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Does Environmental Regulation Improve an Enterprise's Productivity?—Evidence from China's Carbon Reduction Policy

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Abstract: Theoretical research finds that environmental regulation has both positive and negative effects on enterprise productivity. Based on the Energy Conservation and Carbon Reduction policy implemented by the Chinese government, this study empirically analyzed the policy treatment level boundary condition of the positive and negative effects that dominated and its moderating factors. The generalized propensity score matching model (GPSM) was used to analyze the net effect of the policy on the total factor productivity (TFP) of Chinese manufacturing enterprises. The results showed that: (1) the low treatment level of the policy can promote the growth of the enterprises' TFP; (2) in contrast, the treatment level of the policy exceeded a certain threshold, which gradually led to an inhibitory effect on the enterprises' TFP; (3) the mechanism used to enforce the policy caused the enterprises to innovate, which enhanced their TFP, but took time to gradually release; (4) the enterprises with a stronger capacity for innovation or a larger size found it easier to transform the pressure from the policy into an innovative impetus to improve their TFP; (5) however, the government subsidies distorted the forced-innovation effect of the policy on the enterprises' innovation, which restrained the positive effect of the policy on the TFP.

Keywords: Environmental Regulation; Productivity; Chinese Manufacturing Enterprises; GPSM

1. Introduction

China has paid a huge environmental price for its rapid economic development; for example, China became the largest emitter of carbon dioxide (CO₂) in 2006 (whereby its CO₂ emissions grew at a rate of 6% per year), and in 2015, its CO₂ emissions exceeded the total CO₂ emissions of both the US and the European Union (EU), accounting for approximately 27% of the world's total CO₂ emissions [1]. Only 1% of China's 500 large cities have met the air quality standards of the World Health Organization (WHO). Around 2013, widespread smog in the central and eastern regions drew great attention toward environmental pollution as the economic expansion continued [2]. Against a backdrop where the concept of green development became a major direction for socioeconomic growth during the 13th Five-Year Plan (or for an even longer period), Chinese society has come to a general consensus that it is necessary to enhance environmental remediation, reduce environmental pollution, and achieve sustainable economic progress to build a "Beautiful China" (the concept of "Beautiful China" was put forward at the 18th National Congress of the Communist Party of China and written into the 13th Five-Year Plan; a series of environmental regulation policies issued by the Chinese government are the concrete implementation of this ruling concept).

As the globe's largest energy consumer and CO₂ emitter, China committed to diminishing CO₂ emissions and improving its environmental quality. In 2009, the State Council promulgated the

National Plan on Climate Change (2014–2020), which specifies that, compared to 2005, the country shall achieve a 40 to 45% reduction in CO₂ emissions per unit of gross domestic product (GDP) in 2020, while non-fossil energy shall account for approximately 15% of the nation's primary energy consumption. Yet, in reality, while meeting the swiftly growing demand for large amounts of cheap energy in the economy, coal (which is available in large quantities at low costs) has become the primary source of China's CO₂ emissions. The Chinese government has recognized the policy option of lowering fossil fuel combustion (such as coal) in order to shrink CO₂ emissions [3]. China has yet to launch its nationwide carbon emissions trading and carbon tax collection policies. For this reason, the State Council designed the Ten-Thousand Enterprises Energy Conservation and Low Carbon Program (hereafter the TTEP) to fully implement the "outline" of the Energy Conservation and Carbon Reduction (hereafter the ECCR) policy in the 12th Five-Year Plan, as well as to boost energy conservation in key energy-consuming units to improve the efficiency of energy use. According to estimates, the energy consumption of the enterprises under the TTEP comprised 60% of the country's overall energy consumption in 2010. Therefore, the TTEP is currently the most significant carbon reduction policy in China (hereafter, TTEP and ECCR mean the same thing in this paper).

The TTEP policy requires the selection of key energy consumption units (mainly industrial enterprises, where the selection criterion of industrial enterprises is 10,000 tons standard coal), with a total energy consumption of more than 10,000 tons of standard coal in 2010. As there are about 17,000 enterprises nationwide, it is called "Ten-Thousand Enterprises." Therefore, the implementation of the TTEP is an important support and guarantee for achieving a 16% reduction in the energy consumption per unit of GDP during the "Twelfth Five-Year Plan" period and a 17% reduction in carbon dioxide emission per unit of GDP. The TTEP policy requires all local energy conservation authorities to break down the energy conservation targets during the "Twelfth Five-Year Plan" period in the regions into the targets for each of the "Ten-Thousand Enterprises" and report them to the National Development and Reform Commission for recording and assessment. In order to maintain the continuity of the TTEP policy, in principle, major changes will not be made to the list of "Ten-Thousand Enterprises" during the "Twelfth Five-Year Plan" period. The policy's implementation cycle is the entire "Twelfth Five-Year Plan" period and its stability provides an institutional guarantee for scientifically assessing various impacts of the policy. The State Council requires the completion of energy-conservation targets and the implementation of energy-saving measures of the ten thousand enterprises to be included in the provincial government's responsibility assessment system of energy-saving targets. The results of assessing the completion of local Ten-Thousand Enterprises' energy-saving targets will be summarized and published every year, mainly including the overall Ten-Thousand Enterprises' energy-saving target assessment in all provinces, autonomous regions, and municipalities; the completion of state-owned enterprises' energy-saving targets; and the list of enterprises that fail to complete annual energy-saving targets. The assessment results will be sent to relevant departments, such as the State-owned Assets Supervision and Administration Commission of the State Council. The above measures also ensure that the TTEP policy serves as a rigid restraint on the enterprises' energy consumption decisions.

