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How Regulation Might Fail to Reduce Energy Consumption While Still Stimulating Total Factor Productivity Growth

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Abstract

This paper evaluates the impact of a policy that was implemented to reduce the energy intensity of firms in some manufacturing sectors in India, on the total factor productivity (TFP) growth of firms and on its components, scale efficiency and technical change. Using plant-level panel data on the cement industry from 2007-2015 and a difference-in-difference methodology, we find that treated plants had higher rates of TFP growth, compared to control plants. This is largely driven by the fact that they expanded their production compared to control plants, even though they experienced lower rates of technical change compared to control plants. To explain this finding, we verify that treated plants attempted to meet the energy-intensity mandate not by reducing their energy consumption, but instead by increasing their output. Our results suggest that energy intensity regulations may not reduce energy consumption, because firms may find other ways to fulfil targets. The policy implications of this study are related to the design of energy-efficiency regulations, particularly in developing countries where firms in some industries may find it difficult to reduce their energy consumption through investment in new energy-efficient technologies or processes.

JEL Classification: D1, D8; Q4; Q5

Keywords: Total factor productivity; Climate change mitigation; Environmental Regulation; Cement Industry; Energy Intensity; India

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1 Introduction

The acute threats posed by climate change culminated in almost 200 countries signing the Paris Agreement in 2015 to reduce emissions to limit global warming to well below 2 degrees Celsius, preferably to 1.5 degrees Celsius, compared to pre-industrial levels. Given the extent of reduction in average temperatures required to meet this target, it is imperative that concerted efforts are made across sectors to reduce greenhouse gas emissions (GHG emissions). A leading example of a carbon-intensive sector is the industrial sector. Manufacturing currently contributes significantly to greenhouse gas emissions: it consumed about 54% of the world's total delivered energy in 2016, and contributed to about one-fifth of total greenhouse gas emissions in 2010 (U.S. Environmental Protection Agency, 2022). Certain industries in particular involve production processes that are highly carbon-intensive: for example, the cement industry generated about 8% of total global GHG emissions in 2015 (Timperley, 2018), while as a comparison, energy use in the aggregate industrial sector contributed to about 24.2% of total global GHG emissions in 2016 (Ritchie and Moser, 2020). Given the pressing need to cut emissions, it is clear that both firms and policymakers need to implement measures to ensure that emission targets are reached, and global warming is curtailed. The design of effective policies, such as monetary instruments (like a carbon tax) or regulatory instruments (such as energy consumption standards) are critical to stem emissions.

This study mainly tries to shed light on the impact of a regulation targeting the energy intensity of firms in India, on the total factor productivity (TFP) growth of firms, and on its components, namely scale efficiency and technical change. In doing so, it contributes to this literature, by pinpointing the margins of adjustment available to firms to satisfy this regulation on energy intensity, which is defined as the energy consumption per unit of output, in one of the most energy-consuming sectors, cement, in one of the largest emerging economies, India. Moreover, our analysis shows the limits of introducing a regulation based on energy intensity. While the aim of the regulators was to induce firms to improve energy efficiency through the adoption of energy-saving technologies, as shown in this study, another means to satisfy the regulation was to produce more by exploiting economies of scale. Although we observe that the regulation had a positive impact on the TFP growth rates of firms, it didn't have an effect on their total energy consumption, while still resulting in a reduction in the energy intensity. Therefore, this study contributes to three streams of the literature, i.e., the literature on the effectiveness of climate change mitigation strategies in developing countries, the literature on the impact of regulatory measures on TFP growth, and also the literature on the strategies adopted by firms to get around regulatory measures (which thereby may end up making these measures ineffective).

Environmental regulations can influence firm behavior, as well as firm-level economic outcomes in several ways. While the primary goal of implementing such policies is either an emissions reduction or a mitigation in energy consumption, environmental regulations can also influence other dimensions, such as the productivity of firms, which is an important factor contributing to firm performance. For example, evidence suggests that they may have an effect on productivity growth, innovation, plant size, foreign direct investment as well as exports (Dechezleprêtre and Sato (2017) provide a comprehensive review of some of these studies). A strand of this literature provides empirical evidence on the Porter Hypothesis (Porter and Van Der Linde, 1995), the main idea of which was that stricter environmental regulation may in fact incentivise

firms to adopt cost-saving efficiency improvements that can actually outweigh the costs of regulation, and potentially improve productivity. The Porter Hypothesis has been partially validated in some papers, and in other cases not, depending on the nature of the industry, the country of implementation, as well as the on the general stringency of regulation.

Theoretically, it is clear that firm-level responses to regulations are likely to vary, depending on its design, and on its stringency. Firms can either use regulation as a stepping stone to upgrade their technological processes and inputs (as shown in some recent studies, such as Fan et al. (2019), with respect to pollution-intensive industries in China that faced stringent water pollution regulations), or they can try to just meet the regulation (as shown by Houde (2022) in the context of the offer of products by firms in response to voluntary environmental certification policies in the US). They can, of course, also try to get around the regulation: for example, Chen et al. (2018) show that most firms relocated water polluting activity upstream in response to an increase in the stringency of downstream regulations in China.

India, a signatory to the Paris Agreement, committed to reduce the emissions intensity of the economy by at least 46 to 48% from its 2005 levels by 2030, according to its 'nationally determined contributions' (NDCs) (Goswami, 2021). As a large emerging economy, India accounts for 7.3% of global emissions (it is the third largest contributor after the US and China), and its manufacturing and construction sector is also the third largest contributor to its total GHG emissions (after electricity and heat and agriculture) (Ritchie et al., 2020). The cement industry is an important source of GHG emissions: India is the world's second largest cement producer and consumer, accounting for 8% of global installed capacity. In the last five years, India's cement production has exceeded its cement consumption consistently, and cement production was expected to reach about 381 million tonnes by 2021-22 (Joshi et al., 2021). Given its rapid industrialization and urbanisation as well as the impetus the Indian government has provided for large-scale infrastructure projects, it can be expected that cement consumption will increase domestically, and this may require policy action to reduce emissions from this sector.

In this study, we will focus on a regulation specific to energy use, the Perform-Achieve-Trade (PAT) scheme, which was launched by the Bureau of Energy Efficiency in India as a part of the National Mission for Enhanced Energy Efficiency, a mission under the National Action Plan on Climate Change. PAT policy aimed to reduce energy intensity in specific industries characterized by high energy consumption. In its first cycle, which lasted from 2012-13 to 2014-15, plants within these industries that were, on average, consuming more than a certain threshold of energy (called 'designated consumers') between 2008 and 2010 (the base years) were mandated to reduce their energy intensity, i.e, the amount of energy used per unit of production. Moreover, the policy incentivized firms to go beyond the threshold, by certifying the excess energy savings, and enabling them to trade these certificates on a market. On the other hand, firms that were unable to meet the target needed to purchase certificates for their excess energy consumption in order to comply with the regulation. The trade of these certificates began once the implementation of the policy was over, i.e. in 2017. In this study, we are interested in evaluating the effects of the policy till 2015, and not in considering its impact on certificate trades afterwards. We focus on the first cycle of the PAT, and evaluate the effects of the regulation on firms across India from 2007-2015 that were subjected to this regulation. We focus on analysing the impact of the policy on the Indian cement sector in this study.

In the specific case of the PAT, one of the direct influences of the policy is likely to have been on the energy intensity of firms, or on their total energy consumption. However, it is equally interesting, from a scientific point of view, to understand the effect of this policy on the productivity of firms. If firms responded to the policy by upgrading their equipment to reduce energy consumption, we can expect the productivity of firms to improve, to the extent that firms will experience technical improvements and a reduction in energy consumption. On the other hand, since the policy targets energy consumption per unit of output, firms can also respond by mainly increasing their size, and producing more. While this reaction may also result in increases in productivity, the original intention of the policy may then not be fulfilled completely. In this case, the design of this type of policy instrument can be questioned.

In the main analysis of this paper, we investigate the effects of the PAT on the TFP growth rate of cement plants in India, and on its components (scale and technical change). This analysis provides us insights on whether the policy measure resulted in the adoption of new technologies that could also reduce energy consumption, whether it resulted in an increase in output, or both. As further analysis, we evaluate the impact of the policy on energy intensity and on total energy consumption. This analysis provides us the possibility to put in context our results on the effects of PAT on the TFP growth rate and its components, and to thereby judge the true effectiveness of the policy.

Methodologically, we utilize a difference-in-difference estimation approach for evaluating the effect of the PAT policy on the TFP change and its components. We estimate TFP using the cost function-based approach. This is the appropriate methodology for us to use in our context, because it allows us to disentangle the effects of the PAT on both scale efficiency, as well as technical change. Our results highlight that average TFP levels declined slightly across firms in the cement industry during the time period of our study. Moreover, we also find that cement plants experienced economies of scale, implying that in this context, average costs were declining for firms as they increased their output.

The results of our main difference-in-difference analysis suggest that the decline in TFP was mitigated for treatment firms, i.e., they experienced relatively higher TFP growth rates, compared to control firms, a result that emerges across several robustness as well as placebo checks. With the use of the cost function approach, we are able to identify the channel through which the regulation primarily drove higher TFP growth rates for treatment plants: we find that treatment plants are likely to have experienced a stronger scale effect compared to control firms, and that the effect of the regulation on their rate of technical change was, in fact, negative. Thus, treatment firms primarily responded to the regulation by increasing production of cement compared to control plants, whereas they experienced lower rates of technical change improvements, compared to control plants.

