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Econometric Modeling of Urban Energy Efficiency Improvement under Industrial Economic Growth and Assessment of the Effectiveness of Energy Policies

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SUMMARY: *The role played by energy is essential when it comes to the promotion of social and economic advances, and enhancing energy efficiency is very critical towards the attainment of sustainable development in China. This paper will discuss the energy efficiency of 54 Chinese cities located in three large urban clusters during the period 20122024. Through the common frontier dynamic SBM model, which considers non-expected outputs, the research assesses energy efficiencies of these cities. In this framework, energy efficiency is considered as a dependent variable and energy policies as the main explanatory variable. The authors use the difference-in-differences approach (DID) to measure the effect of these policies on energy efficiency in the context of industrial economic growth. The findings indicate that the cities have an average yearly energy efficiency score of 1.0753, which means that the cities work on the efficiency frontier. The energy efficiency ranking of the metropolitan regions is as follows: Beijing-Tianjin-Hebei is ranked first, followed by Yangtze River Delta (YRD), and Pearl River Delta (PRD). Beijing-Tianjin-Hebei has the highest rate of improvement of energy efficiency, followed by PRD and YRD respectively. The standard deviation of energy efficiency also indicates that the greatest changes are experienced by PRD, YRD, and Beijing-Tianjin-Hebei, respectively. Also, the benchmark regression analysis and PSM-DID analysis of the study supports that energy policies have a positive effect on energy efficiency, where industrial economic growth acts as a mediator. The results highlight important regional differences in the effectiveness of energy policies, which are driven by different levels of development of these regions.*

KEYWORDS: *industrial economic growth; urban energy efficiency; energy policy; common frontier dynamic SBM; double difference modeling*

1 Introduction

In recent years, China has experienced a shift in its attitude towards energy. The state is now actively seeking to transform its energy production and consumption patterns with the overall vision of decreasing resource intensity, improving regulatory systems and moving towards a green, low-carbon and circular economy model [1]. Energy is at the core of Chinas development problem. Being an economically intensive country, having limited domestic resources and small per capita energy endowment, its ability to maintain economic growth is largely defined by how well it will handle energy supply and demand [2, 3]. China has achieved a significant advance in the process of industrial base restructuring, abandoning the old trends of heavy industrialization. However, simultaneous with the rise of industrialization and urbanization, the

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energy demand rose to unprecedented rates. These pressures have been exacerbated by inefficient use patterns and occasional mismatch between supply and demand [4-8] The fact that China is highly dependent on coal makes it even more challenging. Coal is the foundation of the energy portfolio of China and it has created serious environmental destruction and environmental damage [9, 10] The economy is now in what policymakers call the new normal, a stage in which industrial growth is intentionally shifted to a focus on quality over the mere increase in output. In the context of growing internal pressures and a volatile international situation, enhancing the rate of energy saving and constraining the excess level of consumption are now strategic priorities to the maintenance of the long-term economic growth [11-13]. As the biggest consumers of energy, cities are often prone to continuing ineffective, traditional ways of growth. The government tools of industrial policy that regulate industrial performance may, though, serve a valuable role in promoting the progress of energy efficiency levels [14]. Energy subsidies are one of the policy options that have proven to be especially successful in both decreasing energy use and emissions, as well as achieving efficiency gains in the short term [15] Based on such setting, it is important to know how the development of the industrial economy relates to the energy use in cities. It is equally urgent to determine which policies could be implemented with more confidence to enhance energy efficiency, encourage conservation, restrain emissions, and support the economy in the long run.

The link between economic development of industry and urban energy efficiency has received a lot of attention in academic literature. E.g., research [16] examined the effect of paper industry spatial concentration on energy efficiency, and discovered a turning point in the agglomeration process. Energy efficiency did not improve significantly until this point had been reached. The research also indicated that regional policies could hinder the enhancement of energy efficiency, and it should be taken into consideration that regions take advantage of their benefits to boost industrial development. Alternatively, research [17] has used a dynamic panel model to determine how China industrial reorganization would affect total energy efficiency. The results showed positive effects but technological innovation inputs were not directly related to efficiency improvements, probably because the conversion rate is low. The research also pointed out that there are differences between regions in terms of energy efficiency where the eastern region was the most efficient, yet the central and the western regions were less effective. The other research [18] based on the STIRPAT model examined the impact of industrial structural improvements on carbon emissions. These findings showed that these upgrades resulted in less carbon emissions as well as the optimal energy mix that further lowered the emissions. Nonetheless, this influence was highly uneven across regions. The study in [19] used a dynamic spatial Durbin model to examine the connection between urban agglomeration economics and industrial energy efficiency. The research revealed that despite the fact that specialization and diversification in industries within urban agglomerations had no significant effect on local energy efficiency, it created negative externalities on the adjacent cities. It was seen that this could be an example of how the free-rider effect and race-to-the-bottom dynamics would prevent the improvement of energy efficiency over the long term. The study [20] in a more general context, concluded that the drive to meet economic growth targets adversely affected the improvement of energy efficiency significantly based on the panel data of 188 Chinese cities. These effects were observed in three main forms: misallocation of investments, inability to upgrade industries and suppressed innovation. As it was shown in the study, every unit of economic pressure decreased the energy efficiency index by 3.3 percent and the results varied both in space and time. According to [21]that used Shepherd’s energy distance function and the entropy weight approach, it is found that there is a U-shaped relationship between energy efficiency and the quality of economic growth. Although the eastern areas showed significant improvements, the central and western areas had negative effects. The research highlighted the importance of industrial structure reforms to address this imbalance. In lastly, the research in [22] explored panel error correction models and reported that clean energy resources such as natural gas and renewables would not be financially feasible than coal and electricity.

In the literature, there are different perspectives on how one can be able to measure effectiveness in energy policies. As an example, study [23] focused on discussing a number of modeling methods that can help to assess the policies of renewable energy. The presented research indicated the advantages and disadvantages of every model, especially in terms of their capability to predict the results of policies and their consequences. It also put forth a scheme of analyzing the applicability of the models. Likewise, another paper [24] discussed 11 renewable energy policy tools and identified tax incentive and strategic planning as the most important factors in promoting wind energy generation. Remarkably, the efficacy of strategic planning was enhanced as the rate of policy changes increased. Literature [25]applied the difference-in-differences approach to determine the effects of fiscal policies on energy conservation and emissions mitigation in China. The research established that although these policies were effective at reducing emissions and increasing the economy in the short term, they were not sustainable in the long term and did not reduce other pollutants. The study recommended that policies must be made stronger and more concentrated on long-term objectives and overall governance of the environment. An analysis of ex-ante and ex-post assessments of industrial energy policies in China, according to literature [26], indicated that energy intensity policies resulted in slight decreases in emissions. On the other hand, the policies of sulfur dioxide emissions were found to be more successful. This conclusion highlighted the significance of taking into account the heterogeneity of enterprises when optimizing the ex-ante assumptions and thus enhancing the credibility of policy design procedures. The evaluation of national carbon pricing strategies, such as carbon taxes, carbon markets, and hybrid models, has been undertaken in the literature [27] to assess the contribution of such policies to emissions reduction in the last ten years. The research showed that, overall, the level of greenhouse gas emissions per capita increased along with economic growth in most countries, except where hybrid policies existed. The study highlighted the necessity of strengthening the current mechanisms to meet the goals specified in the Paris Agreement. In literature [28], non-parametric data envelopment analysis and Tobit analysis showed that environmental innovations were very significant to energy efficiency, especially in economically stable nations due to knowledge spillovers. Nevertheless, this phenomenon was more evident in OECD nations than in non-OECD ones, which means that financial instability is a barrier to the transition to cleaner energy practices. Lastly, it was proposed by study [29] that a five-steps model could be used to assess industrial energy efficiency policies. The model seeks to overcome the complexity of using multiple assessment criteria and offers systematic decision-making support to the EU manufacturing industry in the process of reaching carbon neutrality.

The current research analyses the energy efficiency of the three most populated urban agglomerations in China, including the Yangtze River Delta, Beijing-Tianjin-Hebei, and the Pearl River Delta. The research monitors how energy efficiency has changed over time in these areas based on a shared boundary dynamic SBM model that considers non-expected outputs. Also, it uses the PSM-DID model to examine the effect of energy policies on the urban energy efficiency, and also examine the role of industrial economic growth as an intermediary variable. The paper finishes with an estimation of the strength of the results and talking about the diverse impact of energy policies on the various regions and levels of development, taking into account the location of the city and the economic development that each region has undergone.

2 Urban Energy Efficiency Measurement Based on Improved Dynamic SBM

2.1 Model for measuring urban energy efficiency

2.1.1 Data envelopment analysis

The Data Envelopment Analysis (DEA) is based on the notion of Pareto efficiency and it uses linear programming to compare the relative performance of decision-making units (DMUs). The Slacks-Based Measure (SBM), also known as a variation of conventional DEA, was created to overcome the challenges of dealing with undesirable outputs in the production process. With slack variables added to the measurement framework, SBM provides a more precise and subtle measure of the efficiency of DMUs.