Will such a large-scale ECCR policy inhibit productivity growth and thereby hinder economic development? Productivity growth has played a vital role in China's economic expansion, whereby the rise of the total factor productivity (TFP) contributed to approximately 80% of China's GDP per capita growth from 1978 to 2007 [4] (the TFP measures the efficiency and effectiveness with which both labor and capital resources are used to produce output; in other words, TFP means making smarter and better use of the available labor and capital resources). "Although productivity is not everything, it is almost everything in the long run" [5]. Neoclassicism asserts that strict environmental control can help to eliminate the negative impact of economic activities on the environment in the short term, but can also increase enterprises' production costs, consequently impeding their development [6] and eventually slowing macroeconomic growth in the long run [7]. Some scholars have attributed the productivity decline in the US in the 1970s to the inhibitory effect of environmental regulations [8–10]. However, the Porter hypothesis proposes another possibility [11,12] whereby

reasonable environmental regulations can stimulate technological and product innovation among businesses, thereby partially or completely offsetting costs arising from environmental regulations and ultimately reinforcing competitiveness [13]. According to empirical research on data from different countries, scholars have found that environmental regulations drive innovation and lead to productivity growth [14–17]. Others have even argued that environmental regulations and productivity form U-shaped, inverted N-shaped, and inverted U-shaped relationships, which are not simple linear relationships [18–20].

As demonstrated by the literature mentioned above, empirical studies on environmental regulations' impact on productivity have not reached consistent conclusions. One possible reason is that the measurements of environmental regulations, namely, their intensity or strictness [21,22], determine their effect on productivity. The intensity of a country's or region's environmental regulations has a strong positive correlation with its competitiveness [23]. Environmental regulations can have a positive or negative outcome in economies in various ways. Meanwhile, the influence of different policy tools varies greatly. Hence, when empirically analyzing and testing the effect of environmental regulations on productivity, their intensity inevitably becomes a chief issue. A natural experiment based on the amendment to the Air Pollution Prevention and Control Law in 2000 [24] employed the difference-in-differences (DID) method to evaluate the amendment's impact on growth regarding the TFP of China's industrial sectors. This experiment addressed the problem related to the selection of environmental regulation variables to a certain extent but ignored the measurement of intensity.

In other words, our research has some useful additions to the empirical study of the boundary conditions of the Porter hypothesis. The TTEP is a front-end policy that restricts enterprises' energy use rights and directly constrains their energy use. According to this policy, even if a business faces very good market prospects, it must complete the energy conservation task assigned by the government. Therefore, this policy has a stronger degree of regulation than end-of-pipe treatment strategies. Moreover, to better reflect the causal effect of the ECCR on the export scale of China's manufacturing enterprises, we used the generalized propensity score matching (GPSM) method to examine changes in their relative productivity (i.e., differences in the TFP of enterprises selected to implement the ECCR before and after this policy was implemented, compared to those not chosen to do so). Considering the diverging treatment levels of the ECCR policy experienced by each enterprise, we introduced the GPSM method to further depict the impact of various treatment levels of the ECCR on the enterprises' TFP.

2. Research Methods and Data Sources

2.1. Empirical Model

Scientifically and accurately gauging the ECCR policy's impact on enterprises' TFP can be complicated since their association with ECCR policy is a non-random event. We used the generalized propensity score matching model (GPSM), which was developed by Imbens [25] and Hirano and Imbens [26] to overcome selection bias arising from quantifiable variables. Although it has been widely applied in recent micrometric studies, the traditional propensity score matching model (PSM) can only test the treatment effects of a binary treatment variable. In other words, it can only identify whether the ECCR policy affects an enterprise but cannot identify the difference in enterprises' TFP caused by the carbon reduction intensity. We employed the GPSM to determine the impact of the ECCR policy's intensity on the TFP of the Ten-Thousand Enterprises. Compared to the conventional PSM, it can allow us to appraise the treatment effects of treatment variables, be it multivariate or continuous (i.e., whether the ECCR policy's intensity results in heterogeneity in the enterprises' TFP).

The GPSM is an analytical technique based on a counterfactual framework, where its fundamental theory can be explained as follows. For a set of random samples, subscript i represents different individuals ($i = 1, \dots, N$). Assume that individual i has a set of corresponding potential output levels $Y_i(t)$, known as the individual's "unit-level dose-response function," for each treatment level $t \in D$.

If the treatment variable t 's domain $D = \{0,1\}$, it returns to the problem of the treatment effects of binary variables in PSM. The GPS method allows $D = [t_0, t_1]$ and focuses on the “average dose–response function” (i.e., $\mu(t) = E[Y_i(t)]$). The difference in function value corresponding to an independent variable can be explained as the causal effect due to the change in treatment level. However, for individual i , the only observable data comprise a set of covariates X_i , treatment levels $T_i \in D$, and actual output levels corresponding to the treatment levels $Y_i = Y_i(T_i)$ (subscript i is omitted for simplicity in the remaining sections). Similar to the PSM method, the key setting of the GPS method continues to be the ignorability assumption, as shown in Equation (1):

$$Y(t) \perp T \mid X, \forall t \in D \quad (1)$$

The conditional independence assumption means that after controlling for multivariate covariates X , potential output levels at any treatment level are independent of the actual treatment level accepted by the individual. In other words, when the characteristics of individual covariates are consistent, the selection bias and the endogeneity can effectively be eliminated. The characteristics of multivariate covariate X , also known as “matching variables,” affect the treatment level (T) and output level (Y) of the individual in order to control for the curse of dimensionality (the “curse of dimensionality” means that as the dimensions to be matched increase, the difficulty of successfully matching variables also increases), which is always present in the characteristics of multivariate covariates. However, in the PSM method, high-dimensional indicators are combined into a single propensity score indicator for matching in order to solve this problem [27]. The conditional probability density function of a treatment variable is set as Equation (2):

$$r(t, x) = f_{T|X}(t|x). \quad (2)$$

The GPS is defined as Equation (3):

$$R = r(T, X). \quad (3)$$

Similar to the standard PSM model, the GPS model also needs to satisfy the balance condition. When $r(T, X)$ remains constant, the probability of the occurrence of event $T = t$ is independent of the multivariate covariates X (Equation (4)):

$$X \perp \{T = t\} \mid r(T, X). \quad (4)$$

GPS, which satisfies the balance condition, can also make the ignoreability assumption established (Equation (5)):

$$f_T[t|r(t, X), Y(t)] = f_T[t|r(t, X)]. \quad (5)$$

By controlling for the GPS, it is possible to ensure that any treatment level is independent of its potential output. Hence, the bias arising from differences in covariates can be effectively removed using the GPSM. Furthermore, a GPS is a one-dimensional indicator, which is easier to match than high-dimensional covariates X .

