A Sufficient-Statistic Approach to Green Subsidy Targeting in Production Networks

By NINGJING LI, CHUNDING LI, CHONG LIU[1]

Government subsidies are widely used to promote green transformation. How should governments target green subsidies in the presence of market distortions and production networks? To address this question, we develop a multi-sector general equilibrium model with endogenous green innovation, energy-sector market power, and interregional production linkages. Motivated by China's energy sector, which is characterized by a negative monopolistic externality, a positive technological externality, and dense linkages with downstream production sectors, the model shows that subsidies promote green transformation through two channels: energy-sector green innovation and clean-mode transition in the production sector. Structural frictions partially attenuate these effects. The model yields a sufficient-statistic targeting rule for the wedge between social and private returns: regional targeting priority depends on energy-structure elasticity and production-network centrality, balancing externality internalization against network diffusion capacity. Empirically, we exploit China's Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction as a quasi-natural experiment using firm-level data from 2007 to 2020. We find that green subsidies reduce firm emissions through the two model-implied channels, while price volatility from energy supply-demand mismatches weakens policy transmission. Combining reduced-form estimates with model-based counterfactual allocations, we show that sufficient-statistic targeting raises the predicted aggregate emission-reduction rate by 0.79 percentage points, or 4.7 percent relative to the baseline allocation. The results provide an empirically implementable framework for green subsidy targeting in economies with energy-sector market power and production-network linkages.

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I. Introduction

Industrial green transformation is not merely an environmental objective, but a central component of productivity growth, industrial upgrading, and long-run economic modernization (Aghion et al., 2025; Lemoine, 2024). For developing economies, this transformation is especially consequential because industrialization remains a major source of growth and employment, while production still relies heavily on energy- and resource-intensive activities.

China provides a particularly important setting. As a full-supply-chain economy, China has dense input-output linkages between the energy sector and downstream production activities, so a policy shock to one region or sector may affect emissions elsewhere through the production network. At the same time, the energy sector is characterized by substantial market power and administrative monopoly, which weakens private incentives for green innovation. Green technologies also generate social returns that exceed private returns. These dual externalities create a wedge between private and social incentives for energy-sector green innovation, and the production network determines how this wedge is transmitted across sectors and regions. Government subsidies are therefore potentially necessary as a corrective instrument: they can raise private incentives toward social returns, stimulate energy-sector green innovation, and support cleaner production choices downstream. The production network then determines how these subsidy-induced responses are transmitted across sectors and regions.

Yet in developing economies, fiscal resources, green technology capacity, and administrative capacity are limited, making it infeasible to subsidize all regions, sectors, and firms at the same intensity. The key policy challenge is therefore not only whether subsidies promote green transformation, but where limited resources should be allocated. This challenge is particularly relevant in economies with dense production networks, where energy serves as a key

upstream input and policy effects propagate across sectors and regions. Green transformation in the energy sector can generate emission reductions beyond the targeted firms by altering the inputs available to downstream producers, while downstream production decisions also shape the incentives for upstream energy transformation. Industrial green transformation is therefore a network problem: the locations where subsidies generate the largest system-wide effects need not coincide with the locations where emission reductions are ultimately realized.

The central question of this paper is therefore: in an economy characterized by upstream energy-sector market power, green technology externalities, and production-network linkages, how can governments identify the network nodes where limited green subsidy resources generate the highest marginal emission reductions?

To answer this question, we developed a multi-sector general equilibrium model with production networks, endogenous green innovation, and energy-sector market power. The model formalizes the wedge between private and social returns of energy-sector green innovation that arises from two forces: a negative monopolistic externality generated by market power, and a positive technological externality generated by the diffusion of green technologies. Production networks determine how this wedge is transmitted across sectors and regions. In this environment, the optimal targeting of green subsidies depends both on the local response of the energy sector, and the ability of a policy shock to propagate through energy-production linkages.

The model yields an empirically implementable sufficient-statistic targeting rule. A region's targeting priority is determined by two components: energy-structure elasticity and production-network centrality. Energy-structure elasticity captures the marginal emission response generated by policy-induced green innovation. Production-network centrality captures the ability of a regional policy shock to diffuse through energy supply and production linkages. Regions receive

higher targeting priority when they combine stronger local responsiveness with greater network diffusion capacity. This rule makes the policy problem transparent: green subsidies should not be allocated solely according to emissions, energy resources, or economic scale, but according to the predicted system-wide emission response generated by policy exposure.

Empirically, we exploit China's Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction as a quasi-natural experiment. This policy offers a unique natural experiment to test our theoretical model. Since the policy is a typical cross-regional industrial policy in the form of fiscal subsidies, it allows us to observe the real-world impacts of fiscal incentives on green innovation and emissions reduction, providing a useful opportunity to explore how subsidies might influence industrial green transitions in practice. This policy employs technology-oriented fiscal subsidies as a central policy instrument, with clear targeting of green technologies (low-carbon and clean-energy), and was rolled out in phases across regions in 2011, 2013, and 2014 (see Figure 2). The policy adopts a hierarchical pilot scheme covering the eastern, central, and western regions, including municipalities directly under the central government, provincial capitals, and general prefecture-level cities. This design creates regional heterogeneity of demonstration cities in terms of resource endowment, economic development levels, and local governance capacities, allowing the treatment group to exhibit multidimensional characteristics, thereby enhancing the comparability between the treatment and control groups in causal identification. Following the implementation of the policy, demonstration cities experienced a significant increase in low-carbon and clean-energy patenting (see Figure 3 and Figure 4), consistent with the policy's stated emphasis on technology-oriented fiscal support. Motivated by the theoretical framework, we empirically test the two channels through which green subsidies generate emission reductions. Consistent with the model's predictions, we find that

subsidies reduce firm-level emissions by promoting green innovation in the energy sector and inducing cleaner production choices among downstream firms. Moreover, the effects are amplified for firms and industries with stronger energy dependence and tighter linkages to the energy system, whereas energy supply-demand mismatches weaken policy transmission by increasing price volatility.

We then take the sufficient-statistic rule to the data, adopting a sufficient-statistic approach that combines reduced-form treatment responses with observable production-network characteristics to construct implementable policy counterfactuals. Following the recent sufficient-statistic literature (Baqaee and Farhi, 2024; Baqaee and Burstein, 2025), the approach does not require estimation of the full structural model while remaining directly applicable to policy design. We extend this logic from quantifying the consequences of distortions to identifying where green subsidies should be allocated in production networks. Using the estimated treatment response from the baseline regression, we construct counterfactual allocations that hold fixed the aggregate amount of policy resources, the production-network weights, and the estimated treatment effect. The only object that changes is the spatial allocation of policy exposure. This exercise allows us to compare predicted emission reductions under the observed allocation and under sufficient-statistic targeting. The sufficient-statistic allocation raises the predicted aggregate emission-reduction rate from 16.76 percent to 17.55 percent, corresponding to a 0.79 percentage-point increase and a 4.7 percent predicted efficiency gain. The results also show that where subsidies should be targeted need not coincide with where emission reductions ultimately materialize, because policy effects can travel through energy-production networks.

Specifically, our main work proceeds in three steps. First, we develop a multi-sector general equilibrium model with production networks, endogenous green innovation, and energy-sector market power. The model incorporates two externalities in the energy sector: a negative monopolistic externality, which

weakens private incentives for green innovation under market power, and a positive technological externality, which makes the social returns to green technologies exceed private returns. The model also captures the interdependence between the energy sector and downstream production sectors through production-network linkages. It shows that green subsidies promote industrial green transformation by stimulating green innovation in the energy sector and inducing cleaner production choices downstream, while structural frictions within the network can attenuate these effects. Based on the model, we derive a sufficient-statistic targeting rule: regional targeting priority should balance the internalization of energy-sector externalities with the network diffusion capacity of policy shocks.

Second, we exploit China's Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction as a quasi-natural experiment using firm-level data from 2007 to 2020. The estimates show that green subsidies reduce firm-level emissions by promoting energy-sector green innovation and cleaner downstream production, while price volatility caused by supply-demand mismatches partially weakens the policy effect.

Finally, we take the sufficient-statistic targeting rule to the data. We estimate each region's energy-structure elasticity and production-network centrality, construct regional targeting priority, and evaluate counterfactual allocations under a fixed fiscal envelope. Reallocating policy exposure according to the sufficient statistic increases the predicted aggregate emission-reduction rate by 0.79 percentage points, or 4.7 percent relative to the baseline allocation. The magnitude of these gains is consistent with quantitative evidence showing that better allocation of policy resources can generate meaningful aggregate improvements (Rotemberg, 2019; Liu, 2019). Our contributions are as follows:

Our paper contributes to the literature on production networks and targeting interventions by developing a framework for green subsidy targeting economies with upstream energy-sector market power. Existing work shows that production networks shape the propagation of shocks and the aggregate effects of distortions (Dhyne et al., 2021, 2023; Dainauskas, 2024; Baqaee and Farhi, 2024). This network perspective has also reshaped policy design by showing that distortions are amplified through production linkages and that optimal interventions depend on network centrality and spillovers (Liu, 2019; Galeotti, Golub, and Goyal, 2020). Related work further demonstrates that innovation diffuses through production, trade, and firm networks rather than remaining local (Bernard, Moxnes, and Saito, 2019; Cai, Li, and Santacreu, 2022; Kalyani et al., 2025; Giroud, Liu, and Mueller, 2026).

Less is known about how green innovation interacts with production networks when the upstream energy sector is simultaneously a central input supplier and a distorted network node. This distinction is important because monopoly features in energy sector and complementarities between upstream green innovation and downstream production adjustment imply that the social returns to intervention depend on where policy enters the network. Existing work on green innovation emphasizes how environmental policy redirects technical change toward clean technologies (Acemoglu et al., 2012) More recently, Aghion et al. (2025) show that targeted sectoral subsidies can promote green innovation and that, under limited policy instruments, subsidies for downstream adoption can stimulate upstream innovation through a demand-pull mechanism. While this mechanism is important, it abstracts from a complementary source of underinvestment arising when upstream energy suppliers themselves face market power and incomplete internalization of technology spillovers. This leaves an important question: when

upstream energy sector is itself distorted, where should green subsidies enter the network?

We study this environment, which is characteristic of many manufacturing-based developing economies where energy is a key upstream input and the energy sector exhibits natural-monopoly features, regulatory protection, and market power. We incorporate both a negative monopolistic externality and a positive technological externality into a production-network framework linking energy-sector innovation, downstream production adjustment, and cross-sectoral frictions. In doing so, the model integrates the sufficient-statistic approach with the network economics of distortions, intervention, and transmission (Liu, 2019; Galeotti, Golub, and Goyal, 2020; Monte et al., 2018; Baqaee and Farhi, 2024; Giroud, Liu, and Mueller, 2026).

More broadly, the framework extends the sufficient-statistic literature from characterizing the aggregate consequences of network distortions to identifying policy priorities. Existing work shows that the aggregate effects of microeconomic shocks depend on shock magnitude and network propagation (Baqaee and Farhi, 2024). We extend this logic from quantifying the aggregate effects of distortions to identifying where policy interventions generate the highest marginal returns. Specifically, we introduce policy responsiveness as a complement to network centrality. While our measure of network centrality is closely related to the Domar-weight perspective on network importance, it extends this perspective by incorporating technological interoperability, which captures whether upstream improvements can effectively propagate through production linkages. Building on this, we derive a sufficient-statistic targeting rule in which subsidy priority is jointly determined by energy-structure elasticity and production-network centrality.

This framework further extends the network perspective from shock propagation to policy transmission. While existing network research primarily studies how network structure shapes the aggregate consequences of shocks and distortions, we characterize how policy-induced changes in upstream energy sectors propagate through energy-production linkages and affect downstream emissions. This perspective reveals a distinction between policy nodes and emission-reduction nodes: the regions where subsidies generate the largest system-wide effects need not be the regions where emission reductions are ultimately realized.

Second, the paper contributes to the literature on environmental policy and firm responses by identifying how green subsidies propagate through energy-production networks. Existing work has identified two complementary margins of industrial green transformation. One strand studies how the upstream energy sector shapes downstream energy structure, emission intensity, and abatement costs (Du et al., 2009; Ma, 2011; Ma and Zhao, 2015; Fan et al., 2016; Cao et al., 2021; Ren et al., 2021; Eisenberg, 2024; Lemoine, 2024). Another examines how downstream production feeds back into the energy system through energy demand, input substitution, and cleaner production practices (Moore et al., 2019; Naegele and Zaklan, 2019; Shen et al., 2021; Quan et al., 2023). Related work further analyzes how carbon pricing and environmental regulation affect firms' technology choices and abatement behavior (Ederington et al., 2005; Lo, 2012; Fan et al., 2016; Fried, 2018; Lin and Jia, 2018; Gillingham and Stock, 2018; Cao et al., 2021; Xu and Kim, 2022; Quan et al., 2023).

We connect these strands by identifying how green subsidies propagate through the energy-production network. Using firm-level emissions, green patents, policy timing, and interregional energy-production linkages, we construct firms' network

exposure to policy-induced green innovation in the upstream energy sector and estimate its effect on downstream emissions. The results show that green subsidies reduce firm emissions through both direct local exposure and indirect network exposure. Mechanism analyses identify two complementary transmission channels: green innovation in the energy sector and clean production-mode transformation in downstream industries. We further show that price volatility arising from energy supply-demand mismatches weakens policy transmission, highlighting cross-sector coordination frictions as an important constraint on green industrial policy. These findings shift the evaluation of green subsidies from whether they work to how they propagate through production networks and what limits their effectiveness.

Third, the paper contributes to the literature on quantitative policy evaluation and sufficient-statistic approaches by developing an empirically implementable framework for green subsidy allocation under a fixed fiscal budget. Recent quantitative research increasingly relies on sufficient statistics to evaluate policy counterfactuals without requiring a fully specified structural model. In production networks, Liu (2019) shows that industrial-policy effects are amplified through input-output linkages, while Baqaee and Farhi (2024) characterize how distortions propagate through network structure. More recently, Baqaee and Burstein (2025) demonstrate how sufficient statistics can quantify the efficiency consequences of distortions without solving the full equilibrium problem, and Giroud, Liu, and Mueller (2026) use network connectedness to identify location-specific innovation wedges. We extend this line of research from quantifying distortions to designing green industrial policy by developing an empirically implementable sufficient-statistic rule for allocating a fixed subsidy budget across production-network nodes. China provides an informative setting because it combines dense interregional production networks, substantial regional heterogeneity in energy

structure, and a highly connected upstream energy sector. These features, common to many manufacturing-based developing economies, allow us to quantify the efficiency gains from alternative spatial allocations of green subsidies. Combining the model-implied sufficient statistic with the estimated treatment response, we construct counterfactual allocations of green subsidy exposure across regions. The counterfactual exercises hold fixed the aggregate fiscal envelope, the production-network structure, and the estimated treatment effect, varying only the spatial allocation of policy exposure. Differences in predicted outcomes therefore isolate the efficiency gains from network-based targeting.

The counterfactuals show that sufficient-statistic targeting improves the allocation efficiency of green subsidies under a fixed fiscal budget by directing resources toward nodes with higher predicted system-wide returns. By combining observable network characteristics with estimated policy responses, the framework provides an empirically implementable approach for green fiscal allocation in economies characterized by upstream energy-sector distortions and dense production networks.

II. Market Structure and Institutional Features

A. Sectoral Monopoly and Technology Characteristics

Relative to non-energy sectors, China's energy sector is characterized by a higher degree of market concentration. As shown in Figure 1, monopoly intensity in the energy sector consistently exceeds that of non-energy sectors. These institutional features reflect the historical development path of many developing economies, where the centralization of resources has been used to ensure reliable provision of essential energy inputs. In China, the prominent role of state-owned

capital is associated with a relatively high degree of market concentration. For instance, the State Grid and China Southern Power Grid effectively control electricity transmission and distribution, while CNPC, Sinopec, and CNOOC dominate oil and gas supply. While such a structure has supported energy supply stability during industrialization, it may also pose structural constraints on the transition toward greener industrial systems.

Monopoly in the energy sector generates negative externality and tends to weaken incentives for green innovation. In the absence of effective competition, energy firms can sustain stable returns by relying on established production modes, while green innovation typically involves large upfront costs and substantial uncertainty, making it less aligned with short-term profitability. Meanwhile, Technology generates positive externality: environmental benefits from adopting green technology largely spill over to society and cannot be fully appropriated by individual firms. Consistent with these considerations, Figure 1 shows that regions with higher monopoly intensity tend to display lower levels of low-carbon and clean-energy patenting. Therefore, the coexistence of monopoly market structures and technology spillovers implies a divergence between private and social returns to green innovation in China's energy sector, this divergence is further compounded by the dual constraints commonly faced by developing economies, namely the need to sustain economic growth while reducing emissions and energy intensity.

