CAN POLLUTION MARKETS WORK IN DEVELOPING COUNTRIES? EXPERIMENTAL EVIDENCE FROM INDIA*

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Market-based environmental regulations are seldom used in low-income countries, where pollution is highest but state capacity is often low. We collaborated with the Gujarat Pollution Control Board (GPCB) to design and experimentally evaluate the world's first particulate-matter emissions market, which covered industrial plants in a large Indian city. There are three main findings. First, the market functioned well. Treatment plants, randomly assigned to the emissions market, traded permits to become significant net sellers or buyers. After trading, treatment plants held enough permits to cover their emissions 99% of the time, compared with just 66% compliance with standards under the command-and-control status quo. Second, treatment plants reduced pollution emissions, relative to control plants, by 20%–30%. Third, the market reduced abatement costs by an estimated 11%, holding constant emissions. This cost-savings estimate is based on plant-specific marginal cost curves that we estimate from the universe of bids to buy and sell permits in the market. The combination of pollution reductions and low costs imply that the emissions market has mortality benefits that exceed its costs by at least 25 times. *JEL codes:* O13, Q56, L51.

I. Introduction

Many low-income countries today suffer from extraordinarily high air pollution. In India, nearly the entire population of

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1.4 billion people breathes air more polluted than World Health Organization standards for particulate matter, often by a factor of 10 or more.[1] To face this air pollution crisis, India relies on command-and-control environmental regulations modeled on those in the United States from 50 years ago (Piette 2018). These regulations are stringent on paper but weakly enforced in practice (Duflo et al. 2013, 2018), perhaps because strict enforcement would be too costly for firms.

A powerful alternative to standards is to regulate pollution with markets. Foundational theoretical work has shown that markets can abate pollution at the lowest possible cost (Coase 1960; Dales 1968). Further, the United States and the European Union have had great success in building markets to reduce air pollution (Ellerman et al. 2000; Martin, Muûls, and Wagner 2016; Dechezleprêtre, Nachtigall, and Venmans 2023). In spite of high pollution and a high concern for cost, low-income countries have not followed these examples (Stavins 2003; Blackman, Li, and Liu 2018).[2] As a result, there is no evidence on whether pollution markets can work in countries with low state capacity. The absence of pollution markets in these countries may reflect a correct judgment that they cannot work, or a self-fulfilling policy—pollution markets cannot work only because they have not been tried before.

This article examines how a new pollution market in India affected plant compliance, pollution emissions, and abatement costs. We study the world's first market for particulate-matter emissions. This new market was introduced through a randomized controlled trial that brought treatment plants into the market while keeping similar control plants under existing command-and-control regulations. We designed the market and accompanying experiment in collaboration with the Gujarat Pollution Control Board (GPCB), the environmental regulator in Gujarat, India. Our decade-long collaboration produced the institutions to support an emissions market: monitoring infrastructure to

1. Air pollution harms people by shortening their lives and reducing the human capital they form as children (Ebenstein et al. 2017; Isen, Rossin-Slater, and Walker 2017). Reducing air pollution throughout India to the World Health Organization standard would, by some estimates, increase Indian life expectancy by an average of five years (Greenstone et al. 2015; Greenstone and Hasenkopf 2023).

2. Markets are also rare or absent for common pool resources, like fisheries or groundwater, for which they could bring large efficiency gains (Chu 2009; Ryan and Sudarshan 2022).

measure pollution on a continuous basis, new market regulations, and a platform to enable trade. The experiment allows us to measure causal effects of market-based regulation, which have been elusive in the rich literature on emissions trading (Fowlie, Holland, and Mansur 2012; Martin, Muûls, and Wagner 2016).

GPCB launched the market for industrial plants in and around Surat, Gujarat, a rapidly growing city of 7 million people, in 2019. Under the command-and-control status quo, plants are mandated to install abatement equipment and are sporadically inspected in person by government regulators and auditors to check that they meet limits on the concentration of pollution emissions. Our prior research has shown that enforcement in this regime is undercut by poor information and that many plants violate pollution standards as a result (Duflo et al. 2013, 2018). For the present experiment, GPCB mandated a sample of 318 large, coal-burning plants to install continuous emissions monitoring systems (CEMS) to measure the total mass of particulate matter (PM) emitted, compared with the measurement under the status quo of pollution concentrations during spot visits.[3] The emissions market experiment then randomly assigned 162 out of 318 plants to the market and 156 control plants stayed under the command-and-control regime.

Treatment plants were shifted into a newly built emissions market. GPCB set a cap on the total mass of particulates that could be collectively emitted by all treatment plants over a compliance period. They allocated permits to treatment plants, with permits summing to 80% of the cap distributed for free, in proportion to plant emissions potential, and 20% sold off in weekly auctions. Thereafter, treatment plants could trade permits with each other. At the conclusion of each compliance period, any treatment plant that did not hold enough permits to cover their emissions was subject to fines based on the size of the shortfall. The

3. The change from measuring pollution concentration to pollution mass (also called load) is important. Concentrations of air pollution, measured in mg/Nm^3, are the mass of pollution per volume of gas emitted from the plant's chimney during a half-hour sample on a spot visit. Load, measured in kg, is the total mass of pollution emitted—think of the weight of a giant pile of very fine dust. Measurement of load is preferable because load is what determines a plants' contribution to ambient pollution (thus human health) and because load is measured with CEMS monitors that record pollution continuously, instead of only during spot visits.

evaluation ran from September 2019 to April 2021, with an interruption due to a nationwide COVID-19 lockdown. There were a total of 10 compliance periods, each of four to six weeks' duration.

There are three main findings. First, the market functioned well, with respect to both plant compliance and permit trade. Treatment plants complied—held enough permits to cover their emissions—in 99% of plant-periods. By contrast, the compliance rate with concentration standards at baseline was 66%. The regulator established a reputation for enforcement in the market regime early on by levying fines specified in the market rules on a couple of plants that did not buy enough permits in the first period. We find that the market caused greater compliance; high compliance is a benefit of the market treatment, as opposed to low compliance being an immutable feature of the regulatory context. The permit market also appeared to have low transaction costs. Plants traded often, with daily trading volume reaching up to 20% of the market cap. At the end of each compliance period, plant permit holdings differed greatly from initial allocations, as some became net sellers and others net buyers. Plants consumed 95% of their final permit holdings, on average, and therefore left little money on the table in unused and unsold permits.

Second, the treatment reduced particulate emissions by 20%–30%, relative to control-plant emissions in the command-and-control regime.[4] The regulator set the cap, with incomplete initial data on emissions, to try to match the stringency of control regulation. The relative reduction in emissions for the treatment plants was due to a combination of the initial cap turning out to be more strict than control regulations, the higher rates of compliance in the treatment, and the regulator reducing the cap over the first several compliance periods. The regulator's reduction of the cap was an endogenous tightening of regulation after seeing the relatively low costs of compliance, reflected in low permit prices, in the market regime.

Our third main finding is that the market reduced variable abatement costs by 11% at a constant level of emissions. This estimate is derived from plant-specific marginal abatement cost (MAC) curves that we estimate from the universe of 8,433

4. This range reflects variation in point estimates based on how emissions are imputed during periods when CEMS did not transmit pollution data from plants (see Section IV).

treatment-plant bids to buy and sell permits.[5] We exploit within-compliance-period variation in plant permit bids to estimate MAC functions specific to each plant and compliance period. Although the MAC functions are estimated with data only from treatment plants' bids, the experiment ensures that the distribution of MAC functions is the same in the control group. We compare costs across regimes, at several emissions levels, by evaluating the treatment plants' abatement cost functions at either the efficient, market distribution of emissions or the distribution of emissions actually observed in the control group.

Finally, we combine our pollution and cost estimates, including the fixed costs of setting up the market, to conduct a benefit-cost analysis of a potential market expansion. This analysis finds that under a range of assumptions on the mortality damages from pollution, the benefits of the market exceed costs by at least 25 times, reflecting the high mortality costs of air pollution and the low costs of abatement in the market.

This article contributes to the literatures in development and environmental economics. A main theme of the research on development and the environment has been the Herculean challenge of environmental regulation in low-state-capacity settings (Greenstone and Hanna 2014; Jayachandran 2022). Common findings are that poor or corrupted monitoring impedes regulation (Duflo et al. 2013, 2018; Oliva 2015; Zou 2021), and that coarse regulations, also adopted in response to poor monitoring, are partly undercut by behavioral responses (Davis 2008; He, Wang, and Zhang 2020).[6] Our findings add to this literature by showing that, at least in Gujarat, high private abatement costs

5. We believe these data are a novel contribution in the literature where price data on executed trades has been the best case to date. For example, Ellerman et al. (2000) discuss permit prices and how prices compare to ex ante expected abatement costs in the acid rain program. Klier, Mattoon, and Prager (1997) and Shapiro and Walker (2020) present summary statistics on transaction prices in RECLAIM and U.S. air pollution offset markets.

6. The one previous example of a market targeting particulates with which we are familiar was in Chile. This market in fact regulated boiler capacity, not emissions, because of limitations in pollution monitoring at the time (Montero, Sanchez, and Katz 2002). This coarse proxy removed the prospect of low-cost abatement because most particulate abatement happens after combustion, and plants could receive no credit for actions such as running end-of-pipe abatement equipment or changing fuels. Eventually, the market disbanded after many plants switched to natural gas in response to a fall in prices further weakening the value of this proxy.

are not the primary culprit for high emissions (see Greenstone et al. 2022 on this theme) and that markets can be an effective way to reduce pollution.

The conventional wisdom in environmental economics on market-based regulation is that emissions markets abate pollution at lower cost than extant command-and-control regulations (Ellerman et al. 2000; Fowlie, Holland, and Mansur 2012). A general challenge for the evidence on this point is that plants regulated with markets are vastly different from those left out, making it hard to identify a valid counterfactual.[7] As a result, existing evaluations of emissions markets require strong assumptions to estimate what emissions and plant costs would have been without a market (Fowlie, Holland, and Mansur 2012; Martin, de Preux, and Wagner 2014; Borenstein et al. 2019). This study experimentally assigns plants to the market and command-and-control regimes to provide causal estimates of the effects of an emissions market on both pollution and costs.

The article proceeds as follows. Section II introduces India's status quo environmental regulation and the new emissions market and then describes the data, sample, and experimental design incorporating this market. Section III provides evidence that the market functioned well. Section IV presents estimates of experimental treatment effects on emissions. Section V describes the model and estimates marginal abatement costs from

7. Prior research on emissions markets makes this point explicitly. Fowlie, Holland, and Mansur (2012, 971) write, "Unresolved disagreements about what constitutes an appropriate measure of counterfactual emissions have resulted in a plurality of opinions regarding RECLAIM's overall performance. After 15 years of program evaluations, the emissions impacts of RECLAIM vis-à-vis the subsumed CAC rules remain controversial." Early work on the EU Emissions Trading System (ETS) for carbon dioxide highlighted the difficulty of estimating whether the ETS reduced emissions at all, in an environment with uncertainty about emissions and aggregate shocks (Ellerman and Buchner 2008). This problem has remained prominent in the literature on the EU ETS. Martin, Muûls, and Wagner (2016, 130) write, "An ideal evaluation of the EU ETS would combine a representative firm- or plant-level data set of sufficient detail with a study design that attributes to the EU ETS only those observed behavioral changes it has actually caused. It is difficult to solve this identification problem because there are so many factors that might simultaneously affect firm behavior, thus confounding the impact estimate. The state-of-the-art solution would be to conduct a randomized control trial or field experiment (e.g., Greenstone and Gayer 2009). As in other real-world settings, however, randomizing participation in the EU ETS is neither desirable nor politically feasible."

bids. Section VI compares the costs of abatement under the two regulatory regimes and provides a benefit-cost analysis. Section VII concludes.

II. Context and Experimental Design

We begin by describing the status quo regulatory regime. We lay out the history of our engagement with central and state governments, the development of the Surat market, and the market rules that applied to treatment plants. Then we describe the experimental design, our data sources, and the characteristics of sample plants.

II.A. The Command-and-Control Status Quo

Under the status quo command-and-control regulations, the "command" mandates plants to install pollution-control equipment. The "control" is an intensity standard that limits pollution concentrations (for particulate matter, the limit is typically 150 mg/Nm^3). State pollution control boards (SPCBs) enforce these regulations by visiting plants, measuring pollution, and imposing sanctions.[8]

We collaborated with GPCB on prior research that showed incomplete compliance in the status quo. The regulator is limited in part by poor information about pollution emissions (Duflo et al. 2013). Though sanctions can be large, they are typically reserved for severe offenses, leaving the many plants with routine violations with weak incentives to abate (Duflo et al. 2018). Pollution concentration limits are uniform across plants without regard to their age, size, fuel, or abatement capital. Because of this uniformity, despite large differences across plants, there may be significant heterogeneity in marginal abatement costs across different plants.

II.B. Laying the Groundwork for India's First Emissions Market

The market grew out of a deep collaboration between our research team and environmental regulators to build the mon-

8. The Water Act (1974) set a command-and-control framework for environmental regulation of industrial water pollution and established State Pollution Control Boards (SPCBs) to enforce pollution regulations. The Air Act (1981) expanded their powers to encompass air pollution. SPCBs can introduce additional regulation in highly polluted regions.

itoring, regulatory, and trading infrastructure for an emissions market. At a 2010 conference of Indian state environmental regulators, we proposed that states could use emissions markets as a regulatory tool. India's Ministry of Environment and Forests then solicited a white paper on emissions markets that we coauthored (Duflo et al. 2010). The conference sparked scoping discussions on emissions markets with the SPCBs in India's three leading industrial states, Gujarat, Maharashtra, and Tamil Nadu.

The monitoring infrastructure needed to establish an emissions market had to be built before a market could be launched in any state. Emissions markets rely on continuous emissions monitoring systems (CEMS), for which no Indian standards existed circa 2010. A Central Pollution Control Board (CPCB) panel, including Sudarshan, a coauthor of this article, as a member, in 2013 drafted technical standards for CEMS usage in India (Central Pollution Control Board 2013). These standards were developed with a pilot market in mind but also enabled a nationwide movement toward the adoption of CEMS.[9] Gujarat was the first of the three interested states to mandate CEMS devices when the standards were published, which prompted our research-policy collaboration with GPCB on the development of an emissions market. GPCB pushed the rollout and testing of CEMS at scale, a laborious process that required a new, private ecosystem to install and maintain the devices (Sudarshan 2023). Tamil Nadu and Maharashtra have since adopted CEMS for monitoring larger plants. As of 2024, we are also working with the Maharashtra Pollution Control Board on a market design for sulfur dioxide.

To start an emissions market, GPCB needed to issue regulations, establish a trading platform, and build market participants' capacity. Together with our research team at JPAL South Asia, we collaborated with GPCB on each of these steps. GPCB selected NCDEX e-Markets Limited (NeML), a subsidiary of a leading Indian commodity exchange, to host the market. GPCB, NeML, the coauthors of this article, and our research team jointly developed market rules. The Forest and Environment Department, Government of Gujarat formally notified the market on

9. In 2014, the CPCB mandated installation of CEMS for large plants in 17 manufacturing sectors across India. This mandate is restricted to large plants, and the CEMS data from this mandate is largely not used in the enforcement of regulation; for example, CEMS readings can direct the regulator's priorities but cannot be used as the legal basis for sanctioning plants in the status quo.

