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The Effect of Environmental Information Disclosure on Green Total Factor Productivity: Evidence from Quasi-Natural Experiments on Cities in China

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Abstract: The relationship between environmental regulation and green economic growth has become a focal issue in China. This study utilizes the environmental information disclosure (EID) policy as a quasi-natural experiment in the Chinese context. Using a sample of 280 Chinese cities from 2003–2019 and measuring urban green total factor productivity (GTFP), the propensity score matching and difference-in-difference methods are applied to assess the impact mechanism of EID on urban GTFP in China. The results show that, first, the urban GTFP showed a decreasing trend from 2003 to 2008 and a general increasing trend from 2009 to 2019. The EID policy had a significantly positive impact on GTFP, and this finding remained robust after a series of tests. Second, the policy effect of EID was more pronounced in large and medium-sized cities than in small cities and eastern and central regions. The mechanism analysis shows that a positive effect from EID on GTFP in cities can be achieved through green technological innovation and industrial agglomeration.

Keywords: environmental information disclosure; green total factor productivity; green technological innovation; industrial agglomeration

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1. Introduction

Cleaner production is the key to green economic development [1]. The 2018 Global Environmental Performance Index Report, released by the Yale Center for Environmental Law and Policy, shows that China ranks 120th out of 180 participating countries and regions in the Environmental Performance Index. In this context, the need for the green transformation of the urban economy in Chinese cities is urgent. In economic terms, the green transformation of the economy refers to the process of gradual transformation of economic development to "reducing pollution emissions and increasing sustainable development capacity", i.e., a process of continuous improvement of green total factor productivity (GTFP) [2,3].

As an important tool to promote the green transformation of the economy [4], the effect of environmental regulation on GTFP has become a focal issue in China [5]. Scholars have conducted many studies on the relationship between environmental regulation and GTFP, which mainly involve three perspectives. The first group of views supports the "Porter hypothesis" that environmental regulations can increase GTFP [6–8]. Zhang et al. [9] and Yang et al. [10] conclude that environmental regulations can help increase total factor productivity growth [11]. The second group of arguments supports the "cost of compliance theory" [12–14], which argues that environmental regulation increases the cost of environmental management for firms and reduces firm productivity [15,16]. The third group of views argues that there is uncertainty about the effect of environmental regulation on GTFP [17]. The relationship may be directly related to the heterogeneity of environmental regulation instruments [18,19]. Whether the relationship conforms to the Porter hypothesis or the cost of compliance perspective, the ultimate point is to find a more reasonable environmental regulation policy to enhance GTFP [20]. Environmental information disclosure (EID) has become an important alternative to combat regional environmental pollution problems in Western developed countries [21–23]. Due to differences in the political system, China has long been considered an "environmental-information-poor country" [24,25]. EID has become a focal issue in the process of environmental governance in China [26]. Many studies have begun to focus on environmental-information disclosure behavior and its impact in developing countries, including China. Previous studies have mainly explored the relationship between EID and corporate decision-making, financing constraints, management capability, corporate performance, corporate exports, and stock prices [27–31]. Studies have also analyzed the relationship between EID and environmental pollution [32–34]. In summary, the studies on EID have mostly focused on the micro-firm level, while few studies have examined the impact of EID at the macro level, and its mechanism of action on urban GTFP has not been strongly tested.

For a long time, the rapid urbanization in China, which has been dominated by heavy industries, has been largely responsible for the deterioration of the urban environment. The crude economic development model in China, characterized by high input and emissions, has severely constrained the sustainable development of the urban economy. As the world's largest emerging economy, China has been under enormous pressure to address the challenges of urban environmental pollution. It is imperative that China adopt more environmental regulation policies to enable cities to complete the transition to a green economy [35]. EID policy has been in place in China since 2008. As an important component of the informal environmental regulatory system, the effectiveness of EID has not yet been robustly tested, particularly at the level of the urban economy. In this context, it is important to consider whether EID can improve urban GTFP, whether the effect of EID on GTFP varies according to regional conditions, and what the mechanisms of impact of EID are on urban GTFP. Answering the above questions has become the focus of academic and social attention. Therefore, first, to identify the role of EID on GTFP, using a sample of 280 Chinese cities from 2003–2019, this study applies the propensity score matching and difference-in-difference to examine the effect of EID on urban GTFP in China. Second, to further test the heterogeneity of the role of EID, considering the differences in underlying conditions between cities, this study examines the role of EID in terms of city location and city size. Third, to explore the mechanisms of the effect of EID, this study adopts the mediation effect model to identify the mechanism of the effect of EID on GTFP from the perspective of green technology innovation and industrial agglomeration, respectively.

The rest of this study is as follows. The second part presents the policy background, analyzes the effect mechanisms of EID on GTFP, and proposes the research hypotheses. The third part involves the research design, including model specification, variable selection, and data sources. The fourth part describes the empirical results, including the baseline regression, robustness tests, heterogeneity tests, and mediating effects tests. The fifth part provides the discussion and conclusions.

2. Policy Background and Research Hypotheses

2.1. Policy Background

Command-control regulation and market-based regulation are the main environmental regulation tools used in China. Due to the uncertainty of the legislation and the administrative enforcement interpretation of the State Environmental Protection Administration (SEPA), environmental information has not been actively disclosed for a long time. Compared with other developed countries, China is late in incorporating environmental information disclosure into environmental laws and regulations. In 2008, China began implementing the Measures for Disclosure of Environmental Information (for Trial Implementation). Since then, voluntary environmental regulation has gradually gained attention in China. The environmental non-governmental organization is gradually being established. The China Public Environment Research Center (IPE) and the Natural Resources Defense

Council (NRDC) jointly released the Pollution Source Information Disclosure Index (PITI). This initiative is a useful attempt to evaluate environmental information disclosure in Chinese cities. The first phase of the assessment was released in June 2009 and made public the environmental information of 112 cities, including 24,345 environmental regulatory records. In 2013, the organization publicized the environmental information of 120 cities, including 338,651 environmental regulatory records. After the release of the first PITI evaluation results, cities, including Ningbo and Guangzhou, have also started to release timely information on pollution source supervision.

