Carbon emissions regulation, input-output networks, and firm dynamics: The case of a low-carbon-zone pilot in China

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Abstract

Input-output linkages among sectors and firms are largely overlooked when assessing regulatory policies. Using a carbon emissions regulation in China as an example, we find that the regulation facilitates the transition to green technologies and reduces entry and carbon emissions in the regulated sectors with large carbon emissions. We also find unintended spillovers via the input-output network, resulting in more entry and innovation in the downstream sectors; and less entry and innovation in the upstream sectors. These facts can be rationalized by a firm-dynamics model with input-output linkages. The results of quantitative exercises are much different when taking input-output linkages into account.

JEL Classification: C15, D21, D22, E23, Q56

Keywords: carbon emissions regulation; firm dynamics; innovation; input-output networks

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1 Introduction

Understanding the macroeconomic effects of climate and carbon policy has become an important issue in recent decades (Fried, 2018; Nordhaus, 2019). In this paper, we study how a comprehensive carbon emissions regulation in China affects firm dynamics, including entry and innovation,[1] taking into consideration the general equilibrium mechanisms of spillovers in input-output networks. While the existing literature studies the transition of energy-related technology and firm dynamics under a *hypothetical* carbon tax and research subsidy (Acemoglu et al., 2016a), we are one of the first in the literature to study, both theoretically and empirically how a comprehensive and nationwide-implemented policy affects firm entry and innovation, *in a general equilibrium of the entire economy*,[2] and especially how the policy diffuses in the input-output network and affects the upstream and downstream of the treated (carbon-intensive) sectors.

Carbon emissions regulations are central to mitigating carbon emissions and, thus, play a crucial role in the policy world. Evaluating their effects on firm dynamics, which is an important engine for economic growth (Klette and Kortum, 2004), is of great interest and relevance. In addition, some challenges remain in evaluating carbon emissions regulations. First, carbon emissions regulations encompass various aspects, including regulatory, market-based, and voluntary measures. This adds an empirical challenge to examining the respective effectiveness and welfare implications of each policy measure. In this paper, we disentangle and separately quantify different aspects of a carbon emissions regulation.[3] Second, more importantly, carbon emissions regulations generally overlook the sectoral input-output linkage. The sectors with high direct carbon emissions (hereafter referred to as carbon-intensive sectors) are most heavily regulated, while part of the upstream sectors (which provide raw materials to the carbon-intensive sectors) and downstream sectors (which demand intermediate products from the carbon-intensive sectors) are not directly regulated. The transition of upstream and downstream sectors affects the transition of carbon-intensive sectors, and all three types of sectors jointly determine whether the global zero-emissions goal can be achieved.

China provides a compelling setting in which to answer these research questions. In recent years, the Chinese government started a carbon emissions regulation of low-carbon-zone pilots. The policy has four important features. First, it is a comprehensive regulation that includes various regulatory and incentive policy measures. Second, the policy regulates mainly the carbon-intensive sectors, but may unintentionally affect the entire input-output network via input-output linkages. Third, the staggered nature of the policy's implementation offers identifying variations. Fourth, the

[1] We do not focus on the effects on exit because the results on exit are subject to different possible explanations that cannot be verified. However, we report key results regarding exit in Section 5.5.

[2] The main body of the literature only concerns partial equilibrium and one or a few sectors of the economy, but we examine the entire economy, including agricultural and service sectors, taking into account general equilibrium.

[3] It is less feasible to do so using reduced-form regressions. However, we can link the response of entry to entry, production, and emissions regulation; link the response of emissions to emissions regulation; and link the response of innovation to research subsidies.

implementation of the policy does not exhibit significant regional heterogeneity. Each city has the same policy measures and the same target sectors.[4]

We start with an empirical analysis that motivates the theoretical model. Using a difference-in-difference-in-differences (DDD) specification, we first find that in the pilot cities, after the implementation of the policy and in sectors with high direct carbon emissions (hereafter referred to as carbon-intensive sectors), firm entry and carbon emissions all significantly drop. The drop in entry and carbon emissions are direct results of the entry regulation and carbon emissions regulation. In addition, research subsidies explain our finding of an increase in both zero-carbon patents and energy-efficient patent applications and a drop in non-environment-related patent applications. Additionally, we discover that firms with relatively high carbon emissions in carbon-intensive sectors respond more intensively.

Our study also shows that the effects of the low-carbon-zone pilot propagate through the demand-supply channel in input-output networks. We focus on granular three-digit sectors (472 in total) and classify the upstream (downstream) sectors of the carbon-intensive sectors into regulated ones and unregulated ones. In doing so, we can separately estimate the direct effects of the pilot policy and the indirect inter-sectoral spillover effects.[5] Specifically, we find that in pilot cities, firm entry and innovation significantly decrease in both the regulated and unregulated upstream of carbon-intensive sectors after the policy's implementation. The negative spillover effect is because, after the regulation, carbon-intensive sectors require fewer intermediate inputs produced by the upstream, leading to smaller profit margins for firms in the upstream sectors (negative demand shock).

In contrast, both the regulated and the unregulated downstream sectors experience more positive effects from the low-carbon-zone pilot, with firm entry and innovation significantly increasing. This is because the regulation leads to more innovation in carbon-intensive sectors, resulting in productivity growth and a drop in output price (positive supply shock). We document that the change in the price index of the carbon-intensive, upstream, and downstream sectors is consistent with the proposed demand-supply channel.

Note that the difference-in-difference-in-differences strategy depends on the assumption of a "stable" control group, which is the non-carbon-related sectors that are neither the upstream/downstream of the carbon-intensive sectors nor the regulated sectors with large carbon emissions. Although we have tried our best to define such sectors as those with tiny input-output linkages with the carbon-intensive sectors and are unregulated, these sectors are also indirectly affected by the treatment, since market interactions among firms in different sectors (even in non-carbon-related sectors) are always a mechanism at play. Therefore, we can only interpret the regression coefficients as the net effects of

[4]This argument is further supported by the empirical finding that the effects of the pilot policy do not exhibit strong regional heterogeneity. We also provide support using some examples in Appendix G.

[5]The effects on regulated upstream sectors capture both direct regulation effects and indirect spillover effects, and the effects on unregulated upstream sectors only capture indirect spillover effects.

the treatment on the carbon-intensive and upstream/downstream sectors ***relative to*** the non-carbon-related sectors. On the other hand, we also interpret the DDD estimates by quantifying the market spillover effects using the model, and we can show that the spillovers caused by market interactions do not quantitatively dominate our main empirical findings. [6]

The basis of our identification strategy is the staggered roll-out of the pilot across three waves of cities all with pilot-selection criteria disclosed. We directly control for criteria for pilot city selection interacted with sector-year dummies. As the determinants for pilot city selection are largely at the city-year level, we use city-year, city-sector, and sector-year fixed effects that absorb main variations in the selection criteria. It is also reassuring that balancing tests show that key outcomes of interest do not exhibit systematic differences between pilot and non-pilot cities. Event study analysis further shows parallel pre-treatment trends between the pilot and non-pilot cities. To deal with remaining selection biases that cannot be fully addressed by event study, we conduct two instrumental variable estimations, using standard Hausman-style and Bartik-style instruments constructed by neighboring cities' and national sector-level emissions. We also conduct a propensity-score matching estimation, and the results are still robust.

On the theoretical side, we build a model to rationalize the empirical findings and quantify the importance of various channels. We add input-output linkages, as in Caliendo and Parro (2015) and Shi (2021a) in a stylized firm dynamic model, as in Klette and Kortum (2004), Acemoglu et al. (2018), and Akcigit et al. (2021). Moreover, we include specific policy measures of the carbon emissions regulation in the model, including emissions fees, research subsidies, entry costs, and production regulation. To our best knowledge, this model is the first one that incorporates firm dynamics and endogenous growth, sector-level input-output linkages, carbon emissions, and policy measures ***all in one model***. The model is the minimal one that can generate theoretical predictions that are in line with the data and are further verified by numerical simulations. Since we empirically establish that cross-city spillovers are not a quantitatively salient mechanism at play, we use a model with a single location as our baseline model.[7] We estimate the model using indirect inference, in which the key parameters, including the parameters related to all four policy measures, can be identified using moments of carbon emissions, output, entry and exit, and innovation, which correspond to the policy measures one by one. The results of estimation also do not sensitively rely on the initial condition of the associated minimization problem. We validate the model by comparing model-simulated and actual-data regression coefficients and moments, and by verifying model predictions using counterfactual experiments.

We also use the model to quantify the effects of carbon emission regulation through different policy

[6] We also rule out the scenario that regional spillovers instead of inter-sectoral spillovers drive our main results through several tests.

[7] The model with multiple locations is presented in Appendix E, and the results of the quantitative exercises based on this model are similar to those of our baseline model.

measures and find they have heterogeneous effects on entry, innovation, growth, and welfare. We find that the policy has significant impacts on not only the targeted carbon-intensive sectors but also the (unregulated) upstream and downstream sectors, consistent with empirical results. The aggregate effects depend on the stringency of each regulatory measure and the strengths of input-output linkages. The welfare gains of the policy are over-estimated if one does not take the input-output linkages into consideration. However, the benefit of the policy far outweighs the cost after taking the social benefits of carbon emissions reduction into consideration, even when the input-output linkages are taken into account. We finally discuss the robustness of our results to different functional forms.

The remainder of this paper proceeds as follows. Section 2 reviews the related literature. Section 3 discusses the policy background. Section 4 describes the data. Section 5 presents the results of the descriptive empirical evidence that motivates the model. Section 6 introduces the model. Section 7 conducts the quantitative exercise. Finally, Section 8 concludes.

2 Literature Review

This section discusses the relationship between this paper and the existing literature. This paper contributes to three strands of literature. First, it speaks to the studies of firm and industry dynamics. The model of firm dynamics stems from the canonical papers of Jovanovic (1982) and Hopenhayn (1992), and from more-recent models, such as Acemoglu et al. (2018) and Akcigit et al. (2021). In the model estimation, our paper employs a simulation-based estimation technique, which is similar to that of Acemoglu et al. (2018) and Akcigit et al. (2021). There is also recent literature linking the environment and firm dynamics. Ryan (2012) and Fowlie et al. (2016) are among the first to estimate the dynamic industrial response to environmental regulation by structural estimation. Greenstone et al. (2012) studies the effects of environmental policy on firm productivity. All of the above papers on environment and firm dynamics focus only on some or all manufacturing sectors, while our analysis covers all of the economic sectors, including service sectors. This broad coverage allows us to make a theoretic contribution to the modeling strategy by adding input-output linkages to the firm-dynamics model, a la Caliendo and Parro (2015). This highlights the extent to which input-output linkages in the economy can propagate the impact of environmental regulatory shocks into spheres of the economy in which the consequences may be unintended or even detrimental. Our focus on innovation also contributes to the literature on innovation, especially the influencing factors of directional technological change (Noailly and Smeets, 2015; Acemoglu et al., 2016a).

Second, our paper contributes to the literature on environmental policies. The existing literature studies the impacts of various forms of environmental regulation (Ellison et al., 2013; Wolff, 2014; Gehrsitz, 2017; Shapiro and Walker, 2018; Keiser and Shapiro, 2019; He et al., 2020). There is also a rich literature on the unintended spillover effect of environmental regulations between overlapping policy measures (Perino et al., 2019), countries (Hsiao, 2021; Kortum and Weisbach, 2021), complementary products (Taylor, 2019), and within the ownership network (Cui and Moschini, 2020; Chen et al., 2021). Our paper differs in the following ways: First, the regulations analyzed in prior studies generally involve a single policy measure, whereas some real-world carbon emissions regulations comprise a mix of policy measures that aim to achieve a range of strategic intents (Ossenbrink et al., 2019). Our paper also develops a structural model that quantifies the impact of different policy measures. Second, the literature has paid less attention to the unforeseeable spillover of environmental regulation within the production network. Although some studies have highlighted spillover effects within specific sectors (Hansman et al., 2019; Gerarden et al., 2020), our work considers the general-equilibrium spillover effect that spans all economic sectors. Third, existing studies generally focus on the intensive margin instead of the extensive margin (firm entry). In this paper, however, we focus mainly on the effects on entry, and how those effects contribute to aggregate innovation, which corresponds to the extensive margin. Finally, existing papers studying the same policy mainly focus on the effects on emissions (Yu and Zhang, 2021; Wen et al., 2022), whereas our paper is the first one that focuses on the effects on firm dynamics and inter-sectoral spillovers.

Third, this paper broadly relates to the production network literature. Existing literature examines the role of production network in economic development (Jones, 2011a; Jones, 2011b; Baqaee and Farhi, 2020; Bigio and La'o, 2020), macroeconomic risks (Acemoglu et al., 2012; Acemoglu et al., 2016b; Acemoglu et al., 2017; Baqaee and Farhi, 2019), and industrial policies (Liu, 2019). More closely related, some studies especially emphasize the macroeconomic consequences of the interaction between firm dynamics and production networks, such as Baqaee (2018). We highlight that the ultimate welfare and growth implications depend on the effect size of each policy measure and the existence of input-output linkages. In addition, this paper also echoes the trade literature on the effects of tariff reduction on intermediate input suppliers on productivity (Amiti and Konings, 2007; Goldberg et al., 2010).

3 Background

3.1 Background of the low-carbon-zone pilots

Many cities around the world are voluntarily devising low-carbon development plans.[8] China's city-level carbon emissions regulation, compared with the above-mentioned plans, comes in a more centralized form. China's National Development and Reform Commission (NDRC) designated 82 cities as the first batch of low-carbon-zone pilots in 2010. In 2013 and 2017, 33 and 45 cities (coun-

[8]Examples include `https://www.globalcovenantofmayors.org/` (for global cities), `https://www.epa.gov/statelocalenergy` (for U.S. cities) and `https://www.env.go.jp/en/earth/cc/2050_zero_carbon_cities_in_japan.html` (for Japanese cities).

ties), respectively, were also designated low-carbon-zone pilots.[9] Figure A1 presents the geographical distribution of low-carbon-zone pilots.

The low-carbon-zone pilot program is widely considered one of the most important carbon emissions regulations in China (Zhang, 2013). The regulation also has the unique merit of incorporating many cities and multiple policy measures.[10] Cities' achievements in low-carbon development are regularly examined by the NDRC. The NDRC's evaluation reveals that the first batch of low-carbon-zone pilots cut their carbon intensity in 2012 by 9.2% relative to their 2010 level, much higher than the national average carbon intensity reduction of 6.6%. According to Figure A2 and Table A1, the low-carbon-zone pilot policy succeeded in reducing carbon emissions at the city level.

The NDRC, albeit vaguely, clarified the selection criteria for low-carbon pilots as socioeconomic conditions and representative geographical layout. The details of NDRC documents are presented in Appendix G. Although the NDRC does not have an explicit and quantifiable pilot selection rule, we show that pilot selection is correlated with key socioeconomic variables in the base year, i.e., GDP per capita and carbon emissions. The criterion is also mainly based on time-invariant variations that can be absorbed into city-sector fixed effects in the regression analysis. It is also reassuring that Table A2 shows other key socioeconomic variables of interest are not significantly different between pilot and non-pilot cities conditional on GDP per capita, population, and carbon emissions, lending support to causal identification. In the empirical analysis, we control for key socioeconomic variables in the base year to deal with endogenous pilot selection. Moreover, we control for environmental policies that happened at the same time, and the results are still robust. Event study analyses further indicate that there are no different pre-treatment trends between the pilot and non-pilot cities.

To deal with remaining selection biases that cannot be addressed by fixed effects and controls, we also exploit two strategies to address the potential selection bias, including using the instrumental variable of a standard Hausman-style and a Bartik-style IV, which strongly determines whether the city is selected as the low-carbon pilot. These robustness checks, together with the logic of IVs, will be discussed thoroughly in Section 5.2.3.

Finally, the implementation of the policy in different cities exhibits strong homogeneity. The central government requests that each city take all four policy measures, including entry regulation, production regulation, emissions regulation, and research subsidies. The specific ways of carrying out these measures are proposed in cities' low-carbon development plans with specific emissions reduction targets and paths. Moreover, the regulated sectors in major cities are also the same. Such facts of homogeneity are further supported by the empirical evidence that the effects of the low-carbon

[9] The lists of the three batches of pilots are available at China's government website: `https://www.gov.cn/zwgk/2010-08/10/content_1675733.htm` (1st batch); `https://www.ccchina.org.cn/nDetail.aspx?newsId=28162&TId=60` (2nd batch); `https://www.gov.cn/xinwen/2017-01/24/content_5162933.htm` (3rd batch).

[10] 160 cities (or lower geographical units) are designated as low-carbon pilots, covering above half of the total number of cities in China. Other carbon emission regulations generally only cover a few representative cities. The multiple policy measures used (as will be discussed in Section 3.2) allow us to quantitatively examine their respective effects.

pilot policy on firm and industry outcomes do not exhibit significant regional heterogeneity. We also provide support using some examples in Appendix G.[11]

3.2 Requirements and implementations of the low-carbon-zone pilots

After a comprehensive review of cities' low-carbon development plans,[12] we find that low-carbon cities take mainly two types of measures: Regulatory measures and incentive measures. Regulatory measures include an implicit emissions fee, preferential entry policies, and production regulation. First, firms in cities designated as low-carbon pilots face an increase in implicit emissions fees. Pilot cities propose to inventory their emissions and set binding emissions-reduction targets higher than the targets prescribed by the central government. Firms, therefore, may face regular inspection and lose fiscal support if they are recognized as super-emitting firms. Regarding preferential entry, only firms with superior low-carbon technologies can enter the market. For example, Suzhou's low-carbon pilot plan specifies pre-approval of environmental protection, in which the environmental protection department intervenes in advance in the firm's registration process and forbids projects with high carbon emissions and environmental risks. Cities also set more detailed and specific entry policies, such as building near-zero carbon emissions zones where only zero-emitting firms can open. Production restriction also plays a role in regulatory measures. Some cities put a cap on total coal consumption or carbon emissions, which is achieved by lowering the total production of carbon-intensive goods. The incentive measures mainly include preferential financing and tax for low-carbon innovations. Cities generally use local financial resources to establish special funds and offer financial support to novel low-carbon projects. Most cities spend between 3 million and 5 million yuan in fiscal expenditures, while the most supportive cities arrange 20 million yuan each year as special funds. We provide more detailed discussions in Appendix G. To summarize, the pilot includes fourfold policy measures: (1) emissions fees, (2) entry costs, (3) production regulation, and (4) research subsidies. We link these measures to empirical patterns and separately evaluate their quantitative impacts.

Sectors are targeted differently by the low-carbon-zone pilot. However, all cities mentioned in their policy documents that sectors with high direct carbon emissions (i.e., carbon-intensive sectors) and some upstream and downstream sectors are directly regulated. Cities generally explicitly mention the implementation of regulatory and incentive measures in sectors with high direct emissions. The mining and construction sectors do not generate high direct emissions but are respectively known as upstream and downstream sectors that extensively use carbon-intensive products, such as cement and steel. Some cities also stipulate regulations in mining and construction sectors by restricting mining and proposing the development of green buildings. As an example, in its low-carbon development

[11] In the regression analysis, we exclude each province from the entire sample and then run the baseline regressions. The results are similar regardless of the specific province being excluded. Such a pattern indicates that the effects of the low-carbon pilot do not exhibit strong regional heterogeneity.

[12] The details are shown in Appendix G.

plan, Zhuzhou proposed an increase in the proportion of newly constructed green buildings from 38% in 2015 to 50% in 2020. Other sectors, however, are not frequently mentioned in cities' low-carbon development plans. Therefore, while carbon-intensive sectors are most intensively regulated, we use a granular classification of three-digit sectors and classify upstream and downstream sectors into regulated and unregulated ones. Details are provided in Section 4 below.[13]

4 Data

In the empirical analysis, we compile a balanced city-sector-year panel data set using the following data sources. More details on data compilation can be found in Appendix H.

Throughout our analysis, we use three-digit sectors as our sectoral classification, encompassing 472 sectors in total.[14] We first calculate the upstreamness and downstreamness indices. Denoting intermediate input from sector i to sector j as m_{ij}, upstreamness of sector s relative to carbon-intensive sectors can be computed as $m_{s,carbon}/\sum_j m_{sj}$; downstreamness of sector s relative to carbon-intensive sectors can be computed as $m_{carbon,s}/\sum_j m_{js}$.

Based on the upstreamness and downstreamness indices, we classify all sectors into seven categories. They are (1) carbon-intensive sectors, those with high direct carbon emissions and most intensively regulated under the carbon emissions regulation [15], (2) regulated upstream sectors, those with a top 25% upstreamness index and are regulated in the pilot policy, including mining sectors of fossil fuels and metals, (3) unregulated upstream sectors, those also with a top 25% upstreamness index and are unregulated in the pilot policy, including some manufacturing and service sectors, and we use other values of the cutoff and our main results are still robust (Table C1), (4) regulated downstream sectors, those with a top 25% downstreamness index and are regulated in the pilot policy, including the construction sectors, (5) unregulated downstream sectors, those with a top 25% downstreamness index and are unregulated in the pilot policy, including some manufacturing and service sectors, (6) non-carbon related sectors, those with a bottom 10% upstreamness and downstreamness indices and few carbon emissions, and (7) other sectors that do not belong to the above six categories. Therefore, each one of the 472 sectors belongs to one and only one of the above seven categories, and the detailed classification is provided in Table C2. In most of our analysis, we exclude class (7) (other sectors) from the sample and only include one of the first five classes of sectors as the treatment group and class (6) as the control group. We in particular identify regulated and unregulated sectors separately to separate out the inter-sectoral spillover effects, which are the main interest of our analysis. We

[13]Finally, the initiation of an emissions trading system (ETS) also happened during our sample period. While ETS is a different policy from the carbon pilot policy, it can be confounding so as to bias our estimation of the effects of the pilot policy. Therefore, we also control for the implementation of ETS in a robustness check, and the results are still robust.

[14]All the main results are still robust if we use even more granular, four-digit, sectors.

[15]The carbon-intensive sectors take up around 85% of direct carbon emissions by all economic sectors in 2019.

provide detailed discussions in Section 5.3.

We get the information on pilot participation on China's National Development and Reform Commission (NDRC) website. NDRC designated 82 cities as the first batch of low-carbon-zone pilots in 2010. In 2013 and 2017, 33 and 45 cities (counties), respectively, were also designated as low-carbon-zone pilots.[16] We present the list of low-carbon-zone pilots in Table C3.

In the empirical analysis, the major data set we use is a city-sector-year (balanced) panel data set. Our main area of interest is the firm dynamics in China, especially firm entry, which are calculated using the Chinese firm registration database. This database provides registration information of all firms in China (about 20 million firms), including the location, the year of being established, the year of exit (if any), and the value of registered capital.[17] From individual registration records, we can calculate how many firms enter a specific city-sector-year cell. The details of the data compilation can be found in Appendix H. We use the total size of the registered capital and the number of all firms that register or deregister in a certain city-sector-year cell to measure entry. The summary statistics for the main outcomes are shown in Table A3.

To measure innovation, we use a database of patent applications in China. This database is provided by the China National Intellectual Property Administration. The Center for Enterprise Research (CER) at Peking University matched this database with the firm registration database, so we have information regarding the patents and trademarks that firms applied for. We aggregate the data to the city-sector-year level and calculate how many patent and trademark applications there are in a certain city-sector-year cell. Moreover, we classify the patents into green (zero-carbon) patents, energy-efficient patents, and non-environmental patents, according to the website of the International Patent Classification (IPC) Green Inventory and Dechezleprêtre et al. (2021).

In the main part of our empirical analysis, we use Y as the dependent variable, where Y is the outcome, and conduct Poisson Pseudo Maximum Likelihood and Negative Binomial estimations. As robustness checks, we also use $\log(1+Y)$, $\log(0.01+Y)$, and $arcsinh(Y)$ as the dependent variable, and conduct OLS estimation. The results are qualitatively similar.

5 Descriptive Empirical Analysis

In this section, we present and analyze empirical results. In particular, we address the challenge of causal identification and our solution in Section 5.2. We analyze how we separately identify and estimate the effects of regulation and spillovers in Section 5.3.

[16]The lists of the three batches of pilots are available at China's government website: `https://www.gov.cn/zwgk/2010-08/10/content_1675733.htm` (1st batch); `https://www.ccchina.org.cn/nDetail.aspx?newsId=28162&TId=60` (2nd batch); `https://www.gov.cn/xinwen/2017-01/24/content_5162933.htm` (3rd batch).

[17]According to Chinese Business Law, the registered capital should be proportional to the scale (and the assets) of the firm.

5.1 Baseline Empirical Analysis

The main empirical strategy used in the descriptive empirical analysis is (nonlinear) difference-in-difference-in-differences (DDD). We estimate the following specification:

$$y_{ijt} = \alpha 1\left(Pilot_{it}\right) \times 1\left(Carbon_j\right) + X_{ij,2005}\beta_{jt} + \lambda_{ij} + \lambda_{it} + \lambda_{jt} + \sigma_{ijt} \tag{1}$$

In equation (1), the regression sample only contains the "treated," or carbon-intensive sectors, and all sectors that are not related to carbon emissions regulations, i.e., sectors that are with a bottom 10% upstreamness and downstreamness indices and few carbon emissions. The categorization of sectors is defined in Section 4 and presented in Table C2. y_{ijt} represents the outcome including $Entry$ and $Patent$ for city i, sector j, and year t. In the main part of our empirical analysis, we use Y as the dependent variable, and conduct both Poisson pseudo-maximum likelihood (PPML) and negative binomial estimations.[18] $1(Pilot_{it})$ is a dummy equal to 1 if city i in year t is a low-carbon-zone; $1(Carbon_j)$ is a dummy equal to 1 if sector j is a carbon-intensive sector. $X_{ij,2005}$ is a vector of control variables including the log of the capital stock of all firms in 2005 of each city-sector cell interacted with year dummies, the log per capita GDP, log population, and log carbon emissions in 2005 of each city cell interacted with sector-year dummies, corresponding to the selection criteria of low-carbon pilots. λ_{ij} is city-sector fixed effects, λ_{it} is city-year fixed effects, and λ_{jt} is sector-year fixed effects. Standard errors are two-way clustered at the city and sector levels.

We also estimate how the carbon emissions regulation affects the upstream and downstream sectors, using the following DDD specification [19]:

$$y_{ijt} = \alpha 1\left(Pilot_{it}\right) \times 1\left(Upstream/Downstream_j\right) + X_{ij,2005}\beta_{jt} + \lambda_{ij} + \lambda_{it} + \lambda_{jt} + \sigma_{ijt}. \tag{2}$$

In equation (2), $1(Unstream/Downstream_j)$ is a dummy equal to 1 if sector j is an upstream or downstream sector of a carbon-intensive sector. Based on the calculation results of China's national input-output tables, we define sectors with top 25% upstreamness and downstreamness indexed respectively as upstream and downstream sectors, respectively.[20] Again, only non-carbon-related sectors are included as a control group when conducting regression analysis using equation (2).

The baseline results of the estimation of equation (1) are shown in Table 1. The results of

[18] As robustness checks, we conduct OLS estimations. We also use $\log(Y)$, $\log(0.01 + Y)$, and $arcsinh(Y)$ as the dependent variable and conduct OLS estimations. The results are all robust.

[19] The validity of this specification also relies on the fact that within-city economic linkages are much stronger than inter-city linkages. Using inter-city input-output tables, we find that the within-city input/output share of the carbon-intensive sectors is nearly 50% during our sample period. Table C4 further verifies that the pilot policy does not affect inter-city input-output flows.

[20] Upstreamness is defined as intermediate output share outsourced to carbon-intensive sectors and downstreamness is defined as intermediate input share from carbon-intensive sectors. The detailed categorization of pilot regions and sectors is shown in Tables C3 and C2.

OLS estimation are reported in Table A4. When we report the coefficients for 1(pilot)*1(carbon), only carbon-intensive sectors (treatment group) and non-carbon-related sectors (control group) are included in the sample.[21] PPML results in Table 1 indicate that in pilot cities, after the implementation of the policy and in carbon-intensive sectors, firm entry significantly decreased by 0.115[22] (measured by number, about 1.13% of the sample mean), or by 3.774 (measured by registered capital, about 5.87% of the sample mean).[23] The decrease in entry verifies that the policy has a component of entry regulation in carbon-intensive sectors (as discussed in Section 3). Table 1 also suggests that the low-carbon-zone pilot policy encourages innovation. The number of patent applications increased by 0.137 in pilot cities (about 6.30% of sample mean), after the implementation of the policy and in carbon-intensive sectors. We also use alternative measures, such as log(1+Y), log(0.01+Y), and arcsinh(Y), and according to Tables C5, C6, and C7, the results are qualitatively the same. Finally, we try different definitions of the control group and the treated group, using alternative cutoff values of upstreamness and downstreamness for the definition. The results reported in Table C1 are still robust.

Table 1: Baseline results

	Entry, number		Entry, capital		Patent, number	
	PPML	Negative Binomial	PPML	Negative Binomial	PPML	Negative Binomial
1(pilot)*1(carbon)	-0.115***	-0.124***	-3.774***	-5.413***	0.137***	0.148***
	(0.0203)	(0.0189)	(0.0132)	(0.369)	(0.0209)	(0.0311)
1(pilot)*1(upstream,regulated)	-0.310***	-0.244***	-4.200***	-4.997***	-0.213***	-0.188***
	(0.0336)	(0.0432)	(0.0213)	(0.331)	(0.0221)	(0.0414)
1(pilot)*1(upstream,unregulated)	-0.213***	-0.231***	-4.213***	-6.211***	-0.143***	-0.156***
	(0.0326)	(0.0441)	(0.0251)	(0.315)	(0.0205)	(0.0420)
1(pilot)*1(downstream,regulated)	0.232***	0.238***	4.660***	6.132***	0.194***	0.156***
	(0.0400)	(0.0333)	(0.0144)	(0.332)	(0.0231)	(0.0345)
1(pilot)*1(downstream,unregulated)	0.219***	0.244***	5.661***	5.890***	0.143***	0.132***
	(0.0421)	(0.0379)	(0.0152)	(0.712)	(0.0214)	(0.0368)

Notes: Marginal effects and standard errors are reported. The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Next, we examine how the effects of the low-carbon-zone pilot policy propagate in the input-output networks. Specifically, we estimate the specification of equation (2). First, we look at the effects on regulated and unregulated upstream sectors. The results are displayed in Table 1. Also, only regulated/unregulated upstream/downstream sectors (treatment group) and non-carbon-related sectors (control group) are included in the sample.[24] In the upstream of the carbon-intensive sectors, in pilot cities, after the implementation of the low-carbon-zone pilot, firm entry and innovation significantly decrease. Our interpretation centers on the unregulated upstream/downstream sectors because they are not subject to direct regulation.

[21] This is the same for all other similar tables.
[22] For all PPML and negative binomial regressions in this paper, we report the marginal effects.
[23] Table A5 also suggests that net entry also drops and the total size of the sector shrinks.
[24] This is the same for all other similar tables.

Although the low-carbon-zone pilot does not directly target the (unregulated) upstream of the carbon-intensive sectors, it still has significant impacts on them, and this can be explained by the propagation of the policy's effects through input-output linkages. As the carbon-intensive sectors are regulated, they require fewer intermediate inputs from the upstream, leading to a reduction in profits for the upstream firms. Consequently, firms in the upstream sectors are discouraged from entering the market, innovating, or using cleaner production techniques as they find it less profitable. These factors contribute to the negative effects of the low-carbon-zone pilot on entry and innovation in the upstream sectors.

Next, we look at the effects on downstream sectors. Table 1 shows after the implementation of the low-carbon-zone pilot in pilot cities, there is a significant increase in firm entry and innovation in downstream of the carbon-intensive sectors. The effects on regulated downstream sectors are also more salient than those on unregulated downstream sectors. As the carbon-intensive sectors experience more innovation, productivity growth occurs. Under the CES structure and the constant-markup pricing rule[25], the output's price decreases. Thus, firms in the downstream sectors have a larger profit margin and find it more profitable to enter the market and innovate. These findings can explain the low-carbon-zone pilot's positive effects on entry and innovation in the downstream sectors.

Note that the difference-in-difference-in-differences analysis depends on the assumption of an unaffected control group, which is the non-carbon-related sectors defined in Section 4. However, since market interactions among firms in different sectors are always a mechanism at play, the non-carbon-related sectors are also indirectly affected by the treatment. Therefore, we can only interpret the regression coefficients as the net effects of the treatment on the carbon-intensive and upstream/downstream sectors relative to the non-carbon-related sectors. On the other hand, in Section 7.3 we discuss the market spillover effects quantified by the model, and we can show that the spillovers caused by market interactions are not quantitatively dominating our main empirical findings.

Since the effects of the low-carbon-zone pilot propagate in the input-output networks, the aggregate effects (across all sectors) may differ from those on the carbon-intensive sectors only. Table A6 shows the city-level effects.[26] We can see that the effects at the aggregate city level are no longer economically or statistically significant. This may be due to the heterogeneous effects of the policy in the input-output networks.[27]

Next, we examine the effects of the low-carbon-zone pilot on the different types of patent applications. There are three types of patents: (1) energy-efficient patents (EEP), (2) zero-carbon patents (GP), and (3) non-environmental patents (NEP). The results in Table 2 show that the low-carbon-

[25] Melitz (2003) serves as an example. The model in Section 6 also employs a constant markup pricing rule.

[26] The data set used to obtain these results is a city-year panel data set, in which the outcomes are aggregated at this level.

[27] It is worth noting that Table A1 shows that city-level carbon emissions decrease after the low-carbon-zone pilot. This indicates that the policy causes a trade-off between short-term (as evidenced by city-level emissions reduction) and long-term emissions reduction (which can only be achieved by low-carbon innovation).

zone pilot significantly increases the number of environment-related patents, including both EEP and GP, while crowding out NEP. The results of OLS estimation are reported in Table A4.

Table 2: Effects on patent applications

	EEP		GP		NEP	
	PPML	Negative Binomial	PPML	Negative Binomial	PPML	Negative Binomial
1(pilot)*1(carbon)	0.323***	0.325***	0.373***	0.372***	-0.479***	-0.342***
	(0.0313)	(0.0421)	(0.0634)	(0.0313)	(0.0573)	(0.0700)
1(pilot)*1(upstream,regulated)	-0.277***	-0.345***	-0.400***	-0.459***	-0.479***	-0.312***
	(0.0414)	(0.0611)	(0.0550)	(0.0356)	(0.0223)	(0.0512)
1(pilot)*1(upstream,unregulated)	-0.157***	-0.166***	-0.122***	-0.251***	-0.145***	-0.155***
	(0.0323)	(0.0332)	(0.0256)	(0.0144)	(0.0312)	(0.0205)
1(pilot)*1(downstream,regulated)	0.284***	0.468***	0.282***	0.411***	0.425***	0.403***
	(0.0319)	(0.0631)	(0.0333)	(0.0233)	(0.0621)	(0.0358)
1(pilot)*1(downstream,unregulated)	0.119***	0.125***	0.114***	0.211***	0.199***	0.143***
	(0.0244)	(0.0267)	(0.0188)	(0.0311)	(0.0121)	(0.0122)

Notes: Marginal effects and standard errors are reported. The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. "EEP" refers to "energy-efficient patent"; "GP" refers to "zero-carbon patent"; and "NEP" refers to "non-environmental patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

We also examine the effects of the low-carbon-zone pilot on firm-level carbon emissions in Table 3. We find that the low-carbon-zone pilot is effective in reducing firm-level emissions in carbon-intensive sectors. This corresponds to the previously discussed regulatory effects on entry and green transition of innovation, corroborating that the regulation is effective. For upstream sectors, we observe an increase in firm-level emissions after the regulation. The increase in emissions could be because upstream firms are now less profitable and innovative, thus less likely to adopt clean production techniques. For downstream sectors, we find that the regulation causes an insignificant increase in firm-level direct emissions and a significant increase in firm-level sum of direct and indirect emissions. The results show that downstream firms do not face strong enough regulation to mitigate carbon emissions and the spillover effect from carbon-intensive sectors does not incentivize emissions reduction. We conduct a similar event study design as in equation (3). The outcome variable is the direct and the sum of direct and indirect emissions of carbon-intensive sectors and the upstream of carbon-intensive sectors. The results are reported in Figure A3 indicate that our findings are not driven by pre-trends.

