Opening the Brown Box: Production Responses to Environmental Regulation[†]

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Abstract

We study manufacturing firms' production responses to an emission capping regulation. Firms lower emissions by improving energy efficiency, substituting towards cleaner fuels, and moving from producing electricity to purchasing it from the grid. They move away from coal-intensive products and increase their abatement expenditures. These changes improve firm productivity, supporting theories that regulation prompts technology adoption. In the aggregate, we document lower product variety and an altered firm-size distribution, driven by a reduced likelihood of business formation. Our findings highlight the mechanisms behind how mandated pollution reduction can be effective and the costs it imposes, suggesting a loss of agglomeration externalities.

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Policymakers are directing national efforts to combat climate change with regulations that target firm emissions (IPCC, 2023; World Economic Forum, 2023). At the same time, they care how firms achieve their emissions reductions, seeking firms to improve energy efficiency, investing in abatement, and modernizing their production processes (Stern and Jotzo, 2010). However, policymakers face capacity constraints when enforcing emission regulations and have limited information to effectively target reductions (Duflo et al., 2013, 2018).

Although there is considerable evidence on the effectiveness of environmental regulations in reducing emissions, much remains unknown about their impact on production decisions and the economic mechanisms behind firms' trade-offs when balancing emission reductions with economic impacts.[1] Firms often respond to these kinds of regulations by shifting emissions to less regulated jurisdictions and within their supply chains (Bartram et al., 2022; Ben-David et al., 2021; Copeland and Taylor, 1994; Duchin et al., 2022; Schiller, 2018). At the same time, there is mixed evidence on whether such regulations reduce firm productivity and increase consumer costs (Bertrand et al., 2007; Fowlie, 2010; Greenstone et al., 2012). Alternatively, there is a view that any costs might be temporary and that regulations could boost productivity.[2] Beyond these firm outcomes, the primary challenge in empirically assessing the impacts of environmental regulation is the opacity of responses within firms, including production decisions and energy management.

We study *within-firm* production responses to shed light on the economic forces driving emissions reductions. We combine detailed data on firm production and abatement expenditures with variation from an environmental regulation in India. Using hand-collected regulatory data and satellite measurements, we show that the regulation significantly reduced emissions. We exploit detailed product-level data and find that firms improve their energy efficiency by lowering energy expenditures but not the quantities produced. Further, firms shift from producing electricity in-house to procuring from the grid. At the product portfolio level, they move away from producing their highest-emission and most coal-intensive products. In addition, the average firm invests substantially in pollution abatement at both the extensive and intensive margins. These

[1] See, for example, Greenstone (2002); Greenstone and Hanna (2014); He et al. (2020) and cites therein.

[2] Proposed mechanisms for this include R&D spillovers, first-mover advantages (Harrison et al., 2017; Jaffe and Palmer, 1997; Lanjouw and Mody, 1996; Porter and Linde, 1995), and encouraging firms to optimize energy use and adopt green technologies (Fan et al., 2019; Newell et al., 1999; Wu et al., 2023).

changes collectively improve their revenue and quantity productivity, supporting theories that suggest regulation can drive technology adoption. Importantly, we do not find evidence that firms shift economic activity elsewhere in responding to the regulation. In the aggregate, we document a decline in business dynamism, evidenced by reduced firm entry and lower product variety.

Our setting is an emissions capping regulation targeting industrial clusters—co-located dynamic concentrations of related businesses—imposed by the Central Pollution Control Board (CPCB) in India. In 2009, the CPCB introduced the Comprehensive Environmental Pollution Index (CEPI) to quantify pollution levels of industrial clusters and their impact on local populations. The CPCB used this index to enforce emission reductions for firms located in these clusters based on whether a cluster's CEPI values exceeded *pre-defined* thresholds. We exploit the resulting discontinuities in enforcement intensity, both within and across industrial clusters, in a difference-in-discontinuities (DiRD) design. Combined with detailed firm and product data, this allows us to identify *within-firm* changes in production decisions and to quantify the costs and benefits of the regulation.

The analyses proceed in four parts. First, we show that the regulation reduced aggregate emissions in industrial clusters. Using hand-collected data from follow-up monitoring studies by the CPCB, we find that industrial clusters facing the highest enforcement intensity, on average, experienced a one-third decrease in air emissions relative to pre-treatment average pollution. We complement these analyses with satellite measurements of industrial emissions and document a significant and persistent reduction. To rule out concerns regarding unobserved time-varying trends driving these results, we conduct a placebo test on emissions from energy producers, which are subject to similar seasonality and economic fluctuations but were not targeted by the regulation. Reassuringly, we do not find any change in these emissions, in terms of both economic magnitude and statistical significance.

The average reduction in cluster-level emissions masks significant heterogeneity. Therefore, to better understand the determinants of compliance, we hand-collect information on follow-on assessments and relate them to regulator characteristics. We find that cluster-level improvements are positively associated with regulator quality and enforcement capacity, a greater proportion of small firms, and public-private cost sharing for abatement investments. These findings are consistent with research that argues for the importance of regulators in inducing emissions reductions in environments with low state capacity and large information asymmetries (Duflo et al., 2013; Pande and Datla, 2016).

Second, we study the *within-firm* drivers of the aggregate reduction in emissions. We leverage detailed product-level information on inputs and outputs of private and public manufacturing firms, unique to India, due to mandatory disclosure requirements (Bau and Matray, 2023; De Loecker et al., 2016). We begin by showing that firms respond to the regulation by improving their energy efficiency—decreasing their energy expenditures with no significant change to their product output. We also map product-level energy consumption to carbon emissions to estimate product-level emissions (Lyubich et al., 2018). Consistently, we show that firms decrease the energy intensity of their production, i.e., the amount of energy inputs per product and the estimated CO_2 emissions per unit produced. At the same time, they switch fuels in their production by shifting away from using coal. The shift is meaningful—we find the use of coal as an input in firms decreases by 29% in treated clusters relative to control clusters. These results are relevant for integrated assessment models that require estimates of microeconomic parameters of firm inputs to inform the aggregate path of carbon in the economy. For example, the optimal energy tax depends heavily on the degree of substitution between fuel sources (Golosov et al., 2014), and the long-run sustainability of economic growth depends on the substitutability of dirty and clean inputs (Acemoglu et al., 2012).

We also find that firms shift from producing to purchasing electricity—they increase the proportion of energy they purchase from the grid by 19.6 percentage points. The magnitude of this change exposes firms to risk, as electricity supply is often unreliable.[3] Therefore, as firms move away from producing their own electricity from diesel generators to purchasing from the grid, they lose the value of insurance against outages that generators provide.

Third, at the firm level, we find that treated firms shift their product portfolios *away* from their highest-emission, coal-intensive products—those typically associated with higher pollution. Moreover, these firms increase their abatement expenditures along both the extensive and intensive margins—they are twice as likely to make any abatement expenditure, and they raise

[3]Prior work has documented that unreliable power supply reduces firm productivity (Allcott et al. (2016); Cole et al. (2018); Fried and Lagakos (2023)), increases production costs (Steinbuks and Foster (2010); Fisher-Vanden et al. (2015)), and lowers profitability (Szakonyi and Urpelainen (2013)).

abatement spending by 3.9 percentage points, on average. Importantly, firms facing higher regulatory intensity show larger increases in abatement investment rates. At the same time, we do not see any change in capital, wage bill, or raw material expenditures. These changes collectively improved firm efficiency in converting inputs into revenue (revenue productivity) and into outputs (quantity productivity). This evidence is consistent with regulatory changes altering factor costs or entry costs so as to tip the cost–benefit calculus of adopting new technologies. Economists have proposed numerous reasons for slow technology adoption, including high upfront costs or other adoption barriers (e.g., Hicks (1963); Parente and Prescott (1994)), competitive pressures (e.g., Parente and Prescott (1999)), agency or organizational frictions (e.g., Ambec and Barla (2002)), and uncertainty or information gaps about the benefits of new technology (e.g., Cortazar et al. (1998); Farzin and Kort (2000); Mohr (2002)).

Fourth, we examine the costs of these regulations. Specifically, we find that there is no significant impact on firm production. However, we document a 12 percentage point decrease in the probability that a firm introduces a new product in the five years following the regulation, suggesting lower product variety. At the cluster level, we find a decrease in entry by firms operating in *all industries*, not just manufacturing, and across the firm size distribution. Our estimates suggest a 1.4% drop in new firm registrations in the formal sector versus a baseline rate of 7%. These effects are strongest for clusters subject to the highest enforcement intensity. These results are important, as development strategies in emerging economies often emphasize industrial clusters to drive growth and innovation (Juhász et al., 2022). Overall we document that, while regulated firms improve efficiency by lowering energy use in their production, it remains unclear whether this compensates for the loss in business dynamism, evidenced by reduced firm entry and lower product variety.

Finally, we examine other ways firms may have reduced emissions. A key concern is that firms relocate their production outside the industrial cluster or shift their emissions by expanding capacity elsewhere. We present three pieces of evidence ruling out these possibilities. First, we estimate significant reductions in energy efficiency but no effect on raw material expenses, wage bill, and capital investment, suggesting that firms, on average, do not shift emissions through their product markets. Second, we do not find a change in the average probability of mergers and acquisitions for firms located in the industrial cluster and as a function of enforcement intensity. Third, we do not find a change in the average probability of announcing a new plant or abandoning the expansion of an existing one. These findings are inconsistent with leakage driving the estimated emissions reductions in this context. Instead we show that production changes and adoption of cleaner technology were the main response to the regulation.

Our results on opening up the "brown box" of how firms change their inputs and outputs can inform the design of effective environmental regulations for industrial clusters. A key insight is that these regulations prompted production changes that shifted firms away from high-emission energy sources and reduced energy use. This suggests that emissions reduction could be more effectively targeted by mandating specific energy inputs rather than imposing caps on emissions and monitoring. Importantly, our findings highlight the need for coordinated policies on decarbonization. Even if the shift toward electricity does not necessarily steer companies away from coal at present, it could pave the way for such a transition as the power grid becomes greener, facilitating a smoother transition to cleaner fuels. We also provide evidence that regulatory design and enforcement are key determinants of successfully reducing emissions reductions. Finally, our results point to aggregate costs in terms of lower business dynamism, potentially impairing competitiveness in the global economy.

Related Literature. Our paper contributes to the literature that quantifies the impacts of environmental regulation. We focus on an emissions capping regulation aimed at industrial clusters—common in both advanced and developing economies—often seen as engines of growth, while being responsible for 15 percent to 20 percent of global carbon emissions. As in our setting, the regulations studied in the literature are often localized, targeting specific regions, industries, or pollutants. Specifically, previous research has focused on regulations that take the form of command-and-control or cap-and-trade policies (Fowlie (2010); Harrison et al. (2019); Bartram et al. (2022); Ivanov et al. (2024)). A key insight from this work is that firms often shift their emissions within and across firms to regions with less stringent regulations or pass them along their supply chains (Aichele and Felbermayr (2015); Schiller (2018); Xu and Kim (2022); Ben-David et al. (2021); Dai et al. (2021a); Dai et al. (2021b)). Unlike prior work, we find the average firm reduces its emissions by reallocating inputs, investing in abatement, and modernizing production through technological upgrades, rather than by only shifting emissions elsewhere. This demonstrates the importance of widening the literature to include evidence from the full firm-size distribution, including private firms, and to consider emerging economies to develop a better understanding of the balance between environmental concerns against development and equity considerations.

Several papers have examined the firm impacts of environmental regulations (Berman and Bui (2001); Greenstone et al. (2012); Harrison et al. (2019); He et al. (2020); Kala and Gechter (2023)).[4] There is mixed evidence on the impact on outcomes such as productivity (Duflo et al. (2013); Kala and Gechter (2023)). Our evidence suggests that firms reorganize their production processes to lower emissions. Moreover, our finding that an emissions regulation increases firm productivity complements recent evidence on emissions trading systemColmer et al. (2024); Linn (2008); Lu and Pless (2024); Newell et al. (1999); Wu et al. (2023). We show that firms responded to the regulation by reducing the energy used in production and investing in greener technologies.

More broadly, our study contributes to the literature on how firms impact the environment.[5] Research has highlighted the importance of the nature of ownership (Dimson et al. (2015); Krueger et al. (2020); Naaraayanan et al. (2021); Dimson et al. (2021); Azar et al. (2021); Atta-Darkua et al. (2023); Ilhan et al. (2023); Berg et al. (2023)), disclosures (Jouvenot and Krueger (2019); Tomar (2023); Bonetti et al. (2023)), financial institutions (Kacperczyk and Peydró (2022); De Haas (2023); De Haas and Popov (2023); Ivanov et al. (2024)), and self-commitments (Dahlmann et al. (2019); Freiberg et al. (2021); Comello et al. (2021); Duchin et al. (2022); Bolton and Kacperczyk (2023)). Our contribution lies in documenting how production responses to environmental regulation shape the environmental profile of firms while highlighting firms' trade-offs when balancing emissions reduction with economic impacts.

While our focus is on India, due to the availability of granular data and a quasi-natural experiment, our results have implications for other contexts considering emissions reductions in industrial clusters. For example, the World Economic Forum recently launched a global initiative aiming to reduce heavy industry asset emissions in regional industrial zones (World Economic

[4]Another strand of the literature examines the role of carbon taxes (Metcalf (2021); Brown et al. (2022); Martinsson et al. (2024)) and carbon pricing (Fowlie et al. (2012); Klemetsen et al. (2020); Colmer et al. (2024)), finding mixed evidence on their effectiveness.

[5]In contrast to a literature analyzing the implications of investors' green preferences on asset prices (e.g., Heinkel et al. (2001); Chowdhry et al. (2018); Pástor et al. (2021); Pedersen et al. (2021); Berk and Van Binsbergen (2021); Bolton and Kacperczyk (2021); Broccardo et al. (2022); Zerbib (2022); Oehmke and Opp (2023); and De Angelis et al. (2023).

Forum, 2023).[6] Notably, these clusters account for a significant fraction of global CO_2 emissions, making them a target for emission reductions worldwide. Our study suggests that regulating industrial clusters by capping their emissions may achieve net-zero targets but that such a regulation will likely harm economic competitiveness by damping industrial clusters' agglomeration benefits.

1 Institutional Background

This paper focuses on a regulation in India targeting pollution from industrial clusters—co-located dynamic concentrations of related businesses. These clusters are often associated with positive productivity and innovation spillovers and promote economic growth. At the same time, they also generate significant pollution, posing serious concerns, particularly near densely populated areas.

Recognizing this trade-off, India's principal national emissions regulator, the Central Pollution Control Board (CPCB), implemented a regulation in 2009 to curb cluster emissions and their health impacts. The agency developed a Comprehensive Environmental Pollution Index (CEPI) that identified 88 prominent industrial clusters in consultation with the Ministry of Environment, Forest and Climate Change (MoEF&CC). It conducted a comprehensive environmental analysis and data-gathering effort in these clusters through recognized environmental laboratories. It then developed the CEPI to characterize the environmental quality at a given location that takes a value between 0 and 100. The CEPI combined proxies for (i) the amount and toxicity of pollutants, (ii) the impact of that pollution on humans and ecosystems, and (iii) an assessment of the quality of actions already taken by cluster firms to capture or adequately dispose of emissions. Clusters with a high CEPI were those that were high emitters, located near concentrated population centers, and that were not doing enough to address the problem. Figure 1 describes the construction of the CEPI. See Central Pollution Control Board of India (2009) for a discussion of the components and construction of the CEPI.

[PLACE FIGURE 1 HERE.]

[6] Nine leading industrial clusters in China, Indonesia, Japan, Spain, and the United States have joined the World Economic Forum initiative, "Transitioning Industrial Clusters towards Net Zero," to help industries reduce emissions.

The CPCB used these index values to enforce environmental improvements in these clusters based on whether the values exceeded *pre-defined* thresholds. In our empirical setting, we exploit the resulting discontinuities in enforcement intensity, both within and across clusters.

The CPCB classified those clusters with a CEPI at or above 60 and below 70 as "Severely Polluted Areas" (henceforth $CEPI^{[60,70)}$). These clusters now became subject to central monitoring that involved the installation of online continuous emission/effluent monitoring systems combined with in-person quarterly audits. Further, the regulator classified industrial clusters with a CEPI value of at least 70 as "Critically Polluted Areas" (henceforth $CEPI^{[70,100]}$). Firms within these clusters were subject to the same monitoring treatment as $CEPI^{[60,70)}$ clusters. Additionally, the CPCB, along with the local environmental government agencies (State Pollution Control Boards), mandated remedial plans for firms operating within the $CEPI^{[70,100]}$ clusters. These specified actions and timelines for improving the environmental quality.

If a firm failed to comply with the directives, then it would lose its *Environmental Clearance* and *Consent to Operate* permits, which allow firms to function within the formal economy.[7] Moreover, *Consent to Establish* permits could not be issued to new operations if they do not fully comply with the cluster regulations and action plans. Of the 88 industrial clusters subject to the regulation in 2009, 43 industrial clusters in 17 states had a CEPI value of 70 or above. A further 32 industrial clusters had a CEPI value between 60 and below 70.

The 2009 CEPI reform is an ideal setting for studying the effects of regulation on firm production. Due to disclosure requirements, we observe detailed product input and output data, for both public and private manufacturing firms operating in the formal sector. Moreover, focusing on a large and industrializing economy gives us insight into the potential effects on other similar important countries that will play a pivotal role in growth and decarbonization in the next 50 years. Finally, the structure of this particular reform lends itself to sharp identification, as discussed in the subsequent sections.

A natural concern is that regulations are not always enforced in settings with limited institutional and governance capacity (Duflo et al., 2013, 2018; Greenstone et al., 2023). We provide anecdotal and statistical evidence that this regulation was enforced. First, we see no evidence

[7] All firms, except for those in a few nonpolluting sectors, must apply for and receive approval from their respective state-level Pollution Control Boards. New activities require a permit called *Consent to Establish*, while new activities and renewals require one called *Consent to Operate* (Bhat, 2010; Fenske et al., 2023; Kapur and Khosla, 2019).)

of manipulation of the CEPI score and no anticipation of outcomes, as discussed in Section 3.3. Additionally, we present two direct pieces of evidence to support enforcement. First, we rely on subsequent audits by the CPCB that updated the CEPI values twice in the following five years to assess the effectiveness of the action plans. We hand-collected the results of this follow-up monitoring that recalculated the CEPI for the $CEPI^{[70,100]}$ clusters (according to the 2009 ranking) in 2011 and 2013. Our analyses demonstrate that the regulation reduced aggregate emissions in industrial clusters. The top panel of Figure 2 reproduces the original 2009 CEPI distribution. The vertical line represents the cutoff at 70. The bottom panel reports the distributions of the recalculated CEPI values for the 2009 $CEPI^{[70,100]}$ clusters in 2011 and 2013. The distributions shifted to the left in both follow-up assessments, with significant improvement continuing between 2011 and 2013. This evidence accords with the CPCB's narrative of the regulation as part of an ongoing process of long-term improvement in environment quality at these clusters. We also observe that, while the average cluster improved, several clusters continued to have CEPI values above the cutoffs in 2013, indicating the difficulties of mandating pollution reduction beyond a certain threshold.

[PLACE FIGURE 2 HERE.]

Second, we complement these analyses by using independent satellite measurements and show a significant decline in emissions, detailed in Section 4. Moreover, we compile anecdotal evidence in Appendix B of enforcement from media reports, firm annual reports, and cluster action plans.[8] This evidence covers the timeline of *Consent to Establish* bans in noncompliant sectors. Finally, our empirical approach addresses several alternative explanations and omitted variables, as described in Section 3. Together, these elements mitigate concerns about enforcement limitations in our setting.

2 Data and Summary Statistics

2.1 Data

[8]Appendix Figure IAB6 presents anecdotal evidence collected from media reports of compliance with actions plans. For a discussion on enforcement of environmental regulation in India since the 1980s, see Greenstone and Hanna (2014); Harrison et al. (2019).

Policy Data. We hand-collected data on the 2009 regulation from policy documents published by the CPCB. These include cluster CEPI values and their corresponding components broken down by medium (air, water, and land). Additionally, we hand-collected data from two follow-up rounds of monitoring by the CPCB in 2011 and 2013 in clusters with a 2009 CEPI value at or above 70. These data also include information on the institutional details, monitoring, and enforcement mechanisms of the regulation. See Online Appendix B for more details.

Industrial Clusters. We hand-collected the location of more than 2,000 clusters by name—the near universe of industrial clusters in 2009. As industrial clusters are a dense agglomeration of Small and Medium Enterprises (SMEs), we map them to the most granular regional unit available across different datasets. Specifically, we standardize the cluster names, extract their location from Google API, and match them to PIN codes and cities.[9] For our primary analyses, which use firm data, city is the most granular regional unit, and hence we assign the treatment at this level.[10] Through this procedure, we can match 61 of the 88 industrial clusters for which the CPCB released data on the CEPI score. Overall the firms in our sample represent a significant share of economic activity, producing over 70% of output between 2005 and 2015.

Emissions Datasets. To measure cluster-level changes in air emissions, we rely on the Emission Database for Global Atmospheric Research (EDGAR). EDGAR is a comprehensive global database that documents human-caused emissions of greenhouse gases and other pollutants. We use the highest resolution data available: emissions measured in $0.1° \times 0.1°$ grids at a monthly frequency. This data presents several advantages for assessing the impact of emissions. First, EDGAR's figures are derived independently, using consistent international statistics and an established IPCC methodology.[11] Second, the database disaggregates emissions by pollutant type. We use emissions data for nitrous oxide (NO_x), particulate matter less than 2.5 μm in diameter

[9] We match the location of industrial clusters to the more granular PIN-code level in the business registration dataset. In India, a PIN code, which stands for *Postal Index Number* code, is a numerical code used by the postal system to facilitate the sorting and delivery of mail. On average, a single post office serves an area of approximately 21 square kilometers and a population of around 10,000.

[10] In most cases, we can uniquely match an industrial cluster to a particular city. However, in a handful of cases where this match is not unique, we aggregate CEPI values to the city level by assigning each city the maximum index value among all the industrial clusters.

[11] See https://edgar.jrc.ec.europa.eu/ and Crippa et al. (2019, 2020); European Commission, Joint Research Centre (EC-JRC)/Netherlands Environmental Assessment Agency (PBL) (2020) for more information.

($PM_{2.5}$), and particulate matter less than 10 μm in diameter (PM_{10}). Finally, the data separately report emissions from different sectors. This allows us to focus exclusively on industrial emissions. Importantly, this allows us to mitigate concerns about measurement error such as emissions from agricultural activities, which includes crop burning. These features of the EDGAR dataset make it well suited for studying changes in emissions, a substantial limitation in prior research on environmental regulations in emerging markets (Greenstone and Jack, 2015).

We link emissions from EDGAR to exact locations of clusters identified from the policy documents. This involves two main steps. First, we define the area around each plant as a circle with a five-kilometer radius, creating what we refer to as a footprint. This footprint ensures that we attribute changes in air emissions to firms operating within distinct industrial clusters. Second, we apportion the monthly measurements from the grid to this footprint. If a footprint spans multiple grid cells, we calculate the pollution using a weighted average based on the respective land area of those cells. See Online Appendix D for more details.

