Carbon Footprint of Place-Based Economic Policies*

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Abstract

We evaluate the unintended environmental impacts of Special Economic Zones (SEZs)—a place-based policy aimed at promoting economic development in India—on firms' energy use and carbon emissions. Using detailed firm-level energy data and a spatial regression discontinuity difference-in-differences (RD-DiD) design, we find that firms located within SEZs reduce their carbon emissions by 25% compared to comparable firms outside SEZs. This reduction is primarily driven by a shift from conventional fuels to lower-carbon renewable energy sources, rather than by a decline in output. Guided by a conceptual framework, our heterogeneity analysis shows that emission reductions are more pronounced among larger firms and non-manufacturing firms with greater flexibility in energy substitution, and firms located in regions with better access to clean energy infrastructure.

Keywords: Place-Based Policy; Tax Exemption; Carbon Emission; Energy Consumption
JEL Classification: R13, R58, O18

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1 Introduction

Can economic growth be achieved while sustaining the environment? This long-standing question sits at the heart of debates on sustainable development, where economic expansion and environmental protection often appear at odds. Increased production typically leads to higher energy consumption and pollution, yet development can also drive investment in energy-efficient and cleaner technologies. This question is especially critical for developing countries, which accounted for 95% of increase in the global emissions over the past decade and 75% of global greenhouse gas emissions in 2023, fueled by rapid industrialization and economic growth (Climate Leadership Council 2024).

We shed light on this critical question by examining the unintended environmental consequences of a large-scale place-based policy originally designed to spur economic growth—India's Special Economic Zones (SEZs). Like many other place-based policies widely adopted in emerging economies to foster regional development (Das and Barua 1996; Fleisher, Li, and Zhao 2010; Rothenberg, Wang, and Chari 2025), SEZs in India were explicitly created to stimulate employment, drive economic growth, and facilitate globalization. Established in the 1960s and significantly expanded in 2005, the SEZ program offers substantial tax incentives to firms operating within designated areas, providing a financial impetus for industrial growth. Empirical evidence indicates that, in many aspects, SEZs have successfully driven structural transformation and economic growth in India (Hyun, Ravi, et al. 2018; Gallé et al. 2024). However, this success prompts a critical question: Have these same policies also led to increased energy consumption and carbon emissions at the firm level? This question is particularly pressing given that India has emerged as one of the world's top three carbon emitters, alongside China and the United States (Investopedia 2024). Notably, the industrial sector plays a central role in this trend, accounting for 24.5% of India's total greenhouse gas emissions in 2023 (International Energy Agency 2021).

While SEZs are designed to promote economic activity, their environmental impact can be far-reaching. On one hand, increased industrial output may lead to greater energy demand and emissions. On the other, the financial and institutional support provided by such policies could incentivize firms to adopt greener, more energy-efficient technologies (Barrows and Ollivier 2018). The net environmental impact ultimately depends on a range of contextual factors, including the availability of clean energy infrastructure, firms' technological capabilities, and the regulatory environment. Our study investigates whether SEZs in India have primarily fueled carbon emissions or, conversely, supported a transition toward cleaner industrial production. Understanding these dynamics is essential for designing future development strategies that balance economic growth with environmental sustainability—both in India and in other developing economies pursuing similar policy solutions.

Quantification of the carbon footprint of place-based policies presents some challenges. First, identifying comparable areas that were not targeted by the policy to serve as counterfactuals is inherently difficult for any place-based policy. Second, obtaining high-quality firm-level data on behaviors that contribute to emissions is another major hurdle. Detailed and reliable data on how firms operate and implement changes in response to place-based policies are often scarce. We address these challenges by leveraging rich spatial and temporal variations in the implementation of India's Special Economic Zones. Additionally, our analysis is based on high-quality firm-level data that provide detailed insights into production, sales, and energy use. These data allow us to directly estimate each firm's carbon emissions and investigate the underlying mechanisms, such as energy efficiency improvements, changes in fuel composition, and shifts in production processes.

To evaluate the effects of Special Economic Zones (SEZs), we employ a combined Spatial Regression Discontinuity (RD) and Difference-in-Differences (DiD) methodology. Following Görg and Mulyukova (2024), we use detailed documentation on SEZ locations and sizes to construct treatment buffers that match official records, allowing us to approximate treatment assignment for firms located within SEZ boundaries. To construct counterfactuals, we pair each treated firm with control firms located within 10 kilometers of an SEZ but outside the treatment buffer, using a K-means clustering algorithm based on pre-specified observed characteristics. To mitigate potential misclassification due to boundary imprecision, we exclude firms located within 2 kilometers of the SEZ boundary from the analysis. We then compare changes in carbon emissions before and after SEZ notification within each matched pair.

Although Special Economic Zones were not initially designed with environmental objectives, our findings reveal a significant 25% reduction in carbon emissions among firms within these zones compared to similar counterparts outside of SEZs following policy implementation. Our event study indicates no significant pre-trend, and the SEZ-induced decline in carbon emissions only becomes evident three years after SEZ notification. When examining the underlying mechanisms, we find no evidence of a decline in output among treated firms; on the contrary, there is suggestive evidence of increased production. The observed reduction in emissions is, instead driven by a considerable rise in emissions from renewable energy sources and a statistically significant decline in emissions from conventional energy sources, indicating a shift toward cleaner energy use. Our results are robust across various model specifications, distance boundaries, the application of a staggered DiD specification, and the use of propensity score matching.

To further investigate the underlying mechanisms, we develop a conceptual framework in which manufacturing and non-manufacturing firms choose between cleaner and conventional energy sources. In the model, cleaner energy entails a fixed installation cost and features typically lower marginal costs compared to dirtier alternatives (Allcott and Greenstone 2012; Covert, Greenstone, and Knittel 2016). Moreover, by distinguishing between manufacturing and non-manufacturing firms, recognizing differences in their energy consumption mixes and the substitution patterns across different energy types (Stern 2012), the model predicts that the incentives provided by SEZs will have larger effects in (i) sectors with greater elasticity of substitution between energy types, (ii) locations with lower entry barriers to cleaner energy, and (iii) firms with greater capacity to afford the fixed costs of adopting cleaner energy.

Our empirical evidence, derived from heterogeneity analyses across regions, industrial sectors, and firm types, aligns with these predictions. First, consistent with the model, we find that SEZs have more pronounced effects in the non-manufacturing sector, where firms exhibit a higher elasticity of substitution between energy types. This is mainly because non-manufacturing firms primarily rely on electricity, which can be more easily sourced from cleaner alternatives. In contrast, manufacturing firms depend on a more diverse energy mix, including fossil fuels such as oil, natural gas, and coal—energy sources that are harder to replace with cleaner options. Second, we find that SEZs lead to significant reductions in carbon emissions in regions where renewable energy is rapidly expanding and constitutes a substantial share of the local energy supply—conditions that reduce the entry barriers to cleaner energy. Finally, we show that larger firms and major emitters who are more capable of paying upfront investment costs, reconfiguring their energy use, and have greater incentives to reduce their emissions are more responsive to SEZs' incentives.

Our study contributes to the extensive literature on place-based policies, particularly the emerging strand examining their environmental consequences. While the effectiveness of place-based policies remains widely debated—with mixed evidence from both developed and developing countries (Neumark and Simpson 2015)[1]—evidence from India generally points to positive impacts (Chaurey 2017; Shenoy 2018; Hasan, Jiang, and Rafols 2021; Gallé et al. 2024)[2]. Most existing studies emphasize economic outcomes, with relatively less attention given to environmental externalities—an increasingly important dimension in light of growing concerns over climate change (Jayachandran 2022).

While research on the environmental impacts of place-based policies has advanced—particularly in the context of China (Yu and Zhang 2022; Wang et al. 2023; Song et al. 2023; Wen, Liu, and Huang 2023; Fan et al. 2023)—empirical evidence from other settings remains relatively scarce. A notable exception is Garg and Shenoy (2021), who find that tax incentives for industrial and infrastructure development in the newly created state of Uttarakhand had no significant effect on forest cover. Our study addresses this gap by providing novel, large-scale evidence that SEZs, though not explicitly designed with environmental goals in mind, can lead to meaningful reductions in firm-level carbon emissions. To our knowledge, this is among the first studies to quantify the environmental impacts of place-based policy at the firm level in the context of developing countries.

This study also contributes to the broader debate on balancing economic growth with environmental sustainability, often framed by the Environmental Kuznets Curve hypothesis (Grossman and Krueger 1995). By analyzing the environmental impacts of Special Economic Zones (SEZs), a prominent and widely used policy tool for industrial development, we offer new insights into

[1]Some policies have been shown to successfully stimulate economic activity and promote regional development (Kline and Moretti 2014; Busso, Gregory, and Kline 2013; Ehrlich and Seidel 2018; Wang 2013; Lu, Sun, and Wu 2023), while others have yielded limited or no effects (Neumark and Kolko 2010; Gobillon, Magnac, and Selod 2012; Rothenberg, Wang, and Chari 2025).

[2]An exception is Görg and Mulyukova (2024), who find heterogeneous effects: productivity declined in publicly-owned SEZs, while firms in privately-owned SEZs experienced productivity gains.

how growth-oriented policies can yield environmental benefits. Our findings reveal that SEZs in India, a major carbon emitter, have inadvertently reduced firms' carbon emissions, particularly when supported by policies and technological advancements that facilitate a shift to cleaner energy sources. These insights have significant policy implications, particularly as SEZs and similar place-based interventions are widely adopted in both developing and developed countries. Our results suggest that, under the right conditions, such policies can serve a dual purpose: promoting economic development while supporting climate objectives. In doing so, this study contributes to the growing literature on carbon abatement and sustainable development (e.g., Barbier 2019; Greenstone and Jack 2020; Gillingham and Stock 2018; Colmer et al. 2024; Dechezleprêtre, Nachtigall, and Venmans 2023; Gugler, Haxhimusa, and Liebensteiner 2021), emphasizing the potential to integrate economic and environmental goals in policy design.

The rest of this paper is organized as follows. Section 2 presents the background and history of the SEZ program in India. Section 4 describes the main data sources and presents summary statistics. Section 5 introduces the empirical strategies we adopt. Section 6 discusses our main empirical results and robustness exercises. Section 3 builds a conceptual framework that illustrates potential underlying mechanisms. Section 7 explores the mechanisms and tests the predictions of the model. Lastly, Section 8 concludes.

2 Background

SEZs in India India has undergone a period of rapid economic transformation marked by trade liberalization, rising foreign investment, and expanding service sectors since early 2000s. Despite these positive trends, the country continued to struggle with substantial infrastructure deficits, regulatory complexity, and regional disparities in economic development (Panagariya 2008). In response, policymakers increasingly turned to targeted interventions to foster industrial growth and enhance economic performance. One such approach involved the use of place-based policies aimed at improving the business environment and catalyzing private investment in targeted regions.

India has a long history of utilizing place-based policies. It is one of the first countries in Asia to introduce the Export Processing Zones (EPZs) in the 1960s, a place-based policy aimed at promoting exports and enhancing economic development (Ministry of Commerce and Industry, Government of India 2025; Görg and Mulyukova 2024). Until the 2000s, these zones were few in number and were exclusively owned and managed by the central government. However, the lack of modern infrastructure, unstable fiscal policy, and administrative and bureaucratic delays prompted the need for reform for businesses to develop and thrive (World Bank 2005; Ministry of Commerce and Industry, Government of India 2025). In 2005, the Special Economic Zones Act was passed, allowing for private investment and a more flexible environment with administrative and fiscal benefits. The privatization of these economic zones drastically increased the number of SEZs (see Figure A.1).

According to the SEZ Act of 2005, the stated objectives of the policy include promoting new economic activity, expanding exports, attracting both domestic and foreign investment, generating employment, and improving infrastructure (SEZ Act 2005). These goals were to be achieved through a standardized legal framework governing the establishment and operation of SEZs. Firms operating within SEZs are granted both administrative and fiscal benefits. On the administrative side, the Act provides for a "single-window clearance" system, designed to expedite approvals by consolidating them under one authority. Fiscal incentives include full income tax exemption on export income for the first five years, a 50% exemption for the next five, and an additional five-year

50% exemption on reinvested profits. SEZ units were also exempt from sales and service taxes, and from the Minimum Alternate Tax (MAT) until 2012. In addition, duty-free imports and domestic procurement of inputs are allowed under the Act.

To establish a Special Economic Zone (SEZ), developers must first obtain government approval, followed by official notification and authorization to begin operations. To obtain approval, SEZ developers must demonstrate rightful ownership of sufficiently large parcels of land, which varies depending on the industry. For example, a minimum contiguous area of 10 square kilometers is required for multi-product zones, whereas only 0.1 square kilometers suffices for sector-specific zones such as IT zones. When a developer is still in the process of acquiring land, only in-principal approval can be granted. Formal approval is granted when the following conditions are met: the state government's endorsement of the project, the developer's proof of land ownership, and the state government's provision of tax exemptions, assurance of adequate infrastructure, and clearance from state regulatory bodies. Once approved, a notification authorizing the commencement of operations is issued by the board. Only at this point, investment and construction are permissible (Alkon 2018; Görg and Mulyukova 2024).

While the SEZ Act is a national-level policy, state governments play a critical role in its local interpretation and implementation. Firstly, the acquisition of land required for the SEZ could be challenging (Seshadri 2011). Secondly, the state government is often responsible for providing essential infrastructure, such as electricity (Kale 2014), which has been shown to significantly impact firm productivity in India (Allcott, Collard-Wexler, and O'Connell 2016). Beyond the administrative and fiscal incentives outlined earlier, states may also introduce supplementary regulations, suggesting the possibility of heterogeneous policy impacts across regions.

India's Energy Market The Indian electricity sector, historically overseen by the State Electricity Boards, experienced two major policy shifts: one following the 1991 economic liberalization and another after the enactment of the Electricity Act of 2003 Vardhan et al. 2024. The sector's operations can be categorized into three main segments: (a) generation, (b) transmission, and (c) distribution of electricity. These activities are carried out by state governments, the central government, and private companies. Regulatory oversight is provided by the Central Electricity Regulatory Commission (CERC) at the national level and State Electricity Regulatory Commissions (SERCs) at the state level. Power supply and demand, or load management, are coordinated jointly by the National Load Despatch Centre (NLDC), Regional Load Despatch Centres (RLDCs), and State Load Despatch Centres (SLDCs).

In the financial year 2024–25, electricity generation was distributed among central government-owned entities (25%), state government-owned entities (24%), and independent private producers (51%). Coal remains the dominant source of electricity, accounting for 73% of generation, followed by hydro (8.8%), solar (7.9%), wind (4.6%), and other sources. Transmission is handled by central transmission utilities (CTUIL), state transmission utilities (STUs), and inter-state power transmission companies (IPTCs). Electricity distribution is primarily conducted by state-owned distribution companies, with private distributors serving the remainder.

India ranks third globally in both electricity consumption and renewable energy production. India imports a small amount of their renewable energy. The share of renewable energy in total energy consumption has increased from 17% in 2014 to 22% in 2023, with hydropower leading the sector, followed by solar and wind. While the private sector accounts for the majority of installed renewable capacity, state-owned entities contribute a significant portion as well. There is a push towards renewable sector due to impacts of climate change. However, SEZs do not give tax breaks additionally for the installation of renewable resources.

India's Rising Carbon Emissions Over the past two decades, India has experienced one of the fastest rates of economic growth among major economies, driven largely by industrial expansion, infrastructure investment, and urbanization (Subramanian 2019; Ghosh and Parab 2021). However, this development has come with significant environmental costs (Ghosh 2002, 2010). India is now the world's third-largest carbon emitter, with energy-related emissions more than doubling since the early 2000s (Investopedia 2024). Much of this increase stems from a heavy reliance on coal for electricity generation and the expansion of energy-intensive manufacturing sectors such as steel, cement, and chemicals (Shearer, Fofrich, and Davis 2017).

