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Economic Growth, Environmental Efficiency, and Industrial Transfer Demonstration Zones of China: A Way Forward for CPEC

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ABSTRACT

Environmental efficiency, industrial transfer demonstration zones, and carbon transfer networks can impact the quality of the environment. This paper examines the relationship between environmental efficiency, carbon transfer networks, and national industrial transfer demonstration zones tested by utilizing some prefectural-level Chinese cities' panel data from 2003 to 2017 through the Different-in-Difference method as way forward for China Pakistan Economic Corridor (CPEC). The results show that environmental efficiency improved with industrial transfer demonstration zones by boosting the ability to innovate, government's expenditure on the environment, and regulatory frameworks for the environment. The findings reflect a significant increase in the GDP of the triennial industry while an insignificant decrease. Hence, to promote all-inclusive first-rate development, regional collaborative must be ensured during industrial transformation demonstration.

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1. Introduction

Over the last few decades, China has experienced unprecedented economic growth and emerged as a global manufacturing giant. In 2010, it became the world's second-largest economy by surpassing Japan (Wang et al. 2013). However, this rapid growth track proved unsustainable and eventually enhanced the carbon dioxide (CO₂) emission levels, industrial waste, air, and water contamination. In 2016, China was the largest CO₂ emitter by emitting 27.3% of the total carbon dioxide emissions. Besides, industrial solid waste, CO₂ emissions, and wastewater recorded 4.06;

2.72; and 1.77 times higher, respectively, in 2015 compared to 2000 (National Bureau of Statistics of China 2016).

Additionally, Yale University published the Environmental Performance Index (EPI) in 2018, ranked China 120 positions across 180 countries. EPI further mentioned that China's air quality is rapidly declining and initiating an acute health crisis (Wendling et al. 2018). As a result, the country faces multifaceted and disastrous environmental challenges that are causing socio-economic losses (Lyu et al. 2016; Chen et al. 2019). After recognizing the rapidly deteriorating environmental quality and, therefore, ameliorating it, China's governments at national and regional levels have developed comprehensive legislative frameworks and introduced strict environmental standards. In this regard, the recently introduced air pollution prevention and control action plan of 2013 and the plan for controlling water contamination of 2017 are some of the extraordinary measures (Tang et al. 2019). Moreover, in its 13th five-year socio-economic development scheme, China pledged to implement green economy strategies by securing ecological welfare and lowering greenhouse gases. Nevertheless, maintaining a fair balance between rapid economic growth and environmental capital is an enormous challenge for Chinese policymakers.

In 2010, China started to establish the National Industrial Zones in these areas o accumulates economic development in the western and central regions. Through substantial infrastructure development, fund transfer, and flexible credit services, the government facilitated the investors. As a result of such lucrative policies, industries from China's vibrant coastal areas tended to relocate their manufacturing processes to the relatively low-income central and western regions. According to the official statistics, in 2015, the value of domestically transferred industry within China was 2.5 times higher than the foreign capital influx (Lyons and Grable 2017).

Undoubtedly, industrial transfer generates employment opportunities, transfers advance technology, and spurs economic development (Zeng 2012; Huang et al. 2013). Nonetheless, related studies believed that industrial transfer exacerbates environmental quality through soil erosion, extensive water, and air contamination, acid rain, and massive deforestation. Moreover, the celebrated pollution haven hypothesis (PHH) establishes the industry relocation-environment links and characterizes industrial transfer as a significant reason for the environmental deterioration in the recipient host countries

In China's context, the literature on environment and industry transfer (FDI) contains comprehensive and detailed studies identifying the consequences of foreign capital on environmental performance (Dean et al. 2009; Marconi 2012; Xiao 2015; Salim et al. 2017; Dou and Han 2019). However, the research revealing the nexus between domestically transferred industries and the environment in China's context is limited. More specifically, after an extensive literature review, we could not find studies focusing on the environmental repercussions of National Industrial Zones in China. It indicates a gap in the literature concerning National Industrial Zones and China's environment, seeking immediate and systematic attention. Therefore, this paper conducts a thorough analysis of the environmental consequences of the national industrial transfer demonstration zones and presents an answer to the question. This study is a way forward for the China Pakistan Economic Corridor (CPEC), which has almost the same feasibility plans for industrial clustering and special economic zone.