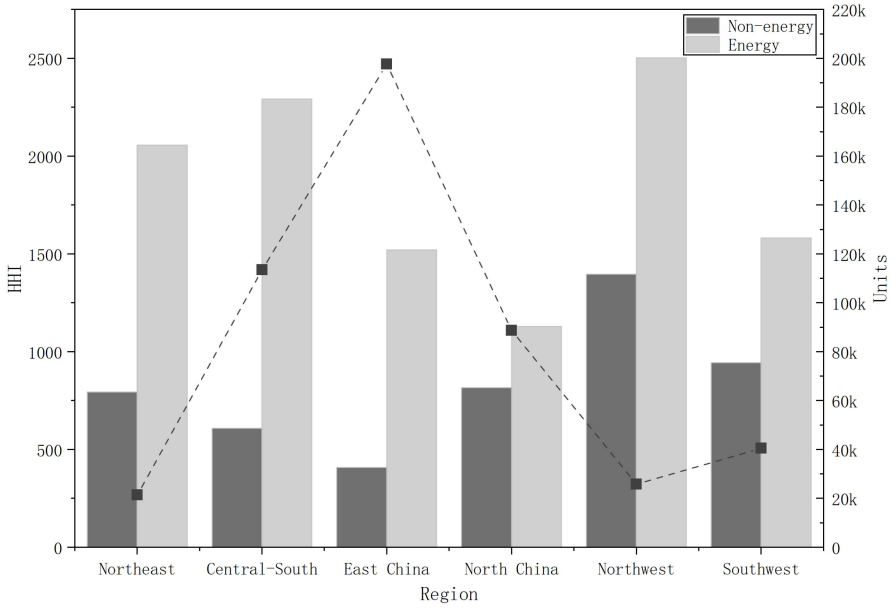


FIGURE1 REGIONAL MONOPOLY AND TECHNOLOGICAL INNOVATION

Notes: The bar chart presents $HHI_l = \sum_{f \in l} (\frac{s_f}{s_l} \times 100)^2$, where $\frac{s_f}{s_l}$ denotes the market share of firm f in region l, calculated based on the National Tax Survey data. Energy sector firms are selected in accordance with the National Economic Industry Classification codes, which are as follows: B06 (Mining and Washing of Coal); B07 (Extraction of Petroleum and Natural Gas); C25 (Processing of Petroleum, Coal and Other Fuels); D44 (Production and Supply of Electric Power and Heat Power); D45 (Production and Supply of Gas). The line chart shows the total number of green technologies (low-carbon and clean-energy technology patents) in the energy sector. Following the International Patent Classification (IPC) standards, patents related to the efficient extraction of fossil energy and the development of green technologies are defined as low-carbon and clean-energy patents in the energy sector.

In addition, considering the structure of China's globally largest and most comprehensive industrial system, the energy sector in China has formed a distinct industrial feature that differentiates it from the U.S. and Europe. China's energy supply is primarily oriented toward serving industrial production, with energy demand downstream dominated by energy-intensive heavy industries, such as steel, electrolytic aluminum, non-ferrous metal smelting, basic chemicals and cement, as well as export-driven manufacturing industries like photovoltaic modules, new energy equipment, and electronics manufacturing. In 2024, the value added of China's secondary industry accounted for 36.5% of GDP (with 33.2% from industry and 3.3% from construction, data from the National Bureau

of Statistics of China), significantly higher than the levels in the U.S. and Europe. This reflects the core position of industry in China's national economy. In contrast, in the U.S. and Europe, the energy downstream is more focused on residential electricity consumption, commercial services, and light passenger vehicle consumption, with energy-intensive industries relocating outside.

Therefore, the monopoly and externality characteristics of China's upstream energy sector, combined with the rigid dependency of its downstream industrial system on energy supply, suggest that government intervention targeting the upstream energy sector may be more efficient for achieving the dual goals of green transformation and energy security. In practice, the Chinese government has provided support for green electricity research and offered subsidies to upstream state-owned enterprises such as the National Energy Group and the Three Gorges Group. This has facilitated the construction of concentrated wind and photovoltaic power stations in the northwest and southwest regions. Using ultra-high-voltage transmission networks (the upstream core infrastructure), green electricity is directly transmitted to downstream energy-intensive clusters, such as electrolytic aluminum and steel industries in the eastern region. By targeting a single upstream link with policy interventions, the government has driven thousands of downstream manufacturing enterprises toward a low-carbon electricity structure, reducing the policy costs and coordination difficulties associated with the transformation across the entire industrial chain. In contrast, if the intervention were to focus solely on downstream enterprises, it would require individual technical transformation subsidies for a dispersed group of small and medium-sized enterprises. This would not only incur extremely high policy costs but also result in inefficiencies in the transformation process due to limited access to green electricity.

Against this background, government intervention provides a natural institutional response to market failures in the energy sector and plays a central

role in facilitating green transformation. This rationale aligns with the core insights of externality theory and China's stage-specific development needs, where industrial policy plays a key role in driving green transformation in the energy sector. In the energy sector, government intervention involves a trade-off between market-based policy that promotes market competition, and industrial policy (such as subsidies) that aim to foster technological innovation. These two policies act as partial substitutes. Market-based policy can mitigate the negative externalities associated with monopoly power, while industrial policy help internalize positive knowledge spillovers from innovation. However, especially in developing countries, market-based policy in the energy sector should be approached with caution. The sector's natural monopoly characteristics and strategic importance for national security imply that excessive reliance on market may lead to unintended consequences, including supply instability and growing regional disparities. In this context, technology-oriented subsidies may constitute a more direct and effective policy instrument. This also helps explain why industrial policy, particularly subsidy-based intervention, are more prevalent form in the energy sectors of developing economies, with China being a prominent example.

B. China's Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction

To advance energy-saving and emission-reduction strategy, China implemented a series of industrial policies, among which the *Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction* is particularly representative. This policy was jointly issued by the Ministry of Finance and the National Development and Reform Commission. Demonstration cities were selected in three waves, in 2011, 2013, and 2014.

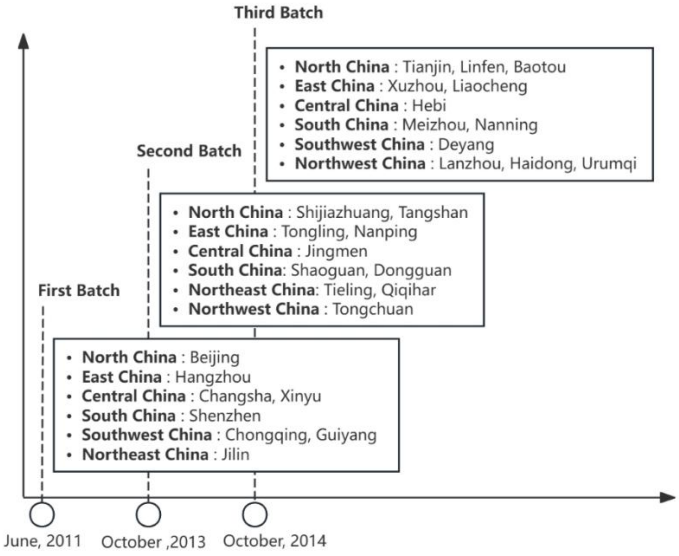


FIGURE2 DEMONSTRATION CITIES

A key feature of this policy is its reliance on technology-oriented fiscal subsidies as a central industrial policy instrument. Government funding was directed toward projects that promote technological upgrading and diffusion, including energy-saving technology and the modernization of urban green infrastructure. Implementation proceeded along two dimensions to support industrial green transformation. First, guiding the development of green technologies. Fiscal subsidies and project-based rewards encourage firms to adopt cleaner technologies, reducing energy use and emissions. Second, promoting green infrastructure. Investments focus on upgrading infrastructure to reduce the fixed costs of clean-mode transportation, key initiatives include expanding the use of photovoltaic and other clean energy technologies.

Subsidy-based industrial policy instruments may support green industrial transformation through two main pathways. First, in the energy sector, fiscal subsidies reduce the costs of green innovation, accelerating the adoption of green technologies such as photovoltaics and clean heating systems. Second, in the production sector, investments in green infrastructure provide stable, low-cost

clean energy, thereby reducing the fixed costs of industrial transformation and accelerating the shift toward greener production practices.

C. Stylized Features of China's Green Industrial Transformation

Figure 3 illustrates the development of green technologies (low-carbon and clean-energy patents) in the energy sector from 2007 to 2020 for demonstration cities (red line) and non-demonstration cities (black line). The data are drawn from the Chinese patent database, with green technologies identified according to the International Patent Classification (IPC) system, covering technologies related to efficient fossil energy extraction and the development of clean energy sources. After the policy was introduced in 2011, green technology patents in demonstration cities rose noticeably relatively to non-demonstration cities. The gap widened further following the phases in 2013 and 2014. This pattern is consistent with the core feature of the intervention, namely the use of technology-oriented fiscal subsidies as a central industrial policy instrument. Compared with untreated cities, demonstration cities exhibited a significant increase in innovative activity in green technologies after the intervention.

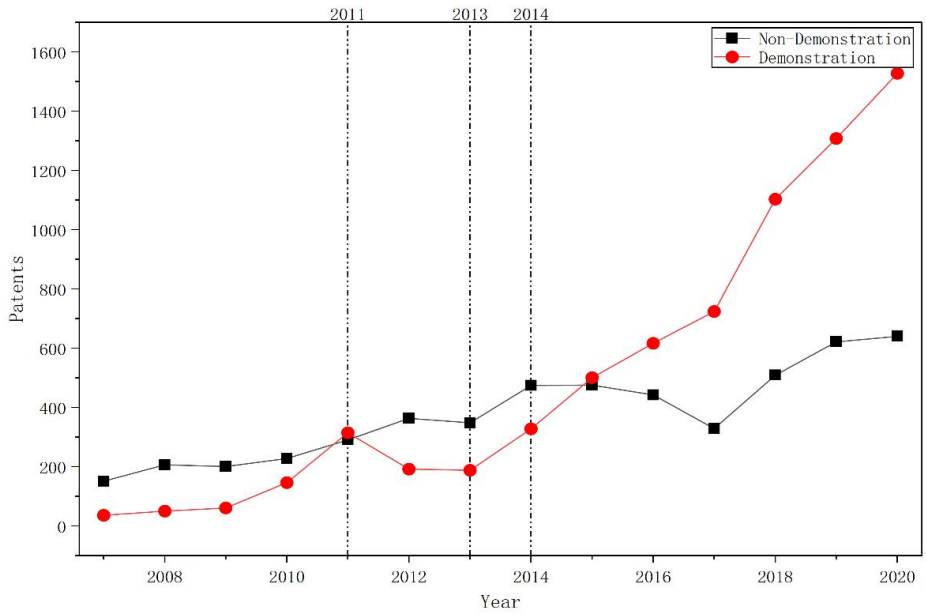


FIGURE3 ENERGY SECTOR PATENTS

Notes: Figure 3 plots the evolution of green technologies (low-carbon and clean-energy patents) in the energy sector for demonstration cities (red line) and non-demonstration cities (black line) over the period 2007–2020. Patent data are obtained from the Chinese patent database. Green technologies are identified based on the International Patent Classification (IPC) system and include technologies related to efficient fossil fuel extraction and clean energy development.

Figure 4 shows the development of green technologies (low-carbon and clean-energy patents) in the production sector for demonstration cities (red line) and non-demonstration cities (black line) over the period 2007–2020. These patents are also identified according to the IPC system, focusing on technologies that improve energy efficiency and production transformation. The pattern resembles that in Figure 3, after the policy was introduced in 2011, patents in demonstration cities grew faster than in non-demonstration cities, and the gap continued to widen following subsequent policy phases.

In addition, green technology development in the production sector is larger than in the energy sector. This difference reflects the dual effects of negative monopoly externality and positive technology externality in the energy sector. The energy sector's administrative monopoly reduces firms' incentives to invest in new technologies, while green technologies often require large upfront

investments and long payback periods, with most environmental benefits accruing to society rather than individual firms. By contrast, manufacturing firms in production sector are closer to market applications, allowing firms to capture cost savings and efficiency gains directly. Combined with more competitive market conditions, this gives manufacturing firms stronger incentives to adopt new green technology practices.

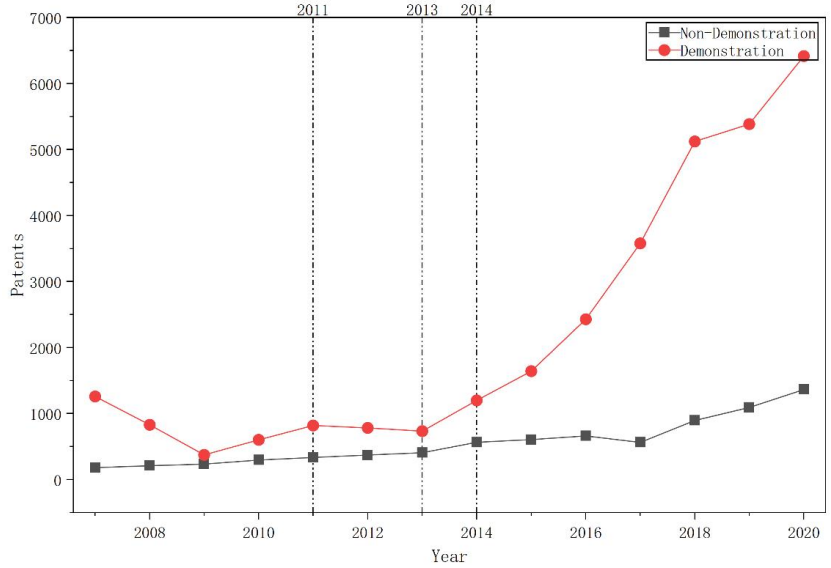


FIGURE4 PRODUCTION SECTOR PATENTS

Notes: Figure 4 shows green technologies (low-carbon and clean-energy patents) in the production sector for demonstration cities (red line) and non-demonstration cities (black line) from 2007 to 2020. Patents are identified using the IPC system and focus on energy-efficient and production-transformation technologies.

Figure 5 presents the intensity of government documents related to Market-based policy (such as fair competition and anti-monopoly). Policy documents are drawn from the Peking University Law Information Network. We used text analysis to extract and quantify mentions of Market-based policy in local government policy documents. The figure shows that there is no clear divergence in the intensity of market-based policy (marketization documents) between demonstration cities (red line) and non-demonstration cities (black line), indicating that the *Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction* issued in 2011, 2013, and 2014 did

not focus on promoting market competition or antitrust enforcement (market-based policies). Instead, the primary policy instrument was technology-oriented fiscal subsidies.

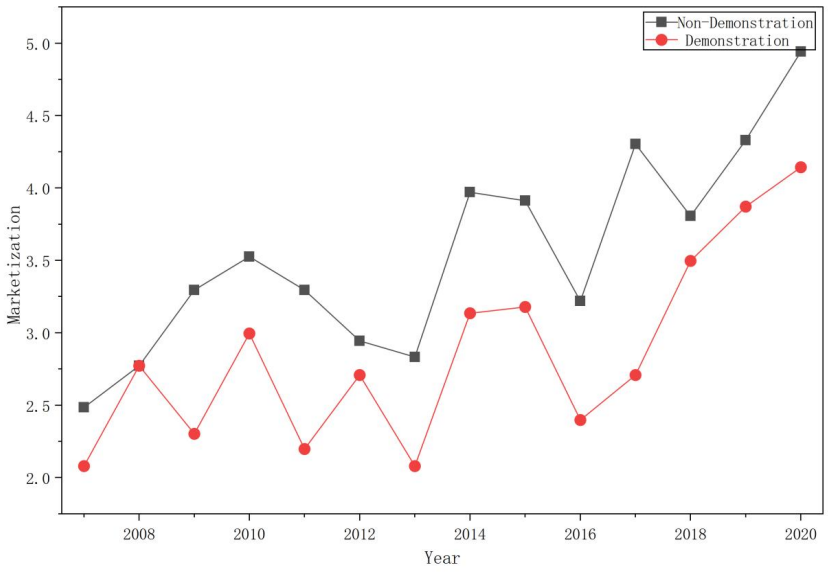


FIGURE5 MARKETIZATION DOCUMENTS

Notes: Figure 5 plots the intensity of marketization documents for demonstration cities (red line) and non-demonstration cities (black line) from 2008 to 2020. Policy data are drawn from the Peking University Law Information Network. Documents related to market-oriented reform were identified using text analysis.

In summary, three patterns emerge. First, following the policy implementation, low-carbon and clean-energy patents in the energy sector increased significantly faster in demonstration cities than in non-demonstration cities, with the gap continuing to widen. Second, patents in the production sector exhibited a similar pattern to the energy sector but on a substantially larger scale. Third, there was no significant divergence in the intensity of market-based policy documents between the two types of cities, confirming that the policy primarily relied on technology-oriented fiscal subsidies rather than market-based competition or antitrust policies.