5.2 Causal Identification

In this section, we discuss potential threats to causal identification and our solution. We begin with discussing the rules of pilot selection that shed light on the solution to endogeneity issues. We then discuss two main strategies to deal with causal identification: event study analysis and instrumental variable estimation.

Table 3: Effects on firm-level emissions

	(1)	(2)
	Direct emis.	Direct and indirect emis.
1(pilot)*1(carbon)	-602.769***	-1471.47**
	(130.65)	(386.58)
Observations	2845918	2845918
R-squared	0.708	0.643

	(1)	(2)
	Direct emis.	Direct and indirect emis.
1(pilot)*1(upstream)	847.21***	2523.04**
	(324.11)	(958.98)
Observations	2845918	2845918
R-squared	0.708	0.643
Number of city-sectors	22256	22256

	(1)	(2)
	Direct emis.	Direct and indirect emis.
1(pilot)*1(downstream)	364.97	2911.65**
	(252.43)	(746.90)
Firm FE	Y	Y
City-sector FE	Y	Y
City-year FE	Y	Y
Sector-year FE	Y	Y
Observations	2845918	2845918
R-squared	0.708	0.643
Number of city-sectors	22256	22256

Notes: The sample covers about 2,800,000 firm-year cells during 2007-2015. The sample period is limited because of the data limitation. In all columns, firm, city-sector, city-year, and sector-year fixed effects are included. * Significant at 10%, ** 5%, *** 1%. "Emis." stands for emissions. Direct emissions (10^4 kg) take into account coal and oil consumption, and the emission factors of coal and oil are taken as 1.89 kgCO_2/kg and 3.02 kg CO_2/kg, respectively. Indirect emissions include emissions from electricity consumption, with a corresponding emission factor of 0.75 kgCO_2/kWh. Data on firm-level energy consumption are retrieved from the Chinese State Administration of Tax. Standard errors are two-way clustered at the city and sector levels.

5.2.1 (Endogenous) Pilot Selection Rules

As per the Background section, the pilot selection depends on key (but unclarified) socioeconomic conditions. Table A7 shows pilot selection is indeed related to pre-policy levels of key socioeconomic factors, such as economic prosperity and carbon emissions. While controlling city-sector fixed effects absorb the time-invariant variations related to the selection rules, we also conduct a series of balancing tests that compare several outcomes of interest in pilot and non-pilot cities, **conditional on these factors**. We do not find systematic differences between the non-pilot cities and the pilot cities (Table A2). Along this thread of reasoning, we conduct a propensity score matching estimation based on these socioeconomic factors, and the results reported in Table A8 are still robust.

Another concern is other carbon emission regulations during the same period drive our results. This is unlikely to be the case, as the low-carbon-zone pilot policy covers above half of the total number of cities in China, which is a much higher coverage compared to other environment-related pilot policies during the same period. Nevertheless, we control for the most important contemporaneous carbon emissions regulations, i.e., the carbon reduction goals in the twelve-five (2011-2015) and thirteen-five (2016-2020) periods, and the implementation of the carbon trading system. Reassuringly, the results in Table A9 indicate that adding these additional controls does not alter the main findings.

5.2.2 Event Study Analysis

We then move to testify pre-treatment parallel trends for the treatment group (carbon-intensive, upstream, or downstream sectors in pilot cities) and the control group. We exploit the event study using the following specification:

$$y_{ijt} = \sum_{\tau \neq -1} \alpha_\tau 1\left(Pilot_i\right) \times 1(t=\tau) \times 1\left(Carbon_j/Upstream_j/Downstream_j\right) + X_{ij,2005}\beta_{jt} + \lambda_{ij} + \lambda_{it} + \lambda_{jt} + \sigma_{ijt}. \tag{3}$$

In equation (3), we decompose the dummy $1(Pilot_{it})$ into the interactions of $1\left(Pilot_i\right)$ and $1(t = \tau)$. We use OLS estimations with the actual count of the outcomes being the dependent variable. The rest of the specification is the same as the baseline specification.

The results of the event study for different outcomes are shown in Figures A4-A8. The figure shows that the significant effects of the treatment are not driven by pre-treatment trends. Entry responds relatively more immediately to the implementation of the policy, whereas innovation responds gradually. This is because new entry is an immediate response to changes in incentives and the economic environment, whereas innovation is a slow process whose changes take time. Moreover, we also conduct the event study analysis according to the method proposed in De Chaisemartin and d'Haultfoeuille (2020) and Borusyak et al. (2022). According to Figures A9-A13, the results are still robust.

The results of the event study indicate that the identification assumption of DDD holds. In addition, since the selection criteria include variations that are either absorbed into fixed effects or can be controlled for by including key socioeconomic factors, our baseline regression with such fixed effects and control variables can address a large part of the endogeneity issue. The only part left unsolved is only one possibility: the endogenous pilot selection results in time-variant (and non-linear) differences between the pilot and non-pilot cities that cannot be fully addressed by event study analyses. To deal with this, we design two sets of instrumental variable estimation.

5.2.3 IV Estimation

Controlling for determinants of pilot selection and event study analyses rule out the scenario in which our baseline results are driven by time-invariant systematic differences in the baseline characteristics and pre-treatment trends between pilot and non-pilot cities. However, a remaining concern is that our results can also be driven by endogenous selection that results in time-variant (often non-linear) differences between pilot and non-pilot cities. To deal with this case, we design two IV estimation approaches. The instrumented pilot selection, interacted with the time dummy $1(Post_{it})$, addresses the issue of time-variant (often non-linear) differences between pilot and non-pilot cities.

Local carbon emissions (growth) are key determinants of pilot selection, as shown by Table A7 and Appendix G. We construct instrumental variables using local carbon emissions. We adopt two standard instrumental variable strategies commonly used in the empirical literature: a Hausman-style instrument and a Bartik-style instrument. The Hausman-style instrument is constructed by calculating the weighted average of carbon emissions in neighboring cities in 2005, the starting year of our sample. It exploits the cross-sectional variations of carbon emissions that are orthogonal to other economic outcomes of interest. This is, in particular, this case, since we find that carbon emissions regulation does not spill over to affect the outcomes of neighboring cities, validating the exogeneity condition. However, the relative ranking of carbon emissions among cities in the same province is a strong predictor for pilot selection. This argument is further validated by a large first-stage F-statistic, thus validating the relevance condition. The Bartik-style instrument is constructed by multiplying the city-level industrial mix and the sector-level growth of carbon emissions in China during 2000-2005. The Bartik-style instrument is valid because it predicts local carbon emissions (growth) exploiting information on carbon emissions of national trends, which are not affected by local economic activities. Thus, the shift of the Bartik IV validates the exogeneity condition. It is also a strong predictor for pilot selection, since past emissions performance strongly determines the selection. The details of the IV construction are relegated to Appendix B2. We estimate the following specification:

$$y_{ijt} = \alpha 1(\widehat{Pilot_i}) \times 1\,(Carbon_j) \times 1(Post_{it}) + \lambda_{ij} + \lambda_{it} + \lambda_{jt} + \sigma_{ijt} \tag{4}$$

In equation (4), $1(\widehat{Pilot_i})$ is the predicted value of the selection of the pilot cities. $1(Post_{it})$ is the time dummy on whether city i has implemented the low-carbon-zone pilot. The first-stage regression is as follows:

$$1(Pilot_i) = \delta IV_i + v_i, \tag{5}$$

where $1(Pilot_i)$ is the instrumented variable, and IV_i is the instrumental variable: a Hausman-style instrument and a Bartik-style instrument. These two instruments are quite standard in the empirical literature. The details of the construction of these two instruments can be found in Appendix B2. The results of the Hausman-IV estimation are reported in Table C8, and the results of the Bartik-IV estimation are reported in Table C9. We also report the first-stage F-statistic in the table notes, and they are both greater than 10. The results are both qualitatively similar to the baseline results. We also conduct event study analyses with IV-2SLS. The results reported in Figures C1-C5 are both qualitatively and quantitatively robust.

5.3 Separating Direct Regulation Effects and Inter-sector Spillover Effects

The coefficients for regulated and unregulated upstream/downstream sectors reported in Table 1 help us separate the direct regulation effects from the inter-sectoral spillover effects which are the main interest of our analysis. We classify the upstream sector into two categories: sectors that are subject to direct regulation, such as the mining sectors of fossil fuels and metals, and sectors that are not, such as some service sectors. These sectors are all the upstream sectors of the carbon-intensive sectors. Thus, using this detailed sectoral classification, we can separately estimate the effects of the pilot policy on upstream and downstream sectors.

As an alternative measure of upstreamness and downstreamness, we use the continuous input/output share, for which each sector can be somewhat upstream and downstream of carbon-intensive sectors, as long as the associated input/output share is strictly positive and the sectors are unregulated. Using such a continuous measure, we rerun the baseline specification (2), and report the results in Table A10. Again, only non-carbon-related sectors and the unregulated upstream/downstream sectors are included in the sample, for comparison. The sign of the interaction terms is exactly the same as that in regressions in which the upstreamness and downstreamness are measured using a dummy variable. Then, we examine whether the effects attenuate for higher-order upstream and downstream sectors. Using the higher-order power of the input-output weight matrix to measure higher-order upstreamness and downstreamness, we find in Table A11 that the effects are smaller and finally become statistically insignificant as the order of upstreamness/downstreamness increases. Thus, the effects attenuate for higher-order upstream and downstream sectors. Such results also indicate the existence of indirect spillover effects, since they decay as the distance between upstream or downstream sectors and the carbon-intensive sectors is larger.

Finally, we estimate inter-sectoral spillover effects using a spatial autoregressive model, as in Lee and Yu (2010). The details of the econometric specification are discussed in Appendix B1. We find that, in Table A12, the outcomes of the carbon-intensive sectors are strongly and positively correlated with those of the upstream and downstream sectors. At the same time, we also find (very small) inter-city regional spillovers with this specification, but the magnitude is smaller than that of the inter-sectoral spillovers.

5.4 Accounting for Spatial Spillovers

In the Chinese economy with labor mobility restrictions and local protectionism, there are substantial frictions for labor and capital that dampen spatial spillovers of economic policies. However, that said, we also rule out the case that our main results are driven by spatial spillovers. Spatial spillovers may lead to a comovement of outcome variables and thus, spurious correlations. To meet this end, we control for several spatial lag variables. To be more specific, we control for the lag of spatial lags of sectoral size and treatment status, where the spatial weights are the inverse of the distance. According to the results in Table A13, the results are robust with respect to considering such regional (and temporal) spillover effects, which are captured by spatial (and temporal) lags. We also estimate the effects of neighbors' policy status conditional on the city's own policy status. According to the results in Table A14, the policy status of neighboring cities does not significantly affect the city's own outcomes. Table A15 further indicates that there is no carbon leakage across cities within the same province. Moreover, we examine whether the pilot policy changes the structure of inter-regional input-output linkages. Regressing the cross-city input/output share with the pilot dummy yields null results, as Table C4 suggests. Thus, regional spillovers or cross-regional influences are not a relevant mechanism at play. Furthermore, we estimate the effects of the pilot policy on intercity migration flows, freight transport flows (in carbon-intensive, upstream, and downstream sectors), and investment flows (also in carbon-intensive, upstream, and downstream sectors). According to the results reported in Table C10, we find null effects of the policy on spatial linkages. Since regional spillover mainly takes effect via these spatial linkages, such results point to the conclusion that regional spillover effects may not be a significant mechanism at play.

According to the related policy documents, we do not find discernible evidence that the implementation of such a pilot policy needs cross-city or even cross-province cooperation and coordination. Moreover, as Tables G2 and G3 indicate, we cannot find evidence that supports the fact that the pilot policy exerts spatial spillover effects on housing prices and other outcomes of neighboring cities. Finally, as the results of spatial autoregressive estimation suggest in Table A12, the regional spillovers are much weaker than intercity spillovers.

5.5 Effects on Exit

The effects on exit are reported in Table A16. The sign of the coefficient is the same as the counterpart of the effect on entry. For example, both the effects on entry and exit in the carbon-intensive sector are negative. One plausible explanation is that less entry leads to less creative destruction and market turnover, as Shi (2021b) and Barwick et al. (2022) suggest. However, we are unable to provide further evidence to support this explanation, and we are unable to rule out other explanations such as the response of the market structure (measured by markup distribution), and, thus, the effects on exit are not the focus of this paper.

5.6 Alternative Specifications

Next, we include all sectors, including carbon-intensive, upstream, downstream, and non-carbon-intensive sectors in the regression sample, stack the data to the city-year level, and calculate the respective outcomes that consist of specific sectors. We estimate a specification as follows:

$$y_{it} = \alpha 1(Pilot_{it}) + X_{it}\beta + \lambda_i + \lambda_t + \sigma_{it}, \tag{6}$$

where y_{it} is the outcome at the city-year level, $1(Pilot_{it})$ is the treatment variable, and λ_i and λ_t are city and year fixed effects. The results are shown in Table A17. We also conduct several event-study analyses based on equation 7, and the results presented in Figures A14-A16. All the results indicate that the difference-in-differences estimates are consistent and not biased due to the unobserved pre-treatment trends.

$$y_{it} = \sum_{\tau \neq -1} \alpha_\tau 1(Pilot_i) \times 1(t = \tau) + X_{it}\beta + \lambda_i + \lambda_t + \sigma_{it}, \tag{7}$$

5.7 Documenting price index changes in production networks

We provide primitive evidence to document the mechanism of demand/supply change through the input-output linkages by estimating the following specification exploiting a difference-in-differences strategy:

$$Target/Upstream/DownstreamPrice_{it} = \alpha Post_{it} + X_{it}\beta + \lambda_i + \lambda_t + u_{it}, \tag{8}$$

where the dependent variable is the price index of the carbon-intensive/upstream/downstream sector, which is obtained by establishing the price deflator for each city-sector-year cell and then calculating a weighted average,[28] where the weight is the associated input/output share; $Post_{it}$ is an indicator variable of whether city i has implemented the low-carbon pilot policy in year t; X_{it} is a vector of controls including log per capita GDP and log population; λ_i is city fixed effects; λ_t is year fixed effects; u_{it} is the error term. We cluster standard errors at the city level.

The price deflator of each city-sector-year cell is constructed using China Statistical Yearbooks and China Price Yearbooks. Due to data availability, we cannot obtain detailed city-sector-year-level price information. We construct the price index as the product of the price deflator at the city level (for all sectors) and sector level (for all cities). We also try different ways to construct the price index, such as raising the deflator at the city and sector level to a certain power that adds up to one (a constant return to scale Cobb-Douglas combination, $CityPrice^a SectorPrice^{1-a}$). We can show that different ways of constructing the price index produce consistent results.

We report the results in Table 4. The implementation of the low-carbon pilot significantly reduces the price index of the carbon-intensive (dependent variable in column (1)), upstream (dependent variable in column (2)), and downstream sectors (dependent variable in column (3)). Such results are consistent with the model prediction illustrated by Figure 1. Thus, we verify that the demand/supply

[28] The formula for calculation is $TargetPrice_{it} = \sum_j Carbon_j \times SectorPrice_{ijt}$; $UpstreamPrice_{it} = \sum_j Upstreamness_j \times SectorPrice_{ijt}$; and $DownstreamPrice_{it} = \sum_j Downstreamness_j \times SectorPrice_{ijt}$.

change due to the low-carbon pilot is a mechanism at play.

Table 4: Effects on price indices

	(1)	(2)	(3)
		log(Pirce Index)	
	Carbon-intensive	Upstream	Downstream
1(Pilot)	-0.00920***	-0.0396***	-0.0204***
	(0.00284)	(0.00209)	(0.00173)
City FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
Prov FE*Year FE	Y	Y	Y
Observations	4,425	4,425	4,425
R-squared	0.974	0.987	0.987
Number of cities	295	295	295

Notes: The sample covers 295 cities during 2005-2019. In all regressions city and year fixed effects are included. Controls include the log per capita real GDP, and the log population of the cities. We cluster the standard error at the city level. * Significant at 10%, ** 5%, *** 1%.

5.8 Further Empirical Analyses

In this section, we conduct a series of further empirical analyses. We first explore the heterogeneous effects in firm size. The results are presented in Table A18. The increase in the patent applications for EEP and GP is driven mainly by large firms, whose registered capital is in the top 10th percentile. Such results are consistent with the policy background of subsidizing green innovation at firms capable of launching low-carbon projects, which are mainly large firms. We then look at the heterogeneous effects with respect to carbon emission intensity. We calculate firm entry and patent applications in different city-year cells for firms whose carbon emission intensity is higher or lower than the sample median, and estimate the effects of the low-carbon-zone pilot on these outcomes. Results in Table A19 indicate that the effects are more pronounced for firms in carbon-intensive sectors with a higher emission intensity. Such results are consistent with the goal of the policy, which targets firms with higher emission intensity. For firms with high and low emission intensities in upstream (downstream) sectors, the effects are equally pronounced. This result reassuringly indicates that the effects in upstream and downstream sectors are caused by input-output networks, instead of by direct regulation.

To sum up, our results link the response of entry to entry, production, and emissions regulation; link the response of emissions to emissions regulation; and link the response of innovation to research subsidies. In the model and quantitative analysis below, we separately quantify the effects of entry costs, emissions fees, production regulation, and research subsidies.

6 Model

The model is a multisector version of Acemoglu et al. (2018)'s model, with input-output linkages, as in Caliendo and Parro (2015). We use the model because it is the minimum one that contains

(1) sector-level input-output linkages, (2) firm dynamics (entry, exit, and productivity dynamics), (3) green and non-green innovation, and (4) carbon emissions.[29] To our best knowledge, this model is the first one that incorporates firm dynamics and endogenous growth, sector-level input-output linkages, carbon emissions, and policy measures ***all in one model***. The model is the minimal one that can generate theoretical predictions that are consistent with the empirical findings, and that can be used to quantify the effects of the carbon emissions regulation. For the baseline case, we use a model with a single location. We do so because we find that (1) the regulation does not affect spatial linkages and (2) the regulation does not exhibit strong spatial spillover effects. However, we indeed build a model with multiple locations in Appendix E. The qualitative and quantitative results using the model are all similar to those with the model of a single location. We also compare the baseline model with the one without sectoral input-output linkages in Appendix D. We provide proof and derivations of some theoretical results in Appendix F.

Time is continuous. Representative households have CRRA preference: $U = \int_0^\infty \exp(-\rho t)\frac{C(t)^{1-\gamma}}{1-\gamma}dt$. There are three sectors: carbon-intensive sector (indexed by (1)); upstream of the carbon-intensive sector (indexed by (2)); and downstream of the carbon-intensive sector (indexed by (3)). Each firm can only produce and innovate in one sector. The upstream and downstream sectors in the model correspond to the unregulated ones in the empirical analysis. Additional inclusion of unregulated upstream and downstream sectors does not alter the main qualitative and quantitative results, but significantly raises the computational burden and makes many analyses infeasible.[30] For ease of exposition, we may omit the sector subscripts when there is no confusion. Final goods $C(t) = C_1(t)^{\alpha_1}C_2(t)^{\alpha_2}C_3(t)^{1-\alpha_1-\alpha_2}$, where $C_i(t)$ is the composite intermediate goods in sector i. α_1 and α_2 are consumption shares, which are calibrated in the next section. Standard derivation yields the Euler equation: $\frac{\dot{C}}{C} = \frac{r-\rho}{\gamma}$.

There are two types of labor, skilled labor l_s and unskilled labor l_u. Skilled labor is used for innovation (h) and product-line maintenance (ϕ), while unskilled labor is used for production (l_{uP}) and emissions reduction (l_{uR}). The supply of skilled and unskilled labor is inelastic. The measure of skilled labor is l_s, and the measure of unskilled labor is 1. The wages of skilled and unskilled labor are w_s and w_u, respectively.

A continuum of intermediate goods is produced in sector i, with the production function:

$$q_i(\omega) = z_i(\omega) l_{uP}^{\beta_i} m_{i1}^{\beta_{i1}(1-\beta_i)} m_{i2}^{\beta_{i2}(1-\beta_i)} m_{i3}^{(1-\beta_{i1}-\beta_{i2})(1-\beta_i)} \tag{9}$$

where $z_i(\omega)$ is the leading-edge productivity draw for ω, which is firm- and sector-specific; l_{uP} is the unskilled labor input, which is both firm- and sector-specific; and m_{ij} is the composite intermediate

[29] Ideally, we can also use other models, such as Akcigit et al. (2021), which are almost homomorphic. Alternative models do not change any theoretical insights, but may change the results of quantitative analysis. However, the earlier generation of firm dynamics models, including Hopenhayn (1992) and even Klette and Kortum (2004), cannot satisfy all modeling requirements.

[30] The computational burden increases significantly with the number of sectors.

goods used to produce ω, which is both firm- and sector-specific. β_{ij} measures the structure of the input-output network, which is calibrated in the next section. Although from equation (9), all sectors use the output of other sectors as inputs, the downstreamness and upstreamness can still be manifested by the magnitude of β_{ij}.

The intermediate goods producers can add one more green product (patent)[31] by hiring h skilled workers at the flow rate $X_G = (1+\tau_1)^\eta \theta^\eta n_G^\eta h^{1-\eta}$, where τ_1 is the innovation subsidy (that exists for all three sectors),[32] and $\eta \in (0,1)$ and n_G is the number of green patents the firm already has.[33] Here we suppress the sector subscripts. Each firm can only innovate and add patents in the same sector that it belongs to. The intermediate goods producers can also add one more non-green product (patent) by hiring h skilled workers at the flow rate $X_{NG} = \theta^\eta n_{NG}^\eta h^{1-\eta}$, where $\eta \in (0,1)$ and n_{NG} are the number of non-green patents the firm already has. θ is the innovation capacity. The cost function of R&D for a green patent is

$$C_G(x_G, n_G, \theta) = w_s n_G x_G^{\frac{1}{1-\eta}} \theta^{-\frac{\eta}{1-\eta}} (1+\tau_1)^{-\frac{\eta}{1-\eta}} \equiv w_s n_G (1+\tau_1)^{-\frac{\eta}{1-\eta}} G(x_G, \theta) \tag{10}$$

where $x_G = X_G / n_G$ is the innovation intensity. The cost function of R&D for non-green patents is

$$C_{NG}(x_{NG}, n_{NG}, \theta) = w_s n_{NG} x_{NG}^{\frac{1}{1-\eta}} \theta^{-\frac{\eta}{1-\eta}} \equiv w_s n_{NG} G(x_{NG}, \theta) \tag{11}$$

We assume that the operation of each product requires $\phi > 0$ units of skilled labor. We also assume that research does not have any direction across all product lines, which means that firms do not know ex ante the particular product line on which they will innovate. This results in the fact that their expected return to R&D is the expected value across all product lines. When a firm innovates over a product line ω, it increases the productivity of the product line by $\Delta \bar{z}$, where $\bar{z} = \int_0^1 z(\omega) d\omega$. That is, $z(t+) = z + \Delta \bar{z}$. Here we suppress the subscripts for the sector and the firm. As in other firm-dynamics models (Klette and Kortum, 2004; Acemoglu et al., 2018; Akcigit et al., 2021), in this model, a product is equivalent to a patent that grants technological access to produce it. The firm with the improved technology in product line ω takes over this product line, but, the firm that previously had the leading-edge technology might still compete if the current owner tries to set a very high price.[34] Here we also suppress sector subscripts.

There is a unit measure of potential entrants. Each entrant has access to an R&D technology $G(x^{entry}, \theta_E)$. Thus, an entrant wishing to achieve an innovation rate of x^{entry} hires skilled labor of

[31] The green patent here consists of both green patents (GP) and energy efficient patents (EEP) in the empirical analysis.

[32] Here subscript "1" does not represent a sector but one type of policy instrument. It works the same for other τ's.

[33] When estimating the model, the number of green patents equals the sum of zero-carbon and energy-efficient patents.

[34] Same as Acemoglu et al. (2018), assume that there is a two-stage pricing game between any firm that wishes to supply a product $\omega \in [0,1]$, whereby each firm first has to enter and pay a small cost $\epsilon > 0$, and then all firms that have entered simultaneously set prices.

$h^{entry} = (1+\tau_2)G(x^{entry}, \theta_E)$, where τ_2 is the intensity of entry regulation for the carbon-intensive and the upstream and downstream of carbon-intensive sectors. Here we omit the subscript for the sector. This specification implies that a potential entrant has access to the same R&D technology as an incumbent with innovative capacity θ_E and a single active product would have had. Following a successful innovation, the entrant improves the productivity of a randomly chosen product line by $\Delta\bar{z}$. This description implies the following optimization problem for entrants:

$$\max_{x^{entry}\geq 0}\{x^{entry}EV^{entry}(z+\Delta\bar{z},\theta) - w_s(1+\tau_2)G(x^{entry},\theta_E)\}. \tag{12}$$

Same as a standard firm dynamics model, there exist three causes for exit (of products and firms): (1) There is an exogenous negative destructive shock at the rate $\varphi > 0$, which leads to firm exit and makes it shut down all its product lines. (2) There will be creative destruction due to innovation by other firms replacing the leading-edge technology in a particular product line. (3) There will be so-called "endogenous obsolescence," which means that firms will voluntarily shut down some product lines because they are no longer sufficiently profitable relative to the fixed cost of operation.

Firms do not differ in terms of their innovative capacities. Upon successful entry, each firm has its fixed type θ. Each firm is also subject to an exogenous destructive shock at the rate $\varphi > 0$. Once a firm is hit by this shock, its value declines to zero and it exits the economy.

Assume that only the producers of intermediate goods in the carbon-intensive sector emit CO_2. The emission function is $E(q, l_{uR}) = \lambda_1 q \times (\frac{q}{l_{uR}})^{\lambda_2}$, where $\lambda_1 > 0$, $\lambda_2 > 0$, and q is the amount of goods produced, and l_{uR} is the unskilled labor used to reduce emissions. The setting of functional form is constructed in pursuit of simplicity and model tractability. The flow cost of carbon emissions is $\tau_0 E(q, l_{uR})$, where τ_0 is the unit cost of carbon emissions. Here we also suppress sector subscripts. In the quantitative analysis, we also try different functional forms of the emissions function, and the theoretical predictions still hold, and the quantitative results remain robust.

We assume that firms and households are not directly affected by the total amount of carbon emissions since they only take effect in the very long run. We only take the social benefits of emissions reduction into account when conducting welfare analysis.

The static profit-maximization problem of intermediate producers in the carbon-intensive sector is:

$$\max_{p_1,l_{uR},l_{uP}} p_1q_1 - w_u(l_{uR}+l_{uP}) - m_{11}P_1 - m_{12}P_2 - m_{13}P_3 - \tau_0\lambda_1q_1 \times (\frac{q_1}{l_{uR}})^{\lambda_2}, \tag{13}$$

subject to $q_1 = (\frac{p_1}{(1-\tau_3)P_1})^{-\sigma_1}Q_1$. $\tau_3 > 0$ implies that the production of carbon-intensive composite intermediate goods is regulated. The static profit-maximization problem of intermediate producers in the upstream or downstream of the carbon-intensive sector is:

$$\max_{l_{uP}} p_iq_i - w_ul_{uP} - m_{i1}P_1 - m_{i2}P_2 - m_{i3}P_3, \tag{14}$$

subject to $q_i = (\frac{p_i}{P_i})^{-\sigma_i} Q_i$ $(i = 2, 3)$. Here $P_i = [\int p_i^{1-\sigma^i} d\omega]^{\frac{1}{1-\sigma_i}}$.

In sum, the model fully captures the four policy measures of the carbon emissions regulation, by four parameters: τ_0, τ_1, τ_2, and τ_3. First, the carbon emission regulation raises the implicit emissions fee, and this is reflected in τ_0. Second, the carbon emission regulation offers research subsidies and encourages green innovation, and this is reflected in τ_1. Third, the carbon emission regulation increases the entry cost in carbon-intensive sectors (by requesting firms to purchase more emissions reduction equipment upon entry), and this is reflected in τ_2. Finally, the policy increases the cost of producing carbon-intensive products, and this production regulation is reflected in τ_3. These parameters fully capture all forms of incentive and regulatory measures in the pilot policy. Although there might be a huge variety of actual forms of policy implementation, these will all fall into one or more categories described by these τ's.

We further define the relative productivity by $\hat{z} = \frac{z}{w_u}$, define the aggregate productivity in sector i as $Z_i = [\int z(\omega)^{\sigma_i - 1} d\omega]^{\frac{1}{\sigma_i - 1}}$, denote the variable X normalized by Z by $\tilde{X}$, and let μ denote the endogenous average creative destruction rate. The stationary value function, V, is

$$\begin{aligned} r\tilde{V}(\hat{PD}) = &\max\{0, \max_{x \geq 0}[\sum_{\hat{z} \in \hat{PD}} [\tilde{\pi}(\hat{z}) - w_s \phi \\ &+ \mu[\tilde{V}(\hat{PD} - \hat{z}) - \tilde{V}(\hat{PD})] + \frac{\partial \tilde{V}(\hat{PD})}{\partial \hat{z}} \frac{\partial \hat{z}}{\partial w_u} \frac{\partial w_u}{\partial t}]] \\ &- n_{NG} \tilde{w}_s G(x_{NG}, \theta) - w_s n_G (1 + \tau_1)^{-\frac{\eta}{1-\eta}} G(x_G, \theta) \\ &+ n_G x_G [E\tilde{V}(\hat{PD} + \{\hat{z} + \Delta\bar{z}\}) - \tilde{V}(\hat{PD})] \\ &+ n_{NG} x_{NG} [E\tilde{V}(\hat{PD} + \{\hat{z} + \Delta\bar{z}\}) - \tilde{V}(\hat{PD})] \\ &+ \varphi(0 - \tilde{V}(\hat{PD}))\}. \end{aligned} \tag{15}$$

The first two lines (inside the summation) include the instantaneous operating profits, minus the fixed costs of operation, plus the change in firm value if any of its products get replaced by another firm through creative destruction at the rate μ, plus the change in firm value due to the increase in the economy-wide wage. This last term accounts for the fact that, as the wage rate increases, the relative productivity of each of the product lines that the firm operates in declines. The third line subtracts the R&D expenditure. The fourth and fifth line expresses the change in firm value when the firm is successful with its R&D investment at the rate x_G and x_{NG}. The last line shows the change in value when the firm has to exit due to an exogenous destructive shock at the rate φ.

The shares of product lines, active and inactive, are Φ and Φ^{NP}, respectively, where $\Phi + \Phi^{NP} = 1$. This condition holds for all three sectors. Unskilled labor market clearing is: $\sum_{i=1}^{3} \int l_{uP,i}(\omega) d\omega + \int l_{uR}(\omega) d\omega = 1$. Skilled labor market clearing is: $\sum_{i=1}^{3} [G(x_i^{entry}, \theta_E) + \Phi[h(w_s) + \phi]] = l_s$. Final goods market clearing is: $Y = C$. Composite intermediate goods market clearing is $Q_i = C_i + \sum_{j=1}^{3} m_{ij}$. The budget constraint of the household is $C(t) + \dot{A}(t) = rA(t) + w_s(t) l_s + w_u(t) + Tr(t)$, where $Tr(t)$

is the lump-sum transfer to the household.

Definition 1. *A stationary competitive equilibrium consists of a tuple*

$$\{\{l_{uR,i}, l_{uP,i}, \Phi_i, \Phi_i^{NP}, x_i, x_i^{entry}, h_i, \tilde{V}_i, \hat{PD}_i, \{z_i(\omega)\},$$
$$\{m_{ij}\}_{j=1}^{3}, P_i, Q_i\}_{i=1}^{3}, \mu, w_s, w_u, r\},$$

such that: (1) intermediate goods producers' profit-maximization problem is solved; (2) firms' value function takes the form of Equation 15; (3) the optimal R&D policy derived below is satisfied for firms; (4) the optimal entry policy derived below is satisfied; (5) labor market and goods markets clearing are satisfied; (6) evolution of productivity follows the below form; (7) the sum of the share of product lines equals 1; and (8) Euler equation is satisfied.

The low-carbon-zone pilot policy can be understood as an increase in $\tau_0, \tau_1, \tau_2, \tau_3$. That is, firms in the carbon-intensive sector have higher emission fee, entry costs, production regulation, and research subsidies. The model has the following empirical predictions, which are all verified by numerical simulations under values of calibrated of parameters (see Tables 5, 6, and A20). For example, Table A20 shows the changes in price indices and equilibrium quantities that are consistent with the implications of the following two predictions.

Prediction 1. *Under more stringent carbon emissions regulation, in the carbon-intensive sector, firm entry decreases, and green innovation increases.*

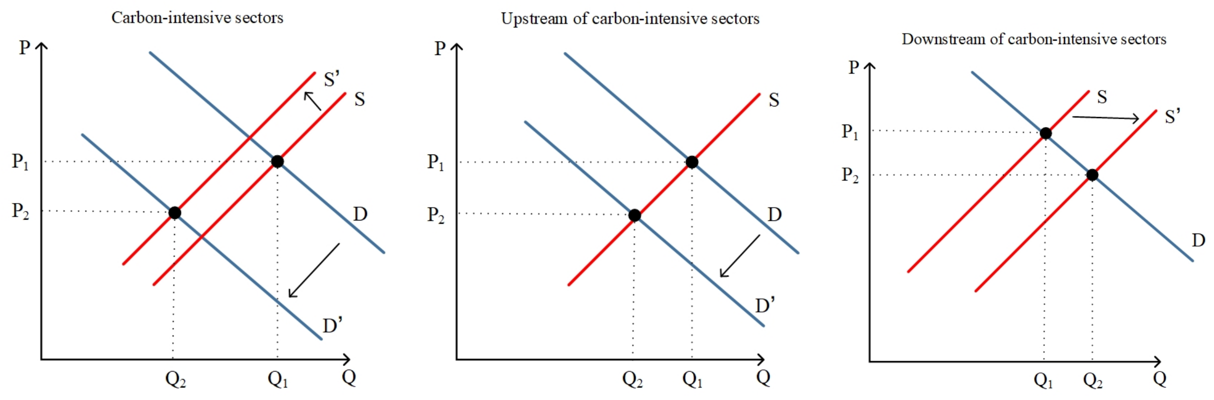
This prediction is derived from the fact that firms in the carbon-intensive sectors have higher emission fees, entry costs, production regulation, and research subsidies. This prediction is also verified by several policy experiments presented below. Again, this prediction, and the predictions below, only hold under some specific values of parameters.

Prediction 2. *There is more entry and innovation in the downstream sector and less entry and innovation in the upstream sector (if both the price and quantity of the intermediate goods in the carbon-intensive sector drop).*

Since the carbon-intensive sectors are regulated, they need fewer intermediate inputs produced by the upstream. As a result, firms in the upstream sectors have a smaller profit margin and find it less profitable to enter the market and innovate. This explains the negative effects of the low-carbon-zone pilot on entry and innovation in the upstream sectors. In addition, since there is more innovation in the carbon-intensive sectors, there is productivity growth in the carbon-intensive sectors. As a result, under the constant-markup pricing rule, the price of the output drops. Therefore, firms in the downstream sectors have a larger profit margin and find it more profitable to enter the market and innovate. This explains the positive effects of the low-carbon-zone pilot on entry and innovation in the downstream sectors.

How the effects of the low-carbon-zone pilot propagate in the input-output networks is shown in Figure 1, and is further validated in Table A20, which shows the changes in price indices and production quantities of Figure 1. Under the emissions regulation, the supply curve of carbon-intensive sectors shifts left. The demand curve also shifts left because the carbon-intensive sectors' output must be sold subject to a wedge. If the left shift of the demand curve is greater than that of the supply curve, decreases in both sectoral size and price are achieved in carbon-intensive sectors. As carbon-intensive sectors shrink, upstream sectors face a decrease in their output demand, shifting the demand curve to the left. Downstream sectors face a decrease in the input price of goods from carbon-intensive sectors, shifting the supply curve to the right.

Figure 1: The mechanisms of policy diffusion



(a) (b) (c)

Notes: These figures depict how the effects of the low-carbon-zone pilot propagate in the input-output networks via affecting the demand and supply of sectors.