The remaining paper is formatted as follows: Section 2 is a literature review; section 3

theoretical background; section 4 contains the method and data; section 5 is empirical results and discussion; and section 6 presents the conclusion and implications.

2. Literature Review

The literature divulging the nexus between industrial transfer and environmental efficiency is scarce. Nevertheless, few studies explain environmental efficiency because of FDI and energy. Moreover, the outcomes of these studies exhibit an inconclusive scenario. For instance, (Li et al. 2020) valuated 283 Chinese cities' environmental efficiency by employing the Super-slack-based measure (Super-SBM). The outcomes concluded that due to economic development, the environmental efficiency of the western and central regions is low, and the differences in these 282 cities' environmental efficiency are apparent. The study further mentioned that through the dynamic perspective, the overall environmental efficiency has enhanced over the survey period from 2003-2016. (Abbas et al. 2020b) have also asserted that Chinese cities' environmental efficiency significantly differs across the cities. Likewise, (Sun et al. 2020) discovered that the linkage between FDI inflows and environmental efficiency in 30 Chinese provinces is U-shaped. It indicates that FDI has reduced the environmental efficiency in Chinese provinces. In another critical study (Chen and Jia 2017), through employing the data envelopment analysis (DEA) method and slacks-based measure (SBM), discovered that the environmental efficiency of China's regional industry is low.

(Yu et al. 2019) discovered that industrial transfer in China significantly affects urban pollutant emissions and that industrial transfer worsens industrial soot and industrial SO₂ emissions. Similarly, (Malley et al. 2016) explored the impact of pollution refuge while the industrial transfer is taking place. The study discovered that the transfer areas' environmental efficiency goes down upon transferring industries in the Pearl River Delta to non-Pearl River Delta areas. Additionally, (Iqbal et al. 2020a) observed that inter-regional industrial transfer could alter the degree of regional energy intensity. Industrial transfer combined with pollution transfer can cause energy intensity to converge between different regions.

While studying the positive effect of the industrial transfer on environmental efficiency, (Abbas et al. 2020a) observed that industrial transfer impacts various regions' industrial structures. It also has a significant influence on the degree of carbon dioxide variation, and that technological innovation contributes significantly to decreasing carbon emissions intensity. In another study, (Xiong et al. 2019) considered Beijing-Tianjin-Hebei urban agglomeration as the research object. The study discovered that industrial transfer goes hand in hand with technology diffusion, enhancing economic development and the environmental quality of the transfer areas.

Thirdly, while analyzing the dual effect of the industrial transfer on environmental efficiency, for instance, (Anser et al. 2020a) investigated the effect of the industrial transfer on energy consumption in urban masses and discovered that industrial transfer between urban clusters could have a dual impact on energy consumption. The industrial transfer can cause a boost in total energy consumption, resulting in reduced energy intensity.

3. Method and Data

Suppose we have N regions, which can split into two divisions. The treatment group comprises the cities that undertook national policy interventions. The monitoring group is composed of the cities not affected by the regional strategy. Let y_{it}^1 and y_{it}^0 represent the i^{th} cities' outcomes with and without the regional strategy in the year t , respectively. For years 1 to T_1 , there is no policy

treatment,

so $y_{it}^1 = y_{it}^0, t = 1, \dots, T_1$ From year $T_1 + 1$ to $T_1 + 1$, few cities will be under treatment; we can only observe (Sen et al. 2016).

y_{it}^1 for $t = T_1 + 1, \dots, T$ and y_{it}^0 for $t = T_1 + 1, \dots, T$. It considers the events with the regional strategy. We cannot examine y_{it}^0 which refers to what would have occurred in the absence of the regional strategy. For other cities without treatment, we can only observe $y_{it}^0, t = T_1 + 1, \dots, T$. Then in year t the treatment effect for the cities under care is as follows:

$$\Delta_{it} = y_{it}^1 - y_{it}^0 \quad \Delta_{it} = y_{it}^1 - y_{it}^0 \quad t = T_1 + 1, \dots, T \quad (1)$$

Nonetheless, y_{it}^1 and y_{it}^0 cannot be examined simultaneously. The observed data, y_{it} , take the following form,

$$y_{it} = d_{it}y_{it}^1 + (1 - d_{it})y_{it}^0 \quad y_{it} = d_{it}y_{it}^1 + (1 - d_{it})y_{it}^0 \quad (2)$$

where $d_{it} = 1$ if the regional strategy treats the cities,
 $d_{it} = 0$ if not.