We treat the *Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction*, issued in 2011, 2013, and 2014, as a quasi-natural experiment to evaluate the impact of government intervention

(with subsidies as the primary policy instrument) on green industrial transformation. The selection of this policy shock is well-suited for causal analysis for two main reasons:

First, the grouping is effectively random and comparable. The selection of demonstration cities was not biased toward regions with pre-existing technological characteristics. As shown in Figures 3 and 4, prior to the 2011 policy, the treatment group (demonstration cities, red line) and the control group (non-demonstration cities, black line) exhibited similar patent levels and trends. And importantly, after the policy, the gap in patenting widened markedly, confirming the randomness and comparability of the groups and providing a basis for identifying policy effects.

Second, the policy instrument is focused, and potential confounding factors can be effectively isolated. The policy relied primarily on technology-oriented fiscal subsidies and did not overlap with market-oriented regulations or other policy instruments. As shown in Figure 5, there is no significant divergence in market-oriented policy intensity between the treatment and control groups, effectively isolating potential interference from market-based regulations and avoiding confounding effects from multiple concurrent policies. This ensures a precise identification of the net effect of the subsidy policy.

Against this backdrop, we examine how government subsidies can drive green industrial transformation through the production network. Specifically, we consider three questions: First, can subsidies accelerate the technology innovation in energy sector and encourage mode transformation in production sector, creating effective greening transformation pathways? Second, does the asymmetric development of energy-production sectors create structural friction on energy supply-demand? Third, how can the optimal prioritization of government subsidies be determined under multi-regional policy implementation?

III. Theoretical Model

This section develops a multi-sector general-equilibrium framework to characterize both how green subsidies promote industrial green transformation through production networks and how a government should target a fixed amount of subsidy resources across heterogeneous regions. The model is motivated by three salient features emphasized above: the negative monopolistic externality induced by energy-sector market power, the positive technological externality generated by green innovation, and the network propagation effects transmitted through dense interregional linkages between upstream energy suppliers and downstream production sectors. These externalities and linkages make green transformation a network-wide process. Upstream green innovation alters the carbon content and quality, shaping downstream production choices, while downstream demand feeds back into upstream innovation incentives. As a result, a policy shock may therefore originate in one region, while its emission effects propagate through energy-production linkages and materialize in other regions and sectors.

The key point of the model is a wedge between the private and social returns to energy-sector green innovation, generated by the dual externalities. On the private side, Market power weakens energy firms' incentives to invest in new technologies by allowing incumbents to preserve rents through established production modes, creating a negative monopolistic externality. On the social side, the same investment generates spillovers that the investing firm cannot fully appropriate, creating a positive technological externality. Moreover, improvements in energy quality affect not only the innovating firm, but also downstream firms connected through the production network. The regional planner therefore values green innovation according to its system-wide return, whereas the individual energy firm considers only the private return it can capture.

The difference between the planner's first-order condition and the firm's first-order condition defines the region-specific wedge between social and private returns.

The model then traces how a subsidy changes this wedge and ultimately affects firm-level emissions. A higher subsidy lowers the effective cost of new technology in the energy sector and raises the quality of energy intermediates, which makes cleaner production modes in the production sector more attractive. These effects operate through two related channels: energy-sector green innovation and clean-mode transition in the production sector. Policy transmission is nevertheless imperfect. Technological distance between upstream energy innovation and downstream production adjustment generates structural frictions during the transition. These frictions attenuate, but do not overturn, the two model-implied channels of green transformation.

To derive the targeting rule, we compare the marginal social return from allocating an additional unit of subsidy to each region. The derivation proceeds in three steps. First, the firm-level optimization problem delivers the private marginal return to green innovation. Second, the regional aggregate problem delivers the corresponding social marginal return. Third, substituting the equilibrium responses into the difference between these two conditions yields an expression for the marginal social return to regional subsidy exposure. Conditional on the aggregate fiscal budget and the production-network structure, sufficient-statistic targeting rule can be summarized by two components: energy-structure elasticity and production-network centrality. Energy-structure elasticity measures the local emission response to subsidy-induced green innovation. Production-network centrality measures the strength of policy transmission through energy-production linkages and increases with upstream–downstream technological interoperability.

The theoretical framework thus serves two purposes. First, it characterizes the mechanisms through which green subsidies reduce emissions—energy-sector green innovation and cleaner downstream production choices—while allowing structural frictions to attenuate policy transmission. Second, it transforms the policy problem from whether subsidies are effective to where they should be allocated. By doing so, we aim to answer two key questions: How do government subsidies drive green transformation through the production network? And what determines the optimal prioritization of subsidies across regions, given heterogeneous network structures and market power?

A. Energy Sector

The production function of firm i in the energy sector of region l is specified as follows:

(1) $$q_{li} = h_{li}^{1-\eta}\left(\prod_{j\in l} h_j^{\gamma_{ij}/\vartheta_j} S_l^{b_l}\right)^{\eta}$$

Firm invests in new technology h_{li} for green innovations, to supply lower-emissions energy intermediates. q_{li} represents the quality of energy intermediates produced by firm i, with higher technological investment yielding higher-quality (lower-emissions) energy intermediates. We assume a negative relationship between energy quality and emissions content: greater technology investment raises energy quality and reduces associated emissions.

Energy quality is not determined by single firms, the investments of new technology by other firm h_j generates positive technological spillovers through technology diffusion. Correspondingly, γ_{ij} captures the positive externality of technology within the energy sector.

We capture the market-power-induced distortion in firms' innovation response using $\vartheta_{il} \in (0,1]$, where $\vartheta_{il} = 1$corresponds to perfect competition and lower values indicate stronger market power. Market power weakens the private incentive to invest in green technology, thereby widening the gap between the private and social responses to innovation. For ease of interpretation, we define $m_{il} \equiv \frac{1}{\vartheta_{il}} \geq 1$. Under perfect competition, $m_{il} = 1$, a larger m_{il} indicates stronger market power and a larger distortion in the private innovation response.

Moreover, production-sector firms' choice of production mode—clean or conventional—also influences the behavior of the energy sector. Cleaner production in the production sector increases demand for green energy, prompting the energy sector to supply lower-emissions energy intermediates. Accordingly, S_l represents the share of clean versus conventional firms in the production sector, while b_l denotes the feedback coefficient of the production sector, $b_l > 0$.

Energy firm i invests in new technology to produce and deliver energy intermediates to the production sector. Its profit-maximization problem is specified as follows:

(2) $$\max_{h_{li}} \frac{p_i}{m_i} h_{li}^{1-\eta} \left(\prod_j h_j^{\gamma_{nj} m_j} S_l^{b_l}\right)^{\eta} - \frac{c_l h_{il}}{s_l}$$

Where c_l denotes the cost of investing in new technology, and s_l represents government subsidies supporting firms' investment in new technology. Larger subsidies s_l reduce the relative cost of green innovation. For a monopolistic firm, marginal revenue is below price, thus, let$\frac{p_i}{m_j}$denote the revenue the firm earns from supplying energy intermediates to the production sector. Solving the above profit-maximization problem yields energy quality q_{li} as:

(3) $$q_{li} = \left[\frac{(1-\eta)}{m_i}\right]^{\frac{1-\eta}{\eta}} \left(\prod_{j \in l} h_j^{\gamma_{nj} m_j} S_l^{b_l}\right) \left(\frac{s_l p_i}{c_l}\right)^{\frac{1-\eta}{\eta}}$$

B. Production Sector

The production function of firm f in the production sector is specified as follows:

(4) $$g_f = \varphi_f q_f^{\alpha} L_f^{1-\alpha}$$

The function includes the traditional labor input L_f and energy intermediates q_f supplied by the energy sector. φ_f denotes the firm's initial productivity, which is assumed to follow a Pareto distribution $P(\varphi_f \geq \varphi) = (\frac{1}{\varphi})^z, z > 0$, The firm with initial productivity φ_f considers two typical production modes, which differ in input and payoff structures:

Clean production mode. This mode requires higher fixed investment but lower variable costs through reduced energy consumption and savings from regulatory compliance (e.g., avoided emissions-related fees and environmental penalties).

Conventional production mode. This mode entails lower fixed investment but is burdened by high variable costs. Returns are largely limited to marginal profits from traditional products and remain constrained by regulatory compliance and competitive pressures.

Accordingly, if firm chooses the clean production mode, its fixed investment cost is denoted by F_{bf} and the product's marginal profit is denoted by P_{bf} . If firm chooses the conventional production mode, the fixed investment cost is denoted by F_{pf} and the product's marginal profit is denoted by P_{pf} , $F_{bf} > F_{pf}$, $P_{bf} > P_{pf}$. In addition, firm purchase energy intermediates q_{li} from different regions, with energy supply denoted by $q_f \equiv \prod_l q_{li}^{\omega_{fl}}$. ω_{fl} represents the trade intensity between firm f and energy suppliers in region l, higher values of ω_{fl} indicate a stronger tendency for firm f to engage with energy suppliers in region l, and a share θ_l of

the profits allocates to energy suppliers. The corresponding profit-maximization problem of production-sector firm f is specified as follows:

(5) $$\max_{L_f}\{P_f g_f - L_f - F_f\},$$

where P_f and F_f denote the market price and input cost of firm f, respectively. If firm chooses the clean production mode, then $P_f \equiv P_{bf}$, $F_f \equiv F_{bf}$, If firm chooses the conventional production mode, then $P_f \equiv P_{pf}$, $F_f \equiv F_{pf}$, g_f and L_f denote the output and labor input, respectively. Solving the profit-maximization problem, the firm's profits under the different production modes can be expressed as follows:

$$\begin{cases} \pi_f^b = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_{bf}\varphi_f)^{\frac{1}{\alpha}} q_f - F_{bf} (\textit{Clean production mode}) \\ \pi_f^p = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_{pf}\varphi_f)^{\frac{1}{\alpha}} q_f - F_{pf} (\textit{Conventional production mode}) \end{cases}$$

Firms choose production mode based on their own productivity φ_f. Let region l have a threshold productivity level φ_l^*. When $\varphi_f > \varphi_l^*$, the profit from the clean production mode is higher ($\pi_f^b > \pi_f^p$); otherwise, the firm chooses the conventional production mode. Denoting $\pi_f^b(\varphi_l^*) = \pi_f^p(\varphi_l^*)$, the threshold productivity level φ_l^* can be derived as:

(6) $$\varphi_l^* = \frac{1}{\Omega}\left(\frac{\hat{F}_{lf}}{\hat{P}_{lf}}\right)^{\alpha}$$

Where $\Omega = \alpha^{\alpha}(1-\alpha)^{1-\alpha}$, $\hat{P}_{lf} = (P_{bf})^{\frac{1}{\alpha}} - (P_{pf})^{\frac{1}{\alpha}}$, $\hat{F}_{lf} = F_{bf} - F_{pf}$ .Given that firm productivity follows a Pareto distribution $P(\varphi_f \geq \varphi) = \left(\frac{1}{\varphi}\right)^z, z > 0$, the share of firms choosing the clean production mode (with productivity above the threshold φ_l^*) is given by $S_l = \left(\frac{1}{\varphi_l^*}\right)^z$.

Collaboration between the energy and production sectors requires technological interoperability: firms need to source energy from upstream suppliers whose technologies are compatible with their own production modes.

For example, electric vehicle firms adopting a clean production mode require low-carbon energy inputs such as green electricity or green hydrogen to avoid efficiency losses due to technological mismatch.

Accordingly, we introduce technological distance k_{if} and assume that the matching probability p follows a Bernoulli distribution. Firms prefer to collaborate with upstream suppliers that are technologically close, with the probability of mass function given by:

$$P(X=\mathrm{x})=\begin{cases}\frac{1}{k_{if}}, x=1\\ 1-\frac{1}{k_{if}}, x=0\end{cases} \tag{7}$$

Where $x=1$ indicates a successful match, and $\frac{1}{k_{if}}$ represents the probability of a successful match. As noted above, θ_l denotes the energy-sector surplus share, which reflects the embeddedness of the region's energy sector within the production network. It should be noted that both m_l and θ_l are related to market power in the energy sector, but they capture distinct margins. m_l captures how market power distorts local green-innovation incentives and thus the corrective role of subsidies. By contrast, θ_l captures the extent to which the upstream energy sector is embedded in downstream production linkages. A larger θ_l indicates that the upstream energy sector is more deeply embedded in the production network. Consequently, subsidy-induced improvements in energy quality generate stronger downstream adjustments and larger network-wide effects. The former therefore governs the local effectiveness of subsidies, whereas the latter governs their network-wide transmission. Given $\pi_f=\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_f\varphi_f)^{\frac{1}{\alpha}}q_f$, if the match is successful, the payoff to energy-sector firm i can be written as $p_i=\frac{\theta_i}{\tau_{lf}}\frac{\delta\pi_f}{\delta q_f}=\frac{\theta_i}{\tau_{lf}}\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_f\varphi_f)^{\frac{1}{\alpha}}$,

where τ_{lf} denotes the search costs. If the match fails, the payoff is zero. Accordingly, the expected payoff can be expressed as $\frac{p_i}{k_{if}} == \frac{\theta_l}{\tau_{lf} k_{if}} \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} (P_f \varphi_f)^{\frac{1}{\alpha}}$.

We now provide a formal characterization of the transmission of emissions between the energy and production sectors through the economy. Given that emissions c_f are not directly involved in value creation but are by-product of production activities, i.e., $c_f \equiv q_f{}^{\kappa}, \kappa \le 0$, the higher the quality of energy intermediates q_f supplied, the lower the associated emissions c_f is. Energy supplied flows into the production sector is aggregated at firm f, denoted as $q_f \equiv \prod_l q_{li}{}^{\omega_{fl}}$, leading to $c_f = \prod_l q_{li}{}^{\kappa\omega_{fl}}$. Combining this with equation (3), the firm's emissions can be expressed as:

(8) $$c_f = \prod_l [(1-\eta)^{\frac{(1-\eta)\kappa\omega_{fl}}{\eta}} \vartheta_i^{\frac{(1-\eta)\kappa\omega_{fl}}{\eta}} (\prod_{j \in l} h_j{}^{\gamma_{lj}/\vartheta_j} S_l{}^{b_i})^{\kappa\omega_{fl}} (\frac{S_l p_i}{c_l})^{\frac{(1-\eta)\kappa\omega_{fl}}{\eta}}]$$

C. Consumers and Government Budget

There are N regions, and the utility function of consumers in region l is given by:

(9) $$U_l = \ln Y_l - L_l \quad , \quad Y_l = [\sum_m \int y_{lm}(v)^{\frac{\sigma-1}{\sigma}} dv]^{\frac{\sigma}{\sigma-1}}$$

Here, Y_l denotes the consumption in region l, $y_{lm}(v)$ is the quantity of product v produced in region m consumed by region l, and L_l represents the labor endowment of region l. Labor is allocated in fixed proportions between the energy and production sectors, $\sigma > 1$ denotes the elasticity of substitution. The consumer budget constraint is given by:

(10) $$\sum_m \int p_{lm}(v) y_{lm}(v) dv = w_l L_l + \prod_l - T_l$$

Let $p_{lm}(v)$ denote the price paid by consumers in region l for product v produced in region m, $w_l L_l$ represents the wage rate in region l, Π_l represents the joint profits generated in region l, $\sum_f \pi_f = \sum_l \Pi_l$, all profits are ultimately distributed as part of consumer income. Let T_l denote taxes in region l. The government can provide subsidies s_l to support green innovation. It may also impose a tax on highly polluting technologies, thereby making green innovation relatively more attractive. The relationship between the emissions tax and the price of clean energy is given by $p_i = p_i + \mu t_l$, due to imperfections in the energy market, the pass-through of the carbon tax to clean energy prices is limited $\mu < 1$. The government budget constraint is given by (11), where the government's subsidy expenditures s_l must be financed through taxation to maintain fiscal balance.

(11) $$\sum_l \sum_i (c_l h_{li} - \frac{c_l h_{li}}{s_l}) = \sum_l T_l + \sum_l t_l$$

Furthermore, the marginal innovation incentives generated by different policy instruments can be derived as the increase in innovation investment induced by a policy of equal intensity. The marginal innovation incentive under subsidies is given by $\frac{\delta h_{li}}{\delta s_l} = \frac{h_{li}}{\eta s_l}$, and that under a emissions tax is expressed as $\frac{\delta h_{li}}{\delta t_l} = \frac{\mu h_{li}}{\eta(p_i + \mu t_l)}$. Given the same policy intensity ($s_l = 1 + \frac{\mu t_l}{p_i}$), it follows that $\frac{\delta h_{li}/t_l}{\delta h_{li}/s_l} = \frac{\mu}{p_i} < 1$, implying that the innovation incentive induced by the emissions tax is weaker than that generated by subsidies. This result reflects the fact that emissions taxes affect innovation through price signals whose effectiveness is attenuated by market imperfections. Subsidies, in contrast, directly offset innovation costs and thus avoid transmission losses, allowing them to stimulate green innovation investment more effectively.