7 Quantitative Exercise

In this section, we first introduce how to calculate the equilibrium defined above and then discuss model estimation given the calculation outcomes and using indirect inference.

7.1 Model Solution

The model can be solved computationally as a fixed point of the following vector of six aggregate equilibrium variables for each sector i

$$\{\tilde{w}^s, P_i, \Phi_i, \Phi_i^{NP}, \bar{\tilde{z}}_i, EY_i(\hat{z} + \Delta\bar{\tilde{z}})\}_{i=1}^3. \tag{16}$$

We can solve for the stationary equilibrium by first posing a conjecture for equation (16) for all the carbon-intensive, upstream, and downstream sectors, then solving for the individual innovation decisions and verifying the initial conjecture. We conduct the computation with and without the implementation of the pilot policy. Specifically, using the guess for these variables:

1. We compute the innovation rates (x_i, x_i^{entry}), R&D values (Ω_i) for all three sectors and aggregate growth rate g.

2. Using the innovation intensities, we can calculate the stationary equilibrium distribution over active/inactive product lines and over values of $\hat{z}$ for all three sectors by using Lemma 3.

3. We can check the labor market-clearing conditions using the innovation intensities and the above distributions and compute the equilibrium wage rates from the market-clearing conditions for skilled and unskilled labor, updating $\tilde{w}^s$.

4. We update the values for $\bar{\hat{z}}$ and $E[Y_i(\hat{z} + \Delta\bar{\hat{z}})]$ for all three sectors by using the productivity distribution and Lemma 2.

5. We update the guess for wage and price indices of each sector. We iterate the above process until convergence.

This procedure gives us (16) as a fixed point and generates the stationary equilibrium distributions of relative productivities. The time needed for convergence in this multi-sector model is much longer than that in a regular single-sector model. Theoretically, suppose X is the number of iterations needed for one sector to converge and N is the number of sectors, then the number of iterations for an N-sector model to converge is X^N. Thus, given our 3-sector model, it takes much longer than a single-sector model.

7.2 Model Estimation

First, we can parameterize the following: (1) $\log(\tau_0) = a_0 + a_1 \times 1(Pilot)$ (emissions fee as a function of policy treatment status); (2) $\log(\tau_1) = b_0 + b_1 \times 1(Pilot)$ (research subsidy as a function of policy treatment status); (3) $\log(\tau_2) = c_0 + c_1 \times 1(Pilot)$ (entry costs as a function of the treatment status); (4) $\log(\tau_3) = d_0 + d_1 \times 1(Pilot)$ (production regulation as a function of the treatment status). a_1, b_1, c_1, d_1 represent the elasticity of the pilot policy on cost parameters of regulation. For example, implementing the policy increases τ_0 by $100a_1\%$. We use the linear specification because $1(Pilot)$ is an indicator variable that only takes values of zero and one. Using a first-order polynomial is equivalent to a higher-order polynomial. However, we do try a linear functional form for robustness checks, expressing τ's as a linear function of $1(Pilot)$.

The set of calibrated parameters is: $\Theta_1 = \{\rho, \gamma, L^S, \epsilon, \eta, \beta_{ij}, \beta_i, \alpha_1, \alpha_2\}$. The set of parameters to be internally estimated is: $\Theta_2 = \{a_0, a_1, b_0, b_1, c_0, c_1, d_0, d_1, \phi, \theta, \theta^E, \Delta, \varphi, \lambda_1, \lambda_2\}$. Θ_2 is estimated using indirect inference.

Following Acemoglu et al. (2018), we set the discount rate equal to $\rho = 2\%$, which corresponds to an annual discount factor of 97% (Song et al., 2011). Also, following Acemoglu et al. (2018), we set the inverse of the intertemporal elasticity of substitution $\gamma = 2$ and set the measure of skilled labor $L^s = 0.166$ (measured by population share of those with a college degree in 2010 Census). We follow

Broda and Weinstein (2006) and set the elasticity of substitution to $\epsilon = 2.9$. Following Blundell et al. (2002) and Hall and Ziedonis (2001) we set the elasticity of innovation with respect to R&D to 0.5.

We then externally calibrate $\beta_{ij}, \beta_i, \alpha_i$ using statistical data. The data required are trade deficit D_i, value-added V_i, gross production Y_i of sector i (i=*upstream*, *carbon*, *downstream*) in China, as well as the input-output table of China. The share of sector i's spending on sector j's goods β_{ij} is calculated from the input-output table of China as the share of intermediate consumption of sector j in sector i over the total intermediate consumption of sector i, times one minus the share of value-added in sector j, 1-β_j. The share of value-added in sector i is given by $\beta_i = V_i/Y_i$. We calculate the final consumption share α_i as the total expenditure of sector i goods, subtract the intermediate expenditure from all sectors, and divided by total final absorption i.e., $\alpha_i = \left(Y_i + D_i - \sum_{j=1}^{J} \beta_{ji} Y_j\right)/I$. The total expenditure of sector i goods is the sum of gross production Y_i and trade deficit D_i in sector i namely, $Y_i + D_i$. The total final absorption of China equals the sum of the national value-added, trade deficit, and tariff revenue. The results are presented in Table A21.

The remaining 15 parameters can be estimated using indirect inference. We simulate $10,000 \times 295 \times 472 \times 15$ firms (to construct a balanced panel data set of 295 cities, 472 sectors, and 15 years), and compute the model-implied regression coefficients and minimize the gap between the model and the actual data. The coefficients are the entry, exit, emission, EEP, GP, NEP, and output for all three sectors, and for large, medium, and small firms.[35] Thus, there are 60 targeted coefficients. Specifically, we solve the following:

$$\min_{\Theta_2} ||ModelCoefficients(\Theta_2) - DataCoefficients||. \tag{17}$$

Standard errors are calculated by the Bootstrap method. Specifically, we estimate the model parameters 5000 times by targeting the empirical coefficients that are randomly generated based on the bootstrapped distribution of the data coefficients, and then obtain their standard errors from the distribution across these 5000 estimations. The model estimates are presented in Table A22.

We would like to make some arguments regarding model identification here. Like the majority of the macroeconomics literature, we cannot provide a formal result on model identification when the parameters are estimated using indirect inference (or simulated method of moments, SMM). However, the key parameters, including the parameters related to each policy measure (τ's) can be (at least partially) identified using moments of carbon emissions, output, entry and exit, and innovation. Moreover, in practice, our estimation results do not rely on the initial condition of the minimization problem of equation (17) and plausibly reach a (globally) unique solution.

We then conduct a policy experiment by looking at how the equilibrium and welfare change with

[35] Large firms are defined as firms with registry capital in the top 10 percentile, medium firms are defined as those whose registry capital belongs to the top 10-50 percentile, and small firms are those whose registry capital belongs to the bottom 50 percentile.

implementing the low-carbon-zone pilot. Under the policy, τ_0, τ_1, τ_2, and τ_3 all change. Implementing the policy reduces entry and increases innovation for the carbon-intensive sector (x_G, x_{NG}, and q^{min} both increase), reduces both entry and green innovation for the upstream sector (x decreases and q^{min} increases), and increases both entry and innovation for the downstream sector (x_G and x_{NG} increases and q^{min} decreases). In addition, implementing the policy leads to a transition to the green economy, which is shown by decreased carbon emissions in carbon-intensive sectors and a larger change in x_G than x_{NG}. However, the net effects on the growth rate of the entire economy and the welfare are not large: the growth rate is improved by only 0.8%, and welfare, measured by consumption, is improved by only 0.01%, as shown in Table 5. Here the welfare is a monotonic function of consumption, and it does not include the social benefits of carbon reduction. Furthermore, Table 6 illustrates the effects of different channels, including (1) emissions fees, (2) research subsidies, (3) entry costs, and (4) production regulation.[36] The effects of channels (1), (3), and (4) on growth and welfare are negative and of similar sizes, while the effects of channel (2) are positive. We also investigate the relationship between the policy parameters and the growth and welfare effects, and plot the relationships in Figure C6. The negative effects are larger if emissions, entry, and production regulations are more stringent, and the positive effects are larger if the research subsidy is larger.[37] This indicates the aggregate effects of a carbon emission regulation depend on the stringency of each policy channel. The change in prices and quantities in the market equilibrium in the simulation is shown in Table A20, which shows the change in prices and quantities in the three sectors are different given different policy parameters. Thus, the observed pattern in market equilibrium is sensitive to parameter values. We also look at the heterogeneity with respect to firm-level carbon emissions. According to Figure 2, the effects on entry and x_G are larger in magnitude if firms emit more, whereas emissions and x_{NG} do not have a salient positive relationship. These patterns are consistent with the empirical findings presented in Table A19.

Table 5: Policy experiment

	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare (consumption-equivalent)
Non-pilot, carbon	0.023	0.512	0.478	1.081	0.0874		
Non-pilot, upstream	0.019	0.487	0.424	1.138			
Non-pilot, downstream	0.027	0.531	0.499	0.945			
Non-pilot, total						0.0481	0.8470
Pilot, carbon	0.026	0.533	0.482	1.119	0.0669		
Pilot, upstream	0.022	0.472	0.421	1.253			
Pilot, downstream	0.023	0.541	0.505	0.901			
Pilot, total						0.0485	0.8471

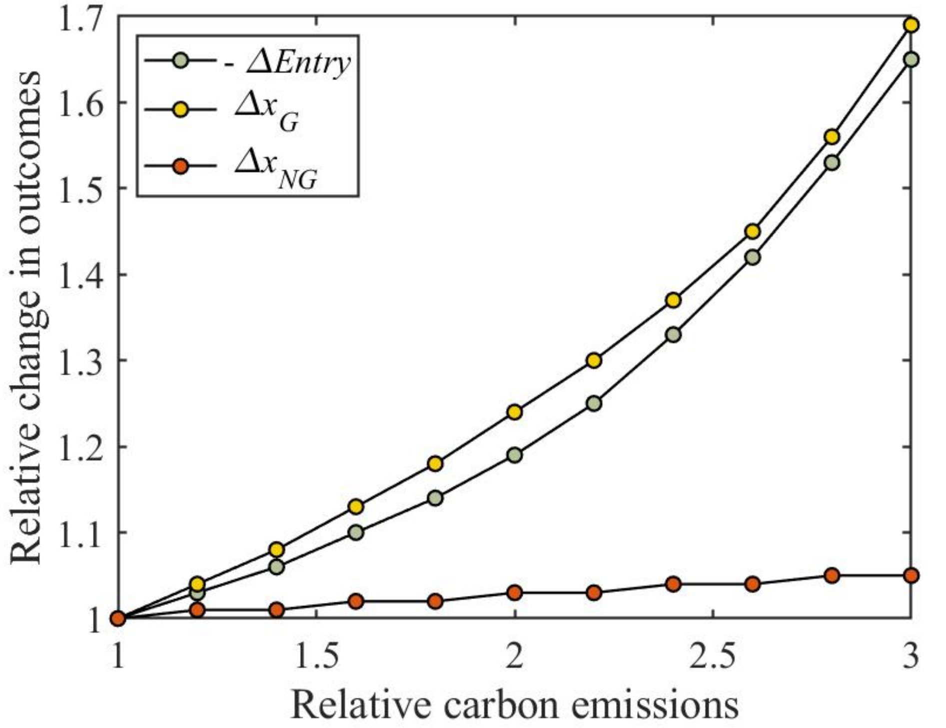
We finally conduct a policy experiment in a model without input-output linkages.[38] In such a model, the upstream and downstream sectors are always not directly affected. Furthermore, the effects

[36]To evaluate the effect of the emissions fee channel, we fix τ_1, τ_2, and τ_3, and let τ_0 vary. The method for separately evaluating other channels is the same.

[37]However, this negative effect can be offset by the welfare improvement led by carbon emissions reduction.

[38]The details of the model and quantitative analysis are presented in Appendix D.

Figure 2: The heterogeneous effects related to carbon emissions



Notes: This figure depicts the relation between relative change in outcomes and relative carbon emissions. The relative change in outcomes includes the negative of relative change in entry and the relative change in x_G and x_{NG}. Relative carbon emissions are the ratio of a firm's emissions to the minimum emissions level of all firms in the economy, or the carbon-intensive sector. Note that in the economy, only the carbon-intensive sector has carbon emissions.

Table 6: Quantifying the effects of different channels

	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare (consumption-equivalent)
					Benchmark case		
Non-pilot, carbon	0.023	0.512	0.478	1.081	0.0874		
Non-pilot, upstream	0.019	0.487	0.421	1.138			
Non-pilot, downstream	0.027	0.531	0.499	0.945			
Non-pilot, total						0.0481	0.8470
					Emissions fee channel		
Pilot, carbon	0.025	0.503	0.465	1.115	0.0674		
Pilot, upstream	0.021	0.476	0.428	1.211			
Pilot, downstream	0.023	0.524	0.478	0.951			
Pilot, total						0.0469	0.8463
					Research subsidy channel		
Pilot, carbon	0.021	0.531	0.481	1.011	0.0873		
Pilot, upstream	0.016	0.496	0.423	1.002			
Pilot, downstream	0.028	0.542	0.503	0.897			
Pilot, total						0.0501	0.8473
					Entry cost channel		
Pilot, carbon	0.024	0.509	0.468	1.113	0.0713		
Pilot, upstream	0.021	0.480	0.431	1.209			
Pilot, downstream	0.022	0.521	0.476	0.949			
Pilot, total						0.0470	0.8465
					Production regulation channel		
Pilot, carbon	0.024	0.503	0.423	1.114	0.0718		
Pilot, upstream	0.021	0.476	0.428	1.209			
Pilot, downstream	0.023	0.519	0.475	0.948			
Pilot, total						0.0471	0.8463

of the policy cannot propagate to the upstream and downstream sectors through input-output linkages. Thus, the negative effects of the emissions fee channel, the entry cost channel, and the production regulation channel are smaller in the model without input-output linkages, while the positive effects of the research subsidy channel are also smaller in the new model. The results of the policy experiment in the new model are displayed in Tables 7 and A23. In total, the welfare impacts of the carbon emissions regulation will be over-estimated (by about 200%[39]) if one overlooks input-output linkages. The fact of overestimation is also sensitive to the value of parameters. If parameters change, then the effect may also be underestimated.

Table 7: Policy experiment without input-output linkages

	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare (consumption-equivalent)
Non-pilot, carbon	0.023	0.512	0.478	1.081	0.0874		
Non-pilot, upstream	0.019	0.487	0.421	1.138			
Non-pilot, downstream	0.027	0.531	0.499	0.945			
Non-pilot, total						0.0481	0.8470
Pilot, carbon	0.025	0.531	0.479	1.118	0.0778		
Pilot, upstream	0.019	0.487	0.421	1.138			
Pilot, downstream	0.023	0.537	0.499	0.897			
Pilot, total						0.0488	0.8473

7.3 Quantifying Market Spillovers and Interpreting DDD Results

A potential concern with our DDD results is the non-carbon-related sectors (the control group in DDD) are indirectly affected by the market spillover effects, which are at play through the price signals. In this section, we use the quantitative model to interpret the results of difference-in-difference-in-differences estimation, similar to that of Chen et al. (2021). We can decompose the market spillover effects of the carbon emission regulation on entry and innovation into the contribution of the change in output price level and the change in wage rate. We then re-interpret our difference-in-difference-in-differences estimator using our quantitative framework.

To quantify the effects on firm dynamics that are specific to changes in price indices and wage rate, we use the production function of a generic firm in the non-carbon-related sector n:

$$q_n(\omega) = z_n(\omega) l_{uP}^{\beta_n} m_{n1}^{\beta_{i1}(1-\beta_n)} m_{n2}^{\beta_{n2}(1-\beta_n)} m_{n3}^{(1-\beta_{n1}-\beta_{n2})(1-\beta_n)} \tag{18}$$

where $z_n(\omega)$ is the leading-edge productivity draw for ω; l_{uP} is the unskilled labor input; and m_{nj} is the composite intermediate goods used to produce ω. β_{nj} measures the structure of the input-output network, which is calibrated in the next section. We calibrate β_n and β_{nj} using input-output tables. The rest of the economic processes for the non-carbon-related sector are the same as those of carbon-related sectors, except that the non-carbon-related sector is not subject to any direct regulation and that the non-carbon-related sector has zero emissions.

39 $\frac{(0.8473-0.8470)-(0.8471-0.8470)}{0.8471-0.8470} \times 100\% = 200\%$.

The non-carbon-related sector is only indirectly affected by market spillovers, or in other words, the changes in price indices and wage rates. Therefore, we can simulate the effects of regulation and separately quantify the effects on firm dynamics through the channel of changing price indices and wage rates. According to Table 8, the effects of carbon pilot on non-carbon-related sectors through the indirect channel of changing prices and wages are much smaller than the direct effects, as shown in Tables 5 and 6. Thus, we quantitatively show that the market spillover effects on non-carbon-related sectors do not matter much for the DDD estimates.

Table 8: Quantify the indirect effects on the non-carbon-related sector

	x^{entry}	x_G	x_{NG}	q^{min}
Non-pilot, non-carbon-related	0.0202	0.5040	0.4630	1.0540
Pilot, non-carbon-related (total)	0.0204	0.5042	0.4632	1.0541
Pilot, non-carbon-related (only price indices change)	0.0203	0.5041	0.4631	1.0540
Pilot, non-carbon-related (only wages change)	0.0203	0.5041	0.4631	1.0540

Finally, we can use model-generated data, which already accounts for the market spillover to non-carbon-related sectors, to re-estimate the difference-in-difference-in-differences specifications. Using the model-generated data, the DDD coefficients are close to those obtained from the actual data. For example, in Table 9, the estimate of the effect on entry for carbon sectors is -0.292 for model-generated data and -0.314 for actual data. The results for other outcomes and other sectors are also qualitatively similar. Therefore, we can use the quantitative model to interpret the results of difference-in-difference-in-differences, and the implication is that the market spillover effects on non-carbon-related sectors are not a dominating force that leads to significant bias.

Table 9: Using model to interpret DDD results

	Carbon Sectors		Upstream Sectors		Downstream Sectors	
	Actual data	Model-generated data	Actual data	Model-generated data	Actual data	Model-generated data
Entry	-0.314	-0.292	-0.803	-0.774	0.859	0.815
Exit	-0.241	-0.201	-0.435	-0.389	0.558	0.567
Patent, all	0.261	0.255	-0.456	-0.441	0.437	0.406
GP	0.037	0.065	-0.322	-0.332	0.365	0.301
NEP	-0.069	-0.058	-0.454	-0.418	0.273	0.246

7.4 Model Validation

We compare the model simulated coefficients and the data coefficients, and the results of the comparison are shown in Table A24. For comparison of moments, the results are shown in Tables C11 and C12, respectively. The results indicate that the model matches the data quite well. In particular, the model yields non-targeted coefficients and moments that match the data well, and, thus, our modeling and calibrating approach is validated.

We can also validate the model by numerically verifying theoretical predictions. First, using Table A20, we can see that the pilot policy results in changes in prices and quantities of each sector that are consistent with theoretical predictions in Figure 1. Second, the results of the counterfactual experiment in Table 5 are all consistent with theoretical predictions. For example, Table 5 indicates that entry and emissions both decrease in the carbon-intensive sector under the pilot policy, which is consistent with the model (and the empirical findings).

7.5 Robustness of Quantitative Analysis

We conduct two robustness checks for our quantitative analysis. First, we use a polynomial up to fourth order to formulate the emissions function. Specifically, we set that $E(q, l_{uR}) = \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_{p,q} q^m \times (\frac{q}{l_{uR}})^{-n}$. Note that this function is more flexible, but still homothetic so all theoretical results still hold. We set $M = N = 4$ so that the polynomial is up to fourth order. We calibrate the parameters using the same approach. Second, we use a linear (instead of log-linear) function of τ's with respect to the pilot status: $\tau_i = a_i + b_i \times 1(Pilot)$ $(i = 1, 2, 3, 4)$ as a robustness check. We calibrate the parameters using the same approach. The results of both robustness checks are presented in Table A25, which are quantitatively robust.

7.6 Cost-benefit Analysis

In this subsection, we conduct a back-of-envelope cost-benefit assessment based on the results of the quantitative experiments. On the cost side, the upper bound of the pecuniary cost of the carbon emissions regulation is 20 million RMB (2.9 million USD). This pecuniary cost is used largely to start the fund for low-carbon research subsidies.[40] The average level of consumption in pilot cities in 2010 was around 19,984 RMB (2,865 USD). According to Table 5, the welfare gain due to the carbon emissions regulation was around 0.0118%. Given CRRA preference ($U(C) = \frac{C^{1-\gamma}}{1-\gamma}$, where $\gamma = 2$), the welfare gain is translated to an increase in consumption of 2.4 RMB (0.34 USD) per person. The average population of a pilot city was about 14.64 million, and, thus, the total consumption gain was about 35.14 million RMB. Since the pecuniary cost of carbon emissions regulation is generally used for low-carbon research subsidies, an alternative for our cost-benefit analysis would be to compare the welfare gain due to the research subsidy channel with the cost. The welfare gain due to the research subsidy channel of the carbon emissions regulation is around 0.0354%. Such a welfare gain translates to an increase in consumption of 7 RMB (1.0 USD) per person, and, thus, the consumption gain is about 102 million RMB (14.6 million USD). In either case, the benefit is far above the cost of the carbon emissions regulation.

Finally, when taking into account the social benefits of carbon reduction, the welfare improvement of the pilot policy is even larger. In the US, given the Biden administration that has recently proposed using a social cost of carbon of 51 dollars per ton (House, 2021) and the effects on carbon emissions,

[40] We collect news on pilot cities' total low-carbon research subsidies. The general amount is around 3 million to 5 million RMB. The most generous cities propose to allocate a fiscal expenditure of 20 million RMB for the low-carbon pilot.

we get an extra welfare benefit of 2062 million RMB (307.8 million USD), which is a huge welfare gain compared to the previous gain from consumption increase.

8 Conclusion

Carbon and climate policies are playing an increasingly important role in shaping growth, innovation, and other macroeconomic outcomes (Van Den Bergh, 2017; Fried, 2018). In the case of carbon emissions regulation, although achieving the global target of net-zero carbon emissions requires emissions reduction efforts by all sectors, current regulations focus largely on the sectors with high direct carbon emissions. In this paper, we analyze, both empirically and theoretically, how a carbon emissions regulation with comprehensive policy measures in China affects firm dynamics, including entry and innovation, especially through input-output networks that span the entire economy. Using a difference-in-difference-in-differences empirical strategy, we find, based on the following outcomes, that the policy instruments are effective: significantly less entry; decreased firm-level carbon emissions; and more patent applications related to green and energy-efficient technologies in low-carbon-zone pilots, in carbon-intensive sectors and after the policy is implemented.

The effects of the regulation propagate through demand/supply channels in the input-output networks. In the upstream sectors, there are fewer entries and patent applications but higher firm-level carbon emissions. In the downstream sectors of the carbon-intensive sectors, there are more entries and patent applications. In upstream and downstream sectors, these effects are equally pronounced for firms with high or low carbon emission intensity. This validates that the carbon emissions regulation impacts mainly upstream and downstream sectors via input-output linkages, instead of via direct regulation. We also rule out the case that our main results are biased by the endogenous selection of pilot cities and regional spillover.

The above-mentioned facts can be rationalized by a firm-dynamics model with input-output linkages. Estimates of the model and policy experiments inform policymakers that the aggregate effects on growth and welfare are overestimated if one overlooks input-output linkages. While the policy context of this paper is specific to that of China, the insights herein can easily be applied to many other scenarios, especially all kinds of multi-faceted regulations in any country.

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Online Appendix

Appendix A Figures and Tables

Figure A1: Geographical distribution of low-carbon pilot cities

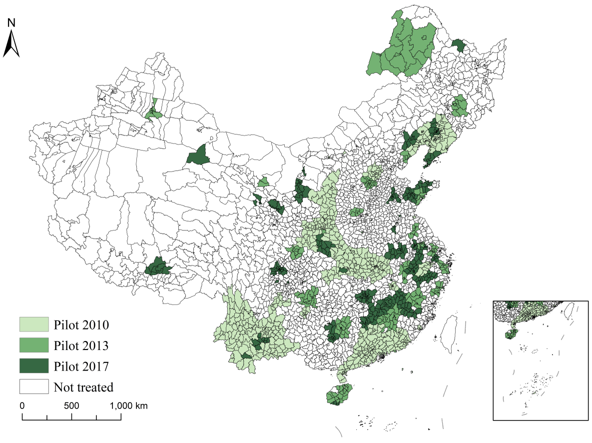
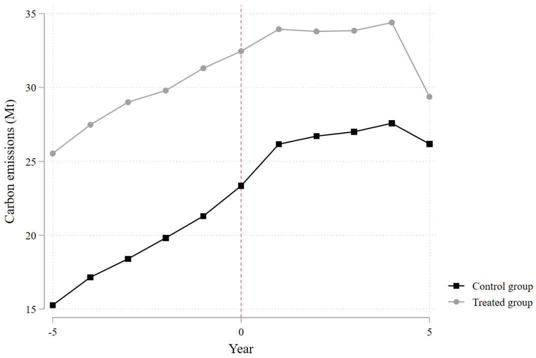
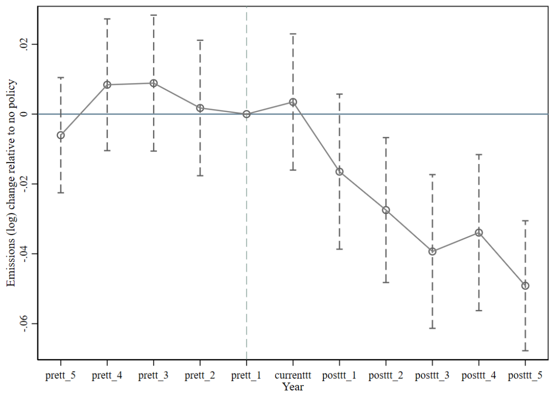


Figure A2: Trends of city-level carbon emissions



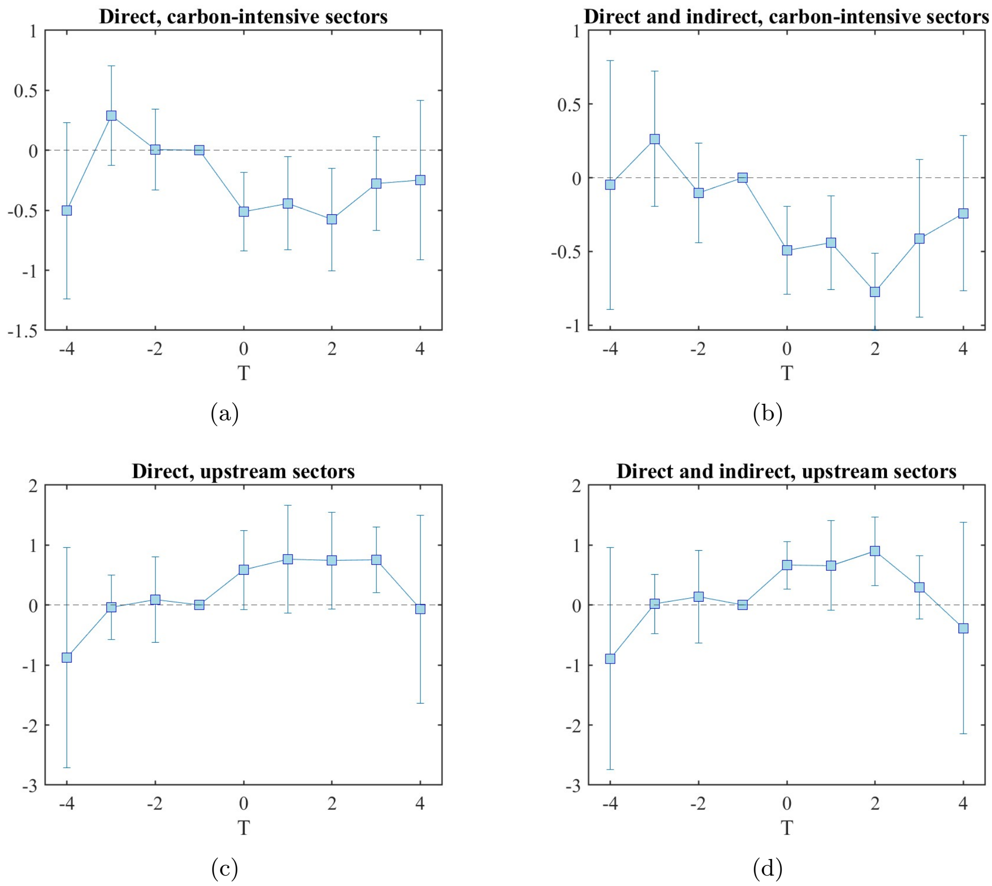
(a)



(b)

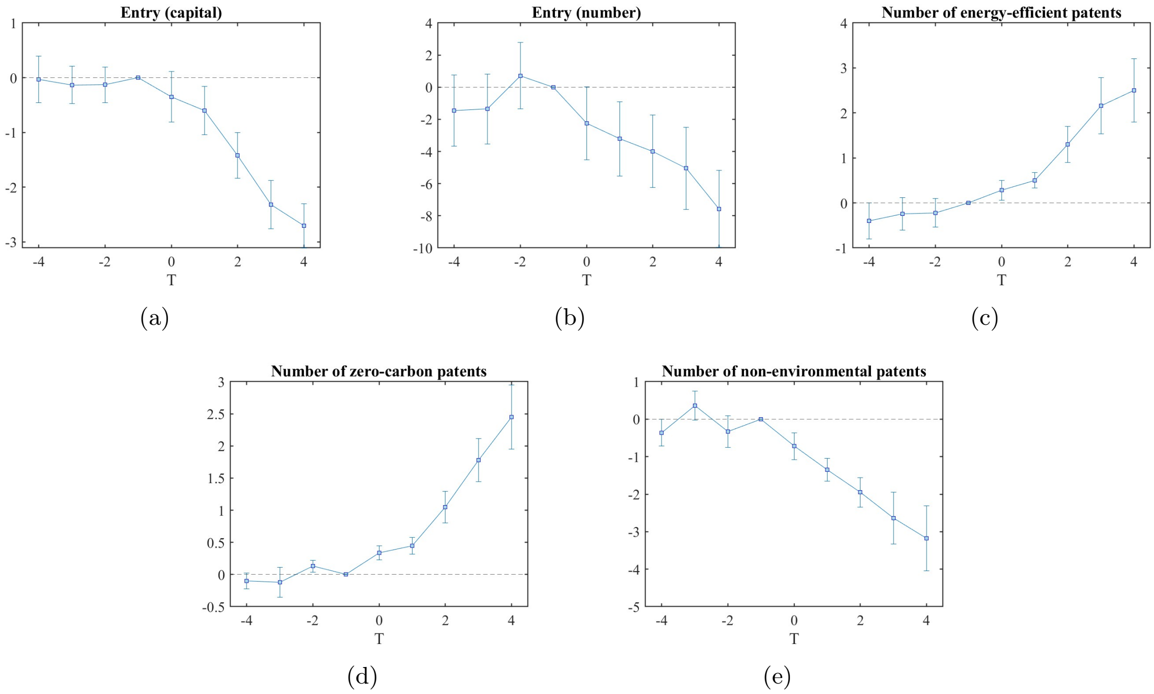
Notes: In Subfigure (a), each dot represents the average city-level carbon emissions of the pilot and never-treated cities relative to the treatment year. The year 0 of the control group is taken as 2010. Subfigure (b) is the event study analysis for carbon emissions, controlling for log per capita real GDP, log population of the cities, and city and year fixed effects. The data source is Chen et al. (2020).