The following explains the three steps of estimating the average dose–response function according to the GPS method [27]. First, given the multivariate covariate X , the conditional probability density function of the treatment variable is determined, as expressed by Equation (2). The treatment variable we considered was the ECCR intensity experienced during policy implementation by the Ten-Thousand Enterprises. The distribution of this variable is severely biased. In 2011, only 9469 manufacturing enterprises were included in the list of Ten-Thousand Enterprises. In other words, only these businesses have positive values of ECCR treatment intensity, while the treatment variable of the remaining enterprises amounts to zero. Such a data distribution contradicts the assumption of the standard GPSM that a normal distribution of the treatment variable is present. Hence, the approach adopted by

Imbens [25] and Hirano and Imbens [26] could not be used directly for our treatment variable. When a large number of zeros are present in the treatment variable [28], the fractional logit model [29] can be employed to estimate the distribution of the treatment variable. Assume that for individual i , given the covariate X_i , the conditional expectation of treatment variable T_i is:

$$E(T_i|X_i) = F(X_i\beta) = \frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)}. \quad (6)$$

In Equation (6), $F(\cdot)$ satisfies the cumulative distribution function of a logistic distribution for $\forall X_i\beta \in R, F(X_i\beta) \in [0, 1]$. Thus, the values of the treatment variable are required to fall within $[0, 1]$. For this study, the treatment variable was defined as the carbon reduction target of each of the Ten-Thousand Enterprises in the 12th Five-Year Plan divided according to its gross output value in the base period (in fact, the carbon reduction percentage is more accurate for measuring the policy impact of ECCR on the enterprises; however, we did not have data on the carbon consumption of each of the Ten-Thousand Enterprises in the base period, and therefore, we standardized the ECCR policy variable with each of the Ten-Thousand Enterprises' gross output value in the base period). Next, in the generalized linear model framework, the Bernoulli log-likelihood function is maximized to correct for the impact of the treatment variable in the data on the estimation of the conditional expectation function (Equation (7)):

$$\max_{\beta} L(\beta) = \sum_{i=1}^N [T_i \cdot \ln(F(X_i\beta)) + (1 - T_i) \ln(1 - F(X_i\beta))]. \quad (7)$$

GPSs are calculated based on the estimation results (Equation (8)):

$$\hat{R}_i = [F(X_i\hat{\beta})]^{T_i} \cdot [1 - F(X_i\hat{\beta})]^{1-T_i}. \quad (8)$$

Next, the samples are split according to the values of the treatment variable and GPS in order to test whether the value of treatment intensity is independent of covariates X (i.e., whether the equilibrium condition for GPS is satisfied) after adjustment through GPS ($T = t$).

Second, the conditional expectation model of the output variable (which we referred to as the enterprises' TFP) is constructed using the treatment intensity variable and GPS values. The specific form of this function can be flexible and changeable; it can consider either the first-order term of two variables, or the second- and third-order terms and the interaction term of two variables for approximation. The conditional expectation model's role is to fit the functional relationship of the output variable with the treatment variable and the GPS variable. Hence, a more robust third-order polynomial is selected to approximate the conditional expectation of the output variable:

$$E(Y_i|T_i, \hat{R}_i) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 \hat{R}_i + \alpha_5 \hat{R}_i^2 + \alpha_6 \hat{R}_i^3 + \alpha_7 T_i \cdot \hat{R}_i. \quad (9)$$

Third, the regression coefficients of Equation (9) are used to calculate the mean of the conditional expectation of the output variable, corresponding to each treatment intensity, and to estimate the average dose-response function $\mu(t)$ (Equation (10)):

$$\mu(t) = \frac{1}{N} \sum_{i=1}^N \{ \hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 t^3 + \hat{\alpha}_4 \hat{r}(t, X_i) + \hat{\alpha}_5 \hat{r}(t, X_i)^2 + \hat{\alpha}_6 \hat{r}(t, X_i)^3 + \hat{\alpha}_7 t \cdot \hat{r}(t, X_i) \}, \quad (10)$$

$$TE(t) = \mu(t) - \mu(0), \quad \forall t = 0.01, 0.02, \dots, 0.99, 1.$$

where N is the sample size. Estimating the function $\mu(t)$ needs some specific values value of t in the range $[0, 1]$. The step size set in this study was 0.01. Hence, $t = 0, 0.01, 0.02, \dots, 0.99, 1$, totaling 101 treatment levels (the calculation is done using the Stata 15 software (StataCorp. 4905 Lakeway Drive, College Station, TX 77845, USA), using the dosereponse2 command package). The treatment effect $TE(t)$

signals the difference in TFP between enterprises under any non-zero ECCR intensity and businesses that are not subject to the ECCR regulation.

2.2. Data Introduction and Processing

The data used in this paper consisted of two parts: The first part was the 2010–2013 China Industry Business Performance Data. The statistical caliber of this database changed in 2011. Before this year, the survey targeted at all state-owned enterprises and non-state-owned enterprises worth CNY5 million and above; whereas, after this year, the target was all state-owned enterprises and non-state-owned enterprises worth CNY 20 million and above. Therefore, from 2010 to 2011, a part of the enterprise samples was not included in China Industry Business Performance Data because of the change in statistical caliber. According to the data, the number of enterprise samples included in the 2010–2013 databases was 348,536, 303,392, 311,557, and 345,101.

The second part was the list of enterprises and energy-saving targets of the “Ten-Thousand Enterprises Energy Conservation and Low Carbon Action” published by the National Development and Reform Commission. The enterprises in the implementation of TTEP all met the requirement of total energy consumption standing at 10,000 tons standard coal and above in the base period (2010). In 2011, a total of 16,076 enterprises were included in the TTEP. Considering that the policy was introduced and put into effect in 2011, the first year of the “Twelfth Five-Year Plan,” the time when the Ten-Thousand Enterprises was recorded and reported by local energy conservation authorities was earlier than 2011, it is possible that the Ten-Thousand Enterprises had taken actions in the starting year of the policy (2011), and enterprises’ core variables should not be used as matching variables to weaken the selection bias. Based on this, the empirical analysis below used the enterprises’ key characteristics in 2010 as the matching variables of the GPSM and the supplementary report in the robustness test was based on the empirical results with 2011 as the base period.