This rise in emissions has drawn increasing domestic and international attention, particularly as India seeks to balance its development goals with commitments to global climate agreements such as the Paris Accord. The government has launched several policy initiatives to promote renewable energy and to improve energy efficiency due to existing barriers to clean energy adoption (Luthra et al. 2015; Mahadevan, Meeks, and Yamano 2023). However, the carbon intensity of industrial production remains a critical concern. Given the growing environmental concerns, it is essential to examine how industrial and regional development policies—such as Special Economic Zones (SEZs)—interact with environmental outcomes as it presents a key opportunity for reform.

3 Conceptual Framework

In this section, we develop a conceptual framework to guide our empirical analysis by modeling firms' energy consumption decisions in the presence of SEZ policies and deriving testable predictions about the impact of SEZs on carbon emissions. Our model illustrates: (a) how tax exemptions associated with Special Economic Zones (SEZs) influence firms' energy consumption decisions, (b) the conditions under which firms are likely to adopt cleaner energy sources, and (c) the differential responses across various types of firms, industrial sectors (Koetse, De Groot, and Florax 2008; Stern 2012; Shapiro and Walker 2018), and regions. Our conceptual framework allow firms to choose their energy consumption in the presence of benefits associated with SEZs, while incorporating heterogeneity in cost structures across different energy types and in access to different electricity markets. Specifically, first, it incorporates energy consumption decisions into firms' profit maximization and cost minimization functions. Second, we differentiate between *dirtier* (conventional) energy sources with higher carbon emissions and *cleaner* (renewable) energy sources with lower emissions, accounting for the differential costs of adoption. Third, we distinguish between manufacturing and non-manufacturing firms by recognizing differences in their energy consumption mixes and the substitution patterns across different energy types (Koetse, De Groot, and Florax 2008; Stern 2012). Lastly, we consider energy-use efficiency, allowing productivity to vary in both the production and energy consumption.

Setup We consider two sectors, indexed by $s \in \{M, N\}$, where M denotes the manufacturing sector and N the non-manufacturing sector. Inspired by Atkeson and Kehoe (1999) and Hassler, Krusell, and Olovsson (2012), we assume that a representative firm in sector s produces output using the following Cobb-Douglas production function, $Y_s = A_s {K_s}^{\psi_K} (E_s A_s^E)^{\psi_E} {L_s}^{\psi_L}$.

Let Y_s denote the total output of a representative firm in sector s and A_s capture total factor productivity (TFP) in that sector. Production requires capital (K_s), energy (E_s), and labor (L_s), with output shares denoted by ψ_K, ψ_E, and ψ_L, respectively. These shares satisfy $0 < \psi_K + \psi_E + \psi_L < 1$, indicating decreasing returns to scale in the short to medium run (Fikkert and Hasan 1998;

Balakrishnan, Pushpangadan, and Babu 2002). To account for the possibility that firms actively pursue energy-saving improvements, we introduce a parameter A_s^E to capture energy-use efficiency. Improvements in energy-saving practices, such as upgrading an air conditioner from energy label E to label A, are reflected through changes in this parameter. Lastly, firms are subject to a constant corporate tax rate, denoted by t. We also assume perfectly competitive product and input markets. Let $P = \{p, p^K, p^E, p^L\}$ denote the price vector, where p is the output price, and p^K, p^E, and p^L are the prices of capital, energy, and labor, respectively.

Energy Consumption Firms in sector s choose between two types of energy inputs: clean energy, denoted by E_s^c, which generates lower carbon emissions, and conventional (dirty) energy, denoted by E_s^d, which produces higher emissions. Total energy use is modeled as a constant returns to scale (CES) aggregate of the two energy types. Formally, the total energy input of a representative firm in sector s is given by: $E_s = \left[\delta_c (E_s^c)^{\rho_s} + \delta_d (E_s^d)^{\rho_s}\right]^{\frac{1}{\rho_s}}$, where δ_c and δ_d are CES share parameters that reflect the relative importance or preference of clean and conventional energy in the energy aggregate, with $\delta_c + \delta_d = 1$. The parameter ρ_s governs the elasticity of substitution between clean and dirty energy in sector s.

The elasticity of substitution between clean and conventional energy, denoted by σ_s, is given by $\sigma_s = \frac{1}{1-\rho_s}$. We assume the substitutability is different for manufacturing sector and non-manufacturing sector. For non-manufacturing firms that primarily use electricity as their main energy source, we assume that they do not distinguish between electricity generated from cleaner energy sources and conventional energy sources. This is consistent with Stern (2012)'s finding that service (non-manufacturing) sectors have high elasticities of substitution (near 1) for electricity, as the energy source of the electricity is less critical. We show in the Appendix Figure A.10

that electricity is the primary source of carbon emissions for non-manufacturing firms (including both the financial and non-financial sectors), while fossil fuels such as oil, natural gas, and coal constitute the major sources of carbon emissions for manufacturing firms. In other words, for non-manufacturing firms, E^c and E^d are approximately perfect substitutes, i.e., $\rho \to 1$, this leads to $E_N = \delta_c E_N^c + \delta_d E_N^d$. For manufacturing firms, a variety of energy is used in production and different energy types are unlikely to be perfect substitute (Koetse, De Groot, and Florax 2008).

Lastly, we assume the energy price is set by a competitive market. We denote the unit price of conventional energy by p^{E^d} and the unit price of cleaner energy by p^{E^c}. In addition, we follow Allcott and Greenstone (2012) and Covert, Greenstone, and Knittel (2016), and assume that there is a fixed cost f associated with adopting clean energy.[3] However, the unit price of cleaner energy is lower than conventional energy, $p^{E^c} < p^{E^d}$.

The total carbon emissions resulting from energy consumption E_s depend not only on the quantity of energy used but also on the composition of clean (E_s^c) and conventional (E_s^d) energy sources, as well as their respective emissions intensities. Let θ_c and θ_d denote the emissions intensity per unit of clean and conventional energy, respectively, where $\theta_c < \theta_d$. Then, the total emissions CE_s for a firm in sector s can be expressed as: $CE_s = \theta_c \cdot E_s^c + \theta_d \cdot E_s^d$

Firm Optimization SEZs offer a tax deduction of c%, applied proportionally to the corporate tax rate t. As a result, the firm's after-tax revenue is given by $(1 - t(1 - c))pY_s$. Assuming that firms operate in a nested decision-making structure where they first choose the optimal input levels of capital (K^*), labor (L^*), and energy (E^*) before determining the optimal energy mix across different

[3] For example, f may reflect costs or new investments associated with purchasing solar panels. Allcott and Greenstone (2012) find that high upfront costs (e.g., for solar panels) deter firms from adopting energy-efficient technologies, despite lower operational costs, particularly for smaller firms. Covert, Greenstone, and Knittel (2016) note that renewable energy sources typically entail high initial capital costs but lower marginal costs compared to fossil fuels.

energy sources, we show that the tax deduction c can affect energy consumption through two channels.[4] The first channel is reflected in the cost minimization problem, where

$$\left.\frac{\partial E_s^*}{\partial c}\right|_{\bar{Y}_s} = \left.\frac{\partial E_s^*}{\partial A_s^E}\right|_{\bar{Y}_s} \cdot \frac{\partial A_s^E}{\partial c} \propto -\frac{1}{\psi}(A_s(A_s^E)^{\psi_E})^{-\frac{1}{\psi}-1} \cdot \frac{\partial A_s^E}{\partial c}$$

We call it the efficiency channel. Intuitively, tax reductions may enable firms to invest in more efficient technologies and adopt energy-saving practices, which means $\frac{\partial A_s^E}{\partial c} > 0$ and $\left.\frac{\partial E_s^*}{\partial c}\right|_{\bar{Y}_s} < 0$. In other words, the efficiency channel implies that tax reduction can reduce firms' energy consumption.

The second channel stems from the profit maximization problem, where energy demand grows with output. Output can expand as a result of reduced unit costs from higher energy efficiency (A_s^E) and the increased effective product price associated with the tax deduction, $(1 - t(1 - c))p$. Accordingly, this channel indicates that total energy use increases as output expands. We refer to it as the output channel.

The overall effect of tax reductions on total energy consumption depends on the relative strength of the two channels. If the output channel dominates, the tax cut will increase total energy consumption. In contrast, if output remains largely unchanged in the short to medium term due to liquidity or capacity constraints that limit production expansion, the efficiency channel will dominate, resulting in a reduction in total energy consumption.[5] Tax-reduction-induced changes in energy consumption have important implications for firm-level carbon emissions, as these emissions depend not only on total energy use but also on the cleanliness of the energy consumed.

After determining the optimal level of total energy consumption, firms in sector s decide how

[4] The formal derivation is provided in Appendix C.

[5] Another caveat is that the observed output increases following a tax reduction may be partly driven by the assumed Cobb-Douglas form of the production function. In a Cobb-Douglas specification, inputs are multiplicatively related to output, so reductions in effective costs (e.g., via lower taxes) automatically translate into higher optimal output. We should recognized that in reality, however, firms may not be able to expand output easily in the short term.

to allocate this energy between cleaner and conventional sources. Specifically, they choose the quantities of energy inputs E_s^x, where $x \in \{c, d\}$ denotes clean and dirty energy, respectively, in order to minimize total energy costs. Owing to differences in the elasticity of substitution between clean and dirty energy across manufacturing and non-manufacturing firms, optimal energy-use choices vary across firm types. As discussed above, because clean and dirty energy are perfectly substitutable for non-manufacturing firms, they adopt clean energy when $E_N^* > f \cdot \left(\frac{\delta_c \delta_d}{p^{E^d}\delta_c - p^{E^c}\delta_d}\right)$. and dirty energy otherwise. This inequality is more likely to be satisfied under the following conditions: (i) the optimal energy demand E_N^* is large, (ii) the fixed cost f of adopting clean energy is low, and (iii) the price gap between conventional and cleaner energy, as captured by a higher p^{E^d}/p^{E^c} ratio, is wide.

Hence, SEZs can affect firms' carbon emission by influencing the adoption of cleaner energy in several ways. First, when the output channel dominates the efficiency channel such that the total energy consumption increases ($\partial E_N^*/\partial c > 0$), SEZs may make it more likely that the energy adoption condition is satisfied, thereby encouraging firms to adopt cleaner energy sources. In this case, the carbon emissions effects of SEZs are twofold: while they lead to higher total energy usage, they also increase the probability of cleaner energy adoption. According to the carbon emissions equation $CE_s = \theta_c \cdot E_s^c + \theta_d \cdot E_s^d$, the total emissions CE_N can decline, provided that the emissions intensity of cleaner energy (θ_c) is sufficiently lower than that of conventional energy (θ_d). Moreover, this condition is more easily satisfied for larger or more emission-intensive firms, which naturally have higher energy requirements (E_N^*). Additionally, when both the unit cost of clean energy (p^{E^c}) and the fixed adoption cost (f) are low, firms are more likely to adopt the all-clean energy corner solution.

While for manufacturing firms, we can show that the share of cleaner energy depends on the relative prices p^{E^d} and p^{E^c}. Importantly, $\partial \left(E_M^{c*}/E_M^*\right)/\partial c = 0$, indicating that this share is unaffected by changes in c. Therefore, unlike non-manufacturing firms, manufacturing firms adjust their cleaner energy consumption only when dirty energy becomes relatively more expensive than clean energy. In this setting, tax deductions have no direct impact on the share of cleaner energy used. Put together, our conceptual model yields the following testable predictions under the specified setting:

Prediction 1. *SEZs may reduce carbon emissions through the following channels:*

(a) reducing total energy use when the efficiency channel dominates the output channel;

(b) shifting the composition of energy use toward clean energy, even when total energy consumption does not decline.

Prediction 2. *Compared to manufacturing firms, non-manufacturing firms are more likely to adopt cleaner energy in response to tax incentives, due to their greater substitutability between cleaner and conventional energy sources. As a result, they are more likely to experience reductions in total carbon emissions, provided that the fixed costs of adoption are sufficiently low and cleaner energy is relatively less expensive than conventional alternatives.*

Prediction 3. *Larger firms are more likely to adopt cleaner energy in response to tax incentives, as they are better positioned to overcome the fixed costs and entry barriers associated with adoption. They may also be more likely to invest in more energy-efficient equipment and assets, and adopt energy-saving practices.*

Prediction 4. *The impact of SEZs is likely to be greater in contexts where the cost of adopting cleaner energy is lower, either due to reduced unit prices or lower fixed adoption costs, for instance in regions with better access to clean energy infrastructure.*

4 Data

We rely on two data sources to investigate the causal impact of SEZ policies on firms' carbon emissions. The first is a panel dataset on Indian firms and the second is the data on SEZs in India.

Data on Firms *Prowess* Database compiled by the Centre for Monitoring the Indian Economy (CMIE) includes data on all publicly traded firms and a substantial number of private firms. It is a firm-level panel dataset that contains detailed information from income statements and balance sheets of companies covering more than 70% of the economic activity in India's organized industrial sector and representing 75% of all corporate taxes collected by the government (Goldberg et al. 2010). The database predominantly features large and medium-sized Indian firms. For our study, we extract information on firm attributes such as location, age, size, entity type, and industry, as well as financial data including annual total income, assets, expenses, and sales.

Since our primary variable of interest is firms' carbon emissions, we begin by extracting data on firms' annual energy consumption from the *Prowess* database. This dataset provides detailed information on energy use by source, with each energy type reported in its corresponding unit. For instance, a firm that consumes both electricity and coal in a given year would have two separate records: one indicating the number of kilowatt-hours (kWh) of electricity and another showing the metric tonnes of coal consumed. To estimate each firm's carbon emissions, we follow a method similar to Barrows and Ollivier (2018), assigning a source-specific carbon emission factor to each type of energy consumed. The emission factors used in our calculations are presented in Table B. 1. By multiplying the quantity of energy used by the corresponding emission factor, we calculate the total annual carbon emissions for each firm.[6] Notably, since electricity, both purchased and

[6]More details regarding the calculation process can be found in the Data Appendix D.

self-generated, is an important source of energy consumed by firms in our sample, we adopt an additional procedure when calculating emissions from electricity consumption, accounting for variations in the energy composition (i.e., fossil fuel-based electricity vs. non-fossil-based electricity) used in electricity generation across states and years.

Data on SEZs Our second data source is the India Ministry of Commerce and Industry, specifically the Department of Commerce's website on Special Economic Zones (SEZs), where information on SEZs is published periodically (Ministry of Commerce and Industry, Government of India 2025).[7] From this website, we obtained detailed data on SEZs established under the SEZ Act of 2005, including their notification dates, developer names, locations (state and address), areas, and types. Figure A.1 illustrates the evolution of the number and total area of notified SEZs since the enactment of the SEZ Act in 2005. The notification of SEZs began in April 2006, with their number rapidly increasing to 260 by the end of 2010 and gradually reaching 308 by late 2016. A brief surge in the first quarter of 2017 further raised the total to 354 by the end of 2020. The expansion in SEZ areas followed a similar pattern, with relatively larger SEZs being established between 2006 and 2010, leading to a faster increase in total area compared to the number of notifications. By 2020, the total area of SEZs reached 38,200 hectares—approximately 64% of the size of Mumbai.

Mapping firms to SEZs We geocode each notified SEZ based on its reported address and area. Figure A.2 illustrates the geographic distribution of the notified SEZs across India, with districts shaded darker indicating a higher concentration of notified SEZs. The figure shows that SEZs are primarily concentrated in populous and developed regions, such as Mumbai, Pune, Hyderabad, and Chennai. We geocode the firm-level data based on the firms' location information and then

[7] Source: https://sezindia.gov.in/notified-list-sez.

map it to the geocoded SEZs. Section 5 provides a detailed explanation of the mapping process. Our analysis is confined to a 10 km by 10 km grid around the SEZ centroids.