We supplement these analyses with data on fine particulate matter ($PM_{2.5}$) from Van Donkelaar et al. (2015). These data are constructed by combining aerosol optical depth (AOD) data from several satellite sources and then calibrating the readings to pollution monitor data using a geographically weighted regression (GWR). The data are available monthly at the spatial resolution of 1km $\times$ 1km.

Firm Financials. We use firm and product data from Prowess, a database maintained by the Centre for Monitoring the Indian Economy (CMIE). Several studies on Indian firms have used this dataset, including Bertrand et al. (2002); Gopalan et al. (2007); Lilienfeld-Toal et al. (2012); Gopalan et al. (2016); Naaraayanan and Nielsen (2021); and Naaraayanan and Wolfenzon (2024). We extract data from the latest vintage of Prowess, which is free from earlier systematic survivorship bias, as highlighted by Siegel and Choudhury (2012).

The CMIE gathers data from balance sheets and income statements for approximately 37,000 publicly listed and private firms. The covered firms account for more than 70% of the industrial output, 75% of corporate taxes, and over 95% of excise taxes collected by the government of India and represent large and medium-sized firms in India (Bau and Matray, 2023).[12] Moreover,

[12] It is worth considering how alternative datasets compare to Prowess. Most prominently, research on India has

in addition to headline firm financial statements, the data also capture firm abatement expenditures, a proxy to measure one of the key levers the regulation used to combat cluster emissions. Therefore, the data are particularly useful for examining how firms adjust over time in response to environmental regulations.

Product-level Inputs and Outputs. To shed light on within-firm decisions, we use detailed product-level data made available due to *mandatory* disclosure requirements set out in the Companies Act of 1956 and the Companies Act of 2013. On the output side, the dataset captures total sales and total quantity sold at the firm-product level, allowing us to compute unit prices and quantities. In addition, it provides information on capacities, production, and sales from company annual reports (see Goldberg et al. (2010) and Bau and Matray (2023) for more details).[13] We construct a panel of product-level output and prices, with unit-level prices for each product defined as the total unit sales over total unit quantity.

On the input side, Prowess captures product-wise energy consumption reported in company annual reports.[14] The data are at the firm-product-year-energy-source level and are expressed in energy input units per reported production unit. We transform energy input into CO_2 output by making assumptions about each energy source's energy content and CO_2 output. We calculate tons of CO_2 emitted per reported production unit for each firm-product-year-energy-source and collapse to the firm-product-year level across energy sources. (See Online Appendix E for details.) To our knowledge, no other data source offers comparable granularity and scope to understand the intersection of firm production and energy consumption.

used the Annual Survey of Industries (ASI) to examine the impact of reforms on the manufacturing sector. The most important difference is that Prowess is a firm-level panel dataset whereas ASI is an establishment-level dataset that surveys a repeated cross-section of 30,000 establishments per year (Martin, 2011; Sivadasan, 2009). Therefore, ASI is limited in terms of panel coverage, making it particularly ill-suited for studying within-firm responses to environmental regulations.

[13]The Companies Act does not mandate or specify the units for reporting, leading to a lack of standardization both across and within firms over time. Therefore, we standardize units within and across firms and drop observations in instances where there is insufficient information to reconcile changes in unit types within a firm-product over time.

[14]Sub-section (1), clause (e) of section 217 within the Companies Act of 1956 stipulates that all companies must report their *total* energy consumption in a specified format. Nevertheless, there is no legal requirement for companies to disclose their product-specific energy consumption per production unit. Consequently, one limitation of the analysis on changes in product-level energy consumption is that firms can decide whether to disclose this information. Not all firms choose to do so. In Online Appendix E, we explore the representativeness of these data. Importantly, we observe in our data that, when a firm initiates the reporting of product-level energy inputs, it typically does so consistently throughout the entire period. Moreover, we find a reduction in the probability of filing energy inputs at all in the post-regulation period but no discontinuity in this probability at the treatment thresholds.

Plant Announcements. We use data on the announcement of new and abandoned plants from the CapEx database maintained by CMIE. This dataset contains information on all new and abandoned plants announced in India since 1990, including information on the project announcement date, location, ownership, cost, and industry classification. CMIE obtains data from multiple sources, including annual reports, news articles, and government press releases. The database is updated daily and contains information on the entire project life cycle whenever information is available. Typically, projects costing more than INR 100 million (approximately USD 2 million) are included in the database (Alok and Ayyagari, 2020; Naaraayanan and Wolfenzon, 2024).

Other Data Sources. We use the near-universe of firm registrations from the Ministry of Corporate Affairs (MCA), allowing us to track business formation across all formal firms in the economy. Furthermore, we use data from the 2001 Population Census to examine whether observables differ significantly in treated and control clusters around the CEPI value treatment thresholds. We also use it to test the assumption that the CEPI thresholds are economically meaningful to firms because of the 2009 regulation and not because they correspond to other policy or economically relevant thresholds.

2.2 Final Sample and Summary Statistics

Our aim is understanding the impact of regulation targeting pollution from industrial clusters, which feature dense agglomeration of manufacturing firms. Our estimation sample, therefore comprises manufacturing firms located in the 61 clusters for which we have a CEPI value. We focus on a five-year window around the 2009 regulation. Moreover, as we aim to study the within-firm response to the regulation, we focus on multiproduct firms, allowing us to better understand different margins of adjustment. These firms represent over 95% of the output during the sample period.[15]

Table 1 presents the descriptive statistics for the sample of manufacturing firms from 2005 to 2015. Included firms are multiproduct manufacturing firms in industrial clusters assigned a 2009 CEPI value. Panel A reports summary statistics at the firm-year level. The average (median)

[15]This focus on multiproduct firms is consistent with prior studies (De Loecker, 2011; De Loecker et al., 2016; Eckel and Neary, 2010).

firm has 3.5 (0.6) million INR in total assets and 3.3 (0.8) million INR in total sales.[16] The sample firms are, on average, moderately indebted, with average (median) leverage ratios (bank borrowing scaled by total assets) of 0.27 (0.25). The average (median) company exports, deriving 16.3% (1.6%) of its total sales from exports. The average (median) firm produces three (two) distinct products a year.[17] The average (median) firm is also moderately profitable, reporting 11% (10%) of the value of year-before sales in new earnings before interest, taxes, depreciation, and amortization. The listed firms in our sample have an average (median) market-to-book ratio of 0.88 (0.41).

[PLACE TABLE 1 HERE.]

Our regression dataset has 2,236 unique manufactured products, in the 22 two-digit manufacturing sectors of the National Industrial Classification (NIC) system of the Central Statistical Organization. As reported in Panel (a) of Figure 3, the average number of products per firm within NIC2 manufacturing sectors ranges from 2 to 6 in a typical year. Panel (b) reports the distribution of the NIC2 sectors in our sample by their share of total output. Basic metals, vehicles, and chemicals account for the largest share of value, while furniture and other wood products have the lowest. These patterns on product distribution are consistent with those reported in the context of US multi-product firms (Bernard et al., 2010) and (De Loecker et al., 2016) in India.

[PLACE FIGURE 3 HERE.]

Panel B of Table 1 describes the product-year-level panel dataset. The overall picture is of significant heterogeneity in operations. Product profit margins—defined as *(unit price - unit cost) / unit price*—tell us that the average (median) firm-product earns 0.01 (0.14) INR per unit produced. This granular evidence is consistent with the firm-level profitability distribution. Finally, the distribution of product sales, cost, and price are all highly skewed, as is the distribution of unit-level CO_2 emissions, calculated for those firms that report product energy inputs. Overall the panel of manufacturing firms involves a broad cross-section of firms and is consistent with industrial clusters composed of a few large firms and many medium-sized ones.

[16] As of March 2009, 1 USD was equivalent to 50.61 INR.

[17] We drop firms that produce one product throughout the sample but not those that switch between being single- and multi-product producers, so that we preserve variation at the extensive margin.

3 Empirical Strategy

In this section, we describe the empirical strategies that we adopt to study the effects of environmental regulation on firm production decisions.

3.1 Difference-in-Discontinuities (DiRD)

Our analysis exploits cross-sectional variation in enforcement around the implementation of the regulation in 2009. As described in Section 1, firms in clusters just to the left of the CEPI value of 60 faced no direct regulatory change, while those in clusters with CEPI just to the right of 60 were subject to heightened emissions monitoring. Firms in clusters to the right of the second CEPI value at 70 were additionally mandated to take targeted steps through the implementation of remedial action plans.

The resulting discontinuities from implementation of the regulation naturally lends itself to a difference-in-discontinuities (DiRD) research design (Bennedsen et al., 2022; De Simone, 2022; Grembi et al., 2016). The empirical design exploits treatment discontinuities at the CEPI thresholds, allowing us to difference out the effect of any potential pre-existing discontinuity at the treatment cutoff. This variation at the threshold sidesteps concerns associated with the difference-in-differences approach, where control firms from outside the 88 industrial clusters might not serve as an appropriate counterfactual for treated firms. Specifically, we estimate:

$$Y_{kijcst} = \beta_1 Post_t \times CEPI_c^{[60,70)} + \beta_2 Post_t \times CEPI_c^{[70,100]} + \beta_3 CEPI_c + \beta_4 Post_t + \gamma_i + \kappa_{jst} + \epsilon_{kijcst}, \tag{1}$$

where k, i, j, c, s, and t represent a product, firm, industry, city, state, and year, respectively. Our running variable, $CEPI_c$, is the pollution index value, defined at the city level, as described in Section 2. We assign firms to industrial clusters based on their headquarters city as of the 2009 regulation. This may result in the misclassification of some firms by labeling them as treated when they are actually controls, and vice versa. However, such misclassification likely biases our estimates *against* finding any effect by narrowing the estimated difference between outcomes in the two treatment groups. Moreover, we show below that the identification assumptions are satisfied, which likely mitigates other sources of bias. $CEPI^{[70,100]}$ takes the value one if the city has a CEPI value at or above 70 and zero otherwise. $CEPI^{[60,70)}$ takes the value one if the city has a CEPI value greater than or equal to 60 and below 70 and zero otherwise. The omitted category includes firms whose city has a maximum industrial cluster CEPI value below 60. Including both $CEPI_c^{[70,100]}$ and $CEPI_c^{[60,70)}$ group indicators captures differences in treatment intensities for firms located in cities where the maximum CEPI value exceeds or equals 70.[18]

The variable $Post_t$ is an indicator variable taking the value one for all years including and after 2009, the year in which the CEPI regulation was implemented. The granularity of the data allows us to mitigate concerns about location- and industry-specific effects that may differentially affect firms' production and emission decisions using the empirical specification. Specifically, we include firm fixed effects (γ_i) to control for unobserved time-invariant firm characteristics. We include state-by-industry-by-year fixed effects (κ_{jst}) to control for time-varying industry shocks within the same state.[19] The stringency of these fixed effects allows us to rule out several location- and industry-specific concerns, such as technical innovation and regulation, which vary considerably over states and industries. We cluster standard errors at the cluster level, the level at which we define treatment (Abadie et al., 2023; Bertrand et al., 2004; Roberts and Whited, 2013).

The DiRD coefficient of interest is, β_1, which quantifies the effect of being located in a cluster with a CEPI value of at least 60 on the outcome Y_{ijcst} relative to the effect of being located in a cluster to the left of the cutoff with a CEPI value below 60, while controlling for additional treatment from being in a cluster subject to a remedial action plan ($Post \times CEPI^{[70,100]}$). Note that the β_2 quantifies the regulation's effect on firms located in clusters with CEPI values above 70 relative to firms located in clusters with values below 60. An advantage of including these firms in our specification is that it allows us to shed additional insight on whether the treatment effects predominantly relate to the extensive margin of treatment (crossing the 60 CEPI threshold) or to the intensity of treatment, which incurs additional regulation and consequences (crossing the 70 CEPI threshold).

A strength of DiRD is that it preserves the advantage of difference-in-differences (DiD) of

[18]In the final sample, 33 cities have a maximum CEPI value greater than or equal to 70 in 2009 and an additional 20 have a maximum 2009 CEPI value greater than or equal to 60 and below 70.

[19]The main effect of $CEPI_c$, which is invariant within a firm, drops out with the inclusion of the firm fixed effects, while the main effect of $Post_t$ drops out with the inclusion of state-by-industry-by-year fixed effects.

controlling for level differences between treated and control groups while directly testing for a key identification threat of DiD. While parallel pre-trends can be tested, one cannot rule out that forward-looking treatment assignment implies nonparallel post-trends, even in the absence of treatment. Defining treatment based on the discontinuity in an observed running variable overcomes this challenge by directly controlling for the treatment assignment rule. Thus, testing for the suitability of the running variable, via the RD tests for manipulation and smooth potential outcomes, also directly tests the parallel trends assumption. We present identification tests below.

3.2 Difference-in-Differences (DiD)

In a second specification, we recover the average treatment effects using a difference-in-differences (DiD) specification that combines the regulatory thresholds without distinguishing between them. This specification estimates the average treatment effect for all firms located in clusters with a CEPI value of at least 60, allowing us to generalize the results beyond the local treatment effects identified by the DiRD specification. Note that, as a matter of deliberate choice, the DiD specification still only includes all firms located in the industrial clusters identified by the regulation. This is to avoid selection issues from differences between firms located in targeted and untargeted industrial clusters. Specifically, we estimate the following DiD empirical specification:

$$Y_{kijcst} = \delta_1 Post_t \times CEPI_c^{[60,100]} + \delta_2 CEPI_c + \delta_3 Post_t + \gamma_i + \kappa_{jst} + \epsilon_{kijcst}, \tag{2}$$

where, as before, k, i, j, c, s, and t represent a product, firm, industry, city, state, and year, respectively. The coefficient of interest is, δ_1, that quantifies the average effect of being located in a cluster with a CEPI value of at least 60 on the outcome Y_{ijcst} relative to the effect of being located in a cluster to the left of the cutoff with a CEPI value below 60. We include the same set of fixed effects.

Implementing both specifications serves two purposes. First, the DiD estimates help evaluate the generalizability of the discontinuity analyses while allowing us to check identification assumptions. Second, from a policy design perspective, they allow us to evaluate differential effects between being assigned to centralized monitoring versus the more hands-on remedial action plan.

3.3 Identification Assumptions

The key identification assumptions of DiRD are parallel trends and that potential outcomes are smooth around the cutoffs. In this section, we test and fail to reject the assumption of smooth potential outcomes. In the following sections, we consider the parallel trends assumption.

First, we test for manipulation of our running variable, the 2009 CEPI. Panel A of Figure 4 plots the 2009 distribution of the CEPI score for the 88 clusters with CEPI values. Two vertical lines indicate the treatment thresholds at 60 and 70. Visually, we observe no bunching around the cutoffs. To formally test for bunching, we combine the CEPI thresholds of 60 and 70 into one variable through a normalized measure of CEPI value, which we create by subtracting the closest threshold from each cluster's CEPI value.[20] Specifically, we fit the distribution of the ranking variable on either side of the pooled cutoffs and then test whether those distributions differ statistically (McCrary (2008). Figure 4 reports the results for the pooled sample.

[PLACE FIGURE 4 HERE.]

We do not find evidence of bunching around the cutoffs, and the *p*-value from a two-sided test is 0.58. Thus, we fail to reject the null hypothesis of no manipulation of the CEPI ranking. A remaining concern is that omitted variables affect the composition of industrial clusters. We assuage these concerns in Section 7.3, where we document no evidence of changes in mergers and acquisitions activity, leading firms to exit the industrial clusters in response to the stringent environmental regulations.

Second, in Figure 5, we present the geographical variation in the industrial clusters selected by the CPCB for the environmental assessment relative to the location of all industrial clusters as of 2009 (gray dots). We find that the industrial clusters targeted by the CPCB are representative of clusters in general, with above- and below-threshold clusters coming from geographically proximate regions within each state.

[PLACE FIGURE 5 HERE.]

Third, we test that there are no discontinuous jumps in our key outcomes and firm and

[20] We have limited observations in the cluster to the left of the CEPI threshold at 60. As a result, we do not have enough power to examine the two cutoffs separately. Hence, to be consistent, we present results with normalized thresholds throughout these tests.

product characteristics at treatment thresholds in the pre-regulation year.[21] For example, ruling out a discontinuous jump would assuage concerns about alternative explanations, such as that some other policy differentially affected firms at these cutoffs, instead of isolating the effect of the environmental regulation.

[PLACE FIGURE 6 HERE.]

Figure 6 presents the scatter plots of means of several firm-level covariates, defined as of 2008, by different bins (each of size 1) around the pooled threshold. We normalize the thresholds to zero by subtracting off their respective threshold values from the CEPI value of the industrial cluster. We find no evidence of discontinuities in baseline covariates. The characteristics we examine include total assets, total sales, leverage, exporting intensity, investment, wage bill, and market capitalization (for listed firms). Panel A of Table 2 demonstrates that none of these characteristics differ statistically across the cutoffs even in a regression setting.

[PLACE TABLE 2 HERE.]

Similarly, Figure 7 tests for discontinuities at the pooled thresholds for product-level covariates defined as of 2008. Again we see no significant discontinuous jumps in the product characteristics. Panel B of Table 2 reports the associated average differences of products of firms in industrial clusters with CEPI values below versus above the threshold and the coefficient and associated p-value of the regression discontinuity specification at the threshold between $CEPI^{[60,70)}$ and $CEPI^{[70,100]}$ cluster status. There is no significant jump, neither statistically nor economically.

[PLACE FIGURE 7 HERE.]

Lastly, in Online Appendix Table IAA1, we examine whether there are discontinuous jumps in cluster-level covariates defined as of 2008, taken from the Population Census conducted in 2001 and Harari (2020). We again see no significant discontinuities in various proxies for economic activity—neither demand nor supply for goods—and determinants of pollution extent and its impact.

[21] This is a test of the assumption that potential outcomes are smooth around the cutoffs.

The preponderance of evidence thus suggests that the treatment thresholds do not proxy for pre-existing differences in policies that affected firms in the same way as the environmental regulation. Furthermore, they alleviate concerns that firms in the control group are not a valid counterfactual for treated firms, thereby allowing us to cleanly identify the effect of environmental regulations.

4 Changes in Cluster-Level Air Emissions

At the industrial cluster level, our primary outcome of interest is emissions As discussed in Section 2, we extract emissions data, measured in milligrams per month within a spatial resolution of 0.1°x 0.1°, from the EDGAR dataset.[22] We build a monthly panel of emissions from industrial activity split by the type of pollutant at the cluster-address level and estimate the following event study specification:

$$Emissions_{pcst} = \sum_{k \in \{-4,-2\}} \beta_k D_k \times CEPI_c^{[60,100]} + \sum_{k \in \{0,6\}} \beta_k D_k \times CEPI_c^{[60,100]} + CEPI_c + \gamma_{cp} + \gamma_{pst} + \epsilon_{pcst} \quad (3)$$

where p is pollutant, c is cluster, s is state, and t is year-month. Figure 8 plots the estimated coefficients (β_k), normalized to the fiscal year of 2008, and their corresponding 95% confidence intervals. This analysis compares the evolution of emissions in treated clusters relative to others. The vertical gray dotted line indicates the regulation year of 2009. Standard errors are clustered at the address level.

[PLACE FIGURE 8 HERE.]

As evident from Panel (a) of Figure 8, there are no differential pre-trends in the average emissions from industrial activities between treated and control clusters. These results suggest that,

[22] In contrast to previous research, which primarily relies on data related to particulate matter ($PM_{2.5}$), there are two key advantages to using the EDGAR dataset. First, it provides information on a wide range of greenhouse gases contributing to anthropogenic emissions across a broad cross-section of industries. Secondly, the data are adjusted to separate emissions from fires and those stemming from industrial activities. This separation allows us to focus exclusively on emissions from industrial sources, including industry, fugitive emissions, and solvents. These features of the EDGAR dataset make it well-suited to study changes in emissions, which has been a substantial limitation in prior research on environmental regulations in emerging markets (Greenstone and Jack, 2015).

in the pre-period, regulators were not targeting clusters that were already improving their air quality. [23] These parallel pre-trends support the DiRD identification assumption that outcomes of the treated and control groups would have evolved similarly, absent treatment, around the thresholds. Moreover, in the post-regulation period, there is an immediate and persistent decrease in the average emissions levels within treated clusters. In Panel (b) of Figure 8, we find a significant decrease in $PM_{2.5}$ emissions.

[PLACE TABLE 3 HERE.]

Table 3 presents these results in a regression framework. Column 1 combines all pollutants into a single regression and accounts for their differential impact by including high-dimensional fixed effects. These fixed effects interact cluster and state$\times$year-month fixed effects with the specific pollutant type. Consistent with Figure 8, we find a statistically significant decrease in relative emission levels for treated clusters compared with industrial clusters having a CEPI value below 60. In terms of the economic magnitude of β_1, clusters with CEPI pollution index values just to the right of 60 have 7.232 mg per month lower pollution, representing a 31.3% decrease relative to the pre-treatment average total pollution of clusters with CEPI just less than 60 of 23.09 mg per month. Note that this effect is relative to the cluster's own mean and controls for state-year-month trends in pollution, such as from production seasonality.

From the table, we see that the effect is statistically indistinguishable in clusters with 2009 CEPI value of at least 70 and in clusters with values between 60 and 70. This suggests that continuous monitoring by regulators led to the immediate reduction in emissions, while action plans are likely more effective in the longer-term.[24] This immediate reduction is consistent with the dynamics of the effect we presented in Figure 8, which showed a significant emissions reduction in the short-run. Lastly, the average treatment effect from the DiD specification resembles in magnitude the DiRD estimate, again suggesting the important role played by continuous monitoring.

Moreover, we do not observe a significant difference between the coefficients across industrial clusters with varying levels of enforcement intensity, as suggested by the p-value testing the

[23]For this analysis, we pool emissions data across the following pollutants: NO_x (nitrogen oxides), $PM_{2.5}$, and PM_{10}.

[24]As we note in Online Appendix B, finalizing the action plans took up to a year, and these typically mandated the implementation with timelines varying up to three years.

difference between β_1 and β_2. However, this average reduction in cluster-level emissions masks significant heterogeneity. Therefore, in Online Appendix C, we set out to better understand the determinants of compliance, we hand-collect information on follow-on assessments and relate them to regulator characteristics. We find that cluster-level improvements are positively associated with regulator quality and enforcement capacity, a greater proportion of small firms, and public-private cost sharing for abatement investments. These findings are consistent with prior work that argues for the importance of regulators in achieving emissions reductions in environments with low state capacity and large information asymmetries (Duflo et al., 2013; Pande and Datla, 2016).

In the remaining columns of Table 3, we separate the estimates by pollutant type. We chose the pollutants highlighted in the section of the action plans devoted to air emissions. Across the columns, we find a similar decrease across different hazardous air pollutants.