Several points need to be explained when matching the data of the Ten-Thousand Enterprises announced by the National Development and Reform Commission with the industrial enterprise database from 2011 to 2013. First, although the National Development and Reform Commission required that the list of the Ten-Thousand Enterprises during the 12th Five-Year Plan remain stable, businesses were still added after 2011. We removed the enterprises that were added to the list in 2012 and 2013 in order to ensure that the enterprises in the control group during the base period would not appear in the treatment group (in the later period). Second, matching the list of Ten-Thousand Enterprises announced in 2011 with the enterprise data of 2010 would result in a sample loss (i.e., a loss of approximately 16% of the Ten-Thousand Enterprises) due to the entry and exit of the enterprises and the changes in statistical caliber. Third, we selected manufacturing enterprises among industrial enterprises as research targets and eliminated non-manufacturing enterprises during the matching of both databases. In the end, we successfully matched 7880 out of the Ten-Thousand Enterprises.

After completing the processing described above, we further retained the enterprise samples that continued to operate from 2010 to 2013 (when expanding the analysis of lagged effects of the ECCR policy, we retained the enterprise samples from 2010 and 2011, 2010 and 2012, and 2010 and 2013 in the data set to prevent excessive sample loss) and processed the samples according to the following steps: (1) The establishment date of each company must be valid (the year of establishment should be earlier than 2010, and the month should be from January to December); otherwise, the enterprise was removed. (2) The gross output of each company should not be negative; otherwise, the enterprise was removed. (3) The number of workers employed by each enterprise should not be less than five people; otherwise, the enterprise was removed. (4) The key financial benchmarks (e.g., total assets, fixed assets, and current liability) of each company should not be negative or missing; otherwise, the enterprise was removed. (5) The research and development (R&D) and subsidy should not be negative or missing; otherwise, the enterprise was removed. (6) The sales volume of each enterprise should not be less than RMB 5 million (for the 2010 samples) or RMB 20 million (for the samples in 2011–2013); otherwise, the enterprise was removed.

2.3. Definition and Estimation of Variables

2.3.1. Core Variables

The ECCR policy and the enterprises' TFP performance were the core variables of concern to us. The basis for determining the target scale of the "energy conservation and carbon reduction" for each of the Ten-Thousand Enterprises during the 12th Five-Year Plan was their carbon consumption in 2010. In fact, the reduction percentage is more accurate to measure the policy impact of ECCR on the enterprises; however, we did not have data on the carbon consumption of each of the Ten-Thousand Enterprises in the base period. For enterprises, the carbon consumption is closely related to the output level. Given that other conditions remain unchanged, the higher the output is, the more the carbon consumption is. The same "energy conservation and carbon reduction" target represents the different impacts of the environmental regulation policy on the enterprises with various output levels [30]. Thus, we divided the ECCR target (measured in tons) of the Ten-Thousand Enterprises during the 12th Five-Year Plan by their gross output values (measured in RMB) during the base period (2010) to gauge the treatment levels of the ECCR policy.

For the non-Ten-Thousand Enterprises, the treatment levels of the ECCR policy were equal to zero. Since the non-Ten-Thousand Enterprises constituted the vast majority of the enterprise samples, we employed the fractional logit model to estimate the conditional distribution function of the ECCR treatment variable. The fractional logit model requires that the domain of the treatment variable fall within the range [0, 1]. Based on the method we defined, the values of the treatment variable basically met this requirement, whereby only 36 of the Ten-Thousand Enterprises had a treatment level greater than 1. These 36 samples represented a negligible proportion in the 7880 Ten-Thousand Enterprises, and we deleted these samples.

We tested for the ECCR policy's impact on the enterprises' TFP. Hence, it was necessary to define the changes in their TFP after the ECCR policy was executed. First, we employed the Olley and Pakes approach [31] (hereafter, the OP) to calculate the TFP of all sample enterprises. Consider a standard Cobb–Douglas production function (Equation (11)):

$$\ln VA_{jt} = \gamma_k \ln K_{jt} + \gamma_l \ln L_{jt} + x_{jt} + \xi_{jt}. \quad (11)$$

where VA_{jt} is the value-added output of enterprise j at year t , K is the net fixed assets, and L is the employment. The conventional measure of productivity is to take the difference between the log value-added output and log factor inputs times their estimated coefficients (in fact, TFP has no measure unit; the difference in TFP values between enterprises reflects their productivity ranking) (Equation (12)):

$$TFP_{jt} = \ln VA_{jt} - \hat{\gamma}_k \ln K_{jt} - \hat{\gamma}_l \ln L_{jt}. \quad (12)$$

Second, since the cycle of implementation of the ECCR policy is the entire period of the 12th Five-Year Plan, our data only covered the first three years of the 12th Five-Year Plan. Thus, the enterprises' TFP could only be estimated until 2013. In order to control for the potential volatility of the enterprises' TFP, we first calculated the average level of each enterprise's TFP over three years as the response variable to smoothen the volatility of their TFP caused by the economic cycle.

Third, in testing whether the ECCR policy's impact on the enterprises' TFP may have emerged gradually, we recognized that enterprises would need time to adjust their production and innovation decisions in response to the policy. Therefore, in the extended analysis, we classified the implementation of the regulatory policy into three scenarios—"one year later," "two years later," and "three years later"—to determine whether the ECCR policy's impact on the enterprises' TFP indeed emerged gradually.

As seen in Figure 1, the distribution of the TFP for two groups of the enterprises (Ten-Thousand Enterprises and non-Ten-Thousand Enterprises) before the ECCR policy was relatively concentrated, while the Ten-Thousand Enterprises revealed a higher TFP than non-Ten-Thousand Enterprises.

This signaled a significant difference in productivities between the two groups of enterprises before the policy was executed. Hence, when we employed the GPSM to test the policy's impact, we had to use the enterprises' TFP in the initial period as a matching covariate of GPS to smooth out the difference in initial productivity.

Figure 1. Total factor productivity (TFP) density before the implementation of the Ten-Thousand Enterprises Energy Conservation and Low Carbon Program (TTEP).