June 4, 2019 (via notification GVN-2019-17-GPCB-SFS-1-2019-ETS-T). The market is supervised on an ongoing basis by a Market Oversight Committee (MOC) chaired by the chairman, GPCB, and with additional members including the GPCB regional officer, GPCB environmental engineers, NeML, the head of the South Gujarat Textile Processor's Association (SGTPA), the concerned industry association, and this article's coauthors. The GPCB and the SGTPA hosted a series of stakeholder capacity-building workshops to train GPCB's officials and regulated plants on the rules of the market, penalties for noncompliance, how to participate in auctions, and how to trade.

II.C. Surat Emissions-Market Design

The Surat emissions trading scheme is the world's first particulate-emissions market and India's first market for any pollutant. GPCB chose to locate the emissions market in Surat, an industrial hub with a population of 7 million, because the city is critically polluted and has a high contribution of point-source industrial emissions to ambient pollution levels.[10] The market is a standard cap-and-trade design in which plants are allocated or can buy permits granting the right to emit and face fines for noncompliance if emissions exceed their permit holdings. Here we detail the market design.

1. *Cap.* The cap in the market limits the load, or mass, of pollution emitted. GPCB initially capped particulate emissions at 280 tons a month. This cap was an approximation that assumed plants would run at the maximum available capacity and produce emissions at the maximum concentration allowed under the status quo the whole time. Once the market began, GPCB got better estimates of load from CEMS devices and judged that the initial cap had been set too high. GPCB then adjusted the cap downward, in steps, to 170 tons a month (see Online Appendix Table A2).

10. Roughly one-third of ambient fine-particle pollution in and around Surat city comes from industrial plants; twice as large as that of the next most significant source, transportation, at 16% (Guttikunda, Nishadh, and Jawahar 2019). A current assessment for Surat is at https://urbanemissions.info/india-apna/surat-india.

2. *Permit Allocation.* Each permit allows a plant to emit 1 kg PM. PM includes suspended particles of all sizes, since neither CEMS devices nor manual monitoring in the status quo differentiate by particle size, as is common in ambient monitoring of PM. Permits are valid only for one compliance period of four to six weeks' duration (see Online Appendix Table A1). Permits expire at the end of each compliance period, so plants cannot bank or borrow across periods. At the start of each compliance period, 80% of issued permits were given to plants for free, proportional to a scale measure, emissions capacity, calculated prior to the market.[11] The balance of 20% of permits were sold to plants at auction.

3. *Permit Trade.* The main means of trade is a uniform price, multiunit two-sided auction held weekly on Tuesday. Plants can bid to purchase or offer to sell permits in the auction by submitting bid price-quantity pairs to the market operator. The market-clearing price is the least price at which permit supply weakly exceeds permit demand. Each compliance period opens with an auction in which GPCB offers 20% of the cap in permits at the market floor price. If GPCB does not sell all these permits during the first auction, they continue to be offered in subsequent weekly auctions. Plants can also buy or sell permits during the week via over the counter (OTC) trades at the most recent auction's permit price. This OTC price restriction was adopted to encourage auction participation and limit price volatility. Market rules impose tight holding limits to prevent plants from gaining market power over permits.[12]

4. *Price Collar.* Prices were limited to between INR 5 and 100 per kg.[13] GPCB supported the floor price with a commitment to buy back permits at the floor at the end of each compliance

11. Emissions capacity, measured in tons of steam equivalent per hour, is the sum of the output capacities of the boiler and thermic fluid heater, the two main fuel-burning pieces of equipment in sample plants.

12. The limit for each plant was the greater of 1.5 times that plant's initial allocation or 3% of the aggregate market cap for the compliance period.

13. This range was informed by engineering estimates that particulate-matter abatement by equipment commonly used in the sample, could occur at an average cost of INR 10–40, depending on the type of equipment installed and plant scale. The ceiling price was sufficiently high that plants would rather abate at these costs than pay the ceiling price for permits.

period. GPCB supported the ceiling price with a commitment to sell permits at the ceiling at the end of each compliance period in unlimited quantity.

5. *Compliance and Penalties for Noncompliance.* Compliance is enforced with financial penalties. At the start of the market, plants had to post an environmental bond known as an Environmental Damage Compensation Deposit (EDCD).[14] The size of EDCD varied with plant scale, and for most plants was INR 200,000, well in excess of permit expenditures at market prices. After a compliance period ended, at which point emissions were known with certainty, plants had a one-week true-up period to make further trades. At the end of the true-up, plant permit holdings were compared against their total emissions in the period. Plants with insufficient permits were fined twice the ceiling price for every unit of emissions above their permit holdings with the fine deducted from the EDCD (which the plant was then required to top up).

6. *Differences Between the Market and the Status Quo.* To summarize, the treatment emissions market differs from control regulation in three main respects. First, the compliance obligation for each treatment plant is tradeable, and ultimately determined by the market-level cap, rather than a fixed plant standard. Second, treatment plants are regulated for total pollution load (i.e., mass), rather than concentration at one point in time. Third, penalties for noncompliance in the market are financial and set based on ex ante rules.

II.D. Experimental Design

The initial sample included 342 plants under the GPCB regional office in Surat with the highest air pollution potential, as captured by the following criteria: (i) the plant must consume solid fuel (coal or lignite, mostly), (ii) have a boiler capacity of

14. While these EDCD bonds were new, GPCB commonly used other environmental bonds for violating plants to guarantee against future noncompliance. The authority to impose fines derives from the "polluter pays principle" widely recognized in Indian environmental law (Piette 2018). Relevant precedent is found in rulings of the National Green Tribunal (NGT), India's environmental high court. For example, the NGT has directed that the CPCB "may also assess and recover compensation for damage to the environment" (WP (CIVIL) No. 375/2012, Paryavaran Suraksha Samiti vs. Union of India & Others).

at least one ton of steam per hour, and (iii) a stack diameter of at least 24 cm (required for CEMS). All sample plants were mandated to install CEMS. Half of the sample plants were randomly assigned to the market treatment. After treatment assignment but before the market began, the GPCB gathered more information on plants' operating status and deemed ineligible any plants that were closed or operated only seasonally. This restriction left 162 and 156 plants in the treatment and control groups, respectively. Online Appendix Table A3 summarizes plant attrition by treatment arm.

Figure I displays sample plants and ambient fine-particulate ($PM_{2.5}$) concentrations. The average pairwise distance between sample plants is 11 km, far below the dispersion of particulate matter from a high plant stack (Guttikunda, Nishadh, and Jawahar 2019). Since plants are close by, relative to how far pollution spreads, trade among nearby plants is unlikely to generate areas of locally increasing pollution. The ambient shading in the background shows that $PM_{2.5}$ concentrations in Surat are 10 to 20 times the WHO standard of 5 μg/m^3.

The experiment ran for 10 compliance periods over about one and a half calendar years. Online Appendix Table A1 shows the timeline. The first of two mock-compliance periods, meant to familiarize plants with trading, began on July 15, 2019. During mock periods, the market rules were the same as described above but plants were endowed with fake money. They were aware that the real market would start after the mock periods. Six real-compliance periods followed from September 16, 2019, to March 21, 2020.[15] Market operations were then suspended as part of a nationwide COVID-19 lockdown that closed all sample plants. The market restarted in December 2020, and we have data from four additional compliance periods up to when the second (Delta) wave of COVID hit in April, 2021.[16] The treatment thus spans roughly one year of market operations spread over one and a half calendar years.

15. The initial schedule envisaged periods starting on the first of the month, but the GPCB pushed it back by two weeks to allow plants more time to calibrate their CEMS devices.

16. The market restarted after the more severe Delta wave shutdowns. Several plants did not reopen immediately or reduced operating hours. Permit prices were correspondingly often at the floor. The GPCB began plans to expand coverage to the control and then implemented this expansion. For these reasons, we prefer not to use data after the Delta wave in our main analysis. We report results including these periods as a robustness check in Online Appendix F.5.

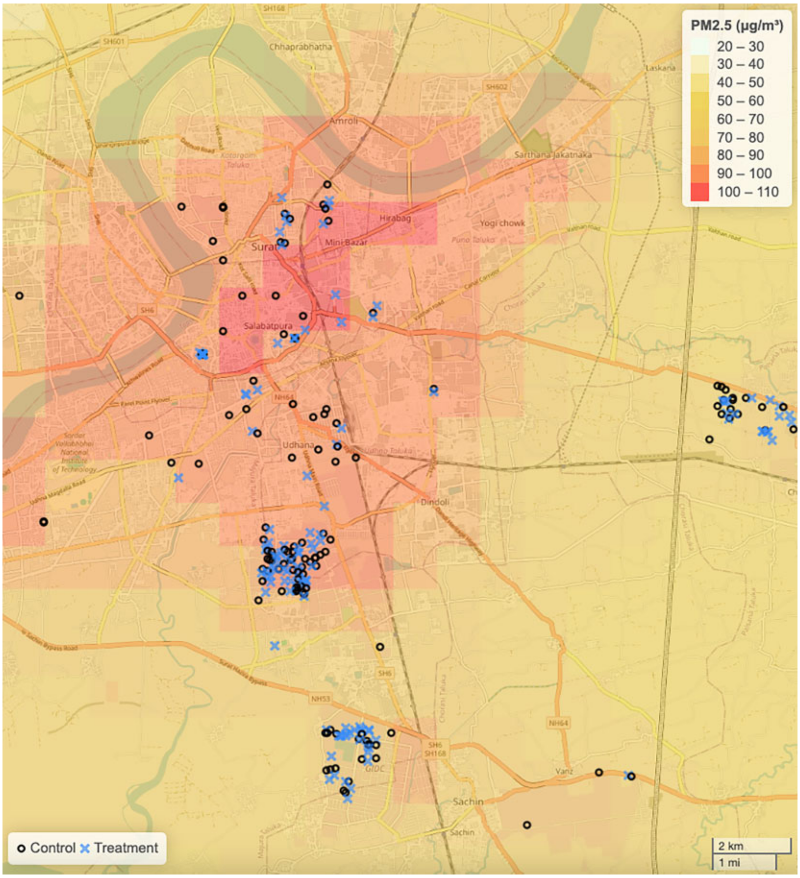

FIGURE I

Ambient Pollution Levels and the Location of Plants in Surat

The figure shows ambient $PM_{2.5}$ μg/m^3 concentrations in Surat, Gujarat averaged over 2018, overlaid with the locations of sample plants. The ambient pollution data is from Guttikunda, Nishadh, and Jawahar (2019). As a basis for comparison, India's National Ambient Air Quality Standard for $PM_{2.5}$ is 40 μg/m^3 and the WHO standard is 5 μg/m^3. The plant locations are geolocations from our plant survey. Treatment plants are represented by $\times$ markers and control plants by circles.

II.E. Data Sources

The article relies on three main sources of data.

1. *Pollution Measurement.* CEMS devices were installed in sample plants to provide high-frequency data on particulate mat-

ter (see Online Appendix C.1 for more information on CEMS). The CEMS devices themselves have no direct effect on emissions.[17] This finding may be surprising, because a lack of information is a major constraint on status quo regulation (Duflo et al. 2013, 2018). However, CEMS installation in the control group was not accompanied by any change in regulation, and existing regulations specify that only in-person samples are legally admissible as a basis for penalizing plants with high emissions. CEMS could therefore be used to direct or coordinate in-person visits but not to impose penalties. This regime is common to the CEMS installations in our experiment and the larger CPCB mandate of CEMS for select industries across India (see footnote 9).

To incentivize CEMS uptime, plants that failed to report CEMS data for any period of time had missing emissions data replaced according to a rule that became increasingly punitive as the share of data missing rose (see Online Appendix Table C2).[18] Emissions with this replacement for missing data were called "validated emissions" and used to calculate compliance. The replacement rule created stronger incentives for treatment plants to report data because not reporting meant plants would have higher emissions and need to buy more permits. For this reason, treatment plants reported data at higher rates throughout the experiment. CEMS data availability for control plants largely caught up in later compliance periods and average weekly data reporting rose to over 85% by the end of the sample (Online Appendix Figure C2).

We use different emissions imputation rules in our data analysis to try to form an unbiased, rather than a punitive, estimate of nonreported emissions.[19] Online Appendix C describes our treatment of missing data. There are two steps to imputing data at the plant-month level. First, we impute missing daily observations

17. The CEMS deployment was evaluated in a randomized control trial prior to the market launch. This trial shows that CEMS alone had no effect on plant pollution emissions (Online Appendix C).

18. Missing CEMS data might occur for different reasons including reasons outside plants' control, such as extended internet and electricity outages or device malfunctions. Replacement rules treated all missing data alike.

19. The emissions replacement rule for the market was designed to punish nonreporting plants by overestimating their emissions. Since control plants complied with CEMS requirements more slowly, using the market replacement rules for missing data in control plants in our analysis would increase control emissions and bias upward in magnitude the treatment effect on emissions.

within a week with the emissions rate from other days in that week or weeks in that month for the same plant. Second, we use several alternative rules, including no further imputation, to fill in plant-week observations when a plant does not report at any time during the week. These rules include using the emissions rate from the same plant at other times in the experiment (rule A) or the emissions of plants in the same treatment arm in the same month (rule B). Plant-weeks are summed in a month and in a plant to get plant-months (for plants with multiple stacks, all of the steps first happen at the stack level before aggregating across stacks to the plant level). We discuss the robustness of our estimated treatment effects on emissions to different imputation rules with the empirical results in Section IV.

2. *Trading Data.* Plants could trade on the platform of the market operator (NeML) via auction bids or over-the-counter trades. We observe initial allocations of permits to plants and data on the universe of plant bids, consisting of a price and quantity pair, irrespective of whether they resulted in a trade. For example, a plant willing to sell permits only at a very high price might submit a series of unfulfilled bids. With initial allocations and subsequent transactions we construct the full history of plant permit holdings and can observe, in particular, whether plants hold enough permits at the end of each compliance period to cover their emissions.

3. *Plant Surveys.* An in-person baseline plant survey was conducted from December 2018 to January 2019 and a phone-based endline survey wave in November 2020. The surveys had two parts, general and technical. The general part was administered to the plant owner or manager and covered economic variables like inputs, outputs, sales, and energy use. For the technical part, our team observed abatement equipment installed on every point source of emissions in the plant and recorded the characteristics of all emissions sources and abatement equipment. They also interviewed plant staff about costs of equipment operation. We use the baseline data to characterize status quo regulation and the endline data to investigate investments in abatement equipment and their cost.

II.F. Summary Statistics

Table I summarizes plant covariates at baseline by treatment arm. Sample plants are large factories with high energy and related input costs, though many are formally classified as "small scale," based on their capital stock at the plant's establishment. The average control plant spends US$350,000 a year on electricity (Panel A). The boiler, the plant's main pollution source, costs $112,000 annually to run, excluding fuel expenditures. The sample is balanced across a wide range of input, output, equipment, and pollution metrics.

The "command" portion of regulation works well: all plants have installed some air pollution control device (APCD). Table I, Panel B shows that 97% of control plants (98% of treatment) have a cyclone installed, 88% (80%) have a bag filter installed, 61% (64%) have a scrubber installed, and 8% (12%) have an electrostatic precipitator. Installation rates are inversely proportional to the cost and efficacy of abatement equipment. Cyclones are inexpensive but have a low efficacy, reducing PM emissions by 60%–90% and $PM_{2.5}$ by only 0%–40%. Larger plants with multiple emissions sources are mandated to install more expensive APCDs like scrubbers, which remove more than 95% of PM.

The "control" portion works less well, as many plants violate pollution standards. At baseline, pollution concentrations and mass rates are balanced across treatment arms (Table I, Panel C). PM concentration in stack gas average 169 mg/Nm^3 in the control group and 179 mg/Nm^3 in the treatment group. Both average emissions levels exceed the PM maximum standard of 150 mg/Nm^3. Roughly 30% of plants in both arms have pollution concentrations above the standard. The distribution of concentrations prior to the market's launch by treatment arm is shown in Online Appendix Figure B1.