4. Environmental efficiency (EFF)

This paper considers the inter-temporal change of environmental efficiency (*EFF*) as a dependent variable to measure environmental efficiency improvement. *Meta-US-SBM* model (*Metafrontier, Undesirable outputs, and Super Slacks-Based Measure*) assesses environmental efficiency, both common frontier and undesirable output, consider into a super-efficient SBM model.

If the homogeneity hypothesis follows without considering the difference in technology perimeter, efficiency measures may deviate (3). DMU's efficiency overestimates because the input (output) relaxation variables do not consider the radial model's efficiency measurement (IEA report 2019). The benefit of this model is that it considers the heterogeneity technology and clears up the problems of cross-period comparability and the differentiation of decision-making units on the frontier. This approach is comparably more thorough and correct. The model briefly elaborates in this way: assuming that the number of DMU is N , the DMU can divide into H ($H > 1$) groups according to some heterogeneous characteristics. It determines that the number of DMU in group h is N_h , and there is $\sum_{h=1}^H N_h = N$. Assuming that each decision-making unit has three types of input-output variables: input, expected output, and non-expected output, which are depicted by the following variables:

$$x = [x_1, x_2, \dots, x_M] \in R_+^M, y = [y_1, y_2, \dots, y_R] \in R_+^M, b = [b_1, b_2, \dots, b_J] \in R_+^J$$

Among them, M , R , and J depict three kinds of variables in turn. Considering both unexpected output and heterogeneous technology, the efficiency of the non-directed non-radial SBM of DMU_{*o*} in group k ($0 = 1, 2, \dots, N_k; k = 1, 2, \dots, H$) concerning the meta-frontier of all groups can be attained by solving the following programming,

$$P_{ko}^{Meta} = \min \frac{1 + 1/M \sum_{m=1}^M S_{mko} \frac{x}{x_{mko}^x}}{1 - \frac{1}{R+J} (\sum_{r=1}^R S_{rko} \frac{y}{y_{rko}^n} + \sum_{j=1}^J S_{jko} \frac{b}{b_{jko}})}$$

s.t.

$$x_{mko} - \sum_{h=1}^H \sum_{n=1, n \neq 0 \text{ if } h=k}^{Nh} \phi_n^h x_{mhn} + S_{mko} x \geq 0$$

$$\sum_{h=1}^H \sum_{n=1, n \neq 0 \text{ if } h=k}^{Nh} \phi_n^h y_{rhn} - y_{rko} + S_{rko} y \geq 0$$

$$b_{jko} - \sum_{h=1}^H \sum_{n=1, n \neq 0 \text{ if } h=k}^{Nh} \phi_n^h b_{mhn} + S_{jko} b \geq 0$$

$$1 - \frac{1}{R+J} ((\sum_{r=1}^R S_{rko} \frac{y}{y_{rko}^n} + \sum_{j=1}^J S_{jko} \frac{b}{b_{jko}})_{\geq \varepsilon})$$

$$\phi_n^h, S^x, S^y, S^b \geq 0$$

$$m = 1, 2, \dots, M; r = 1, 2, \dots, J \quad (3)$$

Here, ϕ_n^h is a non-negative weight vector and ε is a non-Archimedean infinitesimal in formula (a o. S^x, S^y and S^b relaxation variables of input expected output, and non-expected output of DMU_{ko} , respectively. The study purpose of adding this constraint.

$-\frac{1}{R+J} ((\sum_{r=1}^R S_{rko} \frac{y}{y_{rko}^n} + \sum_{j=1}^J S_{jko} \frac{b}{b_{jko}})_{\geq \varepsilon})$ here is to make sure that the denominator of the objective

function is not zero. If it assumes that the scale reward is variable, the constraint $\sum_{h=1}^H \sum_{n=1, n \neq 0 \text{ if } h=k}^{Nh} \phi_n^h = 1$ needs to add. The *Meta-US-SBM* model considers the heterogeneity technology and clarifies the issues of cross-period comparability and the differentiation of decision-making units on the frontier, which is more thorough and correct. Different input variables and output variables should be considered to measure environmental efficiency thoroughly and correctly. The description of relevant variables is.

