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How Does Environmental Law Affect Companies' R&D Capabilities? ——An Example from Guangdong During 11th Five Year Plan

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Abstract: Since reform and opening up, China's economy has grown rapidly, while a heavy environmental price has also been paid. Today under the goal of "dual carbon", it is urgent to promote the transformation and upgrading of enterprises to achieve green development. This paper takes the manufacturing enterprises in Guangdong province as the research sample, and takes the environmental regulation of the "Eleventh Five-Year " policy as the quasi-natural experiment, and empirically explores the impact of environmental regulation on the transformation of enterprises through the PSM-DID method. This work finds that what affect companies' R&D expenses significantly are those nonpolicy factors. And the increase of years of company operation and income will promote the investment in innovation of the enterprise. The paper concludes that increasing the input of R&D by executing environmental restriction policy is not reliable, and environmental regulation may require further intervention in firm internal performance to be effective.

Keywords: PSM-DID, environment protection law, 11th Five Year Plan.

1. Introduction

Over the past 40 years of reform and opening up, China's economy has been growing rapidly at an average annual rate of over 9%. However, this growth is an extensive growth at the expense of the environment [1]. Environmental destruction caused by rapid industrialization and urbanization has not merely led to a negative impact on people's living standards, and also restricted the quality of the industrial economy's development itself [2]. In 2017, the 19th National Congress of the Communist Party of China proposed to improve the quality of economic development to meet people's growing needs for a better life more effectively. In 2020, at the 75th United Nations General Assembly, China proposed the "dual carbon" goal of achieving carbon peaks in 2030 and carbon neutrality in 2060.

In the context of internationally calling for a joint response to global climate change and the growing domestic demands for a better ecological environment, the future development of China's economy must attach great importance to the environmental sustainability issues. To achieve the

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simultaneous development of environmental protection and economic growth, the most fundamental way is to increase investment in technological innovation of enterprises and guide enterprises to transform into a green development mode [3]. In the context of "dual carbon", the ever-increasing efforts of environmental remediation have brought challenges and opportunities for change to Chinese companies. Can enterprises activate their innovative potential under the pressure of environmental regulations to achieve technological innovation and environmental protection efficiency progress?

To answer these questions, this paper observes the quasi-experiment formed under the impact of the exogenous policy "Eleventh Five-Year Plan for National Environmental Protection" in the 2006. This plan proposed requirements for the total control of major pollutants, and it has become a constraint indicator included in evaluation and assessment mechanism of local governments that reduction rate of sulfur dioxide and chemical oxygen demand emission should reach a level of 10%.In the context of tightening environmental protection policies, only through technological innovation and efficiency improvement, enterprises in high polluting industries can realize the transition from extensive growth, so as to maintain their survival and development.

Based on the realistic background and existing research, this paper mainly studies Chinese manufacturing companies during the "Eleventh Five-Year Plan" period. R&D revenue and sales revenue are used as proxy variables of corporate innovation input, and the propensity score matching difference in difference method (PSM-DID) is used to discuss the impact of the "Eleventh Five-Year Plan" on the investment in technological innovation of enterprises.

2. Literature Review

Porter hypothesis claimed that strict or flexible environmental regulations have the power to force firms to innovate[4]. Under the German ban on carcinogenic textile dyes, Chakraborty and Chatterjee observed the impact of the Indian government’s ban on the use of “azo dyes” on the innovation of domestic dye manufacturers [5]. Result showed that the ban increases companies’ R&D fees significantly. However, Ziesemer proposed that Porter hypothesis will not be satisfied [6]. Since only when restrictive environmental law increases the companies’ knowledge capital accumulation, will companies’ motivation to invest on R&D increase. Moreover, Hottenrott and Rexh found out that restrictive law increases the environmental regulation costs,which leads to squeeze the R&D fees, and that negative effect will enhance when companies face with limitation of financing [7]. Other scholars took researches on Chinese industry found out that the mixed effects of environmental law on R&D fees. That is, it first brings negative effect on R&D fees and then increase the R&D fees.

Since the research result is mixed, especially in China, it’s very important to take research on it. And 11th Five-Year Plan, which came up with restrictive environmental laws, provides us with appropriate analysis materials. Since Guangdong province is one of the most polluted areas with the highest GDP in China, it provides a plethora of data to research. Thus, this study object is set as Guangdong.

