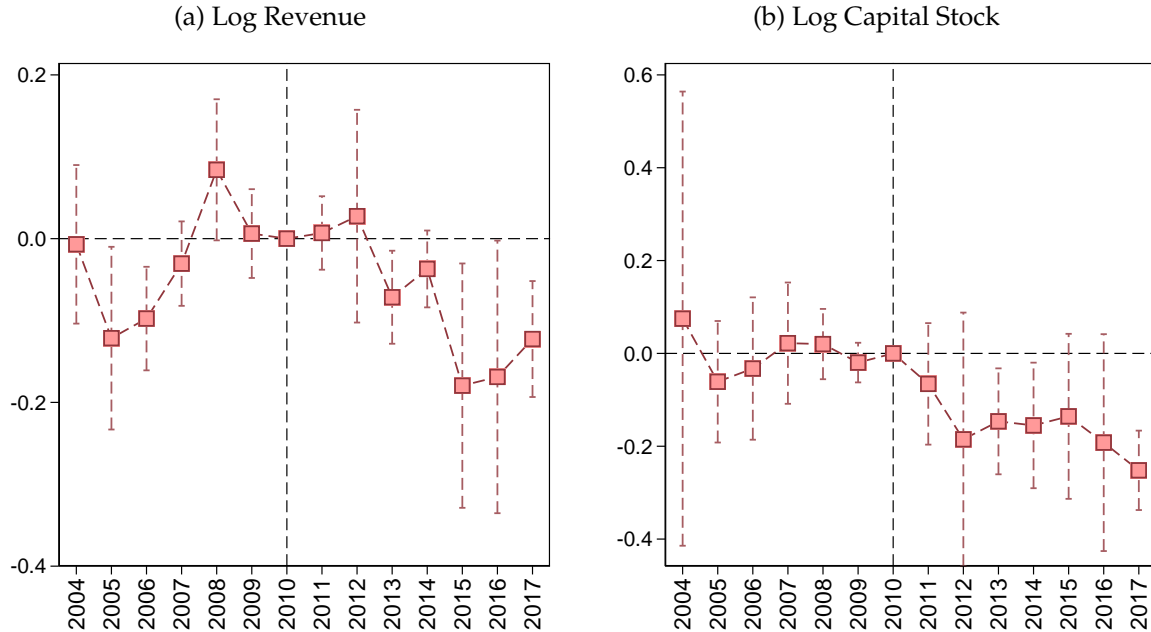
¹⁶In the appendix, we show that these results are robust to controlling for state-year and 2-digit industry-year fixed

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



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



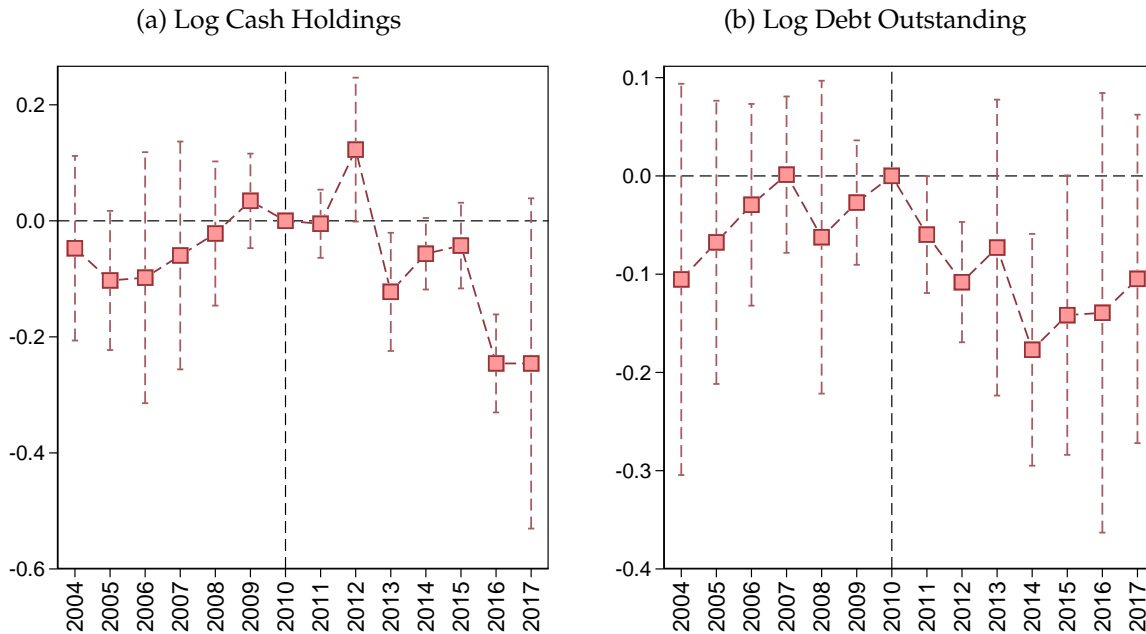
Notes: This figure plots the estimated β_t coefficients from event study (3) with firm and year fixed effects, along with 95 percent confidence intervals. The dependent variable is log revenue (left panel) and log capital stock (right panel) of ASI plants. The event is defined as the first year in which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

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 6. 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



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.

