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Modeling Linkages among Urban Agglomeration, Construction Industry, Non-Renewable Energy, and Zero-Carbon Future

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Abstract: On the one hand, the twin perspectives of the construction industry and urban agglomeration proliferate economic prosperity. However, on the other hand, construction activities and increased population density give rise to environmental challenges. This study is an initial attempt to explore links between the construction industry, urban agglomeration, non-renewable energy utilization, carbon dioxide emissions (CO_2e), and economic output within a system of simultaneous equation modeling. This study develops modeling specifications to include the construction industry as a shifting factor and CO_2e as a determinant of technical efficiency. A heterogeneous fully modified ordinary least squares (FMOLS) technique, capable of providing concrete empirical outcomes even in the presence of modern panel-data econometric issues, is utilized for the data of China's 30 provincial/ city divisions during the 2003–2019 period. It has been revealed that: (i) the influence of urban agglomeration on the economic output was heterogeneous, with an adverse link for China's western part, neutrality connection for the central part, and favorable for China's eastern part; and (ii) shifting from China's western to eastern parts, the expansion of the construction industry has a significant impact on economic output, and, hence, has been described as "the Economic Effects of Urban agglomeration" for the Chinese economy. The policies of this study have crucial lessons for global economies.

Keywords: simultaneous equation modeling; construction industry; urban agglomeration; non-renewable energy utilization; CO_2e; economic output; heterogeneous panel; China

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1. Introduction

During the preceding few decades, the curtailment of greenhouse gas (GHG) emissions, such as carbon dioxide emissions (CO_2e), has become the prime concern of the developed and rapidly developing economies worldwide to pursue climate-change mitigation. For that purpose, the primary step taken by those economies was the FCCC (Framework Convention on Climate Change) framework, established in Kyoto (Japan) in 1997, which was found to be insufficient in strategic plans to obtain the desired aims. Thus, it was followed by the enactment of the Kyoto Protocol in the same year [1]. However, the Kyoto Protocol became effective in 2005, under which around 37 European and some highly industrialized economies of the world agreed to provide emissions reduction targets [2]. Most recently, the number of member countries reached 191 after the backlash of the USA's withdrawal from the Paris Agreement [3]. The members of the Kyoto Protocol are directed to ensure the progress of environment-friendly energy technologies and enforcement of climate-change-mitigation strategies and policies.

In view of the 13th Five-Year Plan of China, the pace of urban agglomeration and infrastructure prosperity is proposed to be boosted through the promotion of urban residency facilitation, urban-infrastructure development, green-energy development for the sustainable-construction sector, the transformation of cities in terms of better environmental quality, the competitiveness of cities, and living standards of people. The lessons drawn from this work comply with the above-mentioned plans. This work would be helpful in policy reforms in countries with varying levels of development, which are undergoing rapid construction-industry development and urban agglomeration, along with confronting environmental-sustainability challenges. The future avenues of this work may involve including renewable-energy consumption in relation to its role in urban and construction-sector development to mitigate environmental degradation.

Considering the long-standing tendency of previous studies on construction industry-energy-environment-urban agglomeration-economy nexuses, the review of existing literature can be classified into the following research streams: (1) *urban agglomeration-environment-economic output,* (2) *non-renewable energy-environment-economic output,* and (3) *construction industry.*

Reviewing the *first research stream*, Zhang et al. [4] mainly focused on what it was, how it was explained, and what effective models were related. Their study demonstrated four steps for urban concentration and different methods and tactics to describe it in detail. The prime focus of Jayasooriya [5] was to investigate the origin of its sustainable progress. It explored the effect of urban concentration in regional China by taking 31 Chinese regions from 2004–2015, in which the population and population density were used as a proxy for urban agglomeration, and tested their relationship with economic output. Population and population density were used to expose the influence of urban agglomeration on economic output. The hypothesis developed stated whether there was any relationship between agglomeration and energy output. The outcomes elaborated their affirmative interlink, which implied that the growth increased with an increase in agglomeration, but it started declining upon reaching a specific point. Tripathi [6] focused on exploring the impacts of urban agglomeration on economic output in India by using dynamic and static panel-data methods from 2000–2009. The study was composed of 52 cities in India. The findings indicated a positive and statistically significant linkage between urban concentration and economic output by considering Williamson's hypothesis that urban concentration increased economic output up to a limited level; after that, it started declining. Economic output could also be increased through human capital. Besides, Ahrend et al. [7] explored the effect of urban concentration on economic output. In addition, it examined the additional factor of labor productivity, and an increase in population caused an increase in labor productivity in large cities as large cities provide 'agglomeration economies' for laborers who worked in bigger cities comparatively.