In case the objective is to assess efficiency in various time intervals, the researchers introduce carry-over variables which provide important connections between the successive steps of the analysis. Such an extension leads to the creation of a dynamic SBM model that can consider undesirable outputs as part of its analytical framework, thus expanding the range of the initial framework. The current research goes a step further in this direction by adapting a shared frontier dynamic SBM model that incorporates non-anticipated outputs in its estimation process allowing a more stringent and thorough evaluation of efficiency across the units analyzed.

2.1.2 Dynamic SBM modeling

The dynamic SBM model divides carry-over variables into desirable, undesirable, free, and fixed variables and creates n decision units $\left(T=1,2,\cdots,T\right)$ on T cycles $\left(j=1,2,\cdots,n\right)$, each with multiple distinct and independent inputs and outputs, with z serving as a carryover from the T cycle to the $T+1$ cycle. The carryover is represented by equation (1):

$$\sum_{j=1}^{n} z_{ij}^{\alpha}\lambda_j^{t} = \sum_{j=1}^{n} z_{ij}^{\alpha}\lambda_j^{t+1} \left(\forall; t=1,\cdots,T-1\right) \tag{1}$$

In equation (1), α denotes the type of variable, including ideal, undesirable, free and fixed variables.

Undirected total efficiency $\left(\delta^*\right)$ is calculated using equation (2), and ω^t and ω_i are the weights of the tth and input terms, respectively:

$$\delta^* = \frac{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1-\frac{1}{m+nbad}\left(\sum_{i=1}^{m}\frac{w_i^- s_{ij}^-}{x_{iot}}+\sum_{i=1}^{nbad}\frac{s_{it}^{bad}}{z_{iot}^{bad}}\right)\right]}{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1-\frac{1}{s+ngood}\left(\sum_{i=1}^{s}\frac{w_i^+ s_{ij}^+}{y_{iot}}+\sum_{i=1}^{ngood}\frac{s_{it}^{good}}{z_{iot}^{good}}\right)\right]} \tag{2}$$

The efficiency $\left(\rho^*\right)$ of the non-oriented indicators is expressed as follows:

$$\rho^{*}=\frac{1-\dfrac{1}{m+nbad}\left(\sum_{i=1}^{m}\dfrac{w_i^{-}s_{iot}^{-*}}{x_{iot}}+\sum_{i=1}^{nbad}\dfrac{s_{iot}^{bad^{*}}}{z_{iot}^{bad}}\right)}{1-\dfrac{1}{s+ngood}\left(\sum_{i=1}^{s}\dfrac{w_i^{+}s_{iot}^{+*}}{y_{iot}}+\sum_{i=1}^{ngood}\dfrac{s_{iot}^{good^{*}}}{z_{iot}^{good}}\right)} \tag{3}$$

Five specific indicators used in this research are applied to assess the energy performance of three largest urban clusters of China during the years between 2012 and 2024. Figure 1 shows the detailed structure of the dynamic SBM model that was used.

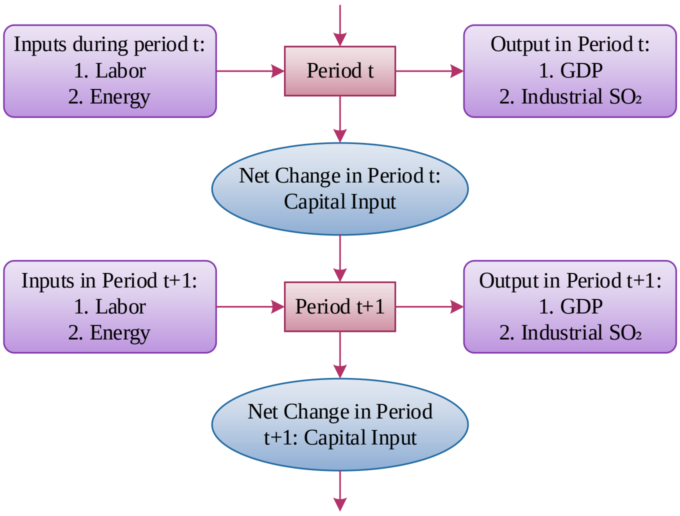

Figure 1: Dynamic SBM model structure

2.1.3 Improved dynamic SBM model with common frontier

The traditional DEA models generally presuppose that all the producers are characterized by the same level of technology. Nevertheless, in practice, it is often the case that the decision-making units (DMUs) being analyzed have different levels of technological capabilities due to geographical aspects or policy systems, and economic circumstances. Consequently, scholars have proposed the use of the common frontier model to compare the technical efficiency (TE) of different clusters and thereby can enable the exact computation of the cluster frontier and the common frontier TE. Since energy consumption will always lead to undesirable outputs, like environmental pollution, the current paper suggests the common frontier dynamic SBM model (MFD-SBM), which considers these non-desired outputs.

(1) Common frontier (MF)

The given model can explain how the variables such as management practice, resources, planning, and environmental factors may vary, this paper assumes that all units (N) are composed of decision-making units (DMUs) g groups $(N=N1+N2+\cdots+NG)$, x_{ij} and y_{rj} denote the input terms $i(i=1,2,\cdots,m)$ and $j(j=1,2,\cdots,N)$ output terms $r(r=1,2,\cdots,s)$ of $j(j=1,2,\cdots,N)$ under the common frontier, respectively.The DMU's k can choose the most favorable final output weights to obtain the maximum value of efficiency.The value of common frontier technical efficiency (MFTE) of a DMU can be solved by equation (4):

$$
\begin{aligned}
&Min : \rho^{*} \\
&s.t.\ \sum_{g=1}^{G}\sum_{\partial=1}^{n} Z_{ijtg}\lambda_{jg}^{t} = \sum_{g=1}^{G}\sum_{\partial=1}^{n} Z_{ijtg}\lambda_{jg}^{t=1} \left(\forall i \middle| t=1,\cdots,i-1\right) \\
&X_{iot} = \sum_{g=1}^{G}\sum_{\partial=1}^{n} x_{ijtg}\lambda_{jg}^{t} + S_{it} \left(i=1,\cdots,m; t=1,\cdots,i\right) \\
&Y_{lot} = \sum_{g=1}^{G}\sum_{l=1}^{s1} y_{lot}^{+g}\lambda_{j}^{t} - S_{lt}^{+g} \left(l=1,\cdots,s1; t=1,\cdots,T\right) \\
&Z_{iot}^{good} = \sum_{g=1}^{G}\sum_{\partial=1}^{n} z_{ijtg}^{good}\lambda_{jg}^{t} - S_{lt}^{t} \left(i=1,\cdots,ngood; t=1,\cdots,i\right) \\
&\sum_{g=1}^{G}\sum_{\partial=1}^{n} \lambda_{jg}^{t} = 1\left(t=1,\cdots,i\right) \\
&\lambda_{jg}^{t} \geq 0, s_{it}^{-} \geq 0, s_{it}^{+} \geq 0, s_{it}^{good} \geq 0
\end{aligned}
\tag{4}
$$

(2) Group Frontier (GF)

The decision-making units (DMUs) are categorized into g groups. For each unit within the cluster frontier, the most optimal final output weights are selected. The efficiency of the decision units within the cluster frontier (GFTE) can be determined using the following equation (5):

$$
\begin{aligned}
&.\theta^{*} = \min \frac{\frac{1}{T}\sum_{t=1}^{T} w^{t}\left[1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_{it}^{-}}{x_{iot}}\right]}{\frac{1}{T}\sum_{t=1}^{T} w^{t}\left[1+\frac{1}{s_{1}+ngood}\left(\sum_{i=1}^{s_{1}}\frac{s_{jt}^{+}g}{y_{iot}^{g}}+\sum_{r=1}^{ngood}\frac{s_{rt}^{good}}{z_{iot}^{good}}\right)\right]} \\
&\sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_{j}^{t} = \sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_{j}^{t+1} \left(\forall i; t=1,\cdots,T-1\right) \\
&x_{iot} = \sum_{g=1}^{G} x_{ijt}\lambda_{j}^{t} + s_{it}^{-} \left(i=1,\cdots,m; t=1,\cdots,T\right) \\
&y_{lot} = \sum_{l=1}^{s1} y_{lot}^{+g}\lambda_{j}^{t} - s_{lt}^{+g} \left(l=1,\cdots,s1; t=1,\cdots,T\right) \\
&z_{iot}^{good} = \sum_{j=1}^{n} z_{iot}^{good}\lambda_{j}^{t} - s_{it}^{good} \left(i=1,\cdots,ngood; t=1,\cdots,T\right) \\
&\sum_{j=1}^{m} \lambda_{j}^{t} = 1\left(t=1,\cdots,T\right) \\
&\lambda_{j}^{t} \geq 0, s_{it}^{-} \geq 0, s_{it}^{+} \geq 0, s_{it}^{good} \geq 0
\end{aligned}
\tag{5}
$$

(3) Technology gap ratio (TGR)

Since the common frontier includes the common frontier of the g group, MFTE cannot be higher than GFTE in the g group. This ratio between these two values is called the Technology Gap Ratio (TGR), which may be calculated by the following equation:

$$TGR = \frac{\rho^*}{\rho_o^{*g}} = \frac{MFTE}{GFTE} \tag{6}$$

Equation (6) indicates that TGR reflects the gap between the technology of the cluster frontier and the common frontier. A greater number means that the production technology of the decisions making unit is nearer to the common frontier technology, implying that the real technological level of production is high.