Figure 2 statistically illustrates the density distribution for the TFP of the two groups after the ECCR policy was carried out. Figure 2 shows that after the ECCR policy was implemented, the TFP of the Ten-Thousand Enterprises became significantly higher than that of the non-Ten-Thousand Enterprises. Meanwhile, the overall TFP density of the Ten-Thousand Enterprises group was skewed to the right. The dispersion degree of the distribution for the TFP of the Ten-Thousand Enterprises after the policy went into effect was higher, thus demonstrating that the ECCR policy's impact on the TFP of the Ten-Thousand Enterprises was heterogeneous. For this study, it was more valuable to conduct empirical research from the heterogeneous perspective in order to investigate whether there was any difference in treatment effects at the different policy treatment levels.

Figure 2. TFP density after implementation of the TTEP.

2.3.2. Covariates

The key to evaluating the ECCR policy's heterogeneous impact on the enterprises' TFP using the GPSM method was to select appropriate covariates to ensure the ignorability condition. Combining existing literature and the characteristics of the enterprise data, we explain the covariates we chose that may affect energy consumption (and thus the ECCR policy's treatment intensity) and

enterprises' TFP as follows: (1) Gross output value (labeled as Output, measured in RMB). This variable accurately gauged businesses' production scale and could be directly obtained from the enterprise data. We used this variable's natural logarithm to eliminate the effects of dimension and outliers. (2) Enterprises' TFP in the base period (labeled as TFP_0). On the one hand, the higher an enterprise's initial TFP, the more this helps to reduce factor inputs and hence lower energy consumption. On the other hand, it is necessary to effectively deal with differences that exist before a policy is implemented. Therefore, we added the enterprises' initial TFP to the covariates of this study. (3) Capital per capita (labeled as Cap, measured in RMB per capita). An enterprise's capital density may influence both its TFP and energy consumption. We divided the net fixed assets by the number of employees, then took the natural logarithm of the results. (4) R&D investment (labeled as R&D, a binary variable). We distinguished R&D investment during the base period from the enterprises' innovative spirit. While innovation may affect energy consumption and the TFP, we also expected that innovation would be an important transmission mechanism for the ECCR policy's impact on the enterprises' TFP. R&D is a binary variable, which was coded 1 if an enterprise had a positive R&D investment value in the initial period, and 0 otherwise. (5) Subsidy income (labeled as Sub, measured in RMB). We calculated this variable's natural logarithm (if an enterprise's subsidy income was zero, we added 1 and took the natural logarithm of the results) using the enterprises' subsidy income reported in the data. As an additional source of income for businesses, subsidies can offset costs arising from the ECCR policy, thereby weakening the negative impact of energy consumption regulations. Subsidies also reflect the "government–enterprise relationship," thus affecting the ECCR policy's impacts across the enterprise. (6) Financial situation (labeled as Fina, a ratio). We measured this variable by determining the ratio of an enterprise's total liability to its total assets (i.e., the debt-to-asset ratio). (7) An enterprise's export characteristics (labeled as EX, a binary variable). This variable is a binary one that was defined based on the enterprises' export value during the base period, which was coded 1 if the value was greater than 0, and 0 otherwise. Furthermore, we controlled for the enterprise's age (labeled as Age, measured in years), property rights features (label state-owned enterprises and private enterprises as Domestic, a binary variable) (the data we used provides the registration type codes for each enterprise, which provides information for identifying the type of the enterprise property), industry characteristics (a group of dummy variables for the four-digit industry codes), and location (a group of dummy variables for the province codes). We divided the enterprise samples into two groups based on whether a company was one of the Ten-Thousand Enterprises. Table 1 summarizes the descriptive statistics of the main variables.

Table 1. Descriptive statistics of the major variables.

Variable	Units	Ten-Thousand Enterprises Group				Non-Ten-Thousand Enterprises Group			
		Mean	Std.	25th	75th	Mean	Std.	25th	75th
ECCR	ton/RMB	0.031	0.084	0.002	0.025				
TFP_0	-	7.991	1.289	7.135	8.779	6.332	1.109	5.588	7.025
Output	RMB	13.552	1.702	12.468	14.639	11.170	1.334	10.337	11.986
Cap	ln(RMB/#)	4.678	1.507	3.594	5.639	3.281	1.409	2.295	4.077
Fina	-	0.915	0.634	0.543	0.925	0.844	0.603	0.485	0.928
Age	years	11.701	13.489	3	13	7.155	7.944	3	9
EX	-	0.605	0.489	0	1	0.427	0.495	0	1
R&D	-	0.385	0.487	0	1	0.171	0.377	0	0
Sub	ln(RMB)	2.735	3.741	0	6.479	0.868	2.113	0	0
Domestic	-	0.313	0.464	0	1	0.493	0.499	0	1

3. Empirical Results and Analysis

3.1. Fractional Logit Regression for Estimating the Conditional Distribution of the ECCR

First, we calculated the conditional distribution of the ECCR based on the fractional logit model. The estimation method is expressed by Equations (3) and (4). Table 2 portrays the related estimation results. Obviously, the enterprises' gross output during the base period (with other conditions remaining unchanged, carbon consumption scale was almost entirely decided by the output) was the key variable to establish the distribution of the ECCR. Based on whether the output variable is added to the control variables or not, Table 2 depicts two types of regression outcomes. By comparing both kinds of regression findings, we made the following observations. First, the output value had a significant, positive impact on the ECCR experienced by the enterprises during the 12th Five-Year Plan. In our research, we gauged the ECCR by dividing the ECCR target by the output during the base period, whereby the larger the output of the enterprise samples, the weaker the ECCR, with other conditions remaining unchanged. In the regression outcomes, the coefficient of the output variable was significantly positive, indicating that the output during the base period had a greater impact on determining the carbon reduction target. Second, the impact of TFP_0 , exports, and R&D on the energy consumption scale in the initial period, and the ECCR target in turn, only appeared after controlling the output variable. This further explained the importance of controlling for the gross output value.

Table 2. Fractional logit regression results.