In Online Appendix Table IAA2, we run the same analysis using satellite data on measurements of fine particulate matter ($PM_{2.5}$) at a more granular, 1km $\times$ 1km, resolution (Van Donkelaar et al., 2015). As before, we build a monthly panel and find a statistically significant decrease in relative emission levels for treated industrial clusters in a five-kilometer and 500-meter radius around the center of each cluster. Relative to the pre-regulation mean in the control group, this change represents a 4.0% decrease, significant at the 95% confidence level.[25]

Finally, to rule out that unobserved time-varying trends drive these results, we conduct a placebo test of emissions from energy producers in treated versus control clusters. The key idea is that these energy producers face similar seasonality and economic fluctuations in those geographies but were not targeted by the regulation. Online Appendix IAA3 presents results. Reassuringly, we do not find any change, in terms of both economic magnitude and statistical significance, in these emissions, suggesting that (unobserved) time-varying trends do not explain the lower emissions. Overall firms targeted by the regulation lowered their emissions.

[25]The differences in economic magnitude relative to the results presented in Table 3 are likely an artifact of the low correlation between $PM_{2.5}$ readings across the two datasets (ρ = -0.06). These differences could arise from variations in calibration methods, differences in spatial resolution, and the level of industrial activity captured. We believe that, given the low correlation, both data sources provide orthogonal measurements that help establish a robust reduction in emission levels in response to the CPCB regulation.

5 Greening Production and Abatement Investments

In this section, we examine the drivers of the aggregate reduction in emissions and document operational responses by firms. We begin by analyzing product data. In Section 5.1, we analyze product-level energy consumption and changes in estimated carbon emissions. In Section 5.2, we focus on abatement expenditures reported in annual financial statements and provide supplementary evidence from annual reports on the actions undertaken by firms.

5.1 Greening Production

In this subsection, we examine changes in energy inputs and production at firms within the industrial clusters. Additionally, at the product level, we focus on the sample of manufacturing firms that reported energy inputs at the product level. We show that firms reduce emissions by changing their energy inputs, i.e., reducing their reliance on coal and shifting from purchasing rather than producing electricity. These changes are accompanied by a significant reduction in product CO_2 emissions. Further, we document that firms shift manufacturing output toward less carbon-intensive products.

Energy Efficiency. Table 4 reports firm production changes around the regulation. Panel A tests the impact on firm energy inputs, controlling for the cost per unit of production. In column 1, the outcome is the natural logarithm of the quantity produced at the firm-product-year level. There is no average difference between the treated and control groups in quantity produced around the reform in either the clusters subject only to monitoring treatment or those that additionally had to agree to specific action plans. In column 2, the outcome is the natural logarithm of the INR value of product-level energy inputs at the firm-year level. The average treated firm reduces its energy expenditures, controlling for its cost of goods sold, relative to the average control firm. The estimate suggests that treated firms operating in a cluster with CEPI value to the right of 60 reduced the value of the per-unit energy inputs in the average product relative to the average control firm in a cluster with CEPI value to the left of 60 by approximately 22% on an annual basis.[26] Overall energy use declines while production remains constant, suggesting that treated

[26]Calculated as exp(-0.244) - 1. The economic magnitude of the change is substantial: Relative to the 2008 average energy expenditure of 8.906 million INR per product, this represents a reduction of about 5.6 million INR on the

firms respond by enhancing the energy efficiency of their production.

[PLACE TABLE 4 HERE.]

Fuel Inputs. Panel B of Table 4 reports *within-firm-product* changes in energy inputs around the regulation. From Table 1, we see that coal is the primary energy input for manufacturing firms in our data and a key source of industrial air emissions. In column 1 of panel B in Table 4, we test for the use of coal by firms in treated relative to control clusters. We find a considerable decrease of 29% in the use of coal as a product input in firms in $CEPI^{[60,70)}$ clusters relative to firms in clusters with CEPI just to the left of 60. This represents a drop from 17% of inputs to 10% of inputs for the average product, relative to the 2008 control use of coal as an input per product.

One margin of adjustment to quickly re-optimize energy use and lower emissions is to increase the proportion of energy from purchased electricity instead of producing it by burning fuels. Firms in India generate their own power generation, even when it is less efficient or costlier, in order to reduce their exposure to unreliable external power supply (Allcott et al., 2016; Cole et al., 2018; Fried and Lagakos, 2023). Column 2 of panel B in Table 4 indicates that firms do shift from producing electricity to purchasing it. Specifically, the average treated firm located in the cluster right above 60 relative to firms located right below 60, increases the proportion of energy that they purchase from the electrical grid by 19.6 percentage points.

During the sample period, coal was the primary source of electricity generation, accounting for roughly two-thirds of total electricity generation in India.[27] Thus, the shift from coal as a direct input does not by itself explain the reduction in net emissions, even assuming that the average electricity plant is more efficient at extracting energy from coal than the average firm establishment. Therefore, we use data on product energy consumption by fuel source to compute emissions to document the important role of energy inputs in contributing to reduction in firm-level emissions.

Appendix Table IAA4 tests whether product-level CO_2 emissions decrease with the energy input changes. We transform energy input into CO_2 output by making assumptions about each

average product, equivalent to a reduction of about 124,740 in 2008 U.S. dollars.

[27] The share of renewables in electricity generation during this time period remained stable at 20%—calculated using data from International Energy Agency.

energy source's energy content and CO_2 output.[28] Note that we conservatively treat all electricity as coal in this calculation, thereby likely biasing against finding an effect. We then calculate tonnes of CO_2 emitted per reported production unit for each firm-product-year-energy-source and collapse to the firm-product-year level across energy sources. Emissions fall sharply relative to control firms. These findings are consistent with the cluster-level emissions evidence in Section 4 and are by construction not driven by the shift from producing to purchasing electricity.

Next we examine changes in the product portfolio composition in terms of product emissions. Panel (a) of Figure 9 plots the effect over time on the weight of the treated firm's portfolio weight on the firm's highest-emission product in 2008, relative to control firms. Emissions are calculated using the fuel-specific CO_2 conversion factors, as in Appendix Table IAA4. We normalize coefficients to one period before the regulation. We clearly see that the weight falls, on average, especially after 2011. In other words, firms in treated clusters shift production away from their highest-emission products. Panel (b) instead uses the weight on the highest coal-use product and shows nearly identical dynamics.

[PLACE FIGURE 9 HERE.]

Table 5 presents the estimates from a regression analysis. Specifically, we find that the average firm shifted its product portfolio away from its highest-emission (column 1) and highest-coal-input (column 2) product in 2008. While the average control firm weighted its highest-emission (coal-input) product at 0.65 (0.78) in 2008, the average treated firm reduced that weight by 31.8 (30.9) percentage points.

[PLACE TABLE 5 HERE.]

5.2 Abatement Expenditures

In addition to changing their energy inputs, firms may also invest in abatement to comply with the regulation.[29] To ascertain whether firms in the targeted industrial clusters invested in abatement, we rely on expenditures for pollution control equipment, as captured in financial statements. Note that this is also the best available proxy for firm exposure to regulation-imposed

[28] See Section 2.1 and Online Appendix E for more details.

[29] Abatement investments include technology adoption, energy-efficiency enhancing changes such as retrofitting boilers, process upgrades such as installing scrubbers, and other activities that often require re-optimizing inputs.

investment mandates because it captures the portion of firm expenditures that contributes to cluster-wide investment.

Table 6 examines changes in abatement expenditures around the environmental regulations. We find that firms increase their abatement expenditures, on average, both on the extensive and intensive margins. Specifically, column 1 reports the extensive margin response. The outcome $1_{Abatement}$ is an indicator that takes the value one if the firm's abatement expenditure as a fraction of total assets is nonzero and zero otherwise. We see that only firms in the clusters with a CEPI value of at least 70—those subject to action plans mandating emissions-reducing investment—significantly increase their likelihood of investing in abatement relative to firms in control clusters. Note that the coefficients between the two treatment groups are statistically significant at the 95% confidence level. The interpretation relative to the 2008 level of abatement among firms in control clusters is a 7.7 percentage point increase in the probability of investing in abatement from 4.8% to 12.5% or a 160% relative increase from baseline following the pollution intervention.

[PLACE TABLE 6 HERE.]

At the intensive margin, we see, in column 2, that abatement expenditures increase significantly among all firms in treated clusters relative to firms in control clusters. The outcome is abatement investments as a proportion of total firm assets. The effect is relatively stronger in clusters with a 2009 CEPI of at least 70, which is as expected since these clusters are those facing mandated abatement investments. Specifically, firms in clusters with CEPI value between 60 and 70 increase their abatement expenses as a ratio of their total assets by approximately four percentage points relative to control firms in clusters with a CEPI just below 60. This is a large effect; at baseline, control firms spent 1.4% of the value of their assets on abatement. Thus, in relative terms, the regulation led to an approximate 286% increase in abatement expenses relative to the abatement undertaken by control firms. Online Appendix B.1 presents supplementary evidence on specific abatement investments mandated by the action plans and as reported by firms in their audited annual financial statements.

Overall we find that the CEPI regulation led to an aggregate reduction in cluster-level emissions through firms decreasing per-unit energy use, reallocating their energy inputs, and investing significantly in abatement technologies, especially those that were mandated to undertake such investments through remedial action plans.

6 Firm Productivity

We have shown that firms change their production to lower emissions in response to the regulation. Specifically, we see that firms lower their energy input by shifting their fuel and power sources and by lowering the energy intensity of production without changing output. We also document firms increasing abatement investments and adopting specific abatement technologies. At the same time, we do not see any change in capital, wage bill, or raw material. Overall, our analyses suggest that firms are adopting new technology to modernize their production processes.

These changes, while aimed at reducing emissions, likely alter the efficiency with which firms transform inputs into outputs—i.e., their productivity. For instance, adopting energy-efficient technologies might lower energy waste while maintaining or even increasing output. However, such regulations might also reduce productivity if they compel firms to use less efficient inputs or constrain their ability to optimize production processes. Thus, examining productivity as a key outcome is natural, as it captures the broader economic implications of firms' responses to environmental regulations.[30]

Table 7 examine revenue and quantity productivity at firms. The dependent variable in column 1 is revenue productivity or the INR of revenue generated for each INR of input—measured as capital, labor, and material inputs (Levinsohn and Petrin, 2003).[31] Our analysis reports a significant increase in revenue productivity for treated firms post reform, supporting the theories that regulatory frameworks can catalyze technology adoption and enhance efficiency.

[PLACE TABLE 7 HERE.]

[30]Theoretically, it is unclear that there should be any effect on productivity if firms respond by scaling back inputs Greenstone et al. (2012). Alternatively, productivity falls if compliance diverts productive resources (Bertrand et al., 2007; Duflo et al., 2013; Greenstone and Hanna, 2014; Harrison et al., 2019; He et al., 2020; Jaraitė et al., 2022) and rises if it instigates the adoption of more efficient technologies or processes (Colmer et al., 2024; Linn, 2008; Lu and Pless, 2024; Newell et al., 1999; Wu et al., 2023).

[31]When estimating the production function, we measure output using total sales, including income from industrial goods, raw materials, by-products, and waste. Inputs include: (i) capital, proxied by gross fixed assets (tangible and intangible), (ii) labor, measured as total employee compensation, (iii) material inputs, combining expenses on raw materials, power, and fuel, (iv) raw materials, including costs for materials, stores, spares, and tools, and (v) energy inputs, proxied by expenses on power, fuel, and water. All values are deflated using industry deflators to reflect real terms, controlling for firm size.

While Levinsohn and Petrin (2003) is the standard for measuring total factor productivity in extant literature, it has widely acknowledged limitations, in particular its reliance on intermediate inputs as proxies for unobserved productivity shocks and a strong monotonicity assumption. Therefore, in column 2 of Table 7, we instead use the quantity productivity measure of De Loecker et al. (2016) or the units of output generated for each unit of input.[32] We again find a significant productivity increase in treated relative to control firms. Moreover, in both TFP proxies the effect is driven by firms operating in action plan clusters with a 2009 CEPI of at least 70, where we also observe a stronger abatement investment response (Table 6). We can speculate that implementing required abatement investments necessitates re-optimizing production. Taken together, this evidence strengthens the finding that the average effect of the CEPI reform was to increase firm productivity, despite the (different) limitations of TFPR and TFPQ analyses.

Our finding that an emissions capping regulation increases firm productivity for treated relative to control firms is consistent with Colmer et al. (2024); Linn (2008); Lu and Pless (2024); Newell et al. (1999); Wu et al. (2023). In line with the model of Colmer et al. (2024), we show that firms lower their energy inputs, switch from high-emission fuels like coal (Table 4), and invest in emissions abatement (Table 6).[33] In Appendix B, we provide direct examples from regulatory and firm documents of firms responding to the reform by investing to increase energy efficiency.

Finally, in Appendix Table IAA5, we test for the effects of the reform on the other factors of production, capital (K), wage bills (L), or raw materials (M). We find no significant change.[34] This suggests that the production changes we document are not distorting other production inputs, on average.

Overall the evidence is most consistent with complementarity between productivity and emissions reduction in this firm population. This finding will be most externally valid among

[32]Online Appendix F discusses its construction and limitations. For example, it relies on structural assumptions about market competition and functional form, but they are sufficiently different limitations that it is informative to look at them together. See Atkin et al. (2019) for a full discussion of the strengths and benefits of the two productivity proxies.

[33]Various models can explain why profit-maximizing firms might forgo adopting more efficient techniques absent regulatory intervention, including fixed costs and financial constraints, evolving technological opportunities amid uncertainty, incomplete information, the effect of prior government policies, and organizational inertia. Furthermore, constraints at the firm level and market distortions, like limited competition, reduce the incentive to invest in productivity enhancements. This paper does not aim to differentiate among these not mutually exclusive models when presenting evidence that the CEPI reform acts as a necessary catalyst for productivity enhancement.

[34]We caution that we cannot observe heterogeneity in labor between high and low-skill employees in our data. There may be a shift in composition in a way that increases the complementarity between labor and capital.

a similarly representative sample of firms, in markets still developing toward the technological frontier, and in those characterized by relatively weak competition. Moreover, combined with the evidence on the characteristics of regulatory effectiveness, it is informative to regulatory design that this regulation was designed to both encourage technological advancement—to the point of mandating certain technologies—and worked best where that kind of investment was subsidized.

7 Cluster Dynamism and Aggregate Impacts

In the last section, we examine the aggregate impact of the CEPI regulation and study its implications for creative destruction through firm entry and product variety.

7.1 Changes to Product-level Outputs

We first examine whether the reallocation of energy inputs was accompanied by other operational changes at firms targeted by the regulation. Specifically, we examine changes in firm output at the product level. It is unclear whether we should observe any treatment effect, given that the manufacturers in our sample are primarily upstream in their supply chains and have long-term production relationships with the firms they supply. On the other hand, changes in energy inputs suggest that firms are re-optimizing their production decisions and hence are likely to change outputs as well. We test between these explanations and report the results in Table 8.

Column 1 of Table 8 reports no differential response, on average, between the production on the intensive margin of firms in treated and control clusters, as proxied for by the natural logarithm of the product-level production quantity. Column 2 shows no evidence of any differential extensive margin response, proxied for by the natural logarithm of the number of product lines at the firm level.

[PLACE TABLE 8 HERE.]

In columns 3 and 4 of Table 8, we test for the effect of the regulation on product variety. In aggregate, treated firms are significantly less likely to introduce new products. The reduction is about a 12 percentage point decrease in the probability that a firm in the highest-treatment clusters with CEPI above 70 will introduce a new product in the five years following the regulation in

2009. The probability of dropping a product is positive but insignificant in the aggregate. Overall there is no significant impact on firm production but a suggestive negative impact on long-term product variety, which has been acknowledged as an important source of consumer welfare since the seminal work of Bresnahan and Gordon (2008).

7.2 Business Dynamism: Firm Entry

We now move beyond within-firm exploration and study the aggregate impact of environmental regulations. The primary motivation for organizing manufacturing activity as part of an industrial cluster is to boost firm productivity through economies of scale and agglomeration externalities (Juhász et al., 2022). We focus on firm entry as a summary measure of the agglomeration benefits since it reflects the net benefits and costs of agglomeration in a given industrial cluster.

Table 9 reports the results from our DiRD design on firm entry, run at the cluster level. The sample for Panel A is the universe of formal firms, not just manufacturing firms, from the firm registry obtained from the MCA. Therefore, we capture the entire distribution of firm size operating in the formal sector within these industrial clusters. Our empirical specification quantifies the effect of entry of the average firm into an industrial cluster. As in the cluster-level emissions tests, the control group comprises clusters for which the CPCB constructed a CEPI value in 2009 but whose values are below the lowest treatment threshold at a value of 60.

[PLACE TABLE 9 HERE.]

The regulation decreases firm entry, driven by the effect in $CEPI^{[70,100]}$ clusters. Column 1 presents a linear probability model on the incidence of new firm creation. We see an approximately 1.4% drop in new firm registrations, versus a baseline rate of 7%. The effects are significant at the 90% confidence level in clusters with a CEPI of at least 70.

Column 2 of Table 9 demonstrates the effect on the natural logarithm of the number of firms in $CEPI^{[70,100]}$ versus control areas. We again see a reduction of comparable size, though the effect is insignificant at conventional confidence levels. Column 3 reports a negative effect of a similar magnitude where the outcome is the inverse hyperbolic sine function (i.e., $asinh(x) = ln(x + sqrt(x * x + 1))$), which, unlike the natural logarithm, is well-defined at zero. Finally, column 4 presents a model with the levels of the number of firms in each cluster as the outcome and estimates a Poisson model instead of ordinary least squares (Cohn et al., 2022; Silva and Tenreyro, 2006). Results are consistent with those of columns 1 and 2.

In panel B of Table 9, we repeat the exercise using only firms in the Prowess database, which are typically larger than the average firm in the economy. These are also the firms in our regression sample. In this subsample, firm entry also significantly decreases with an economically meaningful magnitude relative to the ex ante pattern in control firms.

In summary, we document a decrease in firm entry across the firm-size distribution, suggesting that the regulation's costs were sufficiently large to deter business formation. These findings are consistent with lower competitive pressure within treated clusters and fewer agglomeration benefits. Along with the evidence in Section 7.1 of decreased product variety, we add evidence to the literature that contends that regulation can lower emissions but at a cost to the economy.

7.3 Other Margins of Adjustment

In this section, we consider alternative margins of adjustment to lower emissions among firms in treated clusters. Firms may relocate or expand their operations to regions with less stringent environmental regulations, particularly those related to environmental compliance (Copeland and Taylor, 1994, 2004). Research has documented that localized policies shift emissions within and across geographies (Bartram et al., 2022; Ben-David et al., 2021).

We examine three margins of adjustment by firms, beyond altering their production decisions. First, we focus on changes in mergers and acquisitions around the regulation. Specifically, we examine whether firms in the targeted industrial cluster are more likely to be acquired or merged with firms outside the cluster. In Online Appendix Table IAA6, we show that the average likelihood of being a target or acquirer in a merger or acquisition is unaffected by the reform.

Second, instead of entirely relocating their operations through mergers and acquisitions, firms may relocate their production by building new plants and expanding capacity elsewhere. We explore this possibility in Online Appendix Table IAA7. Specifically, our findings indicate that, on average, firms are unlikely to announce new plant constructions or to abandon the expansion of existing plants.

Third, we estimate significant reductions in energy efficiency but no effect on raw material expenses, wage bill, and capital investment, suggesting that firms, on average, do not shift emissions through their product markets.

8 Conclusion

Policymakers are increasingly setting emission targets while considering their impact on firm productivity and global competitiveness. However, evidence on their effectiveness and associated costs is mixed, often due to opaque within-firm responses, including operational, product, and energy adjustments.

This paper opens up the "brown box" of within-firm production responses to emissions regulations by using novel product data combined with an environmental regulation in India. We find that these regulations lowered emissions by prompting a shift away from high-emission energy sources alongside reduced per-unit energy inputs, product portfolio adjustments away from the highest-emission products, and abatement investments. On average, these production changes and investments increased firm productivity. However, these regulations lowered aggregate business dynamism and product variety, thereby potentially impairing competitiveness.

Our results point to the mechanisms that policymakers could target to balance these costs against lower emissions. First, firms subject to greater monitoring change their energy inputs. Therefore, mandating reductions in the use of specific energy inputs rather than imposing caps on emissions followed by continuous monitoring might effectively reduce emissions. However, conditional on imposing caps, we document the critical role of regulator reputation and public-private cost sharing for firm compliance

Second, our findings inform constrained regulators about where along the supply chain they should focus their monitoring efforts. Firms in our sample are concentrated upstream in the supply chain, which is perhaps the primary reason we find them internalizing costs rather than passing them on to their customers and suppliers.

More broadly, our results highlight the importance of disclosures at different stages of production. Our study informs policymakers on how to effectively target and monitor firms using these data. Such disclosure requirements are already under consideration worldwide. For example, Gary Gensler, the Chair of the US SEC, has called for more detailed emissions disclosures, including indirect emissions and those from the supply chain (Gensler, 2023). Similarly, in the European Union, the Corporate Sustainability Reporting Directive mandates that all public firms report their greenhouse gas emissions, including Scope 3 emissions (European Commission, 2021). Our findings suggest that these disclosures will likely enhance the effectiveness of environmental regulations in encouraging firms to reduce, rather than shift, emissions.

Finally, our findings underscore the need for coordinated policies on decarbonization. While the shift toward purchasing rather than producing electricity that we document may not currently drive firms away from coal, incentivizing electricity use could facilitate a smoother transition to cleaner fuels as the power grid becomes more technically and economically viable to green.