(4) Energy inefficiency (IE) decomposition

Developing the technology gap ratio, this paper breaks down further the underlying factors that cause the difference in energy efficiency among cities within the urban cluster. Relative to the common frontier, the energy inefficiency (IE) per each city is segregated into two factors namely technology gap inefficiency (TIE) and management inefficiency (MIE), which is given as equation (7):

$$\begin{aligned} &IE = 1 - MFTE = TIE + MIE \\ &TIE = GFTE - MFTE \\ &MIE = 1 - GFTE \end{aligned} \tag{7}$$

In equation (7), TIE represents inefficiency stemming from technological differences between cities, while MIE reflects inefficiencies arising from variations in management capabilities at a given technological level.

2.2 Selection of urban energy efficiency indicators and data sources

2.2.1 Selection of indicators

The selection of indicators in this study is designed to capture urban energy efficiency comprehensively, covering both the input side and the output side of the production process. Labor, capital, and energy constitute the three input categories, while outputs are divided into two distinct types: those that are desirable and those that are not. Economic growth at the city level serves as the desired output, whereas environmental pollution represents the undesirable counterpart.

(1) Input Indicators

1) Labor input is measured using the average number of urban employees across the preceding and the current year. This averaging approach is adopted in recognition of the considerable degree of job mobility that characterizes urban labor markets, which makes any single-point measurement less representative of actual labor deployment throughout the period.

2) Capital input is estimated through capital stock data. A particular concern here is data consistency, given that China's GDP statistics underwent substantial revision in 1995, which introduces discontinuities if that benchmark year is not handled carefully. To address this, city-level capital stock is constructed using the perpetual inventory method, with 1995 designated as the base year for all calculations. The specific steps involved in this procedure are as follows:

$$K_{i,t} = K_{i,t-1}\left(1-\tau_{i,t}\right) + \left(I_{i,t} + I_{i,t-1} + I_{i,t-2}\right) \tag{8}$$

where $K_{i,t}$ and $I_{i,t}$ are the capital stock and fixed asset investment in the t th year of the city i, $\tau_{i,t}$ is the depreciation rate of fixed assets in the t th year of the city i, and this paper uniformly chooses 9.6%, and $K_{i,t-1}$ is the capital stock of the city i th year of the city $t-1$.

3) Energy Input: Total energy consumption of each city is used as a measurement of this variable. It is calculated in the following manner: total regional energy consumption = energy consumption per unit of GDP multiplied by the regional GDP. In case of missing individual points, historical data is used to estimate them with a moving average approach.

(2) Output indicators

1) Output Indicator of Choice: Regional GDP has been chosen as the desired output indicator because it will reflect the economic development created through the consumption of energy.

2) Indicators of Non-Desired Output: Although the use of energy is bound to cause the pollution of the environment, full information on the levels of environmental pollution in cities is not always accessible. Hence, industrial SO2 emissions have been employed as an indicator of the undesirable output of environmental damage.

2.2.2 Data sources

The empirical research is based on a set of 54 cities in the three most populous urban areas of China: the Yangtze River Delta (YRD), the Beijing-Tianjin-Hebei region (BTH), and the Pearl River Delta (PRD). Of them, 26 are in the YRD, 13 are in the BTH and 15 are in the PRD. There were five key indicators that were chosen to assess the overall urban energy efficiency, and the observation period was six years, between 2012 and 2017. The sources of all variable data were the China Urban Statistical Yearbook that covers the time between 2013 and 2025 and is supplemented, where appropriate, by the corresponding provincial and municipal statistical yearbooks. These official publications give the dataset a certain level of credibility and create a uniform foundation of comparison between various cities during the analysis process.

2.3 Measurement and analysis of energy efficiency in the three major urban agglomerations

2.3.1 Results of Energy Efficiency Measurement in Three Major Urban Agglomerations

The current research uses the general frontier dynamic SBM model (MFD-SBM) to measure the energy efficiency of 54 cities within three large urban agglomerations in China over the period of 2012-2024, with consideration of unanticipated outputs. The results that were calculated through the use of MaxDEA software are shown in Table 1. Because of the limited space, the analysis is based on the information of seven representative years: 2012, 2014, 2016, 2018, 2020, 2022, and 2024. Remarkably, Taizhou City in Jiangsu Province is marked as number 1 whereas Taizhou City in Zhejiang Province is marked as number 2.

According to a general perspective, the mean energy efficiency of the 54 cities in 2012-24 is 1.0753. The combined energy efficiency of the three largest urban agglomerations exceeds 1, which means that all of them are working at the efficiency frontier. It implies that these areas are efficient in general.

Considering the city clusters, by 2024 the energy efficiency levels of the Yangtze River Delta (YRD), Beijing-Tianjin-Hebei (BTH), and Pearl River Delta (PRD) clusters will be up by 0.76%, 9.95% and 5.43 percent, respectively. Energy efficiency showed the highest growth among the BTH cluster and was followed by the PRD and YRD clusters. This trend suggests that as the two major economic growth drivers in China, the so-called Double-Delta areas could have sacrificed a portion of their ecological advantages to achieve economic growth. It highlights the need to prioritize ecological conservation and effective energy consumption during future development.

Concerning individual cities, the five cities that achieve the highest annual average energy efficiency are Yunfu (1.6451), Tongling (1.5891), Chizhou (1.4910), Langfang (1.4138), and Shanwei (1.4109), all with a level above 1.4. Conversely, the five cities with the least energy efficiency are Chuzhou (0.8520), Zhuhai (0.8207), Huizhou (0.8143), Wuhu (0.6301), and Anqing (0.6168). It is important to note that the most efficient city, Yunfu City with the highest average energy efficiency, is 2.67 times more efficient than Anqing, the city with the lowest score. Moreover, there are huge disparities in energy efficiency between cities in the same cluster, indicating significant imbalance in energy efficiency development across the cities.

Table 1: Energy efficiency calculation results of the three major urban agglomerations