Table II shows the evolution of bid counts, prices, and quantities. Table rows show statistics by compliance period and columns show the number, quantity, and price of bids submitted. The permit market was active from the start, with 1,525 bids, nearly 10 bids per treatment plant, submitted in the first compliance period, at a mean price of INR 12.70/kg (standard deviation INR 16.65/kg) (column (6)). Both the level and dispersion of bid prices fell after the first compliance period, up to the COVID lockdown after period 6, before rising again when the market reopened from

TABLE I

Balance of Plant Characteristics by Treatment Status

	Treatment (1)	Control (2)	Difference (3)
Panel A: Plant-scale measures			
Total electricity cost (US$1,000)	467.6	345.8	121.9
	[869.0]	[327.0]	(78.5)
Log(plant total heat output)	15.6	15.6	0.012
	[0.62]	[0.50]	(0.065)
Size as recorded on environment consent (1–3)	1.37	1.37	0.0052
	[0.64]	[0.62]	(0.075)
Small-scale (size = 1)	0.72	0.71	0.0063
	[0.45]	[0.46]	(0.054)
Large-scale (size = 3)	0.086	0.075	0.011
	[0.28]	[0.26]	(0.032)
Number of stacks	1.08	1.04	0.035
	[0.41]	[0.21]	(0.038)
Textiles sector (= 1)	0.85	0.87	−0.025
	[0.36]	[0.33]	(0.041)
Gross sales revenue in 2017 (US$1,000)	13,010.5	9,755.0	3,255.5
	[43,534.7]	[39,788.2]	(5,043.2)
Panel B: Plant abatement and investment cost			
Boiler-house employment	36.9	32.3	4.62
	[32.9]	[29.4]	(3.69)
Boiler-house capital expenditure (US$1,000)	199.9	171.4	28.5
	[405.0]	[196.6]	(38.3)
Boiler-house operating cost (US$1,000)	140.4	112.4	28.0
	[206.3]	[84.2]	(18.3)
APCD: cyclone present	0.98	0.97	0.0100
	[0.14]	[0.17]	(0.019)
APCD: bag filter present	0.80	0.88	−0.079*
	[0.40]	[0.33]	(0.043)
APCD: scrubber present	0.64	0.61	0.030
	[0.48]	[0.49]	(0.058)
APCD: ESP present	0.12	0.075	0.045
	[0.33]	[0.26]	(0.035)
Panel C: Plant pollution measures			
Plant total PM mass rate (kg/hr)	3.62	3.60	0.027
	[4.94]	[3.82]	(0.52)
Plant mean PM concentration (mg/Nm^3)	179.0	168.8	10.2
	[156.1]	[150.2]	(18.2)
Plant mean Ringelmann score (1–5)	1.37	1.35	0.017
	[0.43]	[0.37]	(0.047)
Above regulatory standard at ETS baseline (= 1)	0.34	0.28	0.054
	[0.47]	[0.45]	(0.055)
Number of plants	156	136	

Notes. This table shows differences in plant scale (Panel A), plant abatement and investment costs (Panel B), and plant pollution (Panel C) between the treatment and control groups of plants in the baseline survey conducted from December 2018 to January 2019. This sample consists of 292 plants that had at least one day of PM data from CEMS devices during the ETS experiment (see Online Appendix Table A4 for the same balance table in the full survey sample). In Panel B, cyclone, bag filter, scrubber, and electrostatic precipitator (ESP) are different air pollution control devices (APCDs). Some plants did not respond to some questions in the survey, and so certain variable rows have fewer observations than the full sample size. The first and second columns show means with standard deviations given in brackets. The third column shows the coefficients from regressions of each variable on treatment, with robust standard errors in parentheses. * $p < .10$; ** $p < .05$; *** $p < .01$.

TABLE II
SUMMARY OF PERMIT-BID DATA

Period	Count	Bids per plant	Bid quantities (kg)			Bid prices (INR/kg)		
			All bids	Buy bids	Sell bids	All bids	Buy bids	Sell bids
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	1,525	9.8	557	428	620	12.70	10.03	14.00
		(10.4)	(1,172)	(604)	(1,361)	(16.65)	(14.47)	(17.47)
2	600	3.9	474	475	474	7.90	6.39	8.43
		(4.1)	(747)	(535)	(810)	(10.72)	(9.16)	(11.18)
3	1,084	7.0	329	344	323	10.89	9.02	11.67
		(6.7)	(533)	(600)	(502)	(11.36)	(12.24)	(10.89)
4	806	5.2	323	332	319	10.88	7.90	12.03
		(6.1)	(551)	(483)	(575)	(9.37)	(6.77)	(9.96)
5	767	4.9	376	449	350	9.60	6.49	10.72
		(7.0)	(515)	(559)	(496)	(10.80)	(1.74)	(12.36)
6	296	1.9	463	533	426	7.50	5.84	8.38
		(3.2)	(558)	(559)	(556)	(6.33)	(3.11)	(7.34)
7	646	4.1	400	468	325	12.76	10.29	15.46
		(4.5)	(533)	(580)	(466)	(6.55)	(4.81)	(7.11)
8	783	5.0	418	501	249	13.51	12.56	15.47
		(6.4)	(588)	(671)	(298)	(13.92)	(16.53)	(4.96)
9	962	6.2	353	397	257	11.41	9.89	14.78
		(9.7)	(423)	(458)	(314)	(6.65)	(7.00)	(4.15)
10	964	6.2	383	428	336	11.18	8.40	14.04
		(8.8)	(533)	(532)	(531)	(9.10)	(5.65)	(10.92)
Total	8,433	54.1	412	430	399	11.25	9.47	12.52
		(51.0)	(708)	(565)	(795)	(11.56)	(10.50)	(12.10)

Notes. The table shows summary statistics on plant permits bids across all 10 compliance periods. Each row shows statistics for a separate compliance period. Each cell has the mean with the standard deviation below in parentheses. The columns show, respectively: (1) the total number of bids in each period; (2) the mean number of bids placed per plant ($N = 156$); (3)–(5) mean quantities for all bids, buy bids, and sell bids; (6)–(8) mean prices for all bids, buy bids, and sell bids. Data source. Market operator NeML.

period 7 onward. Plants were active on the buy and sell sides of the market. The average bid size of 412 kg, across all compliance periods (column (3)), can be compared with average emissions of roughly 1,000 kg per plant-month. The bidding activity volume is large, especially since permits equaling 80% of the overall market cap were allocated to plants before the first auction.

III. Trade and Compliance in the Emissions Market

Emission-market analysis often assumes compliance with market rules, particularly the key rule that plants must hold permits for each unit of emissions. This assumption may fail in low-state-capacity environments such as India where noncompliance is widespread in the status quo regime. It is therefore important to demonstrate that the emissions market functioned, for the policy reason of validating that an emissions market can work in this setting and to understand the first stage for our analysis of how the market affects emissions and costs. We provide a descriptive analysis of the treatment market, demonstrating that (i) trade was vigorous; (ii) final permit holdings differed from initial allocations, consistent with unobservable cost heterogeneity; and (iii) plants complied with the permit holding rule almost perfectly.

III.A. Permit Trade

Figure II shows the weekly time series of permit prices (Panel A) and quantities traded (Panel B). The scattered data points show the weekly mean permit bid. Panel A's solid line reflects weekly clearing prices, which vary between blue (gray; color version available online) and black to indicate the change in permit vintage with each compliance period. The market rules deliberately reduced price volatility by constraining over-the-counter trades to occur at prices revealed by weekly auctions (Section II.C). The red dashed line represents the price floor of INR 5/kg.

Market-clearing prices range from the price floor of INR 5/kg to INR 16/kg depending on the compliance period and the particular week. Prices were generally lower in the pre-Covid-interruption compliance periods (1–6), when the cap was looser, and higher once the market resumed. In several compliance periods, for example periods 9 and 10, prices are moderately high during the compliance period but plummet during the true-up pe-

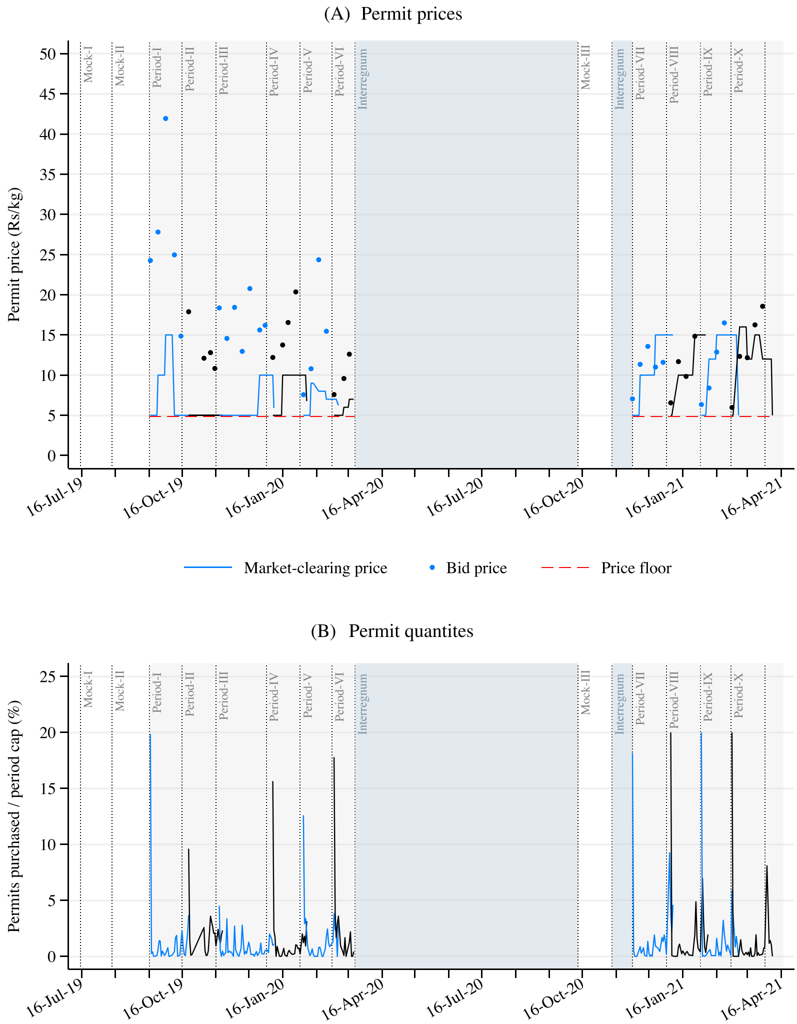

FIGURE II

Permit Prices and Quantities by Compliance Period

This figure shows weekly permit prices (Panel A) and quantities (Panel B) from September 2019 to April 2021. In Panel A, the scattered points are the mean bid prices (both sale and purchase) and the solid lines are the market-clearing price. Since permits of different vintages, from two consecutive compliance periods, are traded simultaneously on some days, the market-clearing price line alternates between black and blue (color version available online) to differentiate them. The dashed red horizontal line shows the price floor at INR 5/kg. In Panel B, quantities are expressed as a percentage of the period emissions cap. The large spike near the start of each compliance period is the weekly auction held on the first Tuesday of the compliance period.

riod, when emissions are known with certainty.[20] Prices generally rise in a compliance period after the regulator sells many permits at the floor price in the first week.[21] Mean bid prices were substantially higher than the market-clearing price in the early periods, but this difference declined over time, consistent with market participants learning that the costs of emissions reductions were lower than initially expected. A similar pattern of declining trading prices was observed at the start of the U.S. Acid Rain Program market for sulfur dioxide (Schmalensee et al. 1998).

Panel B plots daily permit quantities traded as a fraction of the compliance-period cap. The double-sided auction on the first Tuesday of a compliance period typically causes a spike in quantity. Overall trade volume is significant, reaching up to 20% of the monthly cap, or more, on some days. Trade volumes are higher during the first part of a compliance period as plants buy or sell permits to align permit holdings with expected emissions. As plants' uncertainty about total emissions for the period diminishes, toward the end of the period, so do trade volumes.

III.B. Permit Allocations

In the Surat market, permits totaling 80% of the cap were allocated pro rata based on a plant's total heat capacity, the regulator's best ex ante measure of emissions capacity. If there is unobserved heterogeneity in costs across plants, plants should trade away from their initial allocations depending on underlying abatement costs. To test this idea, Figure III plots the distribution

20. This price behavior is consistent with uncertainty, prior to the end of the compliance period, as to whether the market would be short or long on permits in aggregate. After the market closes and this uncertainty is resolved, prices should converge to the ceiling, if the market is short and firms face noncompliance penalties, or to the floor, if the market is long and excess permits will be sold back to the regulator. The market-clearing mechanism of a single auction after the close of the compliance period may mute this end-of-period price volatility.

21. This pattern may be surprising because, in principle, plants could arbitrage price differences in a period by buying permits earlier and selling any excess at the floor price at the end of the compliance period without risk. The simplest explanation for why plants do not exploit this arbitrage is that the potential arbitrage profits are constrained by tight holding limits (see footnote 12). We note that the average bid prices in the first week of the compliance period are well above the floor price, though the market-clearing price typically remains at the floor. In addition, in interviews about their trading strategies, a couple of plants mentioned that they are endowed with a free allocation of permits and they do not look to buy until they consume part of this endowment.

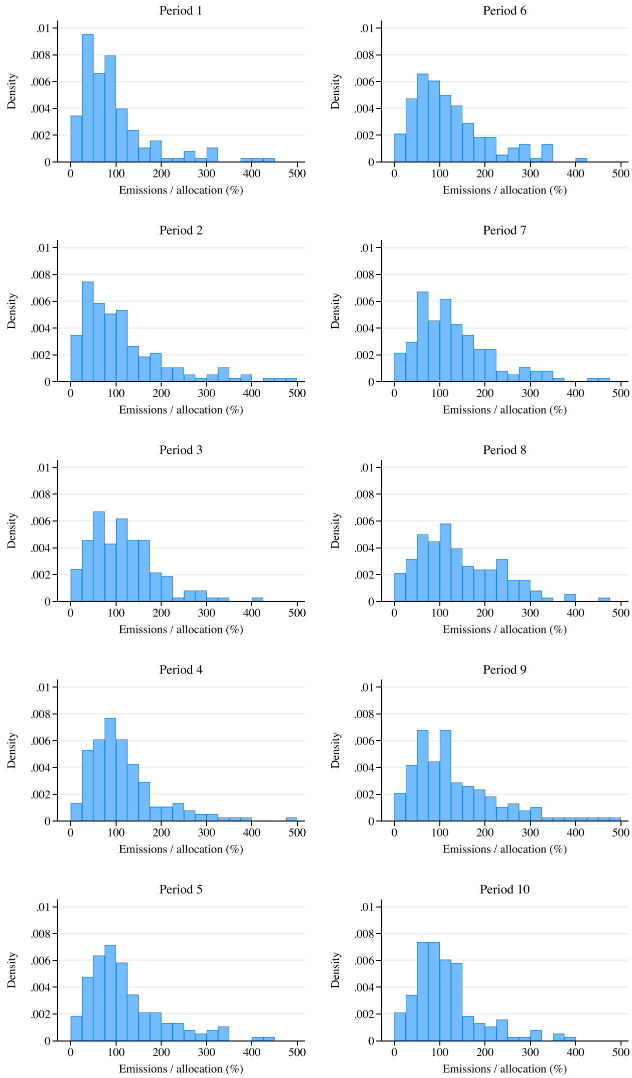

FIGURE III

Distribution of Emissions over Initial Permit Allocation by Compliance Period

This figure plots the distributions of $\frac{\text{emissions}}{\text{initial permit allocation}} \times 100\%$ across treated plants ($N = 156$) by compliance period, truncated at the 97.5th percentile. Emissions data and permit holdings are from the administrative records of the market operator. Emissions are the validated emissions for each plant, which include any imputed emissions filled-in for periods of missing data. These validated emissions are used to determine compliance.

of plant emissions as a percentage of their initial permit allocation in each compliance period. Plants that emit exactly what they were allocated appear at 100%, and plants that emit twice what they were allocated appear at 200%. Because only 80% of the total cap is freely allocated per period, with the rest auctioned, we expect that emissions as a percentage of the initial allocation will equal 125%, unless the price hits the floor or ceiling.

