



# Can a low-carbon development path achieve win-win development: evidence from China's low-carbon pilot policy

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## Abstract

Low-carbon pilot (LCP) policy aims to not only achieve economic development but also address climate change problems in China. With a difference-in-difference (DID) approach, this study provides empirical evidence to support the policy's implementation by analysing its impacts on green total factor productivity (GTFP). We find that the implementation of the low-carbon pilot policy has a significant positive impact on GTFP. The low-carbon pilot policy significantly improves the GTFP in the year following implementation, and its efficacy diminishes over time. In terms of mechanism analysis, the policy enables China to achieve win-win development through industry structure adjustment and foreign direct investment (FDI) inflows. Innovation does not immediately improve GTFP, although the low-carbon pilot policy promotes regional innovation. Our results provide strong support for China's recent third set of low-carbon pilot policies. As for global mitigation strategy, countries should incorporate the low-carbon development path into their strategic planning. In particular, developing countries should enforce more efforts on low-carbon development as such development path may improve their green productivity. It helps narrow the gap between developing and developed countries.

**Keywords** Low carbon pilot policy · Win-win development · Green total factor productivity · Difference-in-difference

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## 1 Introduction

According to the United Nations Framework Convention on Climate Change 21st Conference of the Parties, Paris, France, 2015 (Paris Agreement), the global average temperature increase in this century is no more than 1.5 °C higher than the temperature before the industrial revolution. The method for addressing the temperature increase is reducing greenhouse gas (GHG) emissions, which requires early and more emission reduction efforts worldwide (Duan et al. 2019). As the world's largest carbon emitter and energy consumer, China has made many efforts to reduce GHG. Since 2010, the National Development and Reform of China (NDRC 2010) has issued two sets of LCP policies in several provinces and cities. The LCP policy aims to not only achieve economic development but also solve the climate change problem and reduce the carbon intensity of China's industrialization and urbanization process. Thus, analysing the effect of the LCP policy and deeply understanding its influencing mechanisms are important because of the policy's support for developing a national low-carbon path and its foundation for responding to climate change. However, relevant studies have been very limited.

Empirical evidence on the productivity of environmental regulation is mixed. Traditional wisdom is that environmental regulation may increase enterprises' production costs. Companies need to invest more to achieve emission reduction targets, which are not conducive to productivity or efficiency improvements (Gray 1987). Wanley (1994) pointed out that environmental regulation incurred higher production costs, which crowded out the investment originally used for innovation. Recent empirical studies supporting this argument include Rassier and Earnhart (2010), Rogge et al. (2011) and Greenstone et al. (2012). Greenstone et al. (2012) is of particular relevance to our study. It found that the Clean Air Act Amendments, an environmental regulation, had a particularly large negative effect on productivity in the USA.

In contrast, the Porter Hypothesis argues that environmental regulation can stimulate innovation and improve enterprise competitiveness (Porter and Van der Linde 1995). To reduce pollution control expenditures, regulated companies will improve production technology, which may partially or even fully offset the compliance costs. There is also a vast body of literature supporting the Porter Hypothesis (Ambec et al. 2013; Korhonen et al. 2015; Rubashkina et al. 2015; Zhao and Sun 2016; Ren et al. 2018; Skoczkowski et al. 2018). For example, Hamamoto (2006) found that environmental regulation had a significantly positive effect on the growth of total factor productivity in Japanese manufacturing industries versus the findings of Greenstone et al. (2012).

It is noteworthy that empirical studies typically use environmental protection investments, pollutant removal rates and total discharge of various wastes as indicators of environmental regulation stringency (e.g. Rubashkina et al. 2015; Zhao and Sun 2016; Li and Wu 2017). However, these indicators are collected from survey data and are notoriously known to be susceptible to systematic measurement errors due to pollution multidimensionality (Berman and Bui 2001). Recently, some scholars use natural experiments to measure environmental regulation and construct a DID model to estimate environmental regulation effects. For example, Hering and Poncet (2014) used a DID model to analyse the impact of China's "Two Control Zone" policy on exports. Zhang et al. (2017) treated China's Carbon Trading Pilot policy as a natural experiment and analysed its effect on technological innovation. Chen et al. (2018) and Shi and Xu (2018) took advantage of China's 11th Five-Year Plan and investigated its impact on firms' activities and exports with the DID model, respectively. These studies treat environmental regulation policies as natural experiments so their estimations are less likely to be affected by survey data and individuals (Berrone et al. 2013).

Scholars have not reached a consensus about the effects of environmental regulation. Industrialization and urbanization inevitably increases energy consumption and CO<sub>2</sub> emissions (Li and Lin 2015). Kwakwa et al. (2018) analysed the effect of financial development and natural resource extraction on carbon emissions. Wang et al. (2019) analysed the effect of technological progress on carbon emissions with the panel quantile regression model. However, these studies ignore the influence of environmental regulation on urban carbon emissions and environmental protection. The LCP policy aims to coordinate the regional environmental impact and economic growth (NDRC 2010), but rigorous empirical assessment of the policy's impact is lacking. We want to determine whether the LCP policy creates win-win development for China or only achieves carbon reduction targets while sacrificing economic benefits. Since the GTFP comprehensively considers inputs and both desirable and undesirable outputs, we assess Chinese urban GTFP with a slacks-based measure (SBM) model on the premise of variable returns to scale using urban panel data between 2003 and 2015. Then, we conduct an empirical study with a DID model to analyse the LCP policy impact on the urban GTFP. We also test the policy's impact mechanism through industry structure, innovation and FDI.

Our study contributes to the previous literature in the following aspects. First, some studies have analysed the impact of the LCP policy from a qualitative perspective, but rigorous empirical assessment of the impact has not yet been carried out. Khanna et al. (2014), Wang et al. (2015) and Jiang (2015) collected much data from the LCP cities and offered some significant observations about the responses to the LCP policy. However, these analyses are primarily qualitative and incomplete. Our study complements theirs by empirically examining the effects of LCP policy on GTFP. Specifically, we investigate the influencing mechanisms through industry structure, innovation and FDI. The results can provide support for further development of a low carbon path.