Moreover, Aftab et al. [8] attempted to find the effect of urban agglomeration on energy output in Punjab, Pakistan. For this purpose, data were collected from different districts of Punjab. A recursive economic technique was used. Their outcomes indicated that laws made by the government, the area of districts, and the size of the market positively affect urban agglomeration. But the two factors, the level of urbanized districts and the number of vehicles, affected it negatively. The findings based on the economic output model signposted the existence of a positive and statistically significant impact of urban concentration on economic output. A piece of research by Khobai and Roux [9] explained the influence of urban agglomeration on electricity utilization in South African economies from 1971 to 2013. The labor, capital, and trade openness are taken as confounding variables. After utilizing the Granger causality approach (GCA) and Johansen cointegration, their outcomes revealed cointegration among all variables. Faisal et al. [10] researched the connection among power utilization, energy output, trading, and urban agglomeration in Iceland over the period of 1965 to 2013 by applying GCA under the vector error correction model (VECM). The empirical outcomes illustrated the short- and long-term causality among energy utilization and its variables. In a similar fashion, Wang and Li [11] inspected the relationship of urban agglomeration with energy efficiency by taking data from 77 nations during the 1995–2012 period and employing a random approach. The outcomes demonstrated that agglomeration increased electricity usage but decreased energy-utilization efficiency. The said inefficiency of electric energy utilization was of a profound level for the nations with greater GDP.

Besides, Zhang et al. [12] conducted an exploration of the influence of urban agglomeration on electricity usage and CO_2e in different provinces of China. Their findings illuminated that urban agglomeration contributes a substantial part to increasing electric energy utilization and CO_2 discharge. Also, it varied from province to province, as, in northern China, there was more urban concentration, discharge, and electric energy utilization compared to its southern part. Based on the surveyed literature, Du and Xia [13] studied the linkage between urban agglomeration and GHG emissions over a period of 1971 to 2012, employing panel data from sixty countries and utilizing threshold modeling. They revealed that the urban agglomeration increased those emissions more intensively when the CO_2e surpassed 42,287 kt. Similarly, Liu and Liu [14] investigated the effect of disparity among regions of China and the spatial influence of urban agglomeration on CO_2e by modifying the STIRPAT and spatial Durbin models and found a significant effect of both on CO_2e. Dong et al. [15] took data from 126 countries from 1990 to 2026 and examined the linkage between urban agglomeration and PM2.5 discharge by using a stochastic approach. The results found an inverted U-shaped curve between the variables of interest. In another empirical research, Wang et al. [16] tested the spatial effect of urban concentration on CO_2e in different sectors of China by using a weighted regression model and found there is a different spatial effect of urban agglomeration in different regions for different sectors.

Regarding the *second research stream*, Wang et al. [17] examined the linkage between energy utilization and the progress of the economy in Kazakhstan by integrating labor, capital, and openness to trade as additional factors and used annual data from 1991 to 2014. For this purpose, VECM, GCA, and autoregressive distributed lag (ARDL) bounds testing methods were used. The findings indicated that energy utilization increased energy output and labor-force participation, and that trade openness boosted energy output. Therefore, there was a strong relationship between them in the long run. In another work, Ali et al. [18] focused on examining the linkage between energy utilization, the progress of the economy, and trade for the case of the Indian economy by using GCA, VECM, and the long-run cointegration approach from the period of 1971 to 2016. The findings directed that energy utilization accelerated economic output. The causality that flowed from power consumption to economic output also existed. Li and Wei [19] inspected the correlation between electricity use and economic output in China from 1980–2013 by applying unit root test statistics. Dynamic linkages between both variables were determined using a VECM approach. The results emphasized a bidirectional linkage between electricity use and economic output in the long-term perspective. It meant that economic output was amplified with an expansion in electricity use. In another pioneer research, Sun et al. [20] assessed the linkage between energy utilization and economic output by using GCA in seventeen industries in Taiwan from the time period of 1998 to 2014. The findings designated the presence of bilateral causal linkage, and a long-term linkage existed between both variables. Therefore, energy utilization encouraged economic output. Additionally, the linkages between energy utilization and economic output in different income segments of different countries have focused on the 1970–2015 period by applying the GCA and panel ARDL boundary approach. Besides, Salman et al. [21] inspected the impact of local institutions on economic growth and CO_2e in East Asian economies (Thailand, South Korea, and Indonesia) from 1990 to 2016. They ended up with a significant and affirmative effect of institutions on economic growth and CO_2e as economic growth increased, while CO_2e decreased by using fully modified OLS (FMOLS) and dynamic OLS (DOLS) methods. Yaşar [22] aimed to find whether the strength of the relationship differs in different income group levels of different countries. After testing the hypothesis, it was found that the linkage between power utilization and energy output varies per the variation in various levels of income groups from different countries.