In every compliance period, emissions are widely dispersed with respect to initial permit allocations. Most plants fall between 50% and 200% of their initial allocation, with the relatively modest share between 100% and 125% revealing that a significant number of plants became substantial net buyers or sellers of permits. This dispersion indicates that the market meets two criteria: (i) low transaction costs, as plants are unconstrained by initial permit allocations and trade to adjust permit holdings; and (ii) unobserved heterogeneity among plants, since the heat capacity on which initial allocations are based turns out to be a noisy proxy for ultimate emissions. Differences across plants in capacity utilization, emissions rates, and marginal abatement costs may all contribute to dispersion relative to the capacity-based measure used for permit allocation.

III.C. Compliance with Market Rules

Figure IV plots the distribution of emissions across plants as a fraction of permit holdings at the end of the 10 true-up periods that followed the compliance periods (rather than emissions as a fraction of initial allocations, as shown in Figure III). Any plant that emits more than its final permit holdings (i.e., more than 100% in the figure) is noncompliant. Plants that emit less than their permit holdings (i.e., less than 100%), on the other hand, "leave money on the table" by not selling their excess permits to other plants or back to the regulator at the floor price.

Compliance, defined as emissions during the compliance period being equal to or less than permit holdings at the end of the true-up period, is nearly perfect. Across all panels, plants hold enough permits to cover their emissions in 99% of plant-periods. We observe only a few scattered noncompliant plants (see periods 1, 3, and 8).[22] By contrast, only 66% of treatment plants

22. The permit holdings in Figure IV and our calculations of compliance include permits that GPCB gave to plants in period 7 during the compliance period and above their typical allocations. Period 7 was the initial post-COVID-lockdown

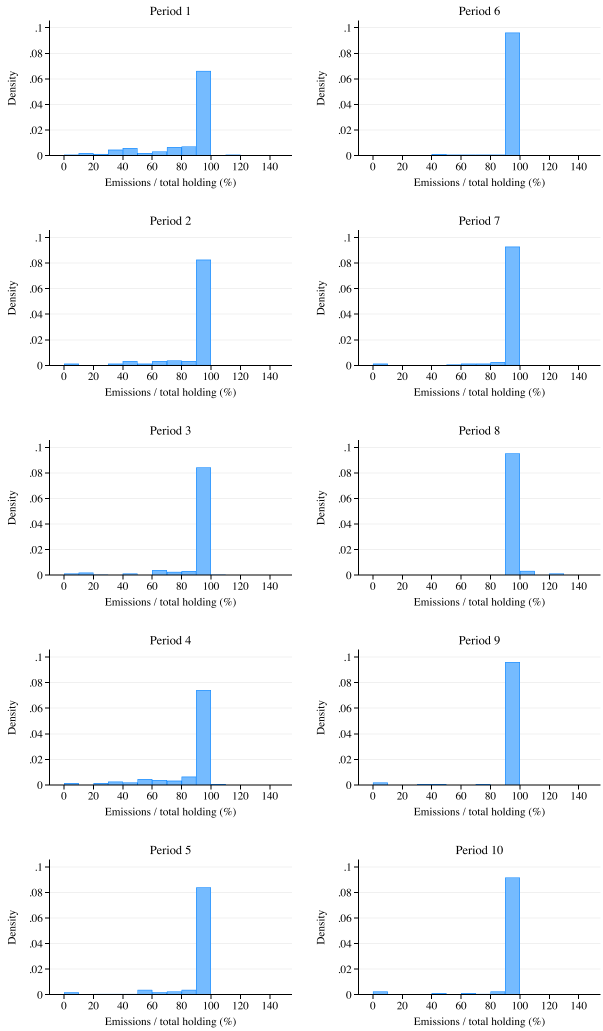

FIGURE IV

Distribution of Emissions over Final Permit Holdings by Compliance Period

This figure plots the distributions of $\frac{\text{emissions}}{\text{final permit holdings}} \times 100\%$ across treated plants ($N = 156$) by compliance period, truncated at the 99.5th percentile. Final permit holdings are the total number of permits a plant held at the end of the true-up period after each compliance period. Emissions data and permit holdings are from the administrative records of the market operator. Emissions are the validated emissions for each plant, which include any imputed emissions filled-in for periods of missing data. These validated emissions are used to determine compliance.

and 72% of control plants were in compliance with concentration standards at baseline (see Online Appendix Figure B1). We believe compliance was high in the market because the regulator established that violators would be penalized immediately and a nondiscretionary rule for fines proportional to permit shortfalls made strict enforcement credible.[23] Plant compliance in the market is an endogenous outcome reflecting a new regulatory regime with rule-based fines. In the status quo, regulators could impose severe penalties, up to closing a plant down. However, the most severe penalties were costly to impose, seldom and unpredictably applied, and did not scale smoothly with the magnitude of a violation (Duflo et al. 2018).

Last, plants did not leave much money on the table. The mass in the histograms is stacked at 100%; the vast majority of plants hold permits that exactly equal or only slightly exceed their total emissions at the end of each period. Looking down the first column of distributions and then down the second, we can see that more plants left money on the table in early compliance periods, when market participants had limited experience and the clearing price was relatively low. In later compliance periods almost all plants hold only the permits they need to cover their emissions.[24]

period, and many plants were not operating but had high imputed emissions. These plants petitioned GPCB that because they were closed they should not be imputed at high rates, and GPCB accepted this argument by adjusting their permit holdings to cover the imputed emissions. We include the adjusted permits in our baseline calculation of compliance because GPCB authorized them. Without these adjustments, 37 plants would have been noncompliant (on the basis of imputed emissions) in period 7. Online Appendix Figure F3 repeats Figure IV deducting these permit adjustments from plants' holdings. We find that plants comply in 97% of plant-periods, instead of 99%, without these adjustments.

23. Emissions for two plants exceeded permit holdings during the initial compliance period. Plant A emitted 3,928 kg against permit holdings of 3,456 kg and Plant B emitted 4,716 kg against permit holdings of 1,456 kg. These plants were levied EDCD in accordance with market rules. Plant A paid the EDCD and then topped up their environmental bond. Plant B failed to post the required bond, and the regulator ordered plant closure. Plant B posted a bond and paid a penalty of INR 652,000, more than 10 times the cost to buy permits on the market to cover emissions in the period. The regulator allowed the plant to reopen after two weeks.

24. On average across all compliance periods, plants consumed 95% of their permits and 78% of plants held permits, at the end of the period, exactly equal to their emissions (down to the last kilogram). The share of plants holding exactly the permits they needed rose from 51% in the first period to 91% and 84% in the

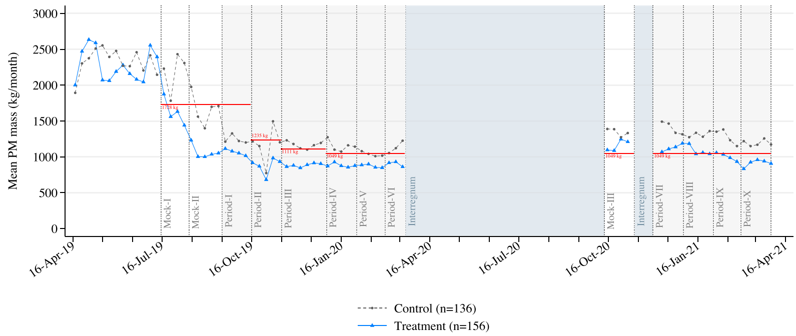

FIGURE V

PM Emissions by Treatment Status

The figure shows the weekly mean plant PM emissions in kilograms (calculated at a monthly rate equivalent) from April 2019 to March 2021 by treatment status. The treatment group is represented by the solid blue line (triangles; color version available online) and the control group by the dashed gray line (circles). The light gray regions mark the 10 compliance periods in the emissions market. The blue (darker gray) regions mark interregnum periods when the emissions market was closed. The horizontal solid red lines denote the market cap for each period expressed per plant-month. The aggregate market caps for each compliance period were: 280 tons per 30 days (for Mock-I, Mock-II, and Period-I), 200 tons per 30 days (for Period-II), 180 tons per 30 days (for Period-III), and 170 tons per 30 days thereafter. Pollution reporting over this period was incomplete and rising from early to late compliance periods (see Online Appendix Figure C2). Missing pollution readings are imputed within a stack-week and then within a stack-month (Online Appendix C.1). The sample consists of 292 plants that had at least one day of PM data from CEMS devices during the ETS experiment.

The precision of permit holdings suggests that plants understood the incentives for permit trade and that transaction costs in the market were low.

IV. EXPERIMENTAL RESULTS ON POLLUTION EMISSIONS

We exploit the randomized assignment of plants to treatment to evaluate if the emissions market reduced pollution emissions. Figure V displays weekly mean emissions per plant in kilograms per month, from April 2019 to April 2021, by treatment arm. The

last two, respectively, and the fraction of permits consumed rose from 87% in the first period to 97% and 95% in the last two.

solid blue (triangles) and dashed gray (circles) lines represent treatment and control plants, respectively. Vertical lines separate market compliance periods. The COVID-19 lockdown, denoted interregnum on the figure, is shaded in blue (darker gray) and divides the sample into early (1–6) and late (7–10) compliance periods.

We include pre-experiment data in Figure V, despite poor data reporting at the time. The time pattern of reporting rates for treatment and control groups, depicted in Online Appendix Figure C2, explains the apparent drop in monthly mean emissions in treatment and control groups before the experiment. Initial reporting is low and concentrated among larger plants, while treatment plants report more than control plants. As data reporting increased, smaller plants began reporting, lowering average emissions for reporting plants. Control-plant reporting also rose such that the treatment-control gap in reporting narrowed to a few percentage points by the end of the experimental period. As described in Section II.E, the main pollution series in Figure V imputes missing plant emissions using observations from the same week or month for the same plant.

Figure V yields two findings. First, treatment plants largely followed the market rules and emissions therefore met or nearly met the cap in all compliance periods, in contrast to the poor compliance with the concentration standard in the status quo. We plot the mean emissions per plant required to meet the cap exactly with red horizontal lines. In later periods, the cap is roughly 1,000 kg (1 metric ton) of PM per plant-month. All compliance periods have mean treatment emissions, shown by the solid blue line, near or below this level, sometimes substantially below (around the Diwali holiday, in November, many plants briefly cease operations and emissions fall). Aggregate emissions exceeded the cap by 3% in period 8, and plants were penalized for excess emissions in accord with the market rules. The seeming overcompliance in early compliance periods reflects the market replacement rule for missing data (Online Appendix Table C2).[25]

25. We are plotting mean emissions with imputations at the plant mean in nearby periods; for the purpose of market operations, missing emissions are replaced with a rule that fills in punitively high values, meant to deter nonreporting. With these higher imputations for missing data the cap binds more or less exactly (as implied by Figure IV).

Second, pollution emissions are consistently lower in the treatment than in the control group. By the start of compliance period 1, in September 2019, treatment plants emit roughly 300 kg/month less PM than control plants. The treatment-induced gap in average emissions remains throughout despite marked increases in control-plant reporting. We use a regression analysis at the plant-month level to estimate the treatment-effect size:

$$\log(Pollution_{it}) = \beta_1 Treatment_i + X_i'\beta_2 + \alpha_t + \epsilon_{it}. \tag{1}$$

$Pollution_{it}$ is the mass of plant-month PM emissions in kg, $Treatment_i$ is an indicator variable equal to one for plants assigned to the emissions-market treatment, α_t are year-month fixed effects, and X_i are plant characteristics including capital expenditure, operating cost, log of total heat output, and boiler installation year. We restrict the data to the period when the experiment was running, when reporting was highest, and report the robustness of our estimates to alternative imputation rules for missing emissions (see also Online Appendix C). Standard errors are clustered at the plant level.

Table III reports the results. Columns (1) to (4) use pollution series that do not impute across plant-months and therefore drop plant-months with no data. Columns (1) and (2) report unweighted regressions. To capture treatment effects on the full plant sample, the column (3) and (4) regressions are reweighted by the inverse probability of a plant reporting emissions (DiNardo, Fortin, and Lemieux 1996), where we use baseline observable characteristics to predict a plant's reporting probability. Columns (5) to (8) report specifications that impute missing pollution observations using two different imputation rules (see Online Appendix C). Briefly, rule A, in columns (5) and (6), imputes a stack missing emissions in a given month at its mean emissions from other months in the experiment. Rule B, in columns (7) and (8), imputes a stack at the monthly mean emissions load of its own treatment group for the same month. Even-numbered columns include year-month fixed effects and odd-numbered columns do not.

The market treatment significantly reduced PM emissions. Without imputation and reweighting, column (2) reports a treatment effect on log emissions of −0.193 log points (std. err. 0.076 log points). Reweighting gives very similar estimates (column (4)). The treatment effect on pollution is larger with either imputa-

TABLE III

TREATMENT EFFECTS ON PM EMISSIONS (LOG(PM MASS/MONTH))

	No imputed months				Imputed months			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETS treatment (= 1)	−0.178**	−0.193**	−0.177**	−0.194**	−0.282***	−0.282***	−0.316***	−0.316***
	(0.076)	(0.076)	(0.075)	(0.075)	(0.074)	(0.075)	(0.057)	(0.057)
Year-month fixed effects		Yes		Yes		Yes		Yes
Imputation rule					Rule A	Rule A	Rule B	Rule B
Reweighted			Yes	Yes				
Mean dep. var (control)	6.67	6.67	6.66	6.66	6.80	6.80	6.88	6.88
R^2	0.13	0.17	0.14	0.17	0.18	0.22	0.16	0.25
Plants	292	292	292	292	292	292	292	292
Observations	3,235	3,235	3,235	3,235	3,796	3,796	3,796	3,796

Notes. This table reports the estimated treatment effects on PM emissions. The outcome variable is the log of plant-level PM mass (kg) per month. A detailed note on the construction of the outcome variable is in Online Appendix C.1. Columns (5) and (6) impute data with Imputation Rule A: Stack-Experiment. Under this rule, missing values of a stack's daily PM mass rate are imputed using the stack's mean PM mass rate across the experiment (July 2019–March 2021, excluding the interregnum). Columns (7) and (8) impute data with Imputation Rule B: Treatment-Month. Under this rule, missing values of a stack's daily PM mass rate are imputed using the monthly mean PM mass rate of the stack's treatment group. All columns control for plant characteristics including capital expenditure, operating cost, log(total heat output), mean boiler installation year, and their corresponding indicators for missing values. In addition to plant controls, columns (2), (4), (6), and (8) add year-month fixed effects to control for time-varying differences common in each plant. We apply the inverse probability weighting method in columns (3) and (4). The probability of reporting in a month is predicted using a probit model where the only explanatory variable is an indicator variable for the treatment status in a prior experiment that randomized CEMS installation timing. Robust standard errors in parentheses are clustered at the plant level. * $p < .10$; ** $p < .05$; *** $p < .01$.

tion rule than with the raw data (columns (5)–(8) compared with columns (1)–(4)). The treatment effect on pollution is −0.282 log points (std. err. 0.074 log points) for rule A and −0.316 log points (std. err. 0.057 log points) for rule B. Imputing missing data increases the magnitude of treatment effects because imputations tend to replace missing control observations for log particulate emissions with values higher than the mean among reporting control plants. Thus using imputed control-plant emissions raises control emissions and the estimated difference between treatment and control emissions.[26] Online Appendix F.5 shows that the results are also robust to subsetting the sample to only include data either before or after the COVID lockdown.[27]

A natural next question is the impact of the market treatment on plant abatement costs. There are two challenges to comparing costs across treatment arms. First, the lower emissions in the treatment group mean that a comparison of costs across arms will not isolate the effect of the emissions market on costs holding constant the level of emissions. Second, permit market bids are the best measure of marginal costs, but they are only available in the treatment group, because only the treatment group participated in the market. For these reasons, we introduce a revealed-preference approach based on permit bidding data to estimate marginal abatement cost functions. We describe how these functions can be used to evaluate costs for any distribution of emissions, and therefore to compare costs across treatment arms holding emissions constant.