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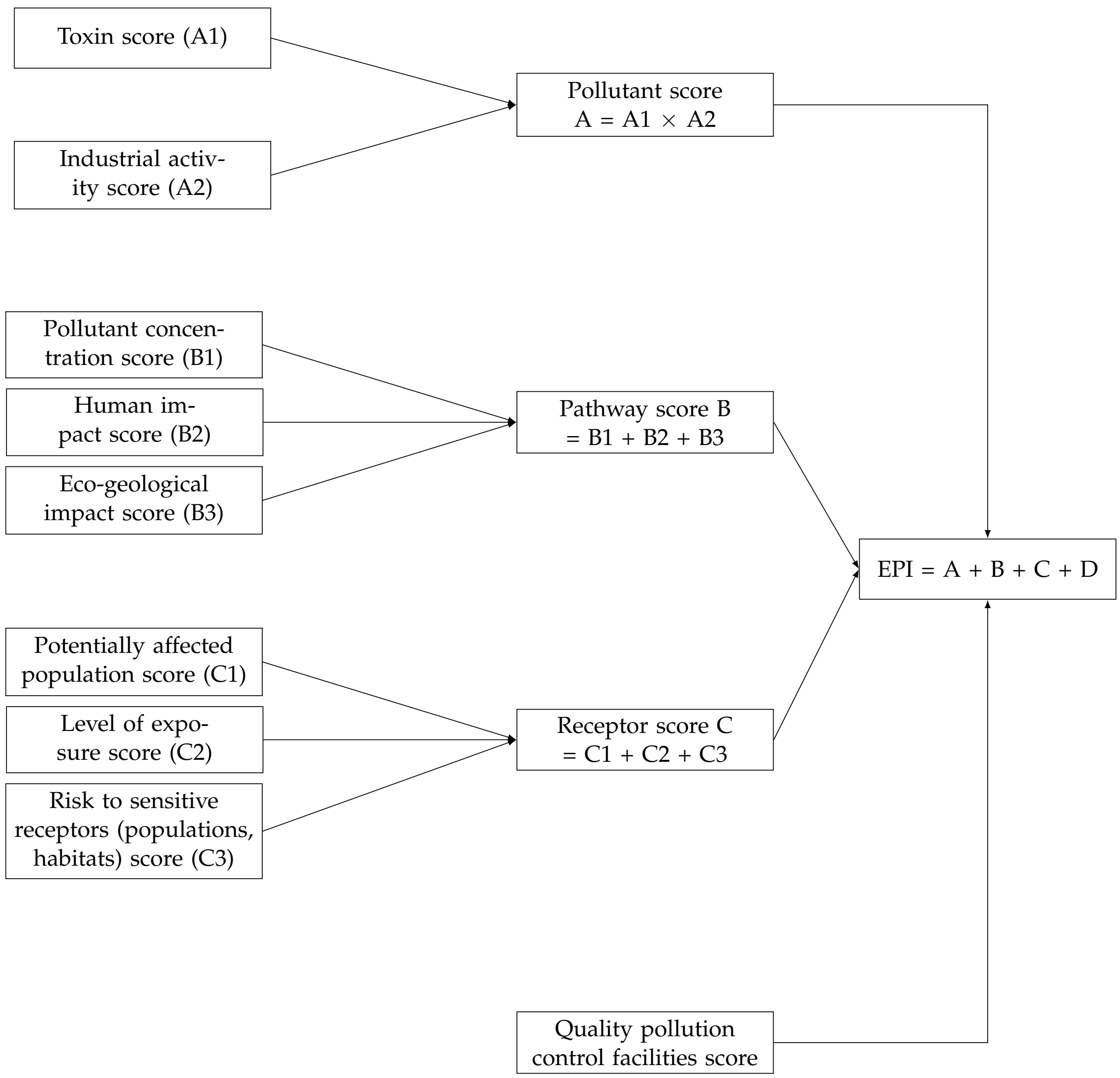
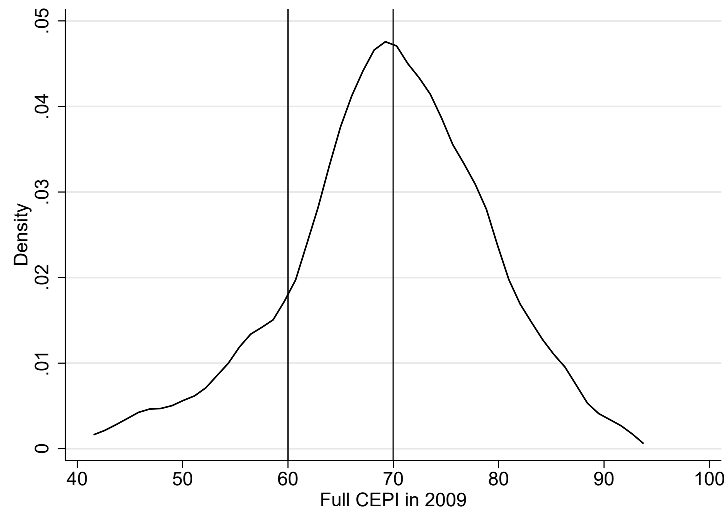
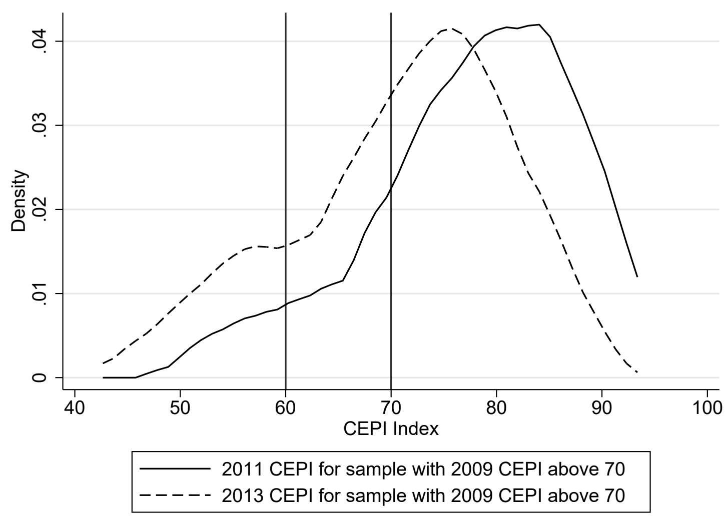


FIGURE 1: THE COMPREHENSIVE ENVIRONMENTAL POLLUTION INDEX

This figure presents the components of the Comprehensive Environmental Pollution Index (CEPI) as it was defined between 2009 and 2016. Calculations are at the industrial cluster level. Source: Central Pollution Control Board.



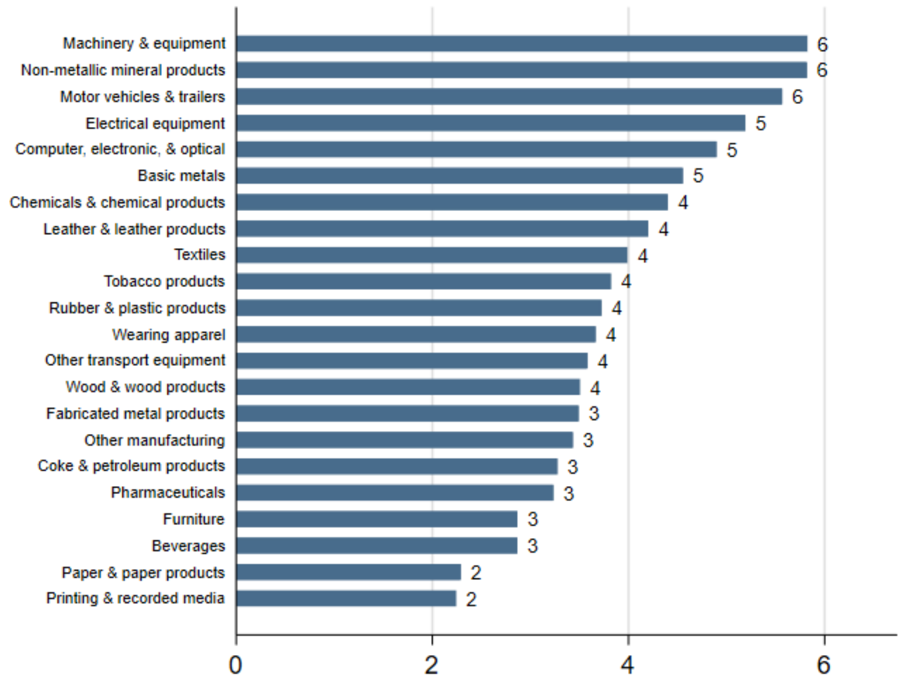
(a) CEPI in 2009



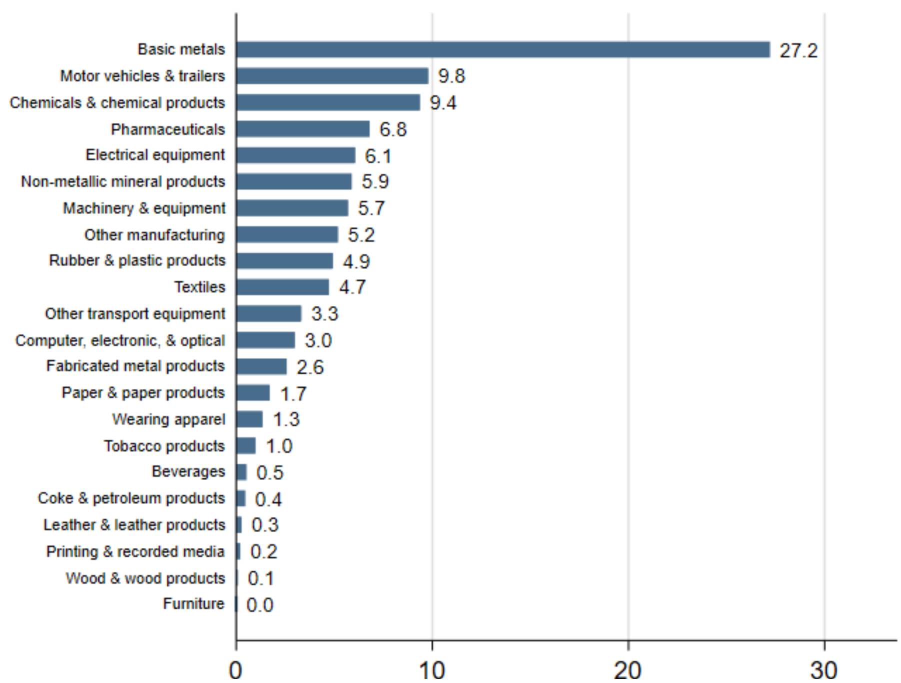
(b) Comparison between 2011 and 2013

FIGURE 2: EVOLUTION OF THE RANKING VARIABLE

This figure illustrates the evolution of the CEPI. Panel A presents the ranking distribution of 88 industrial clusters with CEPI values computed by CPCB in 2009. The vertical line marks treatment thresholds at CEPI = 60 and CEPI = 70. Panel B displays the CEPI distribution in 2011 (solid line) and 2013 (dashed line) government studies, focusing on the subset of clusters initially classified with CEPI values > 70 in 2009.



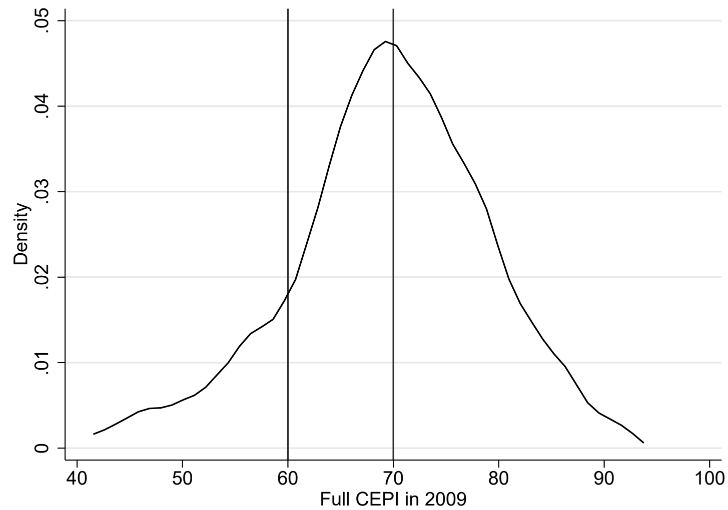
(a) Unique Products per Firm (#)



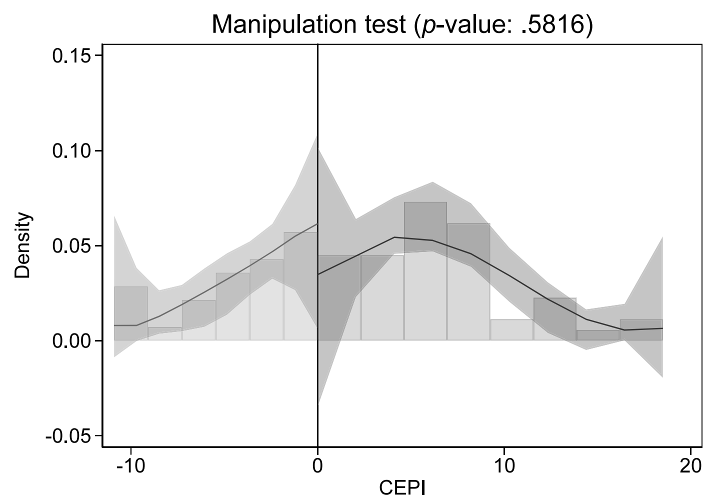
(b) Share of total value (%)

FIGURE 3: SECTORAL DISTRIBUTION OF MANUFACTURING PRODUCTS

This figure displays the distribution of 2,236 manufactured products in the regression sample. Panel (a) reports the average number of products per firm in each 2008 NIC2 manufacturing sector. Panel (b) reports the average share of output by manufacturing sector, calculated as the annual rupee value of total sector output as a percent of the total annual rupee value of all sectors. Data source: CMIE Prowess.



(a) Distribution of 2009 CEPI



(b) McCrary density test of 2009 CEPI at pooled cutoffs

FIGURE 4: TESTING FOR MANIPULATION OF THE RANKING VARIABLE

This figure tests for manipulation of the 2009 CEPI. Panel A presents the ranking distribution of 88 industrial clusters with CEPI values computed by the CPCB in 2009. The vertical line marks treatment thresholds at CEPI = 60 and CEPI = 70. Panel B displays the estimated density functions around the pooled thresholds at the CEPI values of 60 and 70. The *p*-value is from a two-sided test with the null hypothesis that the distributions of the rankings do not differ across the cutoff (Abadie and Cattaneo, 2018; McCrary, 2008)

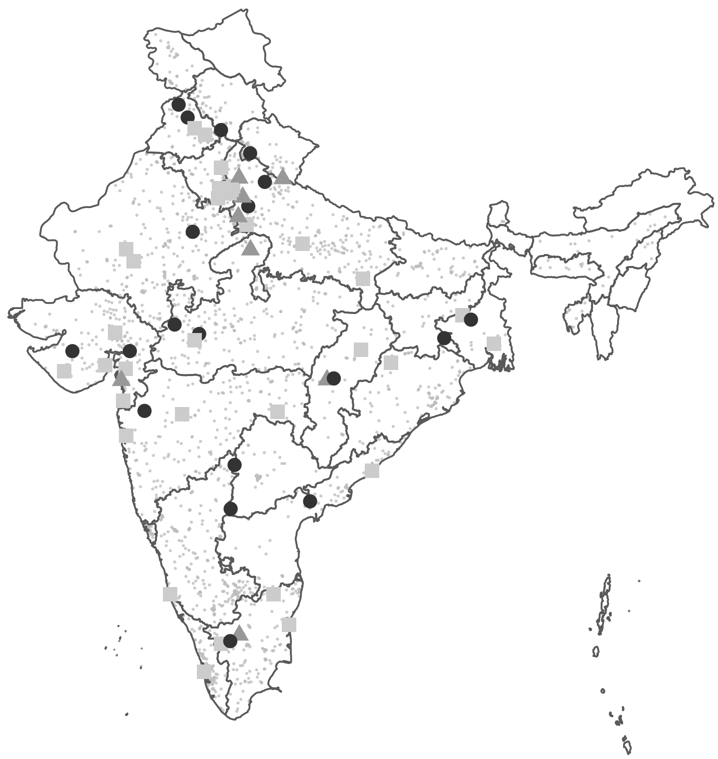


FIGURE 5: GEOGRAPHIC VARIATION OF INDUSTRIAL CLUSTERS

This figure presents the geographic variation of all industrial clusters as of the year 2009. Small gray dots illustrate the location of all industrial clusters. Larger black circles correspond to clusters with CEPI values at or above the 70 threshold, triangles correspond to clusters with index values between the 60 and 70 thresholds and squares correspond to clusters with index values below the 60 threshold.

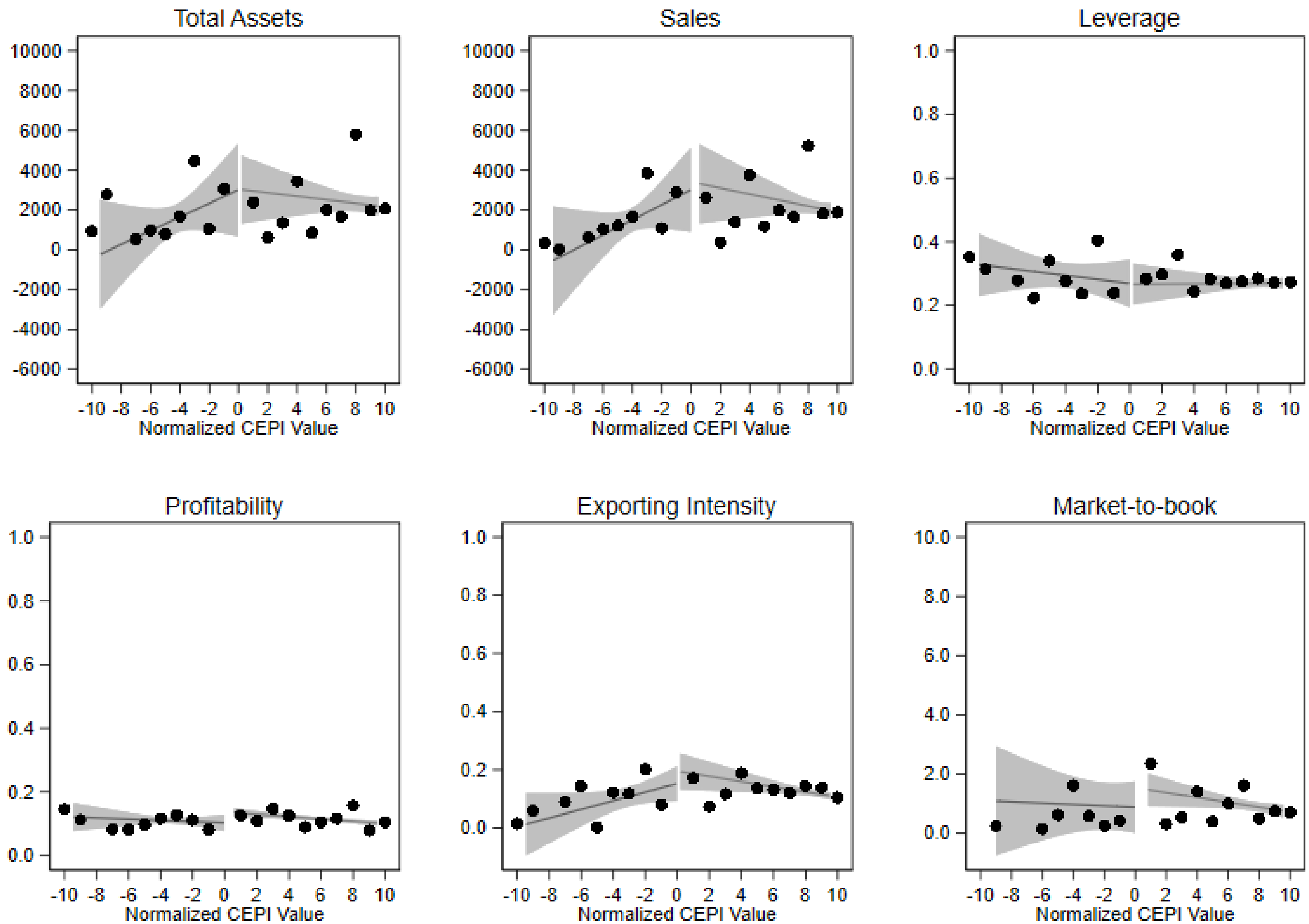


FIGURE 6: FIRM CHARACTERISTICS PRIOR TO THE INTRODUCTION OF THE CEPI

This figure presents regression discontinuity estimates of baseline firm characteristics from 2008, a year before CEPI regulation was introduced. It graphs the average firm characteristic in CEPI bins near the cutoff, pooling data across the CEPI thresholds of 60 and 70, marked as zero in the figures. A linear fit is generated separately for each side of 0, with the 95% confidence intervals displayed.

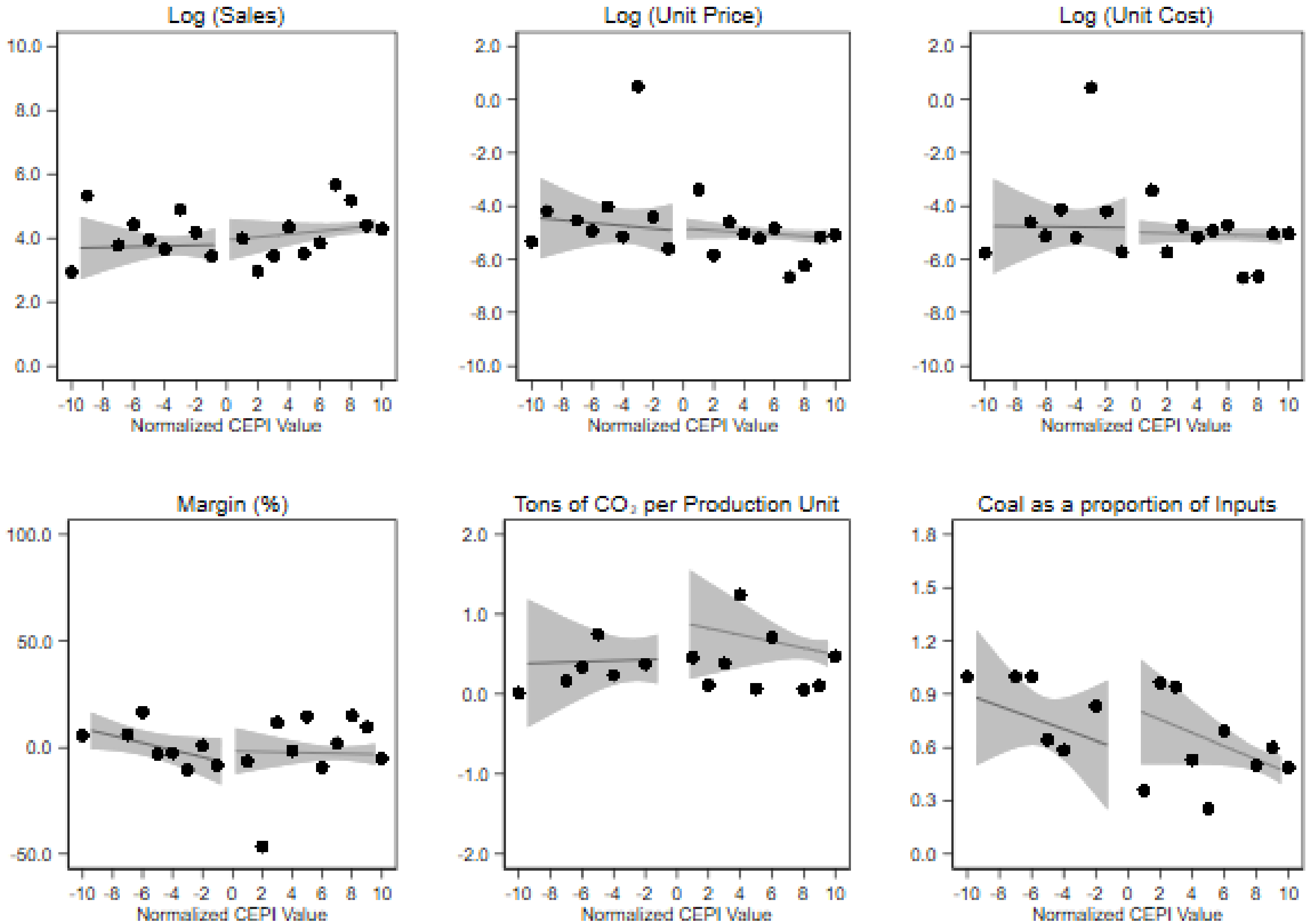
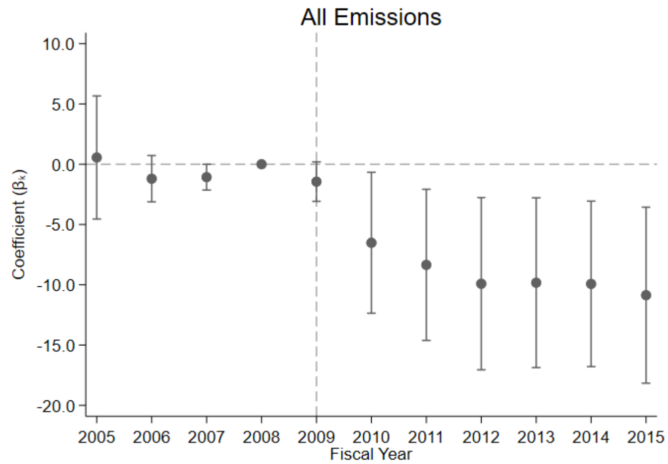
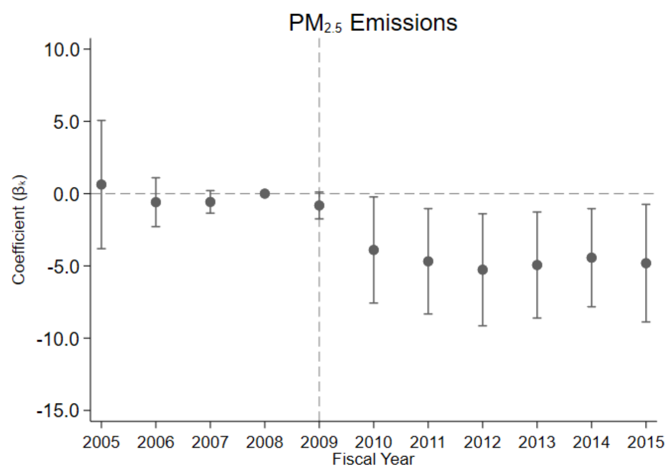


FIGURE 7: BASELINE PRODUCT CHARACTERISTICS PRIOR TO THE INTRODUCTION OF CEPI

This figure presents the average firm-product characteristics from 2008, the year preceding the CEPI regulation, plotted in CEPI bins near the cutoff. The data combines information across the CEPI thresholds of 60 and 70 (represented as zero in the figures). A linear fit is generated separately for each side of 0, with the 95% confidence intervals displayed.