2.2. Research Hypotheses

Environmental information disclosure (EID) can ensure the public's right to know and participate in the environmental protection policies of the government and the pollution reduction of firms, which can generate a direct or indirect effect on green total factor productivity (GTFP). In the face of severe urban pollution, the public can exercise their rights through petitions, complaints, public opinion, and media to put pressure on local government, with the result that the environmental protection department and firms take action to avoid potential loss of reputation and market competitiveness [36]. To remain competitive in the market, firms will focus more on green products [37], which will help improve resource utilization efficiency [9,38]. As an important way to gain social recognition and deliver information on environmental management approaches, EID can disseminate more information about corporate pollution reduction, which can reduce information asymmetry, help enterprises to obtain the support and trust of investors [39], and improve the input–output efficiency of innovation [40], promoting green total factor productivity. As shown in Figure 1, this study focuses on the effects of EID and examines the mechanism of its impact on GTFP.

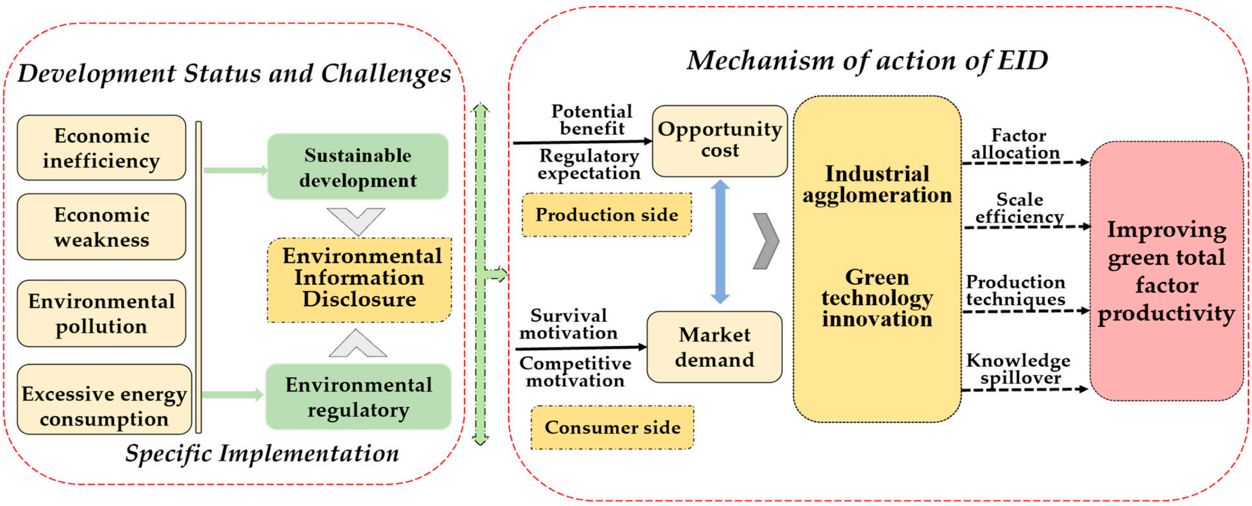

Figure 1. Mechanistic transmission diagram of EID and GTFP.

Hypothesis 1 (H1). *The environmental information disclosure policy has a significant promotional effect on GTFP.*

The EID can improve the GTFP of cities by promoting green technological innovation. As shown in Figure 1, on the production side, according to the opportunity cost theory, after implementing the EID system companies need to respond to environmental regulations passively or actively. Obviously, the active approach (e.g., green technology innovation) is more expensive than the passive approach (e.g., payment of emission fines), but it also has greater potential benefits [22]. However, the Chinese government's commitment to environmental management is evident. Under this expectation, firms are more likely to engage in green technology innovation to reap potential benefits. The existence of an environmental information disclosure system reduces the opportunity cost for firms to achieve technological progress. On the consumer side, with the improvement of public awareness of the need for environmental protection, the market demand for clean products is increasing day by day. Some technologically backward enterprises have to improve the green attributes of their products to meet the market's green consumer demand [39]. Technologically advanced enterprises, on the other hand, strive to improve their green technology level for competitive motives. Green technology innovation reduces unit energy consumption, increases unit output, and enhances green total factor productivity by improving production processes and organization [38].

Hypothesis 2 (H2). *The environmental information disclosure policy can improve GTFP through green innovation technology.*

In addition, EID can improve GTFP by industrial agglomeration. On the one hand, to decrease environmental regulation costs, the diversified service industry will move closer to industrial agglomeration areas [41]. Under the mechanism of sharing and learning, firms can reduce the cost of searching for information and trading products by sharing labor market and intermediate input market information [42]. A degree of industrial agglomeration can improve efficiency in the division of labor and optimize resource allocation [40], with the result that the GTFP is improved. On the other hand, with a strong focus on environmental pollution and improving public environmental protection awareness, there is a direct relationship between environmental policy and industry transfer, and the policy directly affects the choice of company location [43]. Not only does strict policy force highly polluting enterprises to move to other regions or exit from the local market, but it can also force these companies to accelerate technology upgrading and enlarge their agglomeration scale, improving GTFP.

Hypothesis 3 (H3). *The environmental information disclosure policy can improve GTFP through industrial aggregation.*

3. Research Design

3.1. Model Specification

To estimate treatment effects, the double difference-in-difference (DID) method is used to assess the intertemporal effects of the policy implementation. Compared to ordinary regression models, the double difference-in-difference approach (DID) largely avoids interference with endogeneity issues due to the absence of reverse causality problems. Compared with traditional methods for assessing policy effects, the interaction term setting of the double difference-in-difference approach (DID) makes its estimation results more accurate. Based on the environmental information disclosure policy, the PSM-DID model was employed to examine the net effect of policy on GTFP. In 2008, the PITI firstly disclosed the environmental information of 113 cities in China. The number of cities increased to 120 in 2013, offering a quasi-natural experiment using the DID model employed in this study. The list of cities is given in Appendix A [Table A1]. The sample consisted of 280 cities in China. The dummy variable, *treated*, was set based on whether the city disclosed environmental information. $treated_i$ indicated the information disclosure status of city, i, i.e., if city i disclosed environmental information, $treated_i = 1$; if city i did not disclose any information, $treated_i = 0$. We set the dummy variable, $Time_t$ based on when the city disclosed environmental information. $Time_t$ indicated the post-processing period; i.e., when the city disclosed environmental information and the following years, $Time_t = 1$; otherwise. $Time_t = 0$. The core explanatory variable was the $treated_i \times Time_t$, an interaction term (*DID*) of a dummy variable equal to 1 after city i disclosed environmental information, and equal to 0 otherwise.