Table 1: Environmental efficiency index system of prefecture-level cities in China

Classification	Index	Definition
Input	Capital input	Fixed capital stock
	human input	Number of employees in cities over the years
	Energy input	Consumption of all primary energy sources (converted to standard coal)
	Land input	Urban built-up area
Desirable output	GDP	Real regional GDP
Undesirable output	SO ₂ emissions	Industrial SO ₂ emissions in the city
	Wastewater discharge	Industrial wastewater discharge in city
	Soot(dust) emission	Industrial soot(dust) emission in the city

5. Industrial Transfer Demonstration Zone

In January 2010, the National Development and Reform Commission approved and built a demonstration zone for undertaking industrial transfer in the Wanjiang City Belt. In 2011, the demonstration zones for undertaking industrial transfer in Southern Hunan were approved and established. In 2014, the Ningxia Yinchuan-Shizuishan industrial transfer demonstration zone was approved and established. By 2019, China had set up ten national demonstration zones to undertake industrial transfer in 28 prefectural-level cities of the central and western regions. Based on panel data, the PDA assumes that y_{it}^0 is produced by a factor model,

$$y_{it}^0 = a_i + b_i' f_t + \varepsilon_{it} \quad (4)$$

$$i = 1, \dots, N; t = 1, \dots, T$$

where a_i represents the fixed effects, b_i' represents the $1 \times K$ vector of constants, f_t represents the $K \times 1$ common factors that drive all cross-sectional units, and ε_{it} represents the idiosyncratic error with $E(\varepsilon_{it}) = 0$ and $E(\varepsilon_{it}^2) = \sigma^2$. For convenience, equation (4) can be articulated using the following matrix equation:

$$y_t^0 = a + B f_t + \varepsilon_t \quad (5)$$

$$i = 1, \dots, N; t = 1, \dots, T$$

Where:

$$y_t^0 = (y_{1t}^0, \dots, y_{Nt}^0)', a = (a_1, \dots, a_N)', \varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})'$$

And $B = (b_1, \dots, b_N)'$

$B = (b_1, \dots, b_N)'$ is the $N \times K$ factor loading matrix. When equation (4) complies with the following Assumptions 1-5: 1. $\|b_j\| = c < \infty$ for $j = 1, \dots, N$

$$\varepsilon_t \text{ is } I(0) \text{ with } E(\varepsilon_t) = 0 \text{ and } E(\varepsilon_t \varepsilon_t') = V E(\varepsilon_t \varepsilon_t') = v$$

where V is a constant diagonal matrix; 3. $E(\varepsilon_t f_t') = 0$

Then, the ex-post counter-factual of underline cities, y_{1t}^0 , can be estimated by

$$\hat{y}_{1t}^0 = \hat{\alpha}_1 + \hat{b}_1 f_t \hat{y}_{1t}^0 = \hat{\alpha}_1 + \hat{b}_1 f_t \text{ for } t = T_1 + 1, T_1 + 1, \dots, T$$

However, for macroeconomic data, neither NN nor $T T$ is usually significant. In this situation, the cross-sectional dependency (Iqbal et al. 2020b), (Iram et al. 2020) is linked to common factors affected by all related cross-sectional units. Based on this argument, they prove that the outcomes of the untreated units ($y_{2t}, \dots, y_{Nt}$) can be used to estimate y_{1t}^0 , instead of determining α_1, b_1 and f_t as long as the assumption 5

$$E(\varepsilon_{js}|d_{it}) = 0 \text{ for } j \neq i$$

holds; that is,

$$\hat{y}_{1t}^0 = c + \beta_1 \dot{y}_t \quad t = T_1 + 1, \dots, T \quad (6)$$

Where

$$\dot{y}_t = (y_{2t}, \dots, y_{Nt})'$$

Then,

$$\Delta_{it}^{\wedge} = y_{1t} - \hat{y}_{1t}^0 \quad t = T_1 + 1, \dots, T \quad (7)$$