Figure A3: Estimating the dynamic effects on city-sector level emissions



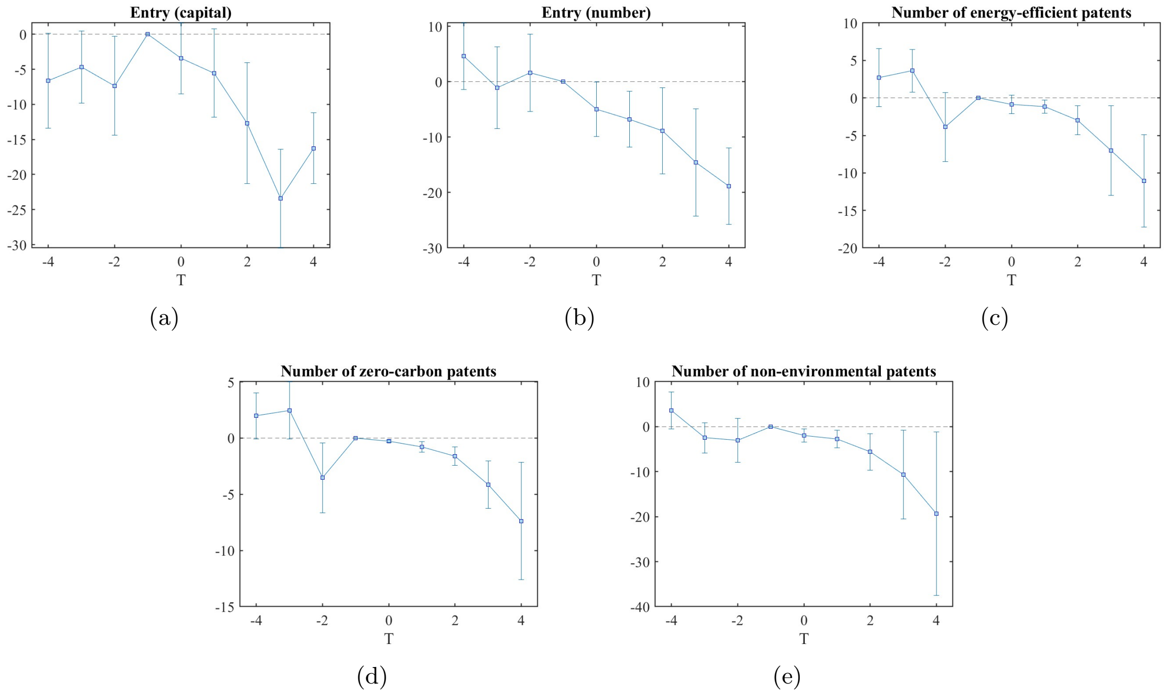
Notes: The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Carbon_j)$ */*$1(Upstream)$ *on* $\log(1 + emissions_{ijt})$ *of the carbon-intensive sectors and upstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The "control group" only consists of non-carbon-related sectors. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Figure A4: Estimating the dynamic effects on the carbon-intensive sectors



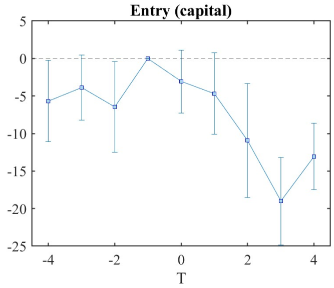
Notes: The sample consists of 14,160 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Carbon_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The "control group" only consists of non-carbon-related sectors. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Figure A5: Estimating the dynamic effects on the regulated upstream sectors

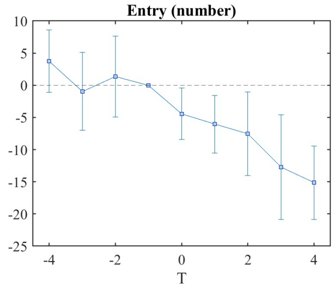


Notes: The sample consists of 16,225 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Upstream, regulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the regulated upstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The "control group" only consists of non-carbon-related sectors. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

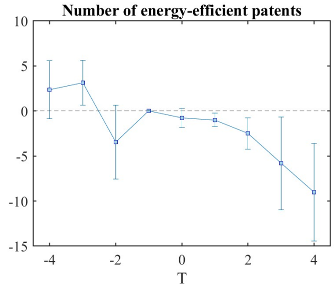
Figure A6: Estimating the dynamic effects on the unregulated upstream sectors



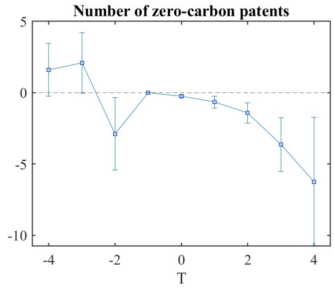
(a)



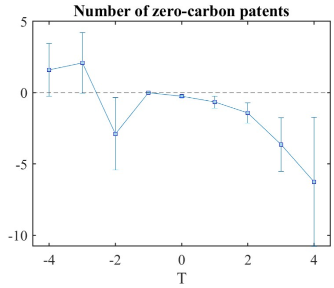
(b)



(c)



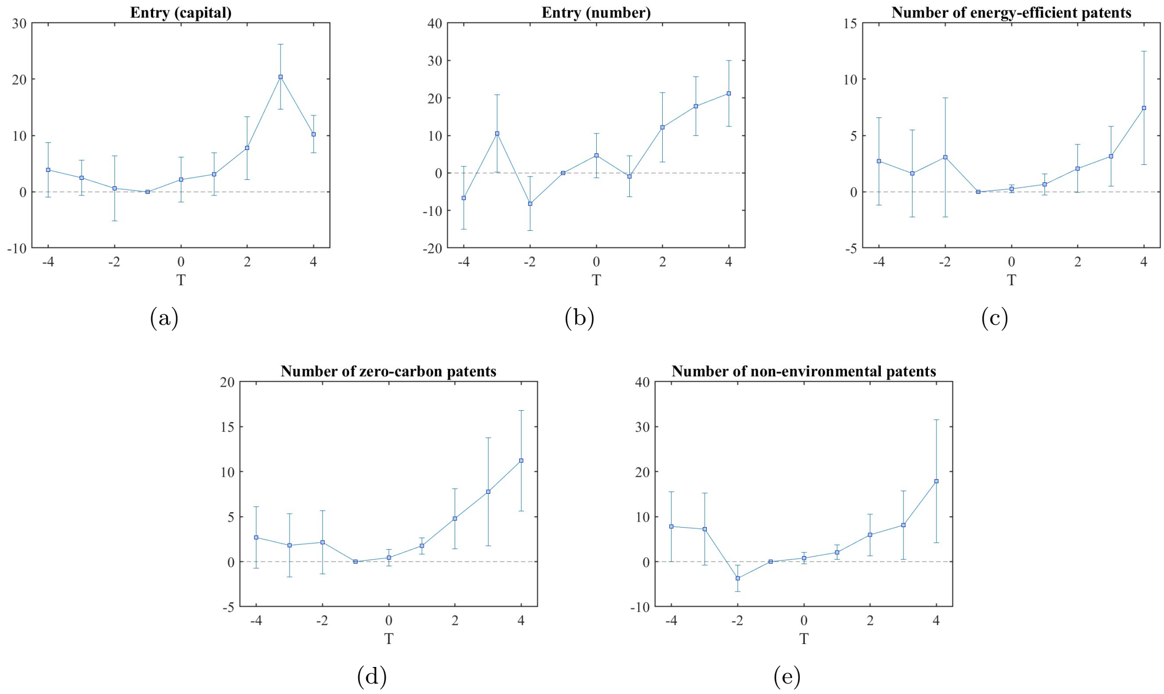
(d)



(e)

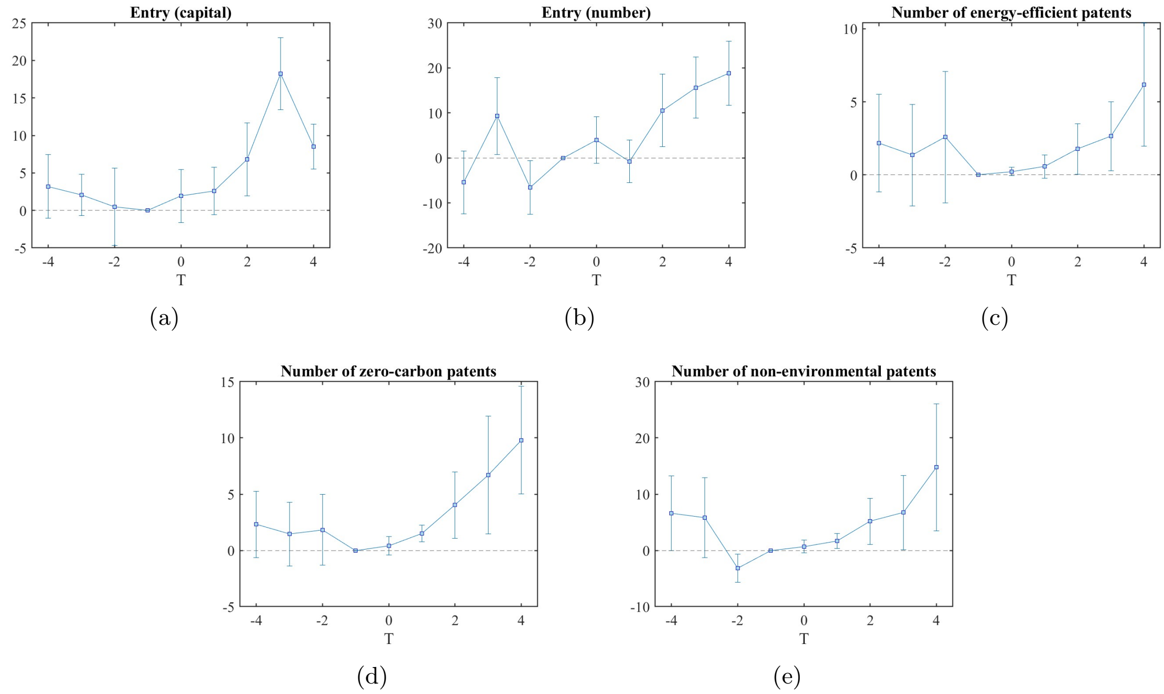
Notes: The sample consists of 38,350 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Upstream, unregulated_j)$ *on* $Entry_{ijt}, capital$*,* $Entry_{ijt}, number$*, and* $Patent_{ijt}$ *of the unregulated upstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The "control group" only consists of non-carbon-related sectors. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Figure A7: Estimating the dynamic effects on the regulated downstream sectors



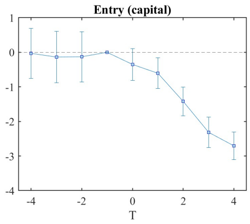
Notes: The sample consists of 14,750 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Downstream, regulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the regulated downstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The "control group" only consists of non-carbon-related sectors. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Figure A8: Estimating the dynamic effects on the unregulated downstream sectors

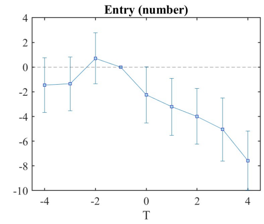


Notes: The sample consists of 26,845 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau)\times 1(Pilot_i)\times 1(Downstream, unregulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the unregulated downstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The "control group" only consists of non-carbon-related sectors. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t=-1$)*, which is standardized to 0.*

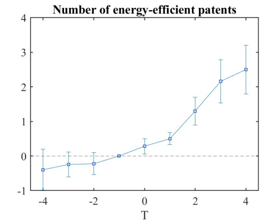
Figure A9: Estimating the dynamic effects on the carbon-intensive sectors, alternative methods



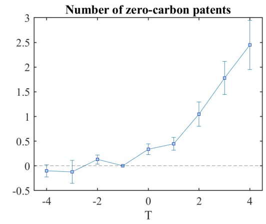
(a)



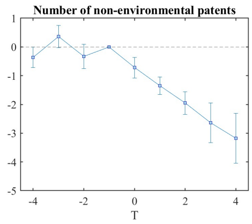
(b)



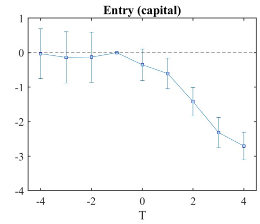
(c)



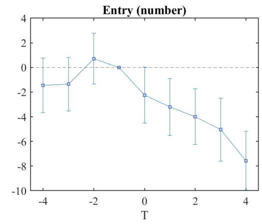
(d)



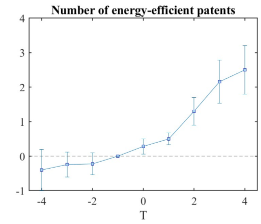
(e)



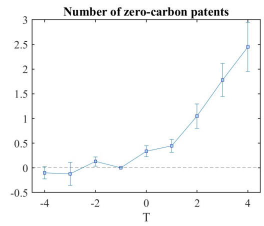
(f)



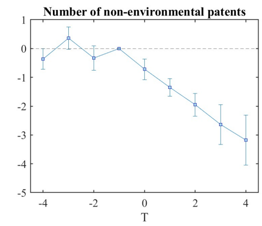
(g)



(h)



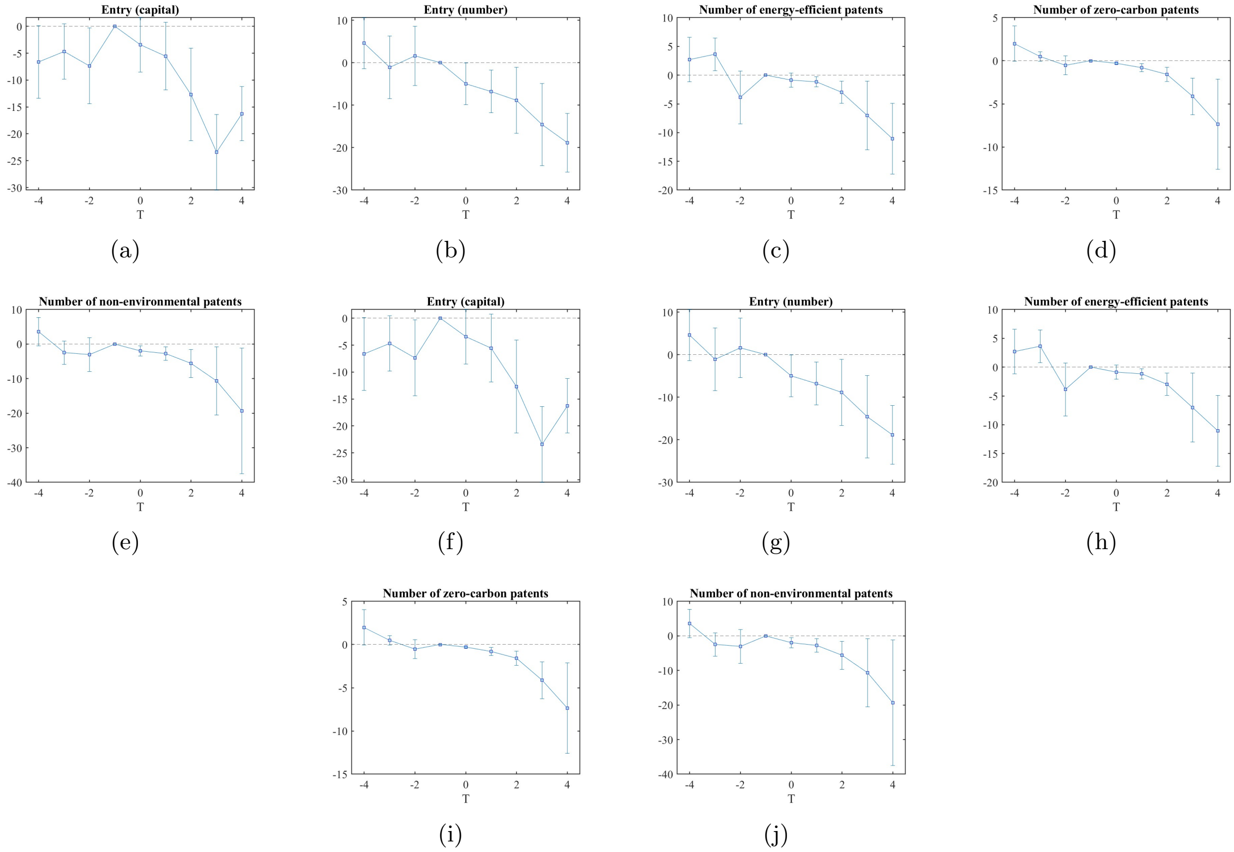
(i)



(j)

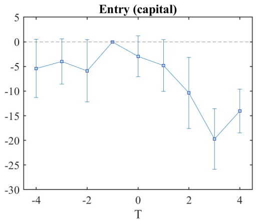
Notes: The sample consists of 14,160 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau) \times 1(Pilot_i) \times 1(Carbon_j)$ *on* $Entry_{ijt}$*,capital,* $Entry_{ijt}$*,number, and* $Patent_{ijt}$ *of the carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Borusyak et al. (2022), while subfigures (f)-(j) are obtained using the method of De Chaisemartin and d'Haultfoeuille (2020). The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t=-1$)*, which is standardized to 0.*

Figure A10: Estimating the dynamic effects on the regulated upstream sectors, alternative methods

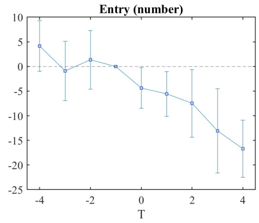


Notes: The sample consists of 16,225 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau) \times 1(Pilot_i) \times 1(Upstream, regulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the regulated upstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Borusyak et al. (2022), while subfigures (f)-(j) are obtained using the method of De Chaisemartin and d'Haultfoeuille (2020). The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

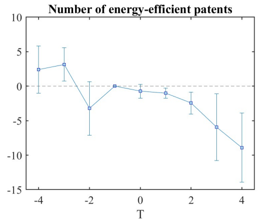
Figure A11: Estimating the dynamic effects on the unregulated upstream sectors, alternative methods



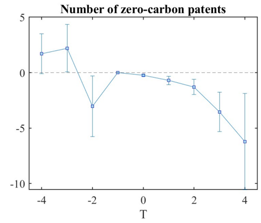
(a)



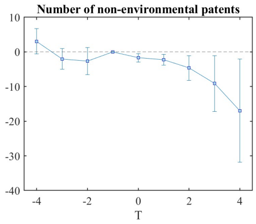
(b)



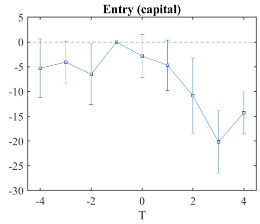
(c)



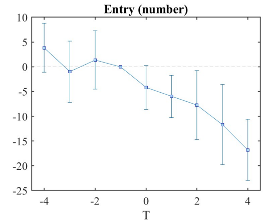
(d)



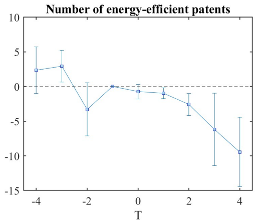
(e)



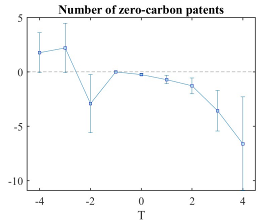
(f)



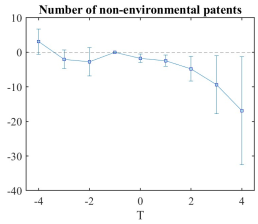
(g)



(h)



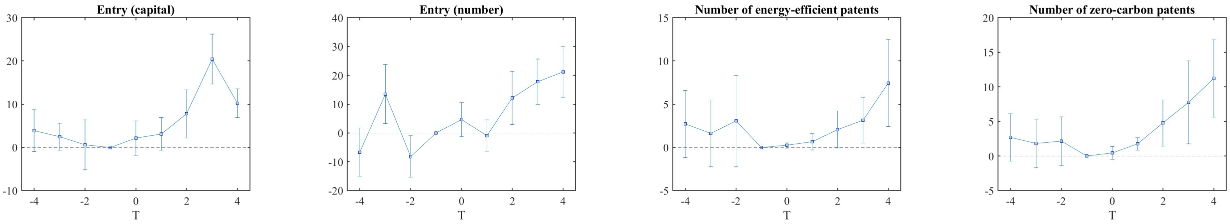
(i)



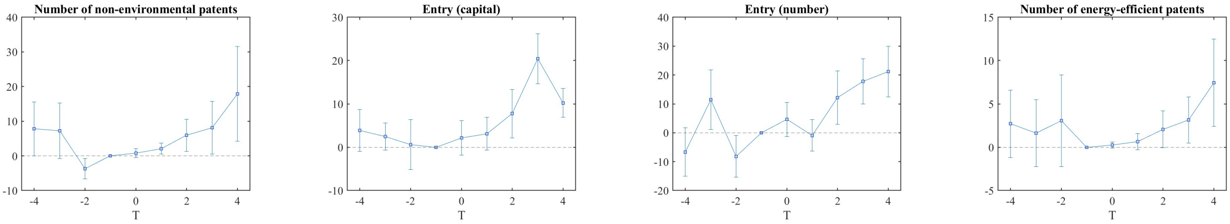
(j)

Notes: The sample consists of 38,350 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Upstream, unregulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the downstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Borusyak et al. (2022), while subfigures (f)-(j) are obtained using the method of De Chaisemartin and d'Haultfoeuille (2020). The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$). *The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$), *which is standardized to 0.*

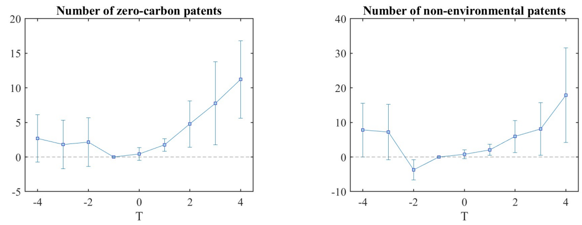
Figure A12: Estimating the dynamic effects on the regulated downstream sectors, alternative methods



(a) (b) (c) (d)



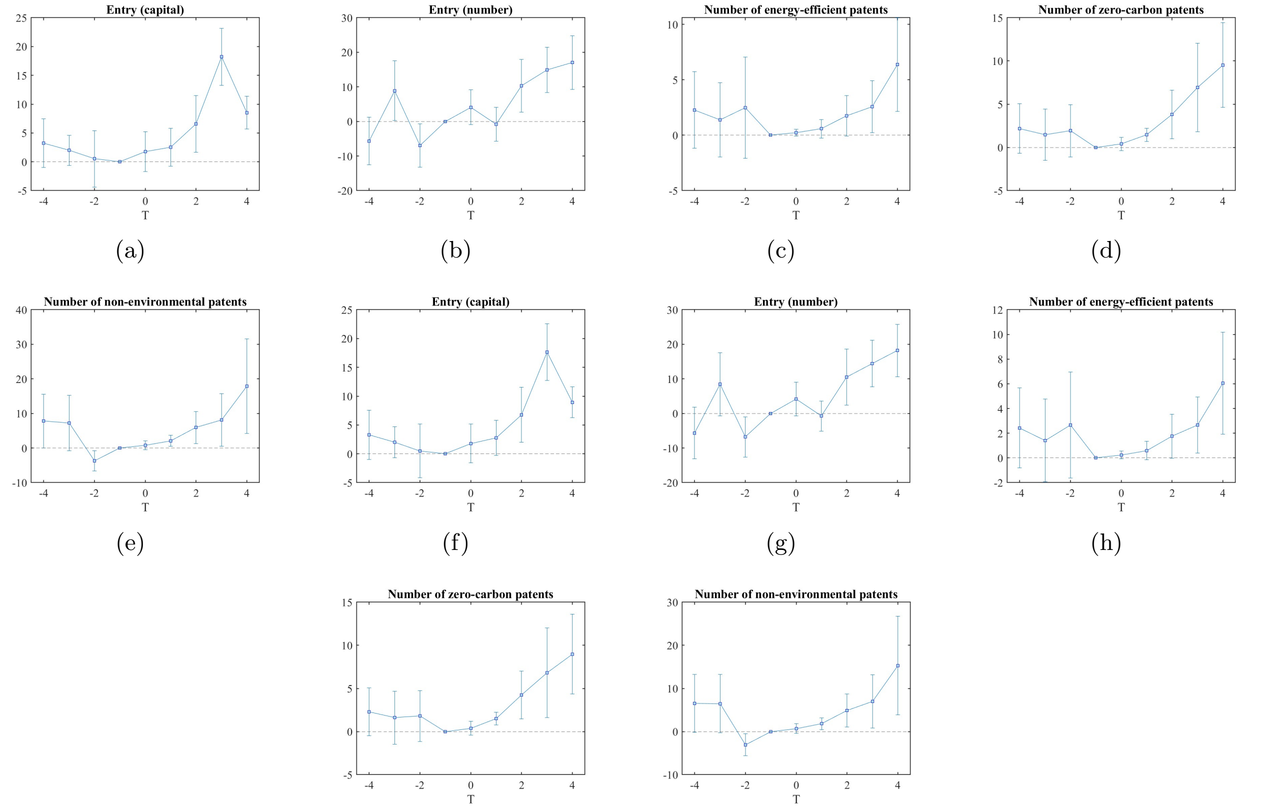
(e) (f) (g) (h)



(i) (j)

Notes: The sample consists of 14,750 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau)\times 1(Pilot_i)\times 1(Downstream, regulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the regulated downstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Borusyak et al. (2022), while subfigures (f)-(j) are obtained using the method of De Chaisemartin and d'Haultfoeuille (2020). The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t=-1$)*, which is standardized to 0.*

Figure A13: Estimating the dynamic effects on the unregulated downstream sectors, alternative methods



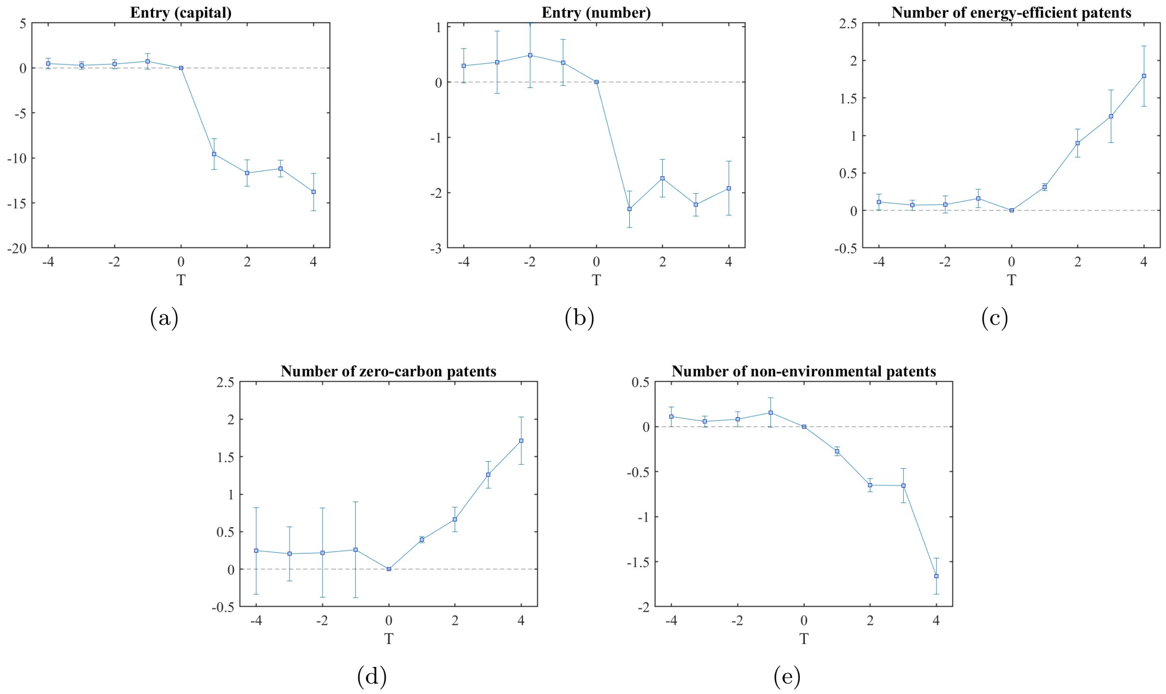
(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j)

Notes: The sample consists of 26,845 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau) \times 1(Pilot_i) \times 1(Downstream, unregulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the unregulated downstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Borusyak et al. (2022), while subfigures (f)-(j) are obtained using the method of De Chaisemartin and d'Haultfoeuille (2020). The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t=-1$)*, which is standardized to 0.*

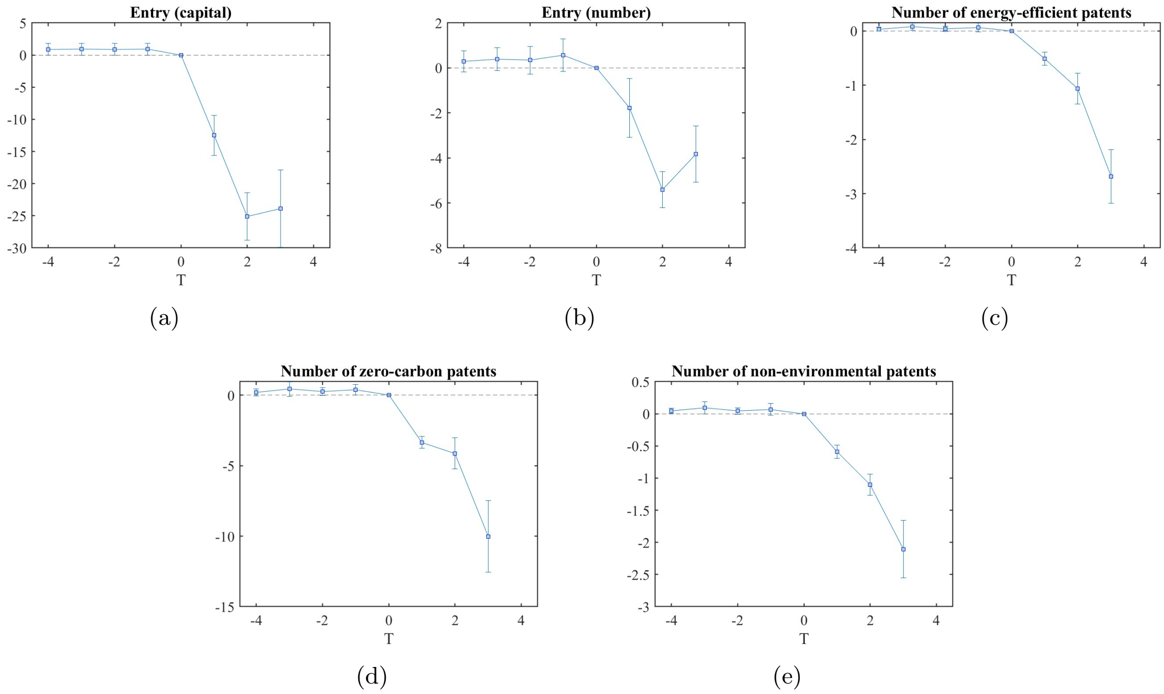
Figure A14: Estimating the dynamic effects on the carbon-intensive sectors (city-year data)



(a) (b) (c) (d) (e)

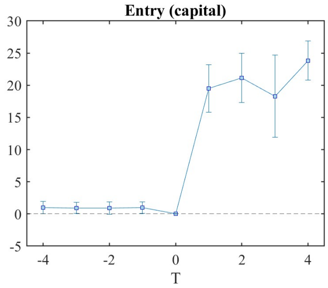
Notes: The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using equation (6), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Figure A15: Estimating the dynamic effects on the upstream sectors (city-year data)

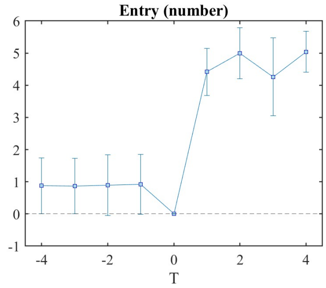


Notes: The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the upstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using equation (6), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors clustered at the city level. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

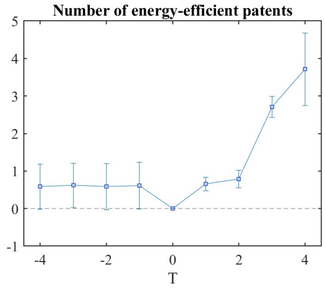
Figure A16: Estimating the dynamic effects on the upstream sectors (city-year data)



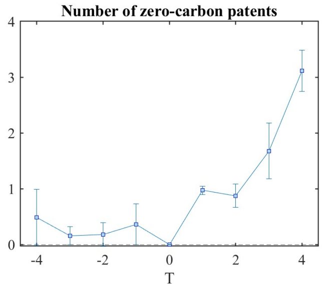
(a)



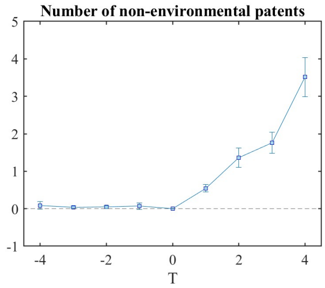
(b)



(c)



(d)



(e)

Notes: The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i)$ *on* $Entry_{ijt}$*, capital,* $Entry_{ijt}$*, number, and* $Patent_{ijt}$ *of the downstream sectors of carbon-intensive sectors. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using equation (6), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors clustered at the city level. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Table A1: The effects of carbon emissions regulation on city-level carbon emissions

	(1)	(2)
	log(Carbon Emissions)	
1(Pilot)	-0.0327**	-0.0264**
	(0.0127)	(0.0119)
Controls	N	Y
City FE	Y	Y
Year FE	Y	Y
Observations	3,770	3,450
R-squared	0.861	0.893
Number of city	290	284

Notes: The sample covers 290 city-sectors during 2005-2017. In all columns, city and year fixed effects are included. Controls include the log per capita real GDP, and the log population of the cities. * Significant at 10%, ** 5%, *** 1%. The data source is Chen et al. (2020). Standard errors are clustered at the city level.

Table A2: Balancing test

Variable in 2005	Difference	Standard Error	t-statistic
Stock of firm number	20.142	19.663	1.024
Stock of firm capital	144.872	180.735	0.802
Stock of GP	-1.321	1.770	-0.746
Stock of EEP	0.442	0.552	0.801
Stock of NEP	-0.228	0.331	-0.689
Population (ten thousand)	-13.55	16.75	-0.81
Population growth	0.08	0.37	0.22
Primary industry employment share	0.59	1.21	0.49
Secondary industry employment share	0.15	2.02	0.07
Tertiary industry employment share	-0.73	1.83	-0.40
Fiscal expenditure	77483.00	57338.00	1.35
Scientific expenditure	14684.00	10518.00	1.40
Number of hospital	68.06	43.74	1.56
Passenger transport	1087.00	694.60	1.56
Freight transport	1180.00	735.50	1.60
Waste recylcing output	2452.00	6323.00	0.39
SO2 emissions	-4554.00	7084.00	-0.64
Nox emissions	-1060.00	3888.00	-0.27
Dust emissions	-1060.00	3888.00	-0.27
SO2 reduction	342744.00	322858.00	1.06

Notes: In the balancing test, we look at the difference of various outcomes in 2005 with respect to the pilot status, conditional on factors that may affect pilot participation: GDP, population, and carbon emissions.