In term of methods, it is traditionally believed that statistics cannot be used for causal inference, and only be used for correlation inference. For example, dummy variables and DID are used to consider the effects of policies. However, with the development of related technologies, Granger Causality in time series was invented and used, and then Newman, Dabrowska and Speed and Rubin proposed and constructed a causal effect model framework based on cross-sectional data, causal inference seems to be possible [8]. One of the contributions that Rubin made is to provide PSM, which is useful in reducing data dimensions and also to provide an unbiased estimator. For the purpose of applying panel data into research, Heckman et al derived casual effect on the basis of PSM-DID.

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Even though these methods were invented early, not many scholars think highly of them until recently. Thus, there are still some gaps in related research and application. In this status quo, this article will apply PSM-DID method to estimate the casual effect.

3. Model and Data

3.1. Data

In order to explore the impact of Chinese "11th Five-Year Plan" period on corporate technological innovation investment, this study selects companies in Guangdong Province from 2002 to 2007 as a sample based on the availability of data. According to the provisions of the relevant environmental protection laws, the sample enterprises are divided into the treatment group affected by the law and the control group with lesser impact of the law. The grouping is based on the 11 pollution intensive industries in China identified in the "First National Pollution Source Census Plan" launched by the State Council in 2007 [9]. Therefore, the pollution-intensive enterprises selected in this article are: paper and paper products, agricultural and sideline food processing industries , Chemical raw materials, and chemical product manufacturing, textile industry, food manufacturing, electric power, heat production and supply industry, leather, fur, feather (velvet) and its products industry, petroleum processing, coking and nuclear fuel processing industry, non-metal Mineral products industry, non-ferrous metal smelting and rolling processing industry. In addition, using 2006 as the boundary of policy implementation, this work explore the processing effect and time effect of the two data set before and after the implementation of the policy for observation. The data comes from historical statistical yearbooks and environmental statistical yearbooks.

3.2. Model

3.2.1. Causal Effect and PSM.

To estimate the effect of an experiment, the gap of two outcomes needs to be investigated. One is the outcome produced by accepting this experiment, $D_i = 1$, and another is the outcome produced by not accepting this experiment, $D_i = 0$. That gap is named Average Treatment Effect on the Treated (ATT). However, individual A cannot be both $D_i = 1$ and $D_i = 0$ simultaneously. Thus, Average Treatment Effect (ATE) on whole sample is considered. And the relationship of ATE and ATT is listed on the following equation:

$$\begin{aligned} ATE &= \mathrm{E}(Y_{1i}|D_i = 1) - \mathrm{E}(Y_{0i}|D_i = 0) \\ &= \underbrace{\mathrm{E}(Y_{1i}|D_i = 1) - \mathrm{E}(Y_{0i}|D_i = 1)}_{ATT} \\ &\quad + \underbrace{\mathrm{E}(Y_{0i}|D_i = 1) + \mathrm{E}(Y_{0i}|D_i = 0)}_{selection\ bias} \end{aligned} \tag{1}$$

In equation (1), when the selection of treated group is random, the selection bias can be eliminated. Though, the selection of treated group is not totally random when we consider the effect of a policy in realistic world, Rosenbaum and Rubin(1983)shown that If we find the factors that determine whether or not an individual participates in the experiment(treated group), then we match those factors in the control group to a sample which is equal to the treatment group, and then we use those samples as the control group that we actually evaluate, then the treatment group selection is approximately random. In this occasion, selection bias will be 0 and $ATE = ATT$.

For the purpose of finding the samples that treated group requires in control group, tools are required to measure the differences. One straightforward way is to investigate the covariates X.

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However, when the data and covariates are huge, the straightforward way will bring high dimension covariates matching problems. In order to avoid that problem, PSM is usually considered. And the implementation of PSM is based on three assumptions:

- Assumption 1: Unconfoundedness

$$(Y_{0i}, Y_{1i}) \perp\!\!\!\perp D_i \,|X_i$$

It's also named ignorability or selection on observables. Rosenbaum and Rubin shown if the equation above can be satisfied, the following one can also be satisfied [8]:

$$(Y_{0i}, Y_{1i}) \perp\!\!\!\perp D_i|p(x)$$

$p(x) = p(D_i = 1|X_i = x)$ is propensity score. The implication of two equations is whether an individual is assigned to control group or treated group is independent to the potential outcome if propensity matching scores or covariates is given. This is just like considering the two methods of taking medicine and surgery. Because the effect of taking medicine is good, all patients should take medicine and no operation should be performed, which obviously will not form a reasonable controlled experiment.