To balance the within-sample fit with the post-sample prediction accuracy, the method of choosing the best prediction model (Anser et al. 2020b) (Qayyum et al. 2019)

(Baloch et al. 2016) and (Sahban and Abbas 2018) is as follows. (1) Use R^2 to select the best predictors for $\hat{y}_{1t}^0$ using j cities out of the $N-1$ cities without treatment, represented by $M(j)^*M(j)^*$, for $j=1, \dots, N-1$. (2) Choose $M(m)^*M(m)^*$ from $M(1)^*M(1)^*, M(2)^*M(2)^*, \dots, M(N-1)^*M(N-1)^*$ in terms of AIC, AICC or BIC. The best predictors are corresponding to $M(m)^*M(m)^*$ form the optimal control group. If L is the actual number of associations, N is the number of nodes existing in the network, and $N \times (N-1)$ is the maximum possible number of associations in the network. The formula for calculating the network density of the directed network is,

$$D_n = \frac{L}{N \times (N - 1)} \quad (8)$$

Network efficiency is an indicator of the degree to which the entire carbon transfer network has excess lines. If R is the number of extra lines in the overall network, and $\max(R)$ is the maximum number of possible extra lines, the network efficiency GE calculates as:

$$GE = 1 - \frac{R}{\max(R)} \quad (9)$$

6. Data source

In this paper, prefectural-level Chinese cities consider as samples with data from 2003 to 2017. At present, 28 prefecture-level Chinese cities belong in the treatment group - these are cities that except industrial transfer demonstration zones. Since obtaining pollution emission data of the above ten areas are challenging, these ten samples are not part of the treatment group. Finally, the "China City Statistical Yearbook" has been used for obtaining all the data in this paper, using

statistical yearbooks of different provinces. For each variable, the descriptive statistics show in Table 2.

Table 2: Description of variables

Category	Variable	Abbr.	Mean	Std.	Min	Max
Dependent variables	Environmental Efficiency	EFF	0.176	0.141	0.053	1.310
Independent variables	Industrial Transfer Demonstration Zone	TRAN	0.084	0.277	0.000	1.000
Interaction effect variables	Environmental expenditure	ENE	0.186	0.075	0.006	0.682
	Environmental regulation	ENV	1.110	0.005	0.003	3.301
	Innovation capability	INN	5.978	0.730	0.001	22.639
	Deviation of foreign direct investment	FDIS	0.959	0.301	0.032	4.659
	Resource curse	RES	0.519	0.271	0.014	2.552
	Rent-seeking behavior	CRP	0.482	0.173	0.000	1.000
Control variables	Population density	POP	3.589	0.601	1.376	4.603
	Government expenditure	GOV	5.405	0.061	5.210	5.622
	Industrialization	IND	3.294	0.690	1.471	4.605
	Human capital	EDU	5.207	0.393	3.552	7.654
	Investment in fixed assets	CAP	2.527	1.066	-3.545	4.712
	Economic development	GDP	4.400	1.641	-1.788	13.220

7. Results and Discussion

7.1 The Treatment Effects of the Economy

The Regional Strategy's treatment effects assess using the method outlined in the methodological framework. In the GDP growth rate, we use R^2 for choosing the best predictors using 1 to 15 cities from the control group, depicted by $M(1)*M(1)^*$, $M(2)*M(2)^*$,, $M(15)*M(15)^*$. Second, we use AICC to select the optimal $M(m)*M(m)^*$ from $M(1)*M(1)^*$, $M(2)*M(2)^*$, ..., $M(15)*M(15)^*$. The OLS estimates for the weights have detail in tables 3 and 4.

Table 3: Weights of the maximal GDP growth treatment group

	Beta	Std.	T
Constant	0.491	0.942	0.52
Zhejiang	0.393	0.082	4.82
Fujian	0.380	0.117	3.25
Guangxi	-0.396	0.134	-2.95
Sichuan	0.515	0.114	4.52
$R^2=0.934$ AICC=3.8942 F=50.			

Tables 3 and 4 demonstrate that almost all variables have a substantial sample match as R-square's value exceeds 0,93 and F-test over fifty. This analysis showed that perhaps the chosen cities respond well in line with the AICC so that their real values are equivalent in the post-intervention era and their projected counter facts.