Descriptive Statistics Appendix Table B.2 provides the summary statistics for our study sample, which consists of 8,256 firms observed from 2000 to 2019. These firms vary in terms of entity types, industries, ages, and sizes. Specifically, approximately 35% of the firms were established after 1991, 17% between 1986 and 1990, and 27% between 1972 and 1985. The vast majority (over 80%) of these firms operate in the manufacturing sector and are publicly listed. On average, each firm emits around 21,857 metric tons of carbon annually.

5 Empirical Strategy

To identify the causal effect of the SEZ policy on firms' carbon emissions, we implement a difference in differences estimation (DiD) design. This approach compares the carbon emissions of similar firms located within and outside SEZs, both before and after SEZ notification. Similar to the strategy adopted by Görg and Mulyukova (2024), we define the treatment zone as a grid centered on the provided address, with dimensions matching the land area specified in the SEZ notification, as shown by the yellow squares in Figure A.3. To minimize bias from misclassified treatment and control firms, we specify a "leave-out" zone, a 1 km × 1 km square centered on the SEZ's centroid (represented by the gray area in Figure A.3). Firms located outside the treatment grid and within the leave-out grid are excluded from the analysis. We further restrict our analysis to firms within a 10 km × 10 km grid (outlined by the purple box in Figure A.3), ensuring that our sample is geographically comparable and minimizing the influence of distant firms with potentially different characteristics.

Our empirical strategy relies on the assumption that, in the absence of the SEZ policy, firms within SEZs would have evolved similarly to those outside SEZs. However, as is common in place-based policy evaluations, treatment assignment is not random. Policymakers may strategically select SEZ locations, and firms may self-select into these zones based on expected benefits. Consequently, firms within SEZs differ statistically from those outside SEZs in terms of observable characteristics. As shown in Appendix Table B.3, which compares the characteristics of treated and control firms as defined above, firms in SEZs tend to be larger in size, are less likely to operate in the manufacturing sector, and are more often organized as public limited companies. To address this selection bias, we complement our DiD design with a matching process to construct a comparable control group of firms outside SEZs. Specifically, we adopt the following procedure. First, we use the K-means clustering algorithm to match firms based on key attributes, including size, age, ownership, and entity type. We set the number of clusters equal to the number of SEZs and determine the starting values using a matrix containing the mean values of the observed attributes for firms located in SEZs during the years prior to SEZ establishment. The K-means algorithm then groups firms into clusters by minimizing the distance between each firm and its cluster centroid. In this way, firms that are most similar in observable characteristics are grouped together. Next, we restrict the clustering to firms located within the analysis zone (the purple box in Figure A.3) and drop firms located outside these areas. This procedure allows us to obtain pairs of firms that are similar in observable characteristics but lie on opposite sides of the SEZ boundaries.[8] This approach ensures that the control group closely mirrors the characteristics of SEZ firms. Appendix Table B.4 confirms the effectiveness of this matching process, showing that differences in age, size,

[8]We do not restrict the matching to a one-to-one format. In other words, the pairing can be one-to-many, such that one SEZ firm can be paired with multiple firms located outside the SEZ, as long as they are similar in terms of the observed attributes.

entity type, and industry type are statistically insignificant in the matched sample. Additionally, to account for the staggered timing of SEZ implementation, the control group includes only firms that were never treated (Callaway and Sant'Anna 2021).

Our estimation model incorporates a comprehensive set of fixed effects to account for time-, state-, district-, and industry-specific confounding factors, as specified in the following equation:

$$Y_{it} = \sigma Treat_i + \beta Treat_i \times Post_t + f(pair, t, s, d, industry) + \varepsilon_{it} \tag{1}$$

where i, t, s, and d denote firm, year, state, and district, respectively. The outcome variable Y_{it} is the log of annual carbon emissions for firm i in year t. $Treat_i$ is a binary indicator equal to 1 if firm i is located within an SEZ, and 0 otherwise. $Post_t$ is a binary indicator equal to 1 if year t is after the SEZ notification year for firm i, and 0 otherwise. The coefficient on their interaction, β, is the parameter of interest and captures the effect of SEZ exposure on firm outcomes. Specifically, β measures the differential change in carbon emissions following SEZ notification between firms located inside SEZs and comparable firms outside SEZs. Function $f(\cdot)$ represents the set of fixed effects for treatment-control pair, year, state, district, and industry (classified by 8-digit CMIE industry codes). To control for time-varying confounding factors, such as state- or district-level policies that could affect firms' carbon emissions, our preferred model also includes state-by-year and district-by-year fixed effects. These fixed effects also absorb time-varying changes in the composition of energy sources used for electricity generation across states and districts, which may otherwise influence the carbon emissions associated with purchased electricity. Although the *Prowess* data and SEZ data extend to 2021, we restrict our sample period to 2000–2018 to avoid attributing the effects of COVID-19 to SEZs. Standard errors are clustered at the district level to account for potential spatial correlation in the error term (Wooldridge 2003; Bertrand, Duflo, and Mullainathan 2004). We also perform robustness checks using alternative clustering levels, including the treatment-control pair level.

To further investigate the dynamic effects of SEZs, we estimate an event-study version of Equation (1), specified as follows:

$$Y_{it} = \sigma Treat_i + \alpha_k \sum_{k=6}^{2} Before_{i,t-k} \times Treat \times Post_{it} + \delta_g \sum_{g=0}^{10} After_{i,t+g} \times Treat \times Post_{it} \qquad (2)$$

$$+ f(pair, t, s, d, industry) + \varepsilon_{it}$$

In this specification, we introduce the terms Before$_{i,t-k}$ and After$_{i,t+g}$, which are event-time indicators, representing k years before and g years after SEZ notification, respectively. Year $t-1$ is omitted. The coefficient α_k captures the pre-treatment trends, allowing us to test the parallel trends assumption. The coefficient δ_g measures the dynamic effects of SEZs on firms' carbon emissions over time.

6 Results

6.1 The Effect of SEZs on Firms' Carbon Emissions

DiD Results Table 1 reports the main estimation results for Equation (1). Column (1) reports the estimated effect of SEZs on firms' total carbon emissions. We find a decline of carbon emission for SEZ firms by approximately 22%, which is statistically significant at the 1 percent level.[9] We further examine the effect of SEZs on firms' energy consumption. Because firms report energy

[9]The effect size is calculated as $(e^{-0.248} - 1) \times 100$.

use in different physical units across fuel types, we first aggregate total energy consumption by converting all sources into British Thermal Units (BTU). A BTU is a standardized measure of energy content defined as the amount of energy required to raise the temperature of one pound of water by one degree Fahrenheit, allowing direct comparison and aggregation across fuels with different physical units.[10] Column (2) presents the estimated effect of SEZs on firms' total energy use measured in BTU. The results indicate that firms located within SEZs experience a statistically significant reduction of 23% in energy related carbon emissions relative to comparable firms outside SEZs. This finding supports our Prediction 1(a).

Event Study To examine the dynamic effects of SEZ exposure and assess the validity of the parallel trends assumption, we conduct an event study analysis based on the specification in Equation (2), using carbon emissions as the outcome variable. Figure 1 plots the estimated coefficients α_k and δ_g from Equation (2). We find no systematic differences in carbon emission trends between firms located inside and outside SEZs prior to SEZ notification, supporting the parallel trends assumption underlying our identification strategy. Following SEZ notification, carbon emissions decline progressively over the first five years, with the effect gradually attenuating and dissipating after approximately eight years.

Robustness We assess the robustness of our results across different samples, model specifications, and clustering levels. Appendix Table B.7 presents the results of various robustness checks, all based on the preferred model specification from column (3) of Table 1, which includes state-year

[10]The energy content of fuels can be derived from estimated carbon emissions by applying the conversion rate between carbon emissions and BTU shown in Column (4) of Table B.D. Alternatively, energy content can be computed directly from fuel quantities using conversion factors between fuel units and BTU, as described in Thompson and Taylor (2008). To maintain consistency in the conversion procedure, and given that Table B.D reports conversion factors by detailed energy types, we adopt the first approach.

and district fixed effects.

First, we test the sensitivity of our findings to different clustering levels. Columns (1) to (3) of Appendix Table B.7 show results with standard errors clustered at the (1) treatment-control pair, (2) state and year, and (3) firm and district-year levels, respectively. In all cases, the standard errors are consistent with those reported in Table 1, indicating that our findings are robust to alternative clustering approaches.

Second, we examine whether our results are driven by firms established during the early years of SEZ implementation (2000–2005). Given that the SEZ policy was first issued in 2000 and fully enacted in 2005, we re-estimate the model using two sub-samples: firms incorporated before 2000 and those incorporated before 2005. Columns (4) and (5) confirm that the estimates remain statistically significant and consistent with the main findings. Although the magnitude of the estimates is slightly larger than in the full sample, these differences are not statistically significant.

Third, we test the robustness of our results to different spatial definitions of the treatment and leave-out zones. Specifically, we re-estimate the model using a 5 km treatment zone and a 2 km leave-out zone. Columns (6) to (8) show that the estimated effects range from -0.2 to -0.3, which are statistically indistinguishable from our main results. This consistency demonstrates that our findings are not sensitive to the spatial extrapolation of the SEZ treatment area.

Fourth, as an alternative to the RD-matching design, we employ the inverse probability weighting (IPW) method. Appendix Figure A.7 illustrates the results using IPW. While the precision of the estimates varies slightly, the direction of the estimated effects and the lagged effect pattern remain consistent with our main findings. This further supports the robustness of our analysis.

Finally, another potential concern relates to the accuracy of self reported energy data. Because Indian firms can typically claim input tax credits for taxes paid on their purchases, including energy inputs, firms may differ in their incentives to report energy consumption accurately. Firms outside SEZs may have stronger incentives to report accurately in order to avoid overpaying taxes, whereas firms benefiting from SEZ tax incentives may face weaker reporting incentives. This asymmetry could generate systematic differences in reporting behavior and in the incidence of missing energy data between treated and control firms, potentially introducing sample selection bias.

We examine this concern and analyze whether SEZ and non-SEZ firms exhibit different trends in accurately tracking their energy consumption before and after the establishment of SEZs. To proxy for potential reporting inaccuracies, we classify observations with missing values as instances of insufficient tracking. These missing values arise either from ambiguous energy source names or unit measures in the energy consumption table, or from missing consumption quantities required to compute carbon emissions. Using this definition, we construct a binary indicator equal to one if any such missing value is present in a firm-year observation. We then replicate our baseline analysis using this binary indicator as the outcome variable. The results for this exercise are reported in Appendix Figure A.8. The event-study results show that the rate of inaccurate reporting increases slightly for SEZ firms after notification. However, this effect disappears after the first period and is not statistically different from zero from three years after notification onward, the periods in which we observe effects on emissions in our main analysis. We therefore interpret these results as indicating no systematic effect of SEZs on the accuracy of energy use reporting. As an additional robustness check, we replicate the main event study analysis on a restricted sample consisting only of firms that consistently and accurately report their energy consumption throughout the sample period. The corresponding results are reported in Appendix Figure A.9. As shown, these results remain qualitatively and quantitatively similar to our main findings.

6.2 Impacts on Income, Sales, and Expenses

To better understand the source of carbon emission reductions, we first examine whether SEZs lead to a contraction in firm production, which could mechanically reduce energy use and emissions.

In particular, we examine whether SEZs significantly affect firms' production outcomes, measured by annual total income, total sales, total expenses, and total assets. We obtain firm level financial information from the *Prowess* database and construct a firm year panel. To maintain consistency with the main analysis, we restrict the sample to firms that report energy use, ensuring comparability between production and energy outcomes. We then re estimate the specification in equation (1), using these financial measures as dependent variables.

Table 3 reports the corresponding estimation results, with each column indicating the outcome variable. We find no statistically significant effects of SEZ designation on firms' production or financial outcomes. Although the point estimates for sales and profits are positive, they are not statistically significant. We also observe suggestive but imprecise evidence of a decline in fuel expenses alongside an increase in total expenses. Overall, the absence of significant changes and if anything weakly positive effects in profit, sales, and expenses indicates that the observed reductions in energy use and emissions are not driven by declines in output or economic activity.

We further examine whether SEZs affect carbon emissions per unit of sales as a measure of energy and emissions intensity. The corresponding estimation results are reported in Table 2. The per-sale results are large and consistent with those observed in Table 1. We find a significant reduction in energy use per sale of around 30% for SEZ firms. The effect of SEZs on carbon emissions per sale is smaller than the effect on the level of carbon emissions, at around 12%.[11]

[11]Note that the sample size varies for the per-unit outcomes due to missing values in the sales variable. However, we conclude that the change in the magnitude of the effects between per-unit and outcomes measured in levels is not driven by sample selection. In Appendix Table B.6, we report results for the outcomes measured in levels using the same sample as in Table 2. The estimates for the level of energy use and carbon emissions are largely consistent with

6.3 Changes in Energy Consumption by Category

Next, we further examine the effects on different categories of energy use to identify which sources drive the main results and whether SEZs induce changes in the composition of the energy mix. Following the IPCC 2011 classification (Edenhofer et al. 2011), we first differentiate emissions by source and group them into two broad categories: conventional and renewable energy. Conventional energy includes the direct use of coal gas and oil as well as electricity generated from these sources, together with the direct use of wood, wood residues and agricultural products. Renewable energy includes the direct use of biomass, such as biodiesel and biogas from captured methane, as well as electricity generated from biomass hydro solar and wind.

We then re-estimate our main specification using source specific energy measures as outcome variables. Column 1 of Table 4 reports the results for conventional energy. We find a statistically significant decline in emissions from conventional energy among firms located within SEZs with an estimated reduction of about 23%. Column 6 reports the results for renewable energy use. Consistent with the close to zero carbon content of most renewable sources-essentially, renewable energy sources such as solar and wind are defined as zero by construction-we find no significant effects on renewable energy related emissions. To capture changes along the extensive margin, we construct a dummy variable indicating if there are any emissions from renewable sources. As shown in Column 7, SEZ increases the probability of adopting renewable energy by about 0.5 percentage points.

We further disaggregate emissions from conventional energy into fossil fuels, coal, oil,We further disaggregate emissions from conventional energy into fossil fuels (coal, oil, and gas), wood and agricultural products, and electricity, including both self generated and purchased power. The

those shown in Table 1.

corresponding estimates are reported in columns (2) through (6) of Table 4. The results show that the overall reduction in conventional energy emissions is primarily driven by declines in electricity related emissions. Specifically, emissions from self generated and purchased electricity fall by approximately 27% and 18%, respectively, for SEZ firms, while we find no statistically significant effects for the direct use of other conventional energy sources.

The decline in electricity related emissions is unlikely to reflect broader decarbonization of India's power grid. SEZ and non SEZ firms in our sample are geographically proximate and are typically connected to the same local electricity grid, and therefore face similar changes in the generation mix over time. and gas wood and agricultural products and electricity including both self generated and purchased power.

6.4 Impacts on Investment, Assets, and Capital

If emission reductions are not driven by output contraction, an alternative explanation is that SEZs facilitate capital upgrading and production modernization, which may improve energy efficiency—particularly electricity efficiency—through embodied technological change. While we do not observe electricity efficiency at the capital level directly, Appendix Figure 12 provides suggestive aggregate evidence consistent with this mechanism. Specifically, the figure shows a steady decline in total energy use per unit of GDP in India over time, indicating that the same level of output is produced with progressively less energy. This decline coincides with periods of rapid capital accumulation and industrial modernization, suggesting that newer capital and modernized production facilities tend to be more energy efficient in the Indian context.