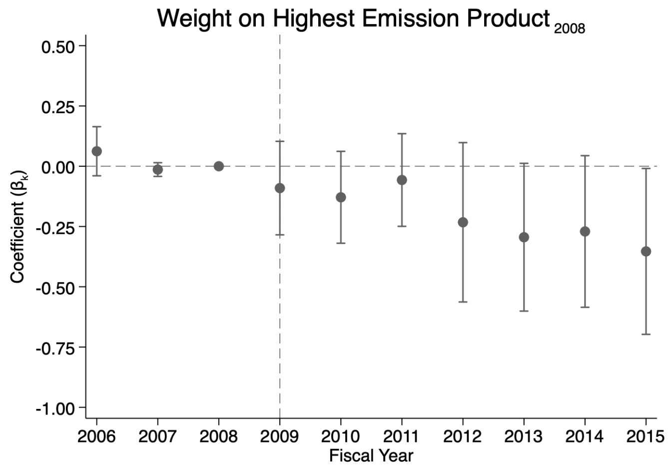
(a) All Pollutants



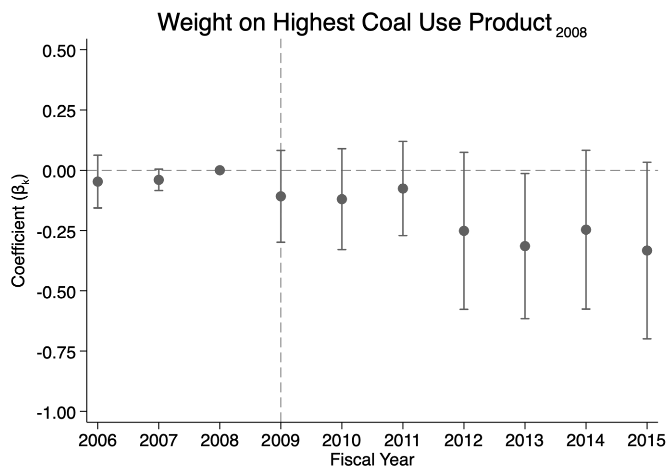
(b) Pollutant: Particulate Matter $< 2.5\mu$

FIGURE 8: CHANGES TO CLUSTER-LEVEL INDUSTRIAL AIR EMISSIONS

This figure presents the dynamic coefficients and their corresponding 95% confidence intervals from a difference-in-differences empirical specification (Equation 3). Panel A incorporates all emissions, while panel B focuses on fine particulate matter less than 2.5 microns. Coefficients are relative to 2008, the year before CEPI regulation, which is normalized to zero. A dotted vertical line indicates the reform. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60. Data source: Emissions Database for Global Atmospheric Research (Crippa et al., 2019, 2020; European Commission, Joint Research Centre (EC-JRC)/Netherlands Environmental Assessment Agency (PBL), 2020).



(a) Product with Highest Emissions$_{2008}$



(b) Product with Highest Coal Weight$_{2008}$

FIGURE 9: CHANGES TO PRODUCT PORTFOLIO

This figure presents the dynamic coefficients and their corresponding 95% confidence intervals from a difference-in-differences empirical specification (Equation 3). The dependent variable in panel A is the weight of the highest emission product as of 2008 while in panel G it is the weight of the highest margin product as of 2008. Coefficients are relative to 2008, the year before CEPI regulation, which is normalized to zero. A dotted vertical line indicates the reform. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60. Data source: CMIE Prowess.

TABLE 1: SUMMARY STATISTICS

This table presents descriptive statistics for the firms and products in our baseline sample. Panel A summarizes the firm-year panel dataset. Panel B summarizes the firm-product-year dataset. All variables are defined in Appendix Table IAA8.

	Panel A: Firm characteristics					
	Obs	Mean	Std. dev.	Min.	Median	Max.
	(1)	(2)	(3)	(4)	(5)	(6)
Assets (000 INR)	11,452	3,524	8,864	6.70	621	52,664
Sales (000 INR)	11,452	3,282	7,274	3.90	755	40,262
Leverage	10,307	0.27	0.20	0.00	0.25	1.13
Exporting Intensity	11,452	16.30	26.09	0.00	1.64	97.84
Ln(Revenue Productivity)	11,452	3.07	1.86	1.02	2.54	8.63
Ln(Quantity Productivity)	2,079	1.36	1.53	-1.75	1.39	4.65
Number Product Lines	11,452	2.84	2.02	1.00	2.00	22.00
Profitability	11,452	0.11	0.08	-0.09	0.10	0.30
Investments/Assets	10,394	0.67	0.41	0.03	0.61	2.42
Abatement Expenditure/Assets	11,452	0.03	0.18	0.00	0.00	2.15
Raw Materials/Sales	11,451	0.58	0.22	0.03	0.60	1.01
Wages/Sales	11,451	0.05	0.05	0.00	0.04	0.30
Market-to-book	1,949	0.88	1.23	0.02	0.41	6.86

	Panel B: Firm-product characteristics					
	Obs	Mean	Std. dev.	Min.	Median	Max.
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Product Sales)	30,143	4.44	2.78	-2.30	4.76	9.63
Ln(Unit Cost)	15,589	-4.97	3.86	-15.35	-3.85	3.44
Ln(Unit Price)	16,329	-4.92	3.87	-15.24	-3.73	3.37
Margin (%)	15,589	0.01	0.70	-5.67	0.14	0.64
Ln(Per Unit CO_2 Emissions)	1,163	-2.35	2.80	-9.83	-1.85	2.42
Ln(Value Energy Input)	1,163	13.81	2.96	5.29	14.39	21.48
$\mathbb{1}_{\text{Coal Use}}$	1,163	0.25	0.43	0.00	0.00	1
Coal's Proportion of Inputs	1,163	0.59	0.46	0.00	1.00	1.00

TABLE 2: COVARIATE BALANCE

This table presents tests for differences in firm and product characteristics before the 2009 reform for the regression sample. Panel A reports balance at the firm level while Panel B reports balance at the firm-product level. In both panels, Column 1 present the unconditional mean for the whole sample while Columns 2 and 3 present the unconditional means for cities below the treatment threshold and cities above the treatment threshold, respectively. Column 4 presents the difference in means between cities below the treatment threshold and cities above the treatment threshold. Column 5 shows the regression discontinuity estimate of the effect of being above the treatment threshold on the baseline variable. The model is estimated within a bandwidth of 10 units of the CEPI around the treatment thresholds at 60 and 70, and accounts for difference across states and within industries. Finally, Column 6 is the *p*-value for this estimate, using bias-corrected, heteroskedasticity-robust standard errors of Calonico, Cattaneo, and Farrell (2020). All variables are defined in Appendix Table IAA8.

	Panel A: Firm characteristics					
	All	Below	Above	Difference	RD Estimate	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)
Assets (000 INR)	2,500	2,127	2,566	-439	-1,317	0.68
Sales (000 INR)	2,418	1,853	2,519	-665	-348	0.90
Leverage	0.27	0.29	0.27	0.02	-0.041	0.39
Exporting Intensity	0.25	0.23	0.25	-0.022	0.095	0.17
Ln(Revenue Productivity)	3.30	3.30	3.30	-0.0028	-0.18	0.72
Ln(Quantity Productivity)	1.50	1.70	1.50	0.20	-0.82	0.46
Number Product Lines	2.9	2.90	2.90	-0.035	0.35	0.35
Profitability	0.11	0.11	0.12	-0.0064	0.023	0.16
Investments/Assets	0.70	0.77	0.69	0.083	-0.16	0.14
Abatement Expenditure/Asset	0.02	0.01	0.02	-0.01	0.03	0.11
Raw Materials/Sales	0.57	0.60	0.57	0.037	0.0006	0.99
Wages/Sales	0.06	0.06	0.07	-0.01	0.03	0.15
Market-to-book	1.10	0.95	1.10	-0.14	0.81	0.35

	Panel B: Firm-product characteristics					
	All	Below	Above	Difference	RD Estimate	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Product Sales)	4.10	3.80	4.10	-0.30	-0.48	0.47
Ln(Unit Cost)	-5.00	-4.70	-5.00	0.33	-0.37	0.52
Ln(Unit Price)	-5.00	-4.70	-5.00	0.36	-0.26	0.59
Margin(%)	-2.30	-1.50	-2.50	1.00	-4.50	0.57
Ln(Unit CO2 Emissions)	-2.50	-2.20	-2.50	0.36	-0.85	0.27
Ln(Value Energy Input)	13.69	13.83	13.66	0.17	-0.65	0.31
$\mathbb{1}_{\text{Coal Use}}$	0.22	0.18	0.23	-0.05	0.08	0.53
Coal's Proportion of Inputs	0.65	0.66	0.65	0.01	0.35	0.09

TABLE 3: CHANGES IN CLUSTER INDUSTRIAL EMISSIONS BY POLLUTANT

This table reports the impact of the 2009 CEPI emissions regulation on industrial emissions. The unit of analysis is at the cluster-year-month level. The dependent variable is the measurement of emissions within a 5 kilometer radius circle around the centroid of the industrial cluster. In column 1, we focus on all pollutants whereas subsequent columns break each out separately: $PM_{2.5}$ (column 2), PM_{10} (column 3) and NO_x (column 4). $CEPI^{[70,100]}$ takes the value of one if the industrial cluster has a CEPI value at or above 70, and zero otherwise. $CEPI^{[60,70)}$ takes the value of one if the industrial cluster has a CEPI value greater than or equal to 60 and below 70, and zero otherwise. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60. All specifications include cluster-address fixed effects and state × year-month fixed effects. The table also reports the *p*-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year of 2008. The standard errors are clustered at the cluster-address level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: The Emissions Database for Global Atmospheric Research (EDGAR).

Dependent variable:	Pollution Measurement (mg per month)			
Pollutant(s):	All	$PM_{2.5}$	PM_{10}	NO_x
	(1)	(2)	(3)	(4)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-7.232**	-3.686*	-7.113	-10.898*
	(3.597)	(2.054)	(5.653)	(6.536)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-7.109**	-3.489*	-7.669	-10.169*
	(3.225)	(1.813)	(4.748)	(5.937)
2008 Dependent Variable Mean (Control)	23.09	16.86	38.95	13.45
Fixed effects:				
Cluster × Pollutant	Yes	Yes	Yes	Yes
State × year-month × Pollutant	Yes	Yes	Yes	Yes
Adjusted-R^2	0.932	0.949	0.946	0.836
Observations	54,648	18,216	18,216	18,216
p-value [$\beta_1 - \beta_2 = 0$]	0.935	0.843	0.840	0.600
ATE	-7.144	-3.545	-7.512	-10.375
t-statistic value	[2.185]	[1.928]	[1.550]	[1.702]

TABLE 4: IMPACT ON ENERGY EFFICIENCY AND INPUTS

This table reports the changes in firm energy use (panel A) and energy inputs (panel B) around the 2009 CEPI emissions regulation. In panel A, the unit of analysis is firm-product-year. The dependent variable in column 1 is the natural logarithm of the quantity of product produced by the firm in the year. In column 2 it is the natural logarithm of the input energy value. In panel B, the unit of analysis is firm-year. The dependent variable in column 1, is an indicator variable for if the product uses coal as an input. In column 2 it is the proportion of electricity purchased for each product. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category as clusters with a CEPI value below 60. All specifications include firm and state × two-digit industry × year fixed effects. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year of 2008. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Data source: CMIE Prowess.

	Panel A: Energy Efficiency	
Dependent variable	Ln(Quantity Produced) (1)	Ln(Value Energy Input) (2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-0.204	-0.244***
	(0.167)	(0.068)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-0.083	-0.156**
	(0.164)	(0.061)
2008 Dependent Variable Mean (Control)	29,784	813
Fixed effects:		
Firm	Yes	Yes
State × Industry × Year	Yes	Yes
Adjusted-R^2	0.543	0.952
Observations	11,878	10,732
p-value [$\beta_1 - \beta_2 = 0$]	0.225	0.028
ATE	-0.106	-0.172
t-statistic value	[0.655]	[2.828]

	Panel B: Energy Inputs	
Dependent variable	$\mathbb{1}_{\text{Coal Use}}$ (1)	Proportion Purchased Electricity (2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-0.289*	0.196***
	(0.150)	(0.059)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-0.301***	0.100**
	(0.092)	(0.036)
Ln(Quantity Produced)	0.033	-0.034
	(0.027)	(0.036)
2008 Dependent Variable Mean (Control)	0.17	0.46
Fixed effects:		
Firm	Yes	Yes
State × Industry × Year	Yes	Yes
Adjusted-R^2	0.185	0.673
Observations	565	901
p-value [$\beta_1 - \beta_2 = 0$]	0.905	0.124
ATE	-0.308	0.151
t-statistic value	[3.350]	[3.159]

TABLE 5: IMPACT ON FIRM PORTFOLIO WEIGHTS

This table reports the changes to firm product portfolios around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. The dependent variable in column 1 is the firm-level weight on the highest emission product in the firm's overall product portfolio, measured in percentage points. For column 2, it is the weight of the product that uses the highest proportion of coal in its energy input mix in the firm's overall product portfolio. $CEPI^{[70,100]}$ takes the value of one if the industrial cluster has a CEPI value at or above 70, and zero otherwise. $CEPI^{[60,70)}$ takes the value of one if the industrial cluster has a CEPI value greater than or equal to 60 and below 70, and zero otherwise. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category comprising clusters with a CEPI value below 60. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. All specifications include firm and State $\times$ two-digit industry $\times$ year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	Product with Highest Emissions Weight$_{2008}$ (1)	Product with Highest Coal Weight$_{2008}$ (2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-0.318**	-0.309**
	(0.118)	(0.123)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-0.184*	-0.139
	(0.101)	(0.114)
2008 Dependent Variable Mean (Control)	0.65	0.78
Fixed effects:		
Firm	Yes	Yes
State $\times$ Industry $\times$ Year	Yes	Yes
Adjusted-R^2	0.758	0.775
Observations	705	705
p-value $[\beta_1 - \beta_2 = 0]$	0.215	0.123
ATE	-0.218	-0.181
t-statistic value	[1.98]	[1.44]

TABLE 6: IMPACT ON ABATEMENT INVESTMENT

This table reports the changes in firm abatement expenditures around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. The dependent variable in column 1 captures the extensive margin of investment with an indicator variable that takes the value one if the firm report environment and pollution control expenses in that year, and zero otherwise. In column 2 captures the intensive margin, defined as the ratio of expenses and total assets, winsorized at 1% tails. $CEPI^{[70,100]}$ takes the value of one if the industrial cluster has a CEPI value at or above 70, and zero otherwise. $CEPI^{[60,70)}$ takes the value of one if the industrial cluster has a CEPI value greater than or equal to 60 and below 70, and zero otherwise. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. All specifications include firm and state $\times$ two-digit industry $\times$ year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	$\mathbb{1}_{\text{Abatement}}$ (1)	Abatement/Assets (2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	0.048	0.039*
	(0.031)	(0.020)
Post $\times$CEPI$^{[70,100]}$ (β_2)	0.077**	0.038**
	(0.029)	(0.016)
2008 Dependent Variable Mean (Control)	0.06	0.01
Fixed effects:		
Firm	Yes	Yes
State $\times$ Industry $\times$ Year	Yes	Yes
Adjusted-R^2	0.638	0.676
Observations	10,752	10,752
p-value $[\beta_1 - \beta_2 = 0]$	0.029	0.933
ATE	0.072	0.038
t-statistic value	[2.419]	[2.385]

TABLE 7: IMPACT ON REVENUE AND QUANTITY PRODUCTIVITY

This table reports the changes in firm productivity around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. The dependent variable in column 1 is the natural logarithm of revenue-based total factor productivity estimated following Levinsohn and Petrin (2003) that controls for firm size. The dependent variable in column 2 is the natural logarithm of quantity-based total factor productivity estimated following De Loecker, Goldberg, Khandelwal, and Pavcnik (2016). $CEPI^{[70,100]}$ takes the value of one if the industrial cluster has a CEPI value at or above 70, and zero otherwise. $CEPI^{[60,70)}$ takes the value of one if the industrial cluster has a CEPI value greater than or equal to 60 and below 70, and zero otherwise. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60. The table also reports the p-value from a joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year (2008). All specifications include firm and state $\times$ two-digit industry $\times$ year fixed effects. Outcomes are winsorized at the 5% and 95% levels. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	Ln(Revenue Productivity) (1)	Ln(Quantity Productivity) (2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	0.100	-0.113
	(0.075)	(0.319)
Post $\times$CEPI$^{[70,100]}$ (β_2)	0.127***	0.155
	(0.039)	(0.280)
2008 Dependent Variable Mean (Control)	2.77	8.04
Fixed effects:		
Firm	Yes	Yes
State $\times$ Industry $\times$ Year	Yes	Yes
Adjusted-R^2	0.805	0.693
Observations	10,752	1,649
p-value [$\beta_1 - \beta_2 = 0$]	0.695	0.231
ATE	0.122	0.094
t-statistic value	[3.238]	[0.315]

TABLE 8: IMPACT ON PRODUCT VARIETY

This table reports the changes to firm product portfolios around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. The dependent variable in column 1 is the natural logarithm of the total quantity produced for each product in a year. In column 2 it is the natural logarithm of the total number of products produced by a firm in a year. In column 3 it is an indicator for whether the firm added a product in a year. And in column 4 it is an indicator for whether the firm dropped a product in that year. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. All specifications include firm and state × two-digit industry × year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	Ln(Product-level Production)	Ln(No. of Products)	$\mathbb{1}_{\text{Add Product}}$	$\mathbb{1}_{\text{Remove Product}}$
	(1)	(2)	(3)	(4)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-0.110	0.013	-0.117***	0.003
	(0.182)	(0.078)	(0.041)	(0.036)
Post $\times$CEPI$^{[70,100]}$ (β_2)	0.030	0.007	-0.057*	0.023
	(0.130)	(0.072)	(0.034)	(0.030)
2008 Dependent Variable Mean (Control)	29,784	2.71	0.27	0.17
Fixed effects:				
Firm	Yes	Yes	Yes	Yes
State × Industry × Year	Yes	Yes	Yes	Yes
Adjusted-R^2	0.506	0.666	0.032	0.005
Observations	15,521	10,752	10,752	10,752
p-value [$\beta_1 - \beta_2 = 0$]	0.429	0.904	0.094	0.314
ATE	0.008	0.008	-0.068	0.019
t-statistic value	[0.063]	[0.118]	[2.138]	[0.621]

TABLE 9: CHANGES IN CLUSTER-LEVEL FIRM ENTRY

This table reports changes in cluster firm entry around the 2009 CEPI emissions regulation. The unit of analysis is cluster-industry-year. Panel A reports changes in firm entry using the universe of business registration from the Ministry of Corporate Affairs while Panel B reports changes in firm entry from CMIE Prowess. Across both panels, the dependent variable in column 1 is an indicator for whether at least one manufacturing firm incorporates in the cluster in a given industry in the year. In column 2 it is one plus the natural logarithm of the number of newly registered manufacturing firms in that year. In column 3 it is the inverse hyperbolic sine of the number of newly registered manufacturing firms in that year. In column 4 it is the raw number of newly-registered manufacturing firms in each cluster in a specific industry in that year. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category as clusters with a CEPI value below 60. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. In both panels, columns 1 through 3 are estimated using ordinary least squares (OLS) while column 4 is estimated using pseudo-Poisson maximum likelihood (PPML). All specifications include cluster, two-digit industry × year, and state × year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: Ministry of Corporate Affairs and CMIE Prowess.

	Panel A: All firms from business registry			
Dependent variable:	$\mathbb{1}_{\text{New Firm}}$	Log(No. of firms)	$asinh$(No. of firms)	No. of firms (Poisson)
	(1)	(2)	(3)	(4)
Post ×CEPI$^{[60,70)}$ (β_1)	-0.005	-0.006	-0.007	-0.154
	(0.011)	(0.010)	(0.013)	(0.129)
Post ×CEPI$^{[70,100]}$ (β_2)	-0.018*	-0.014	-0.018	-0.193*
	(0.010)	(0.009)	(0.012)	(0.115)
2008 Dependent Variable Mean (Control)	0.07	0.19	0.19	0.19
Fixed effects:				
Cluster	Yes	Yes	Yes	Yes
State × Industry × Year	Yes	Yes	Yes	Yes
Adjusted-R^2	0.405	0.534	0.535	
Observations	33,810	33,810	33,810	20,590
p-value [$\beta_1 - \beta_2 = 0$]	0.101	0.284	0.261	0.704
ATE	-0.014	-0.011	-0.014	-0.177
t-statistic value	[1.396]	[1.288]	[1.271]	[1.602]

	Panel B: Large firms in CMIE Prowess			
Dependent variable:	$\mathbb{1}_{\text{New Firm}}$	Log(No. of firms)	$asinh$(No. of firms)	No. of firms (Poisson)
	(1)	(2)	(3)	(4)
Post ×CEPI$^{[60,70)}$ (β_1)	-0.003	0.001	0.001	-0.289
	(0.017)	(0.016)	(0.021)	(0.440)
Post ×CEPI$^{[70,100]}$ (β_2)	-0.041*	-0.035*	-0.045*	-0.795**
	(0.021)	(0.018)	(0.023)	(0.370)
2008 Dependent Variable Mean (Control)	0.01	0.01	0.01	0.01
Fixed effects:				
Cluster	Yes	Yes	Yes	Yes
State × Industry × Year	Yes	Yes	Yes	Yes
Bandwidth	Yes	Yes	Yes	Yes
Adjusted-R^2	0.172	0.212	0.213	
Observations	4,416	4,416	4,416	678
p-value [$\beta_1 - \beta_2 = 0$]	0.018	0.074	0.076	0.103
ATE	-0.024	-0.019	-0.025	-0.655
t-statistic value	[1.351]	[1.433]	[1.439]	[1.672]

INTERNET APPENDIX FOR ONLINE PUBLICATION

Appendix A Additional figures and tables

TABLE IAA1: CLUSTER-LEVEL COVARIATE BALANCE

This table presents mean values for baseline city characteristics, as recorded in Population Census. Column 1 presents the unconditional mean while column 2 (column 3) presents the mean for clusters below (above) the treatment threshold. Column 4 presents the difference in means between cities below the treatment threshold and cities above the treatment threshold. Additionally, column 5 shows the regression discontinuity estimate, following the main estimating equation, of the effect of being above the treatment threshold on the baseline variable and column 6 is the *p*-value for this estimate, using heteroskedasticity-robust standard errors. Data: Population Census and Harari (2020).