Under theoretical naturalistic conditions, the samples should be randomly selected, meaning that the cities in the treated and untreated groups should conform to the random selection process, but it was not a randomized process. To test the robustness of the estimated results, the limitation of random selection was relaxed using the propensity score matching (PSM) method to match the treatment group with the control group. Additionally, the variables, including Fin, Fdi, Sec, Inv, and Hum, were first employed as matching variables, used the logistic model to calculate the propensity scores of every city, and matched the scores. Next, the effect of the environmental information disclosure policy on GTFP was estimated using the DID method. To examine the influence of the EID policy on GTFP, the model was constructed as follows:

$$y_{it} = \beta_0 + \beta_1 \mathrm{DID}_{it} + \sum \gamma_j x_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{1}$$

where y_{it} is the explained variable representing the GTFP, i refers to city, t refers to year, and $\mathrm{DID}_{\mathrm{it}}$ represents the dummy variable interaction term (*treated* × *time*). x_{it} represents the control variable. μ_i and η_t represent individual fixed effect and year fixed effect, respectively. ε_{it} is a random error term. This study focused on the coefficient of interaction term β_1, which represents the net effect of the EID policy on GTFP. To determine the robustness of the baseline regression results, a series of tests (including the parallel-trend hypothesis test, dynamic analysis, counterfactual test, and placebo test) were conducted.

3.2. Selection of Variables

3.2.1. Dependent Variables

Green total factor productivity (GTFP) is based on the traditional total factor productivity framework and incorporates environmental factors, such as environmental pollution and energy consumption. To overcome the problems of DMU effective distinction, slack variable, and cross-period comparison, this study used the GML index to calculate the cities' GTFP based on the SBM formula. Assuming that each decision unit contains N types of factor inputs, $x_{in} = (x_{i1}, x_{i2,}, \ldots, x_{iN}) \in R_N^+$ where i denotes the $i-$ th city, and we obtain M expected output results, $y_{\mathrm{im}} = (y_{i1}, y_{i2,}, \ldots, y_{iM}) \in R_M^+$, and K non-expected output results, $b_{ik} = (b_{i1}, b_{i2,}, \ldots, b_{iK}) \in R_K^+$. Based on the directional distance function of SBM (the specific formula can be found in Appendix B), to avoid the problem of unsolved linear programming, the GML index is calculated as follows:

$$\mathrm{GML}_t^{t+1} = \frac{1 + s_v^G\left(x^t, y^t, b^t, g^x, g^y, g^b\right)}{1 + s_v^G\left(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b\right)} \tag{2}$$

From period t to t + 1, if the values of the GML index are greater than 1, equal to 1, or less than 1, this indicates that the urban GTFP is increasing, constant, or decreasing, respectively. Furthermore, the GML_t^{t+1} index can be decomposed into the product of the global efficiency change index $\left(\mathrm{GEC}_t^{t+1}\right)$ and the global technological change index $\left(\mathrm{GTC}_t^{t+1}\right)$. The specific decomposition is as follows:

$$\mathrm{GEC}_t^{t+1} = \frac{1 + s_v^t\left(x^t, y^t, b^t, g^x, g^y, g^b\right)}{1 + s_v^t\left(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b\right)} \tag{3}$$

$$\mathrm{GTC}_t^{t+1} = \frac{\left[1 + s_v^G\left(x^t, y^t, b^t, g^x, g^y, g^b\right)\right] / \left[1 + s_v^t\left(x^t, y^t, b^t, g^x, g^y, g^b\right)\right]}{\left[1 + s_v^G\left(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b\right)\right] / \left[1 + s_v^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b\right)\right]} \tag{4}$$

From period t to $t + 1$, if the values of GEC_t^{t+1} and GTC_t^{t+1} are greater (or less) than 1, this indicates an increase (or decrease) in combined efficiency and an increase (or decrease) in technological progress, respectively.

The input variables selected in this study included labor, capital, and energy consumption. The labor force indicator was measured as the number of city employees at the end of the period. Considering the availability of the data, the city's electricity consumption was used as a proxy variable for the energy consumption indicator. The capital input indicator was measured by the perpetual inventory method. The desired output indicator was the real GDP of the city. The non-desired output indicators included industrial soot emissions, wastewater emissions, and sulfur dioxide emissions.

3.2.2. Independent Variable

The core explanatory variable was DID, representing whether the environmental information disclosure (EID) policy was implemented. According to the experimental grouping dummy variable (*treated*) and experimental staging dummy variable (*time*), this study defined the interaction items ($treated_i \times Time_t$) as the core explanatory variable.

3.2.3. Control Variables

In line with previous studies, the control variables included government intervention (Gov), measured as the ratio of government expenditure to revenue; foreign direct investment (Fdi), measured as the proportion of foreign capital used in GDP (logarithm); industrial structure upgrade (Sec), measured as the proportion of the added value of tertiary industry in GDP; economic development (Pcgdp), measured as the per capita gross domestic product (logarithm); human capital (Hum), measured as the total number of people employed in the three industries (logarithm). In addition, this study used financial development (Fin), measured as the proportion of total deposits and loans of local financial institutions in GDP, and fixed asset investment (Inv), measured as the proportion of total social fixed asset investment in GDP, when conducting propensity score matching.

3.3. Sample Selection and Data Sources

As some regional data were missing, data from 280 cities were ultimately selected. The data on economy and environment came from the China City Statistical Yearbook (2003–2019) and Statistical Yearbook of Provinces and Cities, and the linear interpolation method was used to supplement missing values. The data on green technology patents were obtained from the China Research Data Service Platform database (CNRDS). In addition, the GDP of each city was adjusted by the GDP deflator, using 2003 as the base period. Although the Chinese Urban Statistical Yearbook for 2021 has been published and relevant data for 2020 were available, data on green innovation patents and some indicators of GTFP have not yet been made publicly available. For consistency, the sample period chosen for this study was 2003–2019. It is noted that to be consistent with the data on the above variables, the GTFP for each city was calculated with the input–output indicator data spanning the period from 2002 to 2019. The descriptive statistics for the variables are shown in Table 1.