To examine whether SEZs promote such capital upgrading at the firm level, we test whether SEZ designation affects firms' investment behavior and capital accumulation. We re-estimate

Equation (1) using firm-level measures of short-term investment, total assets, property, plant, and equipment (PPE), and land and buildings as outcome variables.

The results are reported in Table 5. The estimates indicate that SEZ designation is associated with statistically significant increases across all measures of capital accumulation. In particular, SEZ firms exhibit higher investment and larger capital stocks, with investment rising by 2.7%, total assets by about 3.4%, and PPE by about 4.0%. We also find a 3.0% increase in land and building assets, consistent with expansion or modernization of production facilities rather than downsizing or contraction.

Taken together, these findings support a mechanism in which SEZs induce capital deepening and technological upgrading. In light of the aggregate evidence on declining energy intensity, such capital upgrading plausibly translates into improved electricity efficiency at the firm level. This interpretation aligns closely with our earlier result that emission reductions are driven primarily by declines in electricity-related emissions, rather than by reductions in output or substitution away from electricity toward other energy sources.

7 Heterogeneity Analysis

We further explore the mechanisms driving our results by testing the predictions outlined in Section 3 through an analysis of heterogeneous treatment effects across industries, firm sizes, and regions. These exercises provide insights into how access to clean energy, firms' long-term decision-making capabilities, and industry characteristics influence the observed reductions in carbon emissions.

Heterogeneity by Industry We begin by examining how the impact of SEZs on firm-level carbon emissions varies across industries. Using 6-digit CMIE industry codes, we classify firms into five industry groups: Manufacturing, Non-Financial Services, Mining and Construction, Financial Services, and Diversified. We then estimate our preferred model separately for each of these groups. Figure 2 presents the estimation results.[12] Our findings reveal substantial and statistically significant reductions in carbon emissions for firms in the Services sectors, including both Non-Financial and Financial Services. Specifically, SEZs are associated with a 62% reduction in carbon emissions for firms in the Services sector. In contrast, the estimated effects for the Manufacturing and Mining and Construction sectors are small and statistically insignificant. These results are consistent with our theoretical predictions (Prediction 2) in Section 3, which suggest that firms with greater flexibility in energy use, such as those in the Services sector, are more responsive to SEZ incentives.

Heterogeneity by Firm Size Firms of different sizes may respond differently to SEZs, leading to varied production and energy use decisions, which ultimately affect their carbon emissions. To explore this heterogeneity, we categorize firms into two groups based on size: Top 10% and Bottom 50%.[13] Estimating our preferred model separately for these two groups, we find that larger firms (Group 1) generally experience a more substantial reduction in carbon emissions in response to SEZs. As shown in Figure 3, firms in the top 50% of the size distribution within SEZs reduce their carbon emissions by approximately 27%, an effect more than seven times greater than the 5% reduction observed among smaller firms in the bottom 50%. This finding is consistent with

[12]Due to the small sample size, there is no estimate for the Diversified group.

[13]*Prowess* defines firm size as the three-year average of total income and total assets. The size decile variable indicates a firm's relative position in the overall distribution of companies by size. Group 1 comprises firms in Deciles 1 through 5, and Group 2 includes firms in Deciles 6 through 10. See *Prowess*'s data dictionary for more details on the construction of the firm size variable.

our theoretical prediction 3, which suggests that larger firms are better positioned to adopt cleaner energy due to lower effective entry barriers for adoption.

Beyond firm size, we also explore heterogeneity by emitter type. Specifically, we rank firms based on their average pre-treatment share of carbon emissions and re-estimate our preferred specification across emitter groups. As shown in Appendix Figure A.11, the results indicate that carbon reductions are primarily driven by high-emitting firms, with the effect estimated at around 32%. This is consistent with Prediction 3, as these firms are more likely to overcome the fixed costs associated with adopting cleaner energy and have greater potential for emission reductions.

Heterogeneity by Access to Clean Energy There are significant regional variations in access to clean energy across India. The northern, southern, and western regions have experienced rapid growth in renewable energy markets, with cleaner energy sources accounting for a larger share of their total energy mix. In contrast, the northeastern, eastern, and central regions rely more heavily on conventional, high-emission energy sources, with a much smaller presence of renewable energy. We classify the country into two clusters: Cluster 1 includes the Northern, Southern, and Western Zones and Cluster 2 consists of North Eastern, Eastern, and Central Zones. It is also worth noting that the regions in Cluster 1 are generally more economically developed than those in Cluster 2.[14] Appendix Figure A.13 plots trends in installed electricity capacity (in MW) by energy source and region from 2015 to 2024. The figure reveals a clear increase in clean energy capacity in Cluster 1, while installed capacity in Cluster 2 remains largely unchanged across both clean and conventional sources.[15]

Table 6 presents the main estimation results separately for each cluster. Our findings reveal

[14] Appendix Figure A.14 provides a map of the six zonal divisions, which we collapse into two clusters.

[15] Installed electricity capacity data are available from 2015 onward and are sourced from ICED (https://iced.niti.gov.in/energy).

that SEZs significantly reduce firms' carbon emissions by approximately 23% in Cluster 1, where renewable energy accounts for a larger share of the energy mix. In contrast, the impact of SEZs on carbon emissions in Cluster 2 is statistically indistinguishable from zero, consistent with the lower availability of renewable energy in this region. To further explore regional differences, Table 5 shows the results separately for each zonal region. The results show considerable heterogeneity, with a relatively larger effect for the Northern Zonal region (77%) and sizable effect for the Western (25%) Zonal region. Overall, our findings suggest that the impact of SEZs on firms' carbon emissions is strongly influenced by regional factors, including the composition of the energy mix, access to cleaner energy sources, and the level of economic development. Consistent with our model prediction 4, SEZs are more effective at reducing carbon emissions in regions with greater access to clean energy, where firms can more readily transition to greener energy sources.

8 Conclusion

This paper examines the impact of place-based policies that offer tax incentives to firms, focusing on how these policies influence firms' energy use and carbon emissions. Although SEZs are primarily designed to stimulate economic growth, our findings reveal a significant but unintended outcome: a substantial 25% reduction in carbon emissions among firms located within SEZs compared to similar firms outside these zones. This decline in emissions is both notable and nuanced, driven by a combination of factors. Our analysis shows that access to cleaner energy sources is a key determinant of this reduction. Firms located in regions with rapidly expanding renewable energy infrastructure experience more substantial declines in carbon emissions. Additionally, larger firms demonstrate a greater capacity to adopt cleaner energy in response to SEZ incentives, likely due to their superior production capacity and greater flexibility in adjusting energy use.

These findings present a cautiously optimistic view of the relationship between economic development and environmental sustainability. Place-based policies like SEZs have the potential to steer industrial sectors toward greener practices, promoting the adoption of advanced technologies and renewable energy sources. By aligning economic incentives with environmental objectives, SEZs can serve as a model for balancing growth with sustainability.

However, our study also highlights the complexity of assessing the environmental impacts of place-based policies. The heterogeneous effects observed across regions and firm types underscore the need for targeted approaches to maximize environmental benefits. Policymakers should consider regional energy availability, firm characteristics, and sectoral differences when designing and implementing place-based policies. Future research should further explore other mechanisms driving firms to reduce carbon emissions, particularly the role of technology adoption, regulatory environments, and firm-level characteristics. Such insights will be valuable for designing industrial and environmental policies that promote sustainable economic development.

Declaration of generative AI and AI-assisted technologies in the writing process *During the preparation of this work the author(s) used ChatGPT in order to proofread and improve the language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.*

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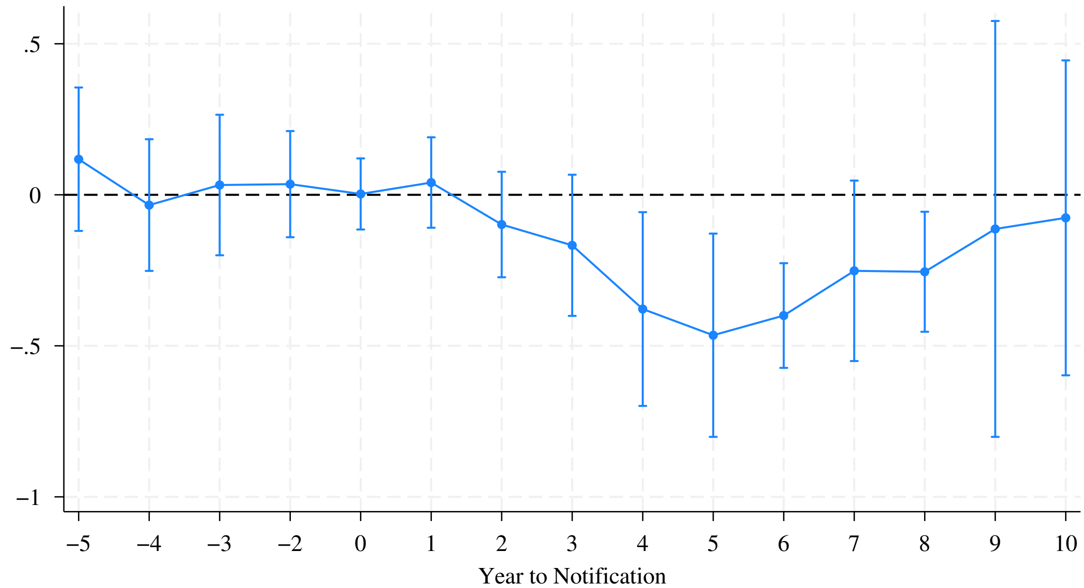


Figure 1: Event-Study Results

Notes: This figure presents the point estimates and their 95% confidence intervals for the event study estimating Equation (2) where the dependent variable is log of annual carbon emissions at the firm-year level. The model includes interaction terms between SEZ treatment and time dummies indicating 1-5 years before the SEZ notification and 1-10 years after the notification, and controls for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. The standard errors are clustered at the district and year level.

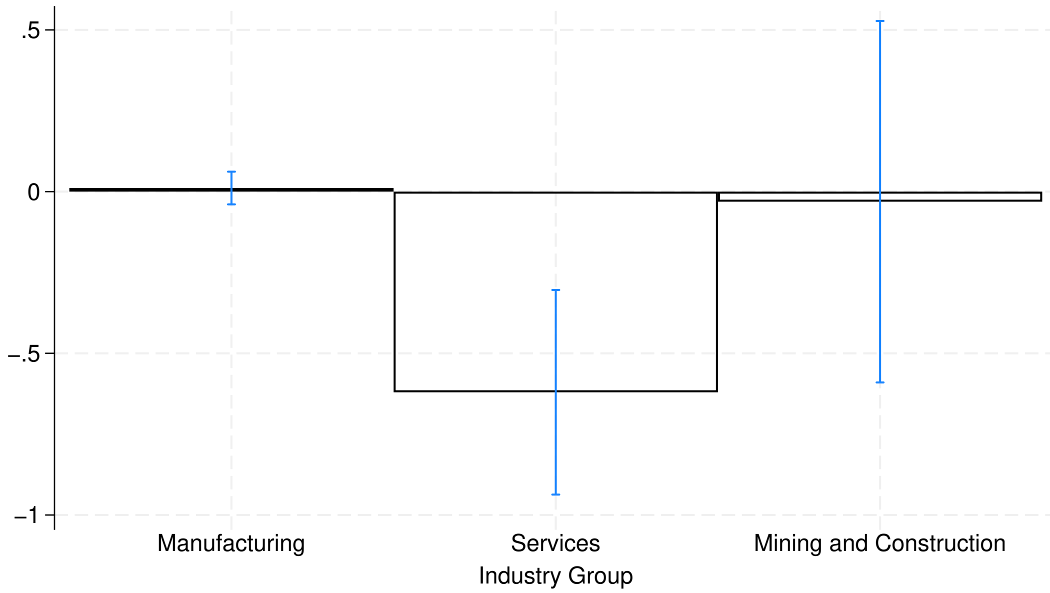


Figure 2: Heterogeneity Results: By Industry Group

Notes: This figure shows the point estimates for Equation (1) where the dependent variable is log of annual carbon emissions and their 95% confidence intervals by industry group. We define four industry groups based on 6-digit CMIE industry codes: Services (combining Financial and Non-Financial), Mining and Construction, and Diversified. The estimation is based on the preferred model controlling for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. Due to the small sample size of the Diversified group, we obtain no estimate for this group. Therefore, it is omitted from the figure. The standard errors are clustered at the district level.

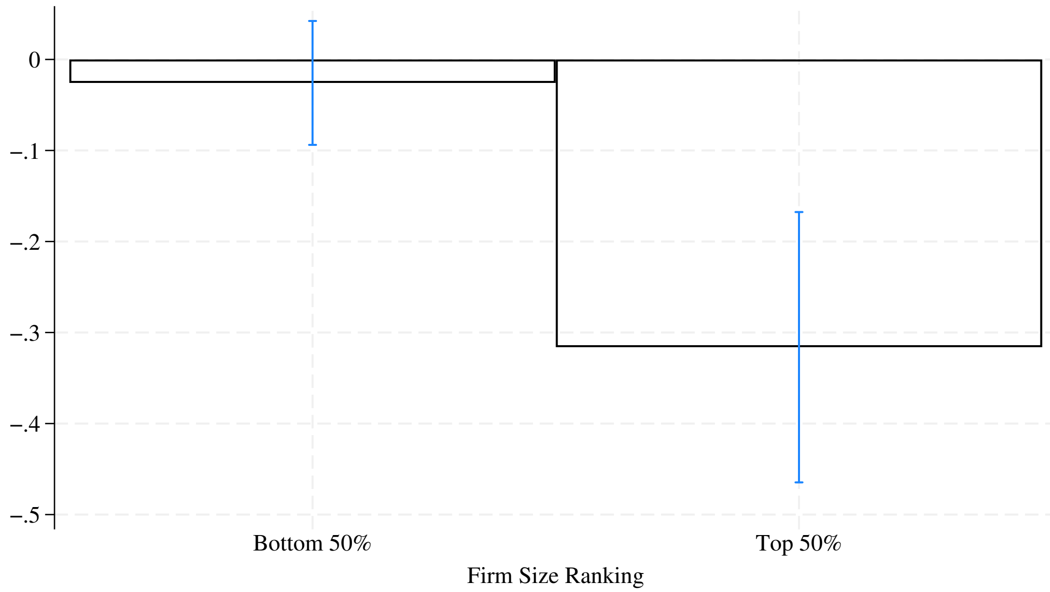


Figure 3: Heterogeneity Results: By Firm Size

Notes: This figure summarizes the point estimates for Equation (1) where the dependent variable is log of annual carbon emissions and their 95% confidence intervals separately for two sub-groups based on firm size deciles: firms in Deciles 1 through 5 and firms in Deciles 6 through 10. The estimation is based on the preferred model controlling for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. The standard errors are clustered at the district level.

Table 1: Estimation Results: Total Energy Consumption (BTU) and Carbon Emissions

	(1)	(2)
	Log(Carbon Emissions)	Log(Energy Use)
β	-0.248***	-0.255***
	(0.0904)	(0.0805)
N	33932	34144
R^2	0.64	0.63

Notes: This table shows the main estimation results using specification (1). * p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the district level are reported in parentheses. All models control for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. Energy consumption is measured in millions of British Thermal Units (BTU).

Table 2: Estimation Results: Total Energy Consumption (BTU) and Carbon Emissions Per Sale

	(1)	(2)
	Log(Carbon Emissions/Sale)	Log(Energy Use/Sale)
β	-0.127*	-0.353***
	(0.0697)	(0.1112)
N	16125	16125
R^2	0.50	0.57

Notes: This table shows the main estimation results using specification (1). * p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the district level are reported in parentheses. All models control for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. Energy consumption is measured in millions of British Thermal Units (BTU).