	All	Below	Above	Difference	Estimate	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)
City roads, km, 1981	337.206	268.936	391.822	-122.886	-297.226	0.486
Log(population), 2001	13.330	13.015	13.572	-0.556	0.403	0.693
Population density (000 per Sq. km), 2001	8.632	9.387	7.993	1.394	-1.081	0.802
Average rent (per Sq. m.), 2008	953.696	907.779	990.430	-82.651	356.072	0.422
Nearest waterway (km), 2008	13.901	17.660	10.948	6.713	-16.694	0.182
Agricultural yields (tons/ha), 2008	1.440	1.485	1.406	0.079	0.111	0.123
Area footprint (Sq. km.), 2008	187.831	114.277	250.069	-135.792	184.250	0.485

TABLE IAA2: IMPACTS ON FINE PARTICULATE MATTER ($PM_{2.5}$)

This table reports the impact of CEPI reform on fine particulate matter using data from Van Donkelaar et al. (2015). The unit of analysis is at the cluster-year-month level. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category as clusters with a CEPI value below 60. All specifications include cluster-address fixed effects and state × year-month fixed effects. The table also reports the *p*-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year of 2008. The standard errors are clustered at the cluster-address level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: Van Donkelaar et al. (2015).

Dependent variable:	Fine $PM_{2.5}$ (μ g/m^3)	
Radii of circle:	5 kilometers (1)	500 meters (2)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-2.311***	-1.893**
	(0.775)	(0.743)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-1.018	-0.560
	(0.756)	(0.673)
2008 Dependent Variable Mean (Control)	84.0	84.0
Fixed effects:		
Cluster	Yes	Yes
State × year-month	Yes	Yes
Adjusted-R^2	0.959	0.954
Observations	17,952	18,216
p-value [$\beta_1 - \beta_2 = 0$]	0.005	0.069
ATE	-1.962	-1.516
t-statistic value	[2.596]	[2.152]

TABLE IAA3: CHANGES IN ENERGY EMISSIONS BY POLLUTANT

This table reports the impact of CEPI reform on the power generation sector using data from EDGAR. The unit of analysis is at the cluster-year-month level. The dependent variable is emissions from the database within a 5 kilometer radius circle around the centroid of the industrial cluster. In column 1, we focus on all pollutants whereas we break them out separately in subsequent columns. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009, with the omitted category as clusters with a CEPI value below 60. All specifications include cluster-address fixed effects and state × year-month fixed effects. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year of 2008. The standard errors are clustered at the cluster-address level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: The Emissions Database for Global Atmospheric Research (EDGAR).

Dependent variable:	Pollution Measurement (mg per month)			
Pollutant(s):	All	$PM_{2.5}$	PM_{10}	NO_x
	(1)	(2)	(3)	(4)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-0.229	-0.112	-0.170	-0.405
	(0.715)	(0.274)	(0.542)	(1.415)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-0.169	-0.181	-0.184	-0.143
	(0.755)	(0.304)	(0.549)	(1.520)
2008 Dependent Variable Mean (Control)	8.18	1.78	3.34	19.43
Fixed effects:				
Cluster × Pollutant	Yes	Yes	Yes	Yes
State × year-month × Pollutant	Yes	Yes	Yes	Yes
Adjusted-R^2	0.756	0.795	0.823	0.734
Observations	29,808	9,936	9,936	9,936
p-value $[\beta_1 - \beta_2 = 0]$	0.915	0.765	0.975	0.792
ATE	-0.186	-0.161	-0.180	-0.217
t-statistic value	[0.266]	[0.579]	[0.357]	[0.153]

TABLE IAA4: IMPACT ON PRODUCT EMISSIONS

This table reports the changes in product CO_2 emissions around the 2009 CEPI emissions regulation. The unit of analysis is firm-product-year. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70 $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. The sample is the 88 industrial clusters targeted by the CPCB in 2009, with the omitted category as clusters with a CEPI value below 60. All specifications include firm and state × two-digit industry × year fixed effects. The table reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	Ln(Product CO_2 Emissions) (1)	Ln(Per Unit CO_2 Emissions) (2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-1.083***	-0.885***
	(0.283)	(0.306)
Post $\times$CEPI$^{[70,100]}$ (β_1)	-0.944**	-0.687**
	(0.346)	(0.270)
Ln(Production Quantity)	0.801**	
	(0.334)	
2008 Dependent Variable Mean (Control)	162,230 Tonnes	2.79
Fixed effects:		
Firm	Yes	Yes
State × Industry × Year	Yes	Yes
Adjusted-R^2	0.836	0.656
Observations	901	901
p-value [$\beta_1 - \beta_2 = 0$]	0.691	0.579
ATE	-1.414	-0.755
t-statistic value	[5.460]	[3.709]

TABLE IAA5: CHANGES IN FIRM-LEVEL FACTORS OF PRODUCTION

This table reports the changes in factors of production around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70 $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. The sample is the 88 industrial clusters targeted by the CPCB in 2009, with the omitted category as clusters with a CEPI value below 60. All specifications include firm and state × two-digit industry × year fixed effects. The table reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	Wage Bill (1)	Raw Material Exp. (2)	Investment (3)
Post $\times$CEPI$^{[60,70)}$ (β_1)	-0.005	-0.030	0.019
	(0.005)	(0.029)	(0.031)
Post $\times$CEPI$^{[70,100]}$ (β_2)	-0.002	-0.035	0.020
	(0.003)	(0.027)	(0.024)
2008 Dependent Variable Mean (Control)	0.05	0.54	0.89
Fixed effects:			
Firm	Yes	Yes	Yes
State × industry × year	Yes	Yes	Yes
Adjusted-R^2	0.806	0.793	0.826
Observations	10,752	10,752	9,643
p-value [$\beta_1 - \beta_2 = 0$]	0.326	0.222	0.429

TABLE IAA6: SHIFTING PRODUCTION: IMPACT ON MERGERS AND ACQUISITIONS

This table reports changes in mergers and acquisitions around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70. The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category as clusters with a CEPI value below 60. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. All specifications include firm and state × two-digit industry × year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess.

Dependent variable:	$\mathbb{1}_{\text{Target}}$	$\mathbb{1}_{\text{Acquired}}$
	(1)	(2)
Post $\times$CEPI$^{[60,70)}$ (β_1)	0.018	-0.000
	(0.012)	(0.008)
Post $\times$CEPI$^{[70,100]}$ (β_2)	0.009	0.005
	(0.009)	(0.007)
2008 Dependent Variable Mean (Control)	0.00	0.00
Fixed effects:		
Firm	Yes	Yes
State × Industry × Year	Yes	Yes
Adjusted-R^2	-0.060	-0.118
Observations	10,752	10,752
p-value [$\beta_1 - \beta_2 = 0$]	0.345	0.430
ATE	0.007	0.003
t-statistic value	[0.740]	[0.534]

TABLE IAA7: SHIFTING PRODUCTION: PLANT ANNOUNCEMENTS

This table reports changes in the probabilities of plant announcements around the 2009 CEPI emissions regulation. The unit of analysis is firm-year. $CEPI^{[70,100]}$ is an indicator variable for if the industrial cluster has a CEPI value at or above 70. $CEPI^{[60,70)}$ is an indicator variable for if the industrial cluster has a CEPI value greater than or equal to 60 and below 70 The sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category as clusters with a CEPI value below 60. The table also reports the p-value from the joint test of the coefficients as well as the mean of the dependent variable in levels in the pre-reform year 2008. All specifications include firm and state × two-digit industry × year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data: CMIE Prowess and CapEx.

Dependent variable:	$\mathbb{1}_{\text{New Plant}}$	$\mathbb{1}_{\text{Abandon Plant}}$
	(1)	(2)
Post $\times$CEPI$^{[60,70)}$ (β_2)	0.008	0.003
	(0.013)	(0.011)
Post $\times$CEPI$^{[70,100]}$ (β_1)	-0.010	-0.004
	(0.011)	(0.010)
2008 Dependent Variable Mean (Control)	0.00	0.00
Fixed effects:		
Firm	Yes	Yes
State × industry × year	Yes	Yes
Adjusted-R^2	0.350	0.284
Observations	10,752	10,752

TABLE IAA8: VARIABLE DEFINITIONS

This table presents definitions to variables used in the paper. EDGAR refers to the 'Emissions Database for Global Atmospheric Research' data, available at https://edgar.jrc.ec.europa.eu/dataset_htap_v3. PROWESS refers to the 'Performance and Ownership with Excellence' available at https://prowessdx.cmie.com/. CBCB refers to the 'Central Pollution Control Board', with supporting data available at https://cpcb.nic.in/. Note, all normalized variables at the firm-level are winsorized at the 1% tails, except for leverage, productivity, and profitability which are winsorized at the 5% tails. All product-level variables are winsorized at the 1% tails except for emissions, which is winsorized at the 2.5% tails.

Variable	Description	Data Source
Panel A: Pollution		
All Pollution	Summation of pollution measures for a given area	EDGAR
$PM_{2.5}$	Particulate Matter with a diameter of 2.5 micrometers or less, measured in Mg/month	EDGAR
PM_{10}	Particulate Matter with a diameter of 10 micrometers or less, measured in Mg/month	EDGAR
NO_x	Nitrous oxides, measured in Mg/month	EDGAR
$PM_{2.5}$	Fine Particulate Matter with a diameter of 2.5 micrometers or less, measured in Mg/month	Van Donkelaar et al. (2015)
Panel B: Firm Characteristics		
Assets (million INR)	Total assets of firm operations in INR	PROWESS
Sales (million INR)	Total revenue from goods and services sold in missions of INR	PROWESS
Leverage	The sum of short- and long-term debt obligations scaled by contemporaneously reported Total Assets.	PROWESS
Exporting intensity	Firm earnings from exports of goods plus services scaled by contemporaneous total sales	PROWESS
Ln(Productivity)	The natural log of firm productivity, calculated following Levinsohn and Petrin (2003) and controls for firm size	PROWESS
Profitability	Earnings Before Interest, Taxes, Depreciation, and Amortization as a ratio of the prior year sales	PROWESS
Investments/Assets	Gross fixed assets as a ratio of the prior year total assets	PROWESS
Raw Materials/Sales	Raw material inputs scaled by contemporaneously reported net sales	PROWESS
Wages/Sales	Total wages scaled by contemporaneously reported net sales	PROWESS
Market-to-book	The total number of listed shares multiplied by the share price at the end of the fiscal year, scaled by contemporaneously reported total assets. Reported for listed firms	PROWESS
Number of Products	Number of unique products for a given firm in a given year	PROWESS
$\mathbb{1}_{\text{File Energy Inputs}}$	Indicator for whether the firm reports inputs	PROWESS
$\mathbb{1}_{\text{New Plant}}$	Indicator for whether the firm announced a new plant in the year	CapEx
$\mathbb{1}_{\text{Abandon Plant}}$	Indicator for whether the firm announced that it abandoned the plant in the year	CapEx
Panel C: Product Characteristics		
Ln(Product Sales)	The natural logarithm of the per-product sales	PROWESS
Ln(Product COGS)	The natural logarithm of the per-product cost of goods sold (COGS)	PROWESS
Unit Price	The natural logarithm of the per-unit price, where unit is unique within but not across firm	PROWESS
Margin	Is measured as (unit price - unit cost)/unit price	PROWESS
Ln(Per Unit CO_2 Emissions)	Author-calculated CO_2 emissions per reported unit of production	PROWESS
TFPQ	Natural logarithm of quantity-based total factor productivity estimated following De Loecker, Goldberg, Khandelwal, and Pavcnik (2016)	PROWESS
TFPR	Natural logarithm of total factor productivity estimated following Levinsohn and Petrin (2003) that controls for firm size	PROWESS
Panel D: Cluster Characteristics		
$CEPI^{[70,100]}$	CEPI equal or greater than 70, and less or equal to 100	PROWESS and CPCB
$CEPI^{[60,70)}$	CEPI equal or greater than 60, and less than 70	PROWESS and CPCB

Appendix B Additional background on the regulation

By 2009, India was an acknowledged industrial powerhouse. However, significant environmental degradation accompanied impressive growth. This pollution concentrated in industrial clusters, which shared infrastructure, administrative structures, and proximity to major population centers made desirable locations for manufacturing and industrial production. District and state authorities have regulated industrial cluster emissions since environmental regulation began in the 1980s. However, enforcement has been uneven, emissions measurements and regulatory thresholds were not standardized, and firms were often allowed to self-monitor, rather than be subjected to independent auditors. Moreover, the government lacked even basic information on industrial environmental impact for most locations.

Against this background, the Central Pollution Control Board (CPCB) of the Ministry of Environment, Forest and Climate Change conducted a comprehensive environmental assessment of industrial clusters. The aims were to enhance, standardize and centralize pollution monitoring. The first step was to design a measure of pollution: The Comprehensive Environmental Pollution Index (CEPI hereafter). Figure 1 describes its construction. The CEPI combines proxies for (1) the amount and toxicity of pollutants, (2) the potential impact of that pollution on humans and ecosystems, and (3) an assessment of the quality of actions already taken by cluster firms to capture or adequately dispose of emissions. We include a complete discussion of each component and its construction as of the 2009 regulation in Central Pollution Control Board of India (2009).

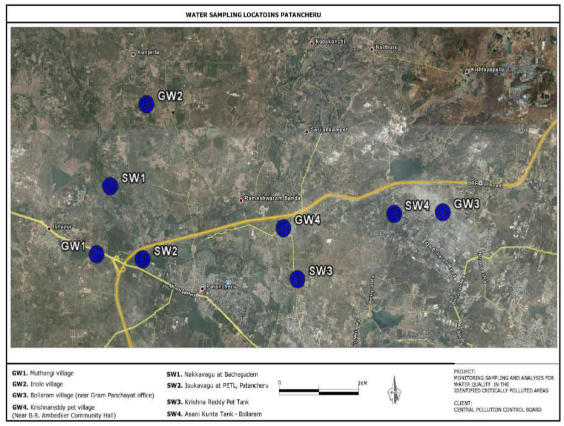
Of the over two thousand industrial clusters in 2009, the CPCB reported CEPI values for the 88 worst-polluting clusters. The CPCB classified those clusters with a CEPI above 60 as Severely Polluted Areas. These became subject to central monitoring at the national level rather than the relatively weak local control. Moreover, the CPCB classified industrial clusters with a CEPI of at least 70 as Critically Polluted Areas, which were additionally mandated to submit a remedial action plan for approval detailing the actions and timelines at the cluster and firm levels.

If a firm within a Critically Polluted Area failed to comply with the directives of the action plan, then they would lose their Environmental Clearance and Consent to Operate permits that allow firms to function within the formal economy. Moreover, Consent to Establish permits could not be issued to new operations if they do not fully comply with the cluster regulations and action plans.

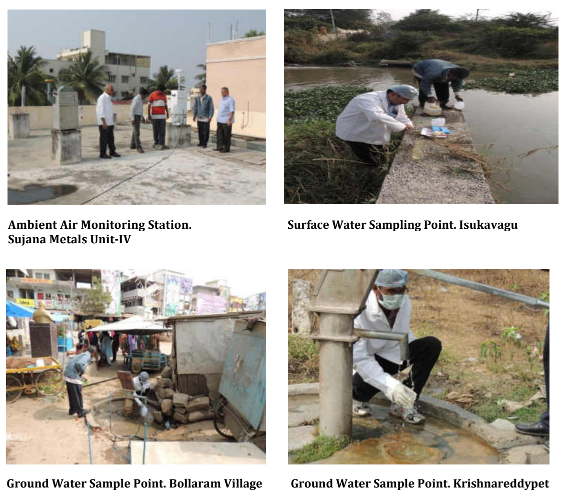
Consider the example of the action plan for the CPA Patancheru-Bollaram Cluster in Andhra Pradesh (Pollution Control Board of Andhra Pradesh, 2010), which contains the operations of 106 establishments and whose CEPI, at 70.07, was just over the cutoff between being classified as a Severely or Critically Polluted Area. The Action Plan specifies a lengthy list of specific actions and deadlines agreed to by the firms of the cluster. For example, the cluster agreed to build a common effluent treatment plant, a treatment storage and disposal facility, and alternative drainage systems so no firm would outlet emissions into significant water bodies. In addition, firms operating in specific high-polluting industries would no longer be allowed to expand, and new firms in these industries could not be established in the cluster. The plan also listed self-policing mechanisms the cluster agreed to in order to prevent illegal dumping. In addition, the cluster agreed to pay compensation to local farmers affected by pollution and to supply drinking water to affected villages. The action plan then details a long list of agreed investments and recorded progress for each of the 106 individual establishments in the cluster.

The CPCB also installed continuous remote pollution sensors for air, water, and land pollution, video cameras (including night cameras) on the premises of factories at the point of their process emissions, and instigated tri-annual CPCB audits (January-February, May-June, and September-October) and quarterly audits from district and state level monitoring committees. These reports were released to the public annually via the CPCB website. Each report specifies the longitude and latitude of the air and water sampling locations, the laboratories used to carry out sampling and analyze the samples, and the date of the sampling. Then for each of air, groundwater and surface water samples the report specifies a particular pollutant (e.g., lead) or parameter (e.g., color (Hazen units)), the measurements of that pollutant and the test method used. Finally, the report includes photographs of the measurements. To give readers an idea, Figure IAB1 provides an example of the monitoring documentation for the Patancheru-Bollaram Cluster in Andhra Pradesh. Panel (a) reports the locations of water sampling locations superimposed over a map of the cluster. Panel (b) reproduces a few of the sampling documentation photographs of air, surface and groundwater sampling in the Patancheru-Bollaram Cluster.

Finally, we complement the analysis presented in Figure 4 testing for manipulation of the original, 2009 CEPI with complementary McCrary (2008) density tests for the re-calculated CEPI values in 2011 and 2013. Note that in 2011 and 2013 only the CEPI values for those firms that had been ranked CPA in 2009 were published, so we are testing for manipulation in these updated values among the 2009 CPA sub-population. In summary, in India, as elsewhere, holding firms accountable for their environmental impact was difficult with unreliable data and weak enforcement. Accordingly, the CPCB centralized control and broadened its scrutiny of emissions. It automated monitoring to the extent possible, increased auditor independence, and instigated overlapping monitoring regimes. Moreover, the CPCB increased engagement specific cutoffs defined escalating severity of regulatory scrutiny.



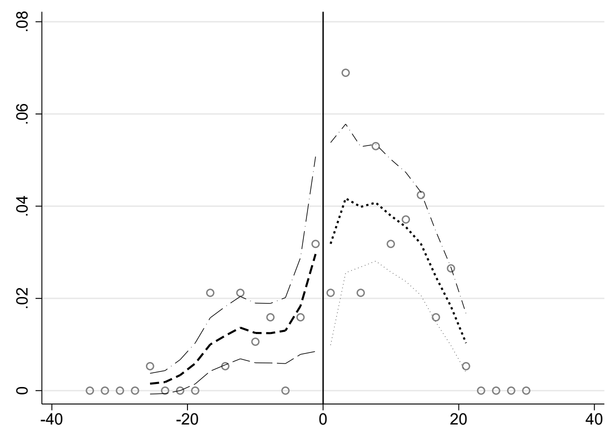
(a) Water sampling locations



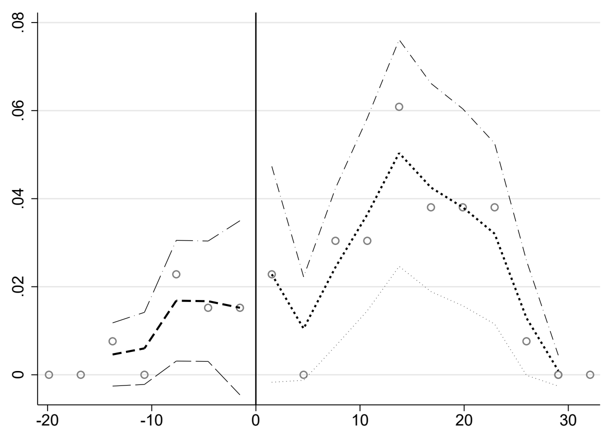
(b) Sampling documentation photos

FIGURE IAB1: PANTANCHERU-BOLLARAM CLUSTER POLLUTION MONITORING

This figure illustrates monitoring around the Pantancheru-Bollaram cluster. Panel (a) illustrates water sampling locations with the blue dots signifying water collection sites. Panel (b) documents sampling at these sites. Source: CPCB annual reports, "Sampling and Analysis of Ambient Air Quality and Water Quality in Industrial/Cluster Areas."



(a) 2011 CEPI



(b) 2013 CEPI

FIGURE IAB2: TEST FOR MANIPULATION OF THE CEPI IN 2011 AND 2013

This figure studies potential manipulation of CEPI. Panel (a) reports the fitted distribution of the 2011 CEPI update around the cutoff at 70 (normalized to zero) for clusters with a 2009 CEPI of at least 70 (Critically Polluted Areas). Panel (b) reports the fitted distribution of the 2013 CEPI update around the (updated) cutoff at 60 (normalized to zero) for the same sample. Source: CPCB.

B.1 Remedial Action Plans

In January 2010, 43 industrial clusters across India with CEPI values above 70 were required to formulate an action plan. These plans include targeted measures to tackle specific sources of pollution, such as stricter effluent and emission norms, upgrading pollution control facilities, and adopting cleaner technologies. The content of the action plans varied significantly across different states and clusters, depending on local environmental priorities and industrial activities. For example, the Howrah industrial cluster in West Bengal concentrated on enhancing air quality monitoring and controlling emissions from small-scale industries.

