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Empirical Analysis of Environmental Regulation on the Digital Transformation of Manufacturing Industry

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Abstract. As an environmental regulation policy, the carbon trading policy is a meaningful attempt by the government to achieve carbon emissions reduction. As a green and low-carbon transformation method, digital transformation is increasingly valued by enterprises. This paper analyzes the annual reports of listed companies by the artificial intelligence algorithm Python tool and obtains the digital transformation level of each manufacturing enterprise for analysis. Python can comprehensively crawl data and has powerful data processing capabilities, which not only improves data acquisition ability but also improves analysis efficiency. This article is based on panel data of Chinese A-share manufacturing enterprises from 2008 to 2021, constructing a differences-in-differences model to explore the influence of carbon trading policies on the digital transformation of manufacturing enterprises, and analyzing its impact mechanism. Empirical research has found that carbon trading policies promote the digital transformation of manufacturing enterprises.

Keywords. Artificial intelligence algorithm, carbon trading policies, differences-in-differences, digital transformation

1. Introduction

Since the Fourth Industrial Revolution, global climate change has become a major challenge facing humanity in the 21st century. At the current stage, China's position in the global economic system and the needs of its own development stage determine that China will continue to develop its manufacturing industry. This makes it more urgent to explore low-carbon and green development in the manufacturing industry[1].

In today's world, the wave of digital development is sweeping across the globe, with digital information becoming a key production factor, bringing about improvements in economic efficiency and economic quality[2]. How to design effective environmental policies to promote the achievement of emission reduction goals has always been an important issue of theoretical research and policy concern. China issued a carbon trading policy at the end of 2011 and officially launched the carbon trading market in 2013. And

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gradually increasing attention and attention has been paid to industries with large scale and high intensity of carbon dioxide emissions.

After the implementation of the policy, scholars often use the differences-in-differences method and composite control method to evaluate its emission reduction effect. Carbon trading policies and digital transformation are currently hot topics in research[3-5]. There are rich research results on the emission reduction effects of carbon trading policies both domestically and internationally, and the differences-in-differences method for policy evaluation is very mature. However, there are few articles linking the two to analyze the effect of carbon trading policies on digital transformation of the manufacturing industry. This article focuses on manufacturing enterprises and evaluates the implementation influence of carbon trading policies using differences-in-differences method. Artificial intelligence algorithms are used for text analysis to measure the level of digital transformation of enterprises, and a series of robustness tests are conducted.

2. Mechanism Analysis

The carbon trading pilot policy is a market incentive environmental regulation policy. Based on the Porter hypothesis, the carbon trading pilot policy is beneficial for enterprises to choose reasonable governance models based on their own situation, thereby obtaining competitive advantages and corresponding economic benefits. Under the carbon trading market mechanism, environmental regulations are stricter. At the same time, enterprises with carbon emission reduction technology advantages can also sell remaining quotas to obtain profits, achieving green economic growth. If we combine blockchain technology to design a technical solution for carbon asset management accounting, and build a carbon asset management accounting system that integrates three subsystems: carbon asset identification, carbon asset disclosure, and carbon asset decision-making, it can help enterprises improve the value of carbon assets [6]. In addition, implementing digital transformation, enterprises can improve their ability to quickly respond to changes in company and market dynamics by processing data and information from both internal and external sources [7], in order to enhance their competitive advantage.

Therefore, this article proposes hypothesis: Carbon trading policies significantly promote the digital transformation of manufacturing enterprises.

3. Research Design

3.1. Dependent Variable

Digital transformation: Empirical analysis is grounded in the statistical data of 6760 listed companies. Wu Fei [8] constructed a keyword list from five universally meaningful levels: artificial intelligence, blockchain, cloud computing, big data, and the application of the aforementioned digital technologies. This article refers to the scholar's approach and uses the Python crawler function to measure digital transformation.

3.2. Explanatory Variable

Policy variables (Treats). In 2011, five cities and two provinces(Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen) were selected as experimental groups, and listed manufacturing enterprises in that province and city were selected as experimental groups. The Treatment value was 1, while listed manufacturing enterprises in other provinces were selected as control groups. The Treatment value was 0.

Time variable (Post). Due to the successive initiation of carbon emission trading in pilot areas in China in 2013, 2013 was used as the base year, and before 2013, the post value was 0; In 2013 and later, the post value was 1.

Differences-in-differences is the product of policy variables and time variables in the differences-in-differences method, representing the net effect of policies on the digital transformation of manufacturing enterprises. The city where the companies included in the carbon trading policy are located takes a value of 1 after the policy implementation year, otherwise it takes a value of 0.