26. In Online Appendix Table C4, we perform a bounding analysis of the treatment effect on pollution that allows for differential imputation rules by treatment arm. This analysis is relevant because treatment and control plants have different incentives to pollute on days when they are not reporting pollution data, though, given the lack of data on these days, we cannot test for such differential polluting behavior directly. We find that given relatively low rates of missing data in the treatment, emissions at treatment plants have to be imputed at a much higher rate than emissions at control plants to meaningfully reduce the estimated treatment effect on emissions.

27. In specifications without imputation or with imputation rule A, there is no statistically significant difference in the treatment effect before and after the lockdown. In specifications with imputation rule B, the treatment effect is statistically smaller in magnitude (less negative) after the lockdown but remains large, negative, and statistically significantly different from zero.

V. Estimating Marginal Abatement Cost Curves

Marginal abatement cost (MAC) curves are the key to measuring the costs of virtually any environmental regulation. With MAC curves, one can evaluate marginal costs for any policy that implies an allocation of emissions to different plants, or integrate these functions to recover the variable costs for any proposed emissions reduction. Although MAC curves are the theoretical foundation for the study of regulation, they are not observable, which makes it difficult to apply these ideas.

We address this problem by using our extraordinarily rich bid data to estimate plants' MAC curves. We outline the two assumptions needed to interpret plants' emissions market bids as measures of their marginal abatement costs and describe how we estimate MAC curves using bidding data. We present the results, emphasizing the heterogeneity in estimated MACs across treatment plants. We argue that the distribution of MAC curves in the treatment group represents the distribution in the control group and can be used to compare abatement costs across these regimes.

V.A. Emission-Market Bids as Measures of Marginal Abatement Costs

We start with the two assumptions required to interpret plant permit bids as observations of marginal abatement cost. The first assumption is that each plant i seeks to minimize its compliance costs in a given period by solving

$$\min_{E_i} \; Z_{i0} + Z_i(E_i) + P(E_i - A_i), \tag{2}$$

where E_i is the plant's choice of emissions, Z_{i0} is the fixed cost of abatement, $Z_i(\cdot)$ gives variable abatement expenditures as a function of emissions, P is the equilibrium permit price, known to the plant, and A_i is the regulator's free allocation of permits to the plant. The substance of this cost-minimization assumption is that plants trade off their in-house emissions abatement with the purchase of permits to lower compliance costs.

Variable abatement costs $Z_i(\cdot)$ include costs associated with running pollution abatement equipment more frequently, changing inputs like filters or chemicals more often, or devoting more labor to operation and maintenance of machines. We expect that $Z_i' < 0$ and $Z_i'' > 0$; abatement expenditures decrease as emissions increase but at a rate that decreases in magnitude as emissions grow. (Equivalently, marginal costs of abatement are increasing in abatement.) Plants are already mandated to install pollution abatement equipment in the status quo, incurring a fixed cost Z_{i0} (see Table I, Panel B). We document in Section V.B that these fixed expenditures do not change in response to the emissions-market treatment.

The second assumption is that plants are price-takers in the market for permits. This assumption is appropriate in our setting because no plant holds a large share of the permit market. For example, the 90th, 95th, and 99th percentiles of plant permit allocations as a share of the emissions market cap are 0.6%, 0.9%, and 4.5%, respectively. Market rules also imposed holding limits to prevent speculative price manipulation (see footnote 12). Under this assumption, the solution to expression (2) satisfies the first-order condition

$$-\frac{\partial Z_i(E_i)}{\partial E_i} \equiv MAC(E_i) = P. \tag{3}$$

This is the familiar condition that the plant's marginal abatement costs at a given level of emissions equal the permit price. This condition holds regardless of the plant's fixed abatement costs Z_{i0} and initial permit allocation A_i. Therefore, under the two assumptions of cost minimization and no market power for permits, plant marginal costs of abatement, which are not observable, equal their permit bids, which we record in our data. Equation (3) therefore provides a basis for estimating MAC curves.

V.B. Marginal Abatement Cost Curve Estimation

We use permit-bid data from treatment plants, participating in the emissions market, to estimate plants' MAC functions. Bids vary across the 10 compliance periods and within each period, because most plants submit multiple bids per period (see Table II, column (2), and Online Appendix Figure B2). Our main specification is an iso-elastic MAC curve that allows for higher or lower cost functions for each plant-period:

$$\log b_{itk} = \beta_1 \log E_{itk} + \xi_{it} + \epsilon_{itk}. \tag{4}$$

The dependent variable is the log of plant i's bid number k in period t, our measure of plant marginal abatement cost at a given emissions level. The main explanatory variable $\log E_{itk}$ is the log of the implied plant emissions if bid k in period t were to be executed.[28] The error consists of a plant-period effect ξ_{it} and an idiosyncratic term ϵ_{itk} that we discuss below. We vary specification (4) by both (i) using plants' observable characteristics or plant fixed effects in place of plant-period effects and (ii) allowing heterogeneity in β_1 for plants with different observable characteristics. We discuss these variants with the estimates and focus on this main specification here.

The main parameter of interest is β_1, the elasticity of marginal abatement costs with respect to emissions. We expect that marginal abatement costs are decreasing in emissions (increasing in abatement) such that $\beta_1 < 0$. The main challenge in estimating the abatement cost elasticity, in general, is that a plant's chosen emissions level E_{it} will be endogenous to abatement cost shocks. If plants with high abatement costs at a given time choose higher emissions levels, then the estimated abatement elasticity would be biased upward ($\hat{\beta}_1 > \beta_1$).

Our specification addresses this challenge and allows for unbiased estimation of β_1 via OLS using variation in bids within a plant-period. This assumes that variation in $\log E_{itk}$ within a period reflects plant bids at different points along their MAC curve, up to an idiosyncratic error. Formally, this assumption is the familiar one of mean conditional exogeneity $\mathbb{E}[\epsilon_{itk}|E_{itk}, \xi_{it}] = 0$. Although plants almost certainly emit more when they face a high abatement-cost shock (e.g., due to a positive demand shock), we find it plausible that they do not adjust emission levels to cost shocks at high frequency. For example, a plant cannot change its set production schedule in a week simply because of higher than expected ash content of its fuel supply.[29]

28. Practically, we calculate the emissions associated with a bid as the plant's permit holdings if that bid were executed, because, given near-perfect compliance, emissions are equivalent to permit holdings in the market. For example, if a plant is first allocated A_{it} = 1,500 kg of permits, and then with bid $k = 1$ seeks to buy 500 kg of permits, $E_{it,k=1}$ = 1,500 + 500 = 2,000 is the sum of the initial allocation and the amount the bid seeks to buy. Generically, let $\mathcal{K}(k) = \{k' : k' < k, k' \text{executed}\}$ be the set of bids already executed at the time k is offered. Then $E_{itk} = A_{it} + \sum_{k' \in \mathcal{K}(k)} B_{itk'} + B_{itk}$, where buy bids are represented as positive quantities B and sell bids with negative quantities.

29. One formal economic justification for this identifying assumption is that plants form unbiased expectations of their emissions, and therefore marginal costs, at the time of bidding, but are uncertain about later shocks and therefore their exact emissions level and marginal cost. For example, assume plants anticipate emissions $\widetilde{E}_{itk} = E_{it}\nu_{itk}$ with $\nu_{itk} \perp E_{itk}, \xi_{it}$ and $\mathbb{E}[\log \nu_{itk}] = 0$. Plants bid-

To align the data with the time horizon of plant abatement choices we estimate equation (4) in a restricted sample of bids from only the first half of each compliance period while exploring estimates in other samples.[30] In our model, plants choose whether to comply by reducing emissions or buying permits, which is a good characterization of decisions in the early portion of a compliance period. As the end of a period approaches, however, plants no longer face the same trade-off, as within-period plant emissions are largely sunk. At the extreme, after the compliance period has ended and the true-up period begins, emissions are fixed, so we expect plant demand for permits to be inelastic and bids no longer to reflect marginal abatement costs.

1. *Alternative Step Function Marginal Abatement Cost Functions.* Equation (4) specifies a smooth, iso-elastic marginal cost function. This functional form may not represent plants' underlying technology, and therefore marginal costs at emissions levels far from those at which plants bid in the data. A simple engineering model of abatement would specify that each piece of capital abatement equipment can abate some fraction of emissions at a fixed marginal cost, beyond which a more expensive piece of equipment must be used. Our data include the type and specifications of abatement equipment in each plant, allowing us to consider this alternative functional form for MAC curves. Online Appendix E provides a step function abatement-cost model based on technologies available to the plants and describes how we use bid data to estimate the height of the steps. We compare the fit of this alternative model to our main specification in Section VI.A.

V.C. Marginal Abatement Cost Function Estimates

1. *Elasticity of Abatement Cost with Respect to Emissions.* Table IV reports β_1, the estimated MAC elasticity for plant emis-

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ding their expected marginal costs will then yield specification (4) with a residual $\epsilon_{itk} = \beta_1 \log \nu_{itk}$ based on the forecast error.

30. This strategy of restricting the sample to the first half of compliance periods is feasible because 3,120 out of the 8,433 total bids were submitted in the first half of a period, and 2,775 were offered by plants that submitted multiple bids in that time. Variation in bids to estimate β_1 within a plant-period comes from plants making multiple bids in the first half of a compliance period. There are a total of 1,560 (= 156 plants $\times$ 10 compliance periods) plant-by-period cells and in 1,140 of these cells plants made more than one bid.

TABLE IV

ELASTICITY OF MARGINAL COST WITH RESPECT TO EMISSIONS

	log(Bid price)				
	(1)	(2)	(3)	(4)	(5)
log(Emissions as bid)	−0.100	−0.143**	−0.269***	−0.609***	
	(0.061)	(0.063)	(0.084)	(0.087)	
log(Emissions as bid) × cyclone/bag filter					−0.707***
					(0.169)
log(Emissions as bid) × scrubber/ESP					−0.566***
					(0.095)
log(Plant total heat output)	0.087**	0.138***			
	(0.041)	(0.048)			
Period fixed effects		Yes	Yes		
Plant fixed effects			Yes		
Plant × period fixed effects				Yes	Yes
p-val: H_0: No unobserved heterogeneity				.000	.000
p-val: H_0: No observed heterogeneity					.468
R^2	0.01	0.07	0.26	0.46	0.46
Plants	146	146	146	146	142
Observations	3,120	3,120	3,120	3,120	3,082

Notes. This table reports the results of regressing log(*bid price*) on log(*emissions as bid*). *Emissions as bid* is defined as the permit holdings that will result if the bid is executed. We run regressions using bids placed in the first half of a compliance period. We include compliance-period fixed effects in columns (2) and (3), plant fixed effects in column (3), and plant × period fixed effects in columns (4) and (5). In column (5), the interacted variables *cyclone / bag filter* and *scrubber / ESP* are indicators of the “maximal” (most effective) abatement technology. If a plant has only cyclones or bag filters, then cyclone/bag filter = 1 and scrubber/ESP = 0. If a plant has scrubbers or ESPs, then scrubber/ESP = 1 and cyclone/bag filter = 0. p-values are reported for two tests of heterogeneity in MACs. The first p-value is for a Hausman test comparing the plant-by-period fixed-effects model against a model with plant-by-period random effects instead. The second p-value is for a test that the coefficient of log(*emissions as bid*) × *cyclone / bag filter* is equal to that of log(*emissions as bid*) × *scrubber / ESP*. To avoid biasing standard errors, singleton fixed effects are dropped during estimation, and as a result the elasticity estimates in columns (4) and (5) are based on 2,775 and 2,753 non-singleton bids, respectively, though in the table we list the full set of bids and plants for which we have data. Robust standard errors in parentheses are clustered at the plant level. * $p < .10$; ** $p < .05$; *** $p < .01$.

sions, using alternative specifications of equation (4). Column (1) reports a specification that controls for only plant heat capacity, the relevant measure of plant scale for emissions, analogous to the horsepower of a car engine. Columns (2) and (3) report specifications with period fixed effects and plant and period fixed effects, respectively, which absorb all time-invariant plant characteristics such as heat capacity. Column (4) reports our preferred specification (4) with plant-by-period fixed effects that nonparametrically control for all plant-period abatement cost shocks. In column (5), we allow the coefficient β_1 to vary with the type of air pollution control devices (APCDs) that the plant has installed at baseline.

Our preferred estimate in column (4) reports an elasticity of bid prices (MAC) with respect to emissions of -0.609 (std. err. 0.087). This estimate validates the standard intuition that marginal costs of abatement fall as emissions rise (e.g., marginal costs are increasing in abatement). A comparison of the column (4) estimate to those in columns (1)–(3) demonstrates the importance of using within-period data to estimate this elasticity. Estimates with basic controls or only period fixed effects are positively biased (columns (1) and (2)) toward zero. Even with plant and period fixed effects (column (3)), the elasticity is less than half the magnitude of our preferred estimate. The upward bias in these estimates suggests that plant emissions are endogenous to cost shocks: plants choose to emit more when they have a high plant-period shock to marginal abatement costs. In column (5) we relax the assumption of a common elasticity of abatement across plants. We find that the MAC curve is slightly more elastic (in absolute terms) for plants which installed the less expensive APCDs (cyclones and bag filters versus scrubbers and ESPs), but that this difference is quantitatively small and not statistically significant.

Three additional pieces of evidence support our preference for the Table IV, column (4) specification. First, the iso-elastic MAC curve fits the bid data well. Figure VI plots log bid prices, after residualizing on plant-period fixed effects, against log plant emissions. Bid prices (marginal costs) rise at lower levels of emissions. The line of best fit corresponds to the constant elasticity of marginal abatement costs with respect to emissions $\hat{\beta}_1 = -0.609$ estimated in Table IV, column (4). The figure shows that there is wide variation in log emissions and that the fit of the iso-elastic MAC curve is quite good across this wide range.