Moreover, we find that while the PAT regulation led to a decline in the energy intensity for treatment firms (as also found by Oak and Bansal (2022)), it did not result in a decline in their total energy consumption. These results together suggest that the PAT regulation resulted in relatively energy-intensive cement plants in India expanding in terms of the scale of production to meet the regulatory requirements, but not being able to achieve significant reductions in energy consumption through technological improvements. Thus, cement firms operated on one margin of adjustment, namely on increasing output, while focusing less on technological improvements to meet their targets.

Our findings have important policy implications for the design of energy-sector policies in developing countries. They suggest that while firms may be able to find means to meet regulations, they may need additional technical as well as financial assistance to introduce technological improvements in their production processes, which is a prerequisite for sustained improvements in energy efficiency as well as for reductions in energy consumption. Moreover, policy design needs to take into account the possible responses of firms, and the different margins of adjustment available to them to meet their targets. As we see in this study, firm-level responses may often just do enough to satisfy the regulation, while not necessarily meeting the overarching policy goals of reducing energy consumption, and therefore emissions.

The rest of the paper is organized as follows: Section 2 provides a review of the previous literature, in Section 3 we provide a short background on the PAT policy, as well as on the Indian cement industry, Section 4 includes details on our data and the empirical strategies, Section 5 presents the main results as well as the results of additional checks, and Section 6 concludes.

2 Previous Literature

The focus of our paper is on the effect of the PAT policy on firm-level productivity. Theoretically, one possibility is that environmental regulation can lead to an increase in firm-level productivity, which manifests as firms experience reduced marginal costs of production by investing in clean technologies; this is important, because higher productivity has been shown to affect exports as well as market shares (Melitz, 2003). On the other hand, investment in clean technologies is also likely to reduce the resources available with the firm for production, and thus it may also have a negative effect on productivity growth.

The possible negative effects of more stringent environmental regulation on firm-level competitiveness was theoretically modeled by Viscusi (1983), who argues that regulation may reduce output (especially when investments are reversible), and that this effect is compounded by regulatory uncertainty. A strand of empirical literature has found that more stringent environmental regulation may have had negative consequences on the productivity of firms. For instance, Hancevic (2016) studied the effect of the Clean Air Act Amendments of 1990 on the productivity and output of coal-fired power plants in the US, and found that the regulation compelled plants to shift towards using coal with lower SO_2 emissions. As a result, plants that were using boilers designed to burn a specific type of coal experienced both declines in productivity, as well as in output, with significant spatial and temporal heterogeneity. Gollop and Roberts (1983), also found that SO_2 regulations reduced productivity growth in fossil-fuel based power plants in the US.

Greenstone et al. (2012) used a large-scale dataset to evaluate the impact of the 1970 Clean Air Act Amendments in the US on productivity across sectors; they found that TFP declined on average by 4.8% for plants in regulated counties compared to those in either weakly or unregulated counties, on controlling for many confounding factors. This supports some evidence that emerged from studies using relatively fewer observations as well (Gollop and Roberts (1983) for the electricity sector and Gray and Shadbegian (1998) for the paper and pulp sector). However, this overall finding hides heterogeneity in effects based on pollutants; while Greenstone et al. (2012) found that higher stringency of regulation for ozone reduction had a negative

effect on productivity, the relationship was positive for carbon monoxide. Rubashkina et al. (2015) also obtained some heterogeneity in their results, but along the temporal dimension; they found that more stringent environmental regulation negatively affected TFP, but that this effect disappeared within two years.

On the other hand, ample evidence also exists to support the notion that environmental regulation can foster TFP improvements.Eli and Bui (2001) found that the increased stringency of air quality regulations (measured through abatement investments) enhanced the productivity of oil refineries in the Los Angeles Air Basin. Hamamoto (2006) also found that stricter environmental regulations (measured through pollution control expenditures) had a positive effect not just on TFP growth rates, but also on R&D expenditures. Telle and Larsson (2007) found that more stringent environmental regulation had a positive effect on Norwegian plant-level productivity, when emissions reductions were accounted for as an 'input' in the derivation of productivity growth. De Santis et al. (2021) found, using cross-country data from 1990-2015, that environmental regulatory stringency was positively associated with productivity, because of higher levels of innovation, and that this result was consistent across both market-based as well as non market-based regulatory instruments. Lanoie et al. (2008) found differential short-run and long-run effects of stricter regulation on TFP growth, using data from manufacturing firms in Quebec, Canada; they observed that while the same-period effect of more stringent regulation on TFP growth was negative, lagged regulatory variables had a positive effect on TFP growth rates, results which partially confirm Porter's hypothesis, and that this effect was stronger for sectors more exposed to competition. However, they also found that the positive effects were only observed for industries that were relatively less polluting, and that environmental stringency had a negative effect on TFP growth in polluting sectors, either due to the large-scale investments needed to satisfy regulations, or due to the high ratio of unproductive to productive investments.

Several studies also point to insignificant ambiguous effects of tightening of environmental regulation on TFP. Becker (2011), for example, by using plant-level cross-industry manufacturing data from the US and estimating Cobb-Douglas production functions, found that plants located in counties with higher environmental compliance costs do not experience significantly higher (or lower) levels of productivity. Conrad and Wastl (1995) also found that mores stringent environmental regulation did not have an effect on TFP of firms across most German industries. They accounted for the fact that environmental regulation depletes the stock of material and capital that can be used for productive purposes, by treating compliance with environmental regulation as an additional input. Barbera and McConnell (1990) used a cost function approach and US data on five polluting industries to estimate TFP, and they separated the effect of environmental regulation on it into a 'direct effect' (the direct cost of abatement equipment) and an 'indirect effect' (a change in the way conventional inputs are used). They found that while the direct effect was always unambiguously negative, the indirect effect may be positive, negative or zero, depending on the industry. The 'non-effect' finding was also partially confirmed by Albrizio et al. (2014), who used cross-country data from several industries to find that environmental regulation did not have any permanent effects on multi-factor productivity growth either at the country or industry level. On the other hand, at the firm level, they found that only the technologically most-advanced firms experienced positive effects on productivity growth, while the less productive firms experienced productivity declines.

The evidence from developing countries in this literature is scant. For example, Alpay et al.

(2002), found that the productivity of plants in the Mexican food processing industry increased strongly in response to more stringent local environmental regulations. However, studies using Chinese data produced somewhat mixed results. Zhao and Sun (2016) first identified relatively carbon-intensive industries (based on the scale and intensity of CO_2 emissions) for China, and tested for the Porter Hypothesis. They found effects varying over time; in the short-run, TFP in these industries increased in response to more stringent regulation, however this trend reversed in the long-run, thus exhibiting an inverted-U relationship (which was also observed by Wang and Shen (2016)). Yang et al. (2021) also used Chinese data on several industries between 1998-2007 to show that aggregate industry productivity only increased when regulation was not too strict, i.e., they also confirmed the inverted-U trend. On the other hand, Filippini et al. (2020) focused on the Chinese iron and steel industry, and found that a policy meant to increase the energy efficiency of firms, the Top 1000 Firms Energy Conservation Program, had a positive effect on the TFP growth rate of firms. These findings were also corroborated by Peng et al. (2021), who found that a form of market-based instrument, the SO_2 emissions trading scheme pilot in China, had a positive effect on TFP of firms, and that the effects were stronger on privately owned, more productive, and less pollution-intensive enterprises.

Lastly, Ryan (2018) found, by conducting a field experiment with energy-intensive Indian manufacturing firms in the textile and chemical sectors that offered energy consulting to raise energy productivity levels, that treated plants in fact consumed more energy, as they increased capacity utilization in response to the treatment. While Ryan (2018) did not conduct a policy evaluation, and we in this study do not explore the effect of the PAT regulation on capacity utilization, we find in a somewhat similar vein that the policy did not lead to a reduction in energy consumption, while it led to an improvement in energy intensity, as treated cement plants produced more.

3 Background on the PAT Policy and the Indian Cement Industry

The Perform-Achieve-Trade (or PAT) scheme was launched by the Bureau of Energy Efficiency (BEE) in India. The first cycle of the scheme lasted from 2012-13 to 2014-15, and involved the identification of 478 designated consumers (DCs) from eight industrial sectors, cement, aluminium, chlor- alkali, fertilizer, iron and steel, paper and pulp, thermal power, and textiles. Each DC was assigned a specific energy consumption (SEC) (or energy intensity, measured as the amount of energy consumed per unit of production) reduction target, which they needed to meet by 2015 (Bureau of Energy Efficiency, 2019).

In order to identify DCs, the BEE calculated the average energy consumption of the firms over the years 2007-08, 2008-09 and 2009-10. In the case of the cement industry, any plant that has a total energy consumption (over all energy services used) greater than 30,000 MTOE (metric tonnes of oil equivalent) is categorized as a DC. These thresholds were not revised during the implementation period, and the treatment status of plants identified as DCs at the beginning of the compliance period remained unchanged during the period. At the overall level, the PAT scheme required the DCs in the cement industry to reduce energy consumption to 0.816 million MTOE. 85 plants from 42 firms in the Indian cement industry were identified, according to the PAT policy, as DCs. The cement industry was set a target to contribute about

12.19% of the overall energy savings under PAT Cycle-I (Bureau of Energy Efficiency, 2022*a*).