Table 3: Estimation Results: Profit, Expenses, and Sales

	(1) LnTotalExpenses	(2) LnExpenses(Fuel)	(3) LnSales	(4) LnProfit
β	0.151	-0.063	0.175	0.129
	(0.119)	(0.062)	(0.132)	(0.118)
N	34294	34294	34294	32079
R^2	0.567	0.587	0.527	0.552

Notes: * p<0.10 ** p<0.05 *** p<0.01. Estimation is based on our preferred model. Standard errors clustered at the district level are reported in the parentheses. Expenses, profit, and sales are measured in million US$.

Table 4: Estimation Results: Carbon Emissions by Energy Source

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Conventional: Log(Emission)					Renewable	
	Overall	Fossil Fuels	Wood& Agri. Products	Electricity (self-generated)	Electricity (purchased)	Log(Emission)	Any Emission
β	-0.267***	0.031	0.026	-0.240***	-0.205*	-0.010	0.005*
	(0.092)	(0.106)	(0.020)	(0.057)	(0.106)	(0.018)	(0.003)
R^2	0.637	0.530	0.437	0.559	0.628	0.576	0.439

Notes: This table summarizes the estimation results by energy source. N = 34484. * p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the district level are reported in parentheses. We further differentiate emissions from conventional energy by subcategory: fossil fuels such as coal, oil, and gas, wood and agricultural products, self-generated electricity, and purchased electricity. The estimation is based on the preferred model controlling for year, state, treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects.

Table 5: Estimation Results: Investment, Assets, and Physical Capital

	(1) LnInvestment	(2) LnTotalAssets	(3) LnPPE	(4) LnLandBuilding
β	0.027*	0.033*	0.040**	0.030*
	(0.015)	(0.018)	(0.019)	(0.015)
N	34294	34294	34294	34294
R^2	0.583	0.545	0.543	0.556

Notes: * p<0.10 ** p<0.05 *** p<0.01. Estimation is based on our preferred model. Standard errors clustered at the district level are reported in the parentheses. Short-term Investment, total assets, PPE (property, plant, & equipment), and land and building are measured in million US$.

Table 5: Estimation Results: Electricity Consumption by Type

	(1)	(2)	(3)	(4)
	Log(Electricity Consumption in Kwh)			
	Purchased	Self-generated		
		Overall	from Conventional	from Renewable
β	-0.235**	-0.391***	-0.433***	-0.211
	(0.099)	(0.133)	(0.157)	(0.298)
N	33286	21943	21691	1018
R^2	0.631	0.667	0.667	0.783

Notes: * p<0.10 ** p<0.05 *** p<0.01. Estimation is based on our preferred model. Standard errors clustered at the district level are reported in the parentheses.

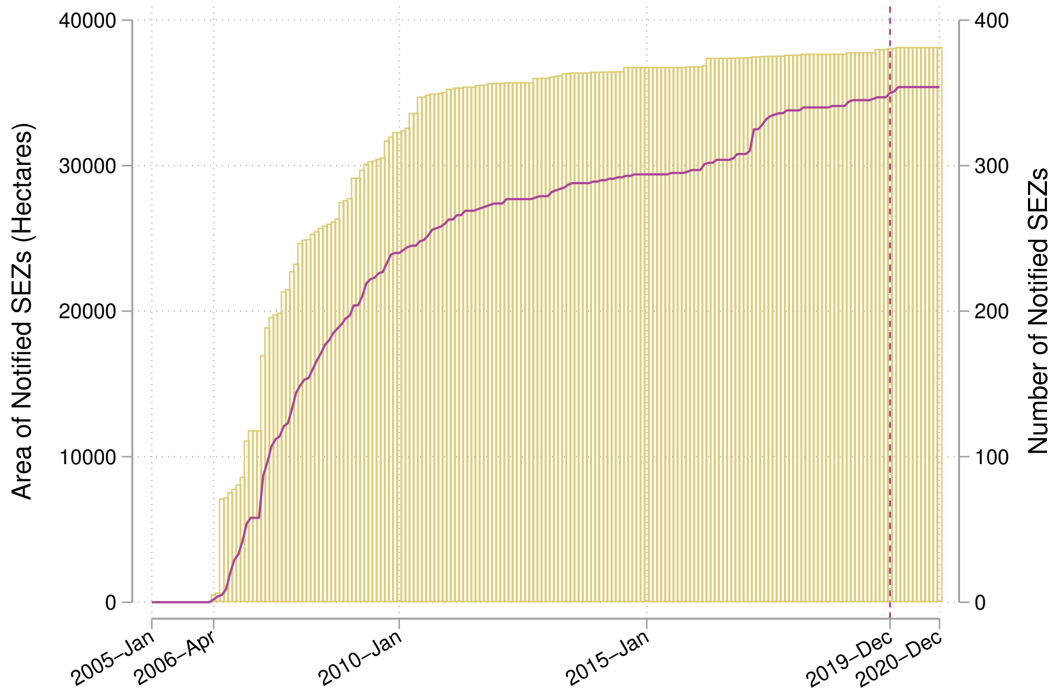
Table 6: Heterogeneity Results: By Region

	(1)	(2)
	Cluster 1	Cluster 2
β	-0.256***	-0.169
	(0.092)	(0.271)
N	29143	4784
R^2	0.640	0.731

Notes: * p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the district level are reported in parentheses. This table summarizes results for two regional clusters, factoring in India's energy distribution. The estimation is based on the preferred model controlling for year, state, treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. Cluster 1 includes the Northern, Southern, and Western Zonals, where renewable energy is rapidly expanding and constitutes a relatively larger share of the total energy mix; Cluster 2 consists of North Eastern, Eastern, and Central Zonals, where renewable energy has a smaller presence.

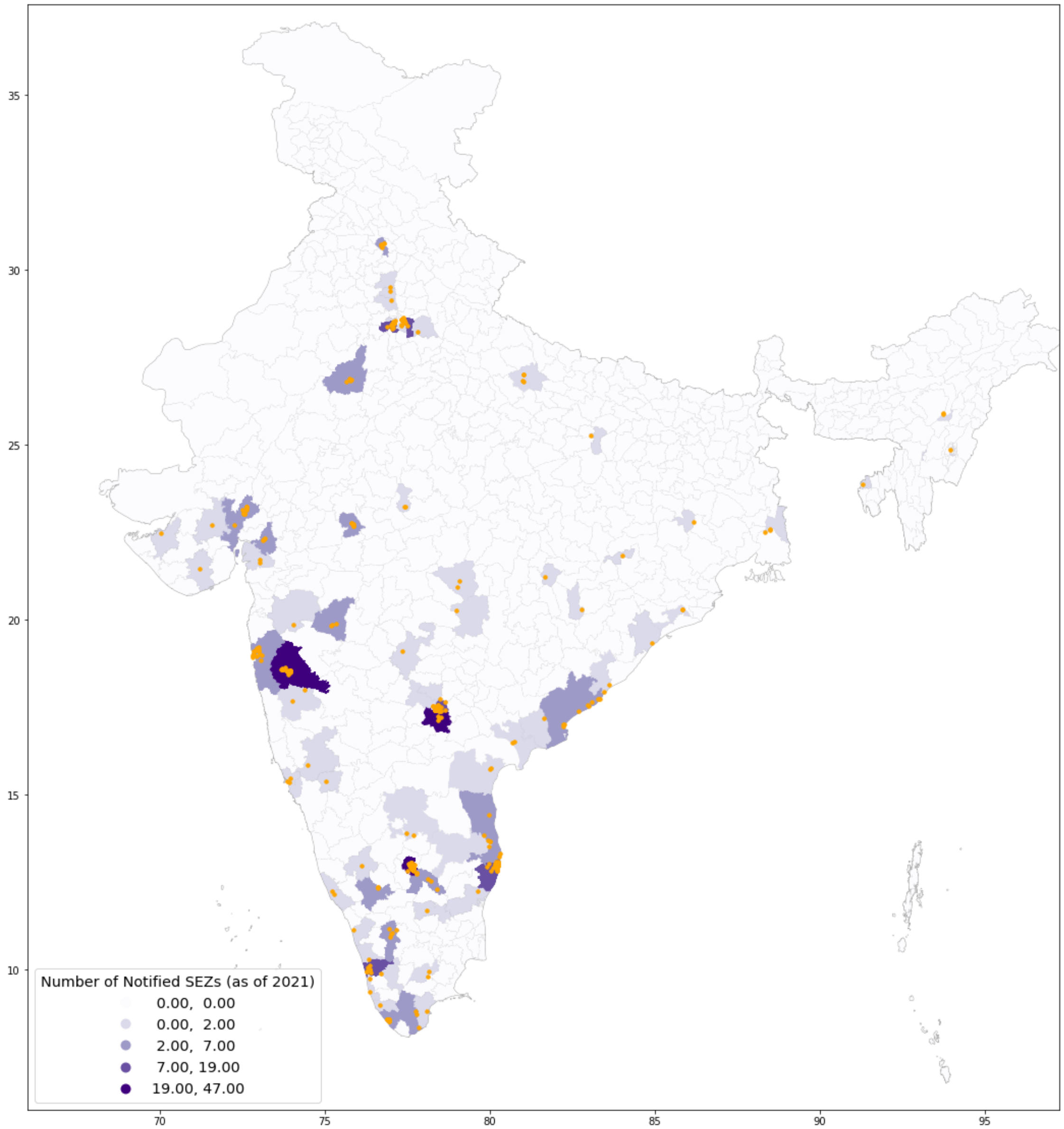
Online Appendix

A Appendix Figures



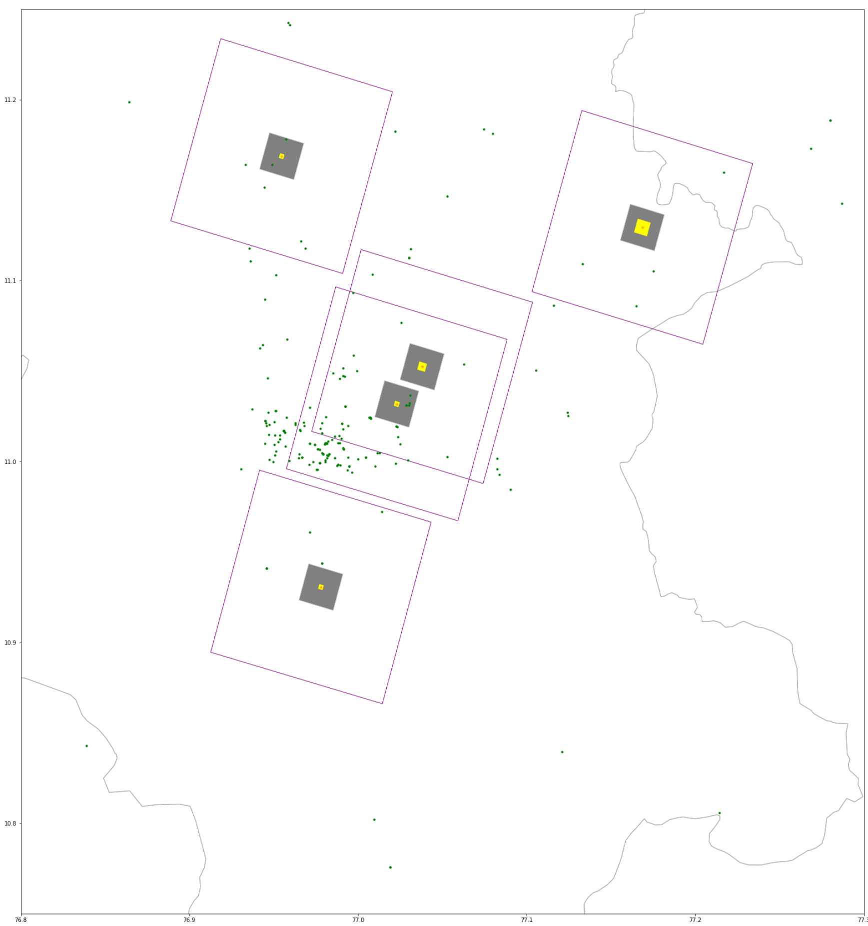
A.1: SEZs in India

Notes: This figure plots the evolution of the number of notified SEZs (purple line) and their areas (yellow bar) since the enactment of the SEZs Act in 2005.



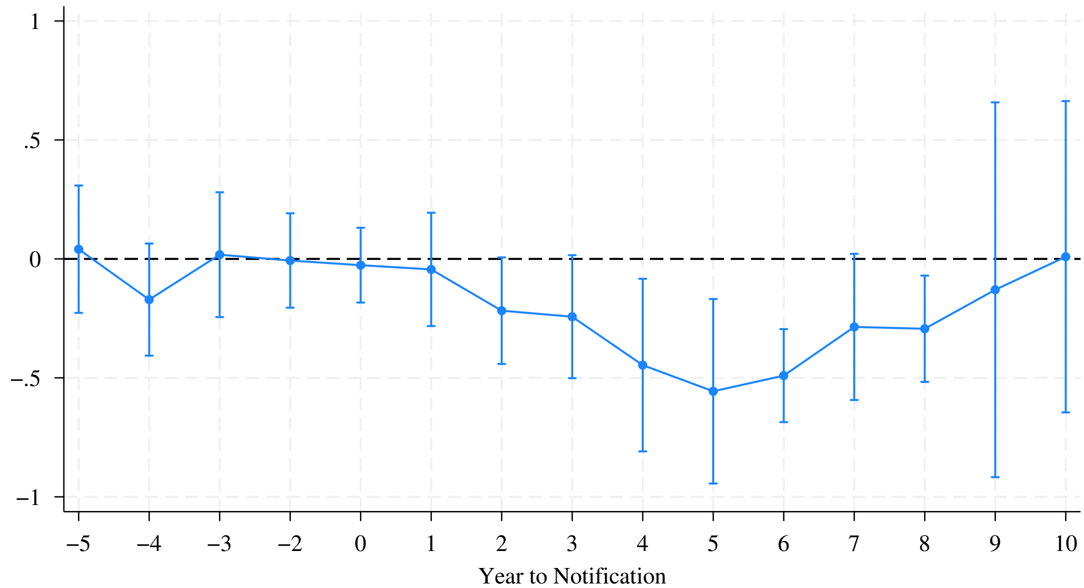
A.2: SEZs in India

Notes: This figure illustrates the geographic distribution of the notified SEZs across India. Districts with a greater number of notified SEZs are shaded darker. The orange markers denote location of individual SEZs across India.