5 Model

To estimate the aggregate effect of the bans and assess the counterfactual regulatory enforcement policy, we build a dynamic quantitative model that focuses on the role of iron ore in the steel supply chain, with heterogeneity between sectors and locations, as well as the financial channel that leads to permanent effects from a temporary shock. 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 locations are differentiated Armington-style. The household block features a representative household in each location. We assume that labor is immobile across locations.¹⁷ The financial sector features imperfectly competitive banks that lend to manufacturing firms.

The model is dynamic and features discrete time periods. At the beginning of each period, the firm must pay employees up front, purchase intermediate inputs, and decide upon investment. At the end of each period, the firm realizes its sales, receives its revenue, and balances its budget. Between periods, capital depreciates at rate δ . For intra-period liquidity, firms use cash M and working capital financing \tilde{M} . For inter-period investment, firms use debt B . Firms face two key frictions. The first is limited commitment: firms cannot commit their future revenue to repay, so firms face a collateral constraint for debt B . Also, firms are uncertain about revenue $y \cdot p$, so working capital financing must be collateralized and lenders are unwilling to approve borrowing above lagged sales.

We focus on periods 0, 1 and 2. At the start of period 0, the economy is in steady state. The regulatory shock occurs at the end of period 0, so affected mining firms cease production in period 1. Downstream steel firms face a higher price of iron ore and a capital expenditure cost Ψ to adjust their equipment for the new composition of iron ore input.¹⁸

5.1 Production Block

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

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. The manufacturer produces output $y_{j,s,t}$ using a Cobb-Douglas bundle of two

¹⁷We will use the 2011 Census migration data to relax this assumption in a future version of this paper

¹⁸Through the Armington-style substitution of iron ore across locations, steel plants implicitly face switching costs across suppliers as well

factors, skilled labor $\ell_{j,s,t}$ and capital $K_{j,s,t}$, as well as an intermediate input bundle $X_{j,s,t}$:

$$y_{j,s,t} = z_{j,s,t} \ell_{j,s,t}^{\alpha_s^L} K_{j,s,t}^{\alpha_s^K} X_{j,s,t}^{\alpha_s^X} \quad (4)$$

where $z_{j,s,t}$ 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 $p_{s,t}$ in each time period. 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 its iron ore consumption $x_{M,jst}$ and the composite input good x_{jst} ; iron ore is a crucial input whose share in the composition of steel products is fixed by chemistry.

$$X_{j,\underline{s},t} = \min\{\gamma_{\underline{s}} x_{M,j,\underline{s},t}, x_{j,\underline{s},t}\}, \quad (5)$$

where $\gamma_{\underline{s}}$ is a scalar for the unit of measurement. For all other sectors, the input X_{jst} is the composite good x_{jst} .

At the beginning of each period t , each manufacturing firm chooses investment $I_{j,s,t}$ with law of motion of capital

$$K_{j,s,t} = (1 - \delta)K_{j,s,t-1} + I_{j,s,t}. \quad (6)$$

Firms finance investment with debt $B_{j,s,t}$, subject to the collateral constraint $\theta K_{j,s,t}$ for $\gamma < 1$. Firms finance other input expenditure $E_{j,s,t}$ with cash $M_{j,s,t}$ and working capital financing $\tilde{M}_{j,s,t}$. For steel sector firms, intermediate input expenditure is the sum of expenditure on iron ore $p_t^M \gamma_{\underline{s}} x_{M,jst}$ with the composite good x_{jst} whose price is normalized to 1, while for other sectors $s \neq \underline{s}$, it is simply $x_{j,s,t}$.