Second, as the LCP policy aims to coordinate the regional environmental impact and economic growth, we select the GTFP indicator to reflect the LCP policy effects. Compared to traditional single-factor productivity, GTFP more comprehensively considers inputs, and both desirable and undesirable outputs, which better reflects the efficiency of an economic system (Shao et al. 2016). Moreover, unlike previous studies that measure GTFP with the SBM model on the premise of constant returns to scale, we estimate the Chinese urban GTFP with SBM on the premise of variable returns to scale. Our method more reasonably reflects GTFP because production may not operate at the optimal scale, given the restriction of factor inputs in an imperfectly competitive market. We use data for Chinese cities at the prefecture level and above and estimate the impact of the LCP policy on city GTFP. Our assessment can help policy makers to determine whether the LCP policy can promote both the economic development and environmental protection (win-win development).

Third, the existing studies typically use environmental protection investments, pollutant removal rates and total discharge of various wastes as indicators of environmental regulation stringency, which are collected from survey data and may have estimation error. Scholars have recently employed the DID method to estimate policy impacts by treating the implementation of policies as natural experiments to avoid estimation error (e.g. Hering and Poncet 2014; Chen et al. 2018; Shi and Xu 2018). Following these studies, we treat the LCP policy implementation as a natural experiment and employ a DID method to analyse the policy impacts. This method can effectively avoid the systematic errors and biased estimation that may arise in the process of measuring environmental regulation.

The remainder of this paper is organized as follows. Section 2 introduces the policy background and analyses influencing mechanisms. Section 3 describes the data and methods.

Section 4 presents empirical results and discussions, as well as a variety of robustness checks. Section 5 concludes the paper with policy suggestions.

## 2 Policy background and influencing mechanisms

### 2.1 The LCP policy

All countries are faced with the major challenge of climate change. China is now exposed to great carbon mitigation pressure. While it remains a towering presence in carbon emissions volume and sees growing energy demand driven by economic growth and urbanization promotion, it takes an active role in carbon reduction. In 2009, the Chinese government committed a mandatory goal of a 40–45% decrease in carbon intensity by 2020 compared to the 2005 level. In 2015, this goal was committed to drop by 60–65% in 2030 compared to the 2005 level. As its economic development continues apace, the Chinese government suffers more from the inescapable pain stemming from the torturing split between economic growth and environmental construction. Its daunting goal is to effectively and properly control GHG emissions while maintaining economic growth. China has taken increasingly proactive measures to deal with GHG emissions. Efforts have been made not only in anchoring energy efficiency as the base of long-run energy transition plans but also in promoting a market-based policy. The latter, namely, the LCP policy, is a keen and promising practice in Chinese carbon reduction trials. It designates several cities and provinces to pilot emissions trading for the future national emission trading system.

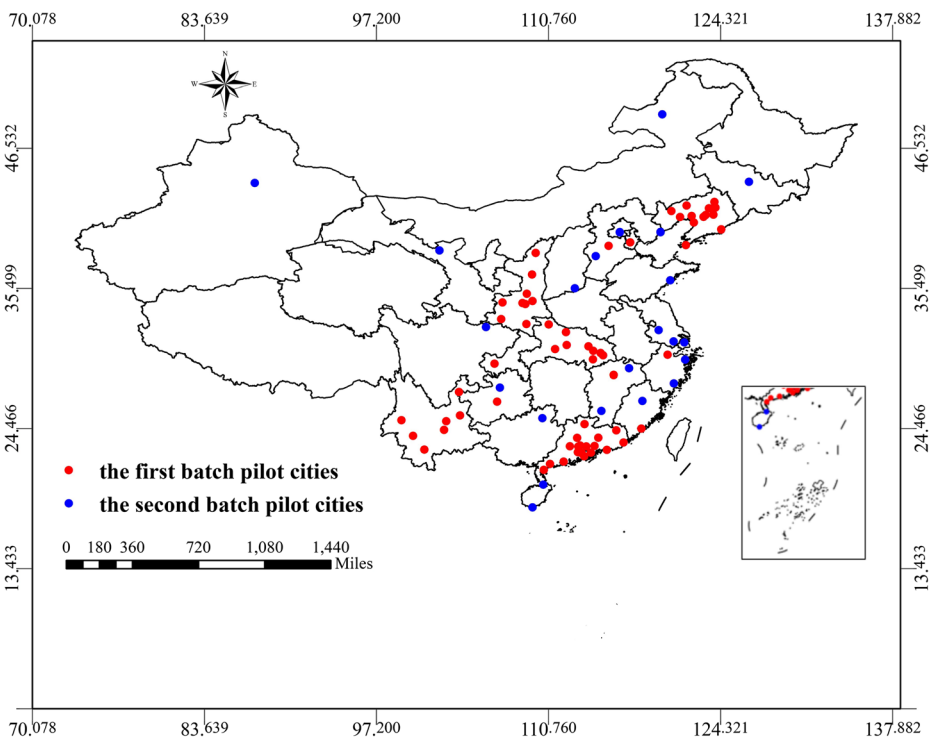
Pilot regions are required to formulate low-carbon programmes and gradually establish and improve low-carbon pilot institutions. They have to formulate supporting policies for low-carbon development, accelerate the establishment of a low-carbon industrial system and promote low-carbon development. During these processes, conceptual policies can be assessed with practices and unexpected issues will be uncovered, which provide lessons and suggest refinements of ongoing ideas. Via this trial, China is able to add to its experience in developing a green economy, which is crucial in today's mixed context of rapid industrialization and urbanization, and heavy reduction missions. The LCP policy has confirmed two groups of pilot regions in August 2010 and November 2012. The first batch includes 5 provinces (Guangdong, Liaoning, Hubei, Shaanxi, Yunnan) and 8 cities (Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, Baoding). The second batch includes Beijing, Shanghai, Hainan, Shijiazhuang, Qinhuangdao, etc. These two sets of LCP policies identified a total of 6 provinces and 36 cities as low-carbon pilots. These pilot regions' population, GDP and carbon emissions account for approximately 40%, 60% and 40% of the country, respectively (Wei 2016). In 2017, China officially launched the third batch of pilots (NDRC 2017). These endeavours clearly show the government's commitment to the low-carbon development path.