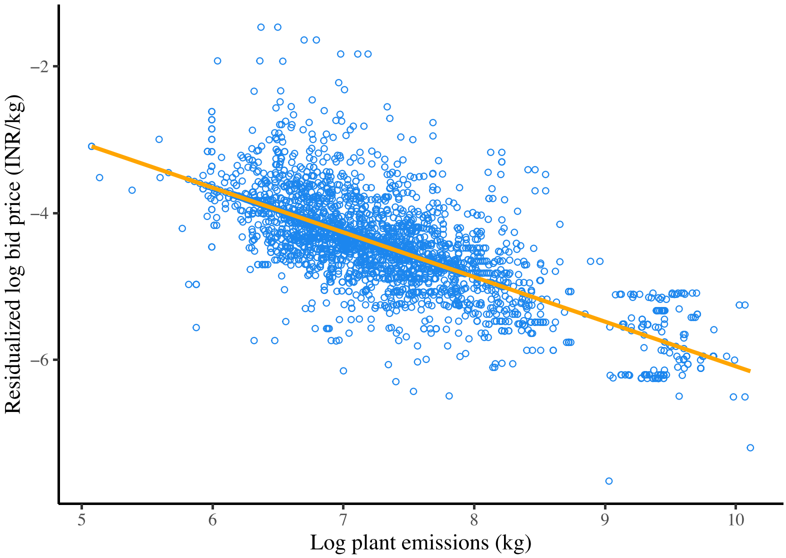

FIGURE VI

Estimation of MAC Elasticity with Respect to Emissions

This figure visualizes the estimation of the marginal abatement-cost elasticity with respect to emissions, as specified in equation (4). The data are restricted to 3,120 bids offered by all plants in the first halves of all compliance periods. The vertical axis is the log bid price residualized on plant-period fixed effects. The horizontal axis are the log plant emissions that would result if a bid was executed. The linear fit shows the iso-elastic curve of best fit for the marginal abatement cost curve.

Second, we test the joint significance of plant-period fixed effects, relative to a model with plant-period random effects. The data strongly reject the random effects model in favor of the plant-period fixed effects model ($p < .001$, column (4)). This clear rejection supports the idea that heterogeneity across plant-periods is an important determinant of marginal costs, suggesting the potential for gains from trade in the emissions market (see Section VI).

Third and finally, Online Appendix Figure F1 supports our sample restriction to bids from the first half of each period. The grounds for this restriction are that plants can no longer trade off own abatement against permit purchases once their emissions are sunk. Consistent with this idea, Online Appendix Figure F1 shows that permit bids are inelastic with respect to emissions when two weeks or less remain in the compliance period. This inelastic demand makes sense near the end of a period, because plants should then have a fixed, high willingness-to-pay to avoid the high penalties they will incur if they do not buy enough permits.

2. *Heterogeneity in Marginal Abatement Cost Curves.* The estimates in Table IV contain different MAC curves for each plant-period. To explore this heterogeneity, we calculate the fitted value of each plant's MAC curve over the range of emissions between a value close to zero and the high level of uncontrolled emissions, which the plant would emit if it did not run any APCDs (see Online Appendix E.1 for how uncontrolled emissions are calculated). These fitted values exponentiate the estimates of equation (4) for each plant to relate the MAC (INR/kg) to the quantity of plant emissions (kg). Therefore, they depend on both the plant-period fixed effects, $\hat{\xi}_{it}$ and the elasticity of marginal abatement costs with respect to emissions $\hat{\beta}_1$. They allow for level differences in costs across plants but assume a common elasticity of marginal abatement costs with respect to emissions.

Figure VII plots these curves for the plants in the treatment group in compliance period 8. The figure shows wide heterogeneity in the level of MACs at any constant emissions level. As an illustrative example, the figure includes a vertical line to indicate a policy requiring all plants to have the average plant emissions load. At this hypothetical standard, plants have a wide range of marginal abatement costs; for example, the ratio of marginal abatement costs for plants at the 75th percentile of costs to ones at the 25th percentile is 2.1 to 1. In practice, loads are not uniform in the control group due to imperfect compliance and the fact that the actual standard limits concentration, not load. The triangle markers on the plot mark the level of marginal abatement costs for each firm at a representative draw of emissions load from the control-group distribution of emissions. As in the case of the strictly uniform standard, there is wide variation in marginal abatement costs across plants. The implication of this heterogeneity is that compliance costs will not be minimized at this allocation of emissions. To minimize costs, the regulator would need to know the MAC curves for all plants. Without such knowledge, command-and-control approaches to regulation will be relatively costly, because they will not equate marginal costs across plants.

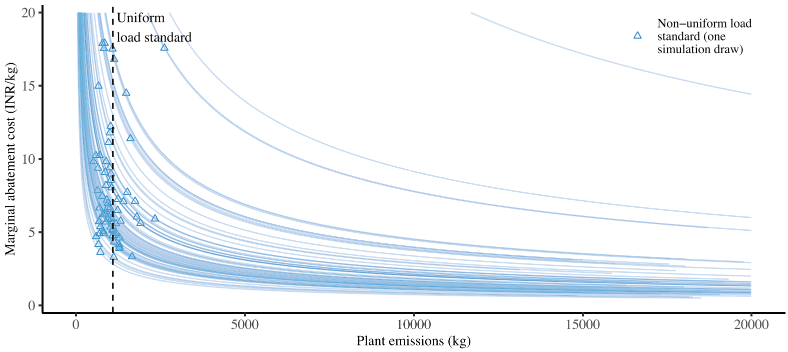

FIGURE VII

MAC Curves for Treatment Plants

The figure illustrates estimated marginal abatement cost curves for all plants that bid in period 8. The domain of each curve extends upward to the uncontrolled emissions level for each plant. The triangles correspond to plant emissions under one simulation of the counterfactual command-and-control regime in which emissions rate are allowed to vary with plant capacity along with an idiosyncratic error term. This corresponds to the regulatory regime simulated in Online Appendix Table D1, Panel A, row B4.

3. *Estimating Changes in Fixed Abatement Costs.* The goal of MAC estimation is to be able to compare abatement costs across regulatory regimes. We have estimated these curves using bid data only from the treatment plants. To use the treatment MAC curves to compare costs, we need to assume that control plants have the same distribution of MACs. Ex ante, this will be true by design, as treatment plants are randomly assigned from the experimental sample of plants. However, it is possible that the treatment caused plants to change their MAC curve, for example, by investing in new pollution-abatement capital. Such changes to fixed costs would not be reflected in bids but may cause treatment and control plants to have different ex post distributions of MAC curves.

We directly test the assumption that the treatment does not cause plants to change their pollution-abatement capital using data collected via a phone survey in November 2020. In the survey, plants reported on abatement equipment costs and other costs for operating the boiler and related equipment (the boiler house includes the equipment that consumes fuel and therefore produces emissions). Table V reports plant-level treatment-effect regressions of abatement capital costs on a treatment-status indicator. Treatment has a small, negative, and statistically insignificant effect on total abatement capital (column (1)). This lack of an impact on abatement capital is consistent with the high rates of APCD installation in sample plants at baseline (Table I). In the Surat market, as is the norm for other emissions markets, the market was imposed on top of a preexisting equipment mandate.[31] Columns (6)–(10) consider other boiler-house input costs including capital, labor, electricity, and fuel. Again, we find insignificant effects overall and no consistent pattern by component. We conclude that plant abatement capital did not change in the treatment group and it is therefore valid ex post to treat the marginal abatement cost curves in the treatment and the control groups as being drawn from the same distribution.

VI. The Gains from Trade and a Benefit-Cost Analysis

This section compares abatement costs under the market to those under the status quo command-and-control regime using the estimated MAC curves. We discuss the model's fit to realized market outcomes in the treatment group and then calculate the gains from trade in the market regime. We compare the market's costs and benefits using our cost and emissions estimates and external estimates of pollution damages. Online Appendix D details these steps.

VI.A. Model Fit

We calculate the market price that would prevail in a particular period, given the estimated plant-specific MAC curves in equation (4). The purpose is to compare modeled market prices, which depend on our MAC estimates and plant-conduct assumptions, with observed market prices.

31. For example, in the United States, the Clean Air Act Amendments (1990) required stationary NO_x sources to install abatement equipment by 1995. In 1999, these sources became part of a regional NO_x cap-and-trade scheme. Schmalensee and Stavins (2013) discusses the interaction of the U.S. SO_2 trading markets with other concurrent policy instruments such as equipment mandates. All carbon markets (e.g., the EU ETS, AB32, and RGGI) coexist with other policy instruments, like renewable purchase obligations, that indirectly regulate carbon.

TABLE V

TREATMENT EFFECTS ON ABATEMENT COSTS IN SURVEY DATA

	Abatement capital costs ($1,000s)					Boiler-house input costs ($1,000s)					
	All (1)	Cyclone (2)	Bag (3)	Scrubber (4)	ESP (5)	Total (6)	Capital (7)	Labor (8)	Electricity (9)	Fuel (10)	Materials (11)
ETS treatment	−3.467	0.602**	0.530*	−0.222	−4.281	11.26	−7.178	1.561	25.21*	26.87*	−0.142
(= 1)	(3.089)	(0.266)	(0.318)	(0.407)	(3.344)	(26.31)	(19.05)	(3.332)	(13.53)	(15.35)	(0.596)
R^2	0.90	0.85	0.83	0.84	0.89	0.93	0.63	0.05	0.65	0.98	0.19
Control mean	44.04	7.80	9.85	9.69	16.70	578.48	190.88	47.86	162.13	299.50	4.33
Plants	276	276	276	276	276	185	218	262	247	225	283

Notes. This table reports the effects of treatment assignment on the capital cost of APCDs (columns (1)–(5)) and boiler-house input costs (columns (6)–(11)). In columns (1)–(5), the abatement capital cost is the product of the number of abatement devices at a plant and the industry-standard cost for that device for the plant's given boiler-house capacity. In columns (6)–(11), specifications use our best estimates for boiler-house costs from the endline survey (FY 2019–20). All specifications control for a corresponding baseline value (FY 2017–18) but in some cases the components of the input-cost aggregate differ slightly within a category between the baseline and endline survey. Electricity costs are only reported at the plant level so are not only for the boiler house. Robust standard errors are given in parentheses. * $p < .10$; ** $p < .05$; *** $p < .01$.

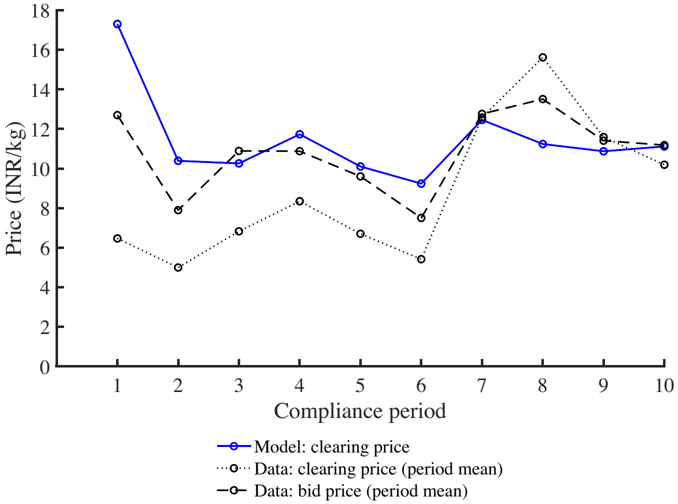

FIGURE VIII

Model Fit to Market-Clearing Prices

The figure shows the fit of the model to the time series of market and bid prices by compliance period. The solid blue line is the time series of market-clearing prices in the fitted model. The model is fit based on bids in the first half of each compliance period. The dashed black line is the time series of mean bid prices in the data and the dotted black line is the time series of market-clearing prices.

Given the MAC curve estimates for all the plants in the market, we solve for the market-clearing permit price at any given cap Q_t. Define the function $E_{it}(P_t) = \widehat{MAC}_{it}^{-1}(P_t)$ as the inverse of the estimated MAC curve for plant i; that is, the level of emissions plant i would choose at a specific market price. The equilibrium permit price is the price at which aggregate emissions equal the cap:

$$E_t(P_t^*) = \sum_i E_{it}(P_t^*) = Q_t. \tag{5}$$

The equilibrium price is unique because the MAC curves imply that emissions for each plant monotonically decrease in price. The resulting allocation of emissions E_{it} across plants is efficient because all plants set their marginal cost of abatement at E_{it} equal to the market price.

Figure VIII shows the modeled market prices P_t^*, calculated this way, alongside the actual market prices. The dashed black line represents mean bids, the dotted black line represents mean clearing prices, and the solid blue line indicates market-clearing prices simulated by the model. The predicted market prices fit mean bid prices and their fluctuations across periods well. Bids and simulated prices are relatively high in period 1, fall to INR 8–10 for periods 2–6 and rise in the final four compliance periods to INR 10–12. Predicted prices are likewise similar to the market-clearing price, but the fit is less good. They are consistently above actual clearing prices in period 1–6, with the gap narrowing in periods 7–10. The initial gap in model fit and later convergence may reflect plants learning about compliance costs over time. Overall, we conclude that this simple model describes market prices well.

1. *Model Fit with Alternative Step Function Marginal Cost.* Because the main tools for particulate abatement are distinct APCDs, we may think that marginal abatement cost has a step function form, with the cost on each step corresponding to the operation of a different device. In Online Appendix E, we simulate market outcomes using this alternative, step function model of MACs. We find this model, fitted to the same bidding data as used before, fits observed market prices and emissions poorly. Market-clearing prices exceed actual prices (see Online Appendix Figure E2). Moreover, the step function technology implies a distribution of emissions that is lumpy and dispersed, relative to the data and modeled outcomes with iso-elastic marginal costs (Online Appendix Figure E3). One interpretation of this poor fit is that the step function model takes an inflexible, all-or-nothing view about how plants run their abatement devices and rules out, in particular, that plants may have ways to adjust emissions even conditional on their abatement capital and technology mix. The remainder of the article reports results using our preferred iso-elastic model of marginal abatement cost functions based on equation (4).

VI.B. Gains from Trade in the Market Regime

We start by illustrating the gains from trade using the estimated MAC curves for two plants. This illustration could be drawn from a textbook on the benefits of trading, except that it uses data from real plants participating in a live emissions market. We describe the steps necessary to calculate the gains from

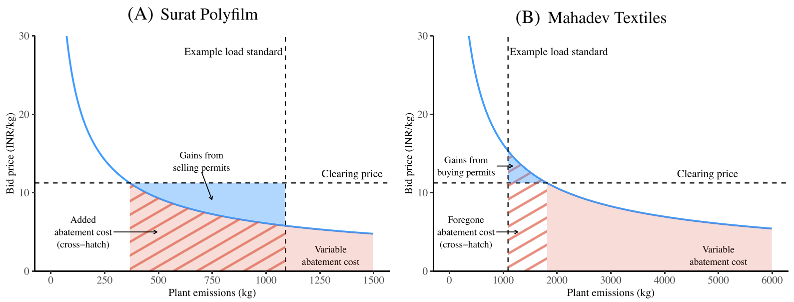

FIGURE IX

An Example of the Gains from Trade in the Market

The figure visualizes gains from trade on the estimated MAC curves for Surat Polyfilm (Panel A) and Mahadev Textiles (Panel B), both pseudonyms. The MAC curves are fit as seen in Figure VII. The vertical dashed line gives a hypothetical load standard set at the average emissions per plant-month, and the shading shows how trading permits allows for price savings for both permit buyers and sellers compared to a command-and-control regime.

trade in the market as a whole and report estimates of these gains.

1. *Illustration of the Potential for Gains from Trade.* To illustrate the mechanism for gains from trade in the emissions market, Figure IX plots the fitted MAC curves for two plants in the market, using the Table IV, column (4) estimates. We give the plants the pseudonyms Surat Polyfilm (Panel A) and Mahadev Textiles (Panel B) for confidentiality. MACs (prices) are on the vertical axis and emissions (quantities) are on the horizontal axis.