Urban agglomeration	City	Year							Mean	Ranking
		2012	2014	2016	2018	2020	2022	2024		
The Yangtze River Delta urban agglomeration	Shanghai	1.5037	1.4684	1.5841	1.3259	1.3441	1.1491	1.1319	1.3582	6
	Nanjing	1.0168	0.9937	1.0515	1.0321	1.0515	1.0605	1.0290	1.0336	29
	Wuxi	1.3122	1.2138	1.0467	1.0295	1.0765	1.1007	1.1043	1.1262	17
	Changzhou	0.7585	0.7151	1.0434	1.1375	1.1683	1.0986	1.0577	0.9970	37
	Suzhou	1.1828	1.1621	1.1222	1.2332	1.2318	1.3135	1.3419	1.2268	10
	Nantong	1.0082	1.0215	1.0693	1.1073	1.0705	1.0922	1.0401	1.0584	25
	Yancheng	1.1407	1.0528	1.0735	1.0515	1.0765	1.1250	1.0951	1.0879	22
	Yangzhou	1.0216	1.0678	1.0709	1.0464	1.0162	1.0270	1.1030	1.0504	27
	Zhenjiang	0.8265	0.7285	1.0256	1.0055	1.0457	1.0786	1.1191	0.9756	39
	Taizhou 1	0.5977	0.6625	0.7387	1.0260	1.0156	1.0181	1.0005	0.8656	49
	Hangzhou	1.0882	1.0847	1.0643	1.1391	1.1048	1.1332	1.0592	1.0962	21
	Jiaxing	1.0211	1.1501	1.0702	1.0132	1.0296	1.0240	1.0017	1.0443	28
	Huzhou	0.8275	0.9230	1.0721	1.0052	1.1240	1.1164	1.0545	1.0175	32
	Zhoushan	1.1296	1.1713	1.1246	1.1048	1.1708	1.0810	1.1339	1.1309	15
	Jinhua	1.2286	1.0909	1.1612	1.1170	1.0678	1.0722	1.0305	1.1097	20
	Shaoxing	1.1391	1.0617	1.0418	1.0824	1.0174	1.0248	1.0129	1.0543	26
	Taizhou 2	1.0199	0.8971	0.6930	1.2150	1.1327	1.1104	1.0305	1.0141	33
	Ningbo	0.7189	1.1260	1.0142	1.0186	0.9482	0.8884	0.9853	0.9571	42
	Xuancheng	1.2640	1.1808	1.6888	1.0492	1.0481	0.8775	0.6799	1.1126	19
	Chuzhou	1.0347	0.6278	0.7359	1.1385	1.0409	0.7138	0.6726	0.8520	50
	Chizhou	1.4555	1.7489	1.4601	1.5860	1.5360	1.4737	1.1765	1.4910	3
	Hefei	0.6409	1.0468	1.0729	1.0748	1.0564	1.0184	0.6438	0.9363	44
	Tongling	1.0454	1.0700	0.6007	1.0126	1.8870	4.2562	1.2516	1.5891	2
	Ma 'anshan	0.7169	1.0082	1.1179	1.1392	1.0444	1.0608	1.0980	1.0265	31
	Wuhu	0.6190	0.5512	0.5682	0.6467	0.6959	0.7307	0.5990	0.6301	53
	Anqing	0.6997	0.5385	0.5564	0.5823	0.5513	0.6260	0.7637	0.6168	54
	Mean	1.0007	1.0140	1.0334	1.0738	1.0982	1.1643	1.0083	1.0561	
The Beijing-Tianjin-Hebei urban agglomeration	Beijing	1.1094	1.1625	1.3048	1.3021	1.3452	1.2140	1.1525	1.2272	9
	Tianjin	1.0884	1.1269	1.1253	1.1016	1.1595	1.1747	1.1868	1.1376	14
	Shijiazhuang	0.7890	1.0435	1.1405	1.0298	1.0750	0.7507	1.2105	1.0056	36
	Tangshan	1.2374	1.1439	1.3588	1.3338	1.2279	1.1976	1.1684	1.2383	8
	Handan	1.0534	1.2280	1.3005	1.0611	1.0377	1.3617	1.5313	1.2248	11
	Zhangjiakou	1.0270	1.0231	1.0241	1.0105	1.0261	1.0275	0.6510	0.9699	40
	Baoding	1.1091	0.7734	0.8027	0.8055	1.0513	0.8022	1.0139	0.9083	48
	Cangzhou	0.5535	1.1123	1.1230	1.1969	1.1551	1.1679	1.1705	1.0685	24
	Qinhuangdao	1.0084	0.7232	0.6927	1.0387	1.0400	1.1449	1.2538	0.9860	38
	Xingtai	1.0150	0.7006	0.7568	1.0300	0.7975	1.0252	1.0698	0.9136	47
	Langfang	1.8510	1.4899	1.4768	1.3281	1.1609	1.3699	1.2202	1.4138	4
	Chengde	0.5336	1.0156	1.0131	1.0092	1.0116	0.9151	1.0449	0.9347	45
	Hengshui	1.0127	1.5629	1.1628	1.0130	1.0426	1.0743	1.0467	1.1307	16
	Mean	1.0298	1.0851	1.0986	1.0970	1.0870	1.0943	1.1323	1.0892	
The Pearl River Delta urban agglomeration	Guangzhou	1.1062	1.0562	1.0780	1.1197	1.0921	1.0778	1.0715	1.0859	23
	Shenzhen	1.1042	1.1842	1.2635	1.1694	1.1554	1.0503	1.1376	1.1521	13
	Zhuhai	0.6678	0.5796	0.6095	1.0072	1.0145	1.1945	0.6718	0.8207	51
	Foshan	1.0295	1.2128	1.2489	1.1102	1.0474	0.8109	0.6377	1.0139	34
	Shaoguan	1.5755	0.5777	0.7049	1.0130	1.1164	1.0160	1.0587	1.0089	35
	Heyuan	0.8817	0.6214	1.0631	1.0726	1.0433	1.0302	0.9934	0.9580	41
	Huizhou	0.5986	0.5581	0.5407	1.0867	1.0286	0.8560	1.0311	0.8143	52
	Shanwei	1.0763	1.0698	1.1040	1.1542	1.7916	1.5077	2.1727	1.4109	5
	Dongguan	1.4247	1.5829	1.3908	1.4207	1.1578	1.1293	1.3724	1.3541	7
	Zhongshan	1.1336	1.0597	1.1786	1.2385	1.1973	1.1971	1.1264	1.1616	12
	Jiangmen	1.0530	1.0224	1.0139	1.0625	1.0159	1.0092	1.0197	1.0281	30
	Yangjiang	1.2451	1.0916	1.0890	1.0844	1.0956	1.1007	1.1560	1.1232	18
	Zhaoqing	1.0429	0.5873	1.0414	0.8456	1.0222	1.0172	1.0314	0.9411	43
	Qingyuan	0.6026	0.6432	1.0764	1.0617	1.0273	1.0688	1.0275	0.9296	46
	Yunfu	1.1851	1.3340	1.1525	4.1676	1.4190	1.1843	1.0735	1.6451	1
	Mean	1.0485	0.9454	1.0370	1.3076	1.1483	1.0833	1.1054	1.0965	
Mean		1.0210	1.0120	1.0501	1.1443	1.1094	1.1249	1.0651	1.0753	

2.3.2 Characteristics of the evolution of energy efficiency in the three major urban agglomerations

The average energy efficiency distribution among urban agglomerations and its change over time was described by calculating the mean and standard deviation of energy efficiency in the whole sample and separately in each of the three main urban agglomerations during the period between 2012 and 2024. The findings are given in Table 2 and suggest a number of observations that should be highlighted in the discussion.

(1) The Pearl River Delta (PRD) city cluster was the most efficient of the three urban agglomerations in terms of mean annual energy efficiency during the 2012 to 2024 period, with an average of 1.0965. Second on the list is the Beijing-Tianjin-Hebei (BTH) cluster with 1.0892, and last on the list is the Yangtze River Delta (YRD) with 1.0561. The relatively high level of efficiency of the PRD may have been partly due to the fact that this region has had more favorable and widespread policy assistance than the other two clusters, and it seems to have resulted in quantifiable improvements in energy consumption efficiency during the research period.

(2) The annual variation of the standard deviation of energy efficiency among the three largest urban agglomerations, and of every single region (YRD, BTH, PRD) was 8.83 percent, 5.76 percent, 5.55 percent, and 20.36 percent, respectively. These numbers indicate that the difference in energy efficiency between cities of these agglomerations is being increased slowly but surely. It is worth noting that the PRD region recorded the highest rate of disparity, and the BTH region had the lowest growth rate.

Table 2: The average energy efficiency and standard deviation of each urban agglomeration

Year	Three major urban agglomerations		The Yangtze River Delta urban agglomeration		The Beijing-Tianjin-Hebei urban agglomeration		The Pearl River Delta urban agglomeration	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2012	1.0210	0.2727	1.0007	0.2519	1.0298	0.3248	1.0485	0.2759
2013	1.0708	0.3875	1.0663	0.3842	1.1809	0.5807	1.0223	0.2784
2014	1.0120	0.2837	1.0140	0.2698	1.0851	0.2600	0.9454	0.3271
2015	1.0592	0.2468	1.0347	0.2513	1.0896	0.4895	1.0632	0.2773
2016	1.0501	0.2539	1.0334	0.2748	1.0986	0.2386	1.0370	0.2399
2017	1.0452	0.2095	1.0216	0.2236	1.0411	0.1684	1.1083	0.2412
2018	1.1443	0.4486	1.0738	0.1837	1.0970	0.1534	1.3076	0.8008
2019	1.0975	0.1951	1.0764	0.2021	1.0787	0.1242	1.1794	0.2014
2020	1.1094	0.2067	1.0982	0.2392	1.0870	0.1301	1.1483	0.2067
2021	1.1377	0.3073	1.1225	0.3263	1.1045	0.1123	1.1408	0.2549
2022	1.1249	0.4670	1.1643	0.6537	1.0943	0.1897	1.0833	0.1609
2023	1.0418	0.2354	1.0154	0.2347	1.0412	0.1806	1.0650	0.3245
2024	1.0651	0.2440	1.0083	0.1862	1.1323	0.1955	1.1054	0.3446
2012-2024	1.0753	0.3263	1.0561	0.3297	1.0892	0.2163	1.0965	0.3936

2.3.3 Patterns of temporal evolution of energy efficiency in the three major urban agglomerations

In order to examine the distribution trends and evolution tendencies of energy efficiency discrepancies among the three largest urban agglomeration, this paper uses Stata 19.0 software to create Kernel density lines on energy efficiency estimates in the years 2012, 2016, 2020 and 2024.