D. Government subsidies

We now analyze how government subsidies affect firms' emissions reduction. Since the issuance of the *Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction*, government spending in demonstration cities has increased. Government spending incentivizes firms to engage in energy-saving and emission-reduction activities, thereby reducing the relative cost of adopting new technologies. as reflected in $d\ln s_l \geq 0$.

Based on Stylized Features, government subsidies are expected to generate the following effects:

First, the structure of the energy sector changes. Increased government spending strengthens incentives for technological innovation, guiding the regional energy sector to invest in green technologies. typically reflected in a higher intensity of new technology in the region, i.e., $d\ln s_l \equiv \sum_{j\in l} d\ln h_j$.

Second, the production-sector mode changes. Increased government spending, through infrastructure upgrades such as the expansion of green electricity supply networks, lowers the fixed costs faced by production-sector firms and encourages a shift toward clean production modes. For instance, public low-carbon infrastructure improvements allow electric vehicle manufacturers to share the foundational costs of clean production, alleviating the burden of bearing fixed investments individually. Consequently, a key feature is a reduction in the fixed-cost gap between clean and non-clean production modes, i.e., $d\ln s_l = -d\ln \hat{F}_{lf}$.

Third, inter-sectoral frictions change. Structural frictions between the production and energy sectors arise from supply–demand mismatches that generate price volatility. If the pace of transformation in the production sector outstrips the expansion of clean energy supply, demand for low-carbon energy may exceed supply, leading to higher prices. Rising energy prices, in turn,

dampen firms' incentives to adopt clean production modes, thereby constraining overall green transformation. Therefore, $t_{lf} d\ln s_l \equiv d\ln \tau_{lf}$, the sign of market frictions t_{lf} therefore depends on whether clean-energy supply in region $l$keeps pace with the demand of production-sector firm f.

Taken together, the effect of government intervention on firm-level emissions can be expressed as:

(12) $$d\ln c_f = \underbrace{-\gamma m \sum_l \omega_{fl} d\ln s_l}_{\text{Energy structure}} \underbrace{-Z\sum_l b_l \omega_{fl} d\ln s_l}_{\text{Production mode}} \underbrace{-\frac{(1-\eta)}{\eta}\sum_l \omega_{fl}(1-t_{fl}) d\ln s_l}_{\text{Market friction}}$$

Proposition 1. Green subsidies reduce firm-level emissions by promoting upstream green innovation and inducing cleaner production modes downstream. These effects are stronger through closer energy linkages but are weakened by supply–demand mismatches, which may generate energy-price volatility.

E. A Sufficient Statistic Targeting Rule for Green Subsidies

In the benchmark scenario without taxation and subsidies, given $s_l \equiv 1, \forall l$, the general equilibrium of the model can be derived by jointly solving the maximization problems of energy-sector firms, production-sector firms, and consumers, subject to the government budget constraint and labor market clearing conditions. In this equilibrium, the intensity of new technology investment in the energy sector is given by $h_{li} = (\frac{1-\eta}{m_i})^{\frac{1}{\eta}} (\prod_{j\in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}) (\frac{p_i}{c_l})^{\frac{1}{\eta}}$,while technology investment is inefficient due to uninternalized externalities. The energy sector exhibits both negative monopoly externality, which weakens incentives for green technology investment, and positive technology externality, whereby the returns to innovation spillover across firms.

Together, these features constitute a fundamental constraint leading to underinvestment in technology. For energy firm i, other firms' investments and

market power are treated as exogenous, and the firm does not account for the external effects of its own actions on others when making investment decisions. Therefore, given $s_l \equiv 1, \forall l$, the intensity of new technology investment by energy firm i does not achieve the socially optimal level. To more precisely characterize this inefficiency, we consider the region's aggregate maximization problem:

$$\max_{h_{li}} \sum_n \left(\frac{p_n}{m_n} h_{ln}^{1-\eta} \left(\prod_j h_j^{\gamma_{nj} m_j} S_l^{b_l}\right)^{\eta} - c_l h_{il}\right) \tag{13}$$

Solving the first-order condition of aggregate maximization problem yields:

$$(1-\eta)\frac{p_i}{m_i} h_{li}^{1-\eta} \left(\prod_j h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta} + \gamma_{ni} m_i \eta \sum_n \frac{p_n}{m_n} h_{ln}^{1-\eta} \left(\prod_j h_j^{\gamma_{nj} m_j} S_l^{b_l}\right)^{\eta} = c_l h_{il} \tag{14}$$

While the first-order condition derived from the firm-level maximization problem is:

$$(1-\eta)\frac{p_i}{m_i} h_{li}^{1-\eta} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta} = \frac{c_l h_{li}}{s_l} \tag{15}$$

It follows that $s_l = \dfrac{c_l h_{li}}{(1-\eta) m_i^{-1} p_i h_{li}^{1-\eta} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta}}$. Combining with equation (14), the optimal subsidy intensity implied by the regional aggregate maximization problem is given by $s_l = 1 + \dfrac{\eta \gamma_{ni} \sum_n m_n^{-1} p_n h_{ln}^{1-\eta} \left(\prod_j h_j^{\gamma_{nj} m_j} S_l^{b_l}\right)^{\eta}}{(1-\eta) m_i^{-2} p_i h_{li}^{1-\eta} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta}}$, using the production function, the optimal subsidy intensity of government subsidies can be expressed as:

$$s_l = 1 + \frac{\eta \gamma_l m_l \sum_n p_n q_n}{(1-\eta) p_l q_l} \tag{16}$$

Therefore, the theoretically derived optimal subsidy intensity exceeds its value under the benchmark scenario （ $s_l \equiv 1, \forall l$ ）, in which no taxes and subsidies are applied. This indicates that government subsidies are required to incentivize firms' technology investment. The underlying reason is the dual-externality feature of the energy sector, which creates a wedge we_l between the social and

private values to technology investment, i.e., $we_l = \frac{\eta \gamma_l m_l \sum_n p_n q_n}{(1-\eta) p_l q_l}$. Thus, the larger the wedge we_l, the higher the priority for government subsidies. The denominator of we_l corresponds to the private value generated by the firm's new technology, while the numerator captures the social value derived from the technology.

The region's total profit equals the sum of individual firm profits, denoted by $\sum_n p_n q_n \equiv \sum_f \frac{\theta_n}{\tau_{nf} k_{nf}} \pi_f$, where θ_n represents the energy-sector surplus share, τ_{nf} denotes the search costs between the energy and production sectors, and k_{nf} captures the technological distance between the two sectors. Under monopolistic competition, firm profits and revenue are as follows: $r_f \equiv \sigma \pi_f$, where σ is the elasticity of substitution. Combining this with the production function of the two sectors, we_l can be expressed as:

(17) $$we_l = \frac{\eta}{(1-\eta)} \gamma_l m_l \sum_c \frac{\theta_l r_c}{k_{lc} \tau_{lc} r_l}$$

Here, γ_l measures the positive technological spillovers from energy-sector green innovation, m_l captures the local market-power distortion that determines the corrective role of subsidies

In summary, we_l represents the wedge between private value and social value in region l. A larger we_l indicates a higher social value relative to private value generated by each unit of technological investment in the local energy sector. When the wedge is large, government intervention in this region, such as subsidizing firms' investments in new technologies, can more efficiently transform private effort into social gains, thereby yielding a higher social return to policy.

Further decomposing we_l reveals that its magnitude is primarily determined by two components. The first is the energy structure elasticity $\beta_l \equiv \gamma_l m_l$, reflecting the

coexistence of positive technology externality and negative monopoly externality in the energy sector, constitutes the micro-foundation of the wedge. The second is the regional production network centrality $Net_l \equiv \sum_c \frac{\theta_l r_c}{k_{lc}\tau_{lc} r_l}$, capturing the extent to which a local energy-sector response is amplified through upstream–downstream linkages. It is higher when the regional energy sector is more deeply embedded in the production network (higher θ_l), faces lower technological frictions with downstream sectors (smaller k_{lc}), and serves a larger surrounding market $\left(\frac{r_c}{\tau_{lc} r_l}\right)$. Together, these factors strengthen the transmission of policy effects through the production network.

Proposition 2(Sufficient-Statistic Targeting Rule). Conditional on the aggregate fiscal budget and the production-network structure, the planner's regional allocation problem is characterized by a single sufficient statistic composed of two components: energy-structure elasticity and production-network centrality.

Energy-structure elasticity captures the local emission reduction generated by subsidy-induced green transformation, whereas production-network centrality captures the extent to which these local effects propagate through network linkages. Together, these two components summarize the regional wedge between the social and private returns to green subsidies, thereby providing a low-dimensional sufficient statistic for ranking regional subsidy priorities without requiring recovery of the model's full set of structural primitives. An immediate implication is that subsidy priority depends on both the magnitude of local emission responses and the extent to which policy effects propagate through the production network.

IV. Empirical Framework and Identification

A. Estimation Method

Theoretically, government subsidies drive changes in the energy structure, production modes, and market frictions, thereby promoting green transformation, which is ultimately reflected in lower firm-level emissions. For analytical simplicity, equation (12) can be further expressed as:

$$d\ln c_f = [\underbrace{-\gamma m}_{\text{Energy structure}} \underbrace{-Zb}_{\text{Production mode}} \underbrace{-\frac{(1-\eta)(1-t)}{\eta}}_{\text{Market friction}}] \sum_l \omega_{fl} d\ln s_l \tag{18}$$

Here, $\sum_l \omega_{fl} d\ln s_l$ captures regional government subsidy intensity from a network perspective, ω_{fl} measures the trade intensity between firm f and region l, s_l denotes government subsidy in region l. $[-\gamma m - Zb - \frac{(1-\eta)(1-t)}{\eta}]$ represents the effect of government subsidies on green transformation, which is the key coefficient to be estimated empirically. Specifically, the production mode elasticity $-Zb$ reflects the effect of government subsidies through inducing changes in firms' production mode choosing. The energy structure elasticity $-\gamma m$ captures the effect through incentivizing green technology innovation by energy firms, and the market friction t depends on the network distance between the firm and targeted regions.

Consistent with the theoretical framework, we exploit the Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction, which primarily operates through technology-oriented fiscal subsidies, as the empirical policy intervention. We construct the core explanatory variable, government intervention (GO_{ft}), from a production-network perspective by weighting regional policy shocks with firms' trade linkages. Specifically, we use the three waves of demonstration cities

introduced in 2011, 2013, and 2014 as exogenous policy shocks. Following Helm (2020) and Xu (2022), the basic idea is to weight these policy-induced shocks by each firm's trade intensity with other regions, thereby capturing the firm's exposure to the intervention. The resulting measure is defined as follows:

(19) $$Go_{ft} = \sum_{l} \omega_{fl} Du_l post_{lt}$$

Here, Du_l is a dummy variable equal to 1 if city l is selected as a demonstration city, and 0 otherwise. $post_{lt}$ is a dummy equal to 1 for periods after the policy implementation in city l, and 0 otherwise. ω_{fl} is a weight variable capturing the trade intensity between firm i and city l.

We exploit the predictive power of the VGG (Visual Geometry Group) convolutional neural network to impute missing data, using firm characteristics and partial supplier–customer information from the National Enterprise Tax Survey and China Stock Market and Accounting Research Database (CSMAR) to classify and identify trade relationships between firms. Specifically, we first match the CSMAR with the National Enterprise Tax Survey to construct training and test sets containing firm characteristics and relationship information. Next, we train a VGG model on these sets. Using the trained VGG model, we predict supplier–customer relationships for all firms in the National Enterprise Tax Survey, which allows us to compute firm–region trade intensity ω_{fl} , ω_{fl} is calculated as equation (20), where Co_{fl} denotes the number of supplier–customer links between firm f and region l. Finally, the government intervention Go_{ft} is constructed by weighting the exogenous policy shocks with ω_{fl} .

(20) $$\omega_{fl} = \frac{Co_{fl}}{\sum_{l} Co_{fl}}$$

B. Data Source and Descriptive Overview

The empirical model is specified as follows:

(21) $$\ln C_{ft} = a_0 + a_1 Go_{ft} + X + \theta_f + \varepsilon_t + v_{ft}$$

Where f and t denote firm and period, respectively, $\ln C_{ft}$ represents the logarithm of firm-level carbon emissions. We use firm-year carbon emissions from the National Enterprise Tax Survey over 2007–2020 as the dependent variable. Consistent with the theoretical framework, carbon emissions are used to measure policy effectiveness because industrial green transformation ultimately manifests itself in lower emission intensity through changes in production technologies, energy use, and production organization. Carbon emissions therefore provide a directly observable and comparable measure of the environmental outcomes of green transformation.

In addition, the coefficient of Go_{ft} measures the green effect of government intervention in the presence of the production network. X is a set of firm–year and region–year control variables from the China Statistical Yearbook and the National Enterprise Tax Survey, capturing other factors that may influence the outcome. θ_f and ϵ_t denote firm and time fixed effects, respectively. The dataset contains 818,129 firm–year observations over 2007–2020. Descriptive statistics for the main variables are presented below:

TABLE 1 SUMMARY STATISTICS

Variable	Description	Mean	Standard Deviation	Min	Max	Observations
lnC	Log Firm Carbon Emissions	4.6552	2.9818	-2.3026	20.6027	818129
Go	Gov Intervention	0.0991	0.10806	0.0000	0.2999	818129
lnk	Log Firm Assets	10.2739	1.97294	0.0000	21.9035	818129
lnl	Log Firm Employment	4.3862	1.47977	0.0000	18.3799	818129
lnc	Log Firm Total Output	9.2727	3.38475	0.0000	25.4841	818129
lnP	Log Regional Manufacturing Employment	3.4940	0.9634	0.0000	4.2819	818129
lnG	Log Regional GDP	16.4740	4.5061	0.0000	19.2780	818129
lnB	Log Regional Rail Freight	8.30494	2.78123	0.0000	11.6095	818129

C. Estimation Results

Table 2 reports the baseline regression results. Column (1) includes the government intervention effect along with firm and time fixed effects. Column (2) adds firm–year controls that may affect energy consumption, including log assets, log average employment, and log total output. Column (3) further incorporates region–year controls, including log regional manufacturing employment, log regional GDP, and log regional rail freight. Column (4) clusters the standard errors by industry. Across all specifications, the coefficient on government intervention is consistently negative and statistically significant at the 1% level, indicating that the policy initiated in 2011 effectively reduced emissions of firms within and outside the targeted region through the domestic production network.

TABLE 2 BASELINE REGRESSIONS

	(1)	(2)	(3)	(4)
Variable	lnC	lnC	lnC	lnC
Gov Intervention	-0.673***	-0.648***	-0.645***	-0.645**
	(0.0861)	(0.0860)	(0.0868)	(0.144)
Firm Assets		0.192***	0.191***	0.191***
		(0.00424)	(0.00423)	(0.00755)
Firm Employment		0.449***	0.449***	0.449***
		(0.00424)	(0.00423)	(0.0320)
Firm Total Output		0.0425***	0.0425***	0.0425**
		(0.000890)	(0.000890)	(0.00766)
Regional Manufacturing Employment			0.0200	0.0200**
			(0.0136)	(0.00593)
Regional GDP			-0.0298***	-0.0298**
			(0.00333)	(0.00560)
Regional Rail Freight			0.0447***	0.0447**
			(0.00258)	(0.00924)
Constant	4.713***	0.385***	0.439***	0.439*
	(0.00868)	(0.0433)	(0.0460)	(0.148)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	824,000	818,129	818,129	818,129
R2	0.815	0.822	0.822	0.822

Notes: Table 2 reports baseline regressions examining the effect of government intervention on firm-level carbon emissions (lnC). Estimates are from firm–year panel regressions including firm and year fixed effects (columns 1–4). Column (2) adds firm–year controls, including log assets, log average employment, and log total output. Column (3) further includes region–year controls, including log regional manufacturing employment, log regional GDP, and log regional rail freight. Column (4) clusters standard errors at the 2-digit industry level. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

D. Robustness

Balance Test.—To identify the causal effect of government intervention on firm emissions, it is essential that firms with different exposure levels do not systematically differ in key pre-policy characteristics. We classify firms into treatment and control groups based on their exposure to the policy shock and compare their pre-policy means. Potential confounders include the tendency of larger firms to receive more government support and to exhibit higher energy consumption. To examine this, we compare the pre-policy means of key firm characteristics (including firm size, upstream input, downstream output) by classifying firms into control and treatment groups based on their exposure to the policy shock and perform pairwise comparisons of mean differences. The results, reported in Table 3, show that firms across different groups do not exhibit significant differences in their key characteristics.