Each manufacturer's profit maximization problem gives the demand functions for factors and intermediate inputs:

$$\max_{\{y_{j,s,t}, \ell_{j,s,t}, K_{j,s,t}, X_{j,s,t}, I_{j,s,t}, B_{j,s,t}, M_{j,s,t}, \tilde{M}_{j,s,t}\}} \sum_{t=0}^{\infty} \beta^t \left[\pi_{j,s,t} - r_{B,t} B_{j,s,t} - r_{\tilde{M},t} \tilde{M}_{j,s,t} \right]$$

subject to the constraints (4), (5), (6), and

$$\begin{aligned} I_{j,s,t} &\leq B_{j,s,t} \leq \theta K_{j,s,t}, \\ E_{j,s,t} &\leq M_{j,s,t} + \tilde{M}_{j,s,t}, \\ \tilde{M}_{j,s,t} &\leq y_{j,s,t-1}, \\ E_{j,s,t} &:= w_{s,t} \ell_{j,s,t} + p_{X,t} X_{j,s,t}, \\ \pi_{j,s,t} &:= p_{s,t} y_{j,s,t} - (E_{j,s,t} + p_{I,t} I_{j,s,t}), \\ \pi_{j,s,t} + B_{j,s,t} + M_{j,s,t-1} + \tilde{M}_{j,s,t-1} &\geq (1 + r_{B,t-1}) B_{j,s,t-1} + M_{j,s,t} + \tilde{M}_{j,s,t-1}. \end{aligned}$$

The last equation is the firm's intertemporal budget constraint. The corresponding Bellman equa-

tion is At the beginning of each period t , a representative competitive manufacturer chooses labor $\ell_{j,s,t}$, intermediate inputs $X_{j,s,t}$, investment $I_{j,s,t}$, new debt $B_{j,s,t}$, and cash holdings $M_{j,s,t}$ to maximize the present value of future profits. Let $V(K_{j,s,t-1}, B_{j,s,t-1}, M_{j,s,t-1}, z_{j,s,t})$ denote the value function at the start of period t , where $K_{j,s,t-1}$ is the firm's inherited capital stock, $B_{j,s,t-1}$ is outstanding debt, $M_{j,s,t-1}$ is cash carried over, and $z_{j,s,t}$ is a productivity shock.

The Bellman equation is

$$V(K_{j,s,t-1}, B_{j,s,t-1}, M_{j,s,t-1}, z_{j,s,t}) = \max_{\ell_{j,s,t}, X_{j,s,t}, I_{j,s,t}, B_{j,s,t}, M_{j,s,t}} \left\{ \underbrace{p_{s,t} y_{j,s,t} - (w_{s,t} \ell_{j,s,t} + p_{X,t} X_{j,s,t} + p_{I,t} I_{j,s,t})}_{\text{(revenue) - (variable + investment costs)}} - \underbrace{(1 + r_{B,t-1}) B_{j,s,t-1}}_{\text{debt repayment}} + B_{j,s,t} + M_{j,s,t} + \beta \mathbb{E} [V(K_{j,s,t}, B_{j,s,t}, M_{j,s,t}, z_{j,s,t+1})] \right\} \quad (7)$$

5.1.2 Aggregation

For all manufacturing sectors $s \in S$, there is a competitive aggregation sector that produces a composite good Q with constant elasticity of substitution σ across sectors:

$$Q_t = \left(\sum_{s \in S} \omega_{Qs} q_{s,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \quad (8)$$

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. Because each sector's good is homogeneous across firms, and each sector-location pair with production has a representative firm, the aggregation across location is a simple sum:

$$q_{s,t} = \sum_{j \in J_s} q_{j,s,t}.$$

The aggregate price index P_t is normalized to 1:

$$P_t = \left(\sum_{s \in S} \omega_{Qs}^{\sigma} p_{s,t}^{-(\sigma-1)} \right)^{-\frac{1}{\sigma-1}} \equiv 1. \quad (9)$$

5.1.3 Mining

Following the geography of ore deposits, assume that only several locations j in the subset $J_m \subseteq J$ of locations have iron ore mines. Each mining location produces a differentiated variety of iron ore.¹⁹ Each location $j \in J_m$ has a mine m that uses labor L_m and the composite manufactured good

¹⁹In 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

X_m to produce iron ore with Cobb-Douglas labor share α^M :

$$y_{m,t} = z_{m,t} L_{m,t}^{\alpha^M} X_{m,t}^{1-\alpha^M}.$$

Assume that iron ore is only used in the production of steel \underline{s} , not in any other sector nor as a final consumption good.²⁰ The steel sector's iron ore input is an Armington-style bundle across mines with elasticity of substitution σ^M :

$$x_{M,jst} = \left(\sum_m \omega_m y_{m,t}^{\frac{\sigma^M-1}{\sigma^M}} \right)^{\frac{\sigma^M}{\sigma^M-1}}.$$

5.1.4 Pollution

Each mine faces a pollution limit $\bar{\pi}_m$. Pollution $\pi_{m,t} = \phi_m y_{m,t}$ 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: $C_m^\pi := \frac{C_m^\omega}{\phi_m}$.