Once the compliance period was over, the compliance of the DCs was checked by accredited energy auditors. DCs that were not able to meet the target SEC were required to purchase energy saving certificates (ESCerts), whereby one ESCert was equivalent to one MTOE of energy consumption. Likewise, DCs that achieved energy savings could sell these certificates. These certificates could be traded on the Indian Energy Exchange (IEX), or on the Power Exchange India Limited (PXIL). However, trading of these ESCerts only began in 2017 (Bureau of Energy Efficiency, 2022*b*).

The Indian cement industry is the second largest in the world, and accounted for over 7% of the global installed capacity of cement. The current installed capacity in India is 500 MTPA (million tonnes per annum), and the annual production is 298 million tonnes. The PAT scheme covered about 65% of the total installed capacity of cement in India. According to the Bureau of Energy Efficiency, the total savings achieved by 75 DCs in the cement industry during PAT Cycle I was 1.48 million MTOE, which was 0.665 million MTOE in excess of the target that was set for them (Bureau of Energy Efficiency, 2022*a*).

Cement production involves using gypsum, clay or shale, as well as limestone to produce 'clinkers', or nodules. Clinker production entails heating a homogeneous mixture of raw materials in a rotary kiln at high temperature. Clinkers are then ground to produce cement. Cement manufacturing is mainly done using two methods: a wet process, and a dry process. The wet process involves mixing the raw materials with water, which leads to a better quality of clinkers. The wet process has higher energy requirements, due to the high moisture content of the slurry. The dry process, on the other hand, involves keeping the raw materials dry, and using heat from the mill for heating the mixture. It has lower energy requirements than the wet process (Bureau of Energy Efficiency, 2022*a*).

In our empirical analysis, we will treat designated consumers as 'treatment' plants, and the remaining as control plants.

4 Methodology and Data

4.1 Methodology

As discussed in the Introduction section, we are interested in evaluating the effect of the PAT scheme on the total factor productivity (TFP) growth rate of cement plants, and on its components. In this section, we describe the methodology adopted for the main analysis of this paper, namely for the evaluation of the effect of the PAT scheme on the TFP growth of cement plants. For this analysis, the first step involves the computation of the TFP growth rate of firms, and the second step involves conducting a policy evaluation.

The estimation of TFP change can be performed using either parametric, or non-parametric approaches. Parametric approaches are broadly categorized as production function-based approaches, and cost function/frontier-based approaches. Non-parametric methodologies involve estimating an index to denote TFP change, such as the Törnqvist index. Our preferred approach in this study is the cost function-based approach (Kumbhakar and Lovell (2000) provide a comprehensive summary of this approach), which enables us to not only disentangle

the driving factors behind TFP change, but it is also less likely to suffer from endogeneity-related problems compared to production function-based approaches. As robustness checks, we also estimate TFP using two production function approaches proposed by Ackerberg et al. (2015) and Wooldridge (2009).

Estimation of TFP Change

Our main TFP change estimation approach involves the estimation of a plant-level cost function, for which we use a trans-log functional form. The cost function approach entails first specifying the total costs of firm 'i' in year t, as shown below:

$$C_{i,t} = f(Y_{L,it}, P_{K,it}, P_{L,it}, P_{M,it}, P_{E,it}, t) \tag{1}$$

Total costs ($C_{i,t}$) are defined in our case as the sum of all intermediate good as well as other input-associated costs, such as those of labor, capital, materials as well as energy. These costs account for depreciation, as well as interest expenses. $Y_{i,t}$ is a measure of the output of firm 'i' in year 't', which we measure by the gross sales in INR. The price of capital $P_{K,it}$ is defined as the ratio of the sum of total depreciation costs as well as interest payments made, to the total opening value of the net assets of the firm. We define the price of labor $P_{L,it}$ as the ratio of total expenditure on wages, bonus payments, welfare, as well as the employee Provident Fund (India's public pension system) to the total "man-days" worked at the plant in period 't'. $P_{M,it}$, the price of materials, is defined as the ratio of total expenditure on indigenous inputs as well as imports (net of the total energy expenditure) to the total tonnes of clay, limestone, gypsum and clinkers consumed in producing cement. $P_{E,it}$ is the price of energy, and it is the ratio of the total energy expenditure to the total quantity of gas, electricity, coal as well as petrol/diesel consumed. 't' denotes a time trend. All monetary values are deflated to 2010 prices World Bank Data (2021).

To estimate the cost function, we utilize a trans-log functional form that does not impose any conditions or restrictions on the model parameters. Utilizing a trans-log production function requires that the approximation of the underlying cost function be made at a local point, which we assume to be the median value of all the variables. Thus, for estimating a cost function of the form shown in equation (1) above, we first normalize the output as well as the prices by their median values. We then treat materials as the numeraire input, and normalize both the output and the input prices by the normalized price of materials. The trans-log cost function that is estimated is as shown:

$$\begin{aligned} c_{i,t} = \beta_0 + \lambda_i + \beta_Y y_{i,t} + \sum_{X=L,K,E} \beta_X p_{X,it} + \frac{1}{2}[\beta_{YY}(y_{i,t})^2 + \sum_{X=L,K,E} \beta_{XX}(p_{X,it})^2] + \\ \sum_{X=K,E} \beta_{LX} p_{L,it} p_{X,it} + \beta_{KE} p_{K,it} p_{E,it} + \sum_{X=L,K,E} \beta_{YX} y_{i,t} p_{X,it} + \\ \beta_T t + \beta_{TT} t^2 + \sum_{X=L,K,E} \beta_{XT} p_{X,it} t + \mu_{i,t} \end{aligned} \tag{2}$$

where lowercase notation for both output ($y_{i,t}$ and input prices ($p_{L,it}$, $p_{K,it}$, and $p_{E,it}$) denote log-transformed variables. We estimate model (3) above using both random as well as fixed

effects and heteroscedasticity-robust standard errors, however we only use the fixed effects specification for computing the TFP growth rate in the next step.

As shown by Coelli et al. (2003), it is possible to use the estimated parameters from the cost function to compute the change in TFP growth between two periods (t and t-1), as indicated in expression (3) below. Change in TFP can be derived as the sum of two components: the change in scale efficiency, and technical change.

$$TFPC_{it} = ln(\frac{TFP_{it}}{TFP_{it-1}})$$
$$= \frac{1}{2}[(1-e_{it}) + (1-e_{it-1})](y_{it} - y_{it-1}) - \frac{1}{2}[\frac{\partial c_{it-1}}{\partial t} + \frac{\partial c_{it}}{\partial t}] \quad (3)$$

The first term in the second line above denotes the scale efficiency change, and the second term denotes the technical change. $c_{i,t}$ and $c_{i,t-1}$ denote the log of total costs in periods t and t-1 respectively, $y_{i,t}$ and $y_{i,t-1}$ represent the log of output in these periods, and $e_{i,t}$ and $e_{i,t}$ are the respective elasticities of costs with respect to output in the two time periods. We use the parameters from the cost function estimation in equation (3) above to derive both the cost elasticity, as well as the technical change factor.[1] Furthermore, the cost elasticity measure $e_{i,t}$ derived from the cost function estimation can also be used to compute the economies of scale for the firm. The measure of economies to scale (ES) is computed as the proportional increase in total cost resulting from a proportional increase in output, holding all input prices fixed. This is equivalent to the inverse of the elasticity of total cost with respect to the output (Caves et al., 1984):

$$ES_{i,t} = \frac{1}{e_{i,t}} \quad (4)$$

Economies of scale are said to exist if $ES_{i,t}$ is greater than 1, and diseconomies of scale exist if $ES_{i,t}$ is less than 1. In case $ES_{i,t} = 1$, no economies or diseconomies of scale are said to exist. The existence of economies of scale is suggestive of the the average costs of cement plants declining, as they increase their output.

Effect of PAT Policy on TFP Change

We then use the difference-in-difference methodology to evaluate the effect of the PAT policy on the rate of TFP change of cement plants, given that some plants were treated after 2012, and other were not.

The model that we estimate is as shown below:

$$TFP_{i,t} = \beta_0 + \beta_1 D_i + \beta_2 P_t + \beta_3 D_i P_t + +\beta_4 X_{i,t} + \rho_i + \gamma_t + \epsilon_{i,t} \quad (5)$$

where $TFP_{i,t}$ denotes the rate of TFP change for plant 'i' between period t and period t-1, and the remaining notation remains same as before. We are interested in deriving the parameter β_3, namely the effect of the PAT policy on the TFP change of treatment plants in the post-treatment period. Once again, we use heteroscedasticity-robust standard errors for

[1] For more details on this approach, Coelli et al. (2003) provide a useful overview of this methodology.

these estimations, along with plant as well as year fixed effects, and we include some covariates.

The advantage of using the cost function-based approach for computing TFP change is that we are able to disentangle the effect of the policy on both scale efficiency, as well as on technical change, which has interesting and important repercussions in our case, as we will show in the Results section. However, as robustness checks, we also use two production function-based methodologies. These methodologies involve estimating the output of the firm as a function of different inputs, under varying assumptions. We will be using the Ackerberg et al. (2015) as well as the Wooldridge (2009) approaches for this purpose.