TABLE 3 BALANCE TEST

	(1)	(2)	(3)	(4)	(5)
Mean Differences Across Groups	Firm Size Total Output, thousand RMB	Firm Size Employment, persons	Firm input External Purchases of Goods and Services, thousand RMB)	Firm output Sales, thousand RMB	Firm output Processing Trade, thousand RMB
Control vs. Treatment	87376	104.2	915.2	273.3	126.9
(Standard errors)	(190696)	(520.9)	(1182)	(416.8)	(133.3)

Notes: Table 3 reports balance tests for key pre-policy firm characteristics across treatment and control groups. Firms are classified based on their exposure to government intervention. Columns (1)–(5) report mean differences in total output, employment, external purchases of goods and services, sales, and processing trade, respectively. Standard errors are reported in parentheses. The results indicate that firms in the treatment and control groups do not exhibit significant differences in these pre-policy characteristics, supporting the comparability of the groups for causal inference.

Dynamic Effects—The core assumption of estimation requires that firms with different levels of exposure to the policy shock do not exhibit systematic differences prior to the intervention. To validate this assumption, we include a set of year dummy variables in the regression to identify the dynamic effects of the policy over time. Specifically, we construct year dummies $post_d_{ct}$ and pre_d_{ct} for the seven years before and four years after the policy. For example, if $t = 2015$ and a region was designated as a demonstration city in 2011, the dummy $post_3_{ct}$ takes value 1, indicating the third year after the intervention. Similarly, if $t = 2007$ and a region became a demonstration in 2014, the dummy pre_7_{ct} takes the value 1, indicating the seventh year before the intervention. The coefficient β_d captures the dynamic effect of the policy shock on firms' emissions. The estimated β_d coefficients are presented in Figure 6, showing that the pre-policy coefficients are not statistically significant, whereas the post-policy coefficients are consistently negetive.

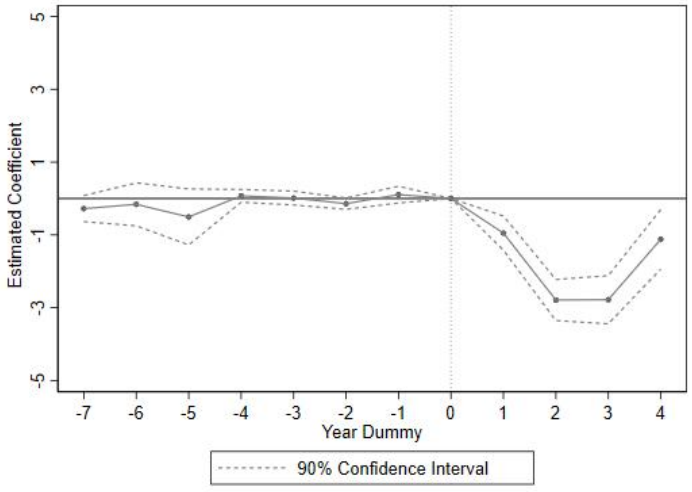


FIGURE6 DYNAMIC EFFECTS

Notes: Figure6 plots event-study estimates from seven years before to four years after policy implementation. The event year is normalized to zero, and dashed lines denote 90 percent confidence intervals. Pre-treatment coefficients are statistically indistinguishable from zero.

Correlation Test—The validity of identification in the baseline regression requires the quasi-randomness of the policy shock (Borusyak et al., 2022), meaning that whether a region becomes a demonstration city is largely uncorrelated with characteristics that affect firm energy consumption. Potential correlations mainly arise at the regional level, for example, regions with higher GDP are more likely to be designated as demonstration cities, and firms in such regions may also exhibit higher energy use due to larger production scales. To examine the relationship between regional characteristics and policy assignment, we follow Xu (2022) and regress the demonstration city indicator Du_c [2]on regional characteristics $X_c = \frac{\sum_l Re_{lc} cha_l}{\sum_l Re_{lc}}$, as in equation (22). Where cha_l represents the characteristics of region l prior to 2011, and ω_{lc} denotes the trade intensity between region l and c, Potential characteristics cha_l include the logarithms of regional economic Variables, such as GDP and industrial shares. Table 4 shows that the coefficients of the regional characteristics are all statistically insignificant, suggesting that most factors that may affect firm behavior are not systematically related to a city's likelihood of being selected as a demonstration.

(22) $$Du_c = a_0 + a_1 X_c + \varepsilon_c$$

TABLE 4 REGIONAL CORRELATION

	GDP	Service-sector share	Domestic firms' share	Passenger Traffic	Telecom Services Volume	Fixed Asset Investment	Retail Sales of Consumer Goods
X_c	0.000445	0.000978	0.000835	-0.000305	-0.000224	0.00154	0.000963
	(0.00284)	(0.0123)	(0.00283)	(0.00465)	(0.00342)	(0.00244)	(0.00297)
Observations	2,896	2,896	2,896	2,896	2,896	2,896	2,896

Notes: Table 4 reports regressions of the demonstration city indicator on pre-policy regional characteristics. Columns (1)–(7) use GDP, service-sector share, domestic firms' share, passenger traffic, telecom services volume, fixed asset investment, and retail sales of consumer goods, respectively, as the regional characteristics cha_l , with the demonstration city indicator as the dependent variable. Coefficients capture the correlation between the likelihood of a region being designated as a demonstration city and each regional characteristic. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

[2] Du_c Takes the value 1 if region $c$is a demonstration city, and 0 otherwise

Selection of the Control Group—The unbiasedness of our estimates requires the sufficient exogeneity of the weights $\omega_{fl} = \frac{Co_{fl}}{\sum_{l} Co_{fl}}$ used to construct the core explanatory variable, which means that firms' positions in the production network be quasi-randomly distributed across the treatment group (exposed firms) and the control group (unexposed firms). A potential concern is that network positions may be correlated with firm size: firms with larger input and output scales are more likely to locate near demonstration cities and thus be assigned to the treatment group, whereas the control group may comprise smaller firms with systematically lower carbon emissions. Such imbalance could amplify systematic differences between treated and control firms and bias the estimated effect upward. To address this endogeneity concern, we exclude from the control group firms whose total output, employment, total costs, or sales fall below the 25th percentile, and re-estimate the regressions using the restricted sample. Figure 7 reports the distribution of the estimated core coefficients for the full sample and for the sample excluding part of the control group. The left and right panels show regression coefficients of government intervention with and without control variables, respectively. The results indicate that the estimated coefficients are highly robust across alternative sample selections and remain stable after adjusting the control group. This stability suggests that the treated and control firms are sufficiently comparable for counterfactual inference, providing further support for the exogeneity of the weights used to construct the core explanatory variable.

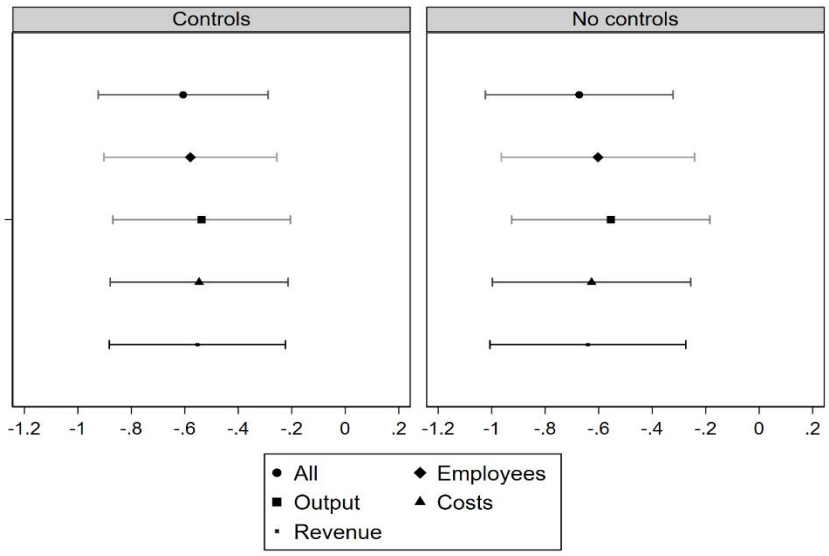


FIGURE7 DISTRIBUTION OF THE ESTIMATED COEFFICIENTS

Notes: Figure 7 presents the distribution of the estimated coefficients on government intervention for the full sample and for the sample excluding part of the control group. The left and right panels correspond to regressions with and without control variables, respectively. Coefficients illustrate the robustness of the estimated government intervention effect across alternative sample selections, confirming that treated and control firms are sufficiently comparable for counterfactual inference and supporting the exogeneity of the weights used in constructing the core explanatory variable.

Ruling Out Confounding Policies.—During the sample period of the regressions, there may be other relevant policies that could interfere with the empirical results, with the *Pilot Policy for China's Carbon Emission Trading Market* and the *Energy Conservation and Low-Carbon Action for Ten Thousand Enterprises* being the most representative ones. Specifically, pilot carbon emission trading markets were launched in Beijing, Tianjin, Shanghai, Shenzhen, Guangdong, Hubei, Chongqing, Fujian and other regions, meanwhile, the National Development and Reform Commission and 11 other ministries jointly issued the *Implementation Plan for the Energy Conservation and Low-Carbon Action for Ten Thousand Enterprises*, which set clear energy conservation and consumption reduction targets for enterprises within the regulatory scope. To isolate potential confounding effects from these policies, we construct two policy dummy variables: (i) a carbon trading pilot indicator CET_{it}, which equals 1 if a firm is

registered in a carbon trading pilot city and the observation year is after policy implementation. (ii) a Ten Thousand Enterprises Action indicator Key_{it}, which equals 1 if a firm is subject to the program and the observation year is after the policy implementation. Table 5 reports the regression results including these policy controls: column (1) controls only for the carbon trading pilot effect, column (2) adds the Ten Thousand Enterprises Action, column (3) further includes other control variables; and column (4) additionally controls for industry–year fixed effects. The results show that the coefficient on the core explanatory variable (government intervention) remains negative and significant, with similar magnitudes, indicating that the baseline estimations are robust after accounting for potential confounding policies.

TABLE 5. REGRESSIONS CONTROLLING FOR OTHER POLICIES.

	(1)	(2)	(3)	(4)
Variable	*lnC*	*lnC*	*lnC*	*lnC*
Gov Intervention	-0.684***	-0.681***	-0.656**	-0.610***
	(0.0862)	(0.0862)	(0.131)	(0.0812)
CET	-0.633***	-0.632***	-0.481	-0.217
	(0.116)	(0.116)	(0.356)	(0.279)
Key Enterprises		0.0173	0.00475	0.0343
		(0.0180)	(0.0412)	(0.0207)
Controls	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector–Year FE	No	No	No	Yes
Observations	824,000	824,000	818,129	817,710
R^2	0.815	0.815	0.822	0.827

Notes: Table 5 reports regressions examining the robustness of the government intervention effect after controlling for other policies. Estimates are regressions based on equation (19), progressively including the Carbon Emissions Trading (CET) pilot (columns 1), the Ten Thousand Key Enterprises Action (columns 2), additional firm- and region-level controls (columns 3), and industry–year fixed effects (column 4). The dependent variable is the log of firm-level carbon emissions. Standard errors are clustered at the 2-digit industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

V. Mechanism Analysis

A. Innovation of Green Technologies

Government intervention, through policy instruments such as fiscal incentives, guides regional energy sectors to engage in green innovation. Energy firms can adopt low-carbon technologies (e.g., high-efficiency clean coal mining) or shift to clean energy alternatives (e.g., photovoltaic and wind power technologies). These technological innovations in the energy sector propagate downstream through the production chain, thereby facilitating emissions mitigation in downstream firms.

To examine whether government intervention operates by promoting regional low-carbon technologies, we decompose the government intervention variable. First, using patent data from the China National Intellectual Property Administration (CNIPA), we measure the number of energy sector's low-carbon technology patents granted in demonstration cities after policy implementation. Low-carbon technologies are identified according to the International Patent Classification (IPC) system, focusing on technologies applied in fossil energy extraction (e.g., clean extraction, low-carbon upgrading, and emission control). Second, we construct a binary indicator $dummy_l$ that equals 1 if the demonstration city's post-policy low-carbon patents exceed the sample median, and 0 otherwise. Third, the government intervention variable is split into Low-Carbon Technology-Intervention $HrdGo_{ft} = \sum_l \omega_{fl} Du_l post_t dummy_l$ and the Residual Intervention $LrdGo_{ft} = \sum_l \omega_{fl} Du_l post_t (1 - dummy_l)$. Finally, we decompose the core explanatory variable into these two components and re-estimate the baseline regression.

In addition, to examine whether government intervention operates by promoting regional clean technologies, we decompose the intervention variable

following a similar approach. Specifically, we measure the number of energy sector's clean technology patents granted in demonstration cities after policy implementation. Clean technologies are defined according to the International Patent Classification (IPC) system, focusing on renewable energy applications (e.g., solar power, wind power, hydrogen storage, and renewable energy equipment). the binary indicator $dummy_l$ is then constructed based on the sample median of Clean Technology patents, and the government intervention effect is decomposed into Clean Technology-Intervention $HncGo_{ft} = \sum_l \omega_{ft} Du_l post_t dummy_l$ and the Residual Intervention. Both components are incorporated into the baseline model for regression analysis.

The regression results, reported in Table 6, show that the coefficients on government intervention through both the low-carbon and clean technology innovation channels are negative and statistically significant, whereas the coefficient on the residual intervention component is not significant. This indicates that demonstration cities effectively transmit the policy effect of intervention by promoting the adoption of low-carbon and clean technologies in the local energy sector, thereby providing support for emissions reduction among firms.

TABLE6 INNOVATION OF LOW-CARBON AND CLEAN TECHNOLOGIES

Variable	(1) lnC	(2) lnC	(3) lnC	(4) lnC
Low-Carbon Technology Intervention	-0.819**	-1.074**		
	(0.173)	(0.228)		
Residual Intervention		1.393		
		(0.640)		
Clean Technology Intervention			-0.919**	-1.074**
			(0.188)	(0.228)
Residual Intervention				0.573
				(0.373)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Observations	818,129	818,129	818,129	818,129
R2	0.822	0.822	0.822	0.822

Notes: Table 6 reports regressions examining the mechanism of government intervention through low-carbon and clean technology innovation. Columns (1)–(2) split the intervention variable into Low-Carbon Technology Intervention and its residual component, while Columns (3)–(4) split it into Clean Technology Intervention and its residual component. All Columns include firm and year fixed effects and control variables at the firm–year and region–year levels. Coefficients on the technology-specific intervention variables capture the effect of government intervention transmitted via regional low-carbon or clean technology innovation on firm carbon emissions. Standard errors are clustered at the 2-digit industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

B. Transformation of Production Modes

To examine whether government intervention mitigates emissions by promoting firms' transformation of production modes, we empirically test this channel. Specifically, we identify firm-level patent applications related to green production in energy utilization, such as renewable energy applications and energy efficiency improvements, based on the International Patent Classification (IPC) system. We construct a binary indicator of Production Mode Transformation, which equals 1 if a firm has any relevant patent applications of energy utilization from 2011 onward, and 0 otherwise. This variable is interacted with the core explanatory variable, Government Intervention, and included in the regression. To ensure robustness, we further use the log of the number of energy utilization patent applications after 2011 as a proxy for Transformation Intensity and similarly interact with Government Intervention in the regression.

The regression results are reported in Table 7. Column (1) presents the interaction term between Production Mode Transformation and Government Intervention, while Column (3) reports the interaction between Production Transformation Intensity and Government Intervention. Columns (2) and (4) further include additional controls to account for potential confounders. The coefficients on both interaction terms are negative and statistically significant, indicating that government intervention effectively promotes mode transformation

in firms. Moreover, the stronger the intensity of a firm's production transformation, the greater the reduction in its emissions attributable to government intervention, confirming that production mode transformation serves as a key channel.

TABLE7 TRANSFORMATION OF PRODUCTION MODES

Variable	(1) lnC	(2) lnC	(3) lnC	(4) lnC
Gov Intervention	-0.623**	-0.632**	-0.633**	-0.643**
	(0.147)	(0.133)	(0.142)	(0.129)
Gov Intervention × Mode Transformation	-0.253*	-0.255*		
	(0.105)	(0.0982)		
Gov Intervention × Transformation Intensity			-0.378***	-0.380***
			(0.0534)	(0.0509)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	818,129	818,129	729,324	729,324
R2	0.822	0.822	0.819	0.819

Notes: Table 7 reports regressions examining whether government intervention mitigates firm emissions through the transformation of production modes. Columns (1) and (2) include the interaction between Government Intervention and a binary indicator of Production Mode Transformation, which equals 1 if a firm has any relevant energy utilization patent applications from 2011 onward, and 0 otherwise. Columns (3) and (4) interact Government Intervention with the log of patent counts as a measure of Transformation Intensity. Columns (2) and (4) further include controls to account for potential confounders. All specifications include firm and year fixed effects. Coefficients on both interaction terms are negative and statistically significant, indicating that government intervention effectively promotes production mode transformation, with stronger transformation intensity associated with larger reductions in emissions. Standard errors are clustered at the 2-digit industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

C. Market Friction

To examine how market frictions, such as price fluctuations, may limit emissions mitigation, we construct a Fuel Price Change Dummy and incorporate it into the regression. Specifically, we first collect annual regional retail price indices[3] for fuel commodities and convert them into a fixed-base index with 2011 as the base year. Second, we compute the regional fuel price increases around

[3] The data are sourced from the National Bureau of Statistics of China.