The LCP policy is set to whip up the interest of all parties in following a low-carbon development path, while helping the country accumulate a green development experience for different regions and industries. It provides appropriate strategies for national low-carbon development and vigorously promotes the construction of ecological civilization. Each pilot is required to develop a low-carbon development plan and supporting policies, establish CO<sub>2</sub> emission statistics and a data management system and encourage low-carbon consumption patterns. Some pilots have achieved several progressive goals, such as the implementation of low-carbon policies and institutions, design of GHG inventories and low-carbon lifestyles

(Wang et al. 2015). Figure 1 shows the geographical distribution of the first two groups of pilots. It indicates that low-carbon pilots are mainly distributed in the eastern and central regions.

## 2.2 The impact mechanisms of LCP policy on GTFP

The LCP policy's three impact mechanisms on GTFP are industry structure, innovation and FDI. First, the LCP policy may affect GTFP through intra-industry production structure, inter-industry structure and inter-regional industry layout adjustments. High pollution and energy demand enterprises are more sensitive to environmental regulation. They have to change their production structure under regulations, which leads to intra-industry structural adjustment (David and Sinclair-Desgagné 2005). Due to the large differences in resource intensity and production technologies among industries, the impacts of environmental regulation on different industries are also different, and these differences may lead to inter-industry structural adjustment. Cole et al. (2005) indicated that environmental regulation could effectively reduce the proportion of polluting industries. According to the Pollution Haven hypothesis (Walter and Ugelow 1979), environmental regulation can affect regional industrial layout. The regions' different regulation intensities lead to their spatial layout—high pollution industries will shift to regions with less stringent regulations. Research by Kheder and Zugravu (2012) showed that environmental regulation affected the spatial layout and location of pollution intensive industries, and thus affected inter-regional industry layout adjustments. The industry structure



**Fig. 1** Locations of China's two sets of LCP cities

reflects the distribution of industries and is an important factor affecting total factor productivity (Liang 2009; Li and Wu 2017). Therefore, the LCP policy may affect enterprises' production structure and lead to industry structure adjustment, which can affect the GTFP among regions.

Second, environmental regulation can successfully affect innovation, which greatly boosts the improvement of GTFP. In the short term, environmental regulation may increase enterprises' pollution control cost, thereby adding to production costs. There exists a crowding-out effect, meaning that the increased cost of pollution controlling processes such as supervision, government regulations and much else will squeeze out investment from other parts that may be more productive, thereby limiting production efficiency. However, in the long term, changes in the corporate cost structure and resource allocation can force enterprises to adjust to the existing production structure and carry out innovation. Such innovation can not only reduce pollution control costs but also cut down demand for energy and materials by using new technologies. Empirical studies by Rubashkina et al. (2015) and Zhao and Sun (2016) had found that environmental regulation could stimulate enterprises to carry out innovation, supporting the Porter Hypothesis. Meanwhile, innovation has significant impact on productivity improvement (Raymond et al. 2015; Ge et al. 2018). Therefore, production cost increases incurred by the LCP policy may, in the long term, encourage investment in green innovation. It ultimately reflects GTFP improvement under the premise of overall technology improvement and resource allocation optimization.

Third, the LCP policy can affect GTFP through FDI. LCP policy implementation may affect the location and flow of FDI, which may impact GTFP. According to the Pollution Haven hypothesis, countries with loose environmental regulation can attract the FDI of polluting industries. Both Chung (2014) and Cai et al. (2016) verified the Pollution Haven hypothesis and found that strict environmental regulation would prevent FDI inflow. Meanwhile, the advanced production technologies and management experience introduced by FDI can also wield clout in GTFP (Newman et al. 2015). Therefore, LCP policy implementation may affect the FDI of pilot areas, and thus affect the improvement of regional GTFP.

Here, we hypothesize that the LCP policy can influence GTFP of pilot regions by changing industry structure, innovation and FDI.

## 3 Empirical methods and data description

### 3.1 Green total factor productivity

For total factor productivity measurement, the data envelopment analysis (DEA) method uses linear programming and constructs non-parametric production frontiers to measure efficiency values. It does not require a detailed production function (Coelli 1998). Therefore, DEA methods are widely used to measure TFP, especially when there are multiple inputs and outputs (Li and Lin 2015; Bai et al. 2018; Zhu et al. 2018). However, such DEA models neglect the importance of slack variables, which may lead to overestimation (Fukuyama and Weber 2009). Tone (2001) first proposed the SBM model, which was then widely applied to environmental performance assessment. Researchers such as Zhou et al. (2013) and Tang et al. (2017) applied SBM to measure TFP on the

premise of constant returns to scale. A conventional SBM model is constructed on the premise of constant returns to scale in the assumption that output changes are proportional to input changes. However, according to microeconomics, production may not operate at the optimal scale given the restriction of factor inputs in an imperfectly competitive market. Therefore, we build the model on the premise of variable returns to scale because the DMUs in such a model are allowed to operate at a non-optimal scale to satisfy real operation (Banker et al. 1984). In addition, when the SBM model considers undesirable outputs, the TFP is generally referred to as the GTFP, an indicator for sustainable development. GTFP can reflect the degree of coordination between economic development and environmental protection (Zhao et al. 2015).

Suppose there are  $n$  DMUs (e.g. cities), each DMU has three factors: inputs ( $x$ ), desirable outputs ( $y^g$ ) and undesirable outputs ( $y^b$ ). These factors can be represented by vectors  $x \in R^m, x \in R^m, y^g \in R^{s_1}$  and  $y^b \in R^{s_2}, y^b \in R^{s_2}$ , respectively.

To derive GTFP, we first have to define the input and output variables explicitly. The relevant indicators, such as economic activity, energy consumption and CO<sub>2</sub> emissions, must be combined holistically in the DEA model for evaluation (Ramanathan 2002). According to the basic economic theory of production, an economic entity uses capital, labour and energy as inputs to produce a certain amount of products, representing desirable output, and CO<sub>2</sub> emissions, an undesirable output (Zhang and Wei 2015). A similar production framework has been widely adopted for TFP and GTFP (e.g., Li and Lin 2016; Zhu et al. 2018). Therefore, in this paper, we suppose that each DMU uses capital, labour and energy as inputs to generate the urban GDP, the desirable output, and CO<sub>2</sub> emissions, the undesirable output. The production possibility set is as follows:

$$P(x) = \left\{ (y^g, y^b) \mid \text{produce}(y^g, y^b), x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \sum \lambda = 1, \lambda \geq 0 \right\} \quad (1)$$

where  $\lambda$  is a non-negative multiplier vector.