- Assumption 2：Common Support

If the design of an experiment satisfies the first assumption, the ATT can be written as:

$$ATT = E\left[\underbrace{E[Y_i|X_i, D_i = 1] - E[Y_i|X_i, D_i = 0]}_{\tau_X}\middle|D_i = 1\right]$$

τ_X is the average difference between the two groups of results in the same covariable X_i layer. Therefore, in order to estimate ATT, individuals with characteristics of X_i in general are required to exist in both the intervention group and the control group. Otherwise, ATT is meaningless and the corresponding matching measure is meaningless. Thus, the second assumption PSM requires is:

$$0 < P[D_i = 1|X_i] < 1$$

- Assumption 3：The Stable Unit Treatment Value Assumption (SUTVA)

This assumption has two implications: first, there is no interaction between the potential outcomes of different individuals. It's like if I take a painkiller, but someone else is bothering me and making me feel worse, then we can't tell if the pill has any effect on pain; Second, the level of treatment is the same for all individuals. If we're going to give drugs to people in the treatment group, we should give them the same dose, the same care and so on. In the social sciences, however, the second implication is often difficult to satisfy, so we generally focus on the first meaning.

3.2.2. DID.

The difference in difference methods is applicable to all individuals who have not received policy intervention before, and only one group of individuals who have received policy intervention afterwards. The group that has received policy intervention is called the treated group, and the group that has not is named the control group. The two variables, the timing of policy implementation and whether this sample is treated by policy, divide whole sample into 4 groups. Its use needs to be constrained by four assumptions: common trend hypothesis, common interval hypothesis, exogenesis hypothesis and the corresponding SUTVA. As DID model has been widely discussed, its assumptions will not be discussed in detail in this paper.

DID is used to calculate ATT after matching data with PSM. And ATT is expressed as [10]:

$$ATT_{PSM-DID}(p) = \{E[Y_{it}|D_i = 1, p(X_{it}) = p] - E[Y_{it-1}|D_i = 1, p(X_{it}) = p]\} - \{E[Y_{it}|D_i = 0, p(X_{it}) = p] - E[Y_{it-1}|D_i = 0, p(X_{it}) = p]\} \quad (2)$$

If the basic regression model is set as:

$$Y_{it} = \alpha_0 + \alpha_1 treat_{it} + \alpha_2 t_{it} + \alpha_3 t_{it} \times treat_{it} + \cdots \tag{3}$$

When t=0 and treat=1, the formula(3) has only α_0 and α_1(Table 1), which means that the averaged effect is exerted beforehand, that is, $E[Y_{it-1}|D_i = 1, p(X_{it}) = p]$ in the formula xx. When t=1 and treat=1, the formula xx is $\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$, which is the averaged effect that is affected afterwards, that is, $E[Y_{it}|D_i = 1, p(X_{it}) = p]$ in the formula xx. Thus $(\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3) - (\alpha_0 + \alpha_1) = \alpha_2 + \alpha_3$ is equal to the second line of formula xxx. Similarly, take t=0, treat=0, and t=1, treat=0, we will get the value of the third line of formula xxx from formula xx, which is α_2. And $\alpha_2 + \alpha_3 - \alpha_2 = \alpha_3$ is exactly the meaning, ATT, of formula xx.

The detailed regression models in this article are:

$$m1: fee_{rd_{it}} = \alpha_0 + \alpha_1 treat_{it} + \alpha_2 t_{it} + \alpha_3 did_{it} + \alpha_4 pfproductvalue_{it} + \alpha_5 employ_{it} + \alpha_6 fixed_a sset_{it} + \alpha_7 liability_{tot_{it}} + \alpha_8 income_{product_{it}} + \alpha_9 runyear_{it} \tag{4}$$

$$m2: fee_{rd_{it}} = \alpha_0 + \alpha_1 treat_{it} + \alpha_2 t_{it} + \alpha_3 did_{it} \tag{5}$$

In order to evaluate whether covariates will affect our result, this article set two formulas. The first formula contains covariates and the second has not. Subscript i is company i, t is year. $treat$ is used to reflect whether this company is affected by Environmental Protection Law, 1 means it is, 0 means not. t is used to measure the non-policy time effect of the implementation of the Environmental Protection Law since 2006, it takes 1 after 2006, 0 before. $pfproductvalue$ is product value, employ is the number of employees, $fixed_a sset$ is fixed asset, $liability\_tot$ is liability, $income\_product$ is revenue from main business products, $runyear$ is years of company operation. fee_rd is R&D spending.