2011 using this fixed-base index. Third, using the median of all sample price increases as the threshold, we assign a value of 1 to regions with price increases above the median and 0 otherwise. This Fuel Price Change Dummy is then interacted with Government Intervention in the regression. The results, reported in Column (1) of Table 8, show that the coefficient of Government Intervention remains significantly negative, while the interaction term, Fuel Price Change Dummy × Government Intervention, is positive and significant. This indicates that in regions experiencing relatively large fuel price increases since 2011, the emission-reduction effects of government intervention are attenuated, suggesting that frictions in energy-production linkages can limit the effectiveness of green policy transmission.

In addition, as implied by the theoretical framework, both monopolistic distortions and technological connectivity amplify the demand for policy intervention. To investigate the roles of monopoly power and technological connectivity in shaping the effectiveness of government intervention, we augment the baseline specification by introducing interaction terms. Specifically, High Connectivity is defined as a binary indicator equal to one if the regional technological distance of energy-production sector is below the sample median, thereby capturing whether the region is embedded in a more tightly connected technological network. High Monopoly is a binary indicator equal to one if the regional market exhibits pronounced monopoly characteristics, proxied by a Herfindahl–Hirschman Index (HHI) above the sample median. The construction of technological distance and the HHI follows the methodology described in Section VI. The regression results reveal substantial heterogeneity in the effects of government intervention across different technological environments and market structures. Column (2) of Table 8 shows that the coefficient on High Connectivity × Government Intervention is significantly negative. Greater technological connectivity implies that a region is embedded in a more integrated technological

network, which enhances intersectoral knowledge diffusion and policy transmission, thereby amplifying the green effect of government intervention. Column (3) indicates that the interaction term High Monopoly × Government Intervention is significantly positive. Market monopoly constitutes friction in policy implementation, attenuating the impact of government intervention. When all interaction terms are simultaneously included (Column (4)), the main results remain unchanged.

From a theoretical standpoint, a higher degree of monopoly is associated with stronger negative monopoly externality, thereby increasing the theoretical importance of the corrective role of subsidies. By bridging the wedge between private and social returns, subsidies serve as a necessary instrument for internalizing negative externalities. This explains why monopolistic regions exhibit a stronger theoretical need for subsidies. However, when accounting for practical implementation constraints, the empirical evidence suggests a more nuanced picture. Although subsidies are more theoretically necessary in monopolistic regions, their effectiveness in practice may be undermined by monopoly-specific rigidities, such as administrative barriers, organizational inertia, and allocative distortions. Consequently, maintaining the same subsidy intensity as in competitive regions may result in a diminished degree of effective externality internalization, which implies that larger subsidies may be required for monopolistic regions.

Overall, the design of government subsidies should balance the trade-off between internalizing externalities and leveraging technological connectivity. Specifically, on one hand, policy formulation should prioritize regions with high market monopoly intensity, where targeted subsidy schemes are essential to mitigate market friction and reinforce the effectiveness of externality internalization. On the other hand, full account must be taken of the amplifying role of technological connectivity. By harnessing such network effects,

policymakers can substantially enhance the implementation efficiency of subsidy policies, enabling the policy dividends to propagate through intersectoral linkages and drive systemic industrial green transformation.

TABLE8 MARKET FRICTION

Variable	(1) lnC	(2) lnC	(3) lnC	(4) lnC
Gov Intervention	-0.817***	-0.382**	-0.989**	-0.790***
	(0.0989)	(0.0860)	(0.196)	(0.0652)
Fuel Price Change × Gov Intervention	0.264**			0.113
	(0.0715)			(0.114)
High Connectivity × Gov Intervention		-0.599**		-0.576**
		(0.165)		(0.172)
High Monopoly × Gov Intervention			0.688**	0.648**
			(0.183)	(0.202)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	818,129	818,129	818,129	818,129
R2	0.822	0.822	0.822	0.822

Notes: Table 8 reports regressions examining the impact of market friction on the effectiveness of government intervention. Column (1) includes an interaction between a Fuel Price Change Dummy and Government Intervention, where the dummy equals 1 if a region's fuel price increase after 2011 is above the sample median, and 0 otherwise. Columns (2)-(4) sequentially introduce interactions of Government Intervention with High Technological Connectivity and Monopoly. All regressions include firm and year fixed effects, and additional controls are included in all columns. Standard errors are clustered at the 2-digit industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Building on this framework, to further explore how market friction can be addressed, we conduct subgroup regressions using the median values of market accessibility and firm size as grouping thresholds. Figure 8 reports the distribution of government intervention coefficients when grouped by market accessibility (Low MA vs. High MA) and by firm size (Small F vs. Large F). We also show the coefficient distribution for the subgroup with both high market accessibility and large firms. The left and right panels in Figure 8 correspond to regressions with and without additional control variables, respectively. The results indicate that higher market accessibility strengthens the green effect of government

intervention, while large firms are more resilient to structural frictions. This finding carries important implications for the targeted design of subsidy policies in monopolistic markets. As our earlier analysis emphasized, policy formulation should prioritize regions with high market monopoly intensity, where targeted subsidy schemes are essential to mitigate market friction and reinforce the effectiveness of externality internalization. In this context, directing subsidies toward large firms with high market accessibility can significantly enhance the efficiency of externality internalization under monopolistic market structures.

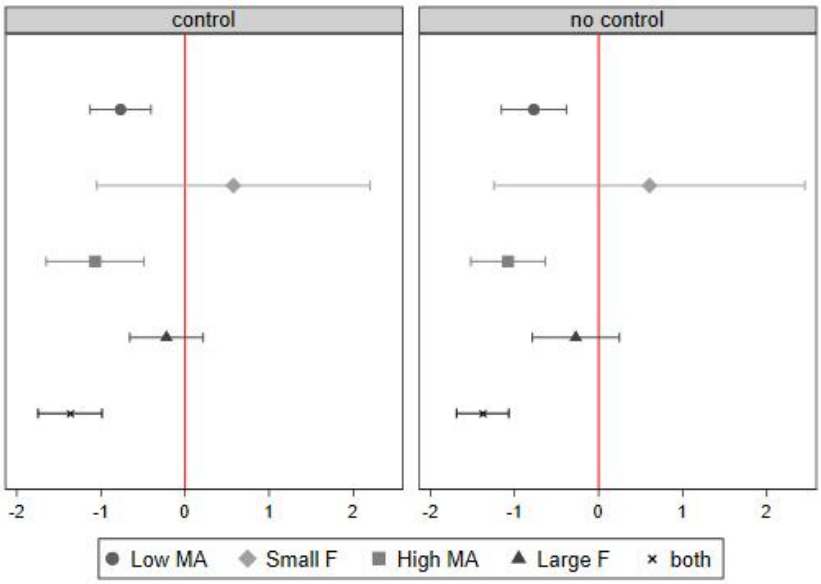


FIGURE8 DISTRIBUTION OF SUBGROUP REGRESSION COEFFICIENTS

Notes: Figure 8 presents the distribution of government intervention coefficients from subgroup regressions, where firms are grouped based on the median values of market accessibility (Low MA vs. High MA) and firm size (Small F vs. Large F), and an additional subgroup combines firms with both high market accessibility and large size. The left and right panels correspond to regressions with and without control variables, respectively. Coefficients illustrate how government intervention's effect on emissions reduction varies across these subgroups, showing stronger effects in regions with higher market accessibility and for larger firms.

VI. Sufficient-Statistic Targeting and Counterfactual Allocation

This section translates the model-implied wedge into an empirically implementable targeting rule. The rule ranks regions using a sufficient statistic that combines the marginal emission response of policy-induced green innovation in the energy sector with the ability of regional policy shocks to diffuse through

the production network. We then use the estimated treatment response from the baseline regression to evaluate counterfactual allocations of a fixed subsidy budget. The exercise quantifies the predicted efficiency gains from reallocating policy exposure according to the sufficient statistic and characterizes where these gains are realized across regions and industries.

A. From the Model to a Targeting Rule

Equation (17) implies that subsidy targeting is governed by two sufficient-statistic components: energy-structure elasticity $\beta_l \equiv \gamma_l m_l$ and production-network centrality $Net_l \equiv \sum_c \frac{\theta_l r_c}{\tau_{lc} k_{lc} r_l}$ .Energy-structure elasticity captures the marginal emission response generated by policy-induced green innovation in the regional energy sector. Production-network centrality captures the ability of a regional policy shock to diffuse through network linkages. Thus, the model implies that regions should receive higher targeting priority when they combine strong local responsiveness with high network diffusion capacity.

We quantify these two components in two steps. First, we estimate the region's energy structure elasticity. We begin by obtaining the government intervention coefficient $\alpha_1 \equiv [-\gamma m - Zb - \frac{(1-\eta)(1-t)}{\eta}]$, using the coefficient of the core explanatory variable from the baseline regression, regressions are run separately by industry, and the resulting coefficients are averaged at the regional level to obtain the region-level average treatment effect accounting for industry heterogeneity. Then we re-estimate the baseline regression while additionally controlling for industry–year fixed effects, which removes industry-specific variation (i.e., isolates the component of the energy structure elasticity $-\gamma m$). Finally, the absolute value of the difference between the two coefficients gives the energy sector elasticity.

Second, we calculate the region's production network centrality. Specifically, the inverse of standardized geographic distance between regions is used as a proxy for interregional search costs τ_{lc} .The standardized difference in the number of green technology patents between energy and production sectors is used as a proxy for technological distance $k_{lc} \equiv \ln(|E_l - P_c|)$, and a narrow-scope HHI of the regional energy sector($HHI_l = \sum_{f \in l} (\frac{s_f}{s_l})^2$) is used as a proxy for θ_l , where $\frac{s_f}{s_l}$ denotes the market share of energy-sector firm f in region l. Finally, these measures are combined according to the production network centrality $Net_l \equiv \sum_c \frac{\theta_l r_c}{\tau_{lc} k_{lc} r_l}$ to calculate each region's centrality.

B. Estimating the Sufficient-Statistic Components

Table 9 reports the estimated targeting priority together with two sufficient statistic components. A central finding is that the sufficient-statistic rule yields a spatial allocation fundamentally different from conventional criteria based on economic size, emissions, or resource endowments. Instead, it prioritizes regions where local green transformation generates the largest network-wide policy returns. This ranking reflects two complementary margins: energy-structure elasticity, which captures local emission responses, and production-network centrality, which captures the propagation of these responses through upstream–downstream production linkages.

The resulting spatial pattern is closely aligned with China's production and energy geography. Northwest China ranks highest because it combines abundant energy resources and resource-based industrial clusters with strong production-network centrality, allowing improvements in upstream energy technology to propagate widely through interregional supply chains while generating substantial local emission reductions. Central-South China also receives high priority, although its energy-structure elasticity is only moderate, because its pivotal

position in China's manufacturing network substantially amplifies the transmission of policy effects. By contrast, Southwest China exhibits the highest energy-structure elasticity, reflecting its comparative advantage in hydropower and clean-energy production, but its relatively weaker production-network centrality limits the network-wide benefits of subsidy allocation. Finally, East China ranks lowest despite being China's largest economic region. Its relatively diversified energy structure and weaker network leverage imply lower marginal policy returns under the sufficient-statistic rule.

Taken together, these findings highlight a distinctive feature of China's production network: the regions with the highest subsidy priority are not necessarily the largest economies or the largest emitters, but those combining strong local emission responses with high production-network leverage. The sufficient statistic rule therefore reallocates subsidies toward regions generating the largest marginal policy returns.

TABLE9 OPTIMAL INTERVENTION INTENSITY ACROSS REGIONS

Region	Targeting Priority	Production-Network Centrality	Energy-Structure Elasticity
Northeast	0.0245	0.0815	0.2994
Central-South	0.0409	0.1459	0.2623
East China	0.0137	0.1145	0.1108
North China	0.0287	0.1277	0.3413
Northwest	0.0603	0.1841	0.3402
Southwest	0.0325	0.0813	0.4138

Notes: Table 9 reports the region-level sufficient-statistic components and the resulting targeting priority. Production-network centrality measures the extent to which local policy effects propagate through network linkages. Energy-structure elasticity measures the responsiveness of regional emissions to subsidy-induced green transformation in the energy sector. Targeting priority is computed as the product of production-network centrality and energy-structure elasticity, as implied by Proposition 2.

Figure 9 decomposes the sufficient-statistic targeting rule into its two components: energy-structure elasticity and production-network centrality. Rather than illustrating provincial rankings, the figure reveals why the sufficient-statistic rule differs fundamentally from conventional allocation criteria based on emissions, economic size, or resource endowments.

First, the figure shows that local emission responses and production-network propagation represent two distinct dimensions of policy effectiveness. Provinces are widely dispersed across the four quadrants, suggesting that energy-structure elasticity and production-network centrality capture distinct but complementary dimensions of policy leverage. Consequently, neither local responsiveness nor network propagation alone provides a sufficient basis for subsidy allocation.

Second, high local responsiveness does not necessarily translate into high targeting priority. Provinces such as Yunnan and Guizhou exhibit relatively high energy-structure elasticity, indicating that green innovation in the regional energy sector generates sizable local emission responses. However, their relatively weak production-network centrality reflects the fact that, despite their abundant clean-energy resources, they remain less deeply embedded in China's manufacturing supply chains and are connected to relatively smaller surrounding markets. Consequently, improvements in upstream energy quality generate substantial local gains but are transmitted less extensively through interregional production linkages, reducing the network-wide returns to subsidy allocation.

Third, strong production-network centrality can substantially increase policy leverage even when local responsiveness is only moderate. Hubei provides a representative example. Located at the intersection of China's major interregional production corridors, Hubei connects upstream energy suppliers with downstream manufacturing clusters across the Yangtze River Economic Belt. This central position enables improvements in upstream energy quality to diffuse widely through production linkages, making network transmission, rather than local emission responses, the primary source of its policy leverage.

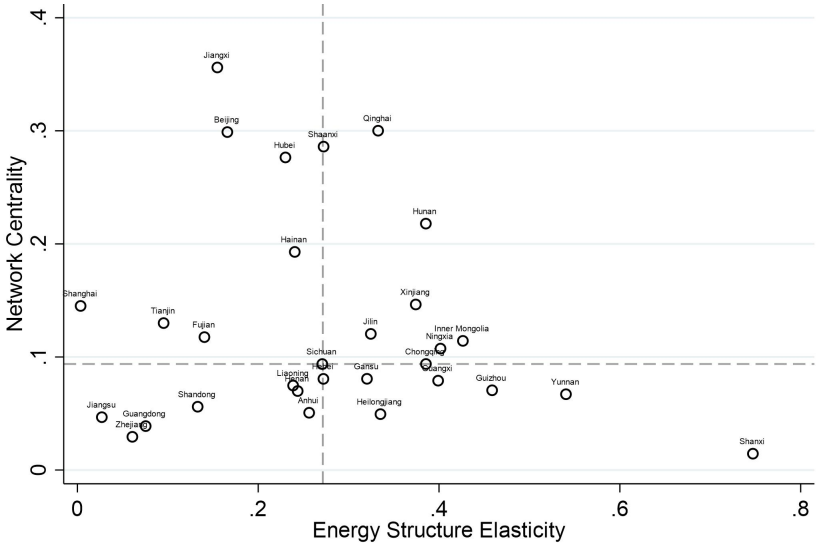


Figure 9. Energy-Structure Elasticity and Production-Network Centrality

Notes: Figure 9 decomposes the sufficient statistic rule into its two components. The horizontal axis reports energy-structure elasticity. The vertical axis reports production-network centrality. Dashed lines denote sample medians.

Finally, the highest targeting priority arises only when both margins are simultaneously strong. Qinghai and Hunan exemplify this interaction. Qinghai combines exceptionally high energy-structure elasticity with strong production-network centrality. As one of China's largest clean-energy bases and a key node in the West-to-East Electricity Transmission Project, improvements in upstream energy technology generate substantial local emission responses while diffusing broadly through interregional energy supply networks. Hunan, by contrast, derives its advantage from its central position in China's manufacturing network. Located at the intersection of major interregional production corridors and closely connected to the Yangtze River Economic Belt and coastal manufacturing clusters, Hunan enables local energy-sector improvements to propagate efficiently through upstream–downstream production linkages.

These mechanisms are further reflected in Table 10, which reports the ranking of optimal intervention intensity. Qinghai, Hunan, Shaanxi, Hubei, and Jiangxi constitute the top five policy nodes, whereas Shanghai, Jiangsu, Zhejiang,

Guangdong, and Shandong rank at the bottom. This contrast highlights a distinctive feature of China's production network. The provinces receiving the highest subsidy priority are predominantly upstream energy bases or strategically located production-network hubs, while the country's largest coastal manufacturing economies receive relatively low priority. Rather than indicating that green transition is less important in coastal provinces, this result suggests that additional local energy-sector subsidies generate relatively smaller marginal social returns there because these regions benefit primarily from cleaner upstream energy supplied through the production network. More broadly, the sufficient-statistic rule shifts policy targeting from economic scale or emissions toward network position and marginal policy returns, reflecting China's pronounced spatial separation between upstream energy production and downstream manufacturing.