Therefore, we propose the following SBM model under variable returns to scale (VRS):

$$\begin{aligned} \phi^* = \min & \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_{i0}^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left( \sum_{r_1=1}^{s_1} \frac{s_{r10}^g}{y_{r20}^g} + \sum_{r_2=1}^{s_2} \frac{s_{r20}^b}{y_{r20}^b} \right)} \\ \text{s.t. } & x_0 = X\lambda + s_{00}^- \\ & y_0^g = Y^g\lambda - s_{00}^g \\ & y_0^b = Y^b\lambda + s_{00}^b \\ & \sum \lambda = 1 \\ & s_{00}^- \geq 0, s_{00}^g \geq 0, s_{00}^b \geq 0, \lambda \geq 0 \end{aligned} \quad (2)$$

where  $i = 1, 2, \dots, m$  are inputs,  $m$  is inputs number,  $r_1 = 1, 2, \dots, s_1$  are desirable outputs,  $r_2 = 1, 2, \dots, s_2$  are undesirable outputs,  $s_1$  is desirable number and  $s_2$  is undesirable number.  $s_{00}^-, s_{00}^g$  and  $s_{00}^b$  are slack variables of input (potential reduction), desirable output (potential increase) and undesirable output (potential reduction), respectively. The objective function is the green total factor productivity. Based on model (2), we can measure GTFP in each region. It should be highlighted that the GTFP reflects not only GDP growth but also emission reduction as it has constraint of desirable output maximization and undesirable output minimization.

### 3.2 Empirical methodology

The key assumption of the DID model is that the treatment and control groups have similar trends before the policy is implemented. We need to conduct a parallel trend test to examine whether there is an exaggerated policy effect. Based on the framework proposed by Kudamatsu (2012) and Alder et al. (2016), we address this concern by conducting the following parallel trend test:

$$\text{GTFP}_{it} = \beta_0 + \beta_1 du_i \times dt_t + \beta_2 x'_{it} + \delta_t + \varepsilon_{it} \quad (3)$$

where the value of  $I_t^{\text{post}}$  is 1 when  $t - \text{post} = n$ , otherwise is 0.  $\text{post}$  is the year of the LCP policy started implementing, in this paper is 2011.  $n$  can be  $-8, -7, \dots, 0, \dots, 4$  and we take  $-1$  as the baseline group.  $x'_{it}$  are control variables.  $du_i$  is a dummy for pilot cities.  $\varepsilon_{it}$  is the idiosyncratic error term.  $\delta_t$  is the year fixed effects. In the parallel trend test, we need to pay attention to the coefficient of  $\rho_t$ .

Due to the different distribution and participation time of pilots in the LCP policy, we use the DID model to identify the LCP policy's effect on GTFP. First, pilot cities in the LCP policy are the treatment group and the non-pilot cities are the control group. Then, based on the year in which the LCP policy was issued, the sample time (2003–2015) is divided into two periods: 2003–2010 and 2011–2015. Finally, two variables  $du$  and  $dt$  are set:  $du$  is a dummy for pilot cities, and  $dt$  is a dummy for the LCP policy start date.  $du$  of the first and second batches of pilots are 1.  $dt$  of the first batch of pilots are 1 since 2011, while  $dt$  of the second batch of pilots are 1 since 2013. Although the LCP was first issued in the middle of 2010, the incentive effect of the policy may appear in 2011. We also select 2010 as the starting year of the first LCP policy and conduct a parallel trends test, which proves that there is no parallel trend. After the above sample definition, basic empirical model is set as follows:

$$\text{GTFP}_{it} = \beta_0 + \beta_1 du_i \times dt_t + \beta_2 x'_{it} + \delta_t + \varepsilon_{it} \quad (4)$$

where  $\text{GTFP}_{it}$  is the estimated GTFP (Eq. (2)) of city  $i$  at year  $t$ .  $\beta_2$  in Eq. (4) captures the average regulatory impact on GTFP. It is also of interest to know whether the LCP policy impact is lagged or prolonged or if it decays. We employ the following model to identify the dynamic effects of the LCP policy on GTFP:

$$\text{GTFP} = \beta_0 + \beta_1 x'_{it} + \sum_{j=2011}^{2015} \beta_j du_i \times dt_t \times \text{year}^j + \delta_t + \varepsilon_{it} \quad (5)$$

where  $\text{year}^j$  are year dummies and  $\beta_2 + a_j \cdot \beta_j$  corresponds to the LCP policy impact on GTFP in year  $j$  ( $j = 2011, 2012, 2013, 2014, 2015$ ).

To identify the influence of the LCP policy on GTFP, in the second section, we set the following regression model to find the effects on innovation, industry structure and FDI:

$$\text{STR}_{it}, \text{RD}_{it}, \text{FDI}_{it} = \chi_0 + \chi_1 du_i \times dt_t + \chi_2 x'_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (6)$$

where  $\text{STR}_{it}$  is industry structure,  $\text{RD}_{it}$  is innovation, and  $\text{FDI}_{it}$  is foreign direct investment.  $\beta_1$  in Eq. (6) identifies the effects of the LCP policy on industry structure, innovation and FDI.  $\alpha_i$  represent city fixed effects.

We conduct a parallel trend test and a series of robustness checks. Our estimation validity hinges crucially on the assumption that there is no differential pretreatment trend between the



pilot and non-pilot cities. We verify that there is no significant deviation from this assumption (Kudamatsu 2012). Then, we run the DID model to find the LCP policy impacts. We also check that our results are robust to the choice of the treatment year. Although the LCP policy was officially announced in the middle of 2010 (NDRC 2010), implementation effects in pilot cities may start in 2010, so we also conduct parallel trends tests with 2010 as the starting year of the first batch of LCP policy. To further check whether there may be an omitted selection, we conduct the propensity score matching (PSM) and rerun the regressions on the matched sample. We address the concern that our results may be biased because the second batch pilots are included in the 2011–2012 control groups by conducting a test where we use only the second batch pilots as control group in 2003–2012.