Table 1: The implication of DID coefficients.

	t=0	t=1	Δ
treat=1	$\alpha_0 + \alpha_1$	$\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$	$\Delta d_1 = \alpha_2 + \alpha_3$
treat=0	α_0	$\alpha_0 + \alpha_2$	$\Delta d_2 = \alpha_2$
DID			$\Delta\Delta d = \alpha_3$

4. Empirical Analysis

4.1. Descriptive Statistics.

The descriptive statistics for each main variable is listed in Table 2. The sample size without PSM treatment is 13801. The sample enterprises employ an average of 593 employees, investing an average of 1213.87 yuan in R&D expenses. The average main business income is 3.011 million yuan, and the average debt is 1.2277 million yuan.

Since the sizes of pfproductvalue, fixed_asset, liability_tot, and income_product are too great, they're all divided by 1000. Before using the data, blank values are deleted and values out of common support are exclude after matching.

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Table 2: Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
fee_rd	13801	1213.87	28470.98	0	1850260
pfproductvalue	13801	17.79	101.25	0	4389.58
employ	13801	593.25	2963.08	6	188151
fixed_asset	13801	77.54	481.85	0	29503.7
liability_tot	13801	122.77	820.66	0	48912.51
income_product	13801	301.10	2858.09	0.32	187387
runyear	13801	12.03	12.19	1	408

4.2. PSM-DID Regression.

4.2.1. Propensity Scores Matching Processing.

In this paper, logit is used to define the propensity score and the "one-to-four matching method" with k=4 is used to determine its weight, and the condition of "common support" is imposed at the same

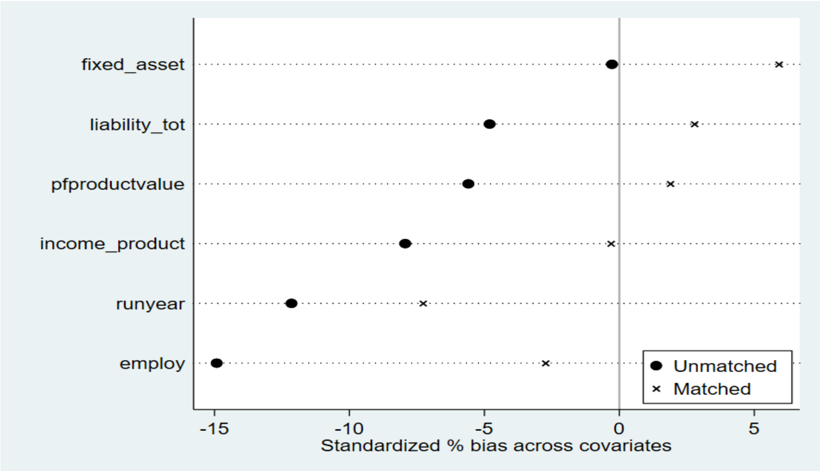

Figure 1: Standardlized % bias across covariates.

Table 3: Balance test.

Variable		Mean treated	Mean control	%Bias
pfproductvalue	Unmatched	13.22	18.068	-5.6
	matched	13.22	11.583	1.9
employ	Unmatched	282.98	612.19	-14.9
	matched	282.98	343.36	-2.7
fixed_asset	Unmatched	76.466	77.609	-0.3
	matched	76.466	51.83	5.9
liability_tot	Unmatched	93.601	124.56	-4.8
	matched	93.601	75.68	2.8
income_product	Unmatched	144.1	310.68	-7.9
	matched	144.1	150.65	0.3
runyear	Unmatched	10.787	12.104	-12.1
	matched	10.787	11.576	-7.3

time. Table 3 and **Figure 1:** Standardlized % bias across covariatesare the results after matching. From the results, the deviations of product value, employees, revenue from main business products, and years of company operation are greatly reduced. In addition, after the matching, a total of 44 samples of companies outside the common value range were eliminated.