3.3. Control Variables

It is necessary to include a series of control variables in the model to improve its accuracy. Based on scholars' research and reference to relevant scholars' literature and comprehensive consideration of data availability and correlation, age of the enterprise (Age), Enterprise size (Size), cash to asset ratio (Cashflow), total asset to net profit margin (ROA), asset liability ratio (Lev), book to market ratio (BM), and top shareholder shareholding ratio (TOP1) are set as control variables[9]. Table 1 shows the interpretation of variables. High order theory suggests that the decisions of top management in a company can affect the formulation of strategic decisions, and the demographic characteristics of top management can affect the emergence of transformation. Major shareholders play an important role in the company's digital transformation decisions. Measure the micro characteristics of a company using five control variables: age, size, ROA, Lev, and BM. According to the theory of enterprise lifecycle, enterprises of different ages in the same industry face different production potential sets, strategic priorities, resource constraints, etc. Enterprises will make different choices based on their own experiences and move towards different digital transformation paths; The material basis for implementing digital transformation is the size of the enterprise, cash asset ratio, total asset to net profit margin, asset liability ratio, and book to market ratio. The calculated coefficients of variance expansion (VIF) for each variable are all less than 10, indicating that the next step of analysis in this article is reliable.

Table 1. SAMPLE REGRESSION RESULTS AFTER MATCHING

Variable	Variable Interpretation
Age	(Current year - the year of establishment of the company + 1) is taken as logarithm
Size	The natural logarithm of total assets at the end of the period
TOP1	The number of shares held by the largest shareholder/the total number of shares
BM	Book-to-market ratio

ROA	(Total assets at the end of the year - Total assets at the beginning of the year)/Total assets at the beginning of the year
Lev	Total Liabilities/Total Assets
Cashflow	Net cash flow from operating activities/total assets

3.4. Sample Selection

This article takes A-share listed companies from 2008 to 2021 as the research object. Manufacturing enterprises are pillar enterprises in China, which generate a large amount of carbon dioxide during their development. Controlling the carbon dioxide emissions of manufacturing enterprises has an important impact on achieving the dual carbon goals on schedule. Listed manufacturing enterprises in six provinces and cities (including Shenzhen in the Guangdong Provincial Research) were selected as the treatment group, and manufacturing enterprises in non-pilot policy provinces and cities were selected as the control group. Finally, 6760 sample observations were obtained from 582 listed companies, and the main continuous variables were subjected to a 1% tail reduction treatment.

3.5. Data Source

One is the annual report data of enterprises sourced from CNINFO; The second is the company's financial data, which is used to measure control variables and is sourced from the Guo Tai'an database.

3.6. Model Design

The double-difference method not only controls for unobservable individual heterogeneity between samples, but also controls for the impact of unobservable overall factors that change over time, allowing unbiased estimates of policy effects [10]. The introduction of natural experiments and the double-difference method from the natural sciences to the Western economic realm dates back to the late 1970s [11], indicating the method's high level of maturity.

To eliminate the differences between enterprises and time, this article uses a differences-in-differences model with bidirectional fixed effects for empirical testing. A model (1) was set up to test it.

$$DLTN_{it}=\alpha_0 + \alpha_1 treat_i * post_t + \alpha_2 control_{it} + \beta_i + \eta_t + \varepsilon_{it}(1)$$

4. Results and Discussion

4.1. Empirical Results and Analysis

Although the differences-in-differences method separates the average processing effect of pilot policies, there may still be a problem of selection effect in observing research data due to the fact that carbon trading pilot policies are not strictly natural experiments. This article adopts the PSM-DID method to further improve the accuracy of the model.

Match two enterprises in the experimental group and the control group with similar probabilities of implementing carbon emission trading policies through observable variables. If the mean difference of observable variables between the two groups after matching is not significant, it indicates that the matching selection method is appropriate and effective, and the estimation results are reliable.

This article refers to the approach of He Jing [12]. and matches based on the data from the previous period. This article uses cross-sectional data from 2012 for PSM matching and performs regression based on the matched samples.

4.2. Analysis of Matching Results

From Figures 1, the standardized% bias across covariates after matching are both within 10%, indicating that the matching is effective and the results are reliable.

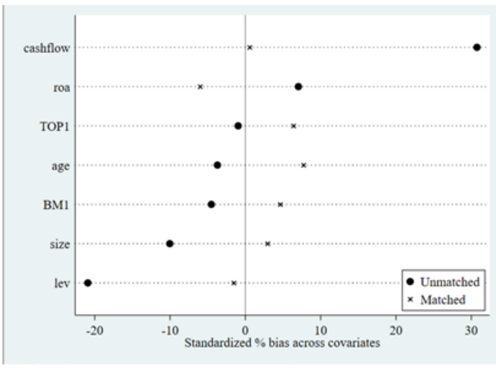

Figure 1. Propensity score matching results

4.3. Empirical Test Results

Regression is conducted based on the matched samples, Table 2 shows the results: column (1) is for samples with non-empty weights, column (2) is for samples that meet the common support assumption, and column (3) is for frequency weighted regression.