### 3.3 Data description

The data comes from “China City Statistical Yearbook” and provincial statistical yearbooks. Taking into account data completeness, we select 283 prefecture-level cities in China from 2003 to 2015, including 96 pilot cities and 187 non-pilot cities. All monetary value data are calculated at constant prices in 2003.

- (1) Input-output variables. To measure urban GTFP, capital, labour and energy are inputs. Regional GDP and CO<sub>2</sub> emissions are desirable and undesirable outputs, respectively. The capital stock data represents the urban capital input. Since the capital stock cannot be obtained directly from the statistical yearbook, the perpetual inventory method is generally used for capital estimation. We use the same method in Xie et al. (2017) and estimate the capital stock of 283 sample cities in 2003–2015. Labour input is measured by the number of people employed in each city at the end of the year. The GDP is measured by urban gross domestic production. The data are obtained from the “China City Statistical Yearbook.” For urban energy consumption and carbon emissions data, we use the measurement method in Xie et al. (2017) and calculate four types of energy consumption, namely, electricity, natural gas, liquefied petroleum gas and transportation energy consumption. We use the electric power consumption data and the carbon emission coefficient of each regional power grid to calculate energy and CO<sub>2</sub> emissions from electricity. The China Certified Emission Reduction Exchange Info-Platform has released the regional grid baseline emission coefficients over the years. The CO<sub>2</sub> emission coefficient for natural gas is 2.1622 kg/m<sup>3</sup> and the CO<sub>2</sub> emission coefficient for liquefied petroleum gas is 3.1013 kg/kg according to the China Energy Statistical Yearbook. Based on Li et al. (2013) and Xie et al. (2017), we use the proportion of freight and passenger transportation of railways, highways and airlines, as well as the energy consumption of the national transportation industry, to calculate the energy consumption and CO<sub>2</sub> emission of urban transportation. We collected these data from the China City Statistical Yearbook and China Statistical Yearbook. The CO<sub>2</sub> emission coefficients are derived from the 2006 IPCC National GHG Inventories. Data are obtained from China City Statistical Yearbook.
- (2) Control variables. We use the innovation index (Kou and Liu 2017) to measure innovation. This index provides an aggregated account of patents and entrepreneurship for each city. To calculate the city innovation index, the patent data are

obtained from the National Intellectual Property Administration, and the enterprise registration capital data are obtained from the National Industry and Commerce Administration. The city innovation index is calculated according to the micro data and location of enterprises. We calculate industry structure by the ratio of the output value of secondary industry to the output value of tertiary industry. FDI is measured by the actual amount of foreign capital. We use the constant price in 2003 to generate deflation and take the logarithm. The local government's degree of economic intervention is measured by the ratio of fiscal revenue to GDP. The urbanization level is presented by the logarithm of population density. Table 1 shows the definition and statistical description of the variables.

## 4 Empirical results

### 4.1 Parallel trends test

The government may select winners or losers when it implements a policy. This pre-screening action may cause significant differences between the treated and control groups. For instance, if the government is more likely to choose regions that are more well-developed and adaptable to green development practices, it will lead to a higher GTFP level for the treated group compared to the control group even before the LCP policy is implemented. Then, the treated group's better performance compared to the control group after the LCP policy is enacted, should to a degree, be attributed to a pre-screening effect. Even if the government does not carry out a policy intervention, they will perform relatively better. Ignoring this effect will cause the LCP policy effect to be exaggerated. Thus, conducting parallel trends test is

**Table 1** Description of variables and data

Variable	Definition	Mean	S.D.	Min	Max
K	Capital stock in 10 <sup>8</sup> Yuan	2212.46	3350.21	34.80	40962.75
L	Total number of employees (10 <sup>4</sup> persons)	87.01	125.20	5.58	1729.08
E	Total energy consumption in 10 <sup>4</sup> metric tons of standard coal equivalent	212.61	339.01	6.75	3818.22
GDP	GDP in 10 <sup>8</sup> Yuan	3797.49	6809.29	31.77	83259.01
CO <sub>2</sub>	CO <sub>2</sub> emissions in 10 <sup>4</sup> metric tons	905.88	1444.21	19.83	14063.24
GTFP	Green total factor productivity by logged	- 0.53	0.30	-	0
				1.-	
				77	
STR	Industry structure indicated by the ratio of the output value of Secondary industry to the output value of third industry	1.50	0.80	0.05	10.60
RD	Enterprise technology innovation indicated by innovation index	0.06	0.32	0	8.49
FDI	Openness level indicated by logged total FDI in billion Yuan	7.02	2.61	0	29.02
GOV	Government intervention indicated by the ratio of fiscal revenue to GDP	0.06	0.03	0.01	0.53
URBAN	Urbanization level measured by logged Population density in persons per squared kilometre	6.55	1.77	1.55	12.44

necessary. In our parallel trends test, we take 2010 as the baseline year. The results can show whether there is a significant GTFP difference between the treatment and control groups compared to the baseline year. The significance of  $\rho_t$  can help us verify whether the parallel trend assumption exists (e.g. Kudamatsu 2012; Alder et al. 2016, for similar practices).

In Table 2, we find that the interaction coefficients are not significant before the LCP policy's implementation year, while it is significant in the second year after implementation. In other words, during the period prior to LCP policy implementation, there is no significant difference in the GTFP between pilot and non-pilot cities. However, after LCP policy implementation, there is a significant difference between the treatment and control groups. Thus, we cannot reject the assumption of parallel trend.