TABLE10 RANKING OF TARGETING PRIORITY

Top 5 provinces and municipalities	Bottom 5 provinces and municipalities
Qinghai	Shanghai
Hunan	Jiangsu
Shaanxi	Zhejiang
Hubei	Guangdong
Jiangxi	Shandong

C. Counterfactual Allocation and Predicted Gains

The preceding analysis identifies the regions with higher model-implied targeting priority. We next quantify the policy implications of this ranking through a counterfactual allocation analysis.

The counterfactual allocation keeps three objects fixed: the baseline treatment response $\hat{\alpha} = -0.645$, the firm-region production network weights ω_{fl}, and the aggregate amount of policy resources. It changes only the regional allocation of policy intensity, D_l, according to the sufficient-statistic rule, and then recomputes firm-level policy exposure as $Go_f^r = \sum_l \omega_{fl} D_l^r$. Predicted

emission reductions are then obtained using the same treatment response. Thus, differences across allocations measure the efficiency gain from reallocating a fixed policy resource across the production network, rather than changes in policy scale, network structure, or estimated treatment effects.

Specifically， Let D_l^r denote the policy intensity assigned to region l under the sufficient-statistic targeting rule r. Given the number of pilot regions, regions are ranked by their sufficient-statistic priority. D_l^r equals one if region l ranks within the number of pilot regions, and zero otherwise. Firm f's counterfactual policy exposure is

$$Go_f^r = \sum_l \omega_{fl} D_l^r, \tag{23}$$

where ω_{fl} measures the strength of the production-network linkage between firm f and region l. We compare the baseline allocation with the sufficient-statistic allocation. The baseline allocation reflects the observed distribution of policy resources. The sufficient-statistic allocation reallocates the same amount of policy resources according to the estimated regional targeting priority. Thus, the counterfactual changes the location of policy exposure while keeping the fiscal envelope fixed.

Using the baseline estimate $\hat{\alpha} = -0.645$, the predicted change in log emissions for firm f under rule r is

$$\widehat{\Delta \ln C_f^r} = \hat{\alpha} Go_f^r. \tag{24}$$

Because the outcome is log firm emissions, the corresponding predicted firm-level emission-reduction rate is

$$\widehat{RR}_f^r = 1 - \exp(\hat{\alpha} Go_f^r). \tag{25}$$

We aggregate firm-level predicted reductions using firm emission weights:

$$\widehat{R}^r = \sum_f w_f \widehat{RR}_f^r. \tag{26}$$

This aggregation converts firm-level predicted emission-reduction rates into an economy-wide predicted reduction measure. The weight w_f is based on firm f's emissions, so firms with larger emissions receive greater weight in the aggregate index. This weighting is useful because a given percentage reduction among high-emission firms contributes more to total emission reductions than the same percentage reduction among low-emission firms. Thus, $\widehat{R}^r = \sum_f w_f \widehat{RR}_f^r$ measures the predicted aggregate emission-reduction rate under allocation rule r, holding the estimated treatment response, network structure, and total policy resources fixed.

Table 11 reports the aggregate results. Sufficient-statistic targeting raises the predicted aggregate emission-reduction rate from 16.76 percent under the baseline allocation to 17.55 percent. This corresponds to a 0.79 percentage-point increase, or a 4.7 percent improvement in efficiency gain. The result therefore shows that reallocating policy exposure according to production-network sufficient statistics can generate additional emission-reduction gains within a fixed fiscal envelope.

TABLE 11. AGGREGATE PREDICTED GAINS FROM SUFFICIENT STATISTIC TARGETING

Allocation rule	Predicted reduction rate (%)	Increase relative to baseline (p.p.)	Efficiency gain (%)
Baseline allocation	16.76	-	-
Sufficient-statistic targeting	17.55	0.79	4.7

Notes: Predicted reduction rates are computed using the baseline treatment response $\hat{\alpha} = -0.645$ and counterfactual policy exposure under Sufficient-statistic targeting allocation rule. The total amount of policy exposure is held fixed. Increase relative to baseline is measured in percentage points. Efficiency gain is the percentage increase relative to the baseline allocation.

We next examine where the predicted gains from sufficient-statistic targeting are realized. Table 12 shows that the regions receiving the highest subsidy priority do not necessarily coincide with those realizing the largest emission reductions. While the targeting rule allocates subsidies to regions generating the highest marginal policy returns, production-network propagation shifts part of the

resulting gains to connected regions. In particular, North China records the largest predicted gain despite only moderate targeting priority, reflecting its strong production linkages with upstream energy-producing regions.

More broadly, these findings illustrate a central implication of the sufficient-statistic rule: optimal subsidy allocation should be based on marginal policy returns rather than the spatial distribution of realized emission reductions. Because policy effects propagate through production networks, the most effective policy nodes need not coincide with the locations where the largest environmental gains are ultimately realized.

Table 12. Regional Distribution of Predicted Gains

Region	Gain from SS targeting (p.p.)	Relative gain (%)
Northeast	1.26	7.7
Central-South	0.31	1.8
East China	0.45	2.6
North China	2.04	13.1
Northwest	2.00	12.9
Southwest	0.92	5.5

Notes: Gain from SS targeting reports the increase in the predicted emission-reduction rate relative to the baseline allocation, measured in percentage points. Relative gain is the percentage increase relative to the baseline allocation. The table describes the regional incidence of predicted gains and does not estimate heterogeneous treatment effects.

Table 13 further examines the industrial distribution of predicted gains following sufficient-statistic targeting. Consistent with the regional results, the industries receiving the largest predicted gains are not necessarily those directly targeted by the policy. Instead, the largest gains are realized in energy-intensive industries, reflecting the propagation of policy effects through production networks.

Transportation, storage, and postal services exhibit the largest predicted gain, with the emission-reduction rate increasing by 1.21 percentage points. Heavy and equipment manufacturing and energy utilities also experience substantial gains.

These sectors are either closely connected to the upstream energy sector or highly dependent on energy inputs, allowing improvements in upstream energy quality to diffuse broadly through production linkages. By contrast, construction, high-tech manufacturing, and light manufacturing display relatively smaller gains.

Table 13. Industrial Distribution of Predicted Gains

Industry	Gain from SS targeting (p.p.)	Relative gain (%)
Light manufacturing	0.66	3.9
Chemical and material-related manufacturing	0.80	4.8
Heavy and equipment manufacturing	0.94	5.7
High-tech and other manufacturing	0.50	2.9
Electricity, heat, gas, and water production and supply	0.91	5.5
Construction	0.33	1.9
Transportation, storage, and postal services	1.21	7.4

Notes: Industries are classified according to national industry codes. Gain from SS targeting reports the increase in the predicted emission-reduction rate relative to the baseline allocation, measured in percentage points. Relative gain is the percentage increase relative to the baseline allocation. The table describes the industry incidence of predicted gains.

D. Scenario Simulation

The preceding analysis establishes the sufficient-statistic targeting rule under the observed institutional environment. We next examine how changes in the structural determinants of production-network centrality affect the targeting rule. As shown in Proposition 2, regional targeting priority depends jointly on energy-structure elasticity and production-network centrality. While the former is estimated from the data, the latter is shaped by several underlying structural primitives. We therefore consider two counterfactual scenarios that vary the upstream energy-sector surplus share and upstream–downstream technological interoperability while holding all other parameters fixed. Table 14 summarizes the scenario design.

TABLE14 SCENARIO SETTINGS

Scenario	Economic Interpretation	Parameter Adjustments
Scenario 1（Baseline）	Observed institutional environment	Parameters estimated based on actual conditions
Scenario 2 (Reduced Upstream Surplus Share)	Weaker production-network propagation due to lower upstream surplus allocation	Other parameters unchanged. Set $\theta_l$to the 10th percentile
Scenario 3（full	Stronger production-network	Other parameters

technological interoperability）	propagation due to full upstream–downstream technological compatibility	unchanged. Set $\frac{1}{k_{lc}}$ to the sample maximum;

Figure 10 reports the resulting regional targeting priorities under each scenario. An important feature is that the regional ranking remains broadly stable across scenarios, while the magnitude of targeting priority changes substantially. This suggests that the sufficient-statistic rule provides a robust ranking of policy nodes, whereas institutional conditions primarily affect the optimal intensity of intervention. Regions such as Northwest China and Central-South China remain among the highest-priority regions across all scenarios, while East China consistently ranks lowest.

First, reducing the upstream energy-sector surplus share lowers targeting priorities in every region. The decline is particularly pronounced in Northwest China and Central-South China, where baseline targeting priorities are highest. This result highlights the role of network surplus in sustaining production-network propagation. When a smaller share of production-network surplus accrues to the upstream energy sector, improvements in energy quality generate weaker feedback from downstream production, reducing the marginal social returns to regional subsidies and lowering the optimal level of intervention.

Second, improving upstream–downstream technological interoperability substantially increases targeting priorities across all regions. The increase is again largest in Northwest China and Central-South China, indicating that stronger technological compatibility amplifies the transmission of upstream green innovation through production networks. As green technologies become more readily adopted by downstream industries, local policy shocks generate larger system-wide environmental benefits, thereby increasing the marginal returns to regional subsidy allocation.

Taken together, the scenario analysis confirms the comparative statics implied by the model. The sufficient-statistic targeting rule is jointly shaped by market structure and production-network connectivity. Weaker upstream surplus allocation reduces the effectiveness of production-network propagation and lowers the optimal intensity of intervention, whereas greater technological interoperability strengthens network spillovers and increases the social returns to targeted green subsidies. More importantly, although these institutional conditions affect the optimal level of intervention, they leave the relative ranking of policy nodes largely unchanged, suggesting that the sufficient-statistic rule provides a robust basis for regional subsidy targeting.

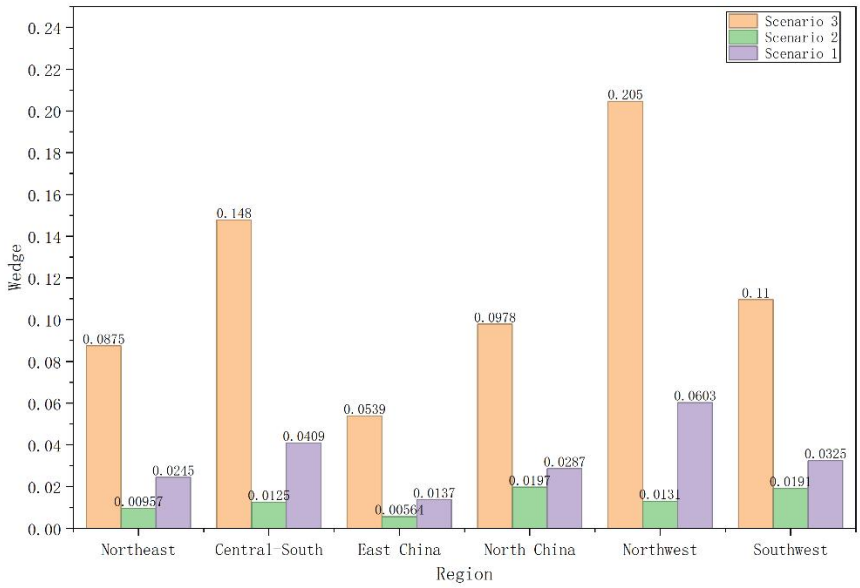


FIGURE10 SCENARIO SIMULATION

Notes: Figure 10 reports regional targeting priorities under three counterfactual scenarios. Scenario 1 corresponds to the baseline economy with parameters estimated from the data. Scenario 2 reduces the upstream energy-sector surplus share (θ_l) to the 10th percentile while holding all other parameters fixed, thereby weakening the propagation of policy effects through the production network. Scenario 3 assumes full upstream–downstream technological interoperability by setting $1/k_{lc}$ to its sample maximum while holding all other parameters fixed. Higher values indicate larger marginal social returns to regional green-subsidy exposure.

E. Sensitivity Analysis

To assess the relative importance of the structural determinants of production-network centrality, we conduct a sensitivity analysis by varying each primitive over its empirical distribution while holding all other parameters fixed. Specifically, we separately vary the upstream energy-sector surplus share (θ_l) and upstream–downstream technological interoperability ($\frac{1}{k_{lc}}$) from the 25th to the 90th percentile and compute the corresponding model-implied intervention wedge. Figure 11 reports the results.

Figure 11 shows that both structural primitives increase the model-implied intervention wedge, but their quantitative effects differ substantially. Increasing the upstream energy-sector surplus share generates a pronounced nonlinear increase in the intervention wedge, with the slope becoming markedly steeper at higher percentiles. This pattern suggests that, as the upstream energy sector becomes more deeply embedded in the production network, improvements in energy quality propagate more extensively through production linkages, causing the marginal social returns to targeted intervention to rise disproportionately. In addition, improvements in upstream–downstream technological interoperability also increase the intervention wedge by facilitating the diffusion of green technologies across sectors. Although stronger technological compatibility enhances production-network spillovers, its quantitative effect remains smaller than that of the upstream energy-sector surplus share.

The sensitivity analysis highlights that the gains from sufficient-statistic targeting are themselves state-dependent. As the upstream energy sector becomes more central to value creation within the production network, the social returns to correctly identifying policy nodes increase disproportionately, making production-network-based targeting increasingly valuable for efficient subsidy allocation.

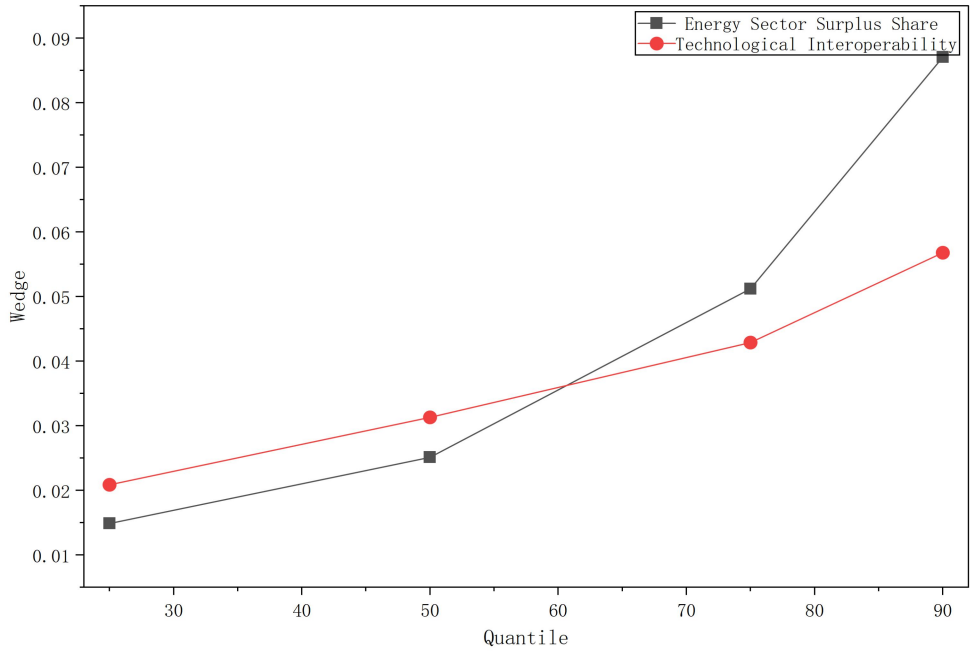


FIGURE11 SENSITIVITY ANALYSIS

Notes: Figure 11 reports the sensitivity of the model-implied intervention wedge to changes in two structural determinants of production-network centrality. The black line varies the upstream energy-sector surplus share (θ_l) from the 25th to the 90th percentile while holding all other parameters fixed. The red line similarly varies upstream–downstream technological interoperability ($\frac{1}{k_{lc}}$). Higher values indicate larger model-implied intervention wedges.

VII. Conclusion

Amid the growing global consensus on accelerating the green transformation of industry, developing economies such as China face distinctive challenges in greening their industrial systems. The dual externalities in energy sector and persistent structural frictions in cross-sector coordination jointly weaken firms' incentives to undertake green transformation. In this context, government subsidies become a necessary corrective instrument. Its effectiveness, however, critically depends on how it addresses the interdependence between the energy sector (the upstream source of emissions) and the production sector (the

downstream locus where emissions are ultimately realized) within production networks.

This paper develops a unified theoretical framework that incorporates production networks, endogenous green innovation, and an energy sector characterized by market power, empirically identifies the causal effects and mechanisms of government intervention using China's *Comprehensive Demonstration Work on Fiscal Policies for Energy Conservation and Emission Reduction* as a quasi-natural experiment, combined with firm-level data spanning 2007–2020.