4.2.2. Average Treatment Effect.

On the basis of PSM processing, this paper uses formula (4) to test the relationship between environmental protection law and enterprise technological innovation investment. The results (Table 4) show that regardless of whether the covariates are considered, the coefficient of did is negative and insignificant, which means that although the implementation of the new environmental protection law has a certain negative impact on the company's technical investment, it is not significant. That result is consistent with Ziesemer, Hottenrott and Rexh. The former found out that environmental restriction brings no significant effect on companies' R&D fees, since only when environmental regulation increases the knowledge capital accumulation of enterprises, can the innovation vitality of enterprises be stimulated to the maximum extent. And the latter found out that restriction law increases the environmental regulation costs and this'll squeeze the R&D fees, and that negative effect will enhance when companies face with limitation of financing. That's also consistent with the coefficient of liability. The coefficient of t is the effect of time or, precisely, the controlled group before and after difference (Table 1). This's also insignificant, which means that time brings no effect. In term of treat, it represents the treatment effect in t=0(Table 1). Its insignificance represents that treatment brings no effect on those two groups. The results of treat and t are consistent with the did.

For the significant control variables, the increased of fixed asset and liability will inhibit the investment in innovation and R&D of the enterprise. Since liability generates interest fees which will squeeze R&D fees, thus its coefficient is consistent with intuition. And the increase of fixed asset brings the similar result.

While the increased years of company operation and income will promote the investment in innovation of the enterprise. Since this paper doesn't take research on technology industry, thus a conclusion that when years of company operation increase, company will accumulate more knowledge and experience which help it to invest more on R&D can be drawn. Product value and income provide more capital and money to the company, which will also increase the R&D fees.

As for those another two covariates, employees and the value of product, the increment of both promote R&D fees. But they are insignificant. That might be due to the characteristics of the companies. For employees, it is not necessarily true that more people companies hire, more R&D fees will be put, since most of those companies are labor intensive companies and they might be careless about research.

Table 4: Regression result.

	m1	m2
did	-49.33	-78.88
t	15.89	101.87
treat	-6.03	-357.94
cons	-375.99	528.03***
pfproductvalue	1.02	
employ	0.05	
fixed_asset	-3.44***	
liability_tot	-1.26***	
income_product	3.668***	
runyear	19.28***	

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5. conclusion

This paper explores how environmental policies affect companies' R&D expenditures. This article selects the data of Guangdong Province from 2002 to 2007, and the variables are fixed asset, reliability, number of employees, years of company operation and income. After that, the PSM method is used to match the data and then perform DID regression, and the regression finds out that: environment protection law doesn't affect companies' R&D expense significantly. And fixed asset, reliability and employees will inhibit the investment in innovation and R&D of the enterprise, while the increase of years of company operation and income will promote the investment in innovation of the enterprise. Thus, to increase the input of R&D by executing environmental restriction policy is not reliable. R&D expenses are more related to the internal performance of the company.

References

[1] *Wang, M., Webber, M., Finlayson, B., & Barnett, J. (2008). Rural industries and water pollution in China. Journal of Environmental management, 86(4), 648-659.*

[2] *Ebenstein, A., Fan, M., Greenstone, M., He, G., Yin, P., & Zhou, M. (2015). Growth, pollution, and life expectancy: China from 1991-2012. American Economic Review, 105(5), 226-31.*

[3] *Zhao,H.(2008) The lmpact of Environmental Regulation on Industrial Technological lnnovation——An Empirical Research Based on the Panel Data from China [J]. Industrial Economics Research,2008(03):35-40.*

[4] *Porter M E，Linde C． Toward a new conception of the environment-competitiveness relationship[J]． Journal of Economic Perspect，1995， 9(4) : 97-118.*

[5] *Chakraborty P，Chatterjee C． Does environmental regulation indirectly induce upstream innovation? New evidence from India [J]． Re- search Policy，2017，46(5) : 939-955．*

[6] *Ziesemer T． A knowledge-based view of the porter hypothesis[J].Environmental Policy and Governance，2013(23) : 193-208．*

[7] *Hottenrott H， Rexh S． Policy-induced environmental technology and inventive efforts: Is there a crowding out? [J]． Social Science Elec- tronic Publishing，2015，22(5) : 375-401．*

[8] *Rosenbaum P R, Rubin D B. The Central Role of the Propensity Score in Observational Studies for Causal Effects[J]. Biometrika, 1983, 70(01): 41-55.*

[9] *General Office of the State Council. (2007) Circular of The General Office of the State Council on printing and distributing the plan for the first National Survey of pollution sources. http://www.gov.cn/gongbao/content/2007/content_663682.htm*

[10] *James H., Hidehiko I., Jeffrey S. & Petra T.Characterizing Selection Bias Using Experimental Data.Econometrica, Vol. 66, no. 5 (1999): 1017-1098.*