In the example, we use MAC curve estimates drawn from compliance period 8, and we represent the command-and-control regime as a fixed load standard for all plants. The load standard, indicated by the dashed vertical line, is set to the average emissions load of 1,090 kg/plant. The dashed horizontal line at INR 11.25/kg shows the market-clearing price that sets total emissions in the hypothetical two-plant market equal to total emissions in the command-and-control regime. Below, we will broaden our estimates of the gains from trade to cover all plants and periods and to use more realistic distributions of emissions in the command-and-control regime.

The differing MAC functions for the two plants create an opportunity for profitable trade. At the command-and-control load standard of 1,090 kg, Surat Polyfilm's marginal abatement cost is roughly INR 6/kg (Panel A) and Mahadev Textiles' is about INR 14/kg (Panel B). This difference in marginal abatement costs means that the two plants could gain from trade: both plants would reduce their costs if Surat Polyfilm abates an additional kilogram of particulate matter and sells a permit to Mahadev Textiles at a price between INR 6/kg and INR 14/kg.

The movement from a fixed load standard to a market would cause large, nonmarginal changes in plant emissions. Under the market, each plant emits until its MAC curve intersects the market-clearing price (equation (3)). The market price here is INR 11.25/kg, at which price Surat Polyfilm would cut its emissions by approximately 66%, to 366 kg, while Mahadev Textiles would increase its emissions by approximately 66%, to 1,814 kg. The reallocation of emissions reduces costs for both plants. Each plant's total variable abatement cost, depicted in pale red (light gray), is the area beneath the MAC curve from the chosen emissions level up to its maximum emissions level. When Surat Polyfilm reduces emissions from the command-and-control limit to 366 kg, it incurs additional abatement costs, indicated by the cross-hatched area, but more than covers these costs with additional permit revenues, because its marginal abatement costs lie below the market price in this range. The shaded blue (darker gray) area above the MAC curve and below the price is its gain from trade in the market (INR 2,533). On the other side of the market, Mahadev Textiles (Panel B) increases its emissions, lowering abatement costs by the cross-hatched area beneath its MAC and purchasing 724 permits (= 1,814 kg − 1,090 kg) at INR 11.25/kg. Mahadev's costs fall because its marginal abatement costs exceed the price of a permit at all emissions levels between 1,090 kg and 1,814 kg; the shaded blue (darker gray) region depicts its gain from trade (INR 1,279). Thus the transition to an emissions market reallocates emissions and reduces plant costs on both sides of the market.

2. *Estimating Total Abatement Costs in the Market Regime.* To quantify the market-level gains from trade, we calculate total abatement costs for all plants at the emissions levels that they would choose in the market and command-and-control regime. The discussion of model fit (Section VI.A) and the example above show how we do this calculation in the market regime. First,

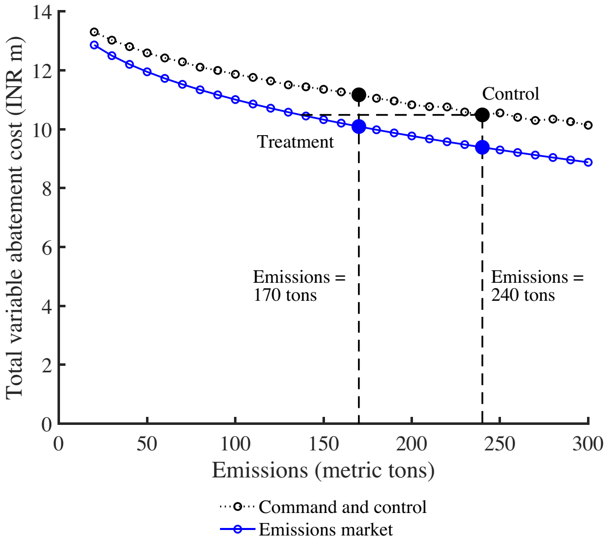

FIGURE X

Variable Abatement Costs by Regime

The figure shows the total (not marginal) variable abatement costs by regulatory regime as estimated for compliance period 8. The dotted black curve shows the total variable abatement cost curve under command-and-control and the solid blue curve shows it under the emissions market. The command-and-control regime uses a capacity-based emissions rate with error to set emissions targets for each plant, as described in Section V. The emissions-market regime sets an emissions cap at each level of emissions on the horizontal axis. The dashed vertical lines show the approximate emissions levels in the treatment and control groups. The control costs are therefore represented by the upper-right shaded circle and the treatment costs by the lower-left shaded circle.

we invert each plant's MAC function to find its emissions at the market-clearing price, as in equation (5). Second, we calculate plant variable abatement costs as the area underneath its MAC curve between its unconstrained emissions level and its chosen emissions, and add these costs across plants. We repeat this calculation for a full range of potential market caps.

The solid blue line in Figure X depicts total variable abatement costs across all plants in the market regime. At each market cap, this curve is calculated as the sum of all plants' total variable abatement costs for compliance period 8, as shown in Figure VII, over market caps ranging from near 0 to 300 metric tons. The vertical dashed line at left depicts emissions at 170 tons, the cap from compliance period 4 onward. An estimated treatment effect of 30% on emissions (Table III) then implies control emissions of approximately 240 tons, shown by the vertical dashed line at right. On each vertical line, we place a filled-in marker at the intersection with the aggregate abatement cost curve.

The most striking finding about the market-level abatement cost curve is that abatement costs rise only slowly in response to reductions in pollution. For example, the arc elasticity of total variable abatement costs with respect to total emissions is −0.23 at the status quo level of pollution (240 tons) and −0.19 at the treatment level of pollution (170 tons). These elasticities depend on, but are naturally lower than, the elasticity of MACs estimated in Table IV, because total abatement costs include inframarginal abatement costs and are therefore less elastic to emissions than marginal costs. The cost estimates indicate that substantial improvements to Gujarat's air quality are available for relatively small increases in plant abatement costs.

3. *Estimating Total Abatement Costs in the Command-and-Control Regime.* To compare costs across regimes, we also need to estimate the total abatement costs that treatment plants would have incurred under the status quo, command-and-control regime. We estimate these costs using two observations. First, because the market was introduced in an experiment, the distribution of MAC curves we estimated for the treatment plants will be the same as that for the control plants. Second, we can use the control distribution of emissions levels to represent the stringency of the command-and-control regime. We evaluate costs in the command-and-control regime by evaluating treatment cost functions at control emissions levels.

This approach to the command-and-control regime treats the world as it is, rather than applying a single uniform standard, as in our simple example of the gains from trade. Roughly 30% of plants in the control group exceed the de jure emissions limits in the command-and-control regime (Online Appendix Figure B1). We model the command-and-control regime not as a single standard, as on paper, but with a distribution of possible emissions levels. We simulate many sets of draws of emissions levels for all plants in the market and evaluate the aggregate costs of abatement for each set by calculating the area under each plants' MAC curve, from the emissions draw up to its unconstrained emissions level, summing these costs across plants. We consider several alternative ways to draw emissions; our preferred method draws residual emissions levels conditional on plant heat capacity. Online Appendix D.2 explains how we conduct these simulations.

Returning to Figure VII, the triangle markers on each MAC curve illustrate one draw from the distribution of control emissions levels for all plants. The figure shows that at this draw, plant emissions load is not uniform across plants and that the implied MACs vary widely across plants.

To isolate the gains from trade, we seek to compare abatement costs at the same aggregate emissions level, though treatment plants emitted less than control plants on average (Table III). For each candidate aggregate emissions cap in the market, therefore, we scale the distribution of control emissions loads up or down by a common factor to match the cap. For example, consider a plant that had estimated emissions of 1,090 kg when aggregate emissions across all plants is 240 tons. We assume that if aggregate emissions were cut to 120 tons, this plant would emit 545 kg. This approach assumes that changes in stringency in the command-and-control regime change emissions at all plants proportionally.

Returning to Figure X, the black dotted line depicts total variable abatement cost as a function of aggregate emissions under the command-and-control (higher, black dotted line) regime (again using compliance period 8 estimates). At each point in the curve, the total variable abatement cost is the sum across all plants, and costs for each plant are estimated with $S = 100$ simulation draws of emissions (residualized on plant heat capacity) from the control group. One can visualize the total cost, in a single simulation draw, as the sum of areas under the MAC curves in Figure VII, down to the emissions draw for each plant.

The comparison in Figure X for period 8 shows that the market regime lowers total variable abatement costs, relative to the command-and-control regime, at any level of emissions. At the control emissions of 240 tons, the market reduces total variable abatement costs by 10% (moving down the vertical dashed line). Because total abatement costs are not very elastic with respect to emissions, the emissions market would cut total emissions by 43% (moving left along the horizontal dashed line) at the same variable abatement costs as in the status quo. Alternately, a range of outcomes with lower emissions and lower costs are available along the arc of the emissions-trading cost curve between the horizontal and vertical dashed lines.

We estimate, across all plants and compliance periods, that the actual market outcome falls in this range of reducing both costs and emissions at the same time. Online Appendix Table D1, Panel A summarizes the results on abatement costs. At the treatment emissions level, 170 tons/month, total variable abatement costs are 12% higher under the status quo (column (3), row B4) than under emissions trading (column (2), row A), so that the market cuts costs by 11%. The cost difference between regimes is great enough that costs are 6% lower under the emissions market—with a 30% cut in emissions—than in the command-and-control regime at the status quo emissions level. We report similar results using different methods to draw counterfactual emissions levels from the control group, with or without conditioning on observables, for example. We find that the cost differences among the alternative representations of the command and control regime are small both in absolute terms and relative to the difference in cost between the market and command-and-control regimes.

VI.C. Benefit-Cost Analysis of Emissions-Market Expansion

The preceding analysis has quantified the benefits of the market in terms of emissions reductions and abatement costs. Table VI uses these estimates as inputs for a benefit-cost analysis of expanding the emission market to all 906 industrial plants that burn solid fuel in Surat. We compare the benefits of lower ambient concentrations of PM increasing life expectancy, valued in monetary terms, against the emission market's operational and abatement costs. All comparisons take as given the existing stock of abatement capital in Surat (Online Appendix G discusses the inputs in depth).

Table VI reports on the benefit-cost analysis for emissions reductions of 10%, 30%, and 50% in columns (1)–(3), respectively. The first two reductions are within the range of our experimental data, with the 30% reduction roughly equal to the experimental treatment effect documented above. The third extrapolates outside that range, using the emissions market's total abatement cost function, founded on our estimates of individual MAC functions.

Table VI, Panel A shows the costs of expanding the market, which are composed of the fixed costs of CEMS monitoring and changes in total variable abatement costs. Improved monitoring

TABLE VI

BENEFIT-COST ANALYSIS OF SCALED-UP ETS IN SURAT

	Emissions reduction				
	10% (1)	30% (2)	50% (3)	Units (4)	Source (5)
Panel A: Annual costs from scale-up of emissions trading					
1. Monitoring costs per plant	5,000	5,000	5,000	\$/year	Author estimates
2. Abatement cost Δ per plant	−1,242	−648	77	\$/year	Author estimates
3. Total costs	3.4	3.9	4.6	\$m/year	= (A1 + A2) × 906
Panel B: Reduction in pollution					
1. Ambient $PM_{2.5}$ conc.	88.5	88.5	88.5	$\mu g/m^3$	Guttikunda et al. (2019)
2. Industry share	0.3	0.3	0.3		Guttikunda et al. (2019)
3. Reduction in industry $PM_{2.5}$	10.0	30	50	%	
4. Reduction in ambient $PM_{2.5}$	2.8	8.5	14.2	$\mu g/m^3$	= B1 × B2 × B3
Panel C: Gain in life-years					
1. Mortality impact	0.1	0.1	0.1	$\frac{\text{years}}{(\mu g/m^3)}$	Ebenstein et al. (2017)
2. Gain in life expectancy	0.3	0.8	1.4	years	= C1 × B4
3. Life expectancy	70	70	70	years	World Bank
4. Per year of ETS	0.004	0.012	0.020	years	$= \frac{C2}{C3}$
5. Population	7.5	7.5	7.5	m	World Pop. Review
6. Total gain in life-years	29,736	89,208	148,680	years	= C4 × C5

TABLE VI
CONTINUED

	Emissions reduction				
	10% (1)	30% (2)	50% (3)	Units (4)	Source (5)
Panel D: Value of gain in life-years					
1. Value of statistical life	665,000	665,000	665,000	$	Nair et al. (2021)
2. Value of one year of life	9,500	9,500	9,500	$/year	$= \frac{D1}{C3}$
3. Value of gain in life-years	282	847	1,412	$m	$= C6 \times D2$
Panel E: Benefit-cost ratio					
1. Ebenstein et al. (2017)	83:1	215:1	307:1		$= \frac{D5}{A3}$
2. Pope, Ezzati, and Dockery (2009)	52:1	134:1	191:1		
3. Correia et al. (2013)	30:1	77:1	110:1		
4. Apte et al. (2018)	10:1	26:1	38:1		

Notes. The table presents the benefit-cost analysis of extending the ETS to the entirety of Surat. We compare the private costs of introducing an emissions market (monitoring and changes in abatement cost, in Panel A) to the social benefits of cleaner air (gains in life-years, calculated and monetized across Panels B–D). There are 906 plants according to the GPCB consent records. Abatement cost savings are based on the capacity-rate estimate (with error) from Online Appendix Table D1, Panel I. World Population Review estimates for the Surat population are from 2021. The number of plants is based on 2022 GPCB consent records. The annualized CEMS costs are based on an assumed system cost of $12,000 with a four-year equipment life and no discounting. This equipment life describes the realized experience of some plants in our sample but is lower than typical manufacturer claims. On the benefits side, we assume that the reduction in ambient pollution comes solely from primary particles. Ebenstein et al. (2017) estimate mortality effects of pollution based on PM_{10} concentrations. We convert their findings using a 0.65 $PM_{2.5}$-to-PM_{10} ratio (Zhou et al. 2016). Columns (1)–(3) show the benefit-cost analysis for reductions in pollution of 10%, 30% and 50%. The cost of abatement is calculated using our model at each emissions level. The benefit of emissions reductions are assumed to be linear and given by the estimate from each respective study in Panel E.

is a necessary condition to start an emissions market. The administrative data record that it costs roughly \$5,000 per plant-year to set up a monitoring system. This cost is fixed with respect to the targeted emissions reduction. For 10% and 30% emissions reductions, these additional costs are counterbalanced by estimated savings in abatement costs of \$1,242 and \$648 per plant-year, respectively, associated with switching to the market. Even at a 50% emissions reduction, the savings from moving to the market nearly cancel out the additional abatement costs from further pollution abatement; on average, plant abatement costs increase by just \$77 annually. Scaling these costs to cover all eligible plants in Surat yields aggregate annual costs of \$3.4 million, \$3.9 million, and \$4.6 million for 10%, 30%, and 50% reductions in emissions, respectively.

On the benefits side, we consider only the mortality benefit of lower pollution extending people's lives, ignoring other possible sources of benefits (better health, productivity improvements, etc.). We convert emissions reductions into a monetary value using three factors: how emissions change ambient pollution (Panel B), how lower ambient pollution lengthens life spans (Panel C), and the value of increased life spans (Panel D). The first factor scales the 10%, 30%, and 50% emissions reductions from industry by the industrial share of ambient $PM_{2.5}$ concentrations, drawn from the best available source apportionment study (Guttikunda, Nishadh, and Jawahar 2019). This scaling yields estimated reductions in ambient $PM_{2.5}$ of 2.8 μg/m^3, 8.5 μg/m^3, and 14.2 μg/m^3, respectively (Panel B). The next factor is the gain in life years in Surat for each cut in ambient pollution. We estimate this relationship with the elasticity of life expectancy with respect to ambient $PM_{2.5}$ from Ebenstein et al. (2017) and report robustness to other estimates (Panel E). The third factor is the value of a statistical life, the willingness-to-pay for a reduction in mortality risk, which we set at \$665,000 (\$9,500 per statistical life-year), following the value chosen by Nair et al. (2021) (Panel D). The estimated benefits of the three emissions reductions scenarios are then the monetized values of life-years saved for each year that the ETS is in force, \$282 million, \$847 million, and \$1,412 million, across the three respective emissions reductions.