Furthermore, Saint et al. [23] assessed the relationship between energy utilization, CO_2e, energy output, and globalization in Turkey from 1970 to 2014 by using the ARDL approach. Their results uncovered that there was an insignificant impact of globalization on CO_2e, while energy utilization and real earnings significantly affected pollutant discharge. Wang et al. [24] examined the effect of economic structure, investment, and intensity of energy on CO_2e by using decoupling and decomposition methods in the USA and found that CO_2e increases due to economic structure and investment effect. At the same time, it decreases due to energy intensity. Similarly, Han et al. [25] studied the trilateral causal linkage between CO_2e, material reserves, and energy output by using decoupling analysis in less urbanized provinces of China and found relative decoupling as average elasticity was smaller than one. Rahman [26] investigated the impact of electricity use, energy output, and globalization on CO_2e by taking data from 1971 to 2013 from the top ten power-utilizing countries. The findings showed that electric energy utilization and output imparted a statistically significant and positive influence on CO_2e. However, globalization demonstrated a significant adverse effect on CO_2e. Kahouli [27] investigated the causality linkage among energy utilization, CO_2e, energy output, and research and development (R&D) stocks in Mediterranean countries. In this regard, a unidirectional causality was found between R&D stocks and electricity consumption in 3SLS, and also unidirectional causality flowing from R&D to CO_2e and R&D to economic growth was found through the generalized method of moments (GMM) estimator. Furthermore, Ardakani et al. [28] tested the influence of energy utilization, economic output, and financial growth on CO_2e by using GCA from 1980 to 2013 in Kuwait. Their findings showed that electricity use, energy output, and foreign direct investment accelerate CO_2e. Zhao et al. [29] discussed that switching towards electrical devices in replacement of fossil-fueled appliances can cause a decrease in CO_2e in China by maintaining economic output and gross domestic product. Thus, coal and oil electricity transformation resulted in a reduction of CO_2e, while there was no significant effect of gas electricity transformation on CO_2e abatement.

Concerning the *third literature stream*, a few studies dealt with establishing linkages of the construction industry with the environment and economy. For instance, Ahmad and Jabeen [30] applied the GMM technique to data from China's 30 provincial divisions to analyze the interactions among the construction sector, aggregate output, and electric power consumption. The authors revealed a positive contribution of the construction sector to electric power consumption. However, they overlooked the consideration of environmental indicators in their study, leaving a critical research void. Cheng et al. [31] applied a Malmquist carbon emissions performance index (MCEPI) to China's provincial data over the 2004–2016 period to examine the contributions of the construction industry to regional CO_2e. They observed the highest performance of those emissions across eastern China. Similarly, Zhao et al. [32] used a Logarithmic Mean Divisia Index (LMDI) approach to data from Hangzhou city, China, in order to estimate the contribution of the construction industry to the CO_2e of the city. They uncovered that the construction industry-based indirect emissions exceeded those produced within Hangzhou by construction activities. In their work, Yao et al. [33] employed the social–technological transition model in China's data to inspect the low-carbon transitional level (LTL) achieved by the construction industry. They found that technological factors could promote the positive effects of LTL within the construction industry.