(1) Overall Kernel density estimation

Figure 2 follows the development of energy efficiency distribution in the 54 cities in three key metropolitan areas over the period 2012-2024. Looking into the Kernel density curves of all the three clusters, the mean of each distribution does not seem to have a significant left or right shift over time and is persistently located on the right side of the midpoint. Such a trend generally indicates that the level of energy efficiency in these urban agglomerations has been relatively functional over the course of this study. All combined, efficiency scores in the clusters have been fairly steady, and no significant increase was seen throughout the years being discussed. Regarding the shape of the distributions, the Kernel density curves have become higher and thinner over time, which means that the total spread of energy efficiency values has shrunk. This change in morphology indicates a gradual narrowing of efficiency results towards the central result, and indicates that the city performance within each agglomeration tends to converge to a more similar performance. However, the distributional tail behavior paints a different picture. During the period between 2012 and 2020, the tails are slowly decreasing, as expected based on the convergence trend previously observed. Starting in 2020, the tails start to increase, and signify a new divergence between cities. This switch means that the energy efficiency improvement between the three urban agglomerations has not been equal but rather the performance difference between the highly efficient and poorly efficient cities widens again in the final part of the study period.

The Kernel density curves show a bimodal form when analyzed over the entire time of the study, with two distinct peaks observed in the distribution. The first peak always has a greater density than the second, indicating that energy efficiency in the three urban agglomerations usually groups around two major values instead of converging towards one value. Such a configuration suggests that there is significant spatial polarization in the performance of energy efficiency, an issue which the current policies and governance structures have not been able to address appropriately.

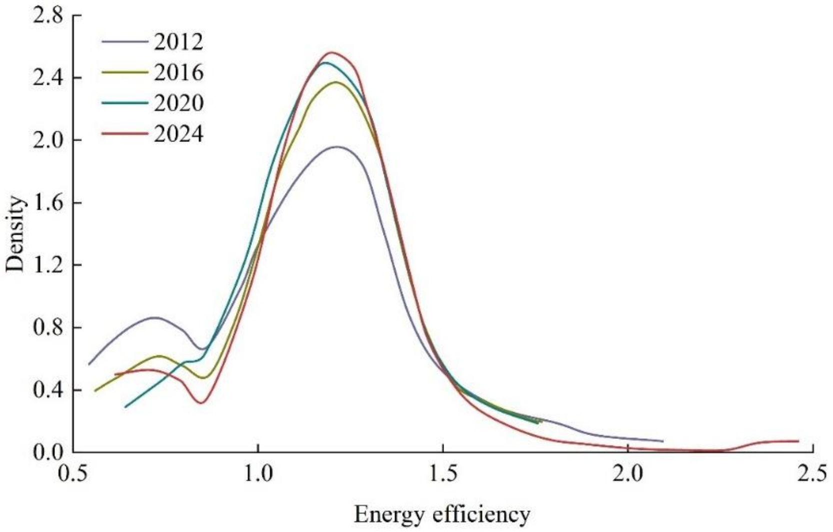

Figure 2: Nuclear density curves of energy efficiency in the three urban agglomerations

(2) Kenel density estimation for the Yangtze River Delta city cluster

As Figure 3 depicts the dynamism of energy efficiency distribution in Yangtze River Delta (YRD) city cluster. The peak of the kernel density curve of the YRD cluster is shifted slightly towards the left between 2012 and 2020, and then it is shifted slightly towards the right between 2020 and 2024. In general, though, this trend in distribution is leftwards showing that the energy efficiency of the YRD city cluster has been decreasing over time. Concerning the distribution pattern, the wave peak grows annually and there is a clear shift between a broader peak and a narrow one. This is an indication of a trend towards energy efficiency, whereby high-efficiency cities are slowly converging on the regional norm. Regarding the spread of the distribution, the length of the tail is approximately constant, implying that there has been more even growth of the region. With respect to wave peak distribution, the energy efficiency in the YRD cluster is mostly a bimodal distribution, where there is a major peak and a smaller secondary peak. The side peak is less pronounced, which indicates a gradient in energy efficiency, which is a sign of mild dichotomy. Although such a convergence in energy efficiency indicates the decrease in differences, the poor spatial differentiation is still present in the YRD city cluster.

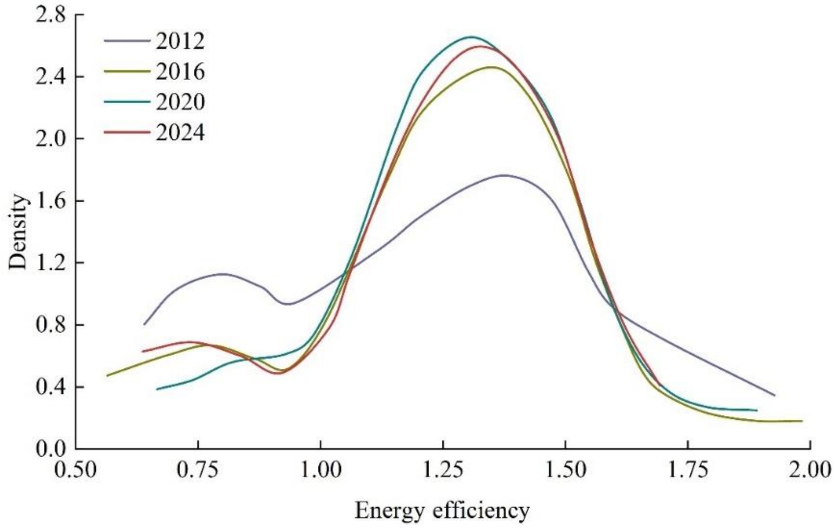

Figure 3: Nuclear density curve of the Yangtze River Delta Urban agglomeration

(3) Kernel density estimation for Beijing-Tianjin-Hebei city cluster

Figure 4 depicts the changing nature of energy efficiency distribution in the Beijing-Tianjin-Hebei (BTH) city group during the study period. The BTH kernel density curve moves rightwards across all years of observation, indicating a widespread increase in energy efficiency across the region. In terms of the form of distribution, the curve measured in 2024 is significantly higher and more squeezed than the one in 2012, indicating that the energy efficiency values in the BTH agglomeration have become more homogeneous with time. The reduction in the distribution indicates that there is an internal convergence in absolute efficiency levels. Looking at the tails of the distribution supports this interpretation. In 2024, the efficiency curve has much less of a tail compared to its 2012 counterpart, which suggests that there has been a reduction in the gap in performance across the cities of the cluster. Those cities, which used to have the least efficient energy consumption, seem to be slowly reducing the gap between them and their more efficient counterparts. Concerning the general distributional trend, the BTH cluster first demonstrated a triple-peak configuration that later merged into a bimodal form by the end of the observation interval. Nevertheless, although this shape simplification occurs, a polarization can still be observed, which means that significant differences in energy efficiency performance still exist within the region and are not entirely eliminated.

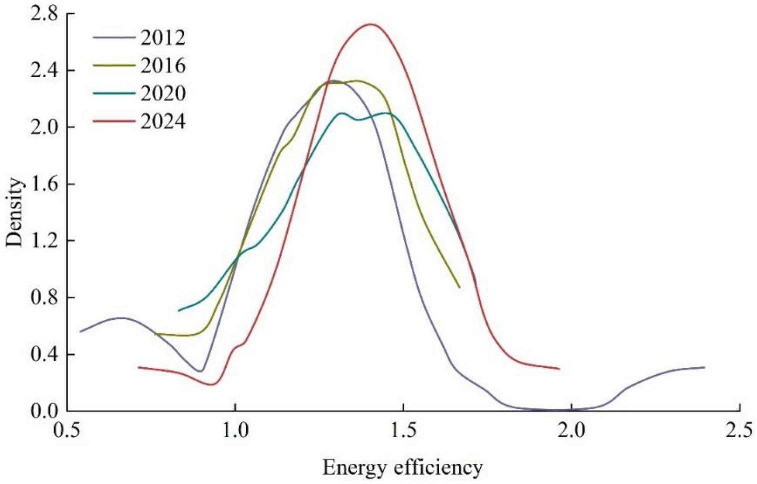

Figure 4: Nuclear density curve of the Beijing-Tianjin-Hebei urban agglomeration

(4) Kernel Density Estimation for PRD Urban Agglomeration

The Figure 5 illustrates dynamic variations in the allocation of energy efficiency of the Pearl River Delta (PRD) city cluster. On the location of the distribution, the Kernel density curve initially moves right and then moves leftward, meaning that energy efficiency of the PRD urban agglomeration has been declining over time. From the aspect of distribution pattern, the 2024 energy efficiency curve indicates the increase in the overall height as well as the expansion of the main peak compared to 2012. It implies that the difference in energy efficiency in the PRD city cluster becomes much more evident. With respect to distribution extensibility, in 2024, the energy efficiency curve has a major rightward tail, in which some cities are significantly more energy-efficient. It implies that distribution of energy efficiency in the PRD region is likely to become more decentralized and more disparities between regions will occur. Considering the wave developing tendency, the Kernel density curve of the PRD city cluster between 2012 and 2020 has a bimodal form. The side peaks are significantly far from the central peak, suggesting that in those years energy efficiency in the PRD cluster stabilized on two different equilibrium levels, namely low-level and high-level energy efficiency levels, creating a polarized situation. This trend is also intensifying by 2024 and the polarization becomes even more evident with the regional differences being expanded, indicating a more explicit multilevel structure of energy efficiency in the cluster.