Table 2. SAMPLE REGRESSION RESULTS AFTER MATCHING

	(1)	(2)	(3)
VARIABLES	**DLTN**	**DLTN**	**DLTN**
did	0.499***	0.453***	0.548**
Constant	-3.321*	-4.830***	-4.002*
Observations	2,616	4,556	2,616
R-squared	0.738	0.730	0.726

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From the above results, it can be seen that regardless of the regression, the impact of carbon trading policies on the digital transformation is significant. Therefore, hypothesis of this article is validated.

4.4. Parallel Trend Test

The use of the differences-in-differences method needs to meet the assumption of a common trend, that is, before implementing carbon emission trading policies, the digital transformation trends should be the same.

Using the event study method to test the influence of carbon trading policies, the testing model is as follows:

$$DLTN_{it}=\alpha_0+\sum_{t=2008}^{t=2021}\beta_t\, period+\alpha_2 control_{it}+\beta_i+\eta_t+\varepsilon_{it}(2)$$

According to Figure 2, there was little to no variation in the coefficients of time dummy variables prior to the policy being introduced. Nonetheless, notable disparities were evident between the two groups post-policy implementation, satisfying the parallel trend assumption and enabling the application of the double difference method.

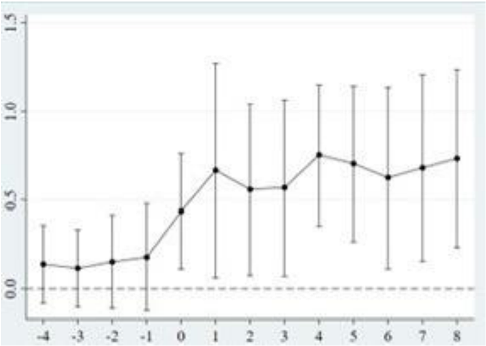

Figure 2. Parallel trend test chart

4.5. Placebo Test

While this study has accounted for numerous enterprise characteristic variables in quasi-experimental settings, there exists the possibility of unobserved enterprise characteristics that could impact the assessment outcomes of carbon trading policies.

The model in this article is a double difference method. When conducting a placebo test, it is necessary to randomly select the same number of provinces and cities as the real pilot from all provinces and cities as the treatment group. Therefore, this study randomly assigns six provinces and cities from the sample as the pseudo-treatment group, while designating the remaining provinces and cities as the pseudo-control group. The policy impact time is also randomly selected, and then regression is performed according to equation (1). This article uses Stata software to construct random shocks of the pseudo carbon trading pilot policy on sample provinces, and acquires regression coefficients along with their associated p-values. The results are shown in Figure 3.

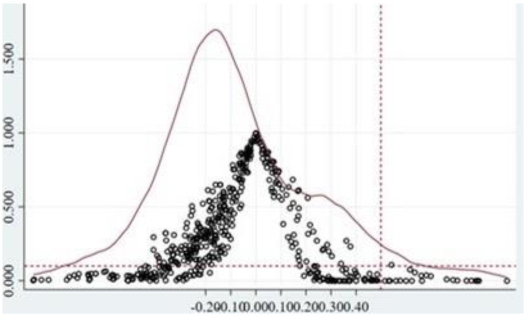

Figure 3. Placebo test chart

The regression coefficients appear to be clustered around zero and are distributed in a manner that resembles a normal distribution, with the majority of P-values distributed above 0.1. The estimated value of the coefficient in benchmark regression is situated at the upper extreme end of the distribution of false regression coefficients, which belongs to a rare occurrence in the placebo test conducted by the enterprise. Based on this, it can be ruled out that the benchmark estimation results in this article are due to hidden factors, indicating that the results obtained in this article are robust.

5. Conclusion

This paper, in the context of artificial intelligence, utilizes Python tools for data scraping from the yearly filings of publicly traded firms and systematically evaluating the influence of carbon emissions trading regulations on the digital transformation of manufacturing enterprises. The study found that carbon trading policies drastically enhanced the level of digitalization in manufacturing companies during the inspection period, and this finding is supported by a series of robustness tests.

Carbon trading policies can not only generate environmental emission reduction effects, but also have an impact on the digital transformation of the manufacturing industry, which not only meets environmental expectations but also conforms to development trends. The carbon trading policy will continue to exert its effects, and the economic effects generated by the carbon trading market through buying and selling carbon as a commodity cannot be ignored. Digital transformation is increasingly valued, and carbon policies can better play their role and promote high-quality development of the manufacturing industry in synergy with other economic policies.

This article theoretically analyzes and quantitatively evaluates the repercussions of carbon trading policies on digital transformation of enterprises, providing reference for better enforcement of environmental regulatory measures and optimization of related policies in the future. However, as this article only focuses on whether the provinces and cities where the relevant enterprises are located have implemented carbon trading policies, it does not analyze the effects of fluctuations in carbon trading costs and scale on the digital transformation of enterprises during the carbon trading process. Therefore, in future research, this aspect can be taken as a starting point to continuously track the consequences of carbon trading regulations on digital transformation of enterprises, and further evaluate the impact of carbon market regulations.

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