The above-illustrated review of previous works identifies the following literature gaps. Firstly, studies on links between urban agglomeration and the construction industry are scarce. Secondly, no single research has been found to examine the interlinks of the construction industry, energy utilization, and urban agglomeration in the economic-modeling framework. Thirdly, the previous studies lack unanimous agreement on the nature of connections based on the urban agglomeration–CO_2e nexus, construction industry–CO_2e nexus, and economic output–CO_2e nexus. Fourthly, concerning the present work, no study has been discovered delving into the combined connections among urban agglomeration, construction industry, energy utilization, economic output, and CO_2e in the economic modeling specifications. Finally, the previous research works did not employ heterogeneous FMOLS, which allows for heterogeneity across cross-sectional units.

This study's objective is to investigate the potential for causal linkages between the construction industry, urban agglomeration, utilization of non-renewable energy sources, CO_2e, and economic output for thirty Chinese provinces and cities throughout the period 2003–2019. The results of this research provide crucial policy recommendations in addition to stylized empirical findings. Hereunder are some innovative additions that this research offers to the growing corpus of the new pool of literature. To put it in more technical words, first, this study expands the economic output model by Ahmad and Jabeen [30] to include the construction sector and urban agglomeration as shift components and CO_2e as a predictor of technical efficiency. This was done in order to make the model more comprehensive. Second, this study develops a theorized connection between the construction industry, urban agglomeration, the utilization of non-renewable energy sources, CO_2e, and economic output. Third, to investigate the five different ways research variables are connected to one another, this study devised a simultaneous five-way structural model system. Fourth, this research work takes into account the potential panel heterogeneity for which the second-generation heterogeneous FMOLS technique developed by Pedroni [34] has been used in order to provide accurate estimates that are resistant to cross-sectional dependency and heterogeneity.

2. Materials and Methods

2.1. Data and Theoretical Modeling

The data for this research, which covers a period spanning from 2003 to 2019, comes from a variety of China Statistical Yearbooks and includes 30 provinces and cities in China. Table 1 provides explanations of variables. The data calculations of CO2e are presented in Figure 1. The data trends of the study variables can be viewed in Figure 2. Besides, the data trend comparisons for value addition of the construction industry across various parts of China are shown in Figure 3.

The official data on CO_2e were unavailable for the Chinese economy's provincial divisions. Hence, a dataset of CO_2e for 30 provincial divisions of China has been calculated. The burning of fossil fuels has been attributed to be the chief source of industry-based [35] and households' direct and indirect CO_2e [36]. According to the methodology set up by the Intergovernmental Panel on Climate Change (IPCC) [37], the CO_2e data are calculated by choosing the nine frequently utilized energy products by both industries and households. These energy products included coal, coke, fuel oil, diesel oil, crude oil, gasoline, natural gas, kerosene, and electricity. Luo et al. [38] opted for the same energy products for the CO_2e data calculation. The following equation has been used to calculate CO_2e:

$$CO_{2e_l} = \sum_{k=1}^{30} \sum_{l=1}^{9} CO_{2e_{k,l}} = 44/12 \times \sum_{k=1}^{30} \sum_{l=1}^{9} CENP_{k,l} \times NCAM_{k,l} \times FCOM_{k,l} \quad (1)$$

where 'k' and 'l' demonstrate China's provincial divisions and energy products, respectively. 44/12 denotes the constant measure of weighted CO_2e fraction in the carbon element of CO_2e, $CENP$ represents the energy products' consumption, $NCAM$ denotes the average net calorific measurement, and $FCOM$ indicates the factor of combined CO_2e from nine energy products. The $CENP$ data are compiled from province-specific China Energy Statistical Yearbooks from 2002 through 2020. Moreover, the parametric values for $NCAM$ and $FCOM$ are extracted from IPCC [37]. Figure 1 shows the average of $NCAM$ and $FCOM$ for the consumption of each energy product. Detailed explanations of the formation and calculations of $NCAM$ and $FCOM$ can be obtained from the previous studies [35–38].

Table 1. Data explanations.