4.2 Data

Our data is primarily drawn from the Annual Survey of Industries (ASI), a national panel database managed by the Ministry of Statistics and Program Implementation (MOSPI) with information on all factories employing 10 or more workers using power, or 20 or more workers if they don't use power in India. This database has been used in other studies using establishment-level analysis for Indian firms (Allcott et al., 2016; Martin et al., 2017). Thus, our data is at the plant (establishment)-level. From this data, we identified plants in the cement industry that produced cement or clinkers (a rocky residue which is often used as an input in cement production). These plants primarily used four types of materials for cement production: gypsum, clinkers, limestone as well as clay. The geographical span of our data is nationwide, while the duration of the data is 2006-2015.[2] After removing observations with invalid input and output values, we are left with an unbalanced panel of 416 unique cement plants in our main estimations. The unique establishment identifiers allowed us to track these plants overtime.

We identified treatment plants, based on their average energy consumption between the years 2008-2010. According to the rules of the Bureau of Energy Efficiency, "designated consumers" (or treatment plants) were those plants that consumed more than 30000 metric tonne oil equivalent (MToE) of energy over that time period, on average. We used the ASI data to identify treatment plants in case we had non-missing values for energy consumption over any of the years in this period. Furthermore, we supplemented this information with doing a manual search to identify treatment plants, based on matching on several variables including location (state and district), year of incorporation, output or sales, energy consumption, etc. In total, in our regression sample, we have 74 treatment plants, and 498 control plants.

Table 1 presents some summary statistics (the mean as well as standard deviation) of the most important variable in our data for the overall sample, for treatment plants as well as for control plants. We find that the mean value of gross sales of cement plants was about 6679 million INR over the period 2006-2015, with treatment plants being much larger in terms of sales (column (3)) than control plants (column (5)), with the difference being statistically significant at the 1% level (column (7)). This is also reflected in most other measures of firm size and economic performance, such as the total value added, total cost incurred, as well as along all measures of inputs (both quantities as well as expenditures, such as energy, materials, capital and labor). For instance, treatment plants consumed about 130677 MTOE (with an expenditure of about 1694 million INR) of energy per year (including quantity of gas, electricity, coal as well as petrol/diesel), whereas control plants consumed about 13321 MTOE, and spent

[2]The first cycle of the PAT lasted from 2012-2015.

about 231 million INR on energy-related expenses. Note that about 27% of the observations are for treatment plants, whereas the rest are control plants. Thus, it is clear that treatment plants were much bigger, and used more inputs (such as energy) compared to the control plants.

We also present the summary statistics for the prices of these inputs in Table 1, that we derived as described in the previous sub-section, using the cost function approach. We find that the mean energy price in our sample was about 0.07 million INR per MTOE for the overall sample: treatment plants paid about 0.05 million INR per MTOE, whereas control plants paid slightly more, at about 0.08 million INR per MTOE, even though this difference is not significant even at the 10% level. In fact, we find the same trend for the prices of other inputs as well, control plants seem to have paid higher prices for capital and materials, but the differences are insignificant with respect to the treatment plants. Only in the case of the price of labor is this difference significant: the price per man-day of labor per year was significantly higher for treatment plants, compared to control plants. We also do not find any differences between the two groups in terms of their sector of location, i.e., whether the plants are located in rural or urban areas.

5 Results

In this section, we present the main estimation results of the paper. In the first part of this section, we present the results of the computation of economies of scale, as well as of TFP growth rates using the cost function approach, and the difference-in-difference results for the effect of the PAT policy on TFP growth rates. In the second subsection, we present an empirical analysis that evaluates the effect of the PAT scheme on energy consumption as well as on energy intensity, to shed light on the mechanisms behind the results in the first section on TFP growth. The final subsection includes the results of some placebo checks as well as of robustness checks on our main results.

5.1 TFP growth rates

5.1.1 Calculation of TFP growth rates and returns of scale

As mentioned in the Methodology section, we use the cost function approach as the main methodology for computing the TFP growth rates of firm. Table A1 in the appendix includes the results of the estimation of the total cost function in columns (1) and (2); column (1) includes the model results using random effects, while in column (2) we introduce plant-level fixed effects. As expected, we find that the total cost function is increasing in output, and non-decreasing in input prices, and concave in input prices at the median values.

Table 2 presents some descriptive statistics on the values of the TFP growth rate and its components derived using the coefficients from the estimation of the fixed effects model in column (2) of Table A1. We report these values for the entire sample, as well as for treatment and control plants respectively.

Using the cost function approach, we find that for the overall sample, the mean TFP growth rate

Table 1: Summary Statistics for the Regression Sample

Sample	Overall Sample		Treatment Plants		Control Plants		Diff. in means
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	P-value
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gross sales (in millions of Rs.) (Deflated to 2010 prices)	6679.3	9314.9	15849	11225	3316.4	5502.4	0
Total value added (in millions of Rs.) (Deflated to 2010 prices)	5048.5	7260.8	12095	8876.4	2464.1	4277	0
Total cost (in millions of Rs.) (Deflated to 2010 prices)	2001.7	2767.3	4558	3498.8	1064.2	1644.9	0
Total energy consumption (in MTOE)	44811.62	87409.91	130676.58	118158.87	13320.93	40391.09	0
Total energy expenditure (in millions of Rs.) (Deflated to 2010 prices)	623.57	978.10	1693.50	1200.30	231.16	453.52	0
Total quantity of materials (in tonnes)	1053628.12	2346350.58	2549178.28	2372745.42	505140.03	2083561.64	0
Total materials expenditure (in millions of Rs.) (Deflated to 2010 prices)	894.51	1400.1	1684	1764.3	604.96	1107.6	0
Total capital stock (in millions of Rs.) (Deflated to 2010 prices)	2368.4	11049	5685.4	20557	1151.9	2555.3	0
Total capital expenditure (in millions of Rs.) (Deflated to 2010 prices)	244.37	517.38	571.96	793.32	124.23	285.50	0
Total man-days worked per year	166822.52	227960.90	385617.31	300257.45	86580.26	118307.34	0
Total labor expenditure (in millions of Rs.) (Deflated to 2010 prices)	125.28	189.11	309.96	254.64	57.55	89.59	0
Price of energy (in millions of Rs. per MTOE)	0.07	0.91	0.05	0.65	0.08	0.99	0.48
Price of materials (in millions of Rs. per tonne)	0.54	18.68	0.08	1.42	0.71	21.82	0.48
Price of capital	0.29	2.29	0.19	1.51	0.33	2.52	0.21
Price of labor (Rs./ man-day worked per year)	595.42	464.82	895.37	468.66	485.41	412.01	0
Plant in rural location (1 = Yes, 0 = No)	0.72	0.45	0.72	0.45	0.72	0.45	0.83

Notes: The overall sample includes a total of 2277 observations for cement plants with non-missing and non-zero prices and output, with 611 observations for the treatment plants and 1666 observations for the control plants.

Table 2: TFP Growth Rates: Descriptive Statistics

Sample	Overall			Treatment Plants			Control Plants		
	Mean	Median	Obs.	Mean	Median	Obs.	Mean	Median	Obs.
TFP growth rate	-0.025	-0.029	1707	-0.026	-0.035	537	-0.025	-0.026	1170
Technical efficiency change	-0.019	-0.026	2277	-0.037	-0.038	611	-0.013	-0.014	1666
Scale efficiency change	-0.0007	0.002	1707	0.013	0.008	537	-0.007	-0.001	1170

Notes: The sample includes cement plants with non-missing and non-zero prices and output. Values for the cost function approach are derived using the parameters of the estimation results provided in Table A1 in the Appendix.

was negative, at about -2.5% (median of about -2.9%). However, we find some heterogeneity between the components of TFP; we find that the mean scale efficiency factor was about -0.07% (median 0.2%), whereas the mean technical change efficiency was about about -1.9% (median -2.6%).Thus, the magnitude of the decline was larger for TEC than it was for scale efficiency.

This pattern is also echoed in the descriptive statistics by treatment group, although we find that the mean value of technical efficiency is lower for treatment plants than for control plants, i.e., treatment plants experienced a larger decline in TEC compared to control plants. On the other hand, scale efficiency increased for treatment plants, while it declined marginally for control plants. While the differences in the mean values of TFP between treatment and control plants are insignificant, the mean TEC value is significantly lower in treatment plants than in control plants (at the 1% level), whereas the mean value of scale efficiency is significantly higher for treatment plants compared to control plants, at the 1% level. Thus, the results of estimating TFP growth rates using the cost function approach suggest that Indian cement plants experienced a decline in TFP growth between 2007 to 2015; this is largely driven by a reduction in the rate of technical change during that period, while it appears that scale efficiency declined only marginally, and that too only for control plants.

Table 3 presents the values for economies of scale for cement plants of varying sizes, based on their deflated value of gross sales. We define small plants as producing output at less than the 25th percentile, medium-sized plants as those producing between the 25th and 75th percentiles, and large plants as those producing at more than the 75th percentile. We compute the economies of scale for the overall sample, for treatment plants, as well as for control plants. Note that there are no treatment plants that produce at less than the 25th percentile of output, because treatment plants were inherently larger in size.