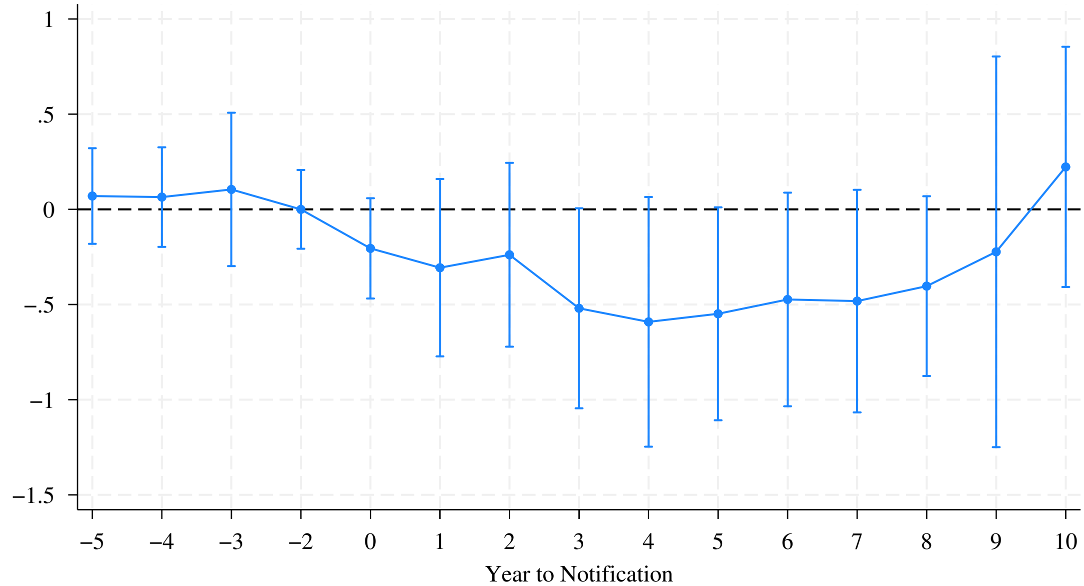
A.3: RD-DiD Matching Example

Notes: This figure illustrates the treatment, control, and leave-out zones in the analysis. Yellow squares represent the treatment zones, which are the same size as reported in the SEZ notification. Grey areas denote the "leave-out" zones, equivalent to a 1 km × 1 km square. The analysis sample is restricted to firms within a 10 km × 10 km grid, indicated by the purple box.



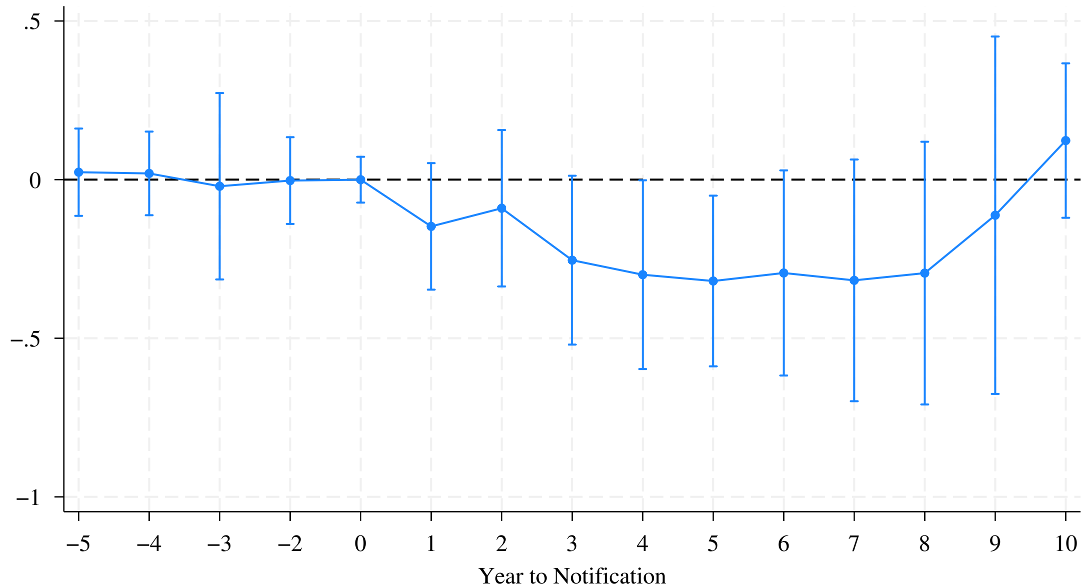
A.4: Event-Study Results: Energy Use

Notes: This figure presents the point estimates and their 95% confidence intervals for the event study estimating Equation (2) where the dependent variable is log of annual energy consumption (in BTU) at the firm-year level. The model includes interaction terms between SEZ treatment and time dummies indicating 1-5 years before the SEZ notification and 1-10 years after the notification, and controls for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. The standard errors are clustered at the district level.



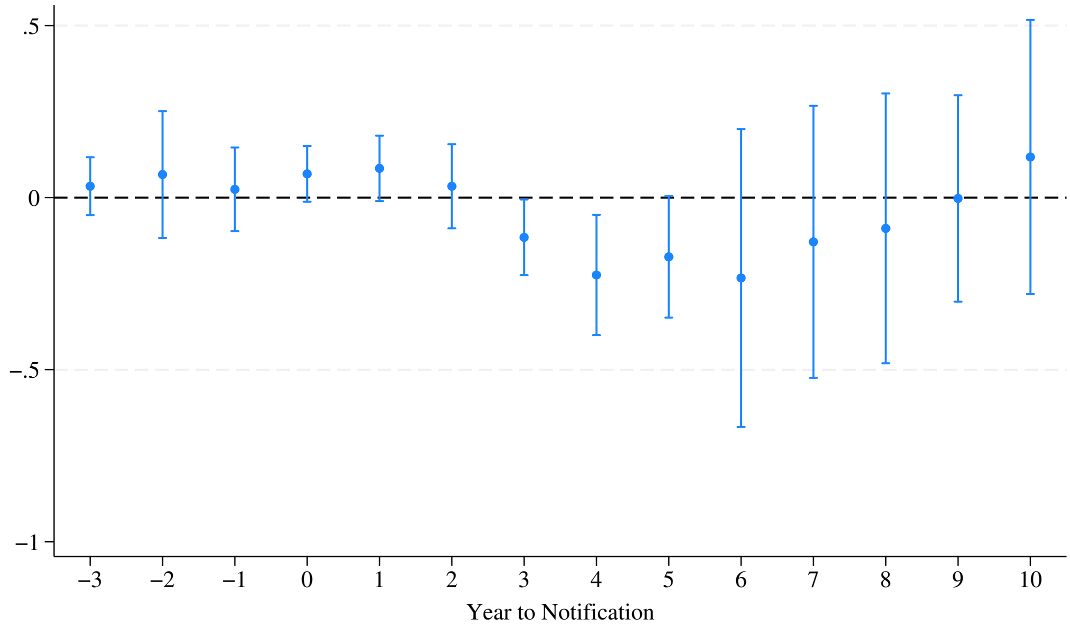
A.5: Event-Study Results: Energy Use per Sale

Notes: This figure presents the point estimates and their 95% confidence intervals for the event study estimating Equation (2) where the dependent variable is log of annual energy consumption (in BTU) per sale at the firm-year level. The model includes interaction terms between SEZ treatment and time dummies indicating 1-5 years before the SEZ notification and 1-10 years after the notification, and controls for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. The standard errors are clustered at the district level.



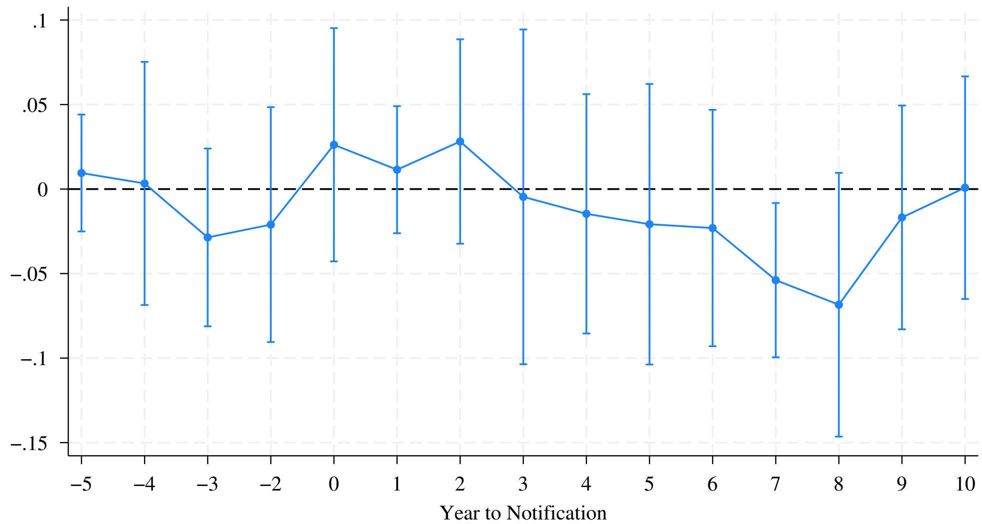
A.6: Event-Study Results: Emission per Sale

Notes: This figure presents the point estimates and their 95% confidence intervals for the event study estimating Equation (2) where the dependent variable is log of annual carbon emissions per sale at the firm-year level. The model includes interaction terms between SEZ treatment and time dummies indicating 1-5 years before the SEZ notification and 1-10 years after the notification, and controls for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. The standard errors are clustered at the district level.



A.7: Robustness: Results of IPW

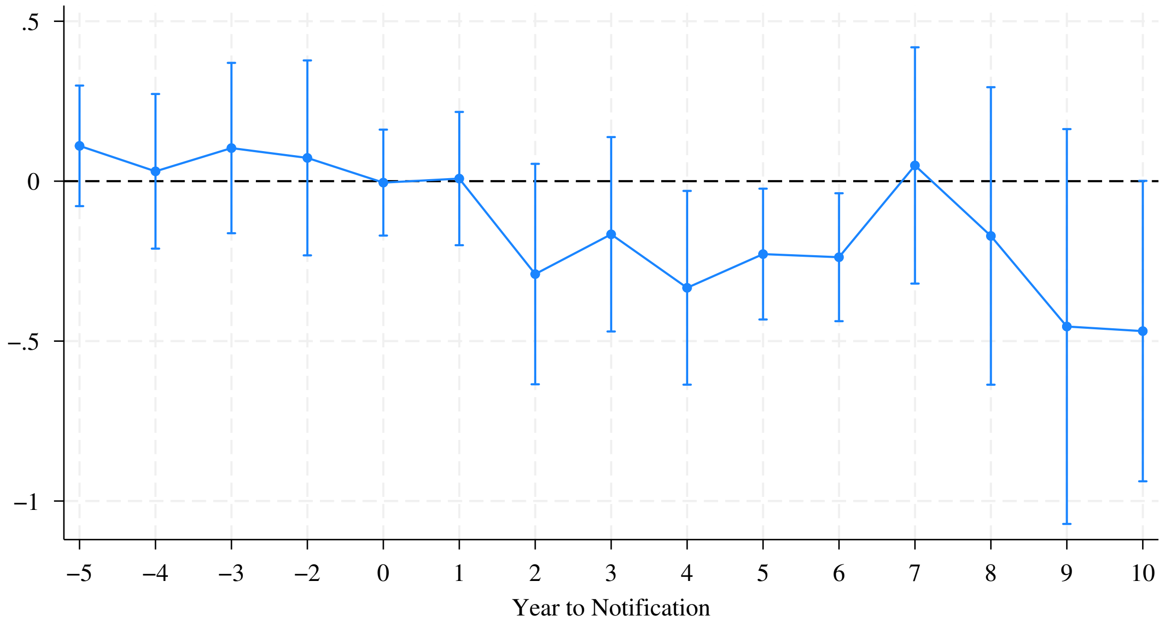
Notes: This figure plots the point estimates of Equation (2) and 95% Confidence Intervals using the inverse probability weighting DiD estimator with stabilized weights. The y-axis measures the log of annual carbon emissions at the firm level. Results are estimated by the *csdid* command in Stata. Standard errors are clustered at the district level. Essentially it is equivalent to a two-way clustering at the panel and district level, see Callaway and Sant'Anna (2021) for more details. The control group is defined as these never treated.



(a) Event Study

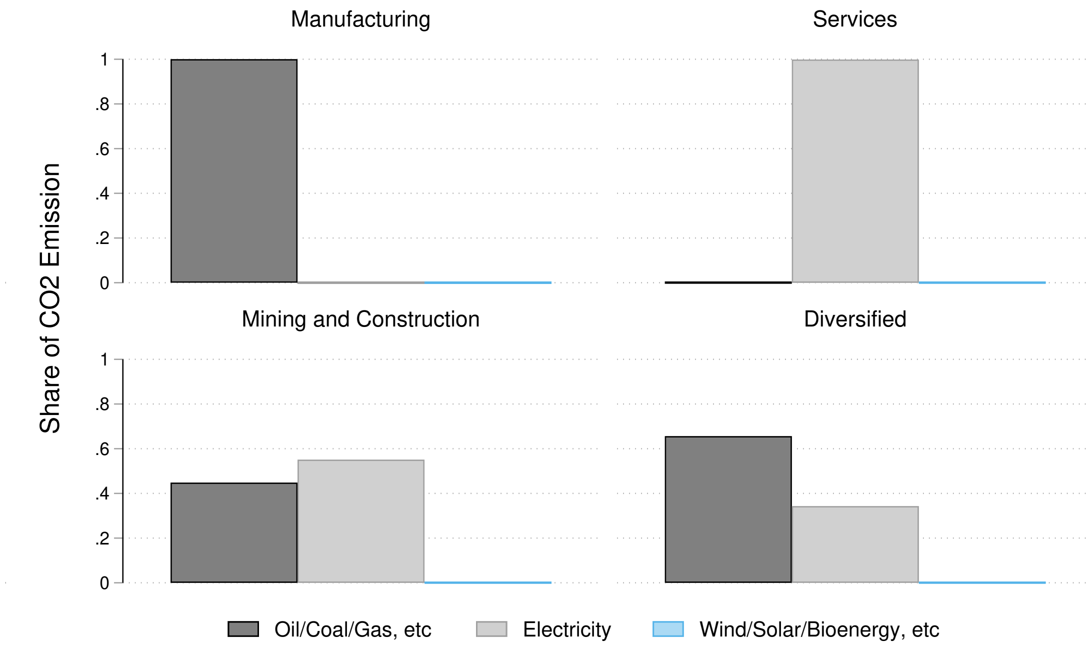
A.8: Examination of Reporting Accuracy

Notes: In this figure, we examine whether SEZ and non-SEZ firms exhibit different trends in accurately tracking their energy consumption before and after the establishment of SEZs. To capture potential inaccuracies in reporting, we treat missing values, arising either from ambiguous energy names and unit measures in the energy consumption table or from missing consumption quantities in the carbon emission calculations, as indicators of inaccurate reporting or insufficient tracking. Based on this, we construct a binary variable that equals one if any such missing values are present. We then replicate our baseline analysis using this binary indicator as the outcome variable.



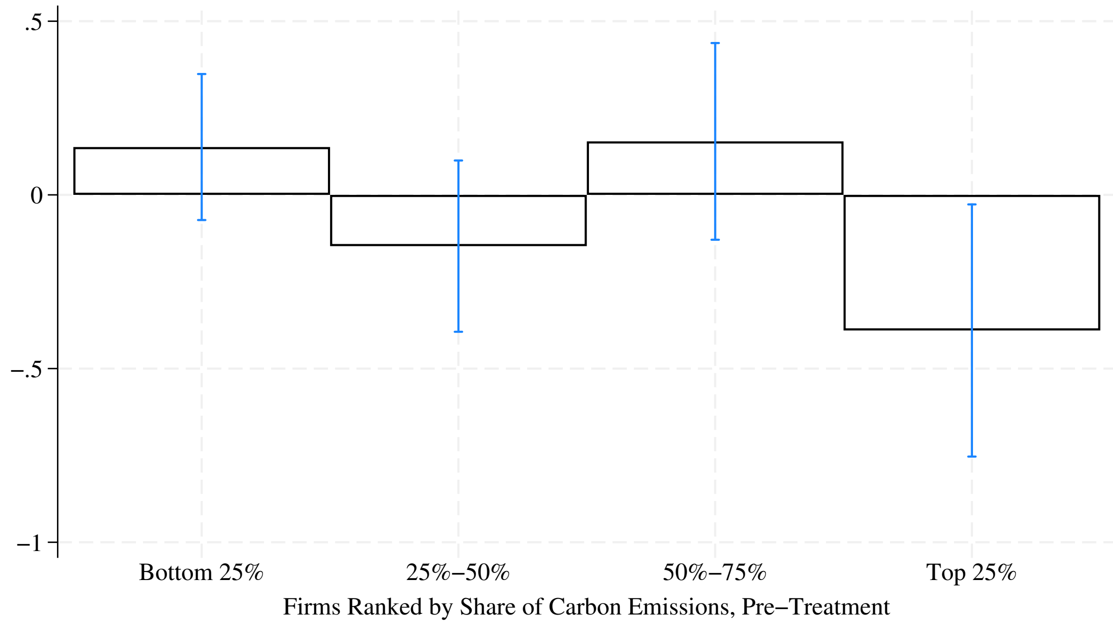
A.9: Additional Event-Study Results

Notes: This figure replicates the event study results from the main analysis using a sub-sample consisting only of firms that consistently and accurately tracked their energy use throughout the sample period. Point estimates and their 90% confidence intervals are reported. The new results remain qualitatively and quantitatively similar to those reported in the main text.