Our main findings can be summarized as follows. First, government intervention significantly reduces firm-level emissions through production-network transmission, operating via two channels: it promotes the innovation of green technologies in the energy sector, and induces clean production mode transformation in downstream firms. Second, structural frictions partially offset the green effects of intervention. This offset is heterogeneous: regions with higher market accessibility and larger firms exhibit greater resilience. Third, the optimal prioritization of government intervention, jointly determined by energy structure elasticity and production network centrality, displays pronounced regional heterogeneity. the optimal prioritization of intervention is highest in Southwest and Central-South China, reflecting their central positions in energy–production networks (e.g., the Southwest's role as the hub of the West-to-East Power Transmission initiative), and it remains relatively low in East and North China.

This paper contributes to literature in three main ways. First, Theoretically, we extend the production network framework of Giroud et al. (2024) by explicitly incorporating both negative monopoly externality and positive technology externality in the energy sector. Our unified analytical framework links energy technology innovation, production mode transformation, and cross-sector friction. Second, empirically, we exploit a multi-wave policy experiment and construct

firm-level exposure using shift-share designs combined with VGG-based convolutional neural networks, providing micro-level causal evidence. Third, from a methodological perspective, we derive an analytical solution for optimal prioritization of intervention, quantifying the trade-off between externality internalization and network leverage. The analytical framework and policy logic elaborated in this paper are applicable to developing countries featuring energy sector concentration, production network interdependence, and incomplete market integration. By explicitly incorporating dual externalities (i.e., negative monopoly externality and positive technology externality) and network heterogeneity, our approach offers a scalable template for designing effective government intervention that reconciles industrialization-driven development with decarbonization objectives in practice. More broadly, the paper illustrates how sufficient-statistic methods can be used not only to evaluate policy interventions but also to design them. Rather than requiring a fully specified planner's problem, the proposed targeting rule combines observable elasticities with production-network structure to generate transparent and empirically implementable policy prescriptions. This framework may be applicable to a broader class of industrial and environmental policies in economies characterized by network distortions.

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Appendix

1. Solving the Firm's Profit-Maximization Problem in the Energy Sector

The maximization problem is formulated as follows:

$$\max_{h_{li}} \frac{p_i}{m_l} h_{li}^{1-\eta} \left(\prod_j h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta} - \frac{c_l h_{il}}{s_l}$$

The first-order condition for investment in the technology h_{li} is given by:

$$(1-\eta)\frac{p_i}{m_l} p_i h_{li}^{1-\eta} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta} = \frac{c_l h_{li}}{s_l} \qquad \text{（A.1.1）}$$

The technological investment intensity h_{li} can further be expressed as:

$$(1-\eta)^{\frac{1}{\eta}} m_l^{-\frac{1}{\eta}} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta} \left(\frac{s_l p_i}{c_l}\right)^{\frac{1}{\eta}} = h_{li} \qquad \text{（A.1.2）}$$

The production function is:

$$q_{li} = h_{li}^{1-\eta} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right)^{\eta} \qquad \text{（A.1.3）}$$

Combining (A.1.2) and (A.1.3) yields:

$$q_{li} = \left[\frac{(1-\eta)}{m_j}\right]^{\frac{1-\eta}{\eta}} \left(\prod_{j \in l} h_j^{\gamma_{ij} m_j} S_l^{b_l}\right) \left(\frac{s_l p_i}{c_l}\right)^{\frac{1-\eta}{\eta}} \qquad \text{（A.1.4）}$$

2. Solving the Firm's Profit-Maximization Problem in the Production Sector

The firm's maximization problem is formulated as follows:

$$\max_{L_f} \{P_f g_f - L_f - F_f\}$$

Using the production function $g_f = \varphi_f q_f^{\alpha} L_f^{1-\alpha}$, the first-order condition is:

$$(1-\alpha) P_f \varphi_f q_f^{\alpha} L_f^{1-\alpha} = L_f \qquad \text{（A.2.1）}$$

Substituting into the objective function, we obtain:

$$\pi_f = \alpha P_f \varphi_f q_f^{\alpha} L_f^{1-\alpha} \qquad \text{（A.2.2）}$$

Total revenue $P_f g_f$ can be expressed as $P_f \varphi_f q_f^{\alpha} L_f^{1-\alpha}$. Substituting $(1-\alpha) P_f g_f = L_f$ yields:

$$P_f g_f = (1-\alpha)^{\frac{1-\alpha}{\alpha}} (P_f \varphi_f)^{\frac{1}{\alpha}} q_f \qquad \text{（A.2.4）}$$

The firm's profit can then be expressed as:

$$\pi_f = \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} (P_f \varphi_f)^{\frac{1}{\alpha}} q_f \qquad \text{（A.2.5）}$$

If a firm adopts a clean-production mode, then $P_f \equiv P_f^b,\ F_f \equiv F_f^b$. If it adopts a conventional production mode, then $P_f \equiv P_f^p,\ F_f \equiv F_f^p$. Here, g_f and L_f denote output and labor input, respectively. Solving the profit-maximization problem, the firm's profit under each mode can be expressed as:

$$\begin{cases} \pi_f^b = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_{bf}\varphi_f)^{\frac{1}{\alpha}}q_f - F_{bf}(\textit{Clean production mode}) \\ \pi_f^p = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_{pf}\varphi_f)^{\frac{1}{\alpha}}q_f - F_{pf}(\textit{Conventional production mode}) \end{cases}$$

Let $\pi_f^b(\varphi_l^*) = \pi_f^p(\varphi_l^*)$. The threshold productivity is given by $\varphi_l^* = \frac{1}{\Omega}(\frac{\hat{F}_{lf}}{\hat{P}_{lf}})^{\alpha}$, with $\Omega = \alpha^{\alpha}(1-\alpha)^{1-\alpha}$, $\hat{P}_{lf} = (P_{bf})^{\frac{1}{\alpha}} - (P_{pf})^{\frac{1}{\alpha}}$, $\hat{F}_{lf} = F_{bf} - F_{pf}$ 。

3. Determinants of Firm-Level emissions

Since emissions does not directly contribute to value creation in the production process, but rather is a by-product of production activities, higher-quality energy supply results in lower emissions $c_f \equiv q_f^{\kappa}, \kappa \le 0$.

Let the energy intermediates flowing into firm f be denoted by $q_f \equiv \prod_l q_{li}^{\omega_{fl}}$, so that $c_f = \prod_l q_{li}^{\kappa\omega_{fl}}$. Combining with equation (3), the firm's emissions can be expressed as:

$$c_f = \prod_l [(1-\eta)^{\frac{(1-\eta)\kappa\omega_{fl}}{\eta}} \vartheta_i^{\frac{(1-\eta)\kappa\omega_{fl}}{\eta}} (\prod_{j\in l} h_j^{\gamma_{lj}m_j} S_l^{b_l})^{\kappa\omega_{fl}} (\frac{s_l p_i}{c_l})^{\frac{(1-\eta)\kappa\omega_{fl}}{\eta}}] \qquad \text{（A.3.1）}$$

Here, $p_i = \frac{\theta_l}{\tau_{lf}}\frac{\delta\pi_f}{\delta q_f} = \frac{\theta_l}{\tau_{lf}}\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}(P_f A_f)^{\frac{1}{\alpha}}$. Applying the log-difference to (A.3.1) gives[4]:

$$d\ln c_f = -\sum_l \frac{(1-\eta)\omega_{fl}}{\eta} d\ln s_l + \sum_l \frac{(1-\eta)\omega_{fl}}{\eta} d\ln\tau_{lf} - \sum_l \omega_{fl}\sum_j \gamma_{lj}m_j d\ln h_j - \sum_l \omega_{fl} b_l d\ln S_l \qquad \text{（A.3.2）}$$

In demonstration cities, government subsidies rose, $d\ln s_l \ge 0$,Based on empirical patterns, this implies the following effects:

[4] To simplify the notation, $\kappa \approx -1$

First, the energy sector's structure changes. Higher government subsidies enhance innovation incentives, as reflected by an increase in the region's intensity of investment in new energy technologies, i.e., $d\ln s_l \equiv \sum_{j\in l} d\ln h_j$.

Second, the production sector adjusts its production mode. Higher government subsidies guide firms toward clean-production mode, as evidenced by a narrowing of the fixed-cost difference between clean and non-clean production modes, $d\ln s_l = -d\ln \hat{F}_{lf}$. Combining with the threshold productivity $\varphi_l^* = \frac{1}{\Omega}(\frac{\hat{F}_{lf}}{\hat{P}_{lf}})^{\alpha}$, we have $ad\ln s_l = -d\ln \varphi_l^*$ .The proportion of firms in the clean-production mode (productivity above φ^*) is $S_l = (\frac{1}{\varphi_l^*})^z$. Therefore, the impact of higher government subsidies on the scale of clean-production firms can be written as $d\ln S_l = -zd\ln \varphi_l^* = z\alpha d\ln s_l$,Denote the probability parameter by $Z \equiv z\alpha$. It follows that $d\ln S_l = Zd\ln s_l$.

Third, friction between sectors are altered. Concentration of high-quality energy projects in demonstration regions generates heterogeneous multidimensional frictions in the energy acquisition $t_{lf} d\ln s_l \equiv d\ln \tau_{lf}$, with the sign of t_{lf} determined by the network distance between region $l$and firm f.

Taken together, the effect of government intervention on firms' emissions can be written as:

$$d\ln c_f = \underbrace{-\gamma m\sum_l \omega_{fl} d\ln s_l}_{\text{Energy structure}} \underbrace{-Z\sum_l b_l \omega_{fl} d\ln s_l}_{\text{Production mode}} \underbrace{-\frac{(1-\eta)}{\eta}\sum_l \omega_{fl}(1-t_{fl}) d\ln s_l}_{\text{Market friction}} \quad \text{（A.3.3）}$$

4. Classification

The China Tax Survey data adopts the coding system of the national standard *Classification of National Economic Industries* (GB/T 4754-2017), with one uppercase letter representing each category. In addition, the IPC patent

classification documents describe the content of patents in different sections and subclasses. Based on the patent content and *Catalogue of Green and Low-Carbon Transition Industries (2024 Edition)*, we screens green and low-carbon related technology patents in the energy sector and production sector.

Table A.1 Classification Standards of *Classification of National Economic Industries*

Industry Classification Code	Category Name	Definition	Contents
C	Manufacturing	industrial sectors where new products are formed through physical or chemical changes	Processing of agricultural and sideline foods, food manufacturing, manufacture of alcoholic beverages and beverages; textiles, apparel, leather products; wood processing, furniture manufacturing; papermaking, printing; petroleum processing, chemical industry, pharmaceutical manufacturing; rubber, plastics, non-metallic mineral products; metal smelting and processing, manufacturing of general/special-purpose equipment; manufacturing of transportation equipment such as automobiles, railways, ships, aerospace; manufacturing of electrical machinery, computers, communications and other electronic equipment; manufacturing of instruments and meters, other manufacturing
D	Production and Supply of Electricity, Heat, Gas and Water	Industries providing energy and water resources services to society	Electricity generation (thermal power, hydropower, nuclear power, wind power, etc.); electricity supply; heat production and supply; gas production and supply; water production (tap water, mineral water) and supply; sewage treatment, reclaimed water utilization
G	Transportation, Warehousing and Postal Services	Industries realizing spatial displacement of people and goods as well as storage of items	Railway transportation, road transportation (including taxis); water transportation, air transportation; pipeline transportation; loading, unloading, handling and transportation agency services; warehousing (general warehousing, cold chain warehousing, etc.); postal services (mail delivery, courier services)
E	Construction	Construction and installation activities of various buildings, structures and their auxiliary facilities	Building construction (residential buildings, commercial buildings, public buildings); civil engineering construction (roads, bridges, tunnels, water conservancy projects, etc.); building installation (installation of electrical, pipeline, ventilation and other equipment); building decoration and finishing; other construction services (project preparation, demolition, etc.)

Table A.2 IPC Classification Codes-Technical Classification of the Energy Sector

IPC Section	IPC Codes	Technology Direction/Content
E	E21 (Mining); Subclasses: E21C, E21F, E21B; Relevant: E02D	Clean mining, low-carbon upgrading, equipment energy conservation, efficient resource utilization, intelligent control
H	Core devices: H01L31, H10K30; Material: H01L21; System: H02M, H02J, H01M50	Solar cell photoelectric conversion, silicon processing/film deposition, inverters, brackets, energy storage
F	Power generation: F03 (F03D, F03B, F03G4, F03G7/05); Thermal use: F24 (F24S, F24T)	Conversion of clean energy to mechanical energy and then to electrical energy (wind power, hydropower, etc.); Direct conversion of clean energy to thermal energy (heating, industrial heat supply)
C	C01B (Non-metallic compounds), C01G/C01F (Metal compounds), C12P/C05F (Biomass energy conversion), C04B (Low-carbon materials)	Hydrogen production/storage, core energy storage material R&D, biomass conversion, carbon capture, waste recycling, low-carbon material application

Table A.3 IPC Classification Codes-Technical Classification of the Production Sector

IPC Section	IPC Codes	Technology Direction/Content
B	B09, B01D53 (emissions control); B03, B04, B09B3 (resource recycling); B01J (energy conversion); B21, B08 (energy-efficient manufacturing)	Solid waste/soil/waste gas treatment, low-energy resource recovery, hydrogen/CO_2 conversion catalysis, industrial process optimization for carbon reduction
C	C03C (energy saving); C02F, C01B39, C07B (efficiency optimization)	Low-carbon material application for energy reduction, high-efficiency treatment and catalysis for energy loss reduction
F	F02D, F01P, F04B (energy efficiency); F02G, F01K, F28D (waste heat recovery); F01N, F02M26 (emission reduction and purification)	Conventional energy efficiency optimization, energy cascade utilization, pollutant and carbon emission control in energy use
H	H01M, H01G, H02J15 (energy storage balance); H02P, H03K (energy efficiency); H01B12, H01B7 (loss reduction); H05B (low-carbon substitution); H02H7 (supporting guarantee)	Battery/capacitor energy storage, power conversion and motor control optimization, low-loss transmission, high-efficiency lighting/electrothermal substitution, battery management and protection
E	E04 (building main structure); E03, E06 (supporting system); E01, E02 (infrastructure)	Thermal insulation and low-carbon building materials, water supply and drainage circulation, door/window shading optimization, low-carbon materials and efficient operation of infrastructure

5. Market-Oriented Policy Documents

Policy documents are sourced from the Peking University Law Information Network. We employ text analysis based on large language models to extract and quantify references to market-oriented reform in local government policy documents. The relevant keywords and categories are presented below.

Table A.4 Keywords of Market-Oriented Policy Documents

Category	Keywords
Property Rights Protection System	Economic property rights, management of case-related property, rights and interests of business entities, property of business entities, cross-regional law enforcement, cross-regional jurisdiction, profit-driven law enforcement and judicial activities, enterprise property rights, personal and property safety of entrepreneurs, intellectual property rights
Fair Competition System	Fair competition, anti-monopoly, unfair competition, local protectionism, cross-regional operation and relocation of business entities
Market Access System	Market access, registration of market entities, general qualification list, market exit, regional barriers
Market Supervision and Law Enforcement	Discretion in administrative punishment, market supervision, punishment list, integrated online and offline supervision, risk monitoring, supervision and random inspection, government-enterprise communication

	mechanism
Energy Marketization	National unified electricity market system, national integrated network, oil and gas market, fair opening of infrastructure, allocation of oil and gas resources, market-oriented reform of natural gas, electricity market system, coal trading
Resource and Environmental Marketization	Resource and environmental factors, pollutant discharge rights, carbon emission rights, water use rights, energy use rights, green product certification and labeling

5. VGG-Based Recovery of Supplier–Customer Links

We use a Visual Geometry Group (VGG) convolutional neural network to recover missing supplier–customer links in the National Enterprise Tax Survey. The labeled sample is obtained by matching supplier–customer disclosures in the China Stock Market and Accounting Research Database (CSMAR) to firms in the tax survey. Each firm is represented by 32 characteristics spanning seven domains: location and industry, firm size, sales and revenue, costs and expenses, assets and liabilities, cash flow, and resource use.

For each potential firm pair, we take the outer product of the two normalized 32-element characteristic vectors, producing a 32×32 bilateral feature matrix. This representation allows the classifier to capture nonlinear interactions among firm characteristics. We estimate the VGG classifier on a training sample, evaluate its out-of-sample performance on a held-out test sample, and apply the trained network to unlabeled firm pairs in the National Enterprise Tax Survey.

We then aggregate predicted links from the firm-pair level to the firm–region level. For each firm and region, the number of predicted supplier–customer links is used to construct the firm–region trade-intensity weight in equation (20), which maps city-level policy shocks into firm-level network exposure. The VGG procedure only recovers missing network links; the identifying variation comes from the staggered rollout of the fiscal demonstration policy.