We find that economies of scale exist, as all of the values mentioned in Table 3 are greater than 1. Moreover, we find that returns to scale decline with firm size, i.e., larger plants tend to have lower returns to scale than smaller plants, while the mean returns to scale of treatment plants are marginally higher than those of control plants. These results suggest that cement plants in India were experiencing declines in average costs, on increasing output.

5.1.2 Effect of PAT Policy on TFP Growth Rates

Table 4 includes the difference-in-difference results of evaluating the impact of PAT on the TFP growth rates. In the final subsection on robustness checks, we also test the validity of our main results to using alternative methods of computing the TFP, such as the Ackerberg et al.

Table 3: Economies of Scale: Descriptive Statistics

Sample	Small-sized plants			Medium-sized plants			Large-sized plants		
	Mean	Median	Obs.	Mean	Median	Obs.	Mean	Median	Obs.
Overall	1.657	1.635	571	1.568	1.548	1135	1.520	1.511	574
Treatment	-	-	-	1.544	1.538	213	1.517	1.512	399
Control	1.657	1.635	571	1.574	1.551	922	1.529	1.510	175

Notes: Size of plants is determined on the basis of the deflated value of gross sales, with small plants producing at less than the 25th percentile of output, medium-sized plants between the 25th and 75th percentiles, and large-sized plants producing at a level higher than the 75th percentile of output. Economies of scale are defined as the inverse of elasticity of total cost with respect to output, which is derived using the parameters of the cost function estimation results provided in Table A1 in the Appendix, and are said to exist if this elasticity is less than 1. The sample includes cement plants with non-missing and non-zero prices and output. Values for the cost function approach are d

(2015) approach, and the methodology proposed by Wooldridge (2009) (results provided in Table A2)). In column (1), we evaluate the effect of the intervention on the TFP growth rate, whereas in columns (2) and (3) we focus on identifying its effect on scale efficiency as well as on technical efficiency. As earlier, all models include plant and year fixed effects, additional covariates, as well as heteroskedasticity-robust standard errors.

These results, based on the cost function estimation, suggest that treatment plants experienced higher TFP growth rates compared to non-treatment plants, in the post-treatment period. In conjunction with the results of Table 2, this suggests the possibility that the PAT scheme may have led to lower levels of decline in TFP change for treatment plants after 2012, compared to the control plants. In this specification, we find that the TFP growth rate was about 0.05 percentage points higher for treatment plants.

The results of columns (2) and (3) reveal the channels through which the PAT scheme may have affected TFP growth rates of cement plants: we find that treatment plants experienced an increase in scale efficiency, i.e., they began producing more in response to the policy, an effect which is significant at the 1% level. However, as observed in column (3), the policy resulted in a decline in the rate of technical change, i.e., treatment plants experienced a rate of technical change that was 0.001 percentage points lower than control plants.[3]

In a sense, these results are synchronous with the nature of the policy; by targeting the energy consumption of firms per unit of output, the implementation of the PAT scheme meant that firms had two margins of adjustment, namely reductions in energy consumption, or increases in output. We find stronger evidence in this study of the latter, while the former effect is weaker as firms may have chosen to divert resources to increasing their output. As we showed in the previous subsection, cement plants on average experienced strong economies of scale in our setting. This finding thus seems to support the fact that firms may have responded to the policy and met the standard by increasing output, rather than by reducing energy consumption or investing in more energy-efficient technologies. With treatment firms circumventing the main objective of the policy in this manner, regulators may not have reached their goal of

[3]We find similar results on using the variable cost function with fixed effects (column (3) of Table A1) for computing TFP growth instead of the total cost function.

reducing energy consumption. For this reason, in the next section, we investigate the impact of the policy on energy consumption and energy intensity.

In Figure 1 below, we present the results of the tests evaluating the common trends assumption for these three dependent variables. We find that the common trends assumption is valid for the estimations with TFP and scale as dependent variables. For the TEC estimation, we find that the difference between treatment and control plants was significant at the 5% level in the years just prior to the treatment, i.e., in 2011 and 2012. This may partially be driven by an announcement or anticipation effect.

Table 4: Difference-in-Difference Results for the effect of PAT on TFP Growth

Dependent variable Column	Total factor productivity growth (1)	Scale efficiency change (2)	Technical efficiency change (3)
PAT indicator	0.050*** (0.018)	0.052*** (0.018)	-0.001*** (0.0005)
Observations	1707	1707	2277
Plant fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Covariates	✓	✓	✓

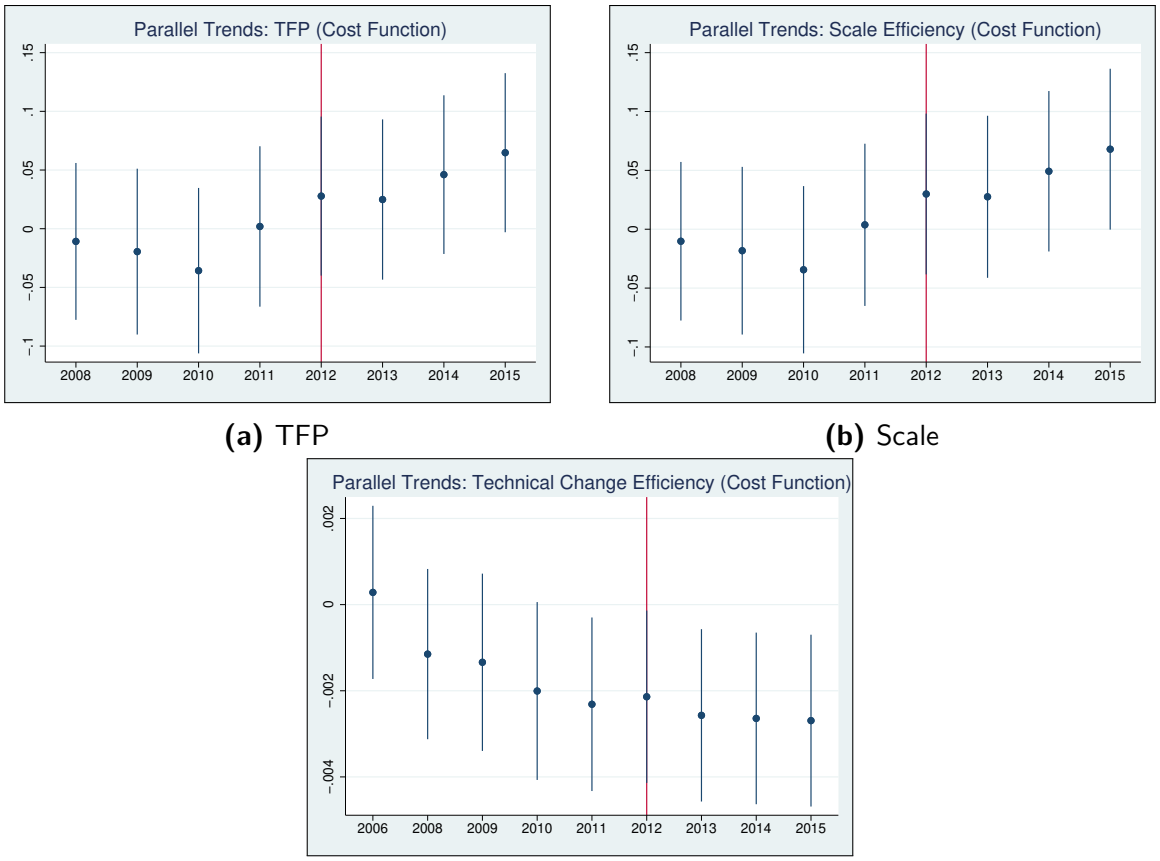
Notes: The regression sample includes cement plants with non-missing and non-zero prices and output. Covariates include controls for the sector of location (urban/rural), as well as for the type of firm. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Huber-White heteroscedasticity-consistent standard errors are reported in parentheses. The coefficient on the constant has not been reported.

5.2 Effect of PAT Policy on Energy Intensity and Energy Consumption

As discussed above, given the results of the previous sub-section, namely the positive effect of the policy on scale efficiency, and the negative effect on technical change, it is important to understand how treatment plants are responding to the policy in terms of its effects on their energy consumption and on energy intensity. Our hypothesis is that treatment plants may have experienced an increase in output, without a significant decline in energy consumption.

A recent study by Oak and Bansal (2022) has evaluated the impact of the PAT regulation on energy intensity and energy consumption. The authors evaluated the effects of the PAT for three industries in India, namely cement, fertilizer and pulp and paper, using a difference-in-difference approach. They found that the scheme reduced the energy intensity of firms (defined as the total expenditure of the firm on power and fuel divided by its gross sales) in the cement and fertilizer industries by 2.7 percent and 1.6 percent respectively, whereas the effect was insignificant in the pulp and paper sector. However, this study didn't use a quantity-based measure of energy consumption, and input prices were not included as explanatory variables. Further, the study was conducted using firm level data, while the policy was implemented at the plant level. These may be relevant limitations, because the use of energy expenditure as a proxy for energy consumption implicitly assumes that the prices of all types of energy sources (such as oil, coal, gas, etc.) are the same. Furthermore, excluding input prices as explanatory variables in the energy demand function may introduce bias in the estimates.