Table 4: Weights of the optimum industrial structure treatment group

	Beta	Std.	T
Constant	6.746	1.019	6.62
Heilongjiang	0.178	0.037	4.77
Shanghai	-0.302	0.044	-6.87
Jiangsu	0.256	0.049	5.24
Anhui	-0.169	0.030	-5.65
Fujian	0.356	0.041	8.69
Guangdong	0.256	0.039	6.51
Guangxi	0.275	0.035	7.77
Guizhou	0.114	0.020	5.60
Yunnan	-0.170	0.041	-4.17
$R^2=0.996$ AICC=-48.475 F=352.95			

Table 5 shows the same conclusion, depicting that zero is comprised of the confidence interval of each year, reflecting the statistical insignificance of the treatment effects. For Table 5, treatment effects point estimates are -1.56, -1.87, -0.98, -1.41 and -1.31 in 2014, 2015, 2016, 2017 and 2018, respectively., which represent the GDP growth in the absence of Regional Strategy. However, the results are not statistically significant. After applying intervention, the counter-factual path shows lower than the actual path for the industrial framework.

Table 5: The treatment effects for GDP (%)

Year	Actual	Counter-factual	Treatment effects	
			Point	Interval
2014	6.4	7.25	-1.56	(-3.44, 0.07)
2015	6.7	6.91	-1.87	(-2.43, 0.70)
2016	6.7	9.79	-0.98	(-2.77, 0.82)
2017	6.5	6.99	-1.41	(-3.21, 0.41)
2018	6.4	8.86	-1.31	(-3.67, 0.56)

Table 6 reflects the point and interval estimates, reflecting that even the interval estimates' lower limits are more than zero, with the effects having a 5% significance level. As shown in Table 6, the treatment effect reports in 2014, 2015, 2016, 2017 and 2018 are 1.09, 3.17, 3.76, 3.75 and 5.16 respectively. It indicates that the tertiary sector's GDP percentage is excluding regional strategy.

Table 6: The treatment effects of the tertiary industry in GDP (%)

Year	Actual	Counter-factual	Treatment effects	
			Point	Interval
2014	37.23	39.16	1.23	(0.67, 1.63)
2015	40.54	39.03	3.45	(2.39, 2.93)
2016	41.56	34.78	3.89	(2.67, 3.69)
2017	44.33	39.46	2.81	(2.77, 4.65)
2018	46.21	41.03	4.76	(3.34, 6.25)

7.2 Results of Different City Scale

Keeping in view that the size of the city is a significant variable that influences environmental efficiency, in this paper, urban samples regressed in correspondence with the city scale. Cities with a population lower than 1 million characterize and small and medium-sized cities, those with a population of between 1 and 3 million characterize as Type II metropolises, the ones with a greater than 5 million population mega-cities. The tangible results in table 10 clearly show that the coefficients of $TRAN \times POST$ in column (1) and column (4) are positive, whereas the ones in column (2) and column (3) are negative. It implies that environmental efficiency has monumentally improved with industrial transfer demonstration zones in small, medium-sized, and mega-cities. In small, medium-sized, and mega-cities, the environmental effects of industrial transfer demonstration zones are positive. In small and medium-sized cities, industrial transfer demonstration zones can boost the environmental expense incurred by local governments and enhance the expenditure of environment-related governance at the domestic level.

Additionally, in mega-cities, industrial transfer demonstration zones' logic in enhancing environmental efficiency can boost large-scale industrial clustering technology integration, hence enhancing eco-friendly technology innovation and strengthening environmental efficiency. In Type II and Type I metropolises, the environmental effect of industrial transfer demonstration areas is negative. It is because large cities experience a distinguished resource distortion.