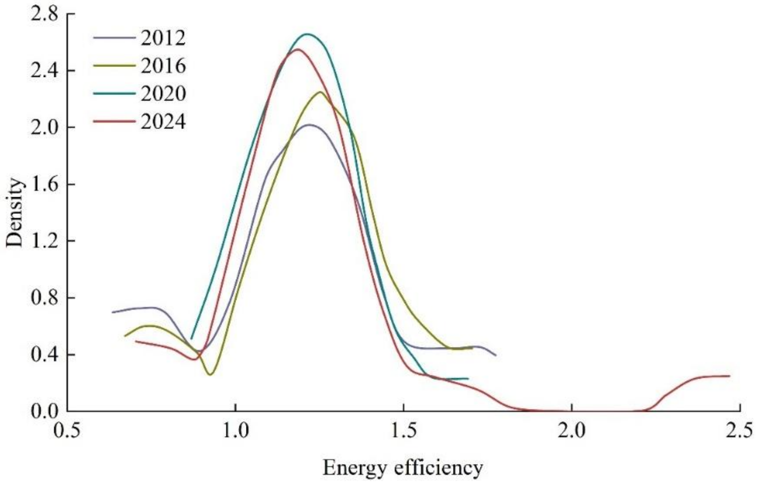

Figure 5: Nuclear density curve of the Pearl River Delta urban agglomeration

3 Study to assess the effectiveness of energy policies in improving urban energy efficiency

In this chapter, the author will turn to the analysis of data on energy efficiency based on 54 cities in three large urban agglomerations. To assess how much energy policies may have affected the results of urban energy efficiency, a difference-in-differences method is used. In addition to the main analysis, it is also investigated whether the industrial economic growth can play a mediating role in the correlation between the policy intervention and efficiency performance.

3.1 Research hypotheses

The main effect of energy policies on the energy efficiency of businesses is through the wider macroeconomic context. These policies have been designed to be offered as a means of policy support and financial incentive to steer corporations into embracing green technology innovations, reforming industries and enhancing energy systems. The changes will result in increased levels of production quality and lower carbon emissions leading to improved energy efficiency. Nevertheless, the effectiveness of such policies in terms of improving energy efficiency can differ according to the regional economic situation and the implementation of these policies. Taking all these factors into consideration, the following hypotheses are stated:

H1: Energy policies can positively influence energy efficiency but their effects differ between various regions.

H2: The industrial economic growth is a mediator of the relationship between energy policies and energy efficiency, which has a positive contribution to the general effect.

3.2 Research methodology and data sources

3.2.1 Double Difference Models

(1) Parallel trend test

The parallel trend assumption must be present to achieve valid results on the difference-in-differences analysis. To be more precise, the energy efficiency level of the experimental group and the control group needs to be the same prior to, after, and during the implementation of the policy. Besides, all the extraneous factors that are irrelevant to the energy policy must have the same effect on the energy efficiency of both the groups. To ensure that this condition is met, the authors conducted a parallel trend test before they implemented the double-difference model. In addition, the event study methodology was used to empirically determine the dynamic effect of the energy policy. The test model is presented as follows:

$$EE_{it} = \beta_0 + \sum_{t=2012}^{2023} \beta_t Treated \times Time + \beta_4 \sum Controls + \gamma_t + \lambda_j + \varepsilon \tag{9}$$

where β is a series of estimates for 2012-2024, the explanatory variable EE_{it} denotes the energy efficiency of the 54 cities in the three major urban agglomerations from 2012-2024, and $Treated$ denotes the implementation variable of the policy, with the pilot areas that implemented the energy policy assigned a value of 1 and the non-pilot areas assigned a value of 0. $Time$ denotes the implementation variable of the energy policy, defined as 0 for the year before the policy is implemented and 1 for the year after the policy is implemented. Interaction term $Treated \times Time$ indicates whether provinces are affected by the energy policy in each period; if a city implements the energy policy in period t, it takes the value of 1 in the current year and the following years $Treated \times Time$, otherwise it takes the value of 0. The dynamic effects are analyzed by using the year before the policy as the base year. Parallel trends are used to test the range of estimates of the interaction term coefficients β_t at the 95% confidence intervals; if the range of estimates contains 0, the coefficient is not significant, and vice versa.

(2) Policy evaluation model

The difference-in-differences (DID) technique has been applied by splitting the study population into two, one that is exposed to the policy intervention and another that is not, and then comparing results between the two groups before and after the policy is implemented. Through this process, the method identifies two different sources of variability. One of them is the time effect that reflects the changes that can be attributed to the time factor, or to the underlying economic trends. The other one is the policy treatment effect that reflects the additional change that occurs only due to the implementation of the policy. In order to enhance accuracy of the estimates, a group of extra control variables is added to the model that controls other variables that could also simultaneously influence the two groups. This is especially valuable since it can offset the lack of randomization of the sample, thus making it possible to identify the actual causal effect of the policy with greater credibility.

This is how the model is built. To differentiate between the two groups being compared, two dummy variables are created. The cities where the policy has been implemented are regarded as the experimental group and given a 1, and all other cities are considered as the control group and given a 0. A temporal dummy variable is also presented at the same time, and the year 2019 is used as the reference point of the policy shock. Any year after 2019 is given a value of one and any year before 2019 gets a value of zero. Using these definitions, the base specification of the difference-in-differences model is written in the format below:

$$\begin{aligned} EE_{it} = \beta_0 + \beta_1 Treated \times Time + \beta_2 treated + \beta_3 time \\ + \beta_4 \sum Controls + \gamma_t + \lambda_j + \varepsilon \end{aligned} \tag{10}$$

where $Controls$ denotes control variables, γ denotes year fixed effects, λ_j denotes region fixed effects, ε denotes the random error term, and the meanings of the other variables are the same as in Equation (9).

3.2.2 Mediated effects model

The mediation effect is modeled as follows:

$$EE_{it} = \alpha_1 Treated \times Time + \sum \beta_x \times Controls + \gamma_t + \lambda_j + \varepsilon \tag{11}$$

$$IEG = \alpha_2 Treated \times Time + \sum \beta_x \times Controls + \gamma_t + \lambda_j + \varepsilon \tag{12}$$

$$EE_{it} = \alpha_3 Treated \times Time + \alpha_4 IEG + \sum \beta_x \times Controls + \gamma_t + \lambda_j + \varepsilon \tag{13}$$

where IEG denotes the mediating variable industrial economic growth, the test steps are:

(1) The first stage is to determine whether or not the interaction term coefficient connected to the energy policy α_1 attains statistical significance. Coefficient that is significantly positive would mean that energy policy has a significant and positive impact on improving urban energy efficiency. In case the coefficient does not achieve significance, the next step of the analysis is to determine if a masking effect can be hiding the actual relationship between the two variables.

(2) The next step is to evaluate whether the coefficients α_2 and α_4 are significant. If both coefficients are significant, this suggests that energy policy exerts a notable influence on the mediating variable, and the analysis moves to step (4). When it is determined that at least one of these coefficients is not significant, then step (3) should be executed.

(3) This stage involves applying the Bootstrap method to assess the significance of the coefficient $H_0 : \alpha_2 \alpha_4 = 0$. In case the coefficient is statistically significant, it means that the indirect effect is also significant, and the next step in the analysis is the step (4). Otherwise, when the coefficient is not significant, the indirect effect is considered too small, and the analysis must be terminated.

(4) The final step involves testing whether the coefficient α_3 is significant. If α_3 is not significant, it suggests that there is no direct effect, and the effect is entirely mediated. If α_3 is significant, compare the signs of coefficients $\alpha_2 \times \alpha_4$ and α_3. If they share the same sign and the absolute value of the total effect α_1 exceeds that of the direct effect α_3, this indicates a partially mediated effect. Conversely, if the signs differ and the absolute value of α_1 is smaller than that of α_3, this suggests the presence of a masking effect.

3.2.3 Description of variables and data sources

(1) Net effect of energy policy implementation

The term that measures the interaction between the dummy variable *Treated* (experimental) and the dummy variable *Time* (policy shock time point) is $Treated \times Time$, which measures the net impact of the implementation of the energy policy.

(2) Energy efficiency

The energy efficiency will be assessed through the use of the MFD-SBM model, which is based on the formulated measurement indices.