Data	Explanations	Variable and Symbols
Gross domestic product	Transformed into per-capital format	Economic output (ECO)
Urban population	Population in urban settings percent of the aggregated population	Urban agglomeration (UBA)
Total non-renewable energy utilization	Transformed into per-capital format	Non-renewable energy utilization (EUT)
Physical capital	Calculated from the perpetual inventory method	Physical capital (PCP)
Carbon dioxide emissions	CO_2e is calculated following [32]	CO_2e
Value-addition by the construction industry	Transformed using the economic output and used in percent format	Construction industry (CNI)

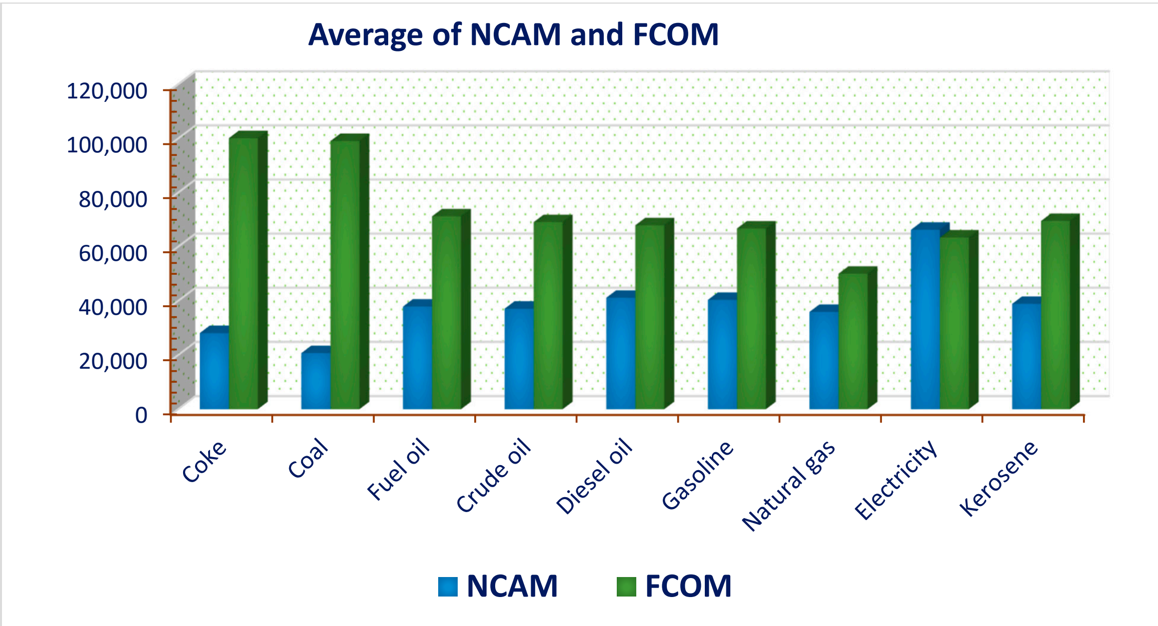

Figure 1. Average of NCAM and FCOM for energy products. Source: Authors' calculations based on China Energy Statistical Yearbooks (2003–2019).