Table 1. Descriptive statistics.

Variables	No. of Obs.	Mean	Std	Min	Max
GTFP	4760	0.421	0.233	0.010	1.469
DID	4760	0.421	0.494	0	1
Gov	4760	2.198	1.836	0.029	2.702
Sec	4760	0.388	0.099	0.058	0.853
Fdi	4760	0.022	0.028	0	0.775
Pcgdp	4760	10.235	0.847	4.595	15.675
Hum	4760	3.415	0.817	1.399	6.895
Fin	4760	2.172	1.114	0.046	21.301
Inv	4760	0.667	0.304	0.110	4.595

4. Results

A sample of 280 cities in China from 2003–2019 was selected for this study. According to the criteria for dividing economic regions published by the National Bureau of Statistics, the sample was divided into eastern, central, and western areas. Before building the model, the green total factor productivity (GTFP) was calculated. We used the 2002 data as the base period. We applied Equation (2) to calculate the GTFP of each city from 2003 to 2019 and, on this basis, used Equations (3) and (4) to decompose it into the global efficiency change index (GEC) and the global technological change index (GTC). The calculation results are shown in Table 2.

Table 2. The results of the GTFP calculation.

Year	GTFP				GEC				GTC			
	Overall	East	Central	West	Overall	East	Central	West	Overall	East	Central	West
2003	1.037	1.007	1.016	1.101	0.982	0.989	0.972	0.988	0.995	0.993	0.966	1.033
2004	1.014	0.989	1.009	1.051	0.986	0.988	0.985	0.986	0.891	0.913	0.874	0.884
2005	1.006	1.019	1.006	0.989	1.004	0.973	0.963	1.092	0.954	0.984	0.969	0.896
2006	0.988	0.999	0.957	1.014	0.979	0.969	0.937	1.008	0.758	0.846	0.678	0.747
2007	0.937	0.922	0.935	0.951	1.039	0.875	0.828	0.755	0.824	0.898	0.764	0.804
2008	0.939	0.980	0.926	0.919	0.972	0.988	0.987	0.967	0.973	0.930	0.956	0.939
2009	1.033	1.060	1.015	1.034	0.958	1.006	0.951	0.917	0.992	1.008	0.985	0.981
2010	1.070	1.128	1.064	1.004	1.043	1.079	1.060	0.976	1.050	1.062	1.029	1.061
2011	1.094	1.082	1.132	1.064	1.061	0.947	1.119	1.132	1.083	1.165	1.059	1.008
2012	1.072	1.130	1.015	1.072	1.091	1.106	1.048	1.125	1.062	1.048	1.085	1.052
2013	1.071	1.092	1.067	1.048	1.093	1.047	1.097	1.146	1.028	1.033	0.991	1.067
2014	1.022	1.027	1.019	1.178	1.018	0.972	1.046	1.040	1.142	1.123	1.148	1.158
2015	1.029	1.035	0.998	1.061	1.108	1.131	1.061	1.137	1.103	1.055	1.119	1.143
2016	1.180	1.148	1.244	1.141	1.075	1.050	1.114	1.059	1.120	1.186	1.087	1.078
2017	1.113	1.102	1.126	1.109	1.374	1.306	1.422	1.400	1.136	1.136	1.144	1.125
2018	1.280	1.356	1.232	1.251	1.781	1.879	1.882	1.531	1.537	1.338	1.632	1.670
2019	1.208	1.215	1.164	1.198	1.124	1.163	1.064	1.074	1.250	1.285	1.132	1.175

During 2003–2019, the overall urban green total factor productivity (GTFP) had an average annual growth rate of 0.90%. It showed a decreasing trend from 2003 to 2008 and a general increasing trend from 2009 to 2019. Specifically, from 2003 to 2008, the mean value of GTFP was 0.987, with a decreasing trend from 1.037 to 0.939. During this period, despite China's rapid economic growth, urban environmental air pollution became increasingly serious, and the amount of industrial solid waste and municipal waste increased. During 2009–2019, the mean value of GTFP was 1.107, and its value increased from 1.033 to 1.208, showing an upward trend with an average annual growth rate of 1.4%. A possible explanation is that after the financial crisis, the government's increasing attention to environmental issues and the enhanced environmental management capacity led to a gradual increase in urban GTFP. It is notable that from 2003–2019, similarly to the trend of GTFP variation, integrated efficiency (GEC) and technological progress (GTC) showed a decreasing and then an increasing trend, with their average annual growth rates being 0.79% and 1.35%, respectively. From 2009 to 2019, the average annual growth rates of GEC and GTC were 1.5% and 2.1%, respectively. This indicates that since 2009, the increase in GTFP has been driven mainly by the growth of technological progress in cities.

In addition, the mean values of GTFP in the eastern, central, and western regions were 1.086, 1.090, and 1.078 from 2003 to 2019, with average annual growth rates of 0.96%, 0.53%, and 0.49%, respectively. During 2009–2019, the average annual growth rates of EC in the Eastern, Central, and Western regions were 1.3%, 1%, and 1.4%, respectively, which indicates that GEC in the Western region was growing faster. Correspondingly, the average annual growth rates of GTC were 2.2%, 1.3%, and 1.6%, respectively. The average annual growth rates of GTC were significantly higher than the corresponding GEC, which indicates that the growth of urban GTFP since 2009, whether in the east, central, or west, is mainly due to the significant increase in technological progress.

4.1. Balance Test of Propensity-Score-Matching Method

To identify whether there was a significant difference between the treated and control groups of matched variables after matching, a balance test of propensity score matching was conducted; the results are shown in Table 3. According to the standard deviation and probability, it was found that the absolute value of the standard deviation was about 5%, and the p-value of the standard deviation was less than 0.1 before matching and more than 0.1 after. The results indicate that there was no significant systematic difference after matching, which met the conditions of the balance test. This suggests that we matched cities that had implemented EID policy with cities that were highly similar to them in all aspects but had not implemented that policy, indicating that the data we matched are suitable for regression analysis using the DID method.