Below, we describe the methodology and results of our analysis, with the purpose of understanding whether the policy had an effect on the energy intensity and on energy consumption



(a) TFP **(b)** Scale

(c) TEC

Figure 1: Testing the Common Trends Assumption for the DiD Model for TFP, Scale and TEC Estimated Using the Cost Function Approach

of firms. We define energy intensity in two ways: firstly, as the total energy consumed by the firm 'i' in year 't' divided by the gross sales of the plant in that year. The second definition is similar to one use in Oak and Bansal (2022), and is defined as the total energy expenditure per year (in Indian rupees (INR)) divided by the gross sales. All monetary values are deflated to 2010 prices. Total energy consumption for a given year is defined as the total units of gas, electricity, coal, as well as petrol/diesel that the firm used in year 't', all of which we convert in terms of metric tonnes of oil equivalent (MTOE) before aggregation.

The model that is estimated for these two dependent variables is as shown below:

$$Y_{i,t} = \alpha_0 + \alpha_1 D_i + \alpha_2 P_t + \alpha_3 D_i P_t + +\alpha_4 X_{i,t} + \nu_i + \delta_t + \epsilon_{i,t} \tag{6}$$

where $Y_{i,t}$ denotes our measure of either energy intensity or total energy consumption, D_i indicates whether the firm was subject to the PAT regulation, and P_t earmarks the treatment period (i.e., 2013 and beyond). Furthermore, $X_{i,t}$ is a vector of plant-level covariates, ν_i denotes plant fixed-effects, δ_t denotes year fixed-effects, and $\epsilon_{i,t}$ denotes the residual term. We are interested in deriving the parameter α_3, namely the effect of the PAT policy on the energy intensity (or energy consumption) of treatment plants in the post- treatment period. Note that on incorporating plant and year fixed effects in the models (as we do in all our specifications), we will derive estimates on this interaction term without deriving the coefficients on the main

effects, i.e., we will only be deriving α_3, and not α_1 and α_2. $X_{i,t}$ denotes a set of firm-specific control variables, such as the sector (whether it is located in a rural or urban area), as well as the type of organisation of the plant (i.e., whether it is a partnership, a public or a private firm, a cooperative, etc.). We compute heteroscedasticity-robust standard errors for these estimations.

We are able to account for time-invariant unobserved heterogeneity (such as differences in geographical factors, management styles as well as quality of inputs such as labor) across cement plants in our data with the inclusion of plant fixed effects. Moreover, we also account for time-variant changes that are likely to affect all plants in our sample (such as changes in market demand, overall technological improvements and the implementation of sector-specific policies) using year fixed-effects.

Table 5 presents the results of this analysis. Column (1) presents the results with energy intensity defined in terms of the total quantity of energy used (measures in metric tonnes of oil equivalent, or MTOE) per Rupee of gross sales, column (2) with the dependent variable defined in terms of the expenditure on energy consumption per Rupee of gross sales, and in column (3), the outcome variable is defined as the total quantity of energy used (again, measured in MTOE). The dependent variables have been log-transformed across estimations in Table 5, and we include plant and year fixed effects as well as covariates (such as whether the plant is located in a rural or urban area, as well as the type of organisation) across all estimations. We report heteroscedasticity-robust standard errors.

The difference-in-difference results of columns (1) and (2) suggest that treatment firms exhibited lower levels of energy intensity than non-treatment firms, at the 10% level of significance. The coefficient of -0.137 in columns (1) and (2) corresponds to treatment plants having an energy intensity about 14.68% lower compared to non-treatment firms, whether energy intensity is measured in terms of MTOE of energy consumed per rupee of gross sales, or in terms of energy expenditure per rupee of gross sales. These results are largely in line with the findings of Oak and Bansal (2022).

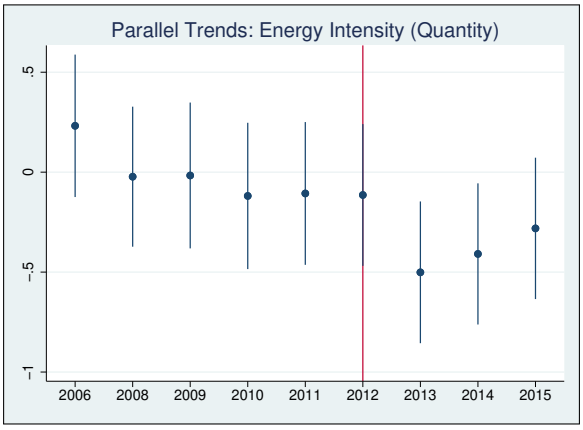
However, the results of column (3) suggest that the PAT scheme may have had a weak effect on total energy consumption, since the coefficient on the PAT indicator is insignificant (with a p-value of 0.250), even though the coefficient is still negative. In combination, these results broadly suggest that the policy may have had a relatively larger effect on the output or gross sales of cement plants, while its effect on the total energy consumption of firms seems to be weak. These results can help explain our findings in the previous subsection on the positive scale effect, and negative technical change effect.

We also present the graphs testing for the common trends assumption for each of these estimations below, in Figure 2. We find that the differences in the pre-treatment period, i.e, before 2012, between both groups for these three outcome variables are largely insignificant (at the 1% level). Thus, we fail to reject parallel trends in the pre-treatment period, suggesting that the main DiD assumption is satisfied.

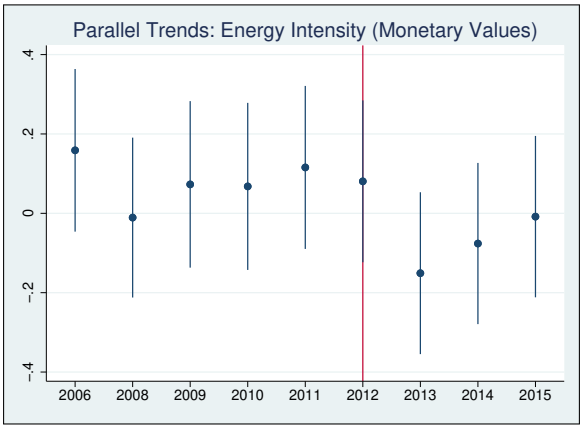
Table 5: Difference-in-Difference Results for the effect of PAT on energy consumption and energy intensity

Dependent variable Column	Total units of energy used divided by gross sales (1)	Total energy expenditure divided by gross sales (2)	Total units of energy used (3)
PAT indicator	-0.137*	-0.137*	-0.086
	(0.079)	(0.079)	(0.076)
Log of price of labor	0.001	0.001	0.011
	(0.046)	(0.046)	(0.041)
Log of price of capital	-0.009	-0.009	0.008
	(0.023)	(0.023)	(0.022)
Log of price of energy	-1.057***	-0.057**	-1.068***
	(0.026)	(0.026)	(0.026)
Log of price of materials	-0.016	-0.016	-0.020
	(0.014)	(0.014)	(0.013)
Log of output			0.640***
			(0.034)
Observations	2277	2277	2277
Plant fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Covariates	✓	✓	✓

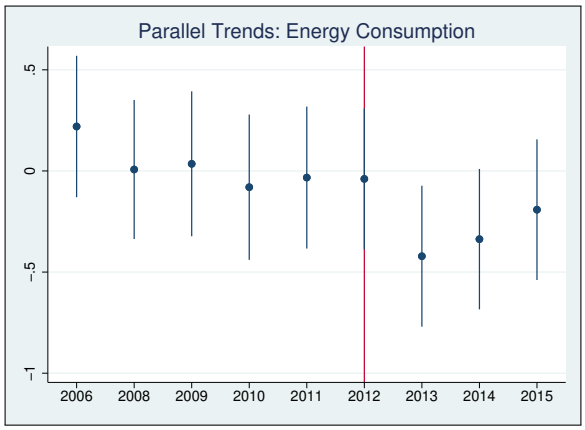
Notes: The regression sample includes cement plants with non-missing and non-zero prices and output. Covariates include controls for the sector of location (urban/rural), as well as the type of firm. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Huber-White heteroscedasticity-consistent standard errors are reported in parentheses. The coefficient on the constant has not been reported.



(a) Energy intensity (Quantity terms)



(b) Energy intensity (Monetary terms)



(c) Total Energy Consumption

Figure 2: Testing the Common Trends Assumption for the DiD Models for Energy Intensity and Energy Consumption

5.3 Robustness Checks and Placebo Checks

5.3.1 Robustness Checks

In this section, we present the results of some robustness checks on our main results, as well as of placebo checks for our main estimation methodology.

Firstly, in Table A2 in the appendix, we present the results of the main diff-in-diff estimations, utilizing two production function-based approaches to compute firm-level TFP growth rates (which involve estimating the output of the firm as a function of different inputs, using a control function-based methodology). The first methodology that we adopt was proposed by Ackerberg et al. (2015) (ACF, in short), and involves using a two-step approach to estimate a trans-log production function with the log of value added as a dependent variable. This methodology is suitable for addressing problems of functional dependence and collinearity that may arise with the estimation of production functions using other approaches, such as the Olley and Pakes (1996) or Levinsohn and Petrin (2003) models. The second methodology follows Wooldridge (2009), and involves using generalised method of moments to derive estimates of the production function, which results in more efficient estimates, compared to the two-step methodology adopted by Ackerberg et al. (2015).