The action plans were implemented by the industries with oversight from state pollution control boards and other regulators. Regular monitoring and assessment were conducted to evaluate the effectiveness of these measures in reducing pollution. The action plan for Howrah, excerpted in Figure IAB3, included upgrading treatment plant technology, promoting the adoption of cleaner production techniques, and improving solid waste management practices to mitigate the impact of hazardous waste on the environment. The Howrah action plan includes the installation of a Common Effluent Treatment Plant (CETP), an Ambient Air Quality Monitoring system (AAAQM), and the development of a proper drainage facility. The plan includes deadlines and specifies about who bears implementation responsibility. In these examples, it is shared between industry associations, individual industries, the West Bengal Pollution Control Board (WBPCB), and the Ministry of Environment and Forests (MOEF). Finally, the action plan includes a projected cost. For example, installation of the treatment plant is projected at approximately 1.5 Crore INR (around 309,917 USD). The cost is expected to be shared between the industry association and the WBPCB. This example is from the Long Term Action points (to be completed in a year or later from agreement) in the category of water emissions. More generally, the action plans typically divide actions into short-term (less than one year) and long-term and between air, water, and land category emissions.

Sl. No.	Action Points (including source & mitigation measures)	Responsible Stake Holders	Time Limit	Cost	Remarks
1	Installation of CETP	Industry Association & Industry, WBPCB, MOEF as per CETP cost sharing principle of MOEF coordinated by SPCB	By June 2012	1.5 Crore	Necessary funding may be granted through WBPCB
2	Installation of AAAQM	Industry Association & Industry	By June 2012	02 Crore	Necessary funding may be granted through WBPCB
3	Development of proper drainage facility	Industry Association & Industry	By June 2012	02 Crore	Necessary funding may be granted through WBPCB. The possibility of accessing Infrastructural Funding Assistance from GOI will be explored.

FIGURE IAB3: INDUSTRY-LEVEL ABATEMENT EVIDENCE FROM ACTION PLANS

This figure reports anecdotal evidence collected from the action plan of the Howrah industrial cluster in West Bengal on specific abatement actions to be taken in the long-term (deadline more than one year) for industrial water emissions. Source: CPCB.

Action plans also included actions for specific firms. Figure IAB4 is an example from the action plan for the action plan for Haldia in West Bengal. Here we observe specific actions to reduce air, water and land-category impact, including the technology to be adopted.

Name	Technology adopted during last one year			Time frame	Remarks
	Air	Water	Land		
5. Tata Chemicals Ltd.	1. Dry Fog system and water sprinkling System. (Coal Handling plant, coke Handling plant, Material Handling System, Wagon Trippler) 2. Fully covered Wagon Tippler and conveyor belts . (Coal unloading station). 3. Green Belt Development. Within factory premises. 4. Power plant with 16 nos of WHRBs. Along with the process.	1. Boiler blow down water is mixed with quenching pond water and is used for Coke quenching purpose in 2 rows 2. Cooling Tower discharge water is mixed with quenching pond water and is used for Coke quenching purpose in other 2 rows 3.Quenching	1.Coke Swamp breeze is the only solid waste (non – hazardous in nature) generated from the process. The average generation of swamp breeze is approx 1000 tons per month which is being sold to third party completely 2. Total 15000 (approx) numbers of trees planted till date, nearly 2000 saplings have been planted	Already impleme nted	1.5 Crs 20 Crs 40 lakhs / year since last two months 850 Crs

FIGURE IAB4: FIRM LEVEL ABATEMENT EVIDENCE FROM ACTION PLANS

This figure reports anecdotal evidence collected from the action plan of the Haldia industrial cluster in West Bengal on specific abatement actions to be taken by Tata Chemicals Limited for the fiscal year 2011 Source: CPCB.

We also observe evidence from the annual reports of listed firms of the types of actions treated firms undertook to reduce their emissions. Annual reports are mandated by the Companies Act, 1956 and include details about firm financial performance, corporate governance, and strategic initiatives. In particular, we examine the sections on corporate social responsibility activities, management discussion and analysis (MD&A), and disclosures on risks and opportunities. In Figure IAB5 we include an example excerpt for JK Lakshmi Cement Limited in the Ankleshwar industrial cluster in Gujarat for fiscal year 2012 (calendar year 2011), the year following the implementation of the action plan in Ankleshwar. We see that the firm specifically mentions that they reduced their energy inputs overall and that they switched to greener energy sources. This is anecdotal evidence consistent with the robust finding in Table 4 that the average treated firm took these exact actions.

> During the year, the Company further improved its operating efficiencies. There was reduction in consumption of both power and fuel per unit of production. In addition, the Company improved usage of alternate fuel of bio-mass from 2% to 6%. These improvements have enabled the Company to also reduce the carbon footprint.

FIGURE IAB5: FIRM LEVEL EVIDENCE FROM AUDITED ANNUAL REPORT

This figure reports anecdotal evidence collected from firm annual reports. It illustrates specific abatement actions taken JK Lakshmi Cement Limited, located in the Ankleshwar industrial cluster in Gujarat, for the fiscal year 2012.

If the cluster's CEPI values failed to improve, then the industries that did not implement action were barred from expanding, either existing businesses or new entrants. We observe emissions significantly decrease for treated relative to control firms (see Section 4), which is consistent with credible enforcement, on average. We also observe media reports of both successful and unsuccessful enforcement. For example, Figure IAB6 blames the CEPI regulation for missed production targets at Coal India Limited, an important state-owned enterprise and the largest government-owned-coal-producer in the world. Specifically, Coal India was not allowed to expand production in clusters with a 2009 CEPI of at least 70.

Steam Coal

Coal India production unchanged in FY 2010-11

Sapna Dogra, New Delhi

304 words
30 May 2011
Platts International Coal Report
CWI
ISSN: 0260–4299, Issue 1024
English
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Indian state-run Coal India Limited (CIL) reported May 25 that production had remained steady at 431.32 million mt for the fiscal year ended March 31, 2011, compared with 431.26 million mt in the previous year, CIL said in a statement while announcing its FY 2010-11 consolidated results.

CIL blamed the low production on the ministry of environment and forests, which introduced the CEPI (Comprehensive Environment Pollution Index) to categorise the environmental quality at given locations and conducted a nationwide assessment of industrial clusters.

"In January 2010, the environment ministry had imposed a temporary moratorium until August 31, 2010, on development projects in 43 clusters labelled critically polluted. In October, the ministry extended the moratorium on 38 clusters out of 43 until March 31, 2011," CIL said.

FIGURE IAB6: EXAMPLE ENFORCEMENT EVIDENCE FROM MEDIA

This figure reports anecdotal evidence collected from media reports of compliance with the action plans for industrial clusters with CEPI of 70 or greater. The article discusses the adverse impact of the regulation on coal production of Coal India Limited. Source: Factiva, Platts International Coal Report.

If instead the CEPI values improved and pollution levels decreased significantly, then the clusters would continue to be subject to regular pollution audits and continuous monitoring stations but would otherwise not be prevented from expanding. From Figure 4a, we can see that compliance with these action plans varied, with some clusters that had a CEPI of 70 or over improving their follow-on CEPI in 2011 and 2013 significantly and others only marginally. We have also gathered regulatory documents assessing compliance with action plans at the cluster level. Figure IAB7 is from a follow-up assessment of the Howrah action plan in September 2014 of the items excerpted in Figure IAB3. We can see that progress is recorded in all three areas, but only one (drainage) was completed by September 2014, despite the original plan calling for compliance by June 2012. In general, we observe that regulator capacity and strong industry groups played a key role in achieving the action plan directives. States like Gujarat and Maharashtra, with well-established industrial bases and stronger regulatory frameworks, saw more rigorous enforcement and regular monitoring. However, in states with less regulatory capacity, such as Uttar Pradesh or West Bengal, enforcement was less consistent, leading to varied levels of compliance and effectiveness.

Long Term Action Points

Sl no.	Action points	Stake holder	Status as on September 2014	Compliance status	Remarks
1	Installation of CETP	Industry Association Industry, WBPCB, MOEF as per CETP cost sharing principle of MOEF, coordinated by SPCB	• Land is identified for CETP installation. Resolution of the formalities in this regard is to be taken up. • Industry Association already taken action to change existing open drainage to a closed type effluent drainage line. • WBPCB already advised Industry Association to develop a system for collection and transportation of effluent from individual industries to the proposed CETP site. • At present process water from all industries of Jalan Complex is routed to Sarswati River which finally meets with River Ganga after treatment by the industries.	Action initiated for compliance	Individual industries are mostly complying with effluent discharge norms
2	Installation of AAAQM	Industry association and Industry	• Installation of AAAQM Station to be done with joint funding of WBPCB and CPCB as discussed during S8th Chairmen and Member Secretaries Conference held at Bangaluru.	Action initiated for compliance	
3	Development of proper drainage facility	Industry association and Industry	• Main drainage system- S.325 Km concreted	Complied	Implemented

FIGURE IAB7: ABATEMENT EVIDENCE FROM ACTION PLAN ASSESSMENT

This figure reports anecdotal evidence collected from regulatory assessments of compliance with the action plans for industrial clusters with CEPI of 70 or greater. It illustrates follow up on long-term (deadline more than one year) action points to reduce industrial water emissions in the Howrah industrial cluster in West Bengal. Source: CPCB.

Appendix C Determinants of Compliance

In this section, we explore heterogeneity in CEPI improvement using hand-collected CEPI reassessments in 2011 and 2013 for $CEPI^{[70,100]}$ clusters (according to the 2009 ranking). We first confirm a large average CEPI improvement, consistent with cluster- and product-level emissions reduction. Next, we characterize what regulator and cluster characteristics predict improvement. In agreement with the literature on regulation enforcement, we find that regulator reputation and lower corruption is key. This underscores the sharp test from our main treatment, which was to switch a relatively weak, local emissions regulator with a relatively strong, state-level one.

The top panel of Figure 2 reproduces the original 2009 CEPI distribution. The vertical line represents the cutoff at 70. The bottom panel reports the distributions of the recalculated CEPI values for the 2009 $CEPI^{[70,100]}$ clusters in 2011 and 2013. The distributions shifted to the left in both follow-up assessments, with significant improvement continuing between 2011 and 2013. We also observe that while the average cluster improved, several clusters continued to have CEPI values above the cutoffs in 2013, indicating the difficulties of mandating pollution below a certain threshold.[35]

Next, we investigate what city- and state-level covariates predict the degree of change in the city's CEPI by 2013 versus 2009 for clusters with a 2009 CEPI of at least 70 (ΔCEPI2013 $-$ 2009). Figure IAC8 presents scatter plots illustrating the relationship between each covariate (x-axis) and the change in CEPI score between 2013 and 2009 ($\Delta CEPI_{2013-2009}$) on the y-axis. These relationships have been residualized to account for the influence of other covariates in the model, ensuring that the plotted relationships reflect the partial effect of each focus covariate. We report the slope of the best-fit line above each sub-figure. A negative $\Delta CEPI2013-2009$ indicates improvement; zero indicates no change; a positive value indicates worsening environmental impact.

The top row of Figure IAC8 looks at regulator-level determinants of $\Delta CEPI2013-2009$. In panel (a) of Figure IAC8, we consider the Environmental Enforcement Index from Kattumuri and Lovo (2018), measuring historical state regulator effectiveness in implementing and enforcing environmental regulations, and judicial and media focus on environmental issues.[36] The direction of the correlation between the enforcement index and the change in CEPI is ex-ante ambiguous. More effective regulators might be associated with larger decreases in CEPI scores, reflecting more zealous enforcement of the 2009 reform. On the other hand, it could be that more effectively regulated areas are already relatively lower emitters and so improve by less. Panel (a) of Figure IAC8 reports a large and highly significantly negative association between the Environmental Enforcement Index and the change in the CEPI score between 2013 and 2009, i.e., a higher index value, associated with a more competent state environmental regulator, is associated with a more considerable improvement in emissions, as proxied by the CEPI.

Next, we examine evidence of cost-sharing between regulators and firms from the 2009 CEPI action plans, proxied by an indicator that takes the value of one if the action plan explicitly calls for cost sharing to implement required investments.[37] We predict that cities where regulators indicate cost-sharing in action plans will experience more substantial CEPI score reductions. Panel (b) of Figure IAC8 confirms that the correlation is indeed negative, large, and highly significant.

We also consider the correlation with survey-based 2008 state-level corruption scores from Transparency International, which asks a representative sample about their direct experiences with corruption. We see in panel (c) that the more corrupt the state, the less improvement in the CEPI score, even after controlling for the effect of the Environmental Enforcement Index, which incorporates a media-based corruption measure. Thus, we see that both aspects of corruption—its perception and its measurement—are important predictors of success.

The second row of Figure IAC8 reports the residualized relationship between CEPI improvement and cluster characteristics. In Panel (d) we examine cluster composition by firm size, a summary measure for many financial and information frictions.[38] The figure reports that the proportion of small firms in a city correlates significantly with improved (more negative) CEPI.

Next, clusters with more industry concentration may be better able to coordinate to reduce emissions. Panel (e) of Figure IAC8 reports that cities with more concentrated industries—proxied by industry-share weighted Herfindahl-Hirschman index (HHI)—improve significantly more, controlling for other factors like corruption.

Finally, we examine whether cities with prior Supreme Court-administered action plans (1996–2003) to reduce ve-

[35]We compiled a database of media assessments of the reform. It highlights examples from the tails of what we systematically observe here: clusters that greatly improved and others where pollution worsened.

[36]The 2006 index includes: (1) civic participation, proxied by environmental NGOs per capita; (2) judicial focus, measured as environmental judgments per capita; (3) state corruption as the number of corruption-related articles in major newspapers; (4) public awareness as the number of environment-related articles per capita; and (5) regulator monitoring capacity, proxied by the number of water monitoring stations per capita.

[37]See Appendix B for an example excerpted from the 2009 action plans, along with rich information on action plan format and enforcement.

[38]We define "small" firms using the regulatory standards in India: paid-up capital not exceeding INR 4 Crores and turnover not exceeding INR 40 Crores (Companies Act, 2013).

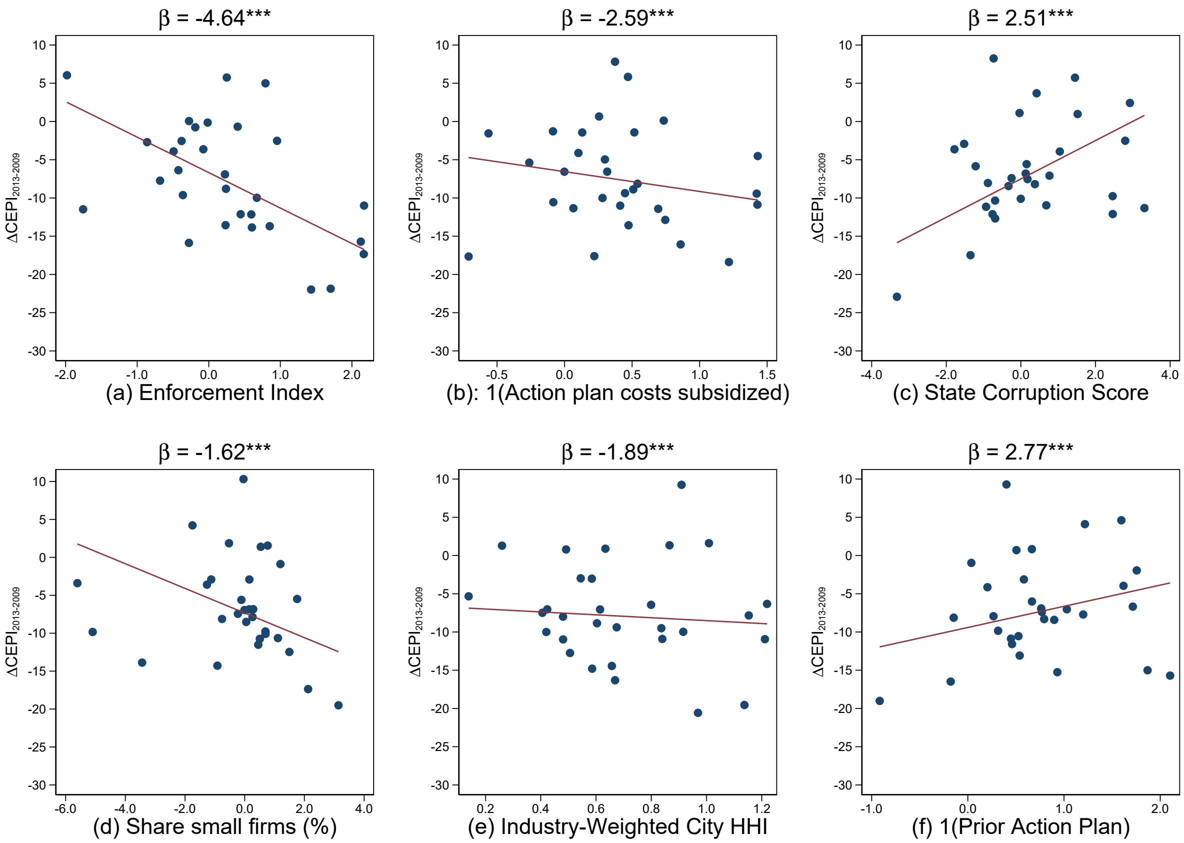

FIGURE IAC8: PRE-DETERMINED PREDICTORS OF IMPROVEMENT BY 2013

This figure investigates the determinants of CEPI improvement for clusters with a CEPI in 2009 of at least 70. Specifically, each panel presents the correlation between the change in the CEPI in 2013 versus 2009 (y-axis) and a pre-determined predictor of CEPI improvement, along with the line of best fit (red). The estimated slope (β) have been residualized to account for the influence of other covariates in the model, so that the plotted relationships reflect the partial effect of each focus covariate. We report the slope of the best-fit line above each sub-figure. The independent variable in panel (a) is the 2006 Environmental Enforcement Index of Kattumuri and Lovo (2018); in panel (b) it is an indicator for explicit regulator subsidies for technology adoption mandated in the cluster's 2010 CEPI action plan; in panel (c) it is the 2006 state corruption score from Transparency International; in panel (d) it is the share of small firms in the city in 2008; in panel (e) it is the weighted average across 2008 industry HHI, where weights are the proportion of sales the industry accounts for; and in panel (f) it is an indicator for a city having been the subject of a prior environmental action plan to reduce vehicular emissions, from Greenstone and Hanna (2014).

hicular emissions (Greenstone and Hanna, 2014) exhibit differential CEPI improvement. We define $1(\text{Prior Action Plan})$ as one if the city was subject to such a plan. The expected correlation is ambiguous: prior experience may enhance implementation or facilitate subversion. Panel (f) reports that cities that experienced a prior emissions regulation implemented through action plans had significantly less CEPI improvement by 2013 than those that had not.

The patterns depicted in Figure IAC8 are correlations. Yet they organize and complement our narrative and statistical evidence. The analysis suggests that the 2009 CEPI regulation's effectiveness is a function of regulator quality, regulation design, and cluster-specific characteristics.

Appendix D Measuring cluster-level pollution

The appendix provides a comprehensive overview of the methodology employed to compile the pollution data panel for each industrial site. We first discuss the Emission Database for Global Atmospheric Research (EDGAR) data, followed dataset by Van Donkelaar et al. (2021) (henceforth, Van Donkellaar). Finally, we detail the steps undertaken to construct the data panel.

D.1 Emission Database or Global Atmospheric Research (EDGAR)

Our primary pollution data comes from the Emission Database or Global Atmospheric Research (EDGAR), with particular emphasis on the Hemispheric Transport of Air Pollution ($HTAP_{v3}$) mosaic. This mosaic is designed to enhance the temporal range, sectoral breakdown, and geographical coverage of existing official data.[39] We use pollution data for nitrous oxide (NO_x), particles less than 2.5 μm in diameter ($PM_{2.5}$), and particles less than 10 μm in diameter (PM_{10}), are available, and each is processed distinctly. The monthly data with the highest resolution (0.1°x 0.1°) is downloaded. Upon reading this raster file, we keep only the industrial pollution layer, given its relevance to our study.

D.2 Fine Particulate Matter ($PM_{2.5}$) from Van Donkelaar et al. (2021)

We also use data from Van Donkelaar et al. (2021), as it offers monthly high-resolution (0.01° x 0.01° grid) estimates of ground-level fine particulate matter ($PM_{2.5}$). These pollution estimates are calculated by merging aerosol optical depth (AOD) data from NASA's MODIS, MISR, and SeaWiFS instruments with outputs from the GEOS-Chem chemical transport model. The dataset is refined through calibration with global ground-based observations via geographically weighted regression (GWR).

D.3 Measurement Procedure

The process of measuring pollution data at the industrial cluster level is broken down into four steps.

1. Extract the cluster location from the PDF titled "Assessment of the Need from Common Effluent Treatment Plants."
2. Geocode each identified location and construct corresponding circles around industrial areas/estate locations.
3. Using the location and pollution data from the previous step, we compute the weighted overlap between the designated circular region and the pollution raster layer.

(1) Extraction of Industrial Clusters: We use the document "Assessment of the Need from Common Effluent Treatment Plants," which is published by the CPCB under the Ministry of Environmental & Forest, Govt. of India. Starting from page 22 in Annexure II, it presents a list of industrial areas and estates of new locations categorized by state. Using this document, we extract these addresses into Excel using PDF converters. Given the document's inconsistencies, research assistants meticulously review the output by hand to guarantee accurate extraction.

(2) Geocoding and Shape Construction: Next, we pinpoint the latitude and longitude of industrial clusters. We send each address to the Google Maps API, and retrieve their geocodes. This helps exclude duplicate locations, proposals that weren't realized, and entries with incomplete information. After this step, we are left with 2914 locations. Using this refined list, a geometry, specifically a circle with a 500m radius, is constructed around each location.

(3) Weight Pollution Data: The final step involves calculating the pollution at each industrial location. For this purpose, we utilize raster files from EDGAR and Van Donkelaar, as discussed above, to assess pollution levels surrounding these sites.

A critical aspect to consider is that the vicinity of an industrial location can span multiple grid cells. To account for this, we calculate a weighted average of the pollution values. This involves determining the proportion of the industrial area's footprint overlapping each grid cell, which then serves as the weight for that cell. By summing these weighted values across the industrial area, we obtain a comprehensive dataset detailing pollution levels by industrial area, month, and pollutant type.

[39] See https://edgar.jrc.ec.europa.eu/dataset_htap_v3 for more information.

Annexure II

List of Industrial Areas /Estates

State/UT: Haryana

	Ambala Cant
1	HSIIDC Ambala
2	IGC Food Park, Phase-I, Saha
3	IGC Phase-II, Saha
	Bhiwani
4	HUDA Sec-21
5	HUDA Sec-21

FIGURE IAD9: SAMPLE FROM THE ASSESSMENT OF THE NEED FROM COMMON EFFLUENT TREATMENT PLANTS

This figure presents an excerpt from the Assessment of the Need from Common Effluent Treatment Plants document. It presents the first 5 observations from page 22.