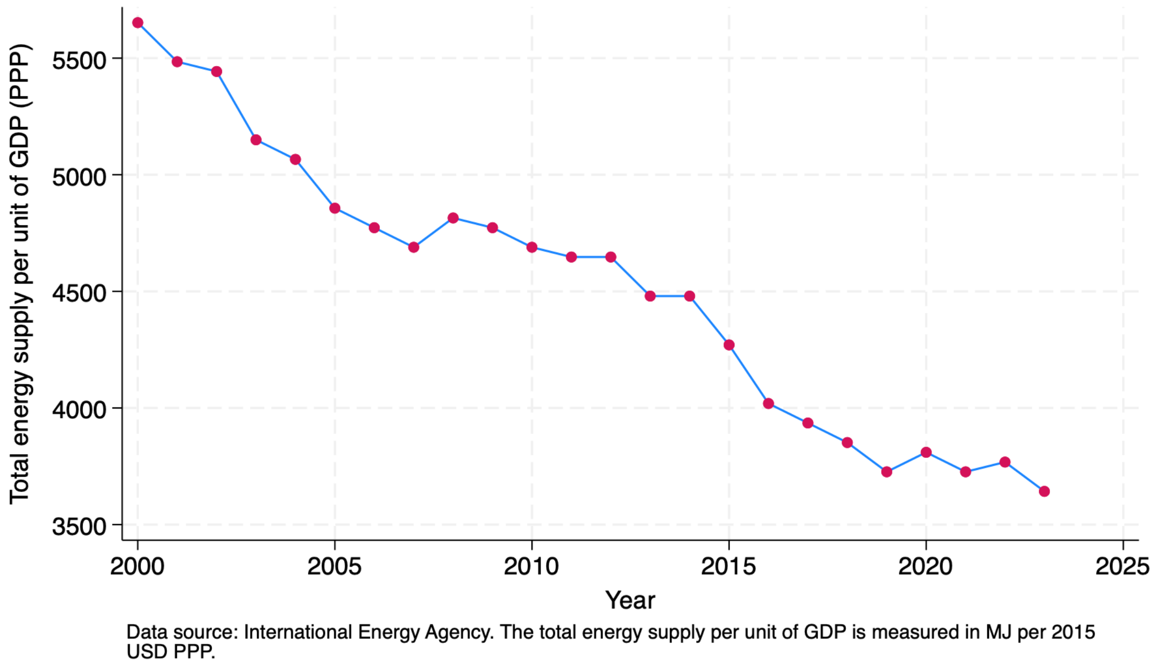
A.10: The Share of Carbon Emission by Industry and Fuel Type

Notes: This figure plots the share of total carbon emission by industry group and fuel type. We classify four industry groups as discussed in the main text: Manufacturing, Services (combining Financial and Non-Financial), Mining and Construction, and Diversified, and three broadly-defined energy categories: a) fossil fuel such as oil, coal, and natural gas, etc, b) electricity, and c) renewable energy including wind, solar, and bioenergy (e.g., biogas or biomass), etc.



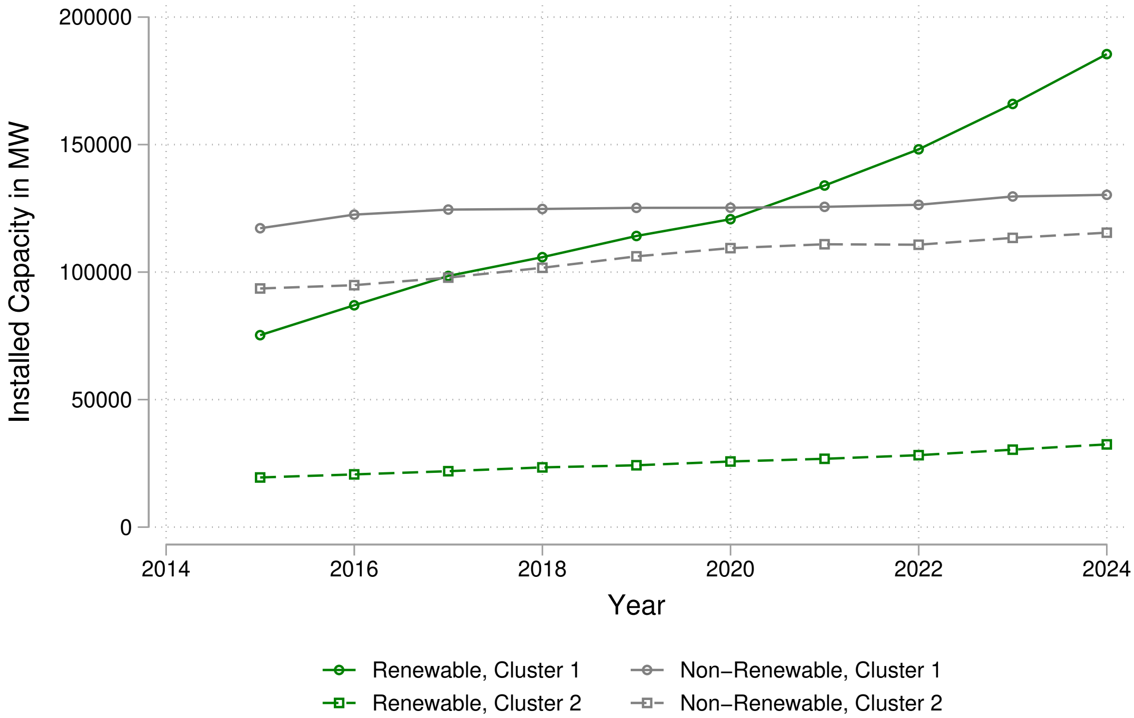
A.11: Marginal Effects of SEZs on Carbon Emissions by Emitter Type

Notes: This figure plots the heterogeneous effects of SEZs on the logarithm of carbon emissions by emitter type. Firms are ranked by their share of carbon emissions during the pre-treatment period and grouped into quartiles. Point estimates and 90% confidence intervals of the marginal effects are reported. The estimation results are based on the preferred model with standard error clustering at the district level.



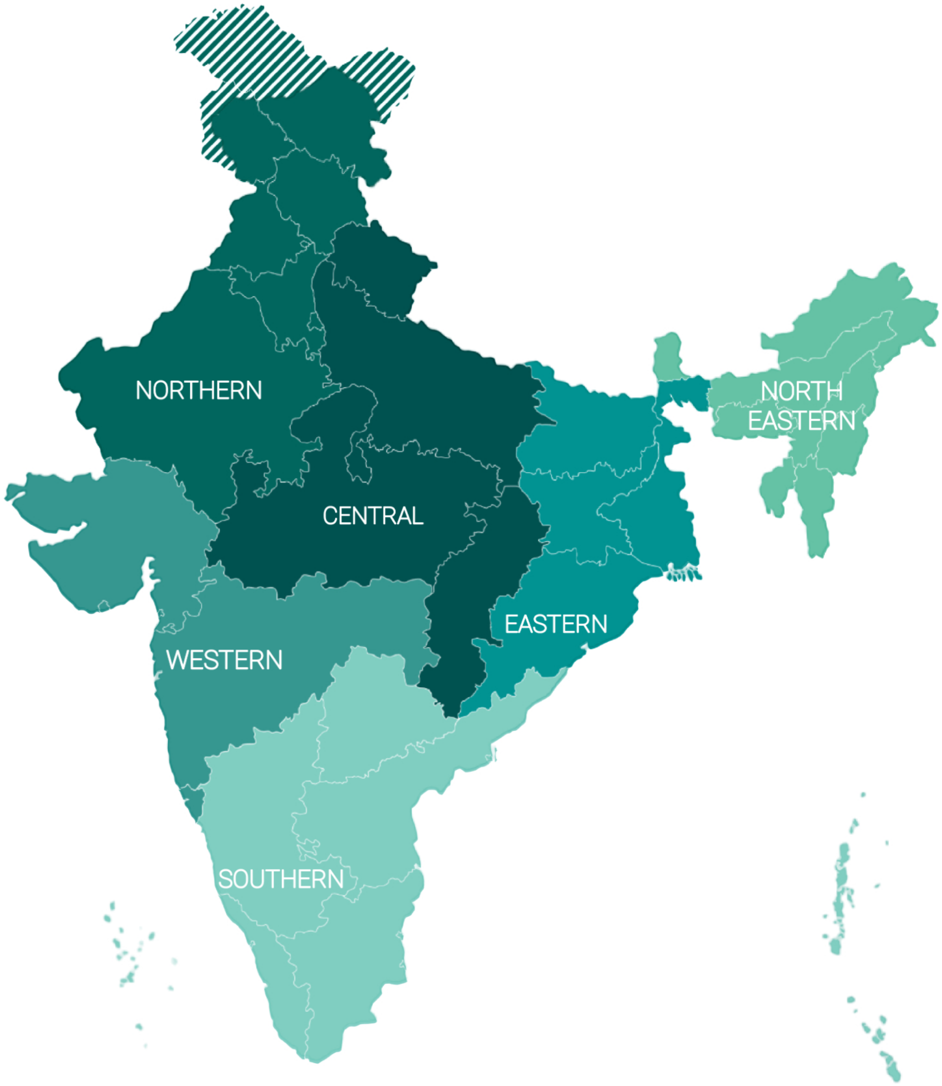
A.12: Energy Use per Unit of Output in India

Notes: This figure plots total energy supply per unit of GDP in India over time, measured in megajoules (MJ) per 2015 USD (PPP). Data are sourced from the International Energy Agency (IEA).



A.13: Installed Electricity Capacity (in MW) by Energy Source and Region

Notes: This figure shows the trend in installed electricity capacity (in MW) by energy source and region. Data are sourced from ICED: https://iced.niti.gov.in/energy. The regional cluster definitions are consistent with those used in the main analysis. The ICED data are only available from 2015 onward.



A.14: India Zonal Divisions

Notes: India zonal divisions figure source: https://en.wikipedia.org/wiki/Administrative_divisions_of_India. India's administrative regional (zonal) divisions split the country into six regions. They are Northern Zonal Council, comprising Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Ladakh, Punjab, and Rajasthan; North Eastern Council, comprising Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland and Tripura; Central Zonal Council, comprising the States of Chhattisgarh, Madhya Pradesh, Uttarakhand and Uttar Pradesh; Eastern Zonal Council, comprising Bihar, Jharkhand, Odisha, and West Bengal; Western Zonal Council, comprising Dadra and Nagar Haveli and Daman and Diu, Goa, Gujarat, and Maharashtra; Southern Zonal Council, comprising Andhra Pradesh, Karnataka, Kerala, Puducherry, Tamil Nadu, and Telangana.

B Appendix Tables

B.1: Carbon Emission Factors

Energy Source	kg CO2 per unit of Energy Source	Unit of Energy Source	kg CO2 per MMBtu of Energy Source
(1)	(2)	(3)	(4)
Agricultural Byproducts	975	short ton	118.17
Biodiesel (100%)	9.45	gallon	73.84
Biogas (Captured Methane)	0.044	scf	52.07
Bituminous Coal	2325	short ton	93.28
Coal Coke	2819	short ton	113.67
Coke Oven Gas	0.03	scf	46.85
Crude Oil	10.29	gallon	74.54
Distillate Fuel Oil No.1	10.18	gallon	73.25
Distillate Fuel Oil No.2	10.21	gallon	73.96
Fuel Gas	0.08	scf	59
Heavy Gas Oils	11.09	gallon	74.92
Kerosene	10.15	gallon	75.2
Lignite Coal	1389	short ton	97.72
Liquefied Petroleum Gases (LPG)	5.68	gallon	61.71
Lubricants	10.69	gallon	74.27
Mixed (Electric Power Sector)	1885	short ton	95.52
Mixed (Industrial Sector)	2116	short ton	94.67
Motor Gasoline	8.78	gallon	70.22
Naphtha (<401 deg F)	8.5	gallon	68.02
Natural Gas	0.05	scf	53.06
Natural Gasoline	7.36	gallon	66.88
Other Biomass Gases	0.03	scf	52.07
Peat	895	short ton	111.84
Petroleum Coke (Solid)	3072	short ton	102.41
Propane	5.72	gallon	62.87
Rendered Animal Fat	8.88	gallon	71.06
Residual Fuel Oil No.5	10.21	gallon	72.93
Residual Fuel Oil No.6	11.27	gallon	75.1
Solid Byproducts	1096	short ton	105.51
Wood and Wood Residuals	1640	short ton	93.8

Notes: This table summarizes the carbon emission factors by energy source used in this paper. The table is extracted from the EPA's GHG Emission Factors Hub (https://www.epa.gov/climateleadership/ghg-emission-factors-hub).

B.2: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
Variable	Obs	Mean	Std. Dev.	Min	Max
CO2 Emission (Metric Ton)	80,070	21856.65	4722007	0	1,320,000,000
Log(CO2 Emission)	78,600	2.70	2.52	-14.03	27.91
CO2 Emission from Renewable	79,964	22.32	2277.12	0	443668.5
CO2 Emission from Conventional	79,909	21900	4730000	0	1,320,000,000
Share from Conventional	78,600	0.98	0.10	0	1
Log(CO2 Emission from Renewable)	80,070	0.13	0.74	-14.57	13.00
Log(CO2 Emission from Conventional)	80,070	2.62	2.52	-14.03	27.91
Total Population, District (in 1 million)	79,765	4.36	2.64	0.14	11.06
Log(Total Population)	79,765	15.08	0.72	11.86	16.22
	Freq.	Percent			
Firm Age					
Before 1950	8,374	10.46			
Between 1951 and 1971	8,714	10.88			
Between 1972 and 1985	21,295	26.6			
Between 1986 and 1990	13,297	16.61			
After 1991	28,389	35.46			
Between 1991 and 2000	21,547	26.91			
Between 2001 and 2005	4,296	5.37			
After 2006	2,547	3.18			
Size by Decile					
Decile 1	13,391	16.72			
Decile 2	12,897	16.11			
Decile 3	11,233	14.03			
Decile 4	10,120	12.64			
Decile 5	9,724	12.14			
Decile 6	8,128	10.15			
Decile 7	5,808	7.25			
Decile 8	4,186	5.23			
Decile 9	2,953	3.69			
Decile 10	1,606	2.01			
Entity type					
Associations/Federations	9	0.01			
Co-operatives	7	0.01			
Departmental undertakings/Boards	2	0			
Foreign Entities	1	0			
Governments	18	0.02			
Partnership firms	8	0.01			
Private Ltd.	14,559	18.18			

Continued on next page

Continued

	Freq.	Percent
Public Ltd.	65,450	81.74
Trusts	7	0.01
Unlimited Liabilities	9	0.01
CMIE 6-digits		
Manufacturing	64,800	80.93
Mining	697	0.87
Electricity	197	0.25
Services (other than financial)	8,514	10.63
Construction & real estate	744	0.93
Asset financing services	40	0.05
Other fund based financial	3,663	4.57
Fee based financial services	2	0
Other financial services	24	0.03
Diversified financial services	234	0.29
Diversified	1,155	1.44
N	80070	

Notes: This table reports the summary statistics for the analysis sample.