Table A3: Summary statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Entry, capital	2,088,660	64.291	7.740	0	3449223282
Entry, number	2,088,660	10.135	7.043	0	13663
Exit, capital	2,088,660	86.834	43.554	0	1000149081
Exit, number	2,088,660	5.286	5.160	0	8353
Patent	2,088,660	2.175	4.402	0	556
EEP	2,088,660	1.084	1.477	0	91
GP	2,088,660	1.334	2.300	0	531
NEP	2,088,660	1.131	1.763	0	450

Table A4: OLS estimation

	Entry, number	Entry, capital	Patent, number	EEP	GP	NEP
			OLS			
1(pilot)*1(carbon)	-2.668***	-17.436***	1.845***	3.799***	3.391***	-2.724***
	(0.258)	(0.218)	(0.266)	(0.0962)	(0.324)	(0.517)
1(pilot)*1(upstream,regulated)	-4.289***	-14.420***	-2.322***	-3.658***	-4.243***	-1.825***
	(0.443)	(0.601)	(0.301)	(0.845)	(0.810)	(0.244)
1(pilot)*1(upstream,unregulated)	-2.677***	-12.326***	-1.978***	-0.749***	-1.531***	-0.868***
	(0.447)	(0.889)	(0.312)	(0.182)	(0.275)	(0.102)
1(pilot)*1(downstream,regulated)	3.348***	23.779***	2.121***	3.568***	3.543***	1.562***
	(0.503)	(0.904)	(0.209)	(0.405)	(0.357)	(0.209)
1(pilot)*1(downstream,unregulated)	2.236***	26.455***	1.709***	1.437***	1.201***	0.844***
	(0.561)	(1.005)	(0.231)	(0.312)	(0.398)	(0.201)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A5: The effects on net entry

	Panel A: Carbon-intensive sectors and non-carbon-related sectors			
	(1)	(2)	(3)	(4)
	net entry, capital	net entry, number	log(1+stock, capital)	log(1+stock, number)
1(pilot)*1(carbon)	-729,115**	-129.5***	-0.335***	-0.388***
	(355,673)	(12.1)	(0.0457)	(0.0132)
	Panel B: Regulated upstream sectors and non-carbon-related sectors			
	(1)	(2)	(3)	(4)
	net entry, capital	net entry, number	log(1+stock, capital)	log(1+stock, number)
1(pilot)*1(upstream, regulated)	-609,731***	-145.4***	-0.156**	-0.476***
	(32,545)	(15.1)	(0.0615)	(0.0313)
	Panel C: Unregulated upstream sectors and non-carbon-related sectors			
	(1)	(2)	(3)	(4)
	net entry, capital	net entry, number	log(1+stock, capital)	log(1+stock, number)
1(pilot)*1(upstream, unregulated)	-445,562***	-122.9***	-0.125**	-0.358***
	(14,691)	(11.1)	(0.056)	(0.0277)
	Panel D: Regulated downstream sectors and non-carbon-related sectors			
	(1)	(2)	(3)	(4)
	net entry, capital	net entry, number	log(1+stock, capital)	log(1+stock, number)
1(pilot)*1(downstream, regulated)	3.673e+06***	187.4***	-0.315***	0.512***
	(1.166e+05)	(21.6)	(0.0334)	(0.0266)
	Panel E: Unregulated downstream sectors and non-carbon-related sectors			
	(1)	(2)	(3)	(4)
	net entry, capital	net entry, number	log(1+stock, capital)	log(1+stock, number)
1(pilot)*1(downstream, unregulated)	2.345e+07***	134.6***	-0.231***	0.442***
	(2.142e+06)	(22.5)	(0.0222)	(0.0121)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A6: The effects on city-level outcomes

	Entry, number			Entry, capital			Patent, number		
	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial
1(pilot)	-0.115	-0.0443	-0.0209	-0.337	-0.177	-0.144	-0.172	-0.115	-0.102
	(0.121)	(0.0374)	(0.0222)	(0.377)	(0.222)	(0.155)	(0.133)	(0.0994)	(0.255)

Notes: The sample covers 295 cities during 2005-2019. In all columns, city and year fixed effects are included. Controls include the log per capita real GDP, the log population of the cities, and the stock of capital of all existing firms in the city, in 2005, interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table A7: Determinants of pilot timing and participation

	(1)	(2)	(3)	(4)	(5)
	Inverse of pilot year	1(2010)	1(2013)	1(2017)	1(Never)
log GDP per capita in 2005	6.97e-05**	0.0729	0.0918**	0.0444	-0.157***
	(2.72e-05)	(0.0515)	(0.0408)	(0.0422)	(0.0559)
log population in 2005	2.67e-05	0.00907	0.0696	0.00142	-0.0603
	(3.54e-05)	(0.0629)	(0.0453)	(0.0510)	(0.0724)
log carbon emissions in 2005	-1.54e-05	-0.0241	-0.0274	-0.0151	0.0399
	(3.32e-05)	(0.0583)	(0.0469)	(0.0463)	(0.0687)
Province FE	N	N	N	N	N
Observations	288	288	288	288	288
R-squared	0.037	0.012	0.043	0.007	0.043
	(6)	(7)	(8)	(9)	(10)
	Inverse of pilot year	1(2010)	1(2013)	1(2017)	1(Never)
log GDP per capita in 2005	4.61e-06	0.0291	0.0594	0.0435	-0.0400
	(3.43e-05)	(0.0253)	(0.0581)	(0.0595)	(0.0671)
log population in 2005	-2.88e-05	0.00625	0.0649	-0.0453	0.0371
	(4.14e-05)	(0.0206)	(0.0661)	(0.0778)	(0.0798)
log carbon emissions in 2005	7.76e-05*	0.0167	0.0156	0.0997	-0.150*
	(4.17e-05)	(0.0251)	(0.0670)	(0.0782)	(0.0815)
Province FE	Y	Y	Y	Y	Y
Observations	284	284	284	284	284
R-squared	0.467	0.918	0.164	0.151	0.518

Notes: The sample covers 284 cities. In all columns, province fixed effects are included. The inverse of the pilot year is defined as $\frac{1}{Year}$, where $Year = \infty$ if the city never implements the pilot policy. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table A8: DDD with propensity score matching

	Entry, number	Entry, capital	EEP	GP	NEP
1(pilot)*1(carbon)	-2.324***	-13.799***	3.705***	5.413***	-2.561***
	(0.331)	(2.238)	(0.449)	(0.369)	(0.421)
1(pilot)*1(upstream,regulated)	-4.277***	-11.658***	-3.106***	-4.997***	-2.467***
	(0.343)	(2.631)	(0.778)	(0.331)	(0.414)
1(pilot)*1(upstream,unregulated)	-1.357***	-5.749***	-1.246***	-2.211***	-1.546***
	(0.500)	(0.449)	(0.340)	(0.315)	(0.623)
1(pilot)*1(downstream,regulated)	4.224***	15.568***	6.972***	6.132***	3.679***
	(0.668)	(2.911)	(1.344)	(0.332)	(0.339)
1(pilot)*1(downstream,unregulated)	2.269***	7.437***	3.238***	3.890***	1.941***
	(0.442)	(1.221)	(0.246)	(0.712)	(0.417)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. We exploit OLS estimations. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. The matching covariates are log per capita GDP, log population, value-added share of secondary industry, and share of urban population in 2005. Nearest neighbor matching is exploited. "EEP" refers to "energy-efficient patent"; "GP" refers to "zero-carbon patent"; and "NEP" refers to "non-environmental patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A9: Baseline results with policy controls

	Entry, number			Entry, capital			Patent, number		
	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial
1(pilot)*1(carbon)	-2.324***	-0.165***	-0.177***	-14.799***	-7.634***	-4.722***	1.741***	0.246***	0.368***
	(0.601)	(0.0203)	(0.0189)	(2.156)	(1.233)	(0.369)	(0.446)	(0.0255)	(0.0324)
1(pilot)*1(upstream,regulated)	-3.277***	-0.245***	-0.212***	-12.658***	-5.713***	-2.959***	-1.610***	-0.272***	-0.368***
	(0.218)	(0.0336)	(0.0432)	(2.641)	(0.802)	(0.331)	(0.331)	(0.0244)	(0.0414)
1(pilot)*1(upstream,unregulated)	-1.357***	-0.266***	-0.255***	-7.749***	-5.233***	-4.466***	-0.622***	-0.163***	-0.166***
	(0.456)	(0.0540)	(0.0441)	(1.822)	(0.301)	(0.325)	(0.112)	(0.0205)	(0.0411)
1(pilot)*1(downstream,regulated)	3.224***	0.268***	0.288***	10.568***	6.133***	5.660***	1.513***	0.238***	0.249***
	(0.404)	(0.0400)	(0.0333)	(2.934)	(0.142)	(0.332)	(0.249)	(0.0241)	(0.0245)
1(pilot)*1(downstream,unregulated)	1.269***	0.225***	0.144***	4.437***	3.301***	3.116***	0.376***	0.105***	0.166***
	(0.324)	(0.0441)	(0.0379)	(1.000)	(0.772)	(0.712)	(0.0531)	(0.0214)	(0.0225)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, the lagged stock of capital of all existing firms in the city-sector-year, the emissions reduction goals at the twelve-five and thirteen-five periods, and the implementation of the carbon trading system, both interacted with sector dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A10: Upstreamness and downstreamness: a continuous measure

	Entry, number			Entry, capital			Patent, number		
	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial
1(pilot)*1(upstream,continuous)	-1.223***	-0.123***	-0.155***	-3.132***	-2.336***	-2.044***	-0.778***	-0.117***	-0.104***
	(0.343)	(0.0344)	(0.0332)	(0.485)	(0.316)	(0.333)	(0.201)	(0.0325)	(0.0225)
1(pilot)*1(downstream,continuous)	1.004***	0.132***	0.110***	2.109***	2.321***	2.220***	0.409***	0.101***	0.105***
	(0.161)	(0.0324)	(0.0359)	(0.313)	(0.254)	(0.316)	(0.111)	(0.0214)	(0.0131)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A11: Higher-order upstreamness and downstreamness (PPML estimation)

	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
Second-order upstream	-0.0813***	-0.115***	-0.0764***	-0.125***	-0.106***
	(0.0332)	(0.0310)	(0.0122)	(0.0233)	(0.0145)
Third-order upstream	-0.0421**	-0.0632***	-0.0467***	-0.0835***	-0.0779***
	(0.0202)	(0.0210)	(0.0113)	(0.0241)	(0.0126)
Fourth-order upstream	-0.0103	-0.0225	-0.0213**	-0.0444**	-0.0386***
	(0.0134)	(0.0226)	(0.0105)	(0.0212)	(0.0103)
Second-order downstream	0.104***	0.126***	0.145***	0.106***	0.113***
	(0.0200)	(0.0211)	(0.0159)	(0.0227)	(0.0208)
Third-order downstream	0.0880***	0.0699***	0.0889***	0.0878***	0.0606***
	(0.0211)	(0.0203)	(0.0144)	(0.0233)	(0.0133)
Fourth-order downstream	0.0144	0.0213	0.0336**	0.0421**	0.0377***
	(0.0166)	(0.0257)	(0.0164)	(0.0203)	(0.0112)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. PPML estimation is exploited. "EEP" refers to "energy-efficient patent"; "GP" refers to "zero-carbon patent"; and "NEP" refers to "non-environmental patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A12: Sectoral and regional spillovers: Spatial autoregressive estimation

	Spatial Autoregressive model estimation				
	Entry, capital	Entry, number	EEP	GP	NEP
Carbon-upstream	0.836***	0.810***	0.679***	0.841***	0.762***
	(0.0321)	(0.0447)	(0.0570)	(0.0614)	(0.0471)
Carbon-downstream	0.889***	0.784***	0.657***	0.795***	0.725***
	(0.0326)	(0.0551)	(0.0416)	(0.0362)	(0.0801)
Inter-city spillover	0.125***	0.0684***	0.125***	0.113***	0.155***
	(0.0232)	(0.0103)	(0.0231)	(0.0123)	(0.0230)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. The "Carbon-upstream" and "Carbon-downstream" spillovers are estimated using equation (B19). The "Inter-city spillover" is estimated using equation (B20). "EEP" refers to "energy-efficient patent"; "GP" refers to "zero-carbon patent"; and "NEP" refers to "non-environmental patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A13: Controlling for regional spillovers

	Entry, capital			Entry, number			EEP		
	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial
1(pilot)*1(carbon)	-2.226***	-0.623***	-0.722***	-1.344***	-0.188***	-0.233***	3.213***	0.323***	0.325***
	(0.542)	(0.0715)	(0.0300)	(0.224)	(0.0634)	(0.0231)	(0.570)	(0.0313)	(0.0421)
1(pilot)*1(upstream,regulated)	-2.278***	-0.416***	-0.214***	-4.243***	-0.213***	-0.278***	-3.658***	-0.277***	-0.345***
	(0.845)	(0.0570)	(0.0456)	(0.810)	(0.0577)	(0.0478)	(0.545)	(0.0414)	(0.0300)
1(pilot)*1(upstream,unregulated)	-0.677***	-0.167***	0.166***	-0.622***	-0.127***	-0.151***	-0.733***	-0.166***	-0.166***
	(0.0312)	(0.0312)	(0.0231)	(0.100)	(0.0256)	(0.0133)	(0.144)	(0.0313)	(0.0441)
1(pilot)*1(downstream,regulated)	3.461***	0.229***	0.404***	2.680***	0.559***	0.416***	2.778***	0.223***	0.423***
	(0.423)	(0.0266)	(0.0317)	(0.371)	(0.0630)	(0.0411)	(0.339)	(0.0556)	(0.0881)
1(pilot)*1(downstream,unregulated)	1.366***	0.139***	0.135***	1.353***	0.158***	0.161***	1.341***	0.129***	0.125***
	(0.0422)	(0.0331)	(0.0367)	(0.327)	(0.0256)	(0.0321)	(0.435)	(0.0264)	(0.0267)
Spatial and temporal lag of sectoral size: same province: Y									
Spatial and temporal lag of treatment status: same province, Y									
Spatial and temporal lag of sectoral size: proximity, Y									
Spatial and temporal lag of treatment status: proximity, Y									
Controls: Y									

	GP			NEP		
	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial
1(pilot)*1(carbon)	3.391***	0.373***	0.372***	2.880***	0.416***	0.374***
	(0.326)	(0.0632)	(0.0331)	(0.517)	(0.0444)	(0.0722)
1(pilot)*1(upstream,regulated)	-4.243***	-0.323***	-0.277***	-2.322***	-0.388***	-0.333***
	(0.631)	(0.0300)	(0.0415)	(0.412)	(0.0245)	(0.0413)
1(pilot)*1(upstream,unregulated)	-1.522***	-0.166***	-0.145***	-0.768***	-0.166***	-0.177***
	(0.215)	(0.0223)	(0.0166)	(0.111)	(0.0412)	(0.0233)
1(pilot)*1(downstream,regulated)	2.543***	0.277***	0.215***	1.488***	0.411***	0.403***
	(0.660)	(0.0441)	(0.0322)	(0.331)	(0.0681)	(0.0428)
1(pilot)*1(downstream,unregulated)	1.268***	0.121***	0.141***	0.668***	0.149***	0.141***
	(0.256)	(0.0388)	(0.0271)	(0.0356)	(0.0321)	(0.0422)
Spatial and temporal lag of sectoral size: same province: Y						
Spatial and temporal lag of treatment status: same province, Y						
Spatial and temporal lag of sectoral size: proximity, Y						
Spatial and temporal lag of treatment status: proximity, Y						
Controls: Y						

Notes: The samples cover various sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects and controls are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. Spatial and temporal lag (same province) stands for the simple arithmetic mean of the lag variable. Spatial and temporal lag (proximity) stands for the weighted arithmetic mean of the lag variable, where the weight is the inverse of distance. "EEP" refers to "energy-efficient patent"; "GP" refers to "zero-carbon patent"; and "NEP" refers to "non-environmental patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A14: Estimating spatial spillover effects

	Panel A: Carbon-intensive and non-related sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(carbon)	-0.436***	-0.256***	0.401***	0.267***	-0.244***
	(0.0221)	(0.0209)	(0.0355)	(0.0101)	(0.0232)
1(max pilot, same province)*1(carbon)	0.000311	0.0237	-0.00877	-0.00693	0.00149
	(0.000216)	(0.0251)	(0.00731)	(0.00523)	(0.00164)
1(average pilot, same province)*1(carbon)	0.000431	0.00165	0.000661	0.0104	0.00220
	(0.00706)	(0.00132)	(0.00127)	(0.0122)	(0.00166)
	Panel B: Regulated upstream and non-related sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream, regulated)	-0.489***	-0.444***	-0.621***	-0.495***	-0.326***
	(0.0321)	(0.0533)	(0.0715)	(0.0331)	(0.0510)
1(max pilot, same province)*1(upstream, regulated)	0.0119	0.00221	0.00117	0.0123	0.0135
	(0.0101)	(0.00149)	(0.00110)	(0.0111)	(0.0126)
1(average pilot)*1(upstream, regulated)	0.00855	0.00838	0.00662	0.00580	0.00339
	(0.00997)	(0.00912)	(0.00751)	(0.00521)	(0.00498)
	Panel C: Unregulated upstream and non-related sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream, unregulated)	-0.489***	-0.444***	-0.621***	-0.495***	-0.326***
	(0.0321)	(0.0533)	(0.0715)	(0.0331)	(0.0510)
1(max pilot, same province)*1(upstream, unregulated)	-0.00523	-0.0174	0.00100	0.0114	0.0111
	(0.0166)	(0.0119)	(0.00155)	(0.0224)	(0.0133)
1(average pilot, same province)*1(upstream, unregulated)	-0.0109	0.00838	-0.0278	0.00320	-0.0101
	(0.0109)	(0.00912)	(0.0525)	(0.0521)	(0.0523)
	Panel D: Regulated downstream and non-related sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream, regulated)	0.416***	0.567***	0.635***	0.422***	0.244***
	(0.0777)	(0.0653)	(0.0714)	(0.0300)	(0.0231)
1(max pilot, same province)*1(downstream, regulated)	0.0356	-0.000412	0.0134	0.00614	0.00646
	(0.0579)	(0.00804)	(0.0243)	(0.00705)	(0.00821)
1(average pilot, same province)*1(downstream, regulated)	0.0102	0.0178	-0.00422	0.00220	0.00610
	(0.00873)	(0.0319)	(0.00544)	(0.00513)	(0.00826)
	Panel E: Unregulated downstream and non-related sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream, unregulated)	0.422***	0.511***	0.600***	0.404***	0.212***
	(0.0448)	(0.0779)	(0.0556)	(0.0250)	(0.0211)
1(max pilot, same province)*1(downstream, unregulated)	0.00761	-0.0104	-0.0115	0.00614	0.00646
	(0.0897)	(0.0869)	(0.0871)	(0.00705)	(0.00821)
1(average pilot, same province)*1(downstream, unregulated)	0.0912	0.0889	0.0244	0.000776	0.0184
	(0.275)	(0.276)	(0.0383)	(0.176)	(0.179)

Notes: In Panels A through E, the sample includes various sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects and controls are included. PPML estimation is employed for the entire table. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. 1(max pilot, same province) takes the value of 1 if another city within the same province is selected as a pilot. 1(average pilot, same province) is the average of pilot dummies in the same province. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A15: Spatial spillover effects on city-level carbon emissions

	(1)	(2)
	log(City-level carbon emissions)	
1(max pilot, same province)	0.0197	
	(0.0135)	
1(average pilot, same province)		-0.0136
		(0.0396)
City FE	Y	Y
Year FE	Y	Y
Observations	2,552	2,552
R-squared	0.992	0.992

Notes: The sample includes 295 cities during 2005-2017. In all columns, city and year fixed effects and controls are included. Controls include city-level log per capita real GDP and log population in 2005 interacted with year dummies. 1(max pilot, same province) takes the value of 1 if another city within the same province is selected as a pilot. 1(average pilot, same province) is the average of pilot dummies in the same province. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table A16: Effects on exit

	Exit, number			Exit, capital		
	OLS	PPML	Negative Binomial	OLS	PPML	Negative Binomial
1(pilot)*1(carbon)	-2.324***	-0.165***	-0.177***	-14.799***	-7.634***	-4.722***
	(0.601)	(0.0203)	(0.0189)	(2.156)	(1.233)	(0.369)
1(pilot)*1(upstream,regulated)	-3.277***	-0.245***	-0.212***	-12.658***	-5.713***	-2.959***
	(0.218)	(0.0336)	(0.0432)	(2.641)	(0.802)	(0.331)
1(pilot)*1(upstream,unregulated)	-1.357***	-0.266***	-0.255***	-7.749***	-5.233***	-4.466***
	(0.456)	(0.0540)	(0.0441)	(1.822)	(0.301)	(0.325)
1(pilot)*1(downstream,regulated)	1.004***	0.132***	0.110***	2.109***	2.321***	2.220***
	(0.161)	(0.0324)	(0.0359)	(0.313)	(0.254)	(0.316)
1(pilot)*1(downstream,unregulated)	1.437***	0.119***	0.125***	1.201***	1.114***	1.211***
	(0.312)	(0.0244)	(0.0267)	(0.398)	(0.188)	(0.311)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A17: City-year DiD: Carbon-intensive sectors

	Panel A: Carbon Sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)	-0.559***	-0.411***	0.372***	0.231***	-0.255***
	(0.0144)	(0.0233)	(0.0356)	(0.0313)	(0.0311)
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Observations	4,425	4,425	4,425	4,425	4,425
R-squared	0.199	0.236	0.159	0.121	0.148
Number of cities	295	295	295	295	295
	Panel B: Upstream Sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)	-0.134***	-0.135***	-0.125***	0.199***	-0.243***
	(0.0113)	(0.0485)	(0.0142)	(0.0331)	(0.0325)
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Observations	4,425	4,425	4,425	4,425	4,425
R-squared	0.169	0.247	0.190	0.131	0.125
Number of cities	295	295	295	295	295
	Panel C: Downstream Sectors, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)	0.299***	0.479***	0.345***	0.425***	0.345***
	(0.0573)	(0.0121)	(0.0223)	(0.0312)	(0.0223)
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Observations	4,425	4,425	4,425	4,425	4,425
R-squared	0.142	0.242	0.144	0.158	0.131
Number of cities	295	295	295	295	295

Notes: The sample covers 295 cities during 2005-2019. In all columns, city and year fixed effects are included. PPML estimation is employed for the entire table. Controls include the log per capita real GDP, the log population of the cities, and the stock of capital of all existing firms in the city in 2005 of the city-sector cell interacted with year dummies. "EEP" refers to "energy-efficient patent"; "GP" refers to "zero-carbon patent"; and "NEP" refers to "non-environmental patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table A18: Patent applications by size

	(1)	(2)	(3)
	EEP, large firms	EEP, medium firms	EEP, small firms
1(pilot)*1(carbon)	0.0599***	-0.0145***	-0.00558***
	(0.00912)	(0.00313)	(0.00112)
	(4)	(5)	(6)
	log(1+GP, large firms)	log(1+GP, medium firms)	log(1+GP, small firms)
1(pilot)*1(carbon)	0.0299**	-0.0790***	0.00445
	(0.0143)	(0.00802)	(0.00905)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. PPML estimation is employed for the entire table. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of the city-sector cell interacted with year dummies. "EEP" refers to "energy-efficient patent," and "GP" refers to "zero-carbon patent." Large firms are defined as firms with registry capital in the top 10 percentile, medium firms are defined as those whose registry capital belongs to the top 10-50 percentile, and small firms are those whose registry capital belongs to the bottom 50 percentile. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A19: Heterogeneity with respect to carbon emission intensity

	Panel A: Carbon-intensive sector, low carbon emissions, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(carbon)	0.0562***	0.0379**	0.0244	0.0268	0.0331
	(0.00912)	(0.0180)	(0.0312)	(0.0360)	(0.0459)
	Panel B: Carbon-intensive sector, high carbon emissions, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(carbon)	-0.0684***	-0.0478***	0.149***	0.355***	0.251***
	(0.0115)	(0.0132)	(0.0413)	(0.0336)	(0.0336)
	Panel C: Regulated upstream sector, low carbon emissions, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream)	-0.0233	-0.0336	-0.0448	-0.0233	0.00990
	(0.0235)	(0.0443)	(0.0809)	(0.0332)	(0.0104)
	Panel D: Regulated upstream sector, high carbon emissions, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream)	-0.0923***	-0.326***	-0.494***	-0.234***	-0.149***
	(0.00615)	(0.0112)	(0.0167)	(0.0314)	(0.0451)
	Panel E: Regulated downstream sectors, low carbon emissions, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream)	0.0123	0.113	0.100	0.156	0.0125
	(0.0144)	(0.144)	(0.132)	(0.166)	(0.0133)
	Panel F: Regulated downstream sectors, high carbon emissions, PPML				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream)	0.0459***	0.369***	0.285***	0.285***	0.203***
	(0.0116)	(0.0374)	(0.0448)	(0.0448)	(0.0226)

Notes: The data set is a city-year panel data set. The sample covers 295 cities during 2007-2015. The sample period is limited because of the availability of firm-level emission data. In all columns city and year fixed effects are included. PPML regressions are employed in all columns. Controls include the log per capita real GDP, the log population, and the stock of capital of all existing firms in 2005 of the city-sector cell in the city. "High emis." refers to firms whose carbon emission intensity is larger than the median of all firms in the city-sector-year cell. "Low emis." refers to firms whose carbon emission intensity is smaller than the median of all firms in the city-sector-year cell. "K" refers to entry measured by registry capital; "#" refers to entry measured by number. "EEP" refers to "energy-efficient patent," and "GP" refers to "zero-carbon patent." * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table A20: Change in market equilibrium

	P_1	Q_1	P_2	Q_2	P_3	Q_3
			Status quo			
Pilot (non-pilot normalized to 1)	0.933	0.894	0.956	0.945	0.947	1.053
			High a_1, $a_1 = 0.3$			
Pilot (non-pilot normalized to 1)	1.025	0.701	0.873	0.895	1.146	0.937
			Low a_1, $a_1 = 0.01$			
Pilot (non-pilot normalized to 1)	0.902	0.928	0.977	0.982	0.931	1.179
			High b_1, $b_1 = 0.5$			
Pilot (non-pilot normalized to 1)	0.909	0.917	0.968	0.973	0.937	1.1
			Low b_1, $b_1 = 0.01$			
Pilot (non-pilot normalized to 1)	1.046	0.675	0.805	0.864	1.269	0.894
			High c_1, $c_1 = 0.4$			
Pilot (non-pilot normalized to 1)	1.079	0.664	0.782	0.833	1.29	0.868
			Low c_1, $c_1 = 0.01$			
Pilot (non-pilot normalized to 1)	0.905	0.934	0.981	0.989	1.155	0.924
			High d_1, $d_1 = 0.4$			
Pilot (non-pilot normalized to 1)	1.077	0.662	0.78	0.831	1.288	0.866
			Low d_1, $d_1 = 0.01$			
Pilot (non-pilot normalized to 1)	0.908	0.937	0.984	0.992	1.158	0.927

Table A21: External calibration

Parameter	β_{11}	β_{12}	β_{13}	β_1	β_{21}	β_{22}	β_{23}	β_2	β_{31}	β_{32}
Value	0.316	0.359	0.326	0.275	0.252	0.647	0.101	0.81	0.309	0.54
Parameter	β_{33}	β_3	α_1	α_2	α_3	ϵ	l_s	η	γ	ρ
Value	0.15	0.967	0.277	0.564	0.159	2.9	0.166	0.5	2	0.02

Table A22: Structural estimates

Parameters	Estimates	S.E.	Parameters	Estimates	S.E.	Parameters	Estimates	S.E.
a_0	-0.012	0.003	c_1	0.079	0.007	θ^E	0.092	0.009
a_1	0.085	0.012	d_0	0.010	0.002	Δ	0.129	0.026
b_0	0.013	0.002	d_1	0.131	0.009	φ	0.053	0.008
b_1	0.132	0.019	ϕ	0.202	0.035	λ_1	0.178	0.020
c_0	0.014	0.002	θ	1.531	0.307	λ_2	0.410	0.038

Table A23: Quantifying the effects of different channels without input-output linkages

	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare
				Benchmark case			
Non-pilot, carbon	0.023	0.512	0.478	1.081	0.0779		
Non-pilot, upstream	0.019	0.487	0.421	1.138			
Non-pilot, downstream	0.027	0.531	0.499	0.945			
Non-pilot, total						0.0481	0.8470
				Emissions fee channel			
Pilot, carbon	0.024	0.505	0.470	1.102	0.0616		
Pilot, upstream	0.019	0.487	0.420	1.138			
Pilot, downstream	0.023	0.526	0.495	0.950			
Pilot, total						0.0471	0.8465
				Research subsidy channel			
Pilot, carbon	0.022	0.519	0.482	1.042	0.0770		
Pilot, upstream	0.019	0.487	0.421	1.138			
Pilot, downstream	0.029	0.539	0.501	0.913			
Pilot, total						0.0497	0.8472
				Entry cost channel			
Pilot, carbon	0.024	0.508	0.472	1.107	0.0645		
Pilot, upstream	0.019	0.487	0.420	1.138			
Pilot, downstream	0.022	0.523	0.497	0.947			
Pilot, total						0.0472	0.8466
				Production regulation channel			
Pilot, carbon	0.024	0.501	0.465	1.108	0.0661		
Pilot, upstream	0.019	0.487	0.420	1.138			
Pilot, downstream	0.023	0.521	0.495	0.946			
Pilot, total						0.0473	0.8464

Table A24: Model fit: Coefficients

	Data	Model	Data	Model	Data	Model	Data	Model
				Carbon Sectors				
	All firms		Large firms		Medium firms		Small firms	
Entry	-0.314	-0.342	-0.125	-0.119	-0.298	-0.309	-0.442	-0.450
Exit	-0.241	-0.257	-0.356	-0.356	-0.221	-0.222	-0.112	-0.114
Emissions	-0.155	-0.148	-0.166	-0.158	-0.134	-0.125	-0.111	-0.106
EEP	0.261	0.268	0.483	0.467	0.254	0.254	0.163	0.160
GP	0.037	0.044	0.030	0.030	-0.079	-0.077	0.004	0.004
NEP	-0.069	-0.065	-0.099	-0.100	-0.071	-0.072	-0.044	-0.043
Output	-0.155	-0.149	-0.177	-0.168	-0.123	-0.118	-0.088	-0.085
				Upstream Sectors				
	All firms		Large firms		Medium firms		Small firms	
Entry	-0.803	-0.763	-0.664	-0.660	-0.789	-0.815	-0.831	-0.857
Exit	-0.435	-0.506	-0.553	-0.561	-0.387	-0.401	-0.225	-0.223
Emissions	-0.044	-0.039	-0.055	-0.053	-0.039	-0.036	-0.033	-0.031
EEP	-0.456	-0.413	-0.556	-0.567	-0.414	-0.401	-0.339	-0.340
GP	-0.322	-0.307	-0.399	-0.394	-0.288	-0.287	-0.215	-0.215
NEP	-0.454	-0.393	-0.654	-0.639	-0.433	-0.414	-0.339	-0.330
Output	-0.233	-0.211	-0.288	-0.278	-0.244	-0.243	-0.184	-0.169
				Downstream Sectors				
	All firms		Large firms		Medium firms		Small firms	
Entry	0.859	0.792	1.233	1.209	0.776	0.806	0.541	0.563
Exit	0.558	0.562	0.336	0.341	0.547	0.524	0.662	0.677
Emissions	0.055	0.057	0.058	0.056	0.049	0.051	0.046	0.044
EEP	0.437	0.486	0.613	0.617	0.401	0.402	0.310	0.296
GP	0.365	0.395	0.456	0.437	0.331	0.334	0.227	0.218
NEP	0.273	0.250	0.304	0.295	0.255	0.246	0.203	0.205
Output	0.255	0.269	0.229	0.218	0.177	0.169	0.143	0.139

Notes: Large firms are defined by firms with registry capital in the top 10 percentile, medium firms are defined by those whose registry capital belongs to the top 10-50 percentile, and small firms are those whose registry capital belongs to the bottom 50 percentile.

Table A25: Robustness checks of quantitative analysis

Panel A: Fourth-order polynomials of emissions function							
	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare
Non-pilot, carbon	0.023	0.512	0.477	1.082	0.0874		
Non-pilot, upstream	0.019	0.488	0.422	1.138			
Non-pilot, downstream	0.027	0.531	0.499	0.944			
Non-pilot, total						0.0481	0.8470
Pilot, carbon	0.025	0.531	0.479	1.118	0.0777		
Pilot, upstream	0.019	0.487	0.420	1.139			
Pilot, downstream	0.023	0.538	0.499	0.897			
Pilot, total						0.0487	0.8473
Panel B: Linear specifications of τ's							
	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare
Non-pilot, carbon	0.023	0.509	0.474	1.084	0.0875		
Non-pilot, upstream	0.019	0.491	0.420	1.134			
Non-pilot, downstream	0.027	0.533	0.497	0.945			
Non-pilot, total						0.0482	0.8471
Pilot, carbon	0.025	0.532	0.479	1.114	0.0778		
Pilot, upstream	0.019	0.484	0.420	1.135			
Pilot, downstream	0.023	0.536	0.499	0.896			
Pilot, total						0.0488	0.8474

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Appendix B More on econometric specifications

B.1 Detecting sectoral and regional spillovers

We use a spatial autoregressive model to estimate spillover through the sector-level input-output linkages, following Lee and Yu (2010). Specifically, we estimate the following specification:

$$y_{ijt} = \alpha \sum_{k \in N(j)} w_{jk} y_{ikt} + \lambda_{ij} + \lambda_{it} + \lambda_{jt} + u_{ijt}, \tag{B19}$$

where y_{ijt} is the outcome of city i, sector j, and year t, w_{jk} is the spatial weights, which can be the input share or the output share in the input-output table, and $\sum_{k \in N(j)} w_{jk} y_{ikt}$ is the weighted sum of the outcome of sector j's neighbors $N(j)$. If w_{jk} is the input share, then $\sum_k w_{jk} y_{ikt}$ is the outcome of the upstream of sector j, and if w_{jk} is the output share, then $\sum_k w_{jk} y_{ikt}$ is the outcome of the downstream of sector j. $\lambda_{ij}, \lambda_{it}, \lambda_{jt}$ denotes city-sector, city-year, and sector-year fixed effects, respectively.

Equation (B19) is a standard spatial autoregressive model used to detect spillover effects. Since we construct a weighted sum of "neighbors" in the input-output table, we are estimating the spillover effects through the input-output linkages.

Similarly, we can use the same specification to estimate the cross-region spillover effects. To meet this end, we need to construct the mean variable of geographical neighbors at the city level. We estimate a similar spatial autoregressive model as follows:

$$y_{ijt} = \alpha \sum_{l \in N(i)} w_{il} y_{ljt} + \lambda_{ij} + \lambda_{it} + \lambda_{jt} + u_{ijt}, \tag{B20}$$

where the only difference is $\sum_{l \in N(i)} w_{il} y_{ljt}$, the weighted sum of the outcome of city i's neighbors $N(i)$, and the weight is the inverse of geographic distance between city i and city l.

The estimation results are reported in Table A12. Inter-sectoral spillovers are quantitatively more salient than inter-city spillovers. One possible explanation is that there are significant spatial frictions due to administrative barriers. Therefore, using a spatial autoregressive model, we demonstrate that spatial spillovers are quantitatively unimportant.

B.2 Construction of instruments

B.2.1 Hausman instruments

First, we construct a Hausman-style instrument using the following equation:

$$HausmanIV_i = \log(\sum_{j \in N(i), j \neq i} w_{ij} CarbonEmission_{j,2005}) \tag{B21}$$

where $N(i)$ is the set of neighboring cities of city i, which is defined as the collection of all other cities in the same province, w_{ij} is the inverse of the distance between cities i and j, $CarbonEmission_{j,2005}$ is the amount of carbon emissions in city j in 2005. The identifying assumptions are (1) neighbors' carbon emissions in the past are orthogonal to the unobservables that may affect current firms' and industries' outcomes, and (2) neighbors' carbon emissions are strongly correlated with the city's own participation in the pilot policy. The Hausman instrument is valid because it exploits information on neighbors' carbon emissions that may affect pilot participation. It is positively related to pilot participation.

B.2.2 Bartik instruments

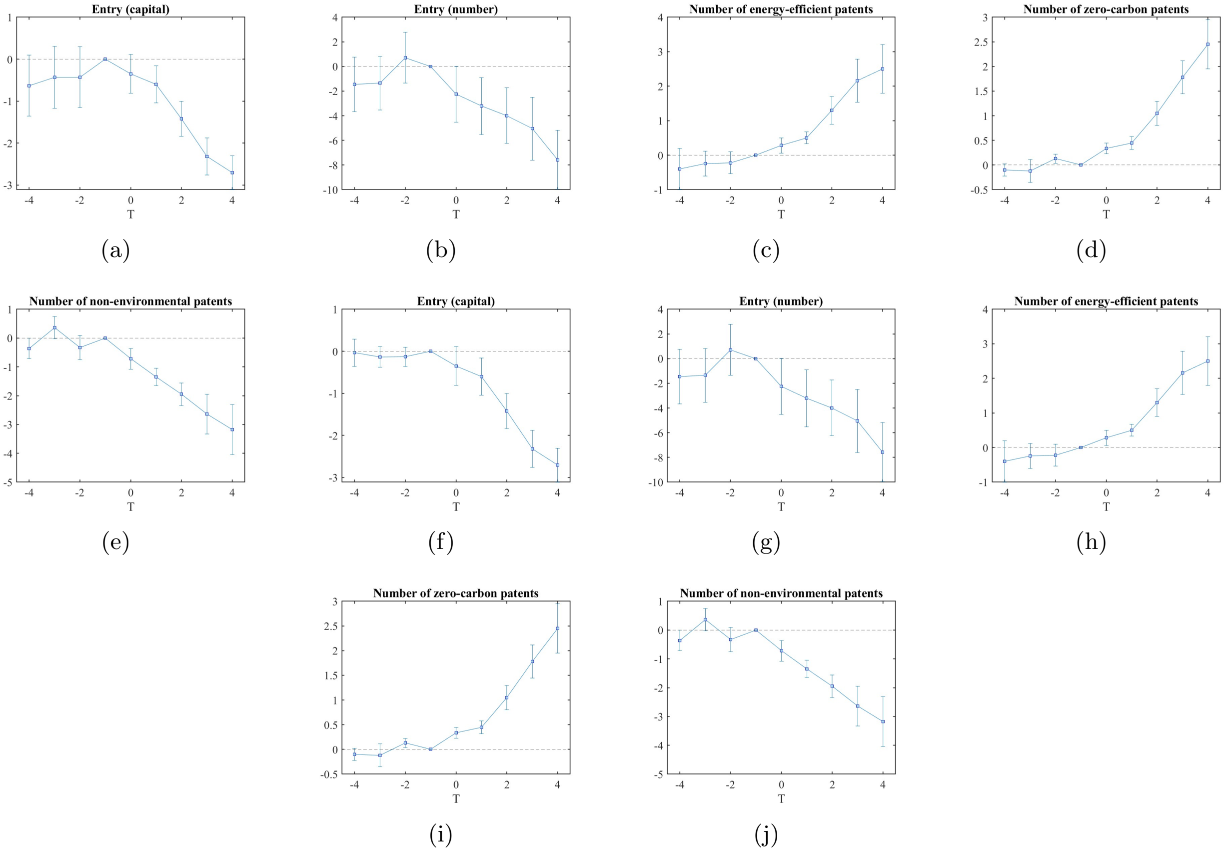
Next, we construct a Bartik instrument using the following equation:

$$BartikIV_i = \sum_k z_{ik} g_k \tag{B22}$$

where z_{ik} the city-sector share (revenue of city i and sector k in the total revenue of city i), g_k is the growth of carbon emissions at the national level in sector k during 2000-2005. Both the shift, g_k, and the share, z_{ik}, are observed in the past so that they can be seen to satisfy exclusion restrictions. The Bartik instrument is also valid because it exploits the focal city's industrial mix of the shift of carbon emissions at the national level. It is also positively related to pilot participation.