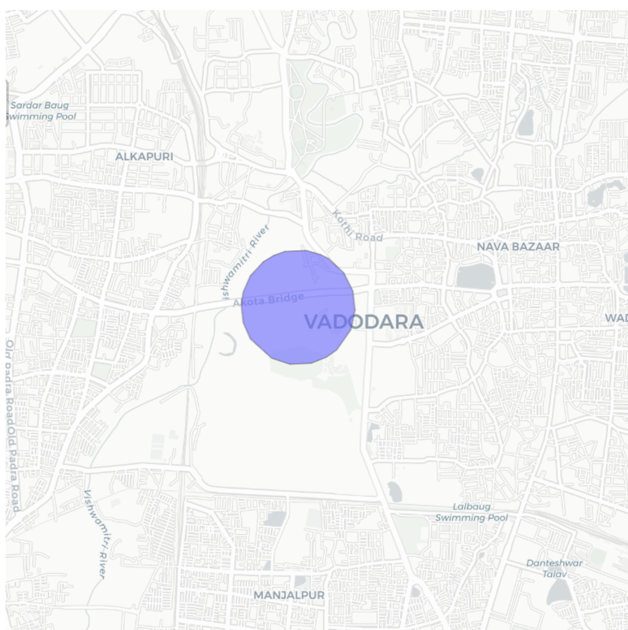

FIGURE IAD10: VADODARA, GUJARAT

This figure presents a shape drawn for a given industrial area/estate using a 500m radius.

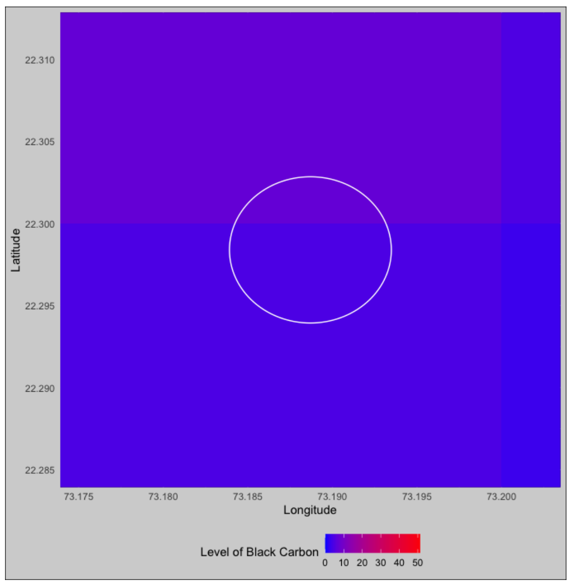

FIGURE IAD11: EXAMPLE OF INTERSECTION

This figure illustrates pollution calculations from December 2012, depicted as a circle divided into two segments: the top segment represents 27%, and the bottom segment represents 73%, indicating the proportional weight calculations

Appendix E Product-Level CO_2 Emissions

This appendix describes how we clean the product-level energy inputs from the Prowess database and transform them into product-level CO_2 emissions. The Prowess product-wise energy consumption data are from company disclosures in their annual reports. Clause (e) of sub-section (1) of section 217 of the Companies Act of 1956 mandates that every company disclose *total* energy consumption in a prescribed format. However, there is no legal obligation to disclose the product-level energy consumption per unit of production. Thus, a limitation of this data is that firms choose whether or not to disclose it, and not every firm chooses to do so. However, once a firm starts reporting product-level energy inputs, however, it tends to continue to do so throughout the entire period. Note that this changes the interpretation of our results to be most directly applicable to these types of firms but is unlikely to violate the identification assumption of no discontinuity in the probability of reporting product-level energy assumption at CEPI treatment thresholds. Figure IAE12 provides evidence supporting this identification assumption.

TABLE IAE9: PROBABILITY OF FILING ENERGY INPUTS

This table reports the effect of the 2009 CEPI emissions regulation on the probability of reporting product-level energy inputs in firm annual reports. The unit of analysis is firm-product-year. Model (1) is on all firms in the Prowess database. Models (2) and (3) are on the regression dataset comprising manufacturing firms in clusters with CEPI within a bandwidth of 10 pollution index units around the cutoffs at 70 and 60. *Post* is an indicator variable taking the value of 1 for all years including 2009 the year in which reform was implemented and after. $CEPI^{[70,100]}$ takes the value of one if the industrial cluster has a CEPI value at or above 70, and zero otherwise. $CEPI^{[60,70)}$ takes the value of one if the industrial cluster has a CEPI value greater than or equal to 60 and below 70, and zero otherwise. In specifications (2) and (3), the sample is restricted to the 88 industrial clusters targeted by the CPCB in 2009 with the omitted category including clusters with a CEPI value below 60 and includes firm and State × two-digit Industry × year fixed effects. The standard errors are clustered at the city level and are robust to heteroscedasticity. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix Table IAA8. Data source: CMIE Prowess.

Dependent variable:	$\mathbb{1}_{\text{File Energy Inputs}}$		
Sample:	All	Regression	
	(1)	(2)	(3)
Post	-0.007***		
	(0.001)		
Post $\times$CEPI$^{[60,100]}$		-0.010	
		(0.010)	
Post $\times$CEPI$^{[70,100]}$			-0.011
			(0.010)
Post $\times$CEPI$^{[60,70)}$			-0.008
			(0.013)
Fixed effects:			
Firm	Yes	Yes	Yes
State × industry × year	No	Yes	Yes
Bandwidth	Yes	Yes	Yes
R^2	0.408	0.417	0.417
Observations	119,943	32,299	32,299

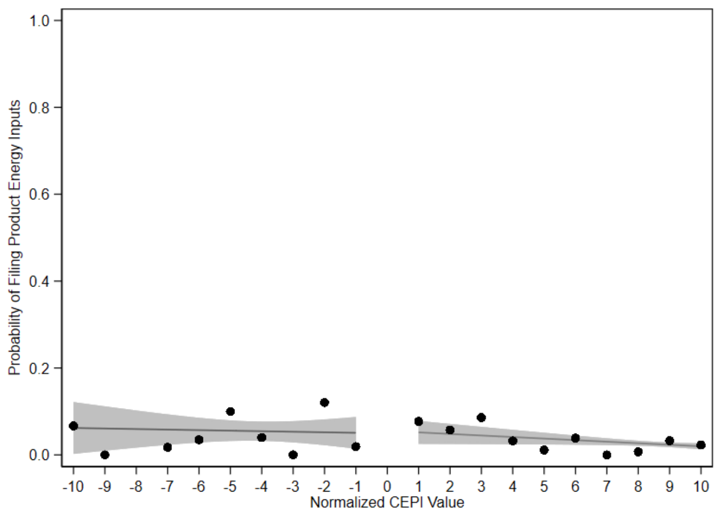

FIGURE IAE12: DISCONTINUITY IN THE PROBABILITY OF FILING PRODUCT ENERGY INPUTS AT BASELINE

This figure presents the average probability that a firm reports product-level energy inputs in its annual statement in 2008 around the CEPI treatment thresholds. We pool across a 10 CEPI-index value window around the two thresholds at CEPI 60 and 70, normalized in the figure to zero. A linear fit is generated separately for each side of 0, with the 95% confidence intervals displayed.

To our knowledge, this dataset offers unique access product-level energy inputs for such a large cross-section of firms. We exploit this unique data to bring new insight into how emission-capping regulations impact production decisions along the input dimension.

The data are at the firm-product-year-energy source level and are expressed in energy input units per reported production unit. For example, A.B.G. Cement Ltd. reported using 70.28 kWh of purchased electricity, 0.14 tonnes of coal, and 3.3 KWh of firm-produced electricity from a diesel generator per tonne of cement produced in 2014. Since regulators do not mandate a particular reporting standard, there exists variation in reporting units in the raw data. Therefore, we first separate the energy and production units and then standardize them. For example, we transform all production units reported in "lakh liters" into "liters" by using the fact that one lakh liter is 100,000 liters. Ultimately, we express all energy inputs in kcal per production unit. This conversion allows us to test for shifts in energy use across energy sources as a proportion of the total energy input in kcal.

Second, we transform energy input into CO_2 output. This exercise requires assumptions about each energy source's energy content and CO_2 output. We use the conversion factors and unit assumptions from the Central Electricity Authority (CEA) of India for 2008 (Central Electricity Authority, 2008), the year before the regulation. This choice fixes the energy technology just before the regulation. We assume that in the five-year window around the regulation, there are no drastic changes to technology that would change the CO_2 emissions of each fuel type significantly. Importantly, they are unlikely to change discontinuously around the thresholds set by CPCB.

Specifically, we use the CEA's assumptions on gross calorific value and CO_2 emission factors per fuel source that this regulator mandated that electricity plants use to quantify their CO_2 emissions in 2008 (Central Electricity Authority, 2008). We supplement this source from the 2008 *Commercial Energy Balance Tables and Conversion Factors* from the Energy and Resources Institute (Energy and Resources Institute, 2008). The latter gives us fuel-specific conversions between, e.g., mass units and volume units for the type of fuel used in Indian manufacturing firms. Table IAE10 reproduces the calculation inputs. Note that energy input from hydro, solar or wind sources are assumed to have zero CO_2 emissions.

Finally, we calculate tonnes of CO_2 emitted per reported production unit for each firm-product-year-energy source. Once all energy sources have the same units on the energy input side (kcal/production unit) and the CO_2 emissions side (tonnes of CO_2/production unit), we collapse the data to the firm-product-year level across energy sources.

Using the unique firm and product codes, we merge with our regression dataset of manufacturing firms, which contains the quantity produced of each product by each firm per reporting year. We next calculate the total CO_2 emissions per firm-product-year. So, in the end, we have a dataset at the firm-year-product level for the fiscal years

TABLE IAE10: PRODUCT-LEVEL ENERGY INPUTS TO CO_2 EMISSIONS

This table reports the assumptions we used when transforming product-level energy inputs into product CO_2 emissions. Note that we assume that CO_2 emissions from burning bio-waste are based on the idea of a closed carbon cycle —the carbon dioxide emitted when bio-waste is burned is offset by the carbon dioxide absorbed during the growth of the plants that produced the waste so that the amount of CO_2 released is approximately equal to the amount of CO_2 absorbed. Data source: Central Electricity Authority CO_2 Baseline Database 2008 (Central Electricity Authority, 2008) and the Commercial Energy Balance Tables and Conversion Factors from the Energy and Resources Institute (Energy and Resources Institute, 2008).

Fuel	Gross Calorific Value (kcal/kg)	Density (t/kls)	Fuel CO_2 Emission Factor	
			Electricity from Fuel (tCO_2/mWh)	Fuel (gCO_2/MJ)
Coal	3,755	0.95	1.04	90.6
Diesel	10,350	0.83	0.78	69.1
Oil	9,850	0.95	0.66	71.9
Gas	11,300	0.86	0.55	49.4
Lignite	3,000	0.83	1.28	100.5
Naptha	10,750	0.70	0.61	66.0
Bio*	3,625	N/A	0.00	0.0
Hydro	N/A	N/A	0.00	0.0
Solar	N/A	N/A	0.00	0.0
Wind	N/A	N/A	0.00	0.0
Nuclear	N/A	N/A	0.00	0.0

2005 to 2015 that tells us the total energy input per product reporting unit, the total CO_2 emissions and the CO_2 emissions per product reporting unit, and the proportion of the total energy from each fuel source. These data are summarized below for our regression sample in Table IAE11.

TABLE IAE11: SUMMARY STATISTICS: ENERGY INPUTS AND CO_2 EMISSIONS

This table presents descriptive statistics of the product energy inputs and CO_2 emissions for our baseline sample. *Ln(Total product energy input)* is defined as the natural logarithm of total product-level energy inputs for the firm-year. *Ln(Total product CO_2)* is defined as the natural logarithm of total product-level CO_2 emissions for the firm-year. *CO_2 per production unit* is defined as the ratio of total product in tonnes and the units the product is quoted in on the firm's annual statement. *Proportion purchased electricity* is defined as the ratio of the total product-level energy from purchased electricity and total product energy input.

	Obs	Mean	Std. dev.	Min	Median	Max.
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Total product energy input)	1,151	13.81	2.96	5.29	14.39	21.48
Ln(Total product CO_2 emissions)	1,151	4.37	4.45	-6.54	4.50	14.79
Tons of CO_2 per production unit	1,151	2.72	17.28	0.00	0.16	168.34
Proportion purchased electricity	1,151	0.56	0.47	0.00	0.99	1.00

Appendix F Quantity Productivity Estimation

Measuring productivity is challenging. In many settings, firms are capital constrained, subject to power blackouts and other infrastructure constraints, regulations limit labor adjustment, firms, among others. The workhorse model, Levinsohn and Petrin (2003) assumes that firms readily adjust their intermediate inputs when faced with a productivity shock. This methodology then calculates revenue-based total factor productivity (TFPR) that reflect changes in productivity however these might also reflect changes in markups, the product mix, and product quality. However, it is reasonable to expect all three to respond to the emissions regulation. On the other hand, if consumers value quality, TFPR may be preferable to TFPQ-based measures since higher prices and revenues may capture the ability to produce high quality (Atkin et al., 2019). Indeed, we confirm that in our data that input prices are an increasing function of product quality.

To circumvent such issues, we adopt the approach proposed by De Loecker et al. (2016), allowing us to flexibly control for quality differences to be consistent with a large class of demand models and any degree of passthrough between input and output prices. Further, it allows us to recover firm-product-year estimates of markups and marginal costs. Estimates are corrected for product quality, as proxied by input price variation, and for sample selection. In this Appendix, we describe the construction of quantity total factor productivity (TFPQ), following De Loecker et al. (2016). We control for input price variation across firms using differences in output quality, which we model as an increasing function of output price, product market share, and product dummies.[40] using the methodology of De Loecker et al. (2016).

F.1 Estimation assumptions

Following De Loecker et al. (2016), our estimation of firm quantity productivity, and firm-product-level marginal cost and markups rely on several key simplifying assumptions, as described below.

1. All producers of the same product use the same production technology, though productivity in producing the product can differ;
2. Firms are equally productive at producing all its products;
3. Firms can only change output in the short term by adjusting material inputs, but not capital and labor, which are sticky;
4. We model firms as minimizing short-turn costs, taking concurrent (time-t) quantity and input prices as given;
5. The production function coefficients are assumed to be constant over the sample period;
6. The number of products manufactured by firms increases with the firm's productivity.

Assumption 2 is not likely to hold but is standard in the literature because it allows estimates of markups for multi-product firms. Assumption 3 allows us to ignore cross-elasticities, which we cannot estimate because we only observe labor and capital at the firm-year level. Note that this does not impose that firms cannot substitute between capital and labor in such a way that output remains constant. If assumption 3, that the only variable input is materials, and assumption 4, that firms minimize costs, hold, then markups are computed as the deviation between the elasticity of output with respect to inputs and that input's share of total revenue. Assumption 4 also implies that input prices, our main proxy for product quality, do not depend on input quantities. Note that this is unrealistic in the sense that it rules out static sources of market power in input markets, i.e., monopsony power. As a result, this approach understates the level of markups and is therefore most useful in explaining *changes* in markups. The intuition is that if market power is static or if contemporaneous changes in market power are not correlated with the 2009 emissions regulation shock then the changes in markups will be estimated without bias. Assumption 5 is necessary because we do not have enough data to estimate production functions for different time periods.

F.2 Addressing empirical bias

There are two main sources of bias in estimating TFPQ: (1) the unobserved allocation of inputs across products for firms that produce more than one product and (2) the unobserved quality of products. To address the first, we estimate the production function on single-product firms only. Of course, firms choose if they will produce one or

[40] Intuitively, output prices are highly correlated with input prices since producers of more expensive products also use more expensive inputs, on average (for example, Kugler and Verhoogen (2012)). Following De Loecker et al. (2016), we also assume that input quality is correlated across the factors of production. Intuitively, manufacturing high-quality products requires combining high-quality materials with labor and capital. This assumption allows us to model input prices as a function of a single index of product quality at the firm-product level.

multiple products, introducing selection bias into our estimates. Assuming that the number of products manufactured by firms is an increasing function of firm productivity (assumption 6 above) allows us to control for selection into being a multi-product firm by estimating the probability that a firm continues to produce one product as a function of the firm's productivity forecast and the state variables (number of products, material inputs, and exogenous factors like firm location). The assumption that multi-product firms use the same production technology as single-product firms producing the same product (assumption 1 above) allows us to extrapolate our single-product estimates to our subsample of multi-product firms.

The second bias, that we do not observe the quality of products, is a fundamental problem of productivity estimation. In particular, TFPQ estimations are downward biased when the econometrician does not observe product quality differences across firms.[41] To overcome this, we proxy for output quality by input quality. We do not observe input quality directly either because we do not observe how firms that produce multiple products allocate inputs across those products. To partially address this, we estimate the production function using the subsample of single-product firms.[42] This approach is attractive because it controls for quality differences flexibly so as to be consistent with a large class of demand models and with any degree of passthrough between input and output prices. The approach also allows us to recover firm-product-year level estimates of markups and marginal costs.

The specific steps we take are to:

1. Estimate the production function parameters and recover the product-specific output elasticity with respect to materials from a subsample of single-product firms. We model the production function using a translog functional form;
2. Correct for selection bias from the non-random decision of how many products to produce by estimating the productivity threshold beyond which firms move from producing one to multiple products and then controlling for the probability that the firm will continue to be below the threshold in a given year as a function of firm productivity and the state variables;
3. Proxy for the (unobserved in our data) product-level materials share of total revenue for each product of multi-product firms using the estimated production function coefficients for single product firms and an input price control function that expresses the product-specific allocation of material inputs to each product as a function of the firm-product-year output price, market share, product and location fixed effects, and the firm's export status;
4. Compute firm-product-year level markups and marginal costs, where the markup is the ratio of the output elasticity of materials to the materials share of total revenue and marginal costs are the ratio of the products price to its markup.

We perform several sanity checks on the data to see if it conforms with our economic intuition and evidence in the literature. Figure IAF13 reports the correlation between demeaned markups and marginal costs and the natural logarithm of product quantity produced.

The left panel of FigureIAF13 demonstrates that quantities and markups are positively related in our sample, indicating that firms producing more output also enjoy higher markups due to their lower marginal costs. The right-hand panel of Figure IAF13 plots marginal costs against production quantities. Our elasticity estimates show that many firms are characterized by increasing returns to scale, an empirical pattern also noted in De Loecker et al. (2016). Consistent with this, we see an inverse relationship between a product's marginal cost and the quantity produced.

Next, we check the reasonableness of our extrapolation of the production function estimates of single-product firms to multi-product firms. Figure IAF14 reports how our estimated firm-product-year markups (left panel) and marginal costs (right panel) vary across products within multi-product firms. Specifically, we de-mean markups and marginal costs using product-year and firm-year fixed effects in order to make these variables comparable across

[41] TFPR includes prices, which means that it captures cross-sectional quality differences between firms within narrowly-defined product categories. However, the TFPR measure also includes markups in prices have both demand and supply determinants, biasing estimates of productivity changes and cross-sectional comparisons. The direction and magnitude of this bias are highly dependent on the specific empirical setting.

[42] We confirm that input prices are an increasing function of product quality and therefore we can control for input price variation across firms using differences in output quality across firms, which we model as an increasing function of output price, product market share, and product dummies. Intuitively, output prices have been found to be highly correlated with input prices since producers of more expensive products also use more expensive inputs, on average (for example, Kugler and Verhoogen (2012)). We also assume that input quality is correlated across the factors of production. Intuitively, manufacturing high-quality products requires combining high-quality materials with high-quality labor and capital. This assumption allows us to model input prices as a function of a single index of product quality at the firm-product level.

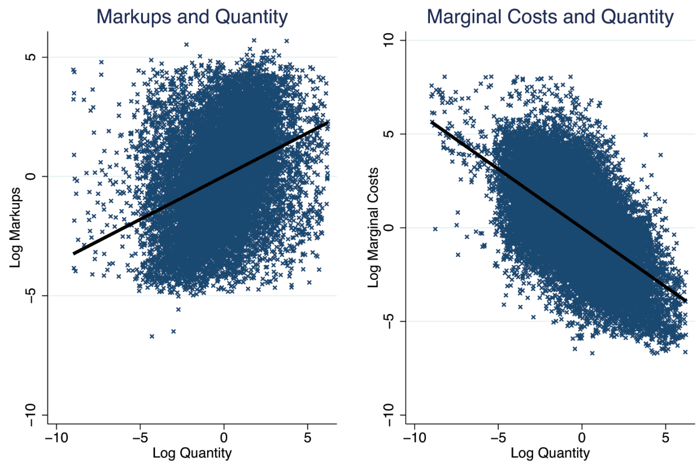

FIGURE IAF13: MARGINAL COSTS, MARKUPS AND QUANTITIES

The left panel presents the correlation between the natural log of product markup and output quantity. The right panel is between the natural log of product marginal cost and output quantity. Data are at the firm-product-year level for the period 2005 to 2015. Data are winsorized at the 3rd and 97th percentiles. Markups, marginal costs, and quantities are demeaned by product-year fixed effects to make them comparable across firms.

products within firms. We then plot the de-meaned markups and marginal costs against the sales share of the product within each firm.

In the left-hand panel of Figure IAF14, marginal costs rise as a firm moves away from the product with the lowest within-firm marginal cost (its "core" product). For the other products, marginal costs rise with a product's distance from the core competency. The right panel reports that firms set their highest markups on their core product, and markups decline as they move away from that main product. Although we do not impose any assumptions on the market structure and demand system in our estimation, these correlations are consistent with the theoretical predictions from the multi-product firm literature (Eckel and Neary, 2010; Mayer et al., 2014; Melitz and Ottaviano, 2008) and the empirical findings of De Loecker et al. (2016) in the Indian manufacturing sector.

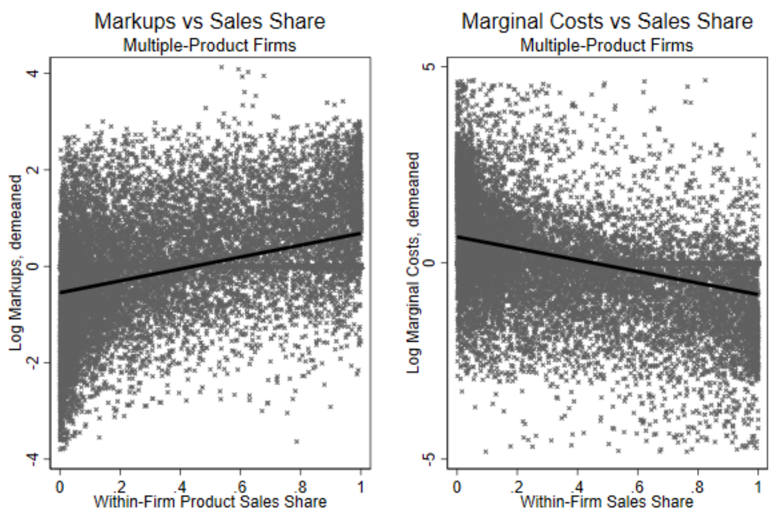

FIGURE IAF14: MARKUPS, COSTS AND PRODUCT SALES SHARE

Notes: The left panel presents the correlation between the natural log of product markup and sales share. The right panel is between the natural log of product marginal cost and sales share. Data are at the firm-product-year level for the period 2005 to 2015. Data are winsorized at the 3rd and 97th percentiles. Markups, marginal costs, and quantities are demeaned by product-year and firm-year fixed effects to make them comparable across firms.

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