Variable	(1)	(2)	(3)	(4)
Output	0.187 * (1.79)	−0.0158 (−0.29)		
TFP_0	−0.291 *** (−2.74)		−0.133 ** (−2.02)	
Cap	0.445 *** (6.30)	0.436 *** (7.10)	0.485 *** (7.25)	0.429 *** (7.61)
Fina	0.0879 (0.57)	0.217 (1.53)	0.189 (1.31)	0.205 (1.51)
Age	0.00677 (0.92)	0.00644 (0.95)	0.00829 (1.13)	0.00610 (0.91)
EX	−0.398 * (−1.69)	−0.402 * (−1.90)	−0.357 (−1.52)	−0.410 * (−1.96)
R&D	−0.295 ** (−2.22)	−0.354 (−1.68)	−0.250 (−1.04)	−0.363 * (−1.74)
Sub	0.0500 ** (2.02)	0.0484 ** (2.14)	0.0554 ** (2.25)	0.0472 ** (2.13)
Domestic	0.0145 (0.10)	−0.0920 (−0.70)	−0.0151 (−0.10)	−0.0875 (−0.67)
Constant	−11.56 *** (−4.91)	−11.01 *** (−4.81)	−10.50 *** (−4.61)	−11.16 *** (−5.00)
AIC	0.027	0.032	0.027	0.032
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	72,817	78,506	72,817	78,506
LR	−916.72	−1177.74	−918.27	−1177.78

Note: Z values in parentheses; *, **, and *** indicate significant values at the 0.1, 0.05, and 0.01 levels respectively; Columns (2),(3) and (4) show the impact of whether to add Output or TPF variables on the regression results of other control variables; Column (1) shows the comprehensive regression results; AIC (Akaike Information Criterion) is a standard to measure the goodness of fit of the model, the smaller the value, the better the model; FE means fixed effect; LR means likelihood ratio value.

According to the results shown in column 2 of Table 2, TFP had a significant, negative impact on the carbon reduction constraint. Given the output was unchanged, the higher the TFP, the lower the inputs; correspondingly, the lower the energy consumption, the weaker the ECCR constraint. Capital per capita had a significant, positive impact on the ECCR, probably because of the higher the capital density, the higher an enterprise's energy consumption, and thus the higher the carbon reduction constraint. The impact of the financial situation (i.e., debt-to-asset ratio) and an enterprise's age on carbon reduction constraint did not pass the significance test. R&D had a negative effect on the ECCR, which was consistent with the fact that R&D can reduce the scale of energy consumption in its output by improving energy use efficiency. Exports also had a positive effect on an enterprise's ECCR. Subsidies can encourage businesses to expand the scope and scale of their products, thereby prompting an increase in energy consumption.

In fact, the fractional logit model performed well at estimating the conditional distribution of the ECCR. This was reflected in the fact that the Akaike Information Criterion (AIC) indicators were very small. In particular, the AIC indicator became smaller when the output variable was added. This justified our use of the initial output level to standardize the constraint of the ECCR policy for each enterprise.

3.2. Equilibrium Condition Testing with GPS Matching

On the basis of the estimated distribution of the ECCR policy's intensity, we calculated and matched GPSs using Equation (8). This kind of matching can remove selection bias arising from measurable variables and needs to be tested for the equilibrium condition. Satisfying the equilibrium condition requires choosing suitable covariates, as well as appropriate matching groups and segments. Since the ECCR values were closer to zero in the range [0, 1], we subdivided the part with smaller values of ECCR, and coarsely divided the part with larger values of treatment intensity. Table 3 presents the final matching results. First, we selected the values of treatment intensity (i.e., 0.045, 0.090, 0.143, and 0.223) as critical values, and divided the enterprise samples into five groups according to the value of treatment intensity. Second, we further divided each group into four segments according to the mean GPS values.

The second column of Table 3 displays the statistical differences in the main covariates between the two groups of samples: the Ten-Thousand Enterprises and the non-Ten-Thousand Enterprises. The averages of all covariates of the Ten-Thousand Enterprises were significantly greater than those of the non-Ten-Thousand Enterprises. The minimum *t*-value that described significance was 6.06, whereas the maximum *t*-value exceeded 90, which is in line with the findings we obtained from Table 1. The third to the seventh columns of Table 3 depict the statistical differences in key control variables between both groups of samples after selecting the reference targets from the enterprise samples in each treatment intensity group through GPS matching. When testing a total of 45 control variables in five treatment groups, significant differences only emerged in individual variables, while there was no significant difference in the remaining variables between different groups after GPS matching. This shows that using GPS matching can better weaken the selection bias arising from measurable variables.

Table 3. Balance condition test of the generalized propensity score (GPS) matching.

Matching Balance	Unmatched	ECCR Intensity Groups				
		(0, 0.045]	(0.045, 0.090]	(0.090, 0.143]	(0.143, 0.223]	(0.223, 1]
Output	1.870 *** (95.33)	0.196 (0.78)	−0.473 * (−1.86)	0.082 (0.49)	0.601 ** (2.55)	0.145 (1.43)
Cap	1.234 *** (60.14)	0.512 ** (2.33)	−0.557 (−1.10)	−0.477 (−1.00)	−0.179 (−0.271)	−0.052 (−0.19)
TFP ₀	1.457 *** (85.70)	0.174 (0.82)	−0.606 (−1.24)	−0.259 (−1.08)	−0.457 (−1.26)	0.234 (1.53)
Fina	0.193 *** (20.37)	0.078 (0.81)	−0.110 ** (−2.49)	−0.074 (−0.972)	0.060 (0.553)	0.037 (0.45)
Age	3.084 *** (25.53)	−1.788 (−1.15)	−1.099 * (−1.84)	−1.075 (−1.05)	0.476 (0.332)	0.534 (0.49)
EX	0.040 *** (6.06)	−0.025 (−0.26)	0.039 (0.94)	0.104 (1.63)	0.143 * (1.78)	0.043 (1.04)
R&D	0.109 *** (20.69)	0.053 (0.69)	0.027 (1.02)	0.045 (0.986)	0.082 (1.28)	0.110 ** (2.27)
Sub	1.519 *** (47.09)	0.721 (1.67)	−0.299 * (−1.87)	−0.404 (−1.47)	0.392 (1.02)	0.496 (1.60)
Domestic	−0.139 *** (−19.50)	0.089 (0.91)	0.025 (0.69)	−0.074 (−1.21)	0.027 (0.31)	−0.014 (−0.22)

Note: *t* values in parentheses; *, **, and *** indicate significant values at the 0.1, 0.05, and 0.01 levels respectively.