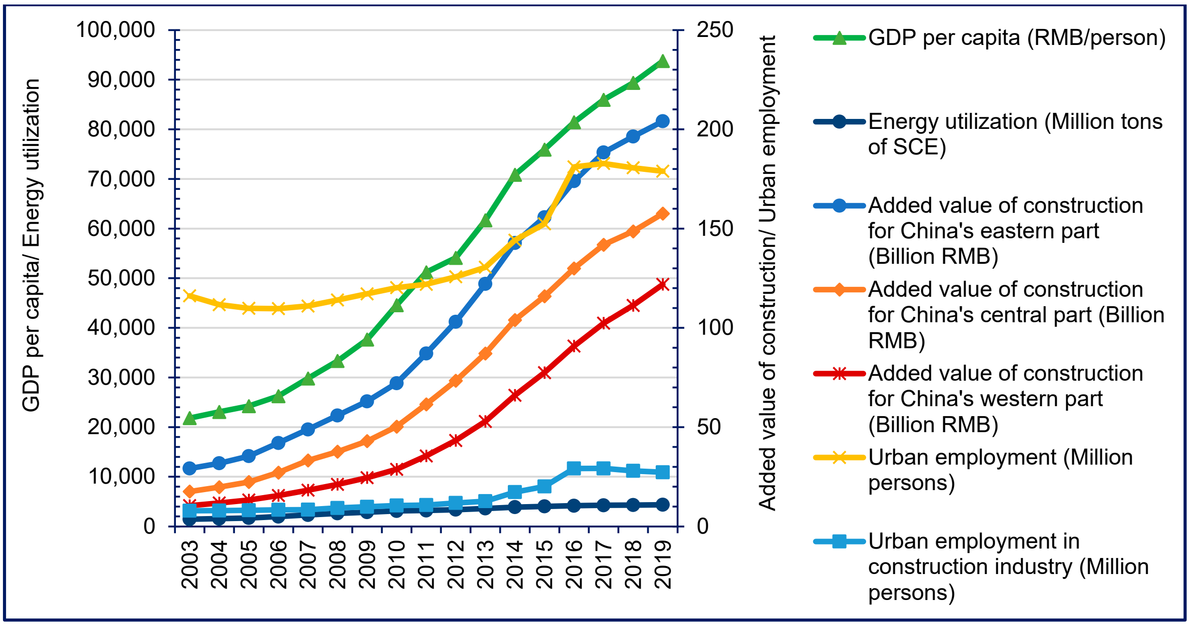

Figure 2. Outlining average trends of the study variables. Source: Authors' calculations based on China Statistical Yearbooks (2003–2019).

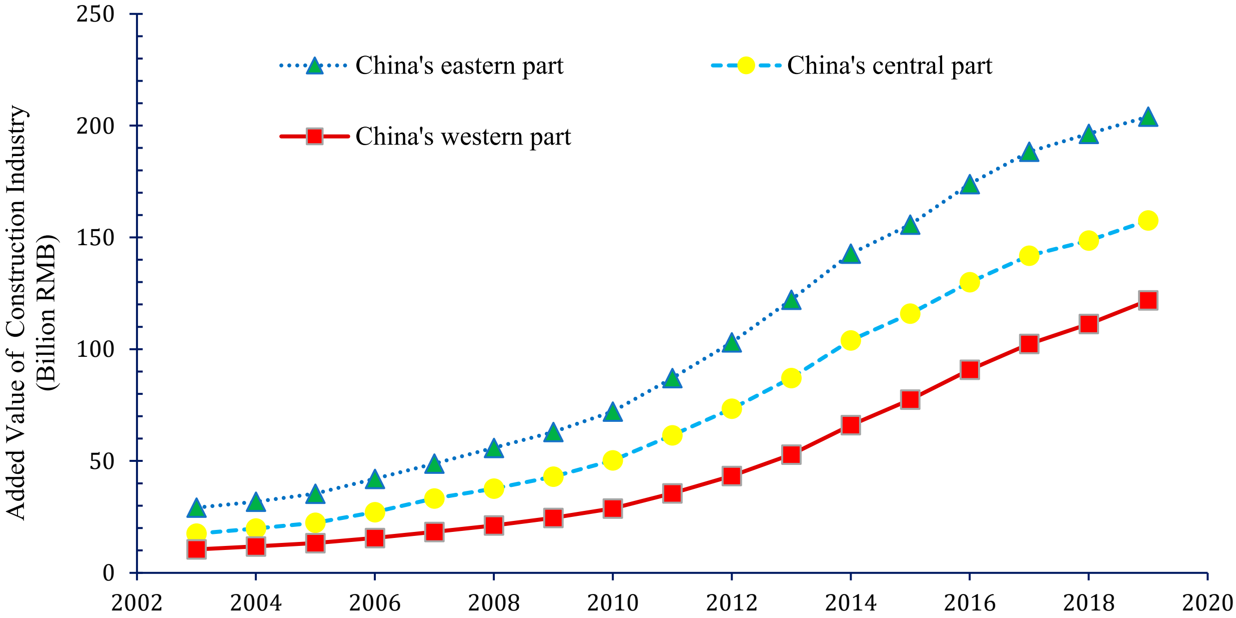

Figure 3. Outlining average trends of the added value of the construction industry across three parts of the Chinese economy. Source: Authors' calculations based on China Statistical Yearbooks (2003–2019).

To begin with, technical efficiency has been added to a model of economic output that is based on the Cobb–Douglas production system and uses the constant scaling returns method described by Ahmad and Jabeen [30]:

$$ECO_{i,t} = A_{i,t}PCP^{\alpha}_{i,t}EUT^{\beta}_{i,t}\ N^{1-\alpha-\beta}_{i,t}(UBA_{i,t})^{\varphi} \tag{2}$$

where ECO denotes economic output, A denotes the technical efficiency, PCP is indicative of the physical capital formation, EUT is the demonstration of the non-renewable energy utilization, N is the demonstration of the skilled and unskilled labor force, and UBA is indicative of the urban agglomeration.