Table 3. The results of the balance test.

Variables	Status	Treated	Untreated	Std (%)	p-Value
Fin	Before matching	2.895	2.379	43.5	0.000
	After matching	2.383	2.309	6.2	0.649
Fdi	Before matching	0.020	0.013	38.6	0.001
	After matching	0.016	0.016	−2.5	0.865
Sec	Before matching	0.457	0.406	−39.8	0.002
	After matching	0.429	0.418	−1.5	0.892
Inv	Before matching	0.781	0.935	−44.8	0.000
	After matching	0.861	0.899	−11.8	0.382
Hum	Before matching	102.4	32.849	80.4	0.000
	After matching	48.234	45.986	2.6	0.538

4.2. PSM–DID Regression Analysis

The DID estimation model was employed to examine the effect of EID on GTFP, controlling for year and individual fixed effects. Table 4 reports the regression results for Equation (1). In Table 4, column (2) shows the estimation results using the DID model. Column (3) shows the estimation results using the PSM-DID model. The regression coefficients of DID are greater than zero in columns (1)–(3), regardless of the inclusion of control variables. Specifically, the regression coefficient of DID in column (3) is 0.144 and significant at the 1% level, indicating that EID can positively affect the green total factor productivity. The results suggest that cities with environmental information disclosure can achieve faster economic green growth, supporting Hypothesis H1. Compared with cities that do not disclose environmental information, cities that disclose environmental information have significantly higher GTFP. As a public-participation type of environmental regulation, environmental information disclosure policy is an important tool to effectively improve the green total factor productivity of cities.

Table 4. Baseline regressive results.

Variables	(1)	(2)	(3)
DID	0.163 ***	0.118 ***	0.144 ***
	(3.64)	(3.09)	(3.39)
Fdi		−0.021 *	−0.020 *
		(−1.87)	(−1.88)
Gov		−0.009	−0.014 *
		(−1.00)	(−1.73)
Pcgdp		0.300 ***	0.289 ***
		(3.02)	(2.73)
Sec		0.003	0.232
		(0.80)	(0.65)
Hum		−0.417 ***	−0.537 ***
		(−7.93)	(−8.47)
constant	−1.630 ***	−3.096 ***	−2.606 ***
	(−50.70)	(−3.23)	(−2.59)
City fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
R^2	0.56	0.62	0.62

Notes: "***", "*" represent 1% and 10% significance levels, respectively, and the value in brackets is the t value.

4.3. Robustness Test

4.3.1. Parallel-Trend Hypothesis Test and Dynamic Analysis

The results of the baseline model reflect the average effect of EID on GTFP and do not reflect the differences in that effect over time. For this reason, the dynamic effects of the EID policy were empirically examined by constructing a multi-period DID parallel-trend test model. In this process, "0" was used to represent the time point when the EID policy started to be implemented, and the numbers on the left and the right represented time differences before and after the policy was put into effect, respectively. If the estimated coefficient for each period on the left was essentially significant at zero, the difference between the treated group and the untreated group was not significant before implementing the EID policy. Figure 2 plots the changes in the estimated coefficients at 95% confidence intervals.

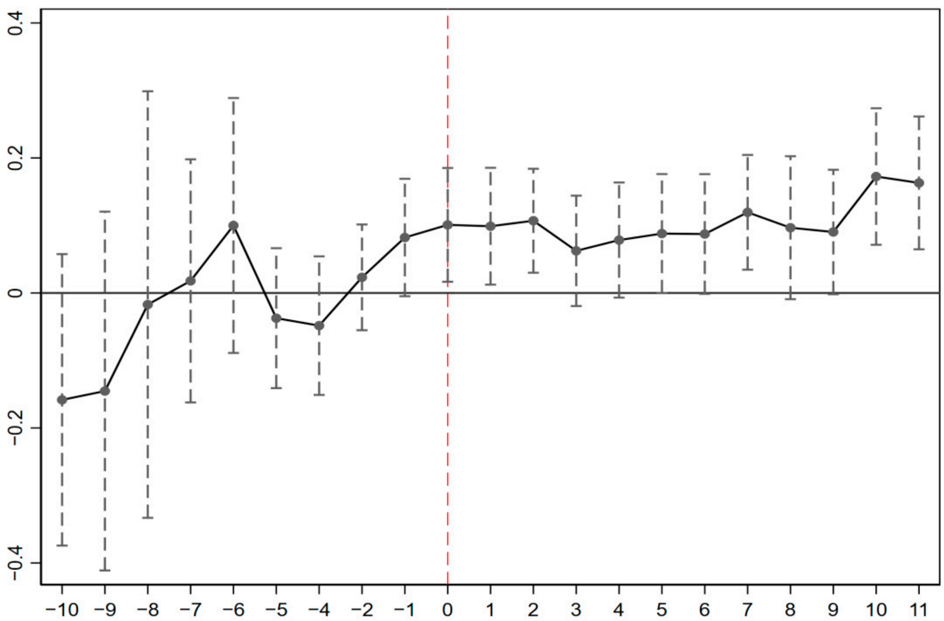

Figure 2. The dynamic effect of policy on GTFP. Notes: the dotted lines shows the change of the tested coefficients over time.

As shown in Figure 2, the estimated coefficients were essentially significant at zero before the policy was carried out, indicating that there was no distinct difference between the treated and untreated groups before the implementation of the EID policy, satisfying the parallel trend hypothesis. The estimated coefficients became remarkably larger after the implementation of the EID policy, indicating that the promotion effect of EID had increased. Therefore, the regression results estimated with the PSM-DID method above are robust.

4.3.2. Counterfactual Test

Although the EID policy contributed significantly to the enhancement of GTFP, as shown in Table 4, the result may have been influenced by other related policies. Therefore, a counterfactual test was performed; i.e., the significance of the coefficient of DID was analyzed before the implementation of the EID policy. If the estimated coefficients did not pass the significance-level test, indicating that there was no systematic difference between the treatment and control groups, the estimation results were given a high degree of confidence; conversely, if the coefficients passed the significance-level test, the baseline regression results were not robust.