**Table 2** Test of parallel trends

	Coefficient of $\rho_t$
8 years before the policy implement $\times$ du	- 0.027 (- 0.88)
7 years before the policy implement $\times$ du	- 0.046 (- 1.47)
6 years before the policy implement $\times$ du	- 0.037 (- 1.20)
5 years before the policy implement $\times$ du	- 0.032 (- 1.01)
4 years before the policy implement $\times$ du	- 0.022 (- 0.71)
3 years before the policy implement $\times$ du	0.038 (1.22)
2 years before the policy implement $\times$ du	0.037 (1.21)
Year of the policy implement $\times$ du	0.046 (1.48)
1 year after the policy implement $\times$ du	0.063** (2.03)
2 years after the policy implement $\times$ du	0.029 (1.04)
3 years after the policy implement $\times$ du	0.010 (0.36)
4 years after the policy implement $\times$ du	- 0.005 (- 0.17)
STR	0.079*** (9.27)
RD	0.019 (1.16)
FDI	0.007** (2.40)
GOV	- 0.654*** (- 3.07)
URBAN	0.029*** (5.99)
Year FE	Yes
No. of Obs.	3679

The standard errors are in parentheses

We also select 2010 as the starting year of the first batch pilots, and use 2009 as the baseline year. The data do not pass the parallel trends test

## 4.2 Average and dynamic LCP policy impacts on GTFP

Because GTFP is estimated from input-output data, we exclude GDP from the set of control variables due to endogeneity concerns. As the GTFP is a limited value estimated by the SBM model, we adopt the tobit regression to deal with the restricted dependent variables. Table 3 presents the average and dynamic impacts of the LCP policy on GTFP.

From Table 3, we find that the coefficient of  $du \times dt$  is 0.034 at the 5% significant level. It indicates that the LCP policy can enhance GTFP in pilot cities. Our result is consistent with the study by Li and Wu (2017) who found that environmental regulation could significantly increase the GTFP in regions with high political attributes. Mulia et al. (2014) also found that low carbon emission development strategies have significant positive economic and ecologic impacts. From the mechanism analysis, we suppose that the LCP policy can influence GTFP through industry structure, innovation and FDI. The GTFP may also be improved through inter-industry structure adjustment. Due to the restriction of variables, we cannot explore these impact mechanisms. However, after controlling industry structure, innovation and FDI, we find that the LCP policy still has a significant positive impact on GTFP. The low-carbon development path not only enhances China's economic productivity and economic growth rate but also enables China to reduce carbon emissions. The policy enables China to fulfil win-win development. While gradually putting control variables such as industry structure, innovation

**Table 3** Average and dynamic LCP policy impact on GTFP

	(1)	(2)	(3)	(4)
$du \times dt$	0.034** (2.43)	0.030** (2.21)	0.035*** (2.57)	
$du \times dt \times \text{year}^{2011}$				0.055** (2.02)
$du \times dt \times \text{year}^{2012}$				0.072*** (2.65)
$du \times dt \times \text{year}^{2013}$				0.037 (1.45)
$du \times dt \times \text{year}^{2014}$				0.018 (0.70)
$du \times dt \times \text{year}^{2015}$				0.003 (0.12)
STR		0.079*** (9.26)	0.077*** (9.12)	0.078*** (9.22)
RD		0.012 (0.74)	0.016 (1.00)	0.019 (1.16)
FDI		0.007** (2.43)	0.007** (2.47)	0.007** (2.37)
GOV			-0.632*** (-2.96)	-0.652*** (-3.05)
URBAN			0.028*** (5.90)	0.028*** (5.97)
Year FE	Yes	Yes	Yes	Yes
Chibar2	2684.54***	2637.74***	2640.71***	2642.52***
No. of Obs.	3679	3679	3679	3679

Z statistics are in parentheses; \*\*\*, \*\*, and \* denotes significance at 1%, 5% and 10%, respectively

Chibar2 shows the results of LR test against pooled models

and FDI into the model, we can see that the role of LCP policy in promoting GTFP is robust, and the regression coefficients of  $du \times dt$  are all significantly positive.

The dynamic regression result is shown in the column (4) of Table 3. The LCP policy promotes GTFP by approximately 3% throughout the sample period. From (4), it is known that the LCP policy effect increases in the first 2 years and is most significant in the second year after it is issued. After 2 years of LCP policy implementation, the GTFP of pilot cities increased by 7.6% compared to non-pilot cities. This positive impact is statistically significant within 2 years of LCP policy implementation and there seems to be a decay of the LCP policy impact over time.

Gradually adding control variables, the results show that the coefficient of industry structure is significantly positive at the 1% level. The increase in the proportion of the secondary industry can improve regional GTFP. Li and Lin (2015) obtained similar empirical results and found that industrial structure change had positive effects on energy and carbon emissions-adjusted total factor productivity. Since the 10th Five-Year Plan, the Chinese government has been accelerating industry structure optimization and internal technology improvements have improved the quality of the secondary industry. The output growth of the secondary industry may avail regions to improve their GTFP. The results also show that regions with higher FDI present higher GTFP. Li and Wang (2019) concluded similar results, which found that FDI had a positive impact on carbon productivity. On the one hand, FDI from developed countries adopts advanced energy utilization technology, which can directly increase green production efficiency. On the other hand, FDI can bring more advanced production equipment, production technology and organizational management experience to Chinese enterprises. The study conducted by Newman et al. (2015) also supported such results.

The innovation effect on GTFP is not significant. This is probably because it takes a long time for the impact of corporate innovation on GTFP to become noticeable. Meanwhile, the innovation of Chinese enterprises may still be profit-oriented, advancing technology and targeting expanded production, while innovation in green technology has yet to become a mainstream conception in their minds such as traditional innovation.

The impact of government intervention on GTFP is significantly negative at the 1% level. It implies that government intervention has a significant impact on resource allocation and energy intensity, which is similar to the results of Han et al. (2018). Under the influence of regional competition and political promotion, there may be races to the bottom, which is not conducive to efficiency improvements. The coefficient of urbanization is significantly positive at 1%. This is different from the result of Wang and Dong (2019), which found that urbanization increased carbon emissions. This may be because their samples are from sub-Saharan African countries that pay attention to environmental degradation.

### 4.3 Industry structure, innovation and FDI impacts mechanisms

According to the theoretical mechanism analysis of the LCP policy, we find that it may influence GTFP by industry structure and innovation as well as by FDI. Therefore, considering control variables such as economic development level and urbanization, we use the DID method to analyse the LCP policy impact on industry structure, innovation and FDI. Table 4 reports the results.