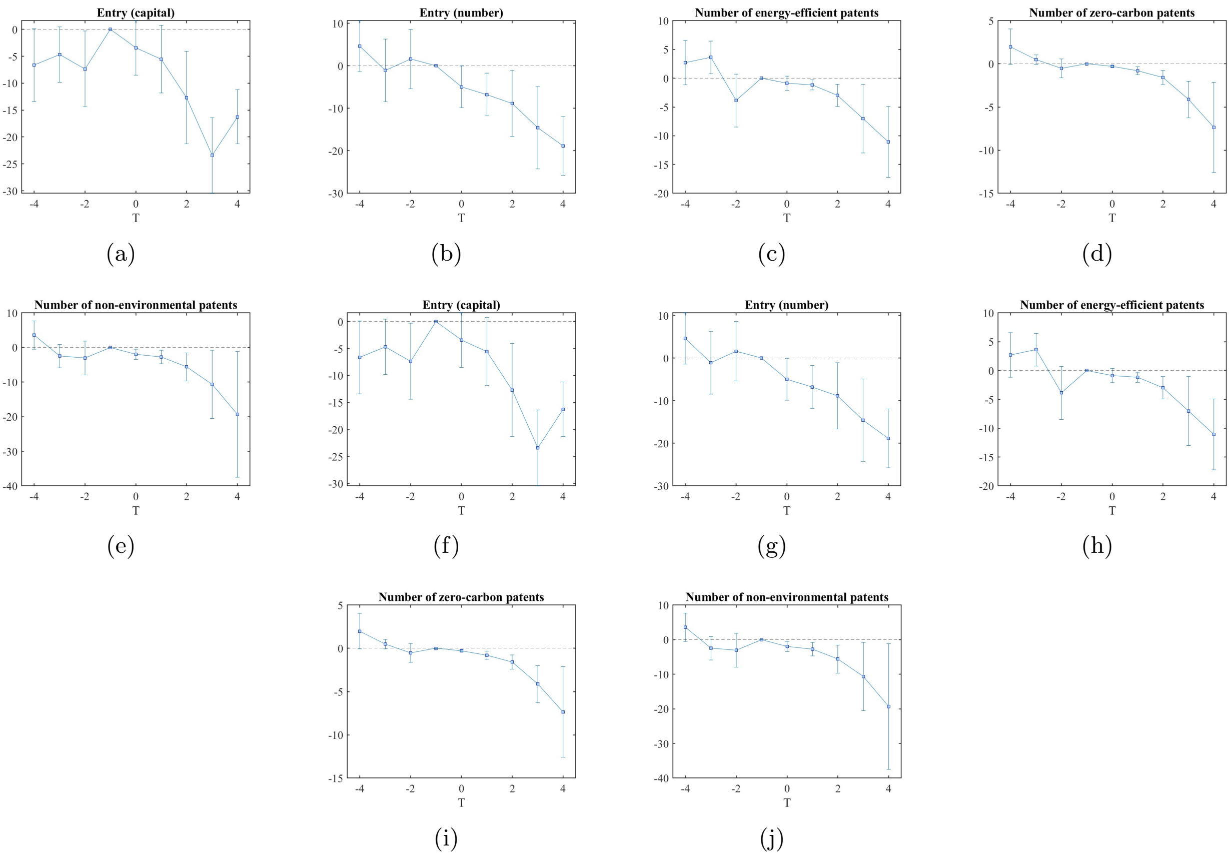
Appendix C Figures and Tables

Figure C1: Estimating the dynamic effects on the carbon-intensive sectors, IV-2SLS



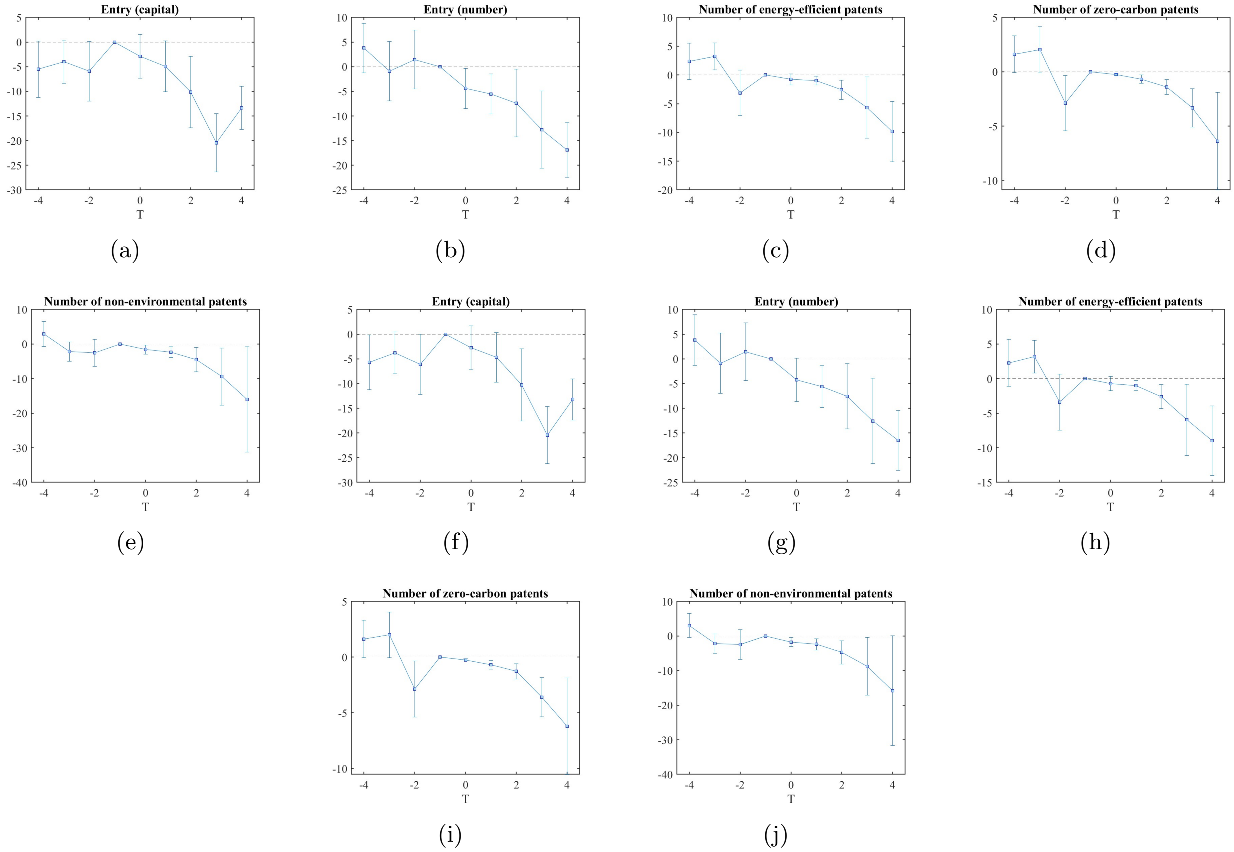
Notes: The sample consists of 14,160 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau)\times 1(Pilot_i)\times 1(Carbon_j)$ on $Entry_{ijt}$,capital, $Entry_{ijt}$,number, and $Patent_{ijt}$ of the carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Hausman IV, while subfigures (f)-(j) are obtained using the method of Bartik IV. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment ($t=-1$), which is standardized to 0.

Figure C2: Estimating the dynamic effects on the regulated upstream sectors, IV-2SLS



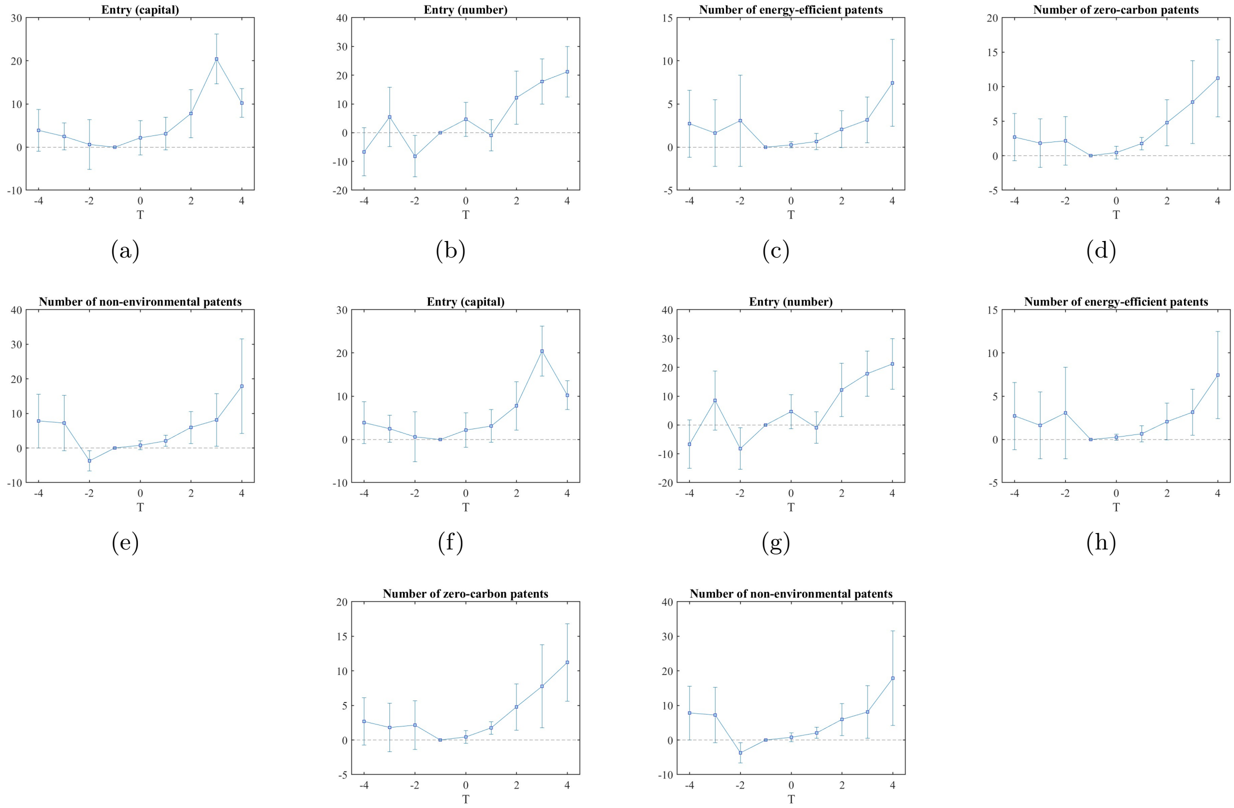
Notes: The sample consists of 16,225 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Upstream, regulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the regulated upstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Hausman IV, while subfigures (f)-(j) are obtained using the method of Bartik IV. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$). *The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$), *which is standardized to 0.*

Figure C3: Estimating the dynamic effects on the unregulated upstream sectors, IV-2SLS



Notes: The sample consists of 38,350 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau) \times 1(Pilot_i) \times 1(Upstream, unregulated_j)$ on $Entry_{ijt}$, capital, $Entry_{ijt}$, number, and $Patent_{ijt}$ of the downstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Hausman IV, while subfigures (f)-(j) are obtained using the method of Bartik IV. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment ($t=-1$), which is standardized to 0.

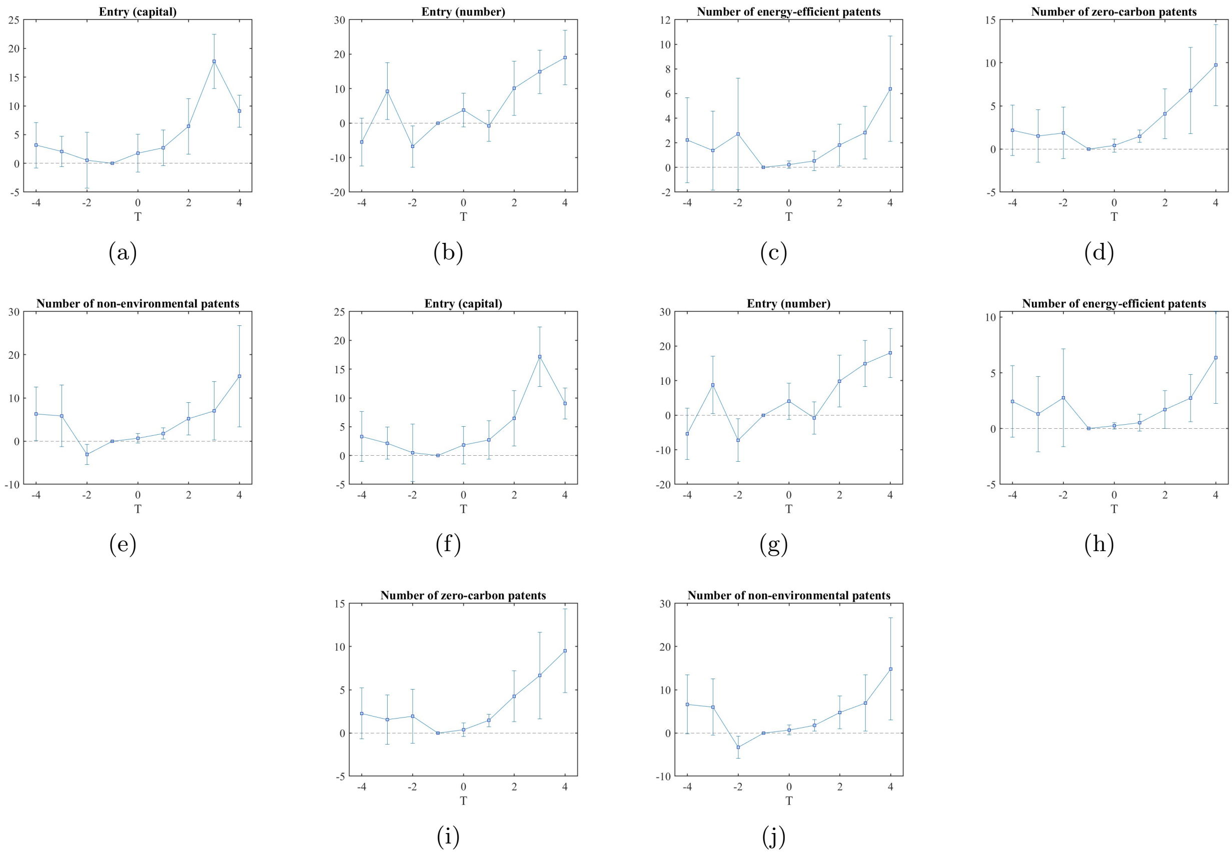
Figure C4: Estimating the dynamic effects on the regulated downstream sectors, IV-2SLS



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

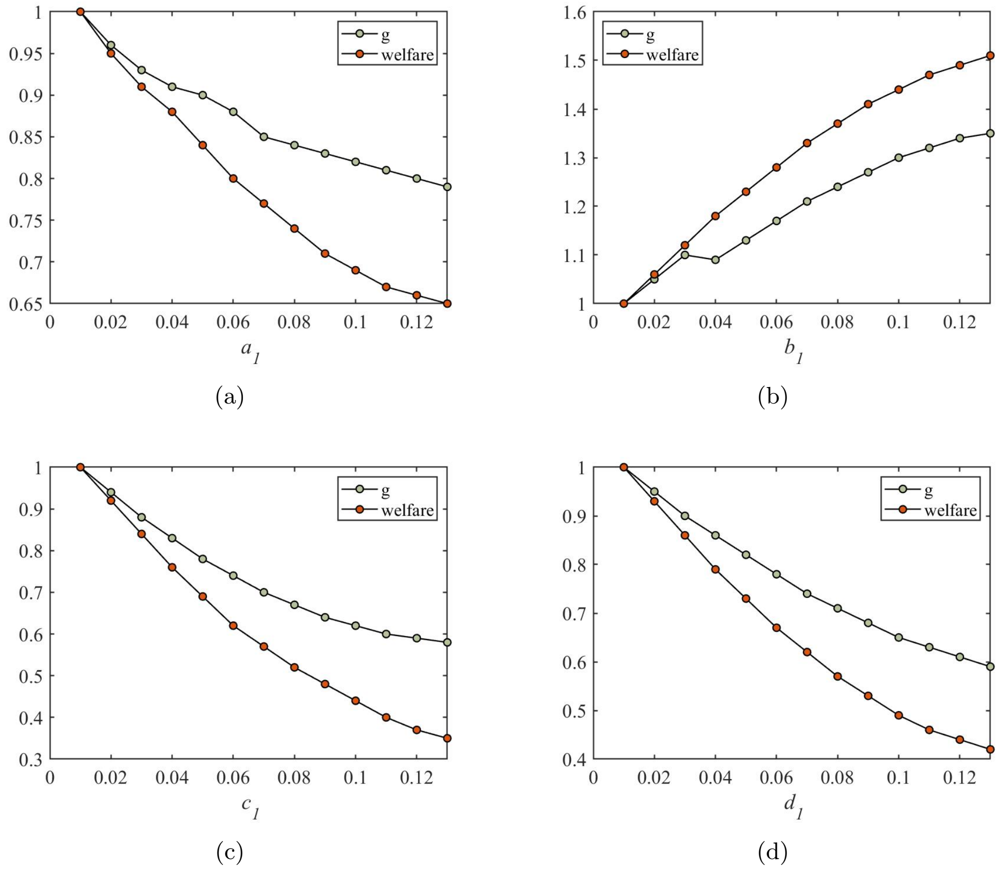
Notes: The sample consists of 14,750 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t = \tau) \times 1(Pilot_i) \times 1(Downstream, regulated_j)$ on $Entry_{ijt}, capital$, $Entry_{ijt}, number$, and $Patent_{ijt}$ of the regulated downstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Hausman IV, while subfigures (f)-(j) are obtained using the method of Bartik IV. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started ($t \geq 0$). The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment ($t = -1$), which is standardized to 0.

Figure C5: Estimating the dynamic effects on the unregulated downstream sectors, IV-2SLS



Notes: The sample consists of 26,845 city-sectors during 2005-2019. The figure illustrates the OLS estimate of dynamic effects of the treatment $1(t=\tau) \times 1(Pilot_i) \times 1(Downstream, unregulated_j)$ *on* $Entry_{ijt}, capital$, $Entry_{ijt}, number$, *and* $Patent_{ijt}$ *of the unregulated downstream sectors of carbon-intensive sectors. Subfigures (a)-(e) are obtained using the method of Hausman IV, while subfigures (f)-(j) are obtained using the method of Bartik IV. The horizontal axis measures the year since the city-sector experienced a treatment. The year 0 represents the first year of the treatment. The vertical axis measures the regression coefficients for the dynamic effects. The coefficients are obtained using the baseline specification (with controls, city-sector fixed effects, city-year fixed effects, and sector-year fixed effects), with the only exception that the dummy for the treatment is replaced by the interaction terms of the dummy for treatment and dummies for time. The figure shows that the effect of the carbon emissions regulation is restricted to the period in which the treatment has started* ($t \geq 0$)*. The vertical line around each plotted coefficient indicates the 95% confidence interval, with standard errors being two-way clustered at the city and sector levels. Every estimated effect is compared to the year that is one year prior to that of the treatment* ($t = -1$)*, which is standardized to 0.*

Figure C6: The effects of varying policy parameters



Notes: These figures depict how the welfare and growth rate vary with policy parameters. One parameter changes at one time, holding other parameters fixed. a_1, b_1, c_1, *and* d_1 *stand for the stringency of policy measures of emissions fees, research subsidies, entry costs, and production regulation, respectively.*

Table C1: Alternative definitions of treated and control groups

Independent variable	Control group	Entry, number		Entry, capital		Patent	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
1(pilot)*1(carbon)	Bottom 6% up(down)streamness	-0.1212	0.0370	-3.0451	0.9235	0.1481	0.0469
1(pilot)*1(upstream,regulated)		-0.2868	0.0941	-3.8238	1.1994	-0.1961	0.0586
1(pilot)*1(upstream,unregulated)		-0.1970	0.0620	-3.1260	0.8705	-0.1465	0.0458
1(pilot)*1(downstream,regulated)		0.2527	0.0722	4.3365	1.3016	0.2573	0.0730
1(pilot)*1(downstream,unregulated)		0.1953	0.0615	2.8563	0.8804	0.1486	0.0461
1(pilot)*1(carbon)	Bottom 8% up(down)streamness	-0.1176	0.0375	-3.0705	0.8966	0.1564	0.0450
1(pilot)*1(upstream,regulated)		-0.2911	0.0917	-4.1925	1.2167	-0.1989	0.0614
1(pilot)*1(upstream,unregulated)		-0.2097	0.0628	-3.1345	0.9445	-0.1539	0.0449
1(pilot)*1(downstream,regulated)		0.2430	0.0765	4.3735	1.3205	0.2492	0.0761
1(pilot)*1(downstream,unregulated)		0.1999	0.0602	3.1029	0.9315	0.1559	0.0462
1(pilot)*1(carbon)	Bottom 12% up(down)streamness	-0.1154	0.0373	-3.1415	0.8556	0.1494	0.0448
1(pilot)*1(upstream,regulated)		-0.3133	0.0905	-3.8826	1.1612	-0.1957	0.0597
1(pilot)*1(upstream,unregulated)		-0.2002	0.0623	-3.0596	0.9307	-0.1445	0.0459
1(pilot)*1(downstream,regulated)		0.2411	0.0755	4.3568	1.3375	0.2591	0.0715
1(pilot)*1(downstream,unregulated)		0.2066	0.0612	3.0908	0.9331	0.1553	0.0439
	Treated group	Entry, number		Entry, capital		Patent	
1(pilot)*1(upstream,regulated)	Top 20% up(down)streamness	-0.2917	0.0900	-3.8978	1.2262	-0.2057	0.0585
1(pilot)*1(upstream,unregulated)		-0.2079	0.0601	-3.0293	0.8976	-0.1467	0.0441
1(pilot)*1(downstream,regulated)		0.2499	0.0782	4.3474	1.3706	0.2518	0.0774
1(pilot)*1(downstream,unregulated)		0.1914	0.0580	2.9278	0.8950	0.1526	0.0459
1(pilot)*1(upstream,regulated)	Top 22% up(down)streamness	-0.2851	0.0879	-4.1354	1.1424	-0.1951	0.0578
1(pilot)*1(upstream,unregulated)		-0.2025	0.0599	-2.9866	0.9114	-0.1529	0.0433
1(pilot)*1(downstream,regulated)		0.2432	0.0742	4.6520	1.3276	0.2418	0.0766
1(pilot)*1(downstream,unregulated)		0.1996	0.0577	3.0058	0.9154	0.1542	0.0466
1(pilot)*1(upstream,regulated)	Top 24% up(down)streamness	-0.2989	0.0899	-3.8988	1.1972	-0.2078	0.0602
1(pilot)*1(upstream,unregulated)		-0.2060	0.0588	-2.8864	0.9017	-0.1539	0.0444
1(pilot)*1(downstream,regulated)		0.2517	0.0767	4.5480	1.3896	0.2531	0.0731
1(pilot)*1(downstream,unregulated)		0.2074	0.0594	3.0253	0.9442	0.1502	0.0463
1(pilot)*1(upstream,regulated)	Top 26% up(down)streamness	-0.2875	0.0932	-4.1813	1.2397	-0.2001	0.0614
1(pilot)*1(upstream,unregulated)		-0.2022	0.0616	-2.9793	0.8601	-0.1531	0.0461
1(pilot)*1(downstream,regulated)		0.2608	0.0727	4.4400	1.3723	0.2500	0.0724
1(pilot)*1(downstream,unregulated)		0.1901	0.0619	3.1288	0.8797	0.1560	0.0435

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. In all columns, city-sector, city-year, and sector-year fixed effects are included. PPML regressions are employed in all columns. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. "Bottom 6% up(down)streamness" defined for the control group means that sectors with a bottom 6% upstreamness and downstreamness are defined as the control group. "Top 22% up(down)streamness" for the treated group means that sectors with a top 22% upstreamness and downstreamness are defined as the treated upstream or downstream sectors. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table C2: Categorization of sectors

Categorization	Sector
Carbon-intensive	251 (refined petroleum product manufacturing), 252 (coal processing), 261 (basic chemical raw material manufacturing), 301 (cement, lime, and gypsum manufacturing), 311 (ironmaking), 312 (steelmaking), 321 (commonly used non-ferrous metal smelting), 441 (power production), 541 (urban public transportation), 542 (road passenger transportation), 543 (road cargo transportation), 544 (auxiliary activities for road transportation)
Upstream & Regulated	061 (bituminous and anthracite mining), 062 (brown coal mining), 069 (other coal mining), 071 (petroleum mining), 072 (natural gas mining), 081 (iron ore mining), 082 (manganese and chromium mining), 089 (other black metal mining), 091 (commonly used non-ferrous metal mining), 092 (precious metal mining), 093 (rare and rare earth metal mining)
Upstream & Unregulated	161, 162, 169, 253, 254, 308, 309, 314, 322, 323, 324, 351, 352, 382, 401, 402, 403, 404, 405, 409, 421, 422, 442, 443, 451, 452, 461, 462, 463, 469, 551, 552, 553, 571, 572, 631, 632, 633, 661, 662, 663, 664, 665, 671, 672, 673, 674, 675, 676, 679, 681, 682, 683, 684, 685, 686, 687, 689, 691, 692, 693, 694, 695, 699, 741, 742, 743, 744, 745, 746, 747, 748, 749, 761, 762, 763, 764, 769, 791, 792, 793, 794, 799, 811, 812, 813, 819, 871, 872, 873, 874, 875, 876, 877
Downstream & Regulated	471 (residential housing construction), 472 (sports venue construction), 479 (other housing construction industries), 481 (railway, road, tunnel, and bridge engineering construction), 482 (water conservancy and water transportation engineering construction), 483 (marine engineering construction), 484 (industrial and mining engineering construction), 485 (wiring and pipeline engineering construction), 486 (energy conservation and environmental protection engineering construction), 487 (power engineering construction), 489 (other civil engineering construction), 491 (electrical installation), 492 (pipeline and equipment installation), 499 (Other construction and installation industries)
Downstream & Unregulated	262, 263, 264, 265, 266, 267, 268, 281, 282, 283, 302, 303, 304, 305, 306, 307, 313, 325, 331, 332, 333, 334, 335, 336, 337, 338, 339, 342, 344, 383, 384, 387, 389, 501, 502, 503, 509, 531, 532, 533, 561, 562, 563, 581, 582, 611, 612, 613, 614, 619, 711, 712, 713, 771, 772
Non-carbon-related	031, 032, 033, 039, 131, 132, 133, 135, 136, 137, 139, 144, 172, 174, 176, 177, 178, 191, 192, 193, 194, 195, 373, 391, 392, 394, 395, 396, 651, 652, 653, 654, 655, 656, 657, 659

Notes: This table shows the categorization of sectors into carbon-intensive (i.e., sectors with high direct carbon emissions), upstream & regulated, upstream & unregulated, downstream & regulated, downstream & unregulated, and non-carbon-related ones. The numbers in parentheses are the China's national economy industry classification codes available at `https://www.mca.gov.cn/images3/www/file/201711/1509495881341.pdf`.

Table C3: Categorization of pilot regions

Year	Pilot regions
2010	Guangdong Province, Liaoning Province, Hubei Province, Shaanxi Province, Yunnan Province, Tianjin City, Chongqing City, Shenzhen City, Xiamen City, Hangzhou City, Nanchang City, Guiyang City, Baoding City
2013	Hainan Province, Beijing City, Shanghai City, Shijiazhuang City, Qinhuangdao City, Jincheng City, Hulunbuir City, Jilin City, Suzhou City, Huai'an City, Zhenjiang City, Ningbo City, Wenzhou City, Chizhou City, Nanping City, Jingdezhen City, Ganzhou City, Qingdao City, Jiyuan City, Wuhan City, Guangzhou City, Guilin City, Guangyuan City, Zunyi City, Kunming City, Yan'an City, Jinchang City, Urumqi City
2017	Wuhai City, Shenyang City, Dalian City, Chaoyang City, Xunke County, Nanjing City, Changzhou City, Jiaxing City, Jinhua City, Quzhou City, Hefei City, Huaibei City, Huangshan City, Liu'an City, Xuancheng City, Sanming City, Gongqingcheng City, Ji'an City, Fuzhou City, Jinan City, Yantai City, Weifang City, Changyang County, Changsha City, Zhuzhou City, Xiangtan City, Chenzhou City, Zhongshan City, Liuzhou City, Sanya City, Chengdu City, Yuxi City, Simao District, Lhasa City, Ankang City, Lanzhou City, Dunhuang City, Xining City, Yinchuan City, Wuzhong City

Notes: This table shows the regions that became pilots in 2010, 2013, and 2017.

Table C4: Effects on cross-city IO linkages

	Input share	Output share
Mean of dep. var.	0.4518	0.4395
1(Pilot)	0.0144	0.0207
	(0.0123)	(0.0153)
City FE	Y	Y
Year FE	Y	Y
Obs	633	633

Notes: Due to the availability of input-output table, the sample covers 317 cities in 2012 and 2015 and the effect of 2013 pilot is estimated. Input share is the ratio of local inputs (from all sectors) to carbon-intensive sectors over total inputs to carbon-intensive sectors. Output share is the ratio of local outputs (from all sectors) to carbon-intensive sectors over total outputs to carbon-intensive sectors. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table C5: Using alternative measures: 1

	(1)	(2)	(3)	(4)	(5)
Panel A: carbon-intensive sectors and non-carbon sectors					
	log(1+entry, capital)	log(1+entry, number)	log(1+EEP)	log(1+GP)	log(1+NEP)
1(pilot)*1(carbon)	-0.415***	-0.487***	-0.535***	-0.494***	0.397***
	(0.0437)	(0.0363)	(0.0225)	(0.0111)	(0.00512)
Panel B: regulated upstream sectors and non-carbon sectors					
	(1)	(2)	(3)	(4)	(5)
	log(1+entry, capital)	log(1+entry, number)	log(1+EEP)	log(1+GP)	log(1+NEP)
1(pilot)*1(upstream, regulated)	-0.242***	-0.288***	-0.188***	-0.151***	-0.128***
	(0.0758)	(0.0205)	(0.0512)	(0.0122)	(0.0700)
Panel C: unregulated upstream sectors and non-carbon sectors					
	(1)	(2)	(3)	(4)	(5)
	log(1+entry, capital)	log(1+entry, number)	log(1+EEP)	log(1+GP)	log(1+NEP)
1(pilot)*1(upstream, unregulated)	-0.142***	-0.212***	-0.153***	-0.133***	-0.113***
	(0.0258)	(0.0205)	(0.0312)	(0.0125)	(0.0303)
Panel D: regulated downstream sectors and non-carbon sectors					
	(1)	(2)	(3)	(4)	(5)
	log(1+entry, capital)	log(1+entry, number)	log(1+EEP)	log(1+GP)	log(1+NEP)
1(pilot)*1(downstream, regulated)	0.526***	0.467***	0.444***	0.342***	0.348***
	(0.0521)	(0.0245)	(0.0417)	(0.0336)	(0.0421)
Panel E: unregulated downstream sectors and non-carbon sectors					
	(1)	(2)	(3)	(4)	(5)
	log(1+entry, capital)	log(1+entry, number)	log(1+EEP)	log(1+GP)	log(1+NEP)
1(pilot)*1(downstream, unregulated)	0.424***	0.325***	0.318***	0.262***	0.279***
	(0.0320)	(0.0231)	(0.0123)	(0.0122)	(0.0147)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. OLS regressions are employed in all columns. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table C6: Using alternative measures: 2

	(1)	(2)	(3)	(4)	(5)
Panel A: Carbon-intensive and non-related sectors					
	log(0.01+entry, capital)	log(0.01+entry, number)	log(0.01+EEP)	log(0.01+GP)	log(0.01+NEP)
1(pilot)*1(carbon)	-0.215***	-0.0987***	0.135***	0.0694***	-0.0797***
	(0.0315)	(0.0112)	(0.0128)	(0.0102)	(0.0115)
Panel B: Regulated upstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	log(0.01+entry, capital)	log(0.01+entry, number)	log(0.01+EEP)	log(0.01+GP)	log(0.01+NEP)
1(pilot)*1(upstream)	-0.400***	-0.331***	-0.392***	-0.296***	-0.215***
	(0.0767)	(0.0205)	(0.0593)	(0.0181)	(0.0503)
Panel C: Unregulated upstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	log(0.01+entry, capital)	log(0.01+entry, number)	log(0.01+EEP)	log(0.01+GP)	log(0.01+NEP)
1(pilot)*1(upstream)	-0.248***	-0.216***	-0.158***	-0.115***	-0.0968***
	(0.0318)	(0.0211)	(0.0119)	(0.00922)	(0.0123)
Panel D: Regulated downstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	log(0.01+entry, capital)	log(0.01+entry, number)	log(0.01+EEP)	log(0.01+GP)	log(0.01+NEP)
1(pilot)*1(downstream)	0.324***	0.325***	0.268***	0.262***	0.144***
	(0.0531)	(0.0244)	(0.0517)	(0.0201)	(0.0302)
Panel E: Unregulated downstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	log(0.01+entry, capital)	log(0.01+entry, number)	log(0.01+EEP)	log(0.01+GP)	log(0.01+NEP)
1(pilot)*1(downstream)	0.228***	0.195***	0.158***	0.0962***	0.0844***
	(0.0390)	(0.0116)	(0.0217)	(0.0122)	(0.0132)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. OLS regressions are employed in all columns. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table C7: Using alternative measures: 3

	(1)	(2)	(3)	(4)	(5)
Panel A: Carbon-intensive and non-related sectors					
	arcsinh(entry, capital)	arcsinh(entry, number)	arcsinh(EEP)	arcsinh(GP)	arcsinh(NEP)
1(pilot)*1(carbon)	-0.284***	-0.146***	0.199***	0.126***	-0.221***
	(0.0416)	(0.0288)	(0.0116)	(0.0133)	(0.0158)
Panel B: Regulated upstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	arcsinh(entry, capital)	arcsinh(entry, number)	arcsinh(EEP)	arcsinh(GP)	arcsinh(NEP)
1(pilot)*1(upstream)	-1.143***	-0.812***	-0.855***	-0.403***	-0.441***
	(0.0758)	(0.0208)	(0.0512)	(0.0125)	(0.0703)
Panel C: Unregulated upstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	arcsinh(entry, capital)	arcsinh(entry, number)	arcsinh(EEP)	arcsinh(GP)	arcsinh(NEP)
1(pilot)*1(upstream)	-0.442***	-0.288***	-0.188***	-0.151***	-0.128***
	(0.0560)	(0.0232)	(0.0133)	(0.0122)	(0.0144)
Panel D: Regulated downstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	arcsinh(entry, capital)	arcsinh(entry, number)	arcsinh(EEP)	arcsinh(GP)	arcsinh(NEP)
1(pilot)*1(downstream)	0.347***	0.493***	0.358***	0.259***	0.269***
	(0.0523)	(0.0244)	(0.0512)	(0.0233)	(0.0551)
Panel E: Unregulated downstream and non-related sectors					
	(1)	(2)	(3)	(4)	(5)
	arcsinh(entry, capital)	arcsinh(entry, number)	arcsinh(EEP)	arcsinh(GP)	arcsinh(NEP)
1(pilot)*1(downstream)	0.256***	0.226***	0.255***	0.128***	0.144***
	(0.0311)	(0.0244)	(0.0336)	(0.0232)	(0.0152)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. OLS regressions are employed in all columns. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table C8: Hausman IV estimation

	Panel A: Carbon-intensive and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(carbon)	-2.424***	-2.451***	2.434***	2.266***	-2.369***
	(0.0621)	(0.0339)	(0.0422)	(0.0122)	(0.0455)
	Panel B: Regulated upstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream)	-2.734***	-2.612***	-2.500***	-2.521***	-2.412***
	(0.0962)	(0.0345)	(0.0682)	(0.0203)	(0.0711)
	Panel C: Unregulated upstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream)	-1.445***	-1.255***	-1.278***	-1.350***	-1.377***
	(0.0367)	(0.0210)	(0.0457)	(0.0441)	(0.0332)
	Panel D: Regulated downstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream)	3.524***	3.422***	3.363***	3.562***	3.444***
	(0.0531)	(0.0244)	(0.0517)	(0.0201)	(0.0502)
	Panel E: Unregulated downstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream)	1.347**	1.246***	1.220***	1.313***	1.378***
	(0.0266)	(0.0423)	(0.0411)	(0.0446)	(0.0310)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. The first-stage F-statistic is 89.044. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table C9: Bartik IV estimation

	(1)	(2)	(3)	(4)	(5)
	Panel A: Carbon-intensive and non-related sectors, Poisson IV				
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(carbon)	-1.317***	-1.694***	1.260***	1.413***	-1.463***
	(0.233)	(0.131)	(0.221)	(0.116)	(0.113)
	Panel B: Regulated upstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream)	-1.561***	-1.467***	-1.546***	-1.679***	-1.941***
	(0.214)	(0.232)	(0.123)	(0.121)	(0.117)
	Panel C: Unregulated upstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(upstream)	-0.354***	-0.238***	-0.266***	-0.388***	-0.466***
	(0.0745)	(0.0210)	(0.0516)	(0.0233)	(0.0553)
	Panel D: Regulated downstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream)	1.314**	1.769***	1.654***	1.963***	1.873***
	(0.0251)	(0.0413)	(0.0258)	(0.138)	(0.0675)
	Panel E: Unregulated downstream and non-related sectors, Poisson IV				
	(1)	(2)	(3)	(4)	(5)
	Entry, capital	Entry, number	EEP	GP	NEP
1(pilot)*1(downstream)	1.107**	1.455***	1.364***	1.509***	1.566***
	(0.248)	(0.0473)	(0.0551)	(0.0248)	(0.0499)

Notes: The sample covers 472 three-digit sectors and 295 cities during 2005-2019. The instrumental variable is the carbon emissions of each city in 2005. The first-stage F-statistic is 18.669. In all columns, city-sector, city-year, and sector-year fixed effects are included. Controls include city-level log per capita real GDP, log population, and log carbon emissions in 2005 interacted with sector-year dummies, and the stock of capital of all existing firms in 2005 of each city-sector cell interacted with year dummies. * Significant at 10%, ** 5%, *** 1%. Standard errors are two-way clustered at the city and sector levels.

Table C10: Effects on spatial linkages

Panel A: Migration flows (DV: Flow/Population)						
	(1)	(2)	(3)	(4)	(5)	(6)
	High-skill	Low-skill	All	High-skill	Low-skill	All
1(Pilot, origin)	-4.34e-08	4.15e-08	-1.83e-09	-4.34e-08	4.15e-08	-1.83e-09
	(6.29e-06)	(2.73e-05)	(3.00e-05)	(5.59e-06)	(2.73e-05)	(3.00e-05)
1(Pilot, destination)	2.73e-08	-2.08e-05	1.26e-06	2.73e-08	-2.08e-05	1.26e-06
	(8.24e-06)	(3.34e-05)	(3.88e-05)	(7.53e-06)	(3.34e-05)	(3.87e-05)
Observations	264,196	264,196	264,196	264,196	264,196	264,196
R-squared	0.004	0.001	0.001	0.812	0.892	0.886
Panel B: Freight transport flows (DV: log(1+Flow))						
	(1)	(2)	(3)	(4)	(5)	(6)
	Carbon-intensive	Upstream	Downstream	Carbon-intensive	Upstream	Downstream
1(Pilot, origin)	0.00415	0.00668	0.00579	0.00322	0.00356	0.00331
	(0.0125)	(0.0103)	(0.0115)	(0.0119)	(0.00945)	(0.0121)
1(Pilot, destination)	0.00565	0.00321	0.00417	0.00328	0.00371	0.00409
	(0.0122)	(0.0213)	(0.0145)	(0.0213)	(0.0117)	(0.00922)
Observations	613,312	613,312	613,312	613,312	613,312	613,312
R-squared	0.043	0.046	0.031	0.623	0.720	0.589
Panel C: Investment flows (DV: log(1+Flow))						
	(1)	(2)	(3)	(4)	(5)	(6)
	Carbon-intensive	Upstream	Downstream	Carbon-intensive	Upstream	Downstream
1(Pilot, origin)	0.0112	0.0155	0.0231	0.0116	0.0114	0.0134
	(0.0152)	(0.0243)	(0.0368)	(0.0109)	(0.0113)	(0.0104)
1(Pilot, destination)	0.00998	0.0232	0.00788	0.00768	0.0112	0.00809
	(0.0116)	(0.0217)	(0.0122)	(0.0119)	(0.00922)	(0.0123)
Origin city FE	Y	Y	Y	N	N	N
Destination city FE	Y	Y	Y	N	N	N
City dyad FE	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	613,312	613,312	613,312	613,312	613,312	613,312
R-squared	0.144	0.153	0.117	0.739	0.889	0.908

Notes: In Panel A, the sample covers 66409 directed city dyads (such as Beijing-Tianjin and Tianjin-Beijing) in 2005, 2010, 2015, and 2020, on which flows are defined. In Panels B and C, the sample covers 87616 city dyads during 2013-2019. High-skill (low-skill) migration corresponds to migrants with (without) a college degree. In Panels B and C, the freight transport flows and the investment flows correspond to a specific sector: the carbon-intensive sector, and the upstream and downstream sectors. The inclusion of fixed effects is the same for the same column in different panels. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table C11: Model fit: Moments 1

	Pilot, carbon		Non-pilot, carbon	
	Data	Model	Data	Model
log Entry	-2.014	-1.899	-1.829	-1.792
log Exit	-2.551	-2.654	-2.270	-2.242
log EEP	-3.992	-3.802	-3.562	-3.585
log GP	-3.640	-3.605	-3.398	-3.514
log Emissions	-2.803	-2.774	-2.314	-2.292
log Output	-1.241	-1.201	-1.435	-1.389
	Pilot, upstream		Non-pilot, upstream	
	Data	Model	Data	Model
log Entry	-1.659	-1.727	-1.383	-1.363
log Exit	-1.794	-1.678	-1.524	-1.538
log EEP	-2.393	-2.301	-2.122	-2.159
log GP	-2.318	-2.259	-2.077	-1.945
log Emissions	-3.261	-3.255	-3.456	-3.441
log Output	-2.437	-2.406	-2.692	-2.581
	Pilot, downstream		Non-pilot, downstream	
	Data	Model	Data	Model
log Entry	-1.585	-1.464	-1.676	-1.750
log Exit	-3.037	-2.867	-2.852	-2.817
log EEP	-6.182	-5.639	-5.343	-5.424
log GP	-5.332	-5.580	-5.057	-5.434
log Emissions	-3.359	-3.315	-2.558	-2.567
log Output	-2.454	-2.418	-2.273	-2.246

Table C12: Model fit: Moments 2

	Pilot, carbon		Non-pilot, carbon	
	Data	Model	Data	Model
log entry, large	-1.861	-1.790	-2.153	-2.081
log entry, medium	-1.658	-1.564	-2.021	-1.839
log entry, small	-1.673	-1.635	-1.846	-1.975
log exit, large	-2.482	-2.723	-2.676	-2.529
log exit, medium	-2.258	-2.348	-2.484	-2.519
log exit, small	-1.814	-1.787	-1.983	-1.800
log emissions, large	-1.742	-1.725	-1.721	-1.741
log emissions, medium	-2.327	-2.339	-2.341	-2.311
log emissions, small	-2.803	-2.845	-2.810	-2.821
log output, large	-1.707	-1.750	-1.718	-1.747
log output, medium	-2.346	-2.320	-2.326	-2.337
log output, small	-2.829	-2.840	-2.840	-2.837
1og EEP, large	-2.908	-2.723	-3.002	-3.214
log EEP, medium	-3.060	-3.128	-3.078	-2.877
1og EEP, small	-3.082	-2.783	-3.086	-3.305
log GP, large	-2.617	-2.619	-2.868	-2.874
log GP, medium	-2.978	-2.965	-3.050	-2.819
1og GP, small	-2.986	-3.134	-3.045	-2.979
	Pilot, upstream		Non-pilot, upstream	
	Data	Model	Data	Model
log entry, large	-0.944	-0.883	-1.019	-1.011
log entry, medium	-0.887	-0.822	-0.930	-0.850
log entry, small	-1.046	-1.148	-0.937	-1.021
log exit, large	-1.187	-1.080	-1.222	-1.119
log exit, medium	-1.035	-1.129	-1.088	-1.166
log exit, small	-0.909	-0.882	-0.871	-0.920
log emissions, large	-1.740	-1.712	-1.707	-1.706
log emissions, medium	-2.326	-2.315	-2.349	-2.329
log emissions, small	-2.810	-2.813	-2.810	-2.819
log output, large	-1.734	-1.749	-1.743	-1.708
log output, medium	-2.313	-2.312	-2.337	-2.322
log output, small	-2.849	-2.844	-2.820	-2.835
1og EEP, large	-1.297	-1.406	-1.316	-1.241
log EEP, medium	-1.332	-1.367	-1.333	-1.236
1og EEP, small	-1.331	-1.287	-1.332	-1.324
log GP, large	-1.233	-1.216	-1.276	-1.281
log GP, medium	-1.327	-1.221	-1.331	-1.380
1og GP, small	-1.322	-1.365	-1.326	-1.368
	Pilot, downstream		Non-pilot, downstream	
	Data	Model	Data	Model
log entry, large	-1.893	-1.972	-2.873	-3.071
log entry, medium	-1.364	-1.260	-2.614	-2.639
log entry, small	-1.843	-1.939	-2.616	-2.631
log exit, large	-3.594	-3.758	-4.248	-4.031
log exit, medium	-3.094	-3.367	-3.843	-3.553
log exit, small	-2.590	-2.609	-3.261	-3.068
log emissions, large	-1.729	-1.714	-1.720	-1.728
log emissions, medium	-2.309	-2.304	-2.339	-2.320
log emissions, small	-2.820	-2.839	-2.848	-2.844
log output, large	-1.725	-1.730	-1.731	-1.737
log output, medium	-2.315	-2.313	-2.343	-2.305
log output, small	-2.842	-2.839	-2.836	-2.838
1og EEP, large	-5.105	-4.598	-5.222	-4.738
log EEP, medium	-5.238	-5.058	-5.257	-5.080
1og EEP, small	-5.251	-5.435	-5.260	-5.485
log GP, large	-4.292	-4.625	-4.956	-4.924
log GP, medium	-5.024	-5.295	-5.216	-4.715
1og GP, small	-5.185	-4.907	-5.245	-5.445

Notes: Large firms are defined by firms with registry capital in the top 10 percentile, medium firms are defined by those whose registry capital belongs to the top 10-50 percentile, and small firms are those whose registry capital belongs to the bottom 50 percentile.

Appendix D Quantitative Analysis Without Input-output Linkages

D.1 Model

The model is a single-sector version of Acemoglu et al. (2018)'s model without input-output linkages, different from the above quantitative model. The model consists of only one sector, and it can be the carbon-intensive sector (sector 1), the upstream (sector 2), or the downstream (sector 3) of the carbon-intensive sector.[41]

Time is continuous. Representative households have CRRA preference: $U = \int_0^\infty \exp(-\rho t)\frac{C(t)^{1-\gamma}}{1-\gamma}dt$. Standard derivation yields the Euler equation: $\frac{\dot{C}}{C} = \frac{r-\rho}{\gamma}$.

There are two types of labor, skilled labor l_s and unskilled labor l_u. Skilled labor is used for innovation and product-line maintenance, while unskilled labor is used for production and emissions reduction. The supply of skilled and unskilled labor is inelastic. The measure of skilled labor is L_s, and the measure of unskilled labor is 1. The wages of skilled and unskilled labor are w_s and w_u, respectively.

A continuum of intermediate goods is produced in sector i, with production function: $q_i(\omega) = z_i(\omega)l_{uP}$, where $z_i(\omega)$ is the leading-edge productivity draw for ω; l_{uP} is the unskilled labor input.

The intermediate goods producers can add one more green product (patent) by hiring h skilled workers at the flow rate $X_G = (1+\tau_1)^\eta\theta^\eta n_G^\eta h^{1-\eta}$, where τ_1 is the innovation subsidy (that exists for the carbon-intensive sector and downstream sector), and $\eta \in (0,1)$ and n_G are the number of green patents the firm already has. The intermediate goods producers can also add one more non-green product (patent) by hiring h skilled workers at the flow rate $X_{NG} = \theta^\eta n_{NG}^\eta h^{1-\eta}$, where $\eta \in (0,1)$ and n_{NG} are the number of non-green patents the firm already has. The cost function of R&D for a green patent is $C_G(x_G, n_G, \theta) = w_s n_G x_G^{\frac{1}{1-\eta}}\theta^{-\frac{\eta}{1-\eta}}(1+\tau_1)^{-\frac{\eta}{1-\eta}} \equiv w_s n_G (1+\tau_1)^{-\frac{\eta}{1-\eta}}G(x_G,\theta)$, where $x_G = X_G/n_G$ is the innovation intensity. The cost function of R&D for non-green patent is $C_{NG}(x_{NG}, n_{NG}, \theta) = w_s n_{NG} x_{NG}^{\frac{1}{1-\eta}}\theta^{-\frac{\eta}{1-\eta}} \equiv w_s n_{NG} G(x_{NG},\theta)$. We assume that the operation of each product requires $\phi > 0$ units of skilled labor.

As in Acemoglu et al. (2018), we assume that research is undirected across all product lines, meaning that firms do not know ex ante the particular product line on which they will innovate. This implies that their expected return to R&D is the expected value across all product lines. When a firm innovates over a product line ω, it increases the productivity of the product line by $\Delta\bar{z}$, where $\bar{z} = \int_0^1 z(\omega)d\omega$. That is, $z(t+) = z + \Delta\bar{z}$. The firm with the improved technology in product line ω takes over this product line, but, in principle, the firm that previously had the leading-edge technology might still compete if the current owner tries to set a very high price. Assume that there is a two-stage pricing game between any firm that wishes to supply a product $\omega \in [0,1]$, whereby each firm first has to enter and pay a small cost $\epsilon > 0$, and then all firms that have entered simultaneously set prices.

[41] The upstream and downstream sectors correspond to regulated ones in the empirical analysis.

There is a unit measure of potential entrants. Each entrant has access to an R&D technology $G(x^{entry}, \theta_E)$. Thus, an entrant wishing to achieve an innovation rate of x^{entry} hires skilled labor of $h^{entry} = (1+\tau_2)G(x^{entry}, \theta_E)$, where τ_2 is the intensity of entry regulation for the carbon-intensive and the downstream of carbon-intensive sectors. This specification implies that a potential entrant has access to the same R&D technology as an incumbent with innovative capacity θ_E and a single active product would have had. Following a successful innovation, the entrant improves the productivity of a randomly chosen product line by $\Delta \bar{z}$. This description implies the following optimization problem for entrants:

$$\max_{x^{entry} \geq 0} \{x^{entry} EV^{entry}(z + \Delta \bar{z}, \theta) - w_s(1+\tau_2)G(x^{entry}, \theta_E)\}. \tag{D1}$$

Same as any firm-dynamics model, exit (of products and firms) has three causes: (1) There is an exogenous destructive shock at the rate $\varphi > 0$, which causes the firm to exit and shut down all its product lines. (2) There will be creative destruction due to innovation by other firms replacing the leading-edge technology in a particular product line. (3) There will be endogenous obsolescence, meaning that firms will voluntarily shut down some product lines because they are no longer sufficiently profitable relative to the fixed cost of operation.

Firms do not differ in terms of their innovative capacities. Upon successful entry, each firm has its fixed type θ. In addition to the transition from high to low type, each firm is also subject to an exogenous destructive shock at the rate $\varphi > 0$. Once a firm is hit by this shock, its value declines to zero and it exits the economy.

Assume that only the producers of intermediate goods in the carbon-intensive sector emit CO_2. The emission function is $E(q, l_{uR}) = \lambda_1 q(\frac{q}{l_{uR}})^{\lambda_2}$, where $\lambda_1 > 0$, $\lambda_2 < 0$, and q is the amount of goods produced, and l_{uR} is the unskilled labor used to reduce emissions. The flow cost of carbon emissions is $\tau_0 E(q, l_{uR})$, where τ_0 is the unit cost of carbon emissions.

The static profit-maximization problem of intermediate producers in the carbon-intensive sector is:

$$\max_{p_1, l_{uR}, l_{uP}} p_1 q_1 - w_u(l_{uR} + l_{uP}) - \tau_0 \lambda_1 q_1 (\frac{q_1}{l_{uR}})^{\lambda_2}, \tag{D2}$$

subject to $q_1 = (\frac{p_1}{(1-\tau_3)P_1})^{-\sigma_1} Q_1$. $\tau_3 > 0$ implies that the production of carbon-intensive products is regulated. The static profit-maximization problem of intermediate producers in the upstream or downstream of the carbon-intensive sector is:

$$\max_{l_{uP}} p_i q_i - w_u l_{uP}, \tag{D3}$$

subject to $q_i = (\frac{p_i}{P_i})^{-\sigma_i} Q_i$ $(i = 2, 3)$. Here $P_i = [\int p_i^{1-\sigma^i} d\omega]^{\frac{1}{1-\sigma_i}}$.

We further define the relative productivity by $\hat{z} = \frac{z}{w_u}$, define the aggregate productivity in sector

i as $Z_i = [\int z(\omega)^{\sigma_i - 1} d\omega]^{\frac{1}{\sigma_i - 1}}$, denote the variable X normalized by Z by $\tilde{X}$, and let μ denote the endogenous average creative destruction rate. The stationary value function, V, is

$$\begin{aligned}
r\tilde{V}(\widehat{PD}) = \max \Bigg\{ 0, \max_{x \geq 0} \Bigg[\sum_{\hat{z} \in \widehat{PD}} [\tilde{\pi}(\hat{z}) - \widetilde{w}_s \phi \\
+\mu[\tilde{V}(\widehat{PD} - \hat{z}) - \tilde{V}(\widehat{PD})] + \frac{\partial \tilde{V}(\widehat{PD})}{\partial \hat{z}} \frac{\partial \hat{z}}{\partial w_u} \frac{\partial w_u}{\partial t} \Bigg] \Bigg] \\
-n_{NG} \widetilde{w}_s G\left(x'_{NG}, \theta\right) - \widetilde{w}_s n_G \left(1 + \tau_1\right)^{-\frac{\eta}{1-\eta}} G\left(x'_G, \theta\right) \\
+n_G x'_G [E\tilde{V}(\widehat{PD} + \{\hat{z} + \Delta \bar{z}\}) - \tilde{V}(\widehat{PD})] \\
+n_{NG} x'_{NG} [E\tilde{V}(\widehat{PD} + \{\hat{z} + \Delta \bar{z}\}) - \tilde{V}(\widehat{PD})] \\
+\varphi(0 - \tilde{V}(\widehat{PD})) \}
\end{aligned} \tag{D4}$$

The first two lines (inside the summation) include the instantaneous operating profits, minus the fixed costs of operation, plus the change in firm value if any of its products get replaced by another firm through creative destruction at the rate μ, plus the change in firm value due to the increase in the economy-wide wage. This last term accounts for the fact that, as the wage rate increases, the relative productivity of each of the products that the firm operates declines. The third line subtracts the R&D expenditure by firm f. The fourth and fifth line expresses the change in firm value when the firm is successful with its R&D investment at the rate x_G and x_{NG}. The last line shows the change in value when the firm has to exit due to an exogenous destructive shock at the rate φ.

The shares of product lines, active and inactive, are Φ and Φ^{NP}, respectively, where $\Phi + \Phi^{NP} = 1$. Unskilled labor market clearing is: $\sum_{i=1}^{3} \int l_{uP,i}(\omega) d\omega + \int l_{uR}(\omega) d\omega = 1$. Skilled labor market clearing is: $\sum_{i=1}^{3} [G(x_i^{entry}, \theta_E) + \Phi[h(w) + \phi]] = l_s$. Final goods market clearing is: $Y = C$. The budget constraint of the household is: $C(t) + \dot{A}(t) = rA(t) + w_s(t) l_s + w_u(t) + Tr(t)$, where $Tr(t)$ is the lump-sum transfer to the household.

Definition 2. *A stationary competitive equilibrium consists of a tuple*

$$\begin{aligned}
&\{\{l_{uR,i}, l_{uP,i}, \Phi_i, \Phi_i^{NP}, x_i, x_i^{entry}, h_i, \tilde{V}_i, \hat{PD}_i, \{z_i(\omega)\}, \\
&\mu, w_s, w_u, r\},
\end{aligned}$$

such that: (1) intermediate goods producers' profit-maximization problem is solved; (2) firms' value function takes the form of equation (15); (3) the optimal R&D policy is satisfied for firms; (4) the optimal entry policy is satisfied; (5) labor market and goods markets clearing are satisfied; (6) evolution of productivity follows the above form; (7) the sum of the share of product lines equals 1; and (8) Euler equation is satisfied.

D.2 Quantitative Analysis

When conducting the quantitative analysis and calculating the welfare effects, we calculate the outcomes for each sector separately, and assign a weight to each sector as in the model with input-output linkages to calculate the aggregate welfare effects, according to the output share C_i. In the model without input-output linkages, final goods are no longer a Cobb-Douglas composite of the composite intermediate good, and firms do not use composite intermediate goods for production.

Appendix E Quantitative Analysis With Multiple Locations

In this section, we lay out a quantitative framework that incorporates multiple locations together with multiple sectors with input-output linkages. We then show that the main theoretical predictions of this framework are the same as those of the framework with only one location. We also show that the quantitative results are similar in these two different frameworks with and without multiple locations. Therefore, in the main text, we still use the simple version of the model with a single location for theoretical and quantitative analysis.

E.1 Model

In this model, labor is supplied by local residents, and firms are established by local investors. We assume so because we find that the carbon pilot policy does not affect migration and cross-regional firm investments. However, firms in different locations can transact with one another, and the input-output networks involve the notion of space. We follow the approach of Caliendo and Parro (2015) to deal with the multiplicity of locations.

There are N locations (cities), indexed by $n \in \{1, 2, ..., N\}$. To match the data, we set the number of cities equal to that in our sample, 295, in the quantitative analysis. The main difference between this framework and that in the main text is that the input-output networks have spatial properties. Thus, still assuming that there are 3 sectors in each city (carbon-intensive, upstream, and downstream), the input-output network is now characterized by a $3N \times 3N$ matrix.

Final goods $C_n(t) = C_{n1}(t)^{\alpha_{n1}} C_{n2}(t)^{\alpha_{n2}} C_{n3}(t)^{1-\alpha_{n1}-\alpha_{n2}}$, where $C_i(t)$ is the composite intermediate goods in sector i. α_{n1} and α_{n2} are consumption shares. The main difference between this version of the model and the baseline model is that the variables here involve a location subscript, n.

A continuum of intermediate goods is produced in sector i in location n, with the production function:

$$q_{ni}(\omega) = z_{ni}(\omega) l_{uP}^{\beta_{ni}} m_{ni1}^{\beta_{ni1}(1-\beta_{ni})} m_{ni2}^{\beta_{ni2}(1-\beta_{ni})} m_{ni3}^{(1-\beta_{ni1}-\beta_{ni2})(1-\beta_{ni})} \tag{E1}$$

where $z_{ni}(\omega)$ is the leading-edge productivity draw for ω; l_{uP} is the unskilled labor input; and m_{nij} is the composite intermediate goods used to produce ω. β_{nij} measures the structure of the input-output network, which is calibrated in the next section. Moreover, the construction of price indices should also account for the elements of space, as in Caliendo and Parro (2015). The rest of the model is the same as the baseline model.

E.2 Quantitative Analysis

First, we set each location as a city. There are 295 cities in the sample. Second, we calibrate β_n and β_{nij} from the input-output table and the cross-city freight transport data in 2012. These parameters already contain information on trade costs and spatial frictions across different cities. Finally, based on these externally calibrated parameters, we use indirect inference to calibrate the rest parameters.

We report the results of counterfactual experiments with the model of multiple locations in Table E1. The outcomes of interests represent the simple average of all cities' outcomes at the national level. Compared to Table 5 of the baseline case, the results with multiple locations are both quantitatively and qualitatively similar. Therefore, we use the model of a single location as our baseline model.

Table E1: Counterfactual analysis with multiple locations

	x^{entry}	x_G	x_{NG}	q^{min}	carbon emissions	g	welfare
Non-pilot, carbon	0.023	0.512	0.477	1.082	0.0874		
Non-pilot, upstream	0.019	0.488	0.422	1.138			
Non-pilot, downstream	0.027	0.531	0.499	0.944			
Non-pilot, total						0.0481	0.8470
Pilot, carbon	0.025	0.531	0.479	1.118	0.0777		
Pilot, upstream	0.019	0.487	0.42	1.139			
Pilot, downstream	0.023	0.538	0.499	0.897			
Pilot, total						0.0487	0.8473

Appendix F Proof of Theoretical Results

We first have several lemmas that establish some preliminary theoretical results. We next provide the proof.

Lemma F1. *The value function of a firm takes an additive form:*

$$\tilde{V}(\hat{PD}) = \sum_{\hat{z} \in \hat{PD}} Y(\hat{z}), \tag{F1}$$

where $Y(\hat{z})$ is the value of a product line and is nondecreasing when greater than zero. There exists a cutoff value $\hat{z}_{min}$ above which $Y(\hat{z}) \geq 0$ and below which $Y(\hat{z}) < 0$, and, thus, the product line will be shut down. Here we omit the subscripts for the sector.

Proof: Same as Acemoglu et al. (2018). The detail of the proof is delegated to Appendix F1.

Lemma F2. *(Acemoglu et al. (2018) Lemma 2): The franchise values of a product line of relative productivity $\hat{z}$ of firms are given by the following differential equations:*

$$(r+\mu+\varphi)Y(\hat{z}) - \frac{\partial Y(\hat{z})}{\partial \hat{z}}\frac{\partial \hat{z}}{\partial w^u}\frac{\partial w^u}{\partial t} = \pi(\hat{z}) - \tilde{w}_s\phi + \Omega,\ if\ \hat{z} > \hat{z}_{min}, \tag{F2}$$

and otherwise,

$$Y(\hat{z}) = 0. \tag{F3}$$

Here, $\pi(\hat{z}) = \max\{(C^{\frac{1}{\epsilon}}c_j^{-\frac{1}{\epsilon}} - \hat{z}_j^{-1})c_j - E(c_j, l_{uR}) - w^u l_{uR}\}$ (where C is the cost index and c_j is the unit cost), and $\Omega_G = \max_{x\geq 0}\{-\tilde{w}_s(1+\tau_1)^{\frac{1-\eta}{\eta}}G(x,\theta^k) + xEY(\hat{z}+\bar{\Delta \hat{z}})\}$, where Ω_G is the R&D value of a firm for green patents. $\Omega_{NG} = \max_{x\geq 0}\{-\tilde{w}_s G(x,\theta^k) + xEY(\hat{z}+\bar{\Delta \hat{z}})\}$, where Ω_{NG} is the R&D value of a firm for non-green patents. Moreover, the R&D policy function of a firm is

$$x_G = \theta[\frac{(1-\eta)EY(\hat{z}+\bar{\Delta \hat{z}})}{\tilde{w}_s(1+\tau_1)^{\frac{1-\eta}{\eta}}}]^{\frac{1-\eta}{\eta}}. \tag{F4}$$

$$x_{NG} = \theta[\frac{(1-\eta)EY(\hat{z}+\bar{\Delta \hat{z}})}{\tilde{w}_s}]^{\frac{1-\eta}{\eta}}. \tag{F5}$$

$\hat{z}_{k,min}$ is given by

$$\frac{\partial Y(\hat{z})}{\partial \hat{z}}|\hat{z} = \hat{z}_{min} = 0. \tag{F6}$$

Here we omit the subscripts for the sector.

Proof: Same as Acemoglu et al. (2018). See Appendix F2 for details.

Proposition F1. *(Acemoglu et al. (2018) Proposition 1): Let g be the equilibrium growth rate of the economy and $\tilde{w}_s$ be the normalized skilled wage rate; let*

$$F(x) = 1 - (\frac{\hat{z}_{min}}{\hat{z}})^x, \tag{F7}$$

Then, the franchise value of a product line with relative productivity of $\hat{z}$ for a firm is

$$Y(\hat{z}) = \frac{\pi(\hat{z})}{r+\mu+\varphi+(\epsilon-1)g}F(\frac{r+\mu+\varphi+(\epsilon-1)g}{g}) + \frac{\Omega - \tilde{w}_s\phi}{r+\mu+\varphi}F(\frac{r+\mu+\varphi}{g}), \tag{F8}$$

where $\pi(\hat{z}) = \max\{(C^{\frac{1}{\epsilon}}c(\omega)^{-\frac{1}{\epsilon}} - \hat{z}(\omega)^{-1})c(\omega) - E(c(\omega), l_{uR}) - w_u l_{uR}\}$. Here we omit the subscripts for the sector.

Proof: Same as Acemoglu et al. (2018). See Appendix F3 for details.

Lemma F3. *(Acemoglu et al. (2018) Lemma 3): Let F denote the overall relative productivity distribution, including both active and inactive product lines. In stationary equilibrium, it satisfies the* *following differential equation:*

$$g\hat{z}f(\hat{z}) = \mu[F(\hat{z}) - F(\hat{z} - \Delta\bar{\hat{z}})], \tag{F9}$$

where $\mu = \Phi x + x^{entry,G} + x^{entry,NG}$, *and* $\bar{\hat{z}} = \int_0^\infty \hat{z}f(\hat{z})d\hat{z}$. *Moreover, let* $\tilde{F}$ *denote the (unnormalized) distribution of relative productivities of active product lines. The measure of active product lines is given by*

$$\Phi = \tilde{F}(\infty). \tag{F10}$$

Here we omit the subscripts for the sector.

Proof: Same as Acemoglu et al. (2018). See Appendix F4 for details.

Proposition F2. *The growth rate of the economy, g, is given by:*

$$g = \Delta\mu. \tag{F11}$$

Proof: Same as Acemoglu et al. (2018). See Appendix F5 for details.

The proofs below follow Acemoglu et al. (2018).

F.1 Proof of Lemma 1

Guess $\tilde{V}(\hat{PD}) = \sum_{\hat{z}\in\hat{PD}} \mathrm{Y}(\hat{z})$:

$$r\sum_{\hat{z}\in\hat{PD}} Y(\hat{z}) = \sum_{\hat{z}\in\hat{PD}} \max\left\{0, \max_{x\geq 0}\left[\begin{array}{c}\tilde{\pi}\left(\hat{z}_j\right) - \tilde{w}^s\phi - \tilde{w}^s G\left(x,\theta\right) + \frac{\partial Y(\hat{z})}{\partial \hat{z}}\frac{\partial \hat{z}}{\partial w^u}\frac{\partial w^u}{\partial t} \\ +xEY(\hat{z}+\Delta\bar{\hat{z}}) - (\mu+\varphi)Y(\hat{z})\end{array}\right]\right\},$$

which implies

$$rY(\hat{z}) = \max\left\{0, \left\{\begin{array}{c}\tilde{\pi}(\hat{z}) - \tilde{w}^s\phi + \frac{\partial Y(\hat{z})}{\partial \hat{z}}\frac{\partial \hat{z}}{\partial w^u}\frac{\partial w^u}{\partial t} - (\mu+\varphi)\mathrm{Y}(\hat{z}) \\ +\max_{x\geq 0}\left[xEY(\hat{z}+\Delta\bar{\hat{z}}) - \tilde{w}^s G\left(x,\theta\right)\right]\end{array}\right\}\right\},$$

where we also use the fact that a firm can choose not to operate an individual product line.

F.2 Proof of Lemma 2

This follows from the proof of Lemma 1.

F.3 Proof of Proposition 1

First note that $\tilde{\pi}(q) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \frac{1}{\sigma-1}\hat{z}^{\sigma-1} = \Pi\hat{z}^{\sigma-1}$. Then, defining $\Psi \equiv r + \mu + \varphi$, equation (F2) can be written as the following linear differential equation

$$\Psi Y(\hat{z}) + g\hat{z}\frac{\partial Y(\hat{z})}{\partial \hat{z}} = \Pi\hat{z}^{\sigma-1} + \Omega - \tilde{w}^{s}\phi \text{ if } \hat{z} > \hat{z}$$

or

$$\xi_1\hat{z}^{-1}Y(\hat{z}) + \frac{\partial Y(\hat{z})}{\partial \hat{z}} = \xi_2\hat{z}^{\sigma-2} - \xi_3\hat{z}^{-1}, \tag{F12}$$

where $\xi_1 \equiv \frac{\Psi}{g}, \xi_2 \equiv \frac{\Pi}{g}$ and $\xi_3 \equiv \frac{\tilde{w}^s\phi-\Omega}{g}$. Then the solution to (F12) can be written as

$$Y(\hat{z}) = \hat{z}^{-\xi_1}\left(\int \left[\xi_2 t^{\xi_1+\sigma-2} - \xi_3 t^{\xi_1-1}\right]dt + D\right) = \frac{\xi_2\hat{z}^{\sigma-1}}{\xi_1+\sigma-1} - \frac{\xi_3}{\xi_1} + D\hat{z}^{-\xi_1}. \tag{F13}$$

Imposing the boundary condition $Y\left(\hat{z}_{min}\right) = 0$, we can solve out for the constant of integration D, obtaining

$$\begin{aligned} \mathrm{Y}(\hat{z}) &= \frac{\xi_2\hat{z}^{\sigma-1}}{\xi_1+\sigma-1} - \frac{\xi_3}{\xi_1} + \left(\frac{\xi_3\hat{z}^{\xi_1}}{\xi_1} - \frac{\xi_2\hat{z}^{\xi_1+\sigma-1}}{\xi_1+\sigma-1}\right)\hat{z}^{-\xi_1} \\ &= \frac{\Pi\hat{z}^{\sigma-1}}{\Psi+(\sigma-1)g}\left(1-\left(\frac{\hat{z}}{\hat{z}}\right)^{\frac{\Psi}{g}+\sigma-1}\right) + \frac{\Omega-\tilde{w}^s\phi}{\Psi}\left(1-\left(\frac{\hat{z_{min}}}{\hat{z}}\right)^{\frac{\Psi}{g}}\right). \end{aligned} \tag{F14}$$

We next provide the derivation of the value for a high-type product line. Let us rewrite the expression in (F14) as

$$\mathrm{Y}(\hat{z}) = \xi_4\hat{z}^{\sigma-1} + \xi_5\hat{z}^{-\frac{\Psi}{g}} - \xi_6$$

where

$$\xi_4 \equiv \frac{\Pi}{\Psi+(\sigma-1)g'}, \xi_5 = \frac{\left(\tilde{w}^s\phi-\Omega\right)\hat{z}_{l,\text{ min}}^{\frac{\Psi}{g}}}{\Psi} - \frac{\Pi\hat{z}_{l,\text{ min}}^{\frac{\Psi}{g}+\sigma-1}}{\Psi+g(\sigma-1)}, \text{ and } \xi_6 = \frac{\tilde{w}^s\phi-\Omega}{\Psi}.$$

Recall the value of a product line

$$\begin{aligned} (\Psi+v)Y(\hat{z}) + \frac{\partial Y(\hat{z})}{\partial \hat{z}}g\hat{z} &= \Pi\hat{z}^{\sigma-1} + \Omega - \tilde{w}^{s}\phi + v\left(\xi_4\hat{z}^{\sigma-1} + \xi_5\hat{z}^{-\frac{\Psi}{g}} - \xi_6\right) \text{ for } \hat{z} \geq \hat{z} \\ (\Psi+v)Y(\hat{z}) + \frac{\partial Y(\hat{z})}{\partial \hat{z}}g\hat{z} &= \Pi\hat{z}^{\sigma-1} + \Omega - \tilde{w}^{s}\phi \text{ for } \hat{z} > \hat{z} \geq \hat{z} \end{aligned}$$

which can be rewritten as

$$K_1Y(\hat{z})\hat{z}^{-1} + \frac{\partial Y(\hat{z})}{\partial \hat{z}} = K_2\hat{z}^{\sigma-2} + K_3\hat{z}^{-\frac{\Psi+g}{g}} - K_4\hat{z}^{-1},$$

where

$$K_1 \equiv \frac{\Psi+v}{g}, K_2 \equiv \frac{\Pi+v\xi_4}{g}, K_3 \equiv \frac{v\xi_5}{g} \text{ and } K_4 \equiv \frac{v\xi_6+\tilde{w}^s\phi-\Omega}{g} \text{ for } \hat{z} \geq \hat{z} \tag{F15}$$

$$K_1 \equiv \frac{\Psi+v}{g}, K_2 \equiv \frac{\Pi}{g}, K_3 \equiv 0 \text{ and } K_4 \equiv \frac{\tilde{w}^s\phi-\Omega}{g} \text{ for } \hat{z}_{l,\text{ min}} > \hat{z} \geq \hat{z} \tag{F16}$$

F.4 Proof of Lemma 3

In a stationary equilibrium, inflows and outflows into different parts of the distributions have to be equal. First, consider overall productivity distribution F. Given a time interval of Δt, this implies that $F_t(\hat{z}) = F_{t+\Delta t}(\hat{z})$,

$$F_t(\hat{z}) = F_t(\hat{z}(1+g\Delta t)) - \mu\Delta t\left[F_t(\hat{z}) - F_t(\hat{z}-\Delta\bar{\hat{z}})\right]$$

Next, subtract $F_t(\hat{z}(1+g\Delta t))$ from both sides, multiply both sides by -1, divide again sides by Δt, and take the limit as $\Delta t \to 0$, so that

$$\lim_{\Delta t\to 0}\frac{F(\hat{z}(1+g\Delta t)) - F(\hat{z})}{\Delta t} = g\hat{z}f(\hat{z}).$$

Using this last expression delivers

$$g\hat{z}f(\hat{z}) = \mu[F(\hat{z}) - F(\hat{z}-\Delta\bar{\hat{z}})].$$

Similarly, for active product line distributions $\tilde{F}$, we can write

$$\begin{aligned}\tilde{F}_t(\hat{z}) = {} & \tilde{F}_t(\hat{z}(1+g\Delta t)) - \tilde{F}_t\left(\hat{z}_{\min}(1+g\Delta t)\right) + \mu\Delta t\left[F_t(\hat{z}-\Delta\bar{\hat{z}}) - \tilde{F}_t(\hat{z}) - F_t\left(\hat{z}_{\min}-\Delta\bar{\hat{z}}\right)\right] \\ & - (\mu+\varphi)\,\Delta t\tilde{F}_t(\hat{z}) + v\Delta t\left[\tilde{F}_t(\hat{z}) - \tilde{F}_t\left(\hat{z}_{\min}\right)\right].\end{aligned}$$

Again, by subtracting $\tilde{F}_t(\hat{z}(1+g\Delta t)) - \tilde{F}_t\left(\hat{z}_{\min}(1+g\Delta t)\right)$ from both sides, dividing by $-\Delta t$, and taking the limit as $\Delta t \to 0$, we get the desired equations in Lemma 3.

F.5 Proof of Proposition 2

As shown in Lemma 3, overall productivity distribution satisfies

$$\hat{z}f(\hat{z}) = \frac{\mu}{g}[F(\hat{z}) - F(\hat{z}-\Delta\bar{\hat{z}})]$$

By integrating both sides of the domain, we get

$$E(\hat{z}) \equiv \int_0^\infty \hat{z}f(\hat{z})d\hat{z} = \frac{\mu}{g}\int_0^\infty [F(\hat{z}) - F(\hat{z}-\Delta\bar{\hat{z}})]d\hat{z}$$

We can write the above equation as follows

$$E(\hat{z}) = \frac{\frac{\mu}{g}}{1+\frac{\mu}{g}}\int_0^\infty [1 - F(\hat{z}-\Delta\bar{\hat{z}})]d\hat{z}.$$

as $\int_0^\infty [1-F(\hat{z})]d\hat{z} = E(\hat{z})$.

By changing of variable as $x = \hat{z} - \Delta\bar{\bar{z}}$, which implies $dx = d\hat{z}$, we have

$$E(\hat{z}) = \frac{\frac{\mu}{g}}{1+\frac{\mu}{g}} \int_{-\Delta\bar{\bar{z}}}^{\infty} [1 - F(x)]dx = \frac{\mu}{g}\Delta\bar{\bar{z}}$$

The last equality follows from the fact that $F(x) = 0$ for $x \leq 0$. In equilibrium we have, $\bar{\bar{z}} = E(\hat{z})$. Therefore

$$g = \mu\Delta$$

Appendix G More Institutional Details

G.1 Determinants of pilot selection

The pilots are selected by the central government according to some predetermined criteria. The determinants of pilot selection are socioeconomic conditions and geographical layout because the pilots are expected to provide low-carbon development experience to regions of similar characteristics. Figures G1, G2, G3, and G4 show how the central government describes each batch of pilots selected. The examples of policy document screenshots and corresponding translations are listed below. The translations of highlighted parts are bold-faced.

Translation for Figure G1: Based on the local application status and **considering the representativeness of the socioeconomic conditions and geographical layout in each region**, our committee has decided to first carry out pilot work in Provinces of Guangdong, Liaoning, Hubei, Shaanxi, Yunnan, as well as cities of Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, and Baoding.

Translation for Figure G2: Based on the local application status, **taking into account factors such as the socioeconomic conditions, demonstrative nature, and representative geographical layout of each pilot**, the National Development and Reform Commission has determined that the second batch of national low-carbon pilots are launched in Beijing City, Shanghai City, Hainan Province, Shijiazhuang City, Qinhuangdao City, Jincheng City, Hulunbuir City, Jilin City, Suzhou City, Huai'an City, Zhenjiang City, Ningbo City, Wenzhou City, Chizhou City, Nanping City, Jingdezhen City Ganzhou City, Qingdao City, Jiyuan City, Wuhan City, Guangzhou City, Guilin City, Guangyuan City, Zunyi City, Kunming City, Yan'an City, Jinchang City, and Urumqi City.

Translation for Figure G3: In order to promote ecological civilization and green and low-carbon development, and ensure the achievement of China's greenhouse gas emission control action goals, our commission organized two batches of low-carbon provinces, regions, and cities in 2010 and 2012, respectively. Each pilot province and city has conscientiously implemented the requirements of the pilot work and achieved positive results in promoting low-carbon development. In accordance with the requirements of the Outline of the 13th Five Year Plan, the National Climate Change Response

Figure G1: Determinants of 1st-batch-pilot selection

二、试点范围

根据地方申报情况，统筹考虑各地方的工作基础和试点布局的代表性，经沟通和研究，我委确定首先在广东、辽宁、湖北、陕西、云南五省和天津、重庆、深圳、厦门、杭州、南昌、贵阳、保定八市开展试点工作。

Source: Notice of the National Development and Reform Commission on Carrying out Pilot Work for Low-carbon Provinces and Cities. Available at: `https://www.ndrc.gov.cn/xxgk/zcfb/tz/201008/t20100810_964674.html`

Figure G2: Determinants of 2nd-batch-pilot selection

根据地方申报情况，统筹考虑各申报地区的工作基础、示范性和试点布局的代表性等因素，经沟通和研究，国家发展改革委确定在北京市、上海市、海南省和石家庄市、秦皇岛市、晋城市、呼伦贝尔市、吉林市、大兴安岭地区、苏州市、淮安市、镇江市、宁波市、温州市、池州市、南平市、景德镇市、赣州市、青岛市、济源市、武汉市、广州市、桂林市、广元市、遵义市、昆明市、延安市、金昌市、乌鲁木齐市开展第二批国家低碳省区和低碳城市试点工作。

Source: Notice of the National Development and Reform Commission on Carrying out Pilot Work for 2nd Batch of Low-carbon Provinces and Cities. Available at: `https://www.ccchina.org.cn/Detail.aspx?newsId=73289&TId=285`

Plan (2014-2020), and the Work Plan for Controlling Greenhouse Gas Emissions during the 13th Five Year Plan, in order to expand the scope of national low-carbon city pilot projects, encourage more cities to explore and summarize low-carbon development experience, our commission organizes the recommendation and expert evaluation of the third batch of low-carbon city pilot projects. **After comprehensive consideration of the pilot implementation plan, socioeconomic conditions, demonstrative nature, and representative pilot layout**, the third batch of low-carbon city pilot projects have been determined to be carried out in 45 cities (districts, counties) .

Translation for Figure G4: The report of the 20th National Congress of the Communist Party of China emphasizes that promoting green and low-carbon economic and social development is a key to achieving high-quality development. Since 2010, in order to encourage local governments to explore green and low-carbon development paths according to local conditions, China implemented three batches of low-carbon pilots in 81 cities, districts, and counties, which **comprise regions of different development levels, resource endowments, and socioeconomic conditions** . To encourage local governments to explore green and low-carbon development paths according to local conditions, pilot cities have solidly implemented pilot tasks in five aspects: formulating low-carbon development plans, formulating policies to promote the development of low-carbon industries, establishing greenhouse gas emission data statistics and management systems, establishing a target responsibility system for controlling greenhouse gas emissions, advocating green and low-carbon lifestyles and consumption patterns, and boldly explored low-carbon development model innovation, institutional innovation, technological innovation, engineering innovation, and collaborative innovation. The pilot work has achieved positive results, accumulating valuable experience for local green and low-carbon development.

Figure G3: Determinants of 3rd-batch-pilot selection

为推进生态文明建设，推动绿色低碳发展，确保实现我国控制温室气体排放行动目标，我委分别于2010年和2012年组织开展了两批低碳省区和城点。各试点省市认真落实试点工作要求，在推动低碳发展方面取得积极成效。按照“十三五”规划《纲要》、《国家应对气候变化规划（2014-2020年）》和《“十三五”控制温室气体排放工作方案》要求，为了扩大国家低碳城市试点范围，鼓励更多的城市探索和总结低碳发展经验，我委组织各自治区、直辖市和新疆生产建设兵团发展改革委开展了第三批低碳城市试点的组织推荐和专家点评。经统筹考虑各申报地区的试点实施方案、工作基示范性和试点布局的代表性等因素，确定在内蒙古自治区乌海市等45个城市（区、县）（名单）开展第三批低碳城市试点。现将有关事项通知如下：

Source: Notice of the National Development and Reform Commission on Carrying out Pilot Work for 3rd Batch of Low-carbon Cities. Available at: `https://www.gov.cn/xinwen/2017-01/24/content_5162933.htm`

Figure G4: Summary on determinants of all three batches of pilot selection

党的二十大报告强调，推动经济社会发展绿色化、低碳化是实现高质量发展的关键环节。为鼓励地方因地制宜探索绿色低碳发展路径，自2010年以来，我国已分三批开展了81个低碳城市试点，涵盖了不同地区、不同发展水平、不同资源禀赋和工作基础的城市（区、县）。试点城市围绕编制低碳发展规划、制定促进低碳产业发展的政策、建立温室气体排放数据统计和管理体系、建立控制温室气体排放目标责任制、倡导绿色低碳生活方式和消费模式等五个方面扎实落实试点任务，并在低碳发展的模式创新、制度创新、技术创新、工程创新和协同创新等五个方面开展大胆探索，试点工作取得积极成效，为地方绿色低碳发展积累了宝贵经验。

Source: Assessment Report on the Progress of National Low-Carbon City Pilots. Available at: `https://www.mee.gov.cn/ywgz/ydqhbh/wsqtkz/202307/W020230713602785966247.pdf`

G.2 Actions by the central government

During pilot policy implementation, the central government mainly takes the role of supervision. Each city is required to devise a low-carbon development plan, including the emission-reduction targets and planned actions. The central government requires that the emission-reduction target be higher than the national average rate of emission reduction. The NDRC's evaluation reveals that the first batch of low-carbon-zone pilots cut their carbon intensity in 2012 by 9.2% relative to their 2010 level, much higher than the national average carbon intensity reduction of 6.6%. Central governments evaluate the progress of emission reduction on a yearly basis, and the results of the evaluation are considered during local government officials' promotion. With actions taken not perfectly quantifiable, the main criteria of evaluation are the level of carbon emissions reduction. For example, in 2016, the NRDC conducted a comprehensive evaluation of the first and second rounds of pilots, with the per capita carbon emission reduction used as a "key indicator" (Yang et al., 2018). The government leaders of cities not reaching emission reduction targets are summoned for explanations by central government officials and face negative performance evaluations during promotions.

G.3 Actions by local governments

Local governments take action to achieve their proposed emission reduction. Although the actions are not specified by the central government, after looking at the low-carbon development plans by local governments, we find that the majority of local governments take four types of actions: emissions fees, research subsidies, entry costs, and production regulation. Since the central government uses the reduction in absolute emission as the main criteria for local governments' pilot performance evaluations, the sectors with the largest direct carbon emissions (defined as carbon-intensive sectors in our study) are most regulated by the central government. For each type of action, we find the corresponding description in the city-level low-carbon development plans. The examples of policy document screenshots and corresponding translations are listed below. The translations of highlighted parts are bold-faced.

G.3.1 Examples of entry costs

Translation for Figure G5: Strictly implement national registration control regulations and industrial policies, **strengthen market access management**, and implement equal or reduced replacement of new production capacity in industries such as chemical, steel, non-ferrous metals, and building materials.

Translation for Figure G6: Strengthen energy conservation and carbon reduction. Develop the "Thousand Enterprises Energy Conservation and Low-Carbon Action Plan", strengthen the responsibility system for energy conservation and carbon reduction targets, establish and improve the energy

Figure G5: Example of entry cost (Lanzhou City)

1.加快淘汰落后产能。认真贯彻落实省政府《关于化解产能严重过剩矛盾的实施意见》（甘政发〔2014〕21号），严格执行国家投资管理规定和产业政策，加强市场准入管理，对化工、钢铁、有色、建材等行业新增产能实行等量或减量置换。2014年完成“十二五”落后产能淘汰任务，2015年根据国家、省上下达的任务，制定工作计划，再淘汰一批铁合金、水泥、电石等行业落后产能。（责任单位：市工信委、各县区政府）

Source: An action plan for low-carbon development of Lanzhou City

and carbon emission management system, and regularly carry out special inspections on the elimination of high energy consuming outdated mechanical and electrical equipment products and high energy consuming products in industrial enterprises. Accelerate the elimination of outdated production capacity in industries such as building materials, chemicals, papermaking, printing and dyeing, and leather making, **strengthen investment project review and management, and strictly control the development of high energy consuming and high emission industries.** Projects with annual energy savings exceeding 300 tons of standard coal will be rewarded at a rate of 400 yuan/ton of standard coal. Strive to achieve the goal of saving 2.5 million tons of standard coal and reducing carbon dioxide emissions by 6 million tons by 2015.

Translation for Figure G7: Strengthen the constraint effect of energy assessment and environmental impact assessment. Strictly implement the project energy assessment and environmental impact assessment system, and the energy efficiency and pollution intensity of newly built high energy consuming and high emission projects must reach the advanced level in China. The total emission index of major pollutants should be used as a prerequisite for environmental impact assessment approval. Energy consumption equivalent or reduced replacement should be implemented for newly added production capacity in high energy-consuming industries such as steel, non-ferrous metals, building materials, petroleum and petrochemical, and chemical industry. **For regions that have not achieved their energy conservation and emission reduction targets, the energy review and approval of new high energy consuming projects and the environmental impact assessment of new major pollutant emission projects in the region will be suspended.** Improve the evaluation management system, standardize evaluation institutions, and optimize the review process.

Translation for Figure G8: Increase the constraint of energy and environmental impact assessments. Further improve the management system for energy and environmental impact assessments, standardize evaluation institutions, and optimize the review process. Strictly implement the project energy assessment and environmental impact assessment system. **Take the total energy consumption control index and the total emission index of major pollutants as the preconditions for the approval of firm registration, and the energy efficiency level and emission intensity of new fixed assets investment projects must reach the advanced level.**

Figure G6: Example of entry cost (Guangzhou City)

28. 强化节能减碳。制定《千家企业节能低碳行动方案》，强化节能减碳目标责任制，建立完善能源和碳排放管理体系，定期开展工业企业高耗能落后机电设备产品淘汰和高耗能产品专项监察。加快淘汰建材、化工、造纸、印染、制革等行业的落后产能，加强投资项目审核管理，严格控制高耗能、高排放产业发展。对年节能量超过 300 吨标准煤的项目按 400 元/吨标准煤标准进行奖励。力争到 2015 年实现节能 250 万吨标准煤，减排二氧化碳 600 万吨的目标。(牵头单位：市经贸委，配合单位：市发展改革委、市财政局、市环保局、市统计局)

Source: Low-carbon development plan of Guangzhou City

Figure G7: Example of entry cost (Hubei Province)

(四)强化能评环评约束作用。严格实施项目能评和环评制度，新建高耗能、高排放项目能效水平和排污强度必须达到国内先进水平，把主要污染物排放总量指标作为环评审批的前置条件，对钢铁、有色、建材、石油石化、化工等高耗能行业新增产能实行能耗等量或减量置换。对未完成节能减排目标的地区，暂停该地区新建高耗能项目的能评审查和新增主要污染物排放项目的环评审批。完善能评管理制度，规范评估机构，优化审查流程。(省发展改革委、省环保厅负责)

Source: Implementation plan for low-carbon development of Hubei Province

Figure G8: Example of entry cost (Xining City)

3. 加大能评、环评约束作用。进一步完善能评和环评管理制度，规范评估机构，优化审查流程。严格实施项目能评和环评制度，把能源消费总量控制指标和主要污染物排放总量指标作为能评和环评审批的前置条件，新建固定资产投资项目能效水平和排污强度必须达到国内同行业先进水平。

Source: Low-carbon development plan of Xining City

G.3.2 Example of emission fee and production regulation

Translation for Figure G9: Improve the level of industrial energy efficiency. Implement an industrial energy efficiency improvement plan, comprehensively promote energy efficiency benchmarking in key energy-consuming industries, and promote the construction of energy control centers for industrial enterprises. **Continuously carry out energy-saving and carbon reduction actions for key energy-consuming enterprises, and promote the establishment of an energy management system.** Strengthen the assessment and management of enterprises with an annual energy consumption of 1000 tons or more of standard coal, and carry out standard management of unit product energy consumption quotas for some key energy-consuming industries; Strengthen the assessment and management of enterprises with an annual electricity consumption of 500000 to 1 million kilowatt hours, **establish an accounting system for energy consumption**, and include enterprises with an annual electricity consumption of 1 million kilowatt hours or an installed power capacity of 315 kilovolt amperes or more in the enterprise assessment and management.

Translation for Figure G10: Industrial energy conservation and carbon reduction. Implement the special action for industrial green development, build a demonstration base for Lanzhou's circular economy, and strive to become a pilot city for industrial green transformation and development. **Implement industrial energy efficiency improvement plans and continue to benchmark and meet energy efficiency standards in high energy consuming industries such as petrochemicals, steel, non-ferrous metals, and building materials.** Promote the construction of energy control centers for key enterprises such as Fangda Carbon Co., Ltd., Guodian Lanzhou Thermal Power, Guodian Fanping Thermal Power, Datang Xigu Thermal Power, Yuzhong Iron and Steel, and Lanzhou Petrochemical. Implement energy-saving transformation of motor systems, cogeneration, and utilization of waste heat and pressure. Eliminate high energy-consuming boilers and adopt high-efficiency energy-saving equipment. Focus on the petrochemical, metallurgical, and non-ferrous circular economy base, efforts will be made to **reduce product consumption and improve energy utilization efficiency**. By 2015, the energy consumption per unit of industrial added value above designated size decreases by 23% compared to 2010, to 2.8 tons of standard coal per 10000 yuan, with an average annual decline rate of 5.1%.

Translation for Figure G11: Expand the scope of clean energy use areas. Vigorously increase the supply of clean energy such as natural gas and electricity, **formulate and implement measures to control the consumption of coal-fired power in the city**, and increase efforts to control the total coal consumption. Promote the use of clean energy such as natural gas, liquefied petroleum gas, and electricity to achieve diversified energy supply and consumption for power units and industrial boilers. By the end of 2014, boilers, kilns, and large stoves in four districts, including Yuexiu District, Haizhu District, Liwan District, and Tianhe District, **were prohibited from using coal and heavy oil,**

Figure G9: Example of emission fee and production regulation (Sanya City)

1．提高工业能效水平。实施工业能效提升计划，在重点耗能行业全面推行能效对标，推动工业企业能源管控中心建设。持续开展重点用能企业节能降碳行动，推动建立能源管理体系。强化对年耗能1000吨标煤以上企业的考核管理，对部分重点用能行业开展单位产品能耗限额标准管理；加强对年用电50-100万千瓦时企业的考核管理，建立能耗台账，年耗电100万千瓦时以上或电力装机容量315千伏安以上企业必须纳入企业考核管理。

Source: Low-carbon development plan of Sanya City

and a “coal-free zone” was basically established. By the end of 2016, all industrial development zones and industrial parks in the city will complete the clean energy transformation or centralized heating of coal-fired boilers. Boilers, kilns, and large stoves in four districts (county-level cities) including Baiyun District, Panyu District, Huadu District, and Conghua City will be prohibited from using coal and heavy oil, and a ”coal-fired free zone” will be basically built. In principle, the use of coal and heavy oil is prohibited in boilers, kilns, and large stoves in four districts (county-level cities) including Huangpu District, Nansha District, Luogang District, and Zengcheng City. The area of highly polluting fuel ”no combustion zones” reaches more than 80% of the built-up area.

Translation for Figure G12: Promote the low-carbon upgrading and transformation of traditional industries. Accelerate the elimination of outdated production capacity in industries such as electricity, steel, chemicals, cement, and printing and dyeing. Strengthen energy-saving supervision over high energy consuming and high carbon-emitting industries such as metallurgy, power, chemical, petroleum, and petrochemical, **fully utilize energy auditing and clean production auditing methods, focus on energy-saving and consumption reduction for key energy consuming enterprises**, and promote low-carbon upgrading and transformation of industries.

Translation for Figure G13: We attach great importance to industrial energy conservation and emission reduction. We will conscientiously implement the industrial energy efficiency improvement plan and **comprehensively promote energy efficiency benchmarking and compliance activities in energy-consuming industries such as steel, electrolytic aluminum, chemical, building materials, and photovoltaics**. By 2015, the energy consumption of value-added industrial units above the designated size will be reduced by 15% compared to 2010. Deepen the special action for industrial green development and the energy-saving and low-carbon action for large enterprises, and actively promote the construction of energy management systems and industrial enterprise energy management centers.

Translation for Figure G14: **Implement quantity control measures for the six high energy consuming industries**, establish a monitoring system for carbon emissions of key enterprises, and implement measures such as production and electricity restrictions for enterprises exceeding emission limits.

Figure G10: Example of emission fee and production regulation (Lanzhou City)

1.工业节能降碳。实施工业绿色发展专项行动，建设兰州循环经济示范基地，争创工业绿色转型发展试点城市。实施工业能效提升计划，继续在石化、钢铁、有色、建材等高耗能行业开展能效对标达标。推动方大炭素有限公司等重点企业能源管控中心建设。以国电兰州热电、国电范坪热电、大唐西固热电、榆中钢铁、兰州石化等大型企业为主体，重点实施电机系统节能改造、热电联产、余热余压利用工程，淘汰高耗能锅炉，采用高效节能设备。以石油化工冶金有色循环经济基地为重点，着力降低产品单耗，提高能源利用率。到2015年，规模以上单位工业增加值能耗比2010年下降23%，降低到2.8吨标煤/万元，年均下降率达到5.1%。(责任单位：市工信委)

Source: An action plan for low-carbon development of Lanzhou City

Figure G11: Example of emission fee and production regulation (Guangzhou City)

4. 扩大清洁能源使用区域范围。大力增加本市天然气、电力等清洁能源的供应量，制定实施全市火力发电燃煤消费量控制措施，加大力度控制煤炭消费总量。推广使用天然气、液化石油气、电等清洁能源，实现电力机组和工业锅炉能源供应及消费的多元化。2014 年底前，越秀区、海珠区、荔湾区、天河区等 4 个区的锅炉、窑炉、大灶等禁止使用煤、重油，基本建成“无燃煤区”。2016 年底前，完成全市所有工业开发区、产业园区燃煤锅炉清洁能源改造或集中供热，白云区、番禺区、花都区、从化市等 4 个区(县级市)的锅炉、窑炉、大灶等禁止使用煤、重油，基本建成“无燃煤区”；黄埔区、南沙区、萝岗区、增城市等 4 个区(县级市)的锅炉、窑炉、大灶原则上禁止使用煤、重油，高污染燃料“禁燃区”面积达到建成区面积 80%以上。(牵头单位：市发展改革委，配合单位：市经贸委、市环保局、市质监局、市规划局，各区、县级市政府)

Source: Guidance of low-carbon development of Guangzhou City

Figure G12: Example of emission fee and production regulation (Tianjin City)

2．促进传统产业低碳化升级改造。加快淘汰电力、钢铁、化工、水泥、印染等行业的落后产能；加强对冶金、电力、化工、石油石化等高耗能、高碳排放行业的节能监管，充分利用能源审计和清洁生产审核手段，抓好重点用能企业的节能降耗工作，推动产业低碳化升级改造。（牵头单位：市经济和信息化委、市发展改革委，协作单位：市环保局）

Source: Implementation plan for Low-carbon development plan of Tianjin City

Figure G13: Example of emission fee and production regulation (Xining City)

9. 高度重视工业节能减排。认真实施工业能效提升计划，在钢铁、电解铝、化工、建材、光伏等耗能行业全面推行能效对标达标活动。到 2015 年，规模以上工业单位增加值能耗比 2010 年降低 15%。深入开展工业绿色发展专项行动和万家企业节能低碳行动，积极推动能源管理体系和工业企业能源管理中心建设。

Source: Low-carbon development plan of Xining City

Figure G14: Example of emission fee and production regulation (Shijiazhuang City)

二是对六大高耗能行业企业实行总量控制，建立重点企业碳排放量监测制度，对于超限排放企业实施限产、限电等措施。（责任单位：市发改委；配合单位：各县(市)、区政府）

Source: Key points for low-carbon development of Shijiazhuang City

G.3.3 Examples of research subsidies

Translation for Figure G15: Increase financial support, actively seek special funds related to low-carbon development at the national and provincial levels, and encourage different entities in the jurisdiction to apply for projects related to low-carbon development through multiple channels. **Establish special funds to support the construction of a low-carbon development capacity system, low-carbon key projects, low-carbon product research and development, and the promotion and application of low-carbon new technologies. Increase government investment in science and technology and tilt towards low-carbon development**, and leverage fiscal funds to guide investment in industries related to low-carbon investment. Expand diversified channels for social capital investment, leverage the leverage of public funds, and guide financial institutions, guarantee institutions, investment companies, and other social funds to invest in various low-carbon development industries. Using the national carbon market launched in 2017, encourage and assist enterprises to obtain economic benefits or emission rights through quota trading and certified emission reduction (CCER) trading.

Translation for Figure G16: Vigorously promote the development of energy-saving and environmental protection industries. Implement various policies and measures to promote the development of energy conservation and environmental protection industries at the national and provincial levels, relying on the construction of Lanzhou Circular Economy Demonstration Base and National "Urban Mineral" Demonstration Base, with a focus on the recycling and utilization of renewable resources, comprehensive utilization of household waste, new urban heating, and comprehensive utilization of waste heat and pressure. Implement circular transformation of industrial parks and cultivate a number of demonstration enterprises and projects. Actively develop energy conservation and environmental protection, **implement fiscal and tax incentives, support key energy consuming units to implement energy-saving transformation through contract energy management methods**, and accelerate the promotion of third-party pollution prevention and control governance.

Translation for Figure G17: Promote technological innovation. Vigorously introduce and promote advanced scientific and technological achievements both domestically and internationally, and actively develop and apply various new technologies, processes, and products. **Establish a low-carbon technology innovation incentive mechanism, implement relevant tax incentives, study and implement other funding incentive policies**, guide production enterprises to develop and apply energy-saving and low-carbon new materials and technologies, and gradually form a low-carbon and efficient technology innovation system.

Translation for Figure G18: Build a capacity support system to promote low-carbon development. Carry out low-carbon demonstrations in key areas such as industry, energy, construction, transportation, and technology, as well as in key industrial parks, communities, and towns, study and formulate implementation plans, and provide models and experiences for low-carbon development in the city. Research and establish a low-carbon city evaluation index system with Tianjin characteristics to lead the construction of low-carbon cities. Accelerate the formulation of local technical specifications and standards to promote low-carbon development. Promote low-carbon product labeling and certification. **Research and establish a special fund for low-carbon city construction in Tianjin, and increase support for key projects, low-carbon technology research and development, and capacity building**. Establish technology innovation institutions and platforms to promote low-carbon development and enhance independent innovation capabilities.

Translation for Figure G19: Timely promote energy-saving and emission reduction policies and regulations to enterprises, guide them to fully utilize and activate relevant preferential policies, and vigorously promote new technologies and processes for energy conservation and emission reduction. Provide training for emission-related management, and technical and statistical personnel. **Integrate energy-saving and emission reduction funds from various fields**, strengthen overall arrangements, improve utilization efficiency, and strictly implement the income tax reduction and exemption policy for energy management projects. **Guide financial institutions to increase their support for energy-saving, emission reduction, and low-carbon projects**, actively guide diverse investment entities and various social funds to enter the field of energy-saving and emission reduction.

G.4 Other Environmental Effects

We estimate the effects of the carbon pilot policy on firms' pollutant emissions and reduction outcomes, using firm-level data that combines the Annual Survey of Industrial Firms with the Pollutant Emissions Database provided by the Ministry of Environmental Protection. We show in Table G1 that the pilot policy does not affect other pollutant emissions and reductions at the firm level. Since the carbon pilot policy does not directly affect the firms' decision to emit other firm-level pollutants (wastewater, SO_2, and NO_x), the results can serve as a placebo test to rule out the fact that other

Figure G15: Example of research subsidies (Sanya City)

（二）加强资金扶持

加大财政支持力度，积极争取国家及省级低碳发展相关专项资金等，鼓励辖区内不同主体多渠道申报与低碳发展相关的项目；设立专项资金，支持、扶持低碳发展能力体系建设、低碳重点工程、低碳产品研发和低碳新技术推广应用；加大政府科技投入资金向低碳发展方面倾斜，发挥财政资金对与低碳投资有关产业投资的引导作用。拓宽多元化社会资金投入渠道，发挥公共资金杠杆撬动功能，引导金融机构、担保机构、投资公司等社会资金投入各类低碳发展产业。利用2017年启动的全国碳市场，鼓励并协

Source: Low-carbon development plan of Sanya City

Figure G16: Example of research subsidies (Lanzhou City)

2.大力促进节能环保产业发展。落实国家和省上促进节能环保产业发展的各项政策措施，依托兰州循环经济示范基地、国家“城市矿产”示范基地建设，以再生资源回收利用、生活垃圾综合利用、新型城市供热、余热余压综合利用为重点,实施产业园区循环化改造，培育一批示范企业和项目。积极发展节能环保服务业，落实财政奖励、税收优惠政策，支持重点用能单位采用合同能源管理方式实施节能改造，加快推动污染防治第三方治理。（责任单位：市工信委、市环保局、市城管执法局）

Source: An action plan for low-carbon development of Lanzhou City

Figure G17: Example of research subsidies (Guangzhou City)

42. 推动科技创新。大力引进推广国内外建设生态城市的先进科技成果，积极开发应用各类新技术、新工艺、新产品。建立低碳科技创新激励机制，贯彻落实相关税收优惠政策，研究推行其他资金奖励政策，引导生产企业开发和应用节能低碳新材料和新技术，逐步形成低碳高效的科技创新体系。（牵头单位：市发展改革委，配合单位：市经贸委、市国土房管局、市建委、市环保局、市水务局、市城管委、市林业和园林局、市财政局、市科技和信息化局、市国税局、市地税局，各区、县级市政府）

Source: Guidance of low-carbon development of Guangzhou City

Figure G18: Example of research subsidies (Tianjin City)

（三）构建促进低碳发展的能力支撑体系。开展产业、能源、建筑、交通、技术等重点领域和园区、社区、小城镇低碳示范建设，研究制定实施方案，为全市低碳发展提供典范和经验；研究建立具有天津特色的低碳城市评价指标体系，引领低碳城市建设；加快制定促进低碳发展的地方技术规范和标准，研究并推广低碳产品标识和认证；研究设立天津市低碳城市建设专项资金，加大对重点项目、低碳技术研发和能力建设的支持力度；组建促进低碳发展的科技创新机构和平台，增强自主创新能力。

Source: Implementation plan for Low-carbon development plan of Tianjin City

Figure G19: Example of research subsidies (Xining City)

(三)加强政策扶持

及时向企业宣传节能减排政策法规，引导企业用足、用活相关优惠政策，大力推广节能减排新技术、新工艺。做好企业管理层和技术、统计人员培训。整合各领域节能减排资金，加强统筹安排，提高使用效率，严格落实合同能源管理项目所得税减免政策。引导金融机构加大对节能减排低碳项目的支持力度，积极引导多元投资主体和各类社会资金进入节能减排低碳领域。

Source: An action plan for low-carbon development of Xining City

policy-related factors are driving our main results. Our review of policy documents also shows other pollutants are not targeted in low-carbon pilots.

G.5 Regional Spillover Effects

From the policy documents of various cities on the planning and organization of the pilot policy, we cannot find discernible evidence that different cities, especially pilot and non-pilot cities, should cooperate and coordinate with one another. This leads to the empirical fact that regional spillover effects of the pilot policy are not dominating forces that drive our main results. As for empirical supports, Table G2 suggests that the pilot policy does not have cross-city spillover effects on housing prices,[42] while Table G3 suggests that the pilot policy does not have cross-city spillover effects on an array of city-level socioeconomic outcomes.[43]

Appendix H Data Compilation

The origin data set of the firm registration information consists of records of registration and deregistration of each firm. Each entry includes information on the registered capital, location, identity of the legal representative(s), ownership information, sectoral classification, and the year of exit (if any). Note that if the firm simply stops production or reallocates but does not deregister, then it is not deemed to exit our data set.

Based on over 40 million registration records of the universe of Chinese firms, we aggregate the granular data into a city-sector-year panel data set. Specifically, we calculate entry and exit in each city-sector-year cell. Entry is defined and calculated as the total registration capital or the total number of firms that have been registered in a specific city, sector, and year. We discard observations whose registered capital is 0 or belongs to the top 0.1%.

We also match the registration data set with the patent application data set, so that we can know which firm applies for which patent. In this way, we calculate the number of patent applications by firms that belong to a certain city-sector-year cell.

[42] The data source of housing prices is Fang et al. (2016).

[43] The data source of these outcomes are the Chinese City Statistics Yearbooks of various years.

Table G1: Effects on firm-level pollutants

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Water use)	log(Wastewater)	log(Nox emissions)	log(SO2 emissions)	log(NOx reduction)	log(SO2 reduction)
1(Pilot)	0.00641	0.0538	0.108	0.117	0.00794	0.0349
	(0.0665)	(0.0913)	(0.125)	(0.0775)	(0.0596)	(0.136)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	366,348	366,348	366,348	366,348	366,348	366,348
R-squared	0.814	0.821	0.677	0.861	0.388	0.577

Notes: The sample covers 366,348 firm-year cells during 2005-2013. In all columns, firm and year fixed effects are controlled for. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table G2: (Spillover) effects on housing price

	(1)	(2)	(3)	(4)
	log(Housing price index)			
1(Pilot)	-0.0710***	-0.0615	-0.108***	-0.118
	(0.0243)	(0.0507)	(0.0335)	(0.0802)
Mean neighbors' 1(Pilot)		-0.0122		-0.535
		(0.0572)		(2.626)
City FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Prov-year FE	N	N	Y	Y
Prov-month FE	N	N	Y	Y
Observations	3,360	3,360	3,360	3,360
R-squared	0.975	0.975	0.995	0.995

Notes: The sample covers 3,360 city-year-month cells during 2005-2014. In all columns, city and year-month fixed effects are controlled for. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.

Table G3: (Spillover) effects on city outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(Population)	GDP growth	log(Pop. Density)	Secondary share	log(SO2)	log(NOx)	log(Dust)
1(Pilot)	0.0155	0.163	-0.000258	-0.0175	-0.0550	-0.140*	-0.107
	(0.0106)	(0.370)	(0.00872)	(0.665)	(0.0630)	(0.0750)	(0.0789)
City FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	3,938	3,644	3,091	3,651	3,791	3,742	3,743
R-squared	0.952	0.601	0.982	0.859	0.825	0.739	0.741
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	log(Population)	GDP growth	log(Pop. Density)	Secondary share	log(SO2)	log(NOx)	log(Dust)
1(Pilot)	0.000526	0.323	0.00391	-0.00364	-0.0702	-0.142*	-0.110
	(0.0108)	(0.369)	(0.0183)	(1.044)	(0.0733)	(0.0850)	(0.0867)
Mean neighbors' 1(Pilot)	0.0276	-0.235	-0.00652	-0.0237	0.0276	0.00397	0.00559
	(0.0186)	(0.568)	(0.0203)	(1.374)	(0.0993)	(0.124)	(0.130)
City FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	3,913	3,622	3,075	3,628	3,791	3,742	3,743
R-squared	0.951	0.602	0.982	0.859	0.825	0.739	0.741

Notes: The sample covers around 3,600 city-year cells during 2005-2014. In all columns, city and year-month fixed effects are controlled for. * Significant at 10%, ** 5%, *** 1%. Standard errors are clustered at the city level.