3.3. The Treatment Effect of the ECCR Policy's Intensity on Enterprises' TFP

Figure 3 reveals the treatment outcomes for GPS, with 2010 as the base period, and the average of the enterprises' TFP over three years as the output variable. Figure 3 illustrates the relationship between the ECCR level and the enterprises' TFP, which was obtained using the GPS matching method, whereby Figure 3(left) reports the average dose-response function curve, and the figure on the right shows the impact of different levels of ECCR on enterprises' TFP, compared to the situation without regulations (i.e., the treatment effect). In the figure on the left, the ECCR level and enterprises' TFP formed a clear N-shaped relationship, where the ECCR changed from zero to non-zero and from low to high, and the enterprises' TFP rose first, then declined, but rose again later on.

Figure 3. The ECCR level and TFP dose-response function (left) and treatment effect (right). Note: Low/Up-95 means the upper and lower 95% confidence interval.

Furthermore, by calculating the differences in the enterprises' TFP under different levels of carbon reduction policy intensity and businesses under a zero-carbon reduction intensity, we revealed the treatment effect of the ECCR policy's intensity on enterprises' TFP, as shown in Figure 3(right). When the carbon reduction intensity fell within the range (0,0.43], the ECCR policy had a positive impact on the enterprises' TFP. When the carbon reduction intensity fell within the range (0.43,0.97], the ECCR policy had a negative impact on the enterprises' TFP. We believe that there are two mechanisms for the

ECCR policy's effect on businesses' TFP. From the perspective of the direct impact, the ECCR policy directly increased the enterprises' cost burden, thereby reducing their competitiveness and inhibiting their TFP. From the perspective of the indirect impact, the motivation to meet carbon reduction targets (including the benefits enterprises receive from the capital market and the government) encouraged businesses to engage in product optimization and innovation, thus "reversing" improvements in their efficiency and strengthening their competitiveness. Under a moderate level of the ECCR policy's intensity, its indirect, positive impact exceeded its direct negative impact, while the treatment effect of the ECCR policy's intensity was positive. This means that its treatment effect continued to rise when the ECCR policy's intensity fell within the range (0,0.19], and the treatment effect reached a maximum of approximately 0.80 when the ECCR policy's intensity was 0.19. As the ECCR policy's intensity rose, its direct negative impact exceeded its indirect positive impact, while its treatment effect also became negative, whereby its treatment effect continued to decline when carbon reduction intensity fell within the range (0.21,0.43]. This indicates that the gap between the policy's positive and negative impacts continued to narrow until its positive impact equaled its negative impact. When the ECCR policy's intensity was 0.75, its treatment effect reached a minimum of approximately −1.19. Overall, the ECCR policy's impact on the enterprises' TFP changed from positive to negative with the carbon reduction intensity. When the carbon reduction intensity was low, the carbon reduction policy was conducive to expanding the enterprises' TFP. Once the carbon reduction intensity exceeded the reasonable range for enterprises, the policy had a negative impact on their TFP.

3.4. Changes in the Treatment Effect over Time and Testing for Different Base Periods

First, in the tests above, the enterprises' TFP was the mean value calculated from 2011 to 2013; its purpose was to smooth out possible cyclical effects. However, by doing so, we were unable to test the ECCR policy's lagged effects on the enterprises' TFP. The direct cost-increasing effect of the regulation on enterprises' TFP may have taken effect very quickly, although it takes longer to engender the indirect effect of innovation and R&D. Next, we conducted empirical research based on the enterprises' TFP in 2011, 2012, and 2013 to examine two problems. First, we classified the implementation of the regulatory policy into three scenarios—"one year later," "two years later," and "three years later"—to evaluate the impact of the ECCR policy's intensity on the enterprises' TFP, and to determine whether the research conclusions on the treatment effect would remain robust over time. Second, we established whether the policy's impact (especially the indirect, positive impact) on the enterprises' TFP emerged gradually by comparing the research outcomes for the three scenarios.

Figure 4 portrays the empirical findings. We made the following observations from Figure 4. First, when the ECCR policy took effect "one year later," "two years later," and "three years later," the impact of the policy's intensity on the enterprises' TFP exhibited an N-shaped relationship. Hence, the conclusions drawn from the fundamental analyses above remained robust over time. Second, the range of the ECCR policy's intensity, which had a positive impact on the enterprises' TFP, expanded over time, whereby the level of policy intensity that had a positive impact "one year later" and "two years later" fell within the range (0, 0.45], and the level of policy intensity that had a positive impact "three years later" fell within the range (0, 0.48]. This signaled that the ECCR policy's indirect, positive impact on enterprises' TFP emerged gradually. Third, the treatment effect curve for the scenario "three years later" fell above the treatment effect curves for the scenarios "two years later" and "one year later." This further indicated that the ECCR's direct, positive impact on the enterprises' TFP appeared progressively, hence leading to the continuous rise in the ECCR's treatment effect on the enterprises' TFP under each level of the ECCR. Based on the test results for implementing the policy "one year later," "two years later," and "three years later," it is easy to see that the impact of carrying out the carbon reduction policy on the enterprises' TFP was persistent, while the N-shaped relationship between the ECCR and the enterprises' TFP was steadily reflected in the samples for at least a three-year lag period. There was an apparent lag in the dynamic adjustment of the carbon reduction policy among the enterprises. The longer the lag period, the more conducive this was for

the carbon reduction policy to facilitate its effect on the TFP, thus demonstrating that the treatment effect curve continued to move to the right over the lag period. Enterprises needed time to react to the ECCR policy. Certain coordination costs for enterprises arose when they faced policy incentives for innovation and R&D. The effects of other factors, such as increasing R&D investments and the number of R&D personnel, will slowly come into play in the future. Hence, the ECCR policy's effect on enterprises' TFP may come into play over a longer period.