Equation (2) is modified by integrating the factor of the construction industry (CNI) to give Equation (3):

$$ECO_{i,t} = A_{i,t}PCP^{\alpha}_{i,t}EUT^{\beta}_{i,t}\ N^{1-\alpha-\beta}_{i,t}(UBA_{i,t})^{\varphi}(CNI_{i,t})^{\psi} \tag{3}$$

Next, according to Ahmad and Wu [39], CO_2e can influence technical efficiency. Herein, CO_2e is injected into Equation (3) to determine the technical efficiency. Ceteris paribus, CO_2e is plugged into Equation (3):

$$ECO_{i,t} = PCP^{\alpha}_{i,t}EUT^{\beta}_{i,t}\ N^{1-\alpha-\beta}_{i,t}(UBA_{i,t})^{\varphi}(CNI_{i,t})^{\psi}\left(CO_{2e_{i,t}}\right)^{\lambda} \tag{4}$$

As per recommended specification of Ahmad and Khan [40], Equation (4) is normalized by the labor force. Furthermore, natural log transformation is applied:

$$ln\widetilde{ECO}_{i,t} = \alpha ln\widetilde{PCP}_{i,t} + \beta ln\widetilde{EUT}_{i,t} + \varphi lnUBA_{i,t} + \psi lnCNI_{i,t} + \lambda lnCO_{2e_{i,t}} \tag{5}$$

where ~ is indicative of the per-labor format of Equation (5). As a next step, Equation (5) has been modified into an empirical modeling format.

2.2. Empirical Modeling

Equation (5) can be expressed as follows in the econometric formulation:

$$ln\widetilde{ECO}_{i,t} = \alpha ln\widetilde{PCP}_{i,t} + \beta ln\widetilde{EUT}_{i,t} + \varphi lnUBA_{i,t} + \psi lnCNI_{i,t} + \lambda lnCO_{2e_{i,t}} + e_{i,t} \tag{6}$$

From Equation (5), five modeling specifications are presented to consider each of economic output, non-renewable energy utilization, urban agglomeration, construction industry, and CO_2e as regressand variables turn-by-turn in each specification:

$$ln\widetilde{ECO}_{i,t} = \alpha_1 ln\widetilde{PCP}_{i,t} + \alpha_2 ln\widetilde{E}UT_{i,t} + \alpha_3 lnUBA_{i,t} + \alpha_4 lnCNI_{i,t} + \alpha_5 lnCO_{2e_{i,t}} + e_{i,t,1} \quad (7)$$

$$ln\widetilde{EUT}_{i,t} = \beta_1 ln\widetilde{ECO}_{i,t} + \beta_2 lnUBA_{i,t} + \beta_3 lnCNI_{i,t} + \beta_4 lnCO_{2e_{i,t}} + e_{i,t,2} \quad (8)$$

$$lnUBA_{i,t} = \gamma_1 ln\widetilde{EUT}_{i,t} + \gamma_2 ln\widetilde{ECO}_{i,t} + \gamma_3 lnCNI_{i,t} + \gamma_4 lnCO_{2e_{i,t}} + e_{i,t,3} \quad (9)$$

$$lnCNI_{i,t} = \theta_1 ln\widetilde{EUT}_{i,t} + \theta_2 lnUBA_{i,t} + \theta_3 ln\widetilde{ECO}_{i,t} + \theta_4 lnCO_{2e_{i,t}} + e_{i,t,4} \quad (10)$$

$$lnCO_{2e_{i,t}} = \varnothing_1 ln\widetilde{EUT}_{i,t} + \varnothing_2 lnUBA_{i,t} + \varnothing_3 lnCNI_{i,t} + \varnothing_4 ln\widetilde{ECO}_{i,t} + e_{i,t,5} \quad (11)$$

In the above specifications, $e_{i,t}s'$ are the demonstrations of residuals; the symbols α_1, α_2, α_3, α_4, and α_5 capture the impact of physical capital, non-renewable energy utilization, urban agglomeration, construction industry, and CO_2e on economic output, respectively; β