To conduct the counterfactual test, the implementation of the EID policy was advanced by 1, 2, and 3 years. The corresponding estimation results are shown in Table 5. As shown in columns (1)–(3), the coefficients of DID were 0.059, 0.036, and 0.017, respectively. They were insignificant at 10%, indicating that the EID policy failed to significantly affect GTFP after advancing the implementation time by 1, 2, and 3 years, respectively.

Table 5. Counterfactual test of the effect of policy on GTFP.

Variables	(1)	(2)	(3)
DID-adcance1	0.059 (1.53)		
DID-adcance2		0.036 (0.94)	
DID-adcance3			0.017 (0.45)
Control variables	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
R^2	0.58	0.58	0.58

4.3.3. Placebo Test

In addition, to test whether the baseline model results were caused by unobservable factors, a placebo test was also conducted by randomly assigning pilot cities. Five hundred random samples were tested, baseline regressions were run according to Equation (1), and the distribution of the 500 estimated coefficients and their associated *p*-values were plotted, as shown in Figure 3. In Figure 3, the coefficients of DID in the placebo test were concentrated around zero, and the corresponding *p*-values were mostly greater than 0.1, while the actual coefficient of DID was 0.144, which is significantly different from the coefficient in the placebo test. Therefore, we were able to basically exclude the influence of other random factors on the baseline model.

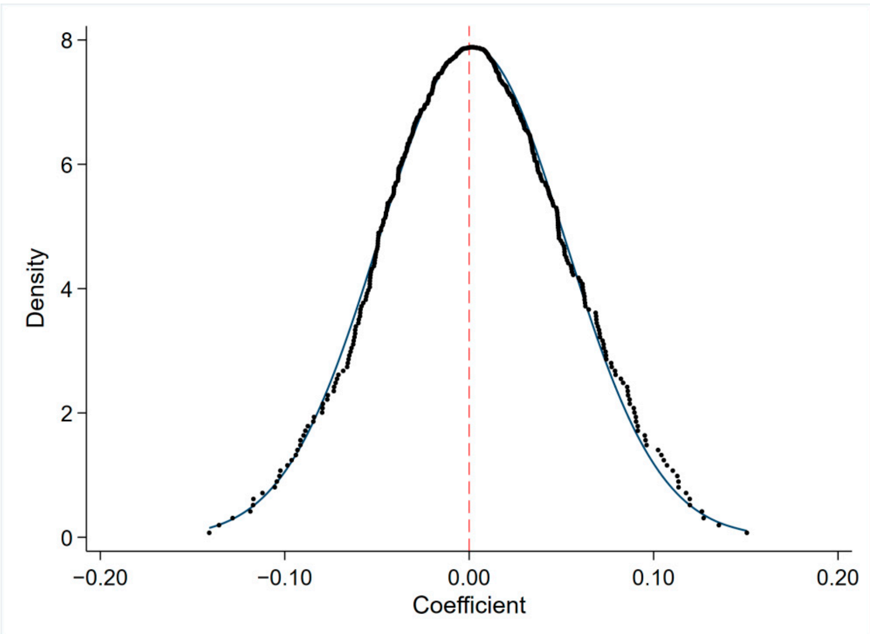

Figure 3. Placebo test. Notes: the dots are from 500 simulations randomly, which show the cumulative distribution of the tested coefficients, and the line shows the normal distribution.

4.4. Heterogeneity Analysis

This study further tested the heterogeneity of the role of EID by considering the differences in location and underlying conditions between cities. Based on the criteria of economic region division, this study divided the sample into eastern, central, and western areas. In addition, according to the classification criteria set by the Chinese State Council, city size is classified into small cities, medium cities, large cities, megacities, and supercities, depending on their resident population. In this study, to avoid model error due to the small sample, the 280 cities were divided into two categories, one comprising small cities and the other comprising large and medium cities (including the latter four groups). In Table 6, columns (1–3) correspond to the regression estimation results for the eastern, central, and western regions, respectively. The regression coefficients of DID in columns (1) and (2) are 0.295 and 0.128, respectively, and are statistically significant at 1%. The coefficient in column (3) is 0.044 and is not significant. This indicates that the effect of EID on green total factor productivity (GTFP) varied significantly between regions. The positive effect of the EID policy was more pronounced in the eastern and central regions. Columns (4) and (5) correspond to the regression estimation results for large and medium-sized cities and small cities, respectively. The regression coefficient of DID in column (4) is 0.168, which passes the significance test at the 1% level, while the coefficient in column (5) is 0.066, which is not significant. The results show that the effect of environmental information disclosure (EID) on green total factor productivity (GTFP) differs significantly across cities of different sizes. The positive effect of the EID policy is more pronounced in large and medium-sized cities. The reason may be that, compared to small cities, the public in large and medium-sized cities is relatively aware of environmental protection issues, more able to actively monitor the government and enterprises and encourage them to disclose environmental information, as well as more able to stimulate innovation among enterprises.

Table 6. Heterogeneity test results.

Variables	East	Central	West	Large-Medium	Small
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DID	0.295 *** (3.11)	0.128 *** (3.03)	0.044 (1.10)	0.168 *** (4.72)	0.066 (1.47)
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes
R^2	0.63	0.58	0.60	0.62	0.61

Notes: "***" represents 1% significance level, and the value in brackets is the t value.

4.5. Mechanism Analysis

Based on the previous theoretical analysis, this study chose industrial agglomeration (IA) and green technology innovation (TE) as intermediary variables and used the mediation effect test to identify the mechanism of the EID policy on GTFP. The model setting was as follows:

$$\mathrm{GTFP}_{it} = \beta_0 + \beta_1 \mathrm{DID}_{it} + \sum \gamma_j x_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (5)$$

$$m_{it} = \alpha_0 + \alpha_1 \mathrm{DID}_{it} + \sum \gamma_j x_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (6)$$

$$\mathrm{GTFP}_{it} = \theta_0 + \theta_1 \mathrm{DID}_{it} + \theta_2 m_{it} + \sum \gamma_j x_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (7)$$

where GTFP_{it} represents the green total factor productivity, DID_{it} represents dummy variable interaction term ($treated \times time$), and x_{it} represents control variables. m_{it} represents intermediary variables, which consist of green technology innovation (TE) measured by the logarithm of the city's number of green patents plus one, and industrial agglomeration (IA) measured by the area entropy index. The coefficient of DID determined in the previous section was 0.144 and passed the 1% significance test. We continuously tested the α_1 in model (6) and θ_2 in model (7). If two coefficients passed the significance test, EID could affect GTFP by influencing intermediary variables. If θ_1 was still significant; this proved that the mediating variable had a partial mediating effect.