(3) Control Variables

In order to consider other factors than the energy policy that can influence the energy efficiency, a number of control variables are used in the model. This set of variables covers elements like the economic development scale, energy structure, green technological innovation, external openness, energy prices, human capital and industrial restructuring.

GDP per capita is used to represent the level of economic development ($PGDP$).

Energy structure (EC) can be stated as a ratio between total energy usage and coal usage because coal remains one of the most important sources of energy in the region.

Green technology innovation has been described as the invention and use of environmentally friendly technologies in the industrial environment. The research measures its impact with the carbon and sulfur emissions to industrial added value ratio (GTI), which provides an exact measurement of the amount of pollutants emitted per unit of industrial production.

The openness index ($OPEN$) can be calculated as a ratio between the value of total goods imported and exported and the regional GDP.

The purchase price index of fuel and power used in energy consumption in various regions is used as a representation of energy prices (EP).

The amount of human capital(PEC) is measured based on the investment in human resources, which is the per capita local education expenditure.

The weighted shares of the three largest industries are used to assess industrial restructuring (ISA), which gives an idea on how the industrial composition of the region has changed over time.

In order to guarantee data accessibility and statistical uniformity, the research will create a panel dataset of 54 cities in the three largest urban agglomerations in China between 2012 and 2024. The information is based on various authoritative sources such as provincial and municipal statistical yearbooks, the China Energy Statistical Yearbook, the China Statistical Yearbook, and the China Environmental Statistical Yearbook.

3.3 Empirical tests

3.3.1 Baseline regression and PSM-DID regression results

All estimations in this study were carried out using Stata 19.0, and the results from both the baseline regression and the PSM-DID approach are reported in Table 3. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively, with coefficient standard errors enclosed in parentheses.

Column (1) presents estimates obtained without any control variables. The coefficient for energy efficiency is positive and statistically significant at the 1% level. The absence of controls, however, introduces considerable estimation error, making it necessary to incorporate additional variables in the models that follow. Column (2) adds time fixed effects to the specification, yielding an interaction term coefficient for energy policy of 0.1583, which remains statistically significant at the 1% level. Column (3) introduces individual fixed effects instead, producing a coefficient of 0.2046 that does not, however, reach conventional levels of statistical significance. Column (4) controls simultaneously for both time and individual fixed effects, with the interaction term coefficient settling at 0.1671 and retaining significance at the 1% level. This result provides fairly robust evidence that the introduction of energy policies has exerted a positive effect on urban energy efficiency. Turning to the control variables, the coefficients associated with economic development level ($PGDP$), energy structure (EC), industrial structure (ISA), energy prices (EP), and external openness level ($OPEN$) are all statistically significant at the 5% level, each exhibiting a positive influence on energy efficiency to varying degrees. The variable capturing green technology innovation (GTI), which is operationalized as the volume of pollutants discharged per unit of industrial value added, stands apart from this pattern. Its coefficient is negative and statistically significant at the 1% level, indicating that this dimension of technological development is associated with a measurable deterioration in energy efficiency performance.

In order to enhance the validity of the baseline estimates, this paper incorporates both the propensity score matching (PSM) method and the difference-in-differences (DID) framework. The findings on the PSM-DID results in Table 5 can be considered generally similar to the results of the baseline regression, which confirms that energy policies have a positive and statistically significant relationship with the urban energy efficiency. The calculated coefficient of 0.1693 is statistically significant at the 1 percent level, and it supports hypothesis H1. The level of economic development among the control variables are positively related to energy efficiency at significance level of 1%. It is consistent with theory because areas with more robust economies are likely to implement stricter environmental regulations, which will establish an environment where higher energy efficiency will be achieved. Similarly, energy structure also has a positive and significant relationship with energy efficiency at the 1% level, indicating that maximization of energy supply composition results in quantified efficiency improvements. The energy price coefficient is 0.2047, meaning that the intuition that increased energy prices would increase the operating cost of a firm and thus lead to a stronger incentive to engage in technological innovation to enhance energy usage. The coefficient of the industrial structure is estimated as 0.2346 and it is statistically significant at 1%. In the context of this study, the industrial structure has been defined by the proportion of the tertiary sector in gross domestic product. Not only does the service sector add significantly to the total economic production but also has much less of an impact on the environment compared to the manufacturing or heavy industries. This shift to services is thus an efficient strategy in improving energy efficiency within a region. Green technology innovation indicator, which is based on volume of industrial pollutants, indicates a negative impact on energy efficiency. Increased pollution per unit of industrial output is viewed as a sign of energy inefficiency, implying that high pollution intensity is linked to poor instead of good efficiency results. Lastly, external openness is positively related to energy efficiency and passes the 1 percent significance level, which means that increased exposure to international markets creates beneficial spillovers, which enhance regional energy efficiency.

Table 3: Benchmark regression and PSM-DID regression results

Variable	(1)	(2)	(3)	(4)	(5)
Treated×Time	0.2064*** (5.291)	0.1583*** (4.172)	0.2046 (5.365)	0.1671*** (4.158)	0.1693*** (4.187)
PGDP		1.5631*** (1.613)	1.6248*** (1.651)	1.7325*** (1.634)	1.7362*** (1.653)
EC		0.4575 (2.696)	0.2494*** (3.582)	0.2275*** (3.531)	0.2047*** (3.568)
GTI		-0.0752*** (-0.219)	-0.0416*** (-0.277)	-0.0594*** (-0.166)	-0.0628*** (-0.183)
OPEN		0.0281* (0.113)	0.0165** (0.125)	0.0092** (0.147)	0.0073* (0.131)
InEP		0.1598*** (2.154)	0.2251*** (2.272)	0.1853*** (2.174)	0.1935*** (2.286)
PEC		0.0868 (0.578)	0.0974*** (0.494)	0.0925*** (0.643)	0.0851*** (0.652)
ISA		0.2324* (7.5932)	0.4157*** (7.705)	0.2319*** (7.683)	0.2346*** (7.724)
Constant	0.7284*** (16.346)	0.7335*** (5.731)	0.3697*** (8.958)	1.5273*** (3.864)	1.4842*** (3.981)
Observations	702	702	702	702	702
R-squared			0.235	0.347	0.379
Fixed time	NO	YES	NO	YES	YES
Individual fixation	NO	NO	YES	YES	YES
The number of cities	54	54	54	54	54

3.3.2 Impact mechanism test

The present paper considers industrial economic growth (*IEG*) as one of the mechanisms that drive energy policy and incorporates interaction between energy policy and industrial economic growth as one composite variable of regression analysis. The findings of the impact mechanism test are given in Table 4.

The findings indicate that when the variable of industrial economic growth is included, the coefficient of the effect of energy policy on energy efficiency goes up to 0.1875. This is consistent with the baseline regression findings, and the coefficient is statistically significant at the 1 percent level. Also, the coefficient of the industrial economic growth is 0.0184, and it is statistically significant at the 5 percent level, and it indicates that industrial economic growth has a positive relationship with energy efficiency. Energy policy and industrial economic growth have a coefficient of 0.0396 as interaction term, which is statistically significant at the 5% level. This means that energy policies lead to optimizing the regional industrial structure, which leads to improving the industrial economic performance. Consequently, the interaction of energy policy and industrial economic growth improves regional energy efficiency and hence confirms hypothesis H2. In particular, energy policy has been found to be a useful mechanism in enhancing the efficiency of energy use in urban areas during industrial economic growth.

Table 4: Examination of the impact mechanism of energy policies on energy efficiency

Variable	The effect of industrial economic growth
Treated×Time	0.1875***(7.583)
IEG	0.0184**(5.394)
Treated×Time×EC	0.0396***(5.278)
Control variable	YES
Individual fixation	YES
Fixed time	YES
Constant	0.7057***(10.231)
Observations	702
R-squared	0.379
The number of cities	54

3.3.3 Robustness Tests

(1) Parallel trend hypothesis test

Since the introduction of an energy policy may be considered a quasi-natural experiment, checking the parallel trend assumption is a necessary first step prior to undertaking the difference-in-differences estimation. The assumption implies that the treatment group and the control group should have similar trends in energy efficiency prior to the policy implementation. If this condition were violated, the validity of the estimated policy effect would be undermined, and the calculated net impact would become unreliable. In this case, the event study approach is used to test this assumption formally.

The test draws on panel data covering 54 cities across the three most populous urban agglomerations over the 2012 to 2024 observation window. The parallel trend analysis incorporates information from four years before the policy was adopted and three years following its implementation, with the interaction term coefficient serving as the primary variable of interest. The results of this econometric exercise are displayed in Figure 6. In the four years leading up to policy introduction, the interaction term coefficients are statistically indistinguishable from zero, indicating that no systematic pre-existing divergence existed between the treatment and control groups in terms of energy efficiency. Once the policy comes into effect, however, the coefficients begin rising consistently, pointing to a positive and progressive impact of energy policy on urban energy efficiency performance. Taken together, these findings confirm that the parallel trend assumption is satisfied and that the difference-in-differences estimates can be interpreted with reasonable confidence.