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 $\pi_{m,t}$. 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 $x_{j,t}^I = z_{j,t}^I L_{j,t}^I$ under perfect competition with labor $L_{j,t}^I$ and no other inputs. Its price is $P_{j,t}^I$.

5.2 Household

Each location j has a representative household. The household has log preferences over a Cobb-Douglas bundle over consumption $\tilde{c}_{j,t}$ of the local informal sector good, as well as consumption of the composite manufactured good $c_{j,t}$, with exponential disutility over a CES bundle $\ell_{j,t}$ between “skilled” manufacturing $\ell_{S,j,t}$ and “unskilled” mining and informal sector labor $\ell_{U,j,t}$:

$$U_{j,t} = \nu \log c_{j,t} + (1 - \nu) \log \tilde{c}_{j,t} - \frac{\ell_{j,t}^{1+\gamma}}{1 + \gamma}, \quad (10)$$

$$\ell_{j,t} = \left(\omega_S \ell_{S,j,t}^{\frac{\xi-1}{\xi}} + \omega_U \ell_{U,j,t}^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}}. \quad (11)$$

In each location, there are two wages: $w_{U,j,t}$ in the informal sector, as well as mining if there is any mining activity, and $w_{S,j,t}$ in the manufacturing sector. The household faces the budget constraint

$$c_{j,t} + P_{j,t}^I \tilde{c}_{j,t} = w_{S,j,t} L_{S,j,t} + w_{U,j,t} L_{U,j,t}. \quad (12)$$

lower elasticity of substitution across varieties of iron ore.

²⁰In India, the steel sector comprises 97% of manufacturing demand for iron ore.

5.3 Equilibrium

Given the productivity shifters $z_{m,t}$, $z_{j,s,t}$, and $z_{j,t}^I$, CES shares $\omega_{Q,s}$, and other parameters ϕ_m , $\alpha_s^L, \alpha_s^K, \alpha_s^X, \alpha^M$, and β , an equilibrium consists of:

1. Prices $p_{s,t}$ and wages $w_{U,j,t}, w_{S,j,t}$
2. Input allocations for manufacturing: $\ell_{j,s,t}, K_{j,s,t}, X_{j,s,t}$ and for mining: L_m, X_m
3. Output $y_{j,s,t}$ and composite good Q_t
4. Financial variables: investment $I_{j,s,t}$, debt $B_{j,s,t}$, cash holdings $M_{j,s,t}$, and working capital financing $\tilde{M}_{j,s,t}$
5. Pollution π_m

such that the household maximizes utility (10) subject to the budget constraint (12), the firms follow the Bellman equation (7), and markets clear:

$$\sum_{j \in J} c_{j,t} + \sum_{s \in S} \sum_{j \in J_s} x_{j,s,t} + \sum_m X_m = Q_t \quad (\text{composite good})$$

$$\sum_{j \in J_{\underline{s}}} y_{j,\underline{s},t} = \sum_{s' \in S} \sum_{j \in J_{s'}} x_{j,\underline{s},t} \quad (\text{steel sector})$$

$$\sum_{j \in J_s} y_{j,s,t} = q_{s,t}, \quad \forall s \neq \underline{s} \quad (\text{other manufacturing sectors})$$

$$\sum_{s \in S} L_{j,s,t} = \ell_{S,j,t} \quad (\text{skilled labor})$$

$$L_{j,t}^I + \mathbb{1}\{j \in J_m\} L_m = \ell_{U,j,t} \quad (\text{unskilled labor})$$

See Section B for the derivation of the model's conditions and the algorithm to take the model to the data.

5.4 Mining Ban

At the start of period 1, firms in the steel sector face several significant challenges. First, higher intermediate input costs arise due to increased iron ore prices, which elevate total expenditure on inputs and push up marginal costs. Second, excess capacity becomes an issue as lower output leads to unused capital, raising average costs. Third, firms reduce investment $I_{j,\underline{s},1}$ in response to higher costs and lower profitability, which in turn reduces the future capital stock $K_{j,\underline{s},2}$. Fourth, deleveraging occurs as a result of a tighter collateral constraint, driven by a decline in lagged output $y_{j,\underline{s},0}$, forcing firms to reduce debt $B_{j,\underline{s},1}$. Finally, firms increase precautionary cash holdings $M_{j,\underline{s},1}$ temporarily, using these reserves as a buffer against uncertainty in input costs and future output.