**Table 4** Industry structure, innovation and FDI impacts of LCP policy

	Industry structure (STR)	Innovation (RD)	Foreign direct investment (FDI)
$du \times dt$	0.056** (2.33)	0.137*** (8.93)	- 0.173** (- 2.38)
Control Vars.	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
R <sup>2</sup>	0.25	0.16	0.63
No. of Obs.	3679	3679	3679

Z statistics are in parentheses; \*\*\*, \*\*, and \* denotes significance at 1%, 5% and 10%, respectively

The control variables include GOV, URBAN, the ratio of capital to labour and per capita GDP in logarithm

From Table 4, the LCP policy has a significant and positive impact on industry structure, reflecting that it has effectively increased the proportion of the secondary industry. It is similar to the findings of Brännlund et al. (2014). His research found that reduction policy could increase the output of Swedish manufacturing and reduce pollution emissions. The scale effect and technology spillover effect of the secondary industry are outstanding. The LCP policy may encourage these high-energy consumption sectors to conduct green innovation, which may optimize their production methods and reduce costs. It enhances the development quality and output of the secondary industry.

The LCP policy has a positive impact on innovation. It effectively stimulates patent accumulation and innovation activities in the pilot regions. LCP policy can encourage companies in pilot regions to conduct more technology progress. The result provides empirical support for the weak version of the Porter Hypothesis (Rubashkina et al. 2015). It is well in line with the literature testing the Chinese Porter Hypothesis (Tanaka et al. 2014; Stavropoulos et al. 2018), although most existing research has verified the Porter Hypothesis from the stronger perspective.

The LCP policy has a negative effect on FDI at the 5% significant level. It confirms the Pollution Haven hypothesis, which believes that developed countries tend to shift energy intensive and high emission processes through transnational investment (e.g. FDI) to developing countries (Grimes and Kentor 2003). Our results show that strict environmental regulation prevents low-quality FDI inflows, which is in line with the findings of Cai et al. (2016). China still attracts low-quality FDI. Properly rigorous environmental regulation can help local government avoid low-quality FDI inflows and the ensuing environmental deterioration.

#### 4.4 Robustness checks

To correct for the potential bias caused by a nonrandom assignment of the pilot cities, we conduct propensity score matching (PSM) method to match the samples and rerun the models. Specifically, we construct a proper counterfactual sample of non-pilot cities that are observably similar to the pilot cities. We used PSM (to the nearest neighbour) to match cities with similar predicted probability so that a particular city is assigned to the LCP policy. The results are shown in Table 5.

Without considering any control variables, the  $du \times dt$  coefficient is 0.036, which is significant at 1%. Considering variables of industry structure, innovation and FDI, the

**Table 5** Results of PSM-DID

	(1)	(2)	(3)	(4)
$du \times dt$	0.036*** (2.61)	0.034** (2.45)	0.038*** (2.78)	
$du \times dt \times \text{year}^{2011}$				0.060** (2.19)
$du \times dt \times \text{year}^{2012}$				0.075*** (2.77)
$du \times dt \times \text{year}^{2013}$				0.040 (1.59)
$du \times dt \times \text{year}^{2014}$				0.021 (0.84)
$du \times dt \times \text{year}^{2015}$				0.002 (0.09)
STR		0.104*** (9.69)	0.100*** (9.35)	0.102*** (9.48)
RD		0.036 (1.43)	0.047* (1.84)	0.050* (1.95)
FDI		0.006** (2.08)	0.006** (2.15)	0.006** (2.04)
GOV			- 0.629*** (- 2.97)	- 0.650*** (- 3.07)
URBAN			0.027*** (5.75)	0.028*** (5.82)
Year FE	Yes	Yes	Yes	Yes
Chibar2	2630.04***	2622.04***	2617.99***	2619.90***
No. of Obs.	3633	3633	3633	3633

Z statistics are in parentheses; \*\*\*, \*\*, and \* denotes significance at 1%, 5% and 10%, respectively

coefficient is still positive at 5%. When adding other control variables into the model, the coefficient is always significantly positive at 1%. It is consistent with the results obtained in the previous section and further verifies the conclusion that the LCP policy can significantly promote GTFP of pilot cities. According to the results of (3) in Table 5, industry structure can significantly improve the GTFP, while FDI has a negative impact on the GTFP. It is consistent with the previous results. Innovation has a positive impact on the GTFP at 10%, while it is still nonsignificant in the first two regressions.

Using the matched samples to test the dynamic effect of the LCP policy, we find that the GTFP in 2011 increases by 0.060 and is significant at 5%. Two years after policy implementation, the GTFP increases by 0.075 at a 1% significant level. After 3 years of implementation, the LCP policy increases the GTFP in pilot cities but is nonsignificant. It is consistent with the previous results, further verifying the robustness of our results.

In the previous empirical regressions, the control group includes the second batch pilots in 2011–2012 (before the LCP policy was issued), while the second batch pilots are a treatment group since 2013. To verify that the impact of the second batch pilots on the GTFP is not significantly different from the first batch pilots, we employ the first and second batch pilots as the treatment group and the control group, respectively. Then, we rerun the DID model to verify that there is no significant influence when we use the second batch pilots as the control group. The results are shown in Table 6. We find that the coefficient of the interaction term is nonsignificant, which

**Table 6** Tests of control group in 2011–2012

	(1)	(2)	(3)
$du \times dt$	0.019 (0.61)	0.001 (0.02)	0.015 (0.41)
STR		0.131*** (6.10)	0.122*** (5.78)
RD		0.071* (1.77)	0.098** (2.46)
FDI		0.022*** (2.61)	0.022** (2.53)
GOV			− 1.610*** (− 2.89)
URBAN			0.036*** (3.46)
Year FE	Yes	Yes	Yes
Chibar2	761.29***	752.68***	766.75***
No. of Obs.	960	960	960

indicates that there is no significant difference between the effect of the second and the first batch of pilots on the GTFP. Therefore, in the previous regression, using the second batch pilots as the control group in 2011–2012 does not affect the regression results, validating the justification of our previous analysis.

## 5 Conclusions and policy implications

As the largest energy consumer and carbon emitter, China faces severe international and domestic pressure to reduce its carbon emissions. Although the LCP policy aims to coordinate the regional environmental impact and economic growth, its impact has not been rigorously assessed. We wonder whether the LCP policy generates win-win development in China or achieves carbon reduction targets while sacrificing economic benefits. This issue is of great significance for China's response to climate change and the promotion of a national low-carbon development path.