In the results of Table A2, we find that the PAT indicator is highly insignificant in the ACF-based model in column (1), whereas it had a positive and significant effect on TFP growth in column (2) (using the Wooldridge (2009) approach to estimate TFP). While the magnitude of the coefficient in column (2) is smaller than that derived in Table 4 using the cost function approach, this result provides support for our main finding. However, given that we are not able to disentangle the driving force behind this effect, we prefer using the cost function-based TFP measure as our main approach. Figure A1 in the appendix includes the plots to test the parallel trends assumption for the ACF and Wooldridge (2009) estimations. We find that the parallel trends assumption is mostly valid for these estimations, i.e., we cannot reject the null hypothesis of the TFP growth being equal for treatment and control plants, before 2012, except in the year 2008 for the ACF production function-based approach.

In Table A3 in the appendix, we present other robustness checks. We conduct further sensitivity analysis for the main diff-in-diff results of this paper evaluating the effect of the PAT policy on TFP (computed using the cost function approach), scale efficiency and technical change efficiency. In panel A, we present the results of an instrumental variable two-stage least squares (IV-2SLS) estimation, whereby we instrument for the PAT indicator using the median value of assets of all the other cement plants in the same state, as well as the median value of the total energy consumption (in MTOE) of all other cement plants in the same state, on which we have data. We estimate this IV-2SLS model including firm and year fixed effects. We find that the main results of our study are robust to this alternative specification: treatment plants experienced smaller reductions in TFP compared to control plants. They had higher levels of scale efficiency than control plants, and lower rates of technical change (column (3)). The first-stage F-statistics are higher than the Stock-Yogo critical value of 16.38 for a 10% maximal IV size, and the results of the Sargan statistic suggest that we cannot reject the null hypothesis of the overidentifying restrictions being valid.

We use another estimation methodology for the check in panel B, namely a pooled non-parametric fuzzy regression discontinuity approach, whereby we assume that the average energy

consumption of the plant over the period 2008-2010 denotes the running variable. Given that treatment plants were identified on the basis of their consumption being higher than 30,000 MTOE in this period, this is the relevant threshold for the running variable at which we estimate the local average treatment effect. Moreover, we restrict this analysis to the time period after 2012, to account for the effect of the treatment on economic outcomes in the post-treatment period, relative to control plants. We find that the effect of the treatment on TFP was positive and significant just at the threshold; we find the same positive effect for treatment on scale efficiency in column (2), however the effect of the treatment on technical change is insignificant in this model. Of course, these effects are to be interpreted as highly localised effects, as opposed to the main results of the paper.

In panel C, we test the robustness of our main results to dropping the top 1% and bottom 1% of the observations, in terms of the distributions of each of the three dependent variables. We find that the main difference-in-difference results of this study are robust to this exclusion.

Lastly, in panel D, we present the results of the difference-in-difference analysis on the impact of the PAT policy on the TFP growth rate computed using the results obtained from an estimation of a variable cost function instead of a total cost function. In this case, the variable cost is estimated as a function of the output, prices of labor, materials and energy, and the fixed factor, namely the capital. Also on using this short-run cost function, we are able to confirm our main finding on the effect of the PAT policy on scale efficiency and on the TFP growth rate. Moreover, even though the effect of the policy on technical change is insignificant, the coefficient on the variable is still negative.

5.3.2 Placebo Checks

In this subsection, we present the results of some placebo checks for our main difference-in-difference estimation methodology. These results are presented in Table A4 in the appendix. This table presents the coefficients and standard errors on the PAT indicator variable across different estimation methodologies (described in the leftmost column), and on using different dependent variables, namely TFP change, the log of energy intensity (measured using the quantity of energy consumed divided by gross sales), and on the log of energy consumption.

In panels A and B, we present the results of assuming alternative treatment periods (instead of post-2012); in panel A, we assume that the treatment was valid after 2007, whereas in panel B we assume that the post-treatment period was after 2008. Given that treatment eligibility under the PAT scheme was defined by the average energy consumption of the firms between 2008 and 2010 and the post-treatment period was after 2012, we would expect that we should not observe similar findings to our main results on using these new treatment indicators. Indeed, we find that the effect of the new treatment indicator on the TFP growth rate is insignificant in both panels. We also find that the alternative "treatment" indicator did not have any effect on either energy intensity, unlike our main results, however it also did not have an effect on the total energy consumption (similar to our main results).

In panel C, we present the results of assuming that firms were treated if their average energy consumption between 2008-2010 was less than 30,000 MTOE, i.e., we reverse the treatment condition. Again, we get opposite results for TFP growth compared to our main results, even though the results for TEC and energy intensity are similar in columns (2) and (3).

Lastly, in Panel D, we are interested in understanding if there were any spillovers from treatment plants to control plants, or if there is a violation of the stable unit value treatment assumption (or SUTVA). If there may have been any spillovers from treatment to control plants in terms of the reduction in the energy intensity, we would observe that control plants also exhibited the same effects that we found for the treated plants. For this analysis, we restrict our sample to control plants, and we define a new "treatment indicator" for this sample, where we define a firm as having been treated if it is relatively large in terms of the size of the labor force, i.e., control plants that have a labor force size greater than the 75th percentile in terms of the distribution of the total number of man-days worked. In defining this treatment measure, we are assuming that larger control plants are more likely to follow the behavior of the treatment plants (which were relatively larger firms). From these results, we find that the new 'treatment' indicator has an insignificant effect on TFP growth, as well as on energy consumption in column (3). However, we find some evidence that the log of energy intensity declined for larger plants.

6 Conclusion and Policy Implications

This study evaluates a climate change mitigation regulation in India, the PAT policy, that required manufacturing plants across different industries to reduce their energy intensity. We focus on the cement industry, which is a relatively energy-intensive sector. Analysing the effects of the policy on the total factor productivity growth of plants, We find that treatment plants experienced higher rates of TFP change than control plants; given that the TFP growth rates declined slightly over the period of study (2007-2015) for Indian cement plants, this implies that treatment plants may have experienced a lower rate of decline in TFP growth, compared to control plants. We are able to confirm this result using various placebo checks as well as robustness checks.

Given that we use the cost function approach to compute TFP, we are also able to disentangle this positive effect for treatment plants in terms of TFP growth into a scale effect, as well as a technical change effect. We find that treatment plants experienced an increase in scale efficiency compared to control plants, while they experienced a decrease in the rate of technical change. We interpret these results as suggesting that treatment plants responded to the PAT policy by increasing their output and exploiting economies of scale, while not undertaking significant investments in energy-efficient technologies. Indeed, we are able to confirm this finding by unraveling the effect of the policy on energy intensity and on energy consumption; we find that PAT-treated firms experienced a decline in energy intensity (what the policy was designed to achieve), but did not experience a significant decline in total energy consumption. We argue that these effects can be expected, given the design of the policy: treated firms were required to reduce their energy intensity, defined as the amount of energy consumed per unit of production, and thus they had two margins of adjustment. Our results suggest that this type of regulation offers firms the possibility to circumvent the main goals of the regulation, and that the regulation could have been better designed.

This study has implications for the design of energy-efficiency policies; the findings suggest that policy-makers need to be aware of the margins of adjustment of firms, in response to policies. It also emerges from this study that alongside the barriers to the adoption of energy-efficient

technologies as well as the technological upgrading of firms, it is equally important to understand the barriers that may prevent policies from achieving reductions in energy consumption. For example, firms in developing countries may require technical and/or financial assistance to adopt new technologies that reduce energy consumption, and current regulations often fail to take this into account.

Our results highlight that the ability of firms to respond to energy-efficiency policies by investing in new technologies may be limited. While the PAT policy was announced in 2007, we find that treated plants were not able to achieve significant reductions in energy consumption even after 2012. A non market-based instrument that could achieve reductions in energy consumption would be a technological standard, which would require firms to adopt certain technologies, however, firms may still need financial or technical assistance to switch to new production processes. Lastly, it is important to understand whether these effects are similar in other industries: cement is one of the most polluting as well as energy-intensive industries, and one can expect that the findings may be different for other sectors that are less energy-intensive. This is an open question for further research to explore.