At the start of period 2, as the ban is lifted, firms begin transitioning back to their steady-state size. Due to reduced investment in period 1, the capital stock $K_{j,\underline{s},2}$ is below its steady-state level, limiting production capacity. In addition, a weakened balance sheet, resulting from lower lagged output and tighter financial constraints, restricts firms' ability to scale up production immediately. Consequently, the recovery is gradual, as firms increase investment to rebuild their capital

stock. However, the transition is slowed by financing frictions and the time required for capital accumulation.

The model highlights how temporary regulatory shocks can have persistent effects on sectoral output and investment through dynamic interactions between input costs, capacity constraints, and financial frictions. The cut in investment during the ban results in a lower capital stock and output in future periods, prolonging the negative effects even after the regulatory shock is lifted.

5.5 Calibration

Table 1: Summary of Model Calibration

| Parameter | Description | Method |
|--|--|--|
| $\{\alpha_s^L, \alpha_s^K, \alpha_s^X\}$ | Cobb-Douglas parameters in manufacturing | ASI expenditure shares at the 2-digit NIC level |
| α^M | Cobb-Douglas parameter in mining | EPW ratio of labor expenditure to revenue |
| ν | Cobb-Douglas utility parameter | NSS household expenditure share on tradeable goods |
| σ | Elasticity of substitution in manufacturing | ASI regression of relative input demand on relative price |
| σ^M | Elasticity of substitution across iron ore varieties | Auction data regression of relative variety sales on relative variety price |
| $\{\omega_{Qs}\}$ | CES manufacturing shares | ASI input shares, given σ |
| $\{\omega_m\}$ | CES mining shares | Auction data variety shares, given σ^M |
| γ | Disutility of labor supply | NSS difference-in-differences of hours worked on wages for workers in the districts affected by the mining ban vs otherwise, to estimate the Frisch elasticity, then invert to obtain γ |
| δ | Depreciation rate | ASI average investment to capital ratio, minus the capital stock growth rate |

Note: This table shows the calibration of each parameter in the model. For more details on the calibration methods, see the appendix.

5.6 Counterfactuals

We consider three counterfactuals. In the first counterfactual, we hold fixed the regulator’s audit rate ρ and pollution limits $\{\bar{\pi}_m\}$, but consider the mines’ responses and the aggregate allocations when varying the penalty P^π , interpreting the ban as the case where P^π is temporarily infinite. In the second counterfactual, we vary ρ , holding fixed pollution limits $\{\bar{\pi}_m\}$, and find the “choke point” at which ρ is high enough to incentivize all mines to comply with the pollution limit. In the third counterfactual, we replace the pollution limits with a market for tradable pollution permits, which currently does not exist due to limited institutional capacity, and consider how output would change when the aggregate pollution limit is set to maximize second best surplus.

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 bans can 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.

References

- Michael Greenstone, Santosh Harish, Rohini Pande, Anant Sudarshan, et al. The solvable challenge of air pollution in india. In *India Policy Forum*, pages 11–12, 2017.
- David Rezza Baqaee and Emmanuel Farhi. Macroeconomics with heterogeneous agents and input-output networks. Technical report, National Bureau of Economic Research, 2018.
- David Rezza Baqaee and Emmanuel Farhi. Productivity and misallocation in general equilibrium. *The Quarterly Journal of Economics*, 135(1):105–163, 2020.
- Ann Harrison, Benjamin Hyman, Leslie Martin, and Shanthi Nataraj. When do firms go green? comparing command and control regulations with price incentives in india. Technical report, National Bureau of Economic Research, 2019.
- Esther Duflo, Michael Greenstone, Rohini Pande, and Nicholas Ryan. Truth-telling by third-party auditors and the response of polluting firms: Experimental evidence from india. *The Quarterly Journal of Economics*, 128(4):1499–1545, 2013.
- Allen Blackman, Zhengyan Li, and Antung A Liu. Efficacy of command-and-control and market-based environmental regulation in developing countries. *Annual Review of Resource Economics*, 10:381–404, 2018.