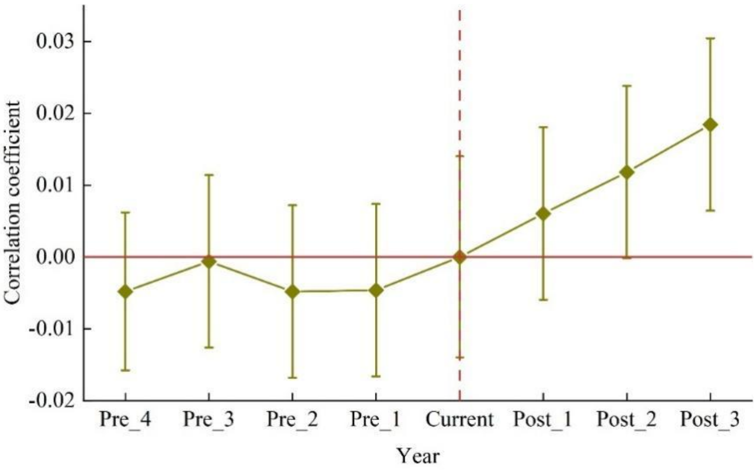

Figure 6: Common trends in energy efficiency

(2) Placebo test

The results of both the benchmark regression and PSM-DID show that energy policy improves energy efficiency. In order to confirm these results, this paper uses the placebo approach. Since the energy policy of this research will start in 2019, we predict that the 54 cities in this sample are influenced by the policy three, four, and five time periods before the real implementation period, which is supposed to be in 2013. And then we check if the correlation coefficients under the sub-cases, i.e. tq3, tq4, tq5 and tq2013 are statistically significant.

The results of the placebo test are given in Table 5. The estimated interaction term coefficient values at different pseudo-treatment intervals are 0.1364, 0.1359, -0.1295, and 0.7836 respectively. These coefficients do not have any statistically significant levels, and as such, it can be confirmed that none of the results produced by the main analysis is caused by chance or confounding variables that are not due to the policy itself. The non-significant outcomes of the placebo tests also add extra weight to the argument that the positive impact of energy policy on urban energy efficiency found in this paper is a real causal association instead of a spurious statistical phenomenon.

Table 5: Placebo test

Variable	(1) Three installments in advance	(2) Four issues in advance	(3) Five installments in advance	(4) Suppose it was 2013
tp3	0.1364 (2.053)			
tp4		0.1359 (3.214)		
tp5			-0.1295 (3.571)	
tp2013				0.7836 (6.948)
Constant	0.4152*** (8.727)	0.4581*** (9.262)	0.5124*** (9.459)	0.3972*** (8.165)
Control variable	YES	YES	YES	YES
Individual fixation	YES	YES	YES	YES
Fixed time	YES	YES	YES	YES
Observations	702	702	702	702
R-squared	0.096	0.098	0.089	0.327
The number of cities	54	54	54	54

3.3.4 Heterogeneity analysis

The influence of energy policy on urban energy efficiency is not the same in different cities. The differences in geographic location, resource endowment, industrial composition, economic development strategy, and timing and sequencing of green transition all lead to the variation in how policy interventions can be translated into efficiency results. In this part of the analysis, these heterogeneous effects are researched through the analysis of how energy policies operate among cities which are classified according to their geographic location and type of development.

(1) Geographic location of cities

The 54 cities included in the sample are divided into 3 clusters that are related to the urban agglomeration to which they belong to, viz. Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta. The regression models are estimated per each group and the heterogeneity results are given in Table 6.

The estimated coefficients on the key explanatory variables across all three regions are positive, which indicates that energy policies have a positive impact on energy efficiency irrespective of geography. The size of this effect, though, varies greatly between regions. The policy effect is particularly strong in the Yangtze River Delta and Pearl River Delta agglomeration but is somewhat weak in the Beijing-Tianjin-Hebei region. This regional difference suggests that geographic context plays a significant role in determining the efficacy of energy policy. There is a reasonable explanation behind why the impact in Beijing-Tianjin-Hebei is rather soft, and it is because this region has been historically less industrialized and economically developed than its eastern neighboring areas, and it has a different structure of energy consumption. The reduced rate of industrial restructuring in this area also constrains the ability of energy policies to produce significant efficiency improvements, implying that policy formulation in this case should be modified to address the local structural factors to obtain more practical outcomes.

Table 6: Analysis of heterogeneity in urban geographical locations

Variable	(1)	(2)	(3)
	The Yangtze River Delta urban agglomeration	The Beijing-Tianjin-Hebei urban agglomeration	The Pearl River Delta urban agglomeration
Treated×Time	0.1257* (3.126)	0.1238 (3.115)	0.0539* (3.143)
Constant	0.4837*** (4.195)	0.4054*** (3.846)	0.8592*** (3.783)
Control variable	YES	YES	YES
Individual fixation	YES	YES	YES
Fixed time	YES	YES	YES
Observations	338	169	195
R-squared	0.349	0.345	0.294
The number of cities	26	13	15

(2) City development type

Further classification of the cities in the sample is based on the fact that the development path of the city can be determined by the natural resource endowment. The 54 cities are then subdivided into 13 resource-based cities and 41 non-resource-based cities respectively. Availability of resources is one of the most important determinants of the patterns in which urban development occurs and it affects the course of urban innovation in particular. Besides this, resource-based and non-resource-based cities usually have significantly different industrial compositions, economic development programs, and green transition orientations. Such structural distinctions lead to significant variation in what kind of effect energy policies may have on the level of urban energy efficiency between the two types of cities.

In order to examine this aspect of heterogeneity, the estimations are made separately, in the case of resource-based cities and in the case of non-resource-based cities. The findings are listed in table 7. The results show that energy policies have positive efficiency impacts on the two types of cities, but the size of such an impact is significantly higher in non-resource-based cities. Such a trend indicates that the development nature of a city plays an important role in moderating the level of responsiveness of urban energy efficiency to policy intervention.

The reason behind this divergence can be explained by the fact that the development logic of each type of city is inherently different. Non-resource-based cities, without immediate access to natural resource wealth at the initial stage of development, have traditionally had no choice but to develop through structural optimization of industries and development of innovation ecosystems. This stance implies that when energy policies are implemented, non-resource-based cities will be in a better position to redirect the policy-related incentives to green and innovative development courses, which will eventually result in significant energy saving gains compared to resource-dependent cities.

Table 7: Heterogeneity analysis of urban development types

Variable	(1)	(2)
	Resource-based city	Non-resource-based city
Treated×Time	0.1284* (3.419)	0.1471** (3.286)
Constant	1.1459*** (1.531)	0.5724*** (1.187)
Control variable	YES	YES
Individual fixation	YES	YES
Fixed time	YES	YES
Observations	169	533
R-squared	0.415	0.382
The number of cities	13	41

4 Conclusion

The present paper examines the issue of urban energy efficiency in 54 Chinese cities that are part of the three largest urban agglomerations based on the information available between 2012 and 2024. The main measurement framework is a common frontier dynamic SBM model which includes undesirable outputs. The study also uses the PSM-DID model to evaluate how energy policies influence energy efficiency and focuses specifically on the mediating effect of industrial economic growth on this relationship.

The average annual value of the energy efficiency of the 54 cities is 1.0753 indicating that the selected areas are operating at a fairly reasonable energy efficiency level. Of the three urban agglomerations, the highest average energy efficiency is achieved by the Pearl River Delta (PRD), next by Beijing-Tianjin-Hebei (BTH) and lastly by the Yangtze River Delta (YRD). Concerning the improvement during the study period, the most significant gains were noted in the PRD and the least in the YRD. On the level of individual cities, Yunfu has become the most energy efficient city and the efficiency value was 2.67 times higher than that of Anqing, the lowest ranking city within the distribution. There is also a high level of disparity in energy efficiency not only across clusters but also within the cities of the same cluster. Moreover, the difference in the efficiency levels of the cities in the PRD, BTH and YRD territories have kept growing over time with PRD showing the greatest disparity and BTH the least.

Energy policies can act in various ways to determine efficiency results. Empirical research presented in this paper aims at analyzing the effect of energy policies on energy efficiency in particular through the economic development of industry using several econometric models to support such a relationship. These findings indicate that energy policy plays a central role in improving energy efficiency, and that when combined with industrial economic development, it creates a synergistic effect that enhances the benefits of efficiency over the levels each factor could have achieved separately. The strength of these findings is verified by parallel trend tests and a set of placebo tests, all of which agree with the main findings. The analysis also shows that the cities being studied exhibit significant heterogeneity in their responses to energy policy, determined by the differences in their geography and the character of their development trajectories.

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