4.5.1. Mediating Effect of TE

Table 7 presents the estimation results for the mediation effect of TE. The coefficient of DID was significantly positive at the 1% level in column (1), indicating that EID had a significant positive impact on the green total factor productivity (GTFP). The coefficient of DID in column (2) was 0.192 and significant at the 1% level, suggesting that EID promoted urban green technology innovation activities. Furthermore, the coefficients of DID and TE in column (3) were 0.115 and 0.076, respectively, passing the significance test at the 1% level and showing that EID affected GTFP partly through green technology innovation, supporting Hypothesis H2. The implementation of the EID policy facilitates public monitoring of environmental pollution. It motivates enterprises to invest in green technology R&D and innovation, thus increasing green total factor productivity.

Table 7. Mediating effect test of TE.

Variables	GTFP (1)	TE (2)	GTFP (3)
DID	0.144 ***	0.192 ***	0.115 ***
	(3.39)	(4.80)	(3.02)
TE			0.076 ***
			(3.70)
Control variables	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
R^2	0.61	0.25	0.61

Notes: "***" represents 1% significance level, and the value in brackets is the t value.

4.5.2. Mediating Effect of IA

Table 8 presents the estimation results for the mediation effect of IA. The coefficient of DID in column (2) is 0.001 and significant at the 1% level, proving the policy plays a significantly positive effect on industrial agglomerations. Furthermore, the coefficients of DID and IA in column (3) are 0.128 and 3.29, respectively. The former passed the 1% level of significance test, and the latter passed the 5% level of significance test, showing that EID affects GTFP partly through industrial agglomerations, supporting Hypothesis H3. The implementation of the EID policy facilitates public monitoring of environmental pollution. It motivates enterprises to invest in green technology R&D and innovation, thus increasing green total factor productivity. The environmental information disclosure policy (EID) will motivate enterprises to join industrial agglomeration parks to reduce production costs. The increase in industrial agglomeration is conducive to promoting the flow and integration of production factors. It improves resource utilization efficiency and reduces pollution emissions per unit through division of labor, thus promoting green economic development.

Table 8. Mediating effect test of IA.

Variables	GTFP (1)	IA (2)	GTFP (3)
DID	0.144 ***	0.001 ***	0.128 ***
	(3.39)	(2.90)	(3.29)
IA			3.29 **
			(1.98)
Control variables	Yes	Yes	Yes
City fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
R^2	0.61	0.03	0.61

Notes: "***", "**" represent 1% and 5% significance levels, respectively, and the value in brackets are the t value.

5. Discussion and Conclusions

5.1. Discussion

The environmental information disclosure system is an important initiative to promote the modernization of ecological and environmental governance capacity. It is of great practical significance to analyze the influence of EID on urban GTFP for the green transformation of the economy. Using 280 cities in China from 2003 to 2019 and measuring urban green total factor productivity, this study constructed a PSM-DID model and a mediating effect model to test the impact of EID on urban GTFP and its mechanisms. Previous studies have explored the relationship between environmental regulation and TFP, but these studies have mainly focused on command-based regulation and market-based regulation. In addition to the formal environmental regulation mentioned above, informal environmental regulation (voluntary environmental agreements, information disclosure, etc.) has become an important environmental protection measure. Studies thus far have mainly focused on examining the effects of EID on corporate behavior, such as corporate financial performance, corporate governance, and corporate reputation value, while few studies have examined the effects of EID on GTFP at the macro level. This study analyzes the macro effects of EID at the city level, which enriches the research on EID assessment. In addition, EID was incorporated into the analytical framework of urban GTFP to explore the role of EID and its influence mechanisms, thereby expanding the research results of green total factor productivity and providing an empirical reference for further understanding the role of environmental information disclosure in developing countries. Generally, the conclusions of this study are the same as Zhong et al. and Feng et al. [33,34].

5.2. Conclusions

This study, using a sample of 280 Chinese cities, tested the impact of EID on urban GTFP and their mechanisms by applying the PSM-DID model and the mediation effect model. Furthermore, this study analyzed the heterogeneity of the effect of EID. The findings are as follows. First, EID effectively promoted green total factor productivity. Huang and Chen [32] found that EID had an inhibitory effect on waste and SO_2 emissions. EID can reduce information asymmetry and ensure the public's right to know about regional pollution reduction [36]. To gain market competitiveness, companies pay more attention to green products and work toward clean production [37]. Second, the effect of EID on GTFP was more pronounced in large and medium-sized cities and in eastern and central regions. In large and medium-sized cities or economically developed areas, the public was relatively more aware of environmental protection and more able to monitor the environmental information of enterprises, which was conducive to stimulating the vitality of green innovation [39]. Third, the mechanism test showed that the effects of EID on GTFP were mainly realized through green technology and industrial agglomeration. Feng et al. [34] found that EID can effectively curb urban haze pollution, in which green technological innovation plays an important role. EID reduced the opportunity cost for firms to achieve technological progress [22]. Enterprises were more likely to make efforts to improve their green technology to reap the potential benefits [38]. To reduce the cost of environmental regulation, enterprises would move closer to industrial clusters [42], which can reduce the cost of trading products and realize the environmental scale effect [41].

Based on the above findings, the recommendations of this study are as follows. First, the authorities should pay attention to environmental information disclosure policies and form scientific environmental regulation systems. On the one hand, environmental protection departments can guide the public and the media to actively supervise urban environmental governance behavior, environmental litigation, and normative environmental constraints, making EID an important means of forcing economic green transformation and development. On the other hand, developing countries need to use public-participation-based environmental tools actively. Coupled with urban development conditions, relevant departments can combine environmental information disclosure policy with command-and-control and market-incentive environmental regulation tools. Second, this study found that green technology innovation has a mediating role. Since investment in technological innovation is characterized by long cycles and high adjustment costs, government departments can introduce a number of policies (including innovation subsidies, tax incentives for green products, intellectual property protection, etc.) to motivate enterprises to carry out green technological innovation activities and support them to upgrade their production technologies. In addition, developing countries can introduce and absorb foreign advanced clean technology, which provides good conditions for upgrading the green technology level in the region. Third, for large-scale central cities, the government can encourage and guide the clustering of high-end industries and promote the sharing of basic resources by using emerging technologies, such as big data and industrial intelligence. For small-scale cities with less developed economies, we can combine the resource endowments and market demands of these regions to reasonably guide their industrial structure and achieve coordinated development of the economy and environment.