- Michael Greenstone. The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of political economy*, 110(6):1175–1219, 2002.
- Michael Greenstone, John A List, and Chad Syverson. The effects of environmental regulation on the competitiveness of us manufacturing. Technical report, National Bureau of Economic Research, 2012.
- W Reed Walker. The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *The Quarterly journal of economics*, 128(4):1787–1835, 2013.
- Yangsiyu Lu and Jacquelyn Pless. Environmental regulation and productivity are not always at odds: Evidence from firms in china. 2021.
- Alex L Marten, Richard Garbaccio, and Ann Wolverton. Exploring the general equilibrium costs of sector-specific environmental regulations. *Journal of the Association of Environmental and Resource Economists*, 6(6):1065–1104, 2019.
- Dan Black, Terra McKinnish, and Seth Sanders. The economic impact of the coal boom and bust. *The Economic Journal*, 115(503):449–476, 2005.
- Fernando M Aragón and Juan Pablo Rud. Natural resources and local communities: evidence from a peruvian gold mine. *American Economic Journal: Economic Policy*, 5(2):1–25, 2013.
- Hunt Allcott and Daniel Keniston. Dutch disease or agglomeration? the local economic effects of natural resource booms in modern america. *The Review of Economic Studies*, 85(2):695–731, 2018.
- Government of India. Indian Minerals Yearbook 2020: Iron Ore, 2022. URL https://ibm.gov.in/writereaddata/files/06102022164225Iron_ore_2020.pdf.
- Government of India. Third report on illegal mining of iron and manganese ores in the state of goa, 2013. URL <https://mines.gov.in/admin/storage/app/uploads/643549c0c25cb1681213888.pdf>.
- Government of India. Indian Minerals Yearbook 2012: Iron Ore, 2014. URL https://ibm.gov.in/writereaddata/files/07092014125520IMYB_2012_iron%20ore.pdf.
- TJ Brown, RA Shaw, T Bide, ERER Petravratzi, ER Raycraft, and AS Walters. *World mineral production 2007-11*. British Geological Survey, 2013.
- Government of India. Report of the commission of enquiry for illegal mining of iron ore and manganese, 2012. URL <https://mines.gov.in/admin/storage/app/uploads/643545ae3acf21681212846.pdf>.
- Hunt Allcott, Allan Collard-Wexler, and Stephen D O’Connell. How do electricity shortages affect industry? evidence from india. *American Economic Review*, 106(3):587–624, 2016.
- Leslie A Martin, Shanthi Nataraj, and Ann E Harrison. In with the big, out with the small: Removing small-scale reservations in india. *American Economic Review*, 107(2):354–386, 2017.

Utkarsh Saxena. *Environmental Regulation in India and the Impact of Court Ordered Mining Bans in Goa and Karnataka*. Phd thesis, Blavatnik School of Government, University of Oxford, 2024. Work in progress.

John Firth. *I've been waiting on the railroad: The effects of congestion on firm production*. 2017.

A Appendix - Regressions

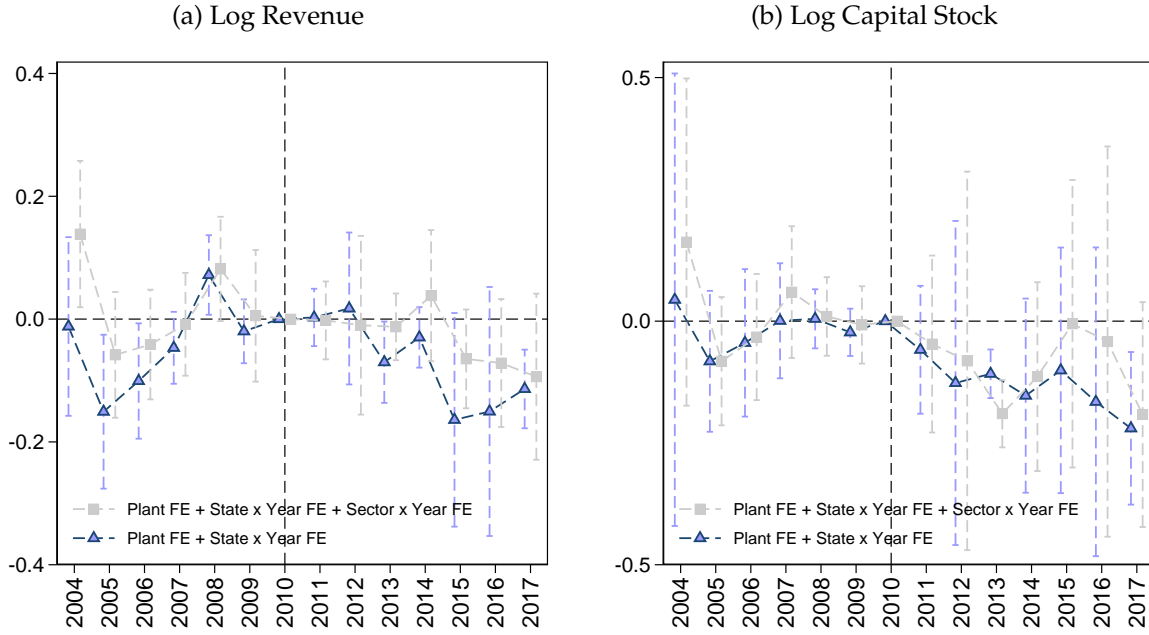
To estimate the impact of the ban on mining of iron ore on downstream sectors, we estimate the event study (3). Figures 7, 8, and 9 show the impact of the mining ban on plants in iron-using sectors relative to plants in sectors that do not consume iron ore, with additional fixed effects beyond what we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