Figure 4. Treatment effect with different time lags

3.5. Impact of Initial Innovation Capacity

The “Energy Conservation and Carbon Reduction” policy promotes enterprises’ TFP improvement indirectly through three factors. The policy forces enterprises to optimize production and increase spending on R&D, which leads to more innovations. For enterprises achieving the “carbon reduction” missions, rich rewards, including a positive corporate social image and preferential policy of the government, are obtained simultaneously. Despite this, the indirect impact can work effectively, depending on the innovation capacity of enterprises. Whether optimizing production links or improving energy consumption technology, enterprises need to have high innovation capacities. In fact, R&D and innovation rely on a huge amount of time and investment. Moreover, there is a great deal of empirical study showing that the innovation activities of enterprises have strong inertia. The further discussion of this paper bases on the innovation ability of the enterprise in the base period. The Ten-Thousand Enterprises can be divided into two groups, namely, the R&D investment group in the base period and the non-invasive R&D investment group, to estimate the treatment effect of the “carbon reduction” policy on the enterprises’ TFP. It must be noted that Schumpeter Innovation consists of product innovation, technological innovation, market innovation, resource allocation innovation, and organizational innovation; however, it is impossible to measure an enterprise’s innovation ability comprehensively solely via its R&D investment. Therefore, this study measured the innovation ability of enterprises only through R&D investment in the base period due to the limitation of data. Additionally, the level of R&D investment in the base period had nothing to do with whether the company was affected by the “carbon reduction” policy and it could avoid endogenous problems).

Figure 5 displays the empirical results of the grouping. For the Ten-Thousand Enterprises with innovative capabilities, the interval of the positive effect of the “carbon reduction” policy became wider to encompass the range (0, 0.57); for enterprises with weak innovation capabilities, the interval of the positive effect was significantly shorter, from 0 to 0.45. Moreover, for the Ten-Thousand Enterprises with innovative capabilities, the invalid intensity interval of the carbon reduction policy that forced enterprises to increase their TFP became smaller. Those Ten-Thousand Enterprises with weak innovation ability lost the coercive effect when the intensity of the “carbon reduction” policy exceeded 0.45.

That is to say, when enterprises with innovative capabilities face the constraints of the “Energy Conservation and Carbon Reduction” policy, they were more likely to obtain advantages by optimizing production lines and improving energy consumption technologies.

Figure 5. Innovation ability and the treatment effect.

3.6. The Impact of Enterprise Size

We further differentiated the sizes of the manufacturing enterprises. The enterprises were split into two groups using data information on the “net fixed assets” in the base period. Within each group, the performance of TFP was repeatedly estimated after the Ten-Thousand Enterprises were subject to the ECCR policy. Intuitively, the larger enterprises had abundant resources that allow them to respond to the ECCR policy via the reasonable allocation of internal resources. Figure 6 shows the analysis results: (1) The difference between the efficient intensity interval and the inefficient intensity interval was not significant, where the ECCR policy “forced” the enterprises’ TFP promotion. (2) However, within the efficient strength interval, the ECCR policy displayed a more substantial impact regarding promoting the TFP for large-scale enterprises than for smaller-scale enterprises; in contrast, within the inefficient intensity interval, the ECCR policy weakened the TFP of larger enterprises rather than smaller enterprises. These empirical findings clearly reflect the fact that the scale of the base period should be a key factor for enterprises to reasonably respond to the ECCR policy and translate the pressure into motivation.

Figure 6. Enterprises size and treatment effect.

3.7. The Impact of Government Subsidies

Government subsidies are important external resources for the enterprises, which affect the decision-making behavior of enterprises to a certain extent. In fact, the amount of government subsidies received by the enterprise reflects the relationship between the management and local government. Those enterprises receiving subsidies normally have a more harmonious political and commercial

relationship with local governors. This potential political and commercial connection further influences the enterprise's access to other resources, such as the market, bank loans, etc., which also affects their decision-making behavior. When exploring the heterogeneous response of the enterprise's TFP performance to the government's ECCR restriction policy, the theoretical prediction is that the company will change its decision-making behavior, especially the strategies in future innovation, on account of the impact of the ECCR policy. However, if it receives the effect of government subsidies at the same time, or if there is heterogeneity in the political and commercial relations, this kind of response may be "distorted." In order to determine the impact of government subsidies, we separated our data source into two subsamples based on whether the enterprise was receiving subsidies in the base period. This was done to identify the differences in the political and commercial relations of enterprises in obtaining subsidies, which further estimated the response of the Ten-Thousand Enterprises in the two groups to the intensity of the ECCR policy. The result is shown in Figure 7.

Figure 7. Subsidy and treatment effect.

4. Basic Conclusions and Policy Implications

Theoretical research found that environmental regulation had both positive and negative effects on enterprise productivity. Based on the policy of the Ten-Thousand Enterprises Energy Conservation and Low Carbon Program (TTEP) implemented by the Chinese government, this study empirically analyzed the policy intensity boundary condition of positive and negative effects that dominated and its moderating factors. The generalized propensity score matching model (GPSM) was used to analyze the net effect of the policy on the total factor productivity (TFP) of Chinese manufacturing enterprises. The results showed that: (1) the low intensity of the TTEP policy could promote the growth of the enterprises' TFP; (2) in contrast, the intensity of the policy exceeded a certain threshold level, gradually leading to an inhibitory effect on the enterprises' TFP; (3) the TTEP policy mechanism forced the enterprises to innovate, which enhanced their TFP, though it took time to release gradually; (4) the enterprises with a stronger capacity for innovation or larger scales found it easier to transform under the pressure from the TTEP policy and utilize the innovative impetus to improve their TFP level; (5) however, government subsidies distorted the forced-innovation effect of the TTEP policy on the enterprises' innovation, which restrained the positive effect of the policy on the TFP.

The above empirical analysis conclusions provide an important microfoundation for understanding the interactive relationship between environmental goals and performance goals of manufacturing enterprises. One of the keys to achieving a win-win situation in environmental development and manufacturing development is the optimal intensity of environmental regulation policies. The reasonable intensity of environmental policies is more conducive to developing manufacturing enterprises' productivity through environmental regulatory pressure. However, it should be noted that the "back door" should not exist while imposing "environmental pressure" on enterprises. For example,

obtaining compensation resources through non-competitive channels, it distorts the positive effect of environmental regulation on the manufacturing enterprises' productivity.

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