5.3. Limitations and Future Directions

The results of this study have some reference for achieving green development in regional economies. Because it is affected by objective conditions, this study has certain limitations. First, this study does not distinguish between the type, manner, or quality of urban environmental information disclosure, resulting in limitations in terms of the content of EID. Second, due to the difficulty of constructing indicators and limited public data, the non-desired output indicators when measuring urban GFTP in this study include only industrial soot emissions, wastewater emissions, and sulfur dioxide emissions but do not include other environmental pollutants. Subsequent research could be conducted with the help of textual analysis or big data technology to extract urban environmental disclosure information and collect regional environmental pollutant emission information to provide a basis for exploring the impact of EID on urban economic green growth.

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Appendix A

Table A1. The 120 cities with environmental information disclosure.

Classification	City
120 cities with environmental information disclosure	Ningbo, Beijing, Wenzhou, Qingdao, Hangzhou, Shanghai, Taizhou, Shenzhen, Changzhou, Guangzhou, Fuzhou, Zhongshan, Dongguan, Hefei, Foshan, Yantai, Suzhou, Nanjing, Nantong, Wuxi, Quanzhou, Jiaxing, Jinan, Shaoxing, Zhenjiang, Zibo, Xiamen, Weihai, Yangzhou, Shenyang, Chengdu, Shijiazhuang, Maanshan, Weifang, Dalian, Huzhou, Baoding, Handan, Tianjin, Yancheng, Chongqing, Wuhan, Lianyungang, Xuzhou, Zhengzhou, Tangshan, Jining, Luoyang, Zigong, Zhuhai, Rizhao, Wuhu, Taian, Nanchang, Nanning, Shantou, Sanmenxia, Jiaozuo, Taiyuan, Zaozhuang, Beihai, Guilin, Zhanjiang, Kunming, Yinchuan, Xian, Weinan, Deyang, Wulumuqi, Yichang, Changzhi, Changsha, Liuzhou, Jingzhou, Changed, Luzhou, Guiyang, Qinhuangdao, Haerbin, Baoji, Mianyang, Yanan, Shaoguan, Xiangtan, Nanchong, Tongchuan, Changchun, Huhehaote, Kaifeng, Shizuishan, Yuxi, Yueyang, Jiujiang, Anyang, Zunyi, Pingdingshan, Xianyang, Zhuzhou, Baotou, Qujing, Fushun, Chifeng, Anshan, Daqing, Xining, Eerduosi, Jilin, Yibin, Mudanjiang, Lanzhou, Qiqihaer, Panzhihua, Jinzhou, Yangquan, Jinchang, Benxi, Linfen, Zhangjiajie, Datong, Kelamayi

Appendix B

Considering the unexpected output, the SBM-based directional distance function is formulated as follows:

$$s_v^G\left(x^{t,i}, y^{t,i}, b^{t,i}, g^x, g^y, g^b\right) = \max \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M+K}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{k=1}^{K}\frac{s_k^b}{g_{ik}^b}\right)}{2} \tag{8}$$

$$s.t. \sum_{t=1}^{T}\sum_{i=1}^{I} z_i^t x_{in}^t + s_n^x = x_{in}^t, \forall n; \sum_{t=1}^{T}\sum_{i=1}^{I} z_i^t y_{im}^t - s_{nm}^y = y_{in}^t, \forall m; \tag{9}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} z_i^t b_{ik}^t + s_i^b = b_{ik}^t, \forall i; \sum_{i=1}^{I} z_i^t = 1, z_k^t \geq 0, \forall i; s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i \tag{10}$$

where $\left(x^{t,i}, y^{t,i}, b^{t,i}\right)$, $\left(g^x, g^y, g^b\right)$, and $\left(s_n^x, s_m^y, s_k^b\right)$ represent the input and output vectors, the direction vector, and the slack vector of the city, respectively.

For each decision unit, the set of production possibilities that contains non-expected outputs in the current period is:

$$P^t(x) = \begin{cases} \left(y^t, b^t\right) : \sum\limits_{i=1}^{I} \beta_i^t y_{im}^t \geq y_{im}^t, \forall m; \sum\limits_{i=1}^{I} \beta_i^t b_{ik}^t = b_{ik}^t, \forall k; \\ \sum\limits_{i=1}^{I} \beta_i^t x_{in}^t \leq x_{in}^t, \forall n; \sum\limits_{i=1}^{I} \beta_i^t = 1, \beta_i^t \geq 0, \forall i \end{cases} \tag{11}$$

where β_k^t s the weight of each cross-sectional observation, and if $\beta_k^t \geq 0$, it indicates constant payoff to scale, the $\sum\limits_{i=1}^{I} \beta_i^t = 1$. if $\beta_i^t \geq 0$, it denotes payoff to scale. Oh proposed the concept of a global production possibility set and constructed a global production possibility set $P^G(x)$, which solves the problem of comparing production frontiers horizontally in previous studies, denoted as follows:

$$P^G(x) = \begin{cases} \left(y^t, b^t\right) : \sum\limits_{t=1}^{T}\sum\limits_{i=1}^{I} \beta_i^t y_{im}^t \geq y_{im}^t, \forall m; \sum\limits_{t=1}^{T}\sum\limits_{i=1}^{I} \beta_i^t b_{ik}^t, \forall k; \\ \sum\limits_{t=1}^{T}\sum\limits_{i=1}^{I} \beta_i^t x_{in}^t \leq x_{in}^t, \forall n; \sum\limits_{t=1}^{T}\sum\limits_{i=1}^{I} \beta_i^t = 1, \beta_i^t \geq 0, \forall i \end{cases} \tag{12}$$

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