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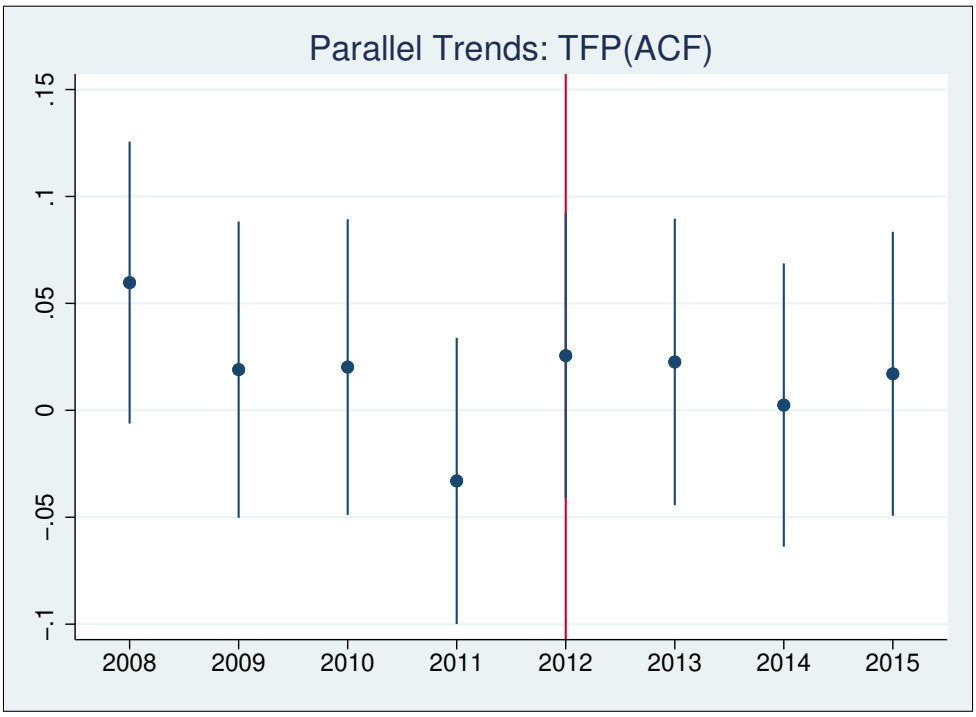
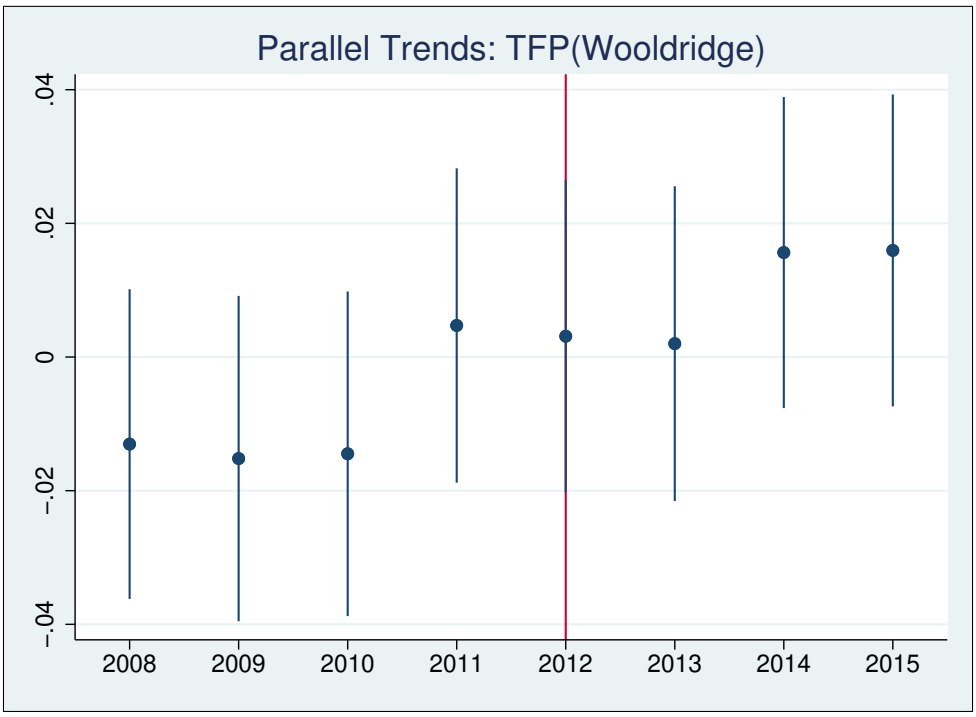
Appendix



(a) TFP: ACF (2015) Approach



(b) TFP: Wooldridge (2009) Approach

Figure A1: Testing the common trends assumption for the DiD Model for TFP estimated using ACF (2015) and Wooldridge (2009) approaches

Table A1: Cost Function Estimation Results: Random and Fixed Effects

Dependent variable Model Column	Total cost Random effects (1)	Total cost Fixed effects (2)
Log of output	0.796***	0.627***
	(0.027)	(0.048)
Log of price of labor	0.471***	0.450***
	(0.057)	(0.060)
Log of price of capital	0.285***	0.281**
	(0.053)	(0.059)
Log of price of energy	0.163***	0.173***
	(0.034)	(0.038)
Log of output squared	0.033**	0.022
	(0.015)	(0.021)
Log of price of labor squared	0.112*	0.075
	(0.064)	(0.066)
Log of price of capital squared	0.036	0.042
	(0.025)	(0.028)
Log of price of energy squared	-0.053***	-0.061***
	(0.012)	(0.014)
Log of output multiplied by price of labor	-0.076***	-0.054
	(0.032)	(0.035)
Log of output multiplied by price of capital	0.078***	0.067***
	(0.025)	(0.028)
Log of output multiplied by price of energy	-0.009	-0.016
	(0.012)	(0.013)
Log of price of labor multiplied by price of capital	-0.070*	-0.061
	(0.041)	(0.043)
Log of price of labor multiplied by price of energy	-0.010	0.006
	(0.030)	(0.030)
Log of price of capital multiplied by price of energy	0.026	0.018
	(0.029)	(0.028)
Time trend	0.017	0.020*
	(0.011)	(0.012)
Time trend squared	0.004	0.002
	(0.003)	(0.003)
Log of output multiplied by time trend	0.005	0.007**
	(0.003)	(0.003)
Log of price of capital multiplied by time trend	-0.002	-0.004
	(0.008)	(0.008)
Log of price of labor multiplied by time trend	0.0005	0.002
	(0.008)	(0.009)
Log of price of energy multiplied by time trend	0.004	0.003
	(0.005)	(0.006)
Observations	2280	2280
R-squared	0.96	0.96

Notes: The regression sample includes cement plants with non-missing and non-zero prices and output. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Huber-White heteroscedasticity-consistent standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table A2: Difference-in-Difference Results for the effect of PAT on TFP (Ackerberg, Caves and Fraser (2015) and Wooldridge (2009) Approaches)

Dependent variable Column	TFP growth rate: ACF (1)	TFP growth rate: Wooldridge (2009) (2)
PAT indicator	-0.0003	0.017***
	(0.017)	(0.006)
Observations	1672	1672
Plant fixed effects	✓	✓
Year fixed effects	✓	✓
Covariates	✓	✓

Notes: The regression sample includes cement plants with non-missing and non-zero prices and output. Covariates include controls for the sector of location (urban/rural), as well as for the type of firm. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Huber-White heteroscedasticity-consistent standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table A3: Additional Robustness Checks

Dependent variable Estimation methodology	TFP growth (1)	Scale efficiency (2)	Technical change efficiency (3)
	Panel A		
IV-2SLS Fixed Effects	0.139*	0.148**	-0.010***
	(0.081)	(0.082)	(0.003)
First-stage F-statistic	32.041	32.041	43.794
Sargan-statistic	1.050	1.102	0.215
P-value	0.306	0.294	0.643
Observations	1612	1612	2099
	Panel B		
Fuzzy regression discontinuity	0.462***	0.230***	0.023
	(0.163)	(0.062)	(0.020)
Optimal bandwidth	15592.67	19296.58	15643.46
Observations	486	486	486
	Panel C		
Trimming top and bottom 1% of observations	0.036***	0.040***	-0.001***
	(0.015)	(0.015)	(0.0005)
Observations	1676	1677	2244
	Panel D		
Estimating a variable cost function	0.035***	0.036***	-0.0001
	(0.013)	(0.013)	(0.0002)
Observations	1707	1707	2277

Notes: The regression sample includes cement plants with non-missing and non-zero prices and output. *,** and *** respectively denote significance at 10%, 5% and 1% levels. In Panel A, the median asset value of all other cement plants in the same state, and median value of total energy consumption of all other cement plants in the same state are used as instruments. These models include firm fixed effects, year fixed effects, and covariates. In panel B, the running variable is the average energy consumption between 2008 and 2010. These estimations use a quadratic polynomial structure, a triangular kernel, and a set of covariates (the sector of location (urban/rural), the type of firm and year fixed effects) and are estimated at the optimal bandwidth. In Panel C, we include firm and year fixed effects, as well as covariates. All models report heteroscedasticity-robust standard errors. The coefficient on the constant has not been reported.

Table A4: Placebo Checks

Dependent variable Estimation methodology	TFP growth (1)	Log of energy intensity (quantity) (2)	Log of energy consumption (3)
		Panel A	
After 2007 as post-treatment period	0.010	-0.042	0.047
	(0.027)	(0.066)	(0.061)
Observations	1707	2277	2277
		Panel B	
After 2008 as post-treatment period	0.023	-0.010	0.072
	(0.021)	(0.062)	(0.059)
Observations	1707	2277	2277
		Panel C	
Alternative treatment condition	-0.037**	0.152**	0.045
	(0.017)	(0.073)	(0.070)
Observations	1707	2277	2277
		Panel D	
Spillover checks	-0.045	-0.270*	-0.016
	(0.035)	(0.164)	(0.140)
Observations	1170	1666	1666

Notes: The regression sample includes cement plants with non-missing and non-zero prices and output. *,** and *** respectively denote significance at 10%, 5% and 1% levels. In Panel A, the median asset value of all other cement plants in the same state, and median value of total energy consumption of all other cement plants in the same state are used as instruments. These models include firm fixed effects, year fixed effects, and covariates. In panel B, the running variable is the average energy consumption between 2008 and 2010. These estimations use a quadratic polynomial structure, a triangular kernel, and a set of covariates (the sector of location (urban/rural), the type of firm and year fixed effects) and are estimated at the optimal bandwidth. In Panel C, we include firm and year fixed effects, as well as covariates. All models report heteroscedasticity-robust standard errors. The coefficient on the constant has not been reported.

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