Table 10: Results of different city scale

	(1)	(2)	(3)	(4)
	Small-medium cities	Type II metropolis	Type I metropolis	Mega-cities
	Population<100	Population (100,300)	Population (300,500)	Population>500
$TRAN \times POST$	0.537*** (2.99)	-0.226* (-1.81)	-0.027* (-1.84)	0.281*** (5.79)
POP	0.005*** (10.11)	0.006*** (10.92)	0.006*** (11.22)	0.005*** (10.14)
GOV	0.003*** (3.41)	0.035 (0.57)	0.305 (0.47)	0.004 (0.11)
IND	0.004*** (2.63)	0.004*** (2.63)	0.004*** (2.66)	0.004*** (2.67)
EDU	0.034 (0.03)	0.404 (0.06)	0.005 (0.14)	0.035 (0.42)
CAP	0.009** (2.26)	0.013*** (3.33)	0.013*** (3.18)	0.015*** (3.94)
GDP	0.004 (1.18)	0.003 (0.73)	0.003 (0.87)	0.002 (0.55)
_cons	0.222*** (11.11)	0.239*** (11.06)	0.236*** (11.59)	0.701*** (6.41)
R square	0.0126	0.0193	0.0799	0.0474

Note: (1) T values are in parentheses (2) ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

Results portray the following: (1) Small-medium cities; the $TRAN \times POST$ value is 0.537, statistically significant at a one percent level. The case for the type II metropolis is (-0.226), which is significant at the ten percent level. The sign of $TRAN \times POST$ concerning type II metropolis is negative, which shows the inverse relationship between these two. The same is the case for type I metropolis. However, it has a one percent level of signification for the mega-cities with positive has positivity interaction.

The POP and IND variables are statistically significant for all the windows from small-medium cities to mega-cities. Their sign is affirmative, which suggestion both are contributing positively to these windows. Here, CAP is positively related to all windows at a one percent level of signification except for small-medium cities, a five percent significance level. According to the results, GOV is only significant for small-medium cities, while EDU and GDP are insignificant for the existing windows.

8. Discussion

This paper examines the causal effect on the economies and the climate of selected industrial transition demonstration regions. The key findings of the Industrial Transition Demonstration Zones are that the GDP industry in highlighted cities has significantly increased. However, their GDP production rate in those regions continues to remain a little affected. The discontinuation tests display the robustness of the treatment effects. The industrial transformation regions have contributed significantly to the city and environmental development, although the GDP growth rate in these cities has not risen or even decreased substantially. The main reason for the inefficiency of GDP growth is that the economy has changed from easy to high-quality growth. The main goal is not to raise the growth pace but to improve the quality of economic development. Consequently, restructuring the growth model and structural reforms focused on ensuring that the economy performs adequately.

The links of carbon exchange between cities were becoming closer and closer, resource coherence and regular trade in goods were common. The total network association continues to grow as the intensity of network correlation declines. The carbon network has a standard structure and is not susceptible to city regulations. There are many other sources for inter-cities business links. The Network Hierarchy is less than 0.1 for three years. The carbon transmission networks do not include a hierarchical framework; therefore, underline cities can adopt transparent trade. Finally, the Cumulative transmission network for greenhouse gas emissions is ineffective and indirectly connects with solid visibility for delivering carbon pollution networks amongst cities. In brief, 2007, 2010, and 2012 carbon network systems stayed stable and positively linked.

The industrial transition demonstration zone has a productive correlation to environmental sustainability. It exacerbates the effects of the industrial transfer zone on environmental expenditure, regulation, and creativity. Therefore, the economic health of the area should be successfully implemented to reap the benefits of policymaking for the industrial transition demonstration zone.

9. Conclusion and Implications

The analytical results obtained in this study portray that industrial transfer demonstration zones can enhance environmental efficiency. While industrial transfer demonstration zones in central China do not contribute positively towards environmental efficiency, those in small, medium-sized, and mega-cities can strengthen environmental efficiency. Industrial transfer demonstration zones in big cities do not act productively towards enhancing environmental efficiency.

There is a constant increase in the carbon transfer amount by China every year. Eastern coastal areas act as the source of carbon transfer for bulky industry centers and energy-intensive locations. In contrast, cities' carbon transfer is most intense in industries involved in metal smelting, rolling processing, electric power, supply, and heat production. Amongst these cities, experience not

only carbon transfer into more significant cities but also carbon-transporting cities. Based on the outcomes of this analysis of the Chinese industrial demonstration zone, authorities related to CPEC are suggested that feasibilities regarding industrial clustering, the special economic zone for economic growth should be sustainable as these projects should not cost the environment in the future.

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