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



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

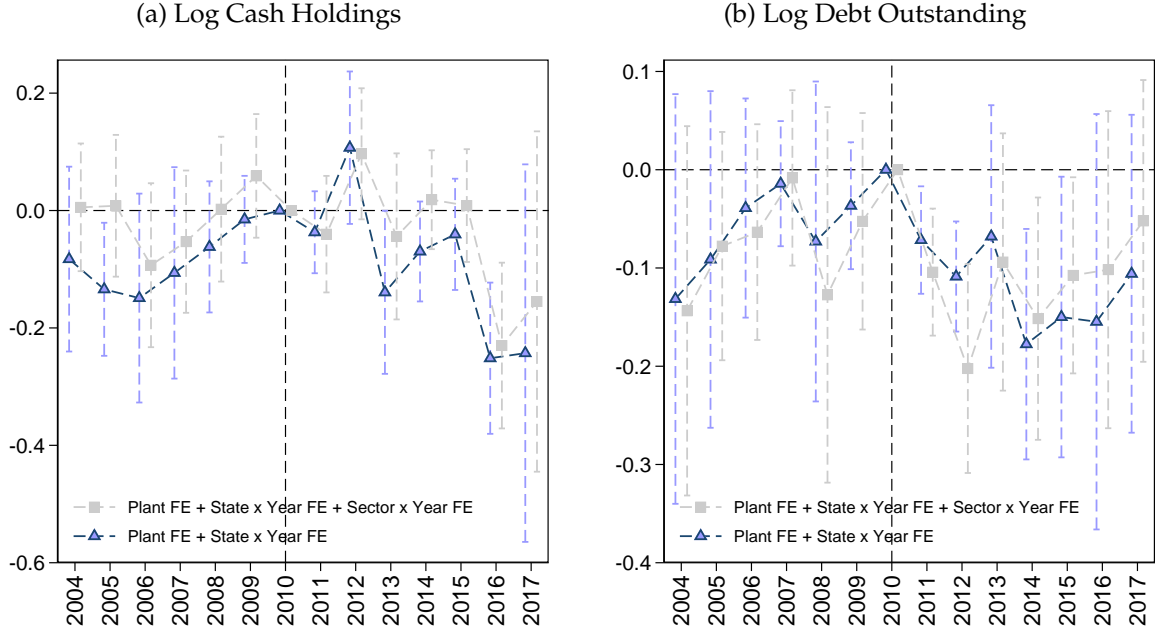


Notes: This figure plots the estimated β_t coefficients from event study (3), with 95 percent confidence intervals. The dependent variable is log revenue (left panel) and log capital stock (right panel) of ASI plants. The event is defined as the first year in which the Karnataka ban came into force, 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 9. 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.

A.0.1 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.²¹ 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.²²

²¹Iron 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.

²²In 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

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.

B Appendix - Model

We have four sets of agents whose optimization leads to first-order conditions (FOCs): steel sector \underline{s} firms, other manufacturing firms in sector s , mines producing iron ore varieties, and households who choose consumption and labor supply across skilled/unskilled activities.

B.1 Dynamic Problem and Bellman Equation

We consider the dynamic problem of a representative competitive manufacturer in sector s and location $j \in J_s$ over an infinite horizon. The firm chooses labor $\ell_{j,s,t}$, intermediate inputs $X_{j,s,t}$, investment $I_{j,s,t}$, and debt $B_{j,s,t+1}$ to maximize the discounted sum of future profits. The state variables at the beginning of each period are the inherited capital stock $K_{j,s,t-1}$, outstanding debt $B_{j,s,t}$, and cash holdings $M_{j,s,t-1}$. Let $V(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t})$ denote the value function at the start of period t .