Panel E reveals that the estimated benefits of scaling the market to all eligible plants greatly exceed the estimated costs. Row 1 uses the mortality dose-response estimated in Ebenstein et al. (2017) and rows 2–4 use alternative estimates. For a 30%

reduction in industrial emissions (column (2)), the benefit to cost ratio ranges from roughly 25:1 to more than 200:1, depending on the estimate of the elasticity of life expectancy with respect to ambient $PM_{2.5}$ (across rows in Panel E). Because a large share of the costs of the market are fixed costs of monitoring, and abatement costs are only moderately convex, the benefit-cost ratio rises with greater reductions in emissions over this range.

VII. Conclusion

This article evaluates the world's first emissions market for particulate matter, which we designed in collaboration with the GPCB. There are three main findings. First, the market functioned well: permit trade was active, and plants obtained permits to meet their compliance obligations almost perfectly. Second, the new regulation caused a 20%–30% reduction in PM emissions, relative to the status quo command-and-control regulatory regime. Third, the market reduced abatement costs by 11%, holding emissions constant. More broadly, we estimate that emissions can be reduced without capital investment and at seemingly small costs in Gujarat. The benefits of pollution reductions under an emissions market therefore exceed the costs of the market by at least 25 times.

Our experimental setting allowed for low-cost abatement in part because the existing regime mandated the installation of air pollution abatement equipment but could not adequately enforce its use. This situation, where a market is layered on top of a command-and-control mandate, is a frequent starting point for introducing markets (see footnote 31). We expect that longer-run changes may augment the efficiency and environmental benefits estimated in this experiment for two reasons. First, the efficiency gains from other emissions markets have been attributed largely to reallocation toward the most cost-effective kinds of abatement capital (Fowlie 2010; Chan et al. 2018; Colmer et al. forthcoming), whereas the gains in efficiency we estimate are due only to reductions in variable abatement costs. Second, regulators often use the lever of a market cap to tighten standards over time. Indeed, the GPCB started such a process during our experiment by tightening the cap when the market revealed that aggregate abatement costs were relatively low.

We believe that this proof-of-concept for an emissions market has broad policy relevance. Based on a review of the performance of the treatment market in Surat, GPCB decided to expand its scope. Surat's control plants were included in the market in September 2022. In September 2023, the GPCB launched a second particulate emissions market for plants in Ahmedabad, Gujarat's largest city and major industrial hub. Currently, the GPCB is exploring expanding the market to additional industrial clusters and pollutants. The Maharashtra Pollution Control Board (MPCB) has started the development of a statewide market for sulfur dioxide emissions from thermal power plants and other industrial sources. The coauthors of this article are advising MPCB and are in discussions with several other Indian states on how to use environmental markets.

The larger question remains why environmental quality is so poor in many developing countries. Our results suggest that industrial air pollution remains high not because of high abatement costs, at the level of individual plants, but due to high fixed costs of monitoring and enforcement. State capacity may limit the use of sophisticated regulatory instruments, but state capacity is not a universal constant. Although the establishment of the emissions market in Gujarat took years, the results from investments in new monitoring and forms of regulation are extraordinary in terms of reducing pollution while lowering abatement costs.

Pollution markets, as a policy tool, are not exclusively reserved for high-income countries. The Gujarat evidence shows a market shifting abatement to firms with low abatement costs, just as markets have done in rich countries. In developing countries, markets can also have an additional benefit of helping to solve the first-order problem of low compliance with environmental regulation in any form. Given pollution's high costs to human wellbeing in these countries, emissions markets have great potential to raise both environmental quality and economic growth.

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Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

The data underlying this article are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/PDFDKR (Greenstone et al. 2025).

References

Apte, Joshua S., Michael Brauer, Aaron J. Cohen, Majid Ezzati, and C. Arden Pope, III, "Ambient $PM_{2.5}$ Reduces Global and Regional Life Expectancy," *Environmental Science and Technology Letters*, 5 (2018), 546–551. https://doi.org/10.1021/acs.estlett.8b00360

Blackman, Allen, Zhengyan Li, and Antung A. Liu, "Efficacy of Command-and-Control and Market-Based Environmental Regulation in Developing Countries," *Annual Review of Resource Economics*, 10 (2018), 381–404. https://doi.org/10.1146/annurev-resource-100517-023144

Borenstein, Severin, James Bushnell, Frank A. Wolak, and Matthew Zaragoza-Watkins, "Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design," *American Economic Review*, 109 (2019), 3953–3977. https://doi.org/10.1257/aer.20161218

Central Pollution Control Board, "Specifications and Guidelines for Continuous Emissions Monitoring Systems (CEMS) for PM Measurement with Special Reference to Emission Trading Programs," CPCB/e-PUBLICATION/2013-14, 2013.

Chan, Ron, B. Andrew Chupp, Maureen L. Cropper, and Nicholas Z. Muller, "The Impact of Trading on the Costs and Benefits of the Acid Rain Program," *Journal of Environmental Economics and Management*, 88 (2018), 180–209. https://doi.org/10.1016/j.jeem.2017.11.004

Chu, Cindy, "Thirty Years Later: The Global Growth of ITQs and Their Influence on Stock Status in Marine Fisheries," *Fish and Fisheries*, 10 (2009), 217–230. https://doi.org/10.1111/j.1467-2979.2008.00313.x

Coase, Ronald H., "The Problem of Social Cost," *Journal of Law & Economics*, 3 (1960), 1–44. https://doi.org/10.1086/466560

Colmer, Jonathan, Ralf Martin, Mirabelle Muûls, and Ulrich J. Wagner, "Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence from the European Union Emissions Trading System," *Review of Economic Studies*, forthcoming. https://doi.org/10.1093/restud/rdae055

Correia, Andrew W., C. Arden Pope, Douglas W. Dockery, Yun Wang, Majid Ezzati, and Francesca Dominici, "Effect of Air Pollution Control on Life Expectancy in the United States: An Analysis of 545 U.S. Counties for the Period from 2000 to 2007," *Epidemiology*, 24 (2013), 23–31. https://doi.org/10.1097/EDE.0b013e3182770237

Dales, John Harkness, *Pollution, Property & Prices: An Essay in Policy-Making and Economics*, (Toronto: Toronto University Press, 1968).

Davis, Lucas W., "The Effect of Driving Restrictions on Air Quality in Mexico City," *Journal of Political Economy*, 116 (2008), 38–81. https://doi.org/10.1086/529398

Dechezleprêtre, Antoine, Daniel Nachtigall, and Frank Venmans, "The Joint Impact of the European Union Emissions Trading System on Carbon Emissions and Economic Performance," *Journal of Environmental Economics and Management*, 118 (2023), 102758. https://doi.org/10.1016/j.jeem.2022.102758

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach," *Econometrica*, 64 (1996), 1001–1044. https://doi.org/10.2307/2171954

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan, "Towards an Emissions Trading Scheme for Air Pollutants in India," Report, MIT Center for Energy and Environmental Policy Research, Cambridge, MA, 2010.

———, "The Value of Regulatory Discretion: Estimates from Environmental Inspections in India," *Econometrica*, 86 (2018), 2123–2160. https://doi.org/10.3982/ECTA12876

———, "Truth-Telling by Third-Party Auditors and the Response of Polluting Firms: Experimental Evidence from India," *Quarterly Journal of Economics*, 128 (2013), 1499–1545. https://doi.org/10.1093/qje/qjt024

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou, "New Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy," *Proceedings of the National Academy of Sciences of the United States of America*, 114 (2017), 10384–10389. https://doi.org/10.1073/pnas.1616784114

Ellerman, A. Denny, and Barbara K. Buchner, "Over-Allocation or Abatement? A Preliminary Analysis of the EU ETS Based on the 2005–06 Emissions Data," *Environmental and Resource Economics*, 41 (2008), 267–287. https://doi.org/10.1007/s10640-008-9191-2

Ellerman, A. Denny, Paul L. Joskow, Richard Schmalensee, Juan-Pablo Montero, and Elizabeth M. Bailey, *Markets for Clean Air: The U.S. Acid Rain Program*, (Cambridge: Cambridge University Press, 2000). https://doi.org/10.1017/CBO9780511528576

Fowlie, Meredith, "Emissions Trading, Electricity Restructuring, and Investment in Pollution Abatement," *American Economic Review*, 100 (2010), 837–869. https://doi.org/10.1257/aer.100.3.837

Fowlie, Meredith, Stephen P. Holland, and Erin T. Mansur, "What Do Emissions Markets Deliver and to Whom? Evidence from Southern California's NOx Trading Program," *American Economic Review*, 102 (2012), 965–993. https://doi.org/10.1257/aer.102.2.965

Greenstone, Michael, and Ted Gayer, "Quasi-Experimental and Experimental Approaches to Environmental Economics," *Journal of Environmental Economics and Management*, 57 (2009), 21–44. https://doi.org/10.1016/j.jeem.2008.02.004

Greenstone, Michael, and Rema Hanna, "Environmental Regulations, Air and Water Pollution, and Infant Mortality in India," *American Economic Review*, 104 (2014), 3038–3072. https://doi.org/10.1257/aer.104.10.3038

Greenstone, Michael, and Christina Hasenkopf, "Air Quality Life Index Annual Update," Technical report, Energy Policy Institute at Chicago, Chicago, 2023.

Greenstone, Michael, Janhavi Nilekani, Rohini Pande, Nicholas Ryan, Anant Sudarshan, and Anish Sugathan, "Lower Pollution, Longer Lives: Life Expectancy Gains if India Reduced Particulate Matter Pollution," *Economic and Political Weekly*, 50 (2015), 40–46.

Greenstone, Michael, Rohini Pande, Nicholas Ryan, and Anant Sudarshan, "Replication Data for: 'Can Pollution Markets Work in Developing Countries? Experimental Evidence from India'," (2025), Harvard Dataverse. https://doi.org/10.7910/DVN/PDFDKR

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu, "Can Technology Solve the Principal-Agent Problem? Evidence from China's War on Air Pollution," *American Economic Review: Insights*, 4 (2022), 54–70. https://doi.org/10.1257/aeri.20200373

Guttikunda, Sarath K., K. A. Nishadh, and Puja Jawahar, "Air Pollution Knowledge Assessments (APnA) for 20 Indian Cities," *Urban Climate*, 27 (2019), 124–141. https://doi.org/10.1016/j.uclim.2018.11.005

He, Guojun, Shaoda Wang, and Bing Zhang, "Watering Down Environmental Regulation in China," *Quarterly Journal of Economics*, 135 (2020), 2135–2185. https://doi.org/10.1093/qje/qjaa024

Isen, Adam, Maya Rossin-Slater, and W. Reed Walker, "Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970," *Journal of Political Economy*, 125 (2017), 848–902. https://doi.org/10.1086/691465

Jayachandran, Seema, "How Economic Development Influences the Environment," *Annual Review of Economics*, 14 (2022), 229–252. https://doi.org/10.1146/annurev-economics-082321-123803

Klier, Thomas H., Richard H. Mattoon, and Michael A. Prager, "A Mixed Bag: Assessment of Market Performance and Firm Trading Behaviour in the NOx Reclaim Programme," *Journal of Environmental Planning and Management*, 40 (1997), 751–774. https://doi.org/10.1080/09640569711895

Martin, Ralf, Laure B. de Preux, and Ulrich J. Wagner, "The Impact of a Carbon Tax on Manufacturing: Evidence from Microdata," *Journal of Public Economics*, 117 (2014), 1–14. https://doi.org/10.1016/j.jpubeco.2014.04.016

Martin, Ralf, Mirabelle Muûls, and Ulrich J. Wagner, "The Impact of the European Union Emissions Trading Scheme on Regulated Firms: What Is the Evidence after Ten Years?," *Review of Environmental Economics and Policy*, 10 (2016), 129–148. https://doi.org/10.1093/reep/rev016

Montero, Juan-Pablo, Jose Miguel Sanchez, and Ricardo Katz, "A Market-Based Environmental Policy Experiment in Chile," *Journal of Law and Economics*, 45 (2002), 267–287. https://doi.org/10.1086/324657

Nair, Moorthy, Hemant Bherwani, Shahid Mirza, Saima Anjum, and Rakesh Kumar, "Valuing Burden of Premature Mortality Attributable to Air Pollution in Major Million-Plus Non-Attainment Cities of India," *Scientific Reports*, 11 (2021), 1–15. https://doi.org/10.1038/s41598-021-02232-z

Oliva, Paulina, "Environmental Regulations and Corruption: Automobile Emissions in Mexico City," *Journal of Political Economy*, 123 (2015), 686–724. https://doi.org/10.1086/680936

Piette, Lauren, "Improving Environmental Enforcement in India," Mimeo, University of Chicago Law School, 2018.

Pope, C. Arden, Majid Ezzati, and Douglas W. Dockery, "Fine-Particulate Air Pollution and Life Expectancy in the United States," *New England Journal of Medicine*, 360 (2009), 376–386. https://doi.org/10.1056/NEJMsa0805646

Ryan, Nicholas, and Anant Sudarshan, "Rationing the Commons," *Journal of Political Economy*, 130 (2022), 210–257. https://doi.org/10.1086/717045

Schmalensee, Richard, and Robert N. Stavins, "The SO_2 Allowance Trading System: The Ironic History of a Grand Policy Experiment," *Journal of Economic Perspectives*, 27 (2013), 103–122. https://doi.org/10.1257/jep.27.1.103

Schmalensee, Richard, Paul L. Joskow, A. Denny Ellerman, Juan Pablo Montero, and Elizabeth M. Bailey, "An Interim Evaluation of Sulfur Dioxide Emissions Trading," *Journal of Economic Perspectives*, 12 (1998), 53–68. https://doi.org/10.1257/jep.12.3.53

Shapiro, Joseph S., and Reed Walker, "Is Air Pollution Regulation Too Lenient? Evidence from US Offset Markets," Working Paper no. 28199, National Bureau of Economic Research, Cambridge, MA, 2020. https://doi.org/10.3386/w28199

Stavins, Robert N., "Experience with Market-Based Environmental Policy Instruments," in *Handbook of Environmental Economics*, vol. 1, Karl-Göran Mäler and Jeffrey Vincent, eds. (Amsterdam: Elsevier Science, 2003), 355–435. https://doi.org/10.1016/S1574-0099(03)01014-3

Sudarshan, Anant, "Monitoring Industrial Pollution in India," in *Introduction to Development Engineering*, Temina Madon, Ashok J. Gadgil, Richard Anderson, Lorenzo Casaburi, Kenneth Lee, and Arman Rezaee, eds. (Cham, Switzerland: Springer, 2023). 161–182, https://doi.org/10.1007/978-3-030-86065-3_7

Zhou, Xuehua, Zhaoyu Cao, Yujie Ma, Linpeng Wang, Ruidong Wu, and Wenxing Wang, "Concentrations, Correlations and Chemical Species of PM2.5/PM10 Based on Published Data in China: Potential Implications for the Revised

Particulate Standard," *Chemosphere*, 144 (2016), 518–526. https://doi.org/10.1016/j.chemosphere.2015.09.003

Zou, Eric Yongchen, "Unwatched Pollution: The Effect of Intermittent Monitoring on Air Quality," *American Economic Review*, 111 (2021), 2101–2126. https://doi.org/10.1257/aer.20181346