B.3: Summary Statistics by Treatment Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment Group		Control Group		Control-Treatment	
	Mean	Std.	Mean	Std.	Diff.	t-stats
Log(CO2 Emission)	2.483	2.695	2.695	2.501	0.212***	(5.947)
Firm Age	3.555	1.248	3.560	1.361	0.005	(0.277)
Size Decile	3.996	2.491	4.207	2.430	0.211***	(6.437)
Entity Type	2.136	0.349	2.189	0.392	0.053***	(11.329)
Industry Group						
Manufacturing	0.781	0.414	0.815	0.388	0.034***	(6.306)
Non-Financial Services	0.131	0.338	0.106	0.308	-0.025***	(-5.669)
Mining and Construction	0.020	0.141	0.017	0.128	-0.004*	(-1.989)
Financial Services	0.054	0.226	0.046	0.210	-0.008**	(-2.613)
Diversified	0.014	0.117	0.016	0.126	0.002	(1.430)
N	6328		62426		68754	

Notes: $*p < 0.10 ** p < 0.05 *** p < 0.01$. This table reports the summary statistics by treatment status and the results of t-test for the difference between the two groups.

B.4: Differences in Firm Attributes by Treatment Status, Matched v.s. Unmatched Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm Age	Size Decile	Entity Type	Industry Group Indicator				
				Manufacturing	Non-Financial Services	Mining and Construction	Financial Services	Diversified
	Unmatched Sample							
SEZs	-0.0046	-0.211***	-0.053***	-0.0342***	0.0251***	0.0037**	0.0077***	-0.0022
	(0.0166)	(0.0328)	(0.0047)	(0.0054)	(0.0044)	(0.0019)	(0.0030)	(0.0016)
N	68753	68730	68754	68754	68754	68754	68754	68754
Pair FEs	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*
	Matched Sample							
SEZs	-0.0063	0.0042	0.0244	-0.0354	0.0354	0.0004	-0.0018	0.0014
	(0.0412)	(0.0585)	(0.0301)	((0.0349)	(0.0275)	(0.0165)	(0.0167)	(0.0147)
N	38817	38817	38817	38817	38817	38817	38817	38817
Pair FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Notes: * p<0.10 ** p<0.05 *** p<0.01. This table reports the results regressing firm attributes on the within SEZs indicator separately for matched and unmatched samples, where for the matched sample, pair FEs are included. Standard errors are reported in parentheses. For the unmatched sample, we report robust standard errors, as the model includes no fixed effects or control variables, and the estimates simply reflect the sample mean difference between the treatment and control groups. For the matched sample, we report clustered standard errors at the treatment-control pair level.

B.5: Heterogeneity Results: By Region (2/2)

	(1)	(2)	(3)	(4)	(5)	(6)
	Northern	North Eastern	Central	Eastern	Western	Southern
β	-1.478***	0.000	0.231	0.063	-0.283***	-0.048
	(0.313)	(.)	(0.254)	(0.305)	(0.099)	(0.132)
N	4679	92	1615	3076	15756	8706
R^2	0.69	0.91	0.82	0.69	0.61	0.73

Notes: * p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the district level are reported in parentheses. This table reports the estimation results separately for six regions, adopting the definition of India's administrative regional (zonal) divisions. The estimation is based on the preferred model controlling for year, state, treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects.

B.6: Additional Results: Total Carbon Emissions and Energy Consumption (BTU)

	(1)	(2)	(3)	(4)
	Log(Energy Use/Sale)	Log(Carbon Emissions/Sale)	Log(Energy Use)	Log(Carbon Emissions)
β	-0.353***	-0.127*	-0.418***	-0.393***
	(0.1112)	(0.0697)	(0.1482)	(0.1352)
N	16125	16125	16056	15965
R^2	0.57	0.50	0.73	0.74

Notes: This table shows the main estimation results using the spatial RD-DiD design. * p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the district level are reported in parentheses. All models control for treatment-control pair, industry (8-digit CMIE industry codes), state by year, and district fixed effects. Energy consumption is measured in millions of British Thermal Units (BTU).

B.7: Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Carbon Emissions)							
β	-0.277**	-0.277***	-0.277**	-0.283***	-0.276**	-0.203**	-0.328**	-0.288**
	(0.124)	(0.085)	(0.114)	(0.104)	(0.112)	(0.092)	(0.126)	(0.133)
N	16494	16494	16494	15110	15921	28239	22177	16482
R^2	0.679	0.679	0.679	0.700	0.688	0.657	0.696	0.717
Cluster-Level	Pair	State + Year	Firm + District-Year					
Sub-Sample				Inc. Yr $\leq$ 2000	Inc. Yr $\leq$ 2005			
Sample Zone	10 km	10 km	10 km	10 km	10 km	10 km	5 km	5 km
Leave-out Zone	1 km	1 km	1 km	1 km	1 km	2 km	1 km	2 km

Note: This table summarizes the results of robustness check. Standard errors in parentheses. Unless otherwise specified, standard errors clustered at the district level are reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns (1) to (3) report the results with standard errors clustered at treatment-control pair, state and year, and district and year levels, respectively. Columns (4) and (5) re-estimate the preferred model on sub-samples of firms incorporated before 2000 or 2005. Columns (6) to (8) experiment with different sample zones, such as a 5 km zone, and different leave-out zones, such as a 1 km zone.

C Model Derivation

Solve for the optimal total energy consumption Here, we formally derive the optimal energy consumption, by solving the firm's optimization problem. First, firms choose the optimal production level Y to maximize profits:

$$\max_{Y_s} \Pi = (1 - t(1-c))pY_s - C(Y_s, P)$$

and the optimal input levels to minimize costs:

$$\min_{K,E,L} C(Y_s, P) = p^K \cdot K_s + p^E \cdot E_s + p^L \cdot L_s,\ s.t.\ Y_s \geq \bar{Y}_s$$

Solving the first-order conditions of the cost minimization problem, we obtain the optimized cost function:

$$C^*(Y_s, P) = \left(\frac{Y_s}{A'_s}\right)^{\frac{1}{\psi}} \left(\frac{p^K}{\psi^K}\right)^{\frac{\psi^K}{\psi}} \left(\frac{p^L}{\psi^L}\right)^{\frac{\psi^L}{\psi}} \left(\frac{p^E}{\psi^E}\right)^{\frac{\psi^E}{\psi}} \psi$$

and the conditional energy demand:

$$E^*(\bar{Y}_s, P) = \left(\frac{\bar{Y}_s}{\tilde{A}_s}\right)^{\frac{1}{\psi}} \left(\frac{p^K}{\psi^K}\right)^{\frac{\psi^K}{\psi}} \left(\frac{p^L}{\psi^L}\right)^{\frac{\psi^L}{\psi}} \left(\frac{p^E}{\psi^E}\right)^{\frac{\psi^E - \psi}{\psi}}$$

where $\psi = \psi^K + \psi^E + \psi^L$ and $\tilde{A}_s = A_s(A_s^E)^{\psi_E}$. We can see from the conditional energy demand function that holding the production level constant, a higher energy efficiency (i.e., a larger A_s^E) reduces energy demand. Plugging this into the profit function and solving the first-order condition gives the optimal output level:

$$Y_s^* = \tilde{A}_s^{\frac{1}{1-\psi}} \left[(1 - t(1-c))p\right]^{\frac{\psi}{1-\psi}} \cdot \left(\frac{\psi^K}{p^K}\right)^{\frac{\psi^K}{1-\psi}} \cdot \left(\frac{\psi^L}{p^L}\right)^{\frac{\psi^L}{1-\psi}} \cdot \left(\frac{\psi^E}{p^E}\right)^{\frac{\psi^E}{1-\psi}}$$

The corresponding optimal energy demand is:

$$E_s^* = (Y_s^*)^{\frac{1}{\psi}} \tilde{A}_s^{-\frac{1}{\psi}} \left(\frac{p^K}{\psi^K}\right)^{\frac{\psi^K}{\psi}} \left(\frac{p^L}{\psi^L}\right)^{\frac{\psi^L}{\psi}} \left(\frac{p^E}{\psi^E}\right)^{\frac{\psi^E - \psi}{\psi}}$$

□

Solve for the optimal energy consumption across types After determining the optimal level of total energy consumption, firms in sector s decide how to allocate this energy between cleaner and conventional sources. Specifically, they choose the quantities of energy inputs E_s^x, where $x \in \{c, d\}$

denotes clean and dirty energy, respectively, in order to minimize total energy costs:

$$\begin{aligned} \min_{E_s^c, E_s^d} \quad & p_s^{E^d} E_s^d + p_s^{E^c} E_s^c + f\,\mathbb{1}(E_s^c > 0) \\ \text{s.t.} \quad & \begin{cases} E_s^* = \delta_c E_s^c + \delta_d E_s^d, & s = N \\ E_s^* = \left[\delta_c (E_s^c)^\rho + \delta_d (E_s^d)^\rho\right]^{\frac{1}{\rho}}, & s = M \end{cases} \end{aligned} \tag{3}$$

First, consider non-manufacturing firms, where clean and dirty energy sources are perfectly substitutable. In this case, corner solutions arise: a firm will adopt only cleaner energy when the following condition holds:

$$E_N^* > f \cdot \left(\frac{\delta_c \delta_d}{p^{E^d} \delta_c - p^{E^c} \delta_d} \right). \tag{4}$$

We show below that this is not the case for manufacturing firms. Solving the first-order condition of the optimization problem in Equation (3), we obtain:

$$\frac{E_M^{c*}}{E_M^{d*}} = \left(\frac{(1-\delta_c) p^{E^c}}{\delta_d p^{E^d}} \right)^{\frac{1}{\rho_M - 1}} \quad \text{and} \quad \frac{E_M^{c*}}{E_M^*} = \frac{\gamma}{(\delta_c \gamma^{\rho_M} + \delta_d)^{1/\rho_M}}$$

where $\gamma = \left(\frac{(1-\delta_c) p^{E^c}}{\delta_d p^{E^d}} \right)^{\frac{1}{\rho_M - 1}}$. □

D Calculation of Firms' Carbon Emissions from Energy Consumption

In this appendix, we provide additional details on the data sources and computation procedures used to construct firm-level carbon emission data based on firms' energy consumption.

Firm-level energy use data comes from *Prowess*. *Prowess* contains information on the annual total energy consumption reported by energy source, each with its corresponding unit. For example, a firm that consumed electricity and coal in a given year would have two separate records: one for the number of kilowatt-hours (kWhs) of electricity and another for the number of metric tonnes of coal.

To calculate the annual total carbon emissions from the total energy consumption, similar to Barrows and Ollivier (2018), we assign a source-specific carbon dioxide emission factor to each energy source type.[16] Several steps involved in this process. First, we match and create a crosswalk between the energy source types reported in *Prowess* and the energy categories listed in the EPA's emission factors table. 127 over 148 (86%) energy sources in the *Prowess* are matched to the emission factors table. Then, we standardize the unit of measurement for each type of energy source with the unit of the corresponding emission factor and assign a conversion factor for each energy source-unit pair. We are unable to standardize the energy units for 182 energy source-unit pairs (over 852 total pairs) due to missing observations of the measurement unit and typos in the measurement unit. For example, in some cases, the unit of coal is measured in "Liters" or "Kiloliters", which are volume measures typically used for liquids or fluids. Without knowing the density of the coal being used, it is difficult to convert a volume measure to a weight measure.

It is worth noting that instead of assigning a single carbon emission factor to the energy source type "electricity" (e.g., Barrows and Ollivier 2018), we distinguish electricity purchased by the firm and electricity generated by the firm from various sources, such as coal, gas and oil, and biomass fuels. Emissions from electricity generation vary by types of energy source. For example, electricity generated by the so-called green energy, such as solar and wind, produces zero direct carbon emission, while electricity generated by conventional fuels, such as coal and natural gas, emits carbon dioxide ranging from 0.35 kg/kWh to 0.87 kg/kWh (Schlömer et al. 2014), depending on the type and efficiency of electric power plants. In other words, electricity generated by solar or wind and electricity generated by coal or natural gas are essentially two energy products in terms of carbon emissions and should be recognized as two different energy source types.

To capture this feature, we adopt an additional procedure when calculating emissions from electricity consumption, accounting for variations in the energy composition (i.e., fossil fuel-based electricity vs. non-fossil-based electricity) used in electricity generation across states and years. Specifically, in our approach, we distinguish between purchased and self-generated electricity. For self-generated electricity, the consumption records in the data specify a single generation source. The generation sources include both conventional fuels, such as coal, oil, and gas, and renewable fuels, such as biomass, solar, and wind. We assign different carbon factors to electricity generated from each source. To obtain these carbon emission factors, we first collect data on India's electricity generation by energy source and fuel consumption from the India Climate and Energy Dashboard (ICED).[17] These data allow us to calculate the average amount of fuel needed to generate one kWh of electricity in India. Then, we transform the amount of fuel to the heating content (measured

[16]Following existing literature, we adopt the emission factors provided by the US Environmental Protection Agency (EPA). Appendix Table B1. summarized these factors.

[17]Data source: https://iced.niti.gov.in.

in million British thermal units, MMBtu) and multiply it by the carbon emission factor of the corresponding fuel (which is measured in kg/MMBtu). For example, in India, the average amount of coal needed to generate one kWh of electricity is about 1.54 pound (averaged over years from 2012 to 2019), with a heating value equivalent to about 0.0219 MMBtu. The carbon emission factor for coal used in electric power sector is 95.52 kg/MMBtu. By multiplying the number of coals needed by 95.52, we can obtain the carbon emissions for one kWh electricity generated by coal. We conduct this calculation separately for each fuel by year, to capture the temporal variation in the efficiency of electricity generation in India.[18] Note that in this calculation, we assume that the electricity generation within a firm is as efficient as in a representative electric power plant with average efficiency. It is likely that the efficiency of electricity generation is lower than that of a power plant, possibly due to differences in technology and a lack of economic scale. In that case, our calculation would provide a lower bound estimation of the carbon emissions for electricity generated by firms from various energy sources. For electricity generated from solar or wind, the carbon emission factor is set to zero, according to IPCC's estimate.

For purchased electricity, it is unclear whether the consumed electricity is generated from fossil or non-fossil fuels, as these sources are aggregated within the power grid. Therefore, the corresponding carbon emissions per unit of electricity consumption may vary across states, reflecting differences in the energy composition of their power systems. Considering this, we collect state-year level data on electricity generation by power source (including both fossil fuel and non-fossil fuel categories) from ICED. The ICED dataset provides information on the annual amount of electricity generated across states and the corresponding amounts of fuel consumed. This information allows us to compute both the share of electricity generated from each source and the average amount of fuel from each source used to produce one unit of electricity across states. Using these metrics, we then calculate the carbon emissions associated with purchased electricity as a weighted average of the carbon emissions from generating one kWh of electricity by energy source, with the shares of electricity generation by power source serving as the weights. Notably, variation in the carbon emissions of purchased electricity arises from two sources: (1) temporal and spatial variation in the shares of energy sources used for electricity generation, and (2) variation in the average generation efficiency for producing one unit of electricity.

In total, we have 216,686 observations of the firm-energy source-year pair for 8256 unique firms spanning 1988 to 2021. There are 146 observations missing the quantity of energy consumption and 13368 observations for which we cannot assign a carbon emission factor. We drop those observations, which consists of about 6% of the data.

[18]Since the electricity generation data is only available from 2012 to 2019, we approximate the amount of fuel needed for generating a kWh of electricity before 2012 using the 2012 statistics.