Bellman Equation. The dynamic optimization problem can be written as:

$$V(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t}) = \max_{\ell_{j,s,t}, X_{j,s,t}, I_{j,s,t}, B_{j,s,t+1}, M_{j,s,t}} \left\{ \underbrace{p_{s,t} y_{j,s,t} - (w_{s,t} \ell_{j,s,t} + p_{X,t} X_{j,s,t} + p_{I,t} I_{j,s,t})}_{\text{current period profit}} - \underbrace{(1 + r_{B,t}) B_{j,s,t} - r_{M,t} M_{j,s,t-1}}_{\text{financial costs}} + B_{j,s,t+1} + M_{j,s,t} + \beta \mathbb{E} \left[V(K_{j,s,t}, B_{j,s,t+1}, M_{j,s,t}, z_{j,s,t+1}) \right] \right\}$$

subject to the following constraints:

$$\begin{aligned} \text{Production function:} \quad & y_{j,s,t} = z_{j,s,t} \ell_{j,s,t}^{\alpha_s^L} K_{j,s,t-1}^{\alpha_s^K} X_{j,s,t}^{\alpha_s^X} \\ \text{Capital accumulation:} \quad & K_{j,s,t} = (1 - \delta) K_{j,s,t-1} + I_{j,s,t} \\ \text{Collateral constraint:} \quad & B_{j,s,t+1} \leq \theta K_{j,s,t} \\ \text{Working capital constraint:} \quad & E_{j,s,t} \leq M_{j,s,t} + \tilde{M}_{j,s,t} \\ \text{Intermediate expenditure:} \quad & E_{j,s,t} := w_{s,t} \ell_{j,s,t} + p_{X,t} X_{j,s,t}. \end{aligned}$$

change from early 2011 to late 2011.

B.1.1 First-Order Conditions (FOCs)

We derive the FOCs with respect to the control variables $\ell_{j,s,t}$, $X_{j,s,t}$, $I_{j,s,t}$, $B_{j,s,t+1}$, and $M_{j,s,t}$.

Labor and Intermediate Inputs. Taking the derivative of the Bellman equation with respect to $\ell_{j,s,t}$ and $X_{j,s,t}$:

$$\begin{aligned}\frac{\partial V}{\partial \ell_{j,s,t}} : \quad w_{s,t} &= p_{s,t} z_{j,s,t} \alpha_s^L \ell_{j,s,t}^{\alpha_s^L - 1} K_{j,s,t-1}^{\alpha_s^K} X_{j,s,t}^{\alpha_s^X}, \\ \frac{\partial V}{\partial X_{j,s,t}} : \quad p_{X,t} &= p_{s,t} z_{j,s,t} \alpha_s^X \ell_{j,s,t}^{\alpha_s^L} K_{j,s,t-1}^{\alpha_s^K} X_{j,s,t}^{\alpha_s^X - 1}.\end{aligned}$$

Investment. Taking the derivative with respect to $I_{j,s,t}$:

$$\frac{\partial V}{\partial I_{j,s,t}} : \quad p_{I,t} = \beta \mathbb{E} \left[\frac{\partial V(K_{j,s,t}, B_{j,s,t+1}, M_{j,s,t}, z_{j,s,t+1})}{\partial K_{j,s,t}} \right].$$

The marginal cost of investment $p_{I,t}$ equals the discounted marginal value of future capital.

Debt. Taking the derivative with respect to $B_{j,s,t+1}$:

$$\frac{\partial V}{\partial B_{j,s,t+1}} : \quad 1 = \beta \mathbb{E} \left[\frac{\partial V(K_{j,s,t}, B_{j,s,t+1}, M_{j,s,t}, z_{j,s,t+1})}{\partial B_{j,s,t}} \right].$$

The firm borrows up to the point where the marginal benefit of additional debt equals its discounted cost.

Cash Holdings. Taking the derivative with respect to $M_{j,s,t}$:

$$\frac{\partial V}{\partial M_{j,s,t}} : \quad 1 = \beta \mathbb{E} \left[\frac{\partial V(K_{j,s,t}, B_{j,s,t+1}, M_{j,s,t}, z_{j,s,t+1})}{\partial M_{j,s,t-1}} \right].$$

Firms choose cash holdings such that the marginal benefit of holding cash equals the discounted marginal value of cash in future periods.

B.1.2 Policy Functions

The FOCs yield policy functions for labor $\ell_{j,s,t}$, intermediate inputs $X_{j,s,t}$, investment $I_{j,s,t}$, new debt $B_{j,s,t+1}$, and cash holdings $M_{j,s,t}$. These policy functions depend on the current state variables

$(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t})$:

$$\begin{aligned}
\ell_{j,s,t}^* &= \ell^*(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t}), \\
X_{j,s,t}^* &= X^*(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t}), \\
I_{j,s,t}^* &= I^*(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t}), \\
B_{j,s,t+1}^* &= B^*(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t}), \\
M_{j,s,t}^* &= M^*(K_{j,s,t-1}, B_{j,s,t}, M_{j,s,t-1}, z_{j,s,t}).
\end{aligned}$$

These policy functions describe the optimal behavior of the firm in response to changes in its state variables and exogenous shocks.