Because GTFP comprehensively considers inputs and both desirable and undesirable outputs, we assess the Chinese urban GTFP with the SBM model on the premise of variable returns to scale using urban panel data between 2003 and 2015. Then, we conduct an empirical study with the DID model to analyse the LCP policy impact on urban GTFP. We also test the policy's impact through industry structure, innovation and FDI. We conclude the following:

First, the implementation of the LCP policy has a significant positive impact on the GTFP. The low-carbon development path will not only enhance China's economic growth but will also enable China to reduce carbon emissions. It is possible for Chinese cities to attain win-win development. Regulated by the LCP policy, high-emitting companies need to pay extra costs during the production process, which drives them to learn from advanced companies and produces a catch-up effect. Stronger incentives also induce these enterprises to eliminate high polluting and inefficient production, thereby promoting GTFP improvement. Moreover, over time, the LCP policy significantly improved the GTFP in the year following implementation, and the effect decayed over time.



Second, we analyse how the LCP policy affects GTFP through industry structure, innovation and FDI. The LCP policy has a positive impact on industry structure. Since the 10th Five Year Plan, the Chinese government has accelerated industry structure optimization and improved the quality of the secondary industry. The scale and technology spillover effects of the secondary industry are outstanding, and a higher portion of the secondary industry can improve GTFP. The LCP policy stimulates innovation activities in the pilot regions, although the long-term productivity effect of innovation remains to be seen. The policy has a significant negative impact on FDI, as China is still a pollution haven for developed countries. While FDI has a significant positive effect on GTFP, the LCP policy can effectively reduce the inflow of low-quality FDI. The technology spillover effect of FDI can promote GTFP, indicating that local governments need to attract high-quality FDI.

Based on the conclusions above, we also identify some implications for the Chinese government to formulate environmental regulation policies and promote a national low-carbon development path. As the LCP policy facilitates the improvement of GTFP in the pilot regions, the Chinese government should promote a low-carbon development path by expanding the low carbon development area. The low carbon development path meets China's development needs. The government should learn from the past experience in the pilot regions, strengthen the communication among regions, and promote the most successful practices of the pilot regions. Policy makers should also formulate supporting policies such as financial policy and tax policy, to extend the policy effects and bolster green development as long as possible.

In addition, as enterprise-led technological progress has a nonsignificant impact on GTFP, the government should encourage enterprises to accelerate green technology application in production. More efforts are needed to increase green innovation such as energy saving and emission reduction technology. Furthermore, we need to speed up the elimination of backward industries and optimize the inter-industry structure. More detailed LCP policies, including emission measurements and industry emission limitations, should be formulated to create a favourable environment for regions to transfer industry structures. As China remains a pollution heaven, environmental regulation policies hinder FDI inflows. Local governments should attract high-tech FDI inflows and effectively capitalize on the technology spillover effect. Advanced environmental protection technology and management experience should be promoted and adopted from foreign enterprises.

Furthermore, our study also provides implications for global mitigation strategy. In addressing global climate change, the low-carbon concept should be widely promoted, making it a global consensus and achieving low-carbon development globalization. Countries should incorporate the low-carbon development path into the strategic planning. In particular, developing countries are often in a technically weak position. They should enforce more efforts to promote low-carbon development path, implement corresponding industrial development and supporting policies. Such development path may improve their green productivity, which helps narrow the gap between developing and developed countries, and achieve sustainable development of the global economy.

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## Appendix

We select six variables, including per capita GDP (PGDP), industrial structure (IND), innovation (RD), FDI, government intervention (GOV) and urbanization (URBAN) to calculate the propensity. The logit regression results are shown in Table 7 in the Appendix. According to the matching process, we obtain 3633 matched samples. We find that the coefficients of most variables are statistically significant at the 1% level and are thus significantly related to the implementation of the LCP policy.

We obtain the differences in the characteristics between pilots and non-pilots before and after matching, as shown in Appendix Table 8, and find significant differences before matching. After matching, these differences are acceptable, as verified by the *t* test in Appendix Table 8.

The results of sample comparison before and after matching are shown in Appendix Table 9. This shows that the differences of the samples after PSM are much smaller than those before PSM. The *P* value of the LR test is over 10%, which indicates that there is nonsignificant difference between pilot cities and matched non-pilot cities after matching. This illustrates that the samples are appropriate after PSM.

**Table 7** The logit regression results for the PSM

	Coef.	S.E.	Z statistic	<i>P</i> value
PGDP	0.017	0.04	2.40	0.09
IND	− 0.259	0.06	− 4.14	0.00
RD	0.438	0.17	2.54	0.00
FDI	0.051	0.02	3.02	0.00
GOV	6.209	1.58	3.93	0.00
URBAN	− 0.025	0.02	− 1.03	0.30
Constant	− 1.424	0.38	− 3.70	0.00

The dependent variable in Logit model is CET. CET = 1 if the city is the pilot; otherwise, CET = 0. Coef. indicates the variable coefficient; S.E. indicates the standard error

**Table 8** Comparison between variables before and after employing matching

Variable	Sample	Mean		<i>t</i> test	
		Pilot	Non-Pilot	T Statistic	<i>P</i> value
PGDP	U	10.878	10.689	4.46	0.00
	M	10.868	10.963	− 1.83	0.07
IND	U	1.379	1.543	− 5.54	0.00
	M	1.384	1.390	− 0.22	0.82
RD	U	0.117	0.035	6.94	0.00
	M	0.087	0.087	− 0.02	0.99
FDI	U	7.435	6.862	5.97	0.00
	M	7.542	7.542	− 1.01	0.31
GOV	U	0.071	0.062	8.09	0.00
	M	0.070	0.069	0.44	0.66
URBAN	U	6.630	6.526	1.59	0.11
	M	6.625	6.712	− 1.13	0.26

U denotes before matching; M denotes after matching

**Table 9** Results of test before and after matching

Sample	Pseudo-R	LR test	<i>P</i> value	B(%)
U	0.03	112.60	0.00	37.4
M	0.00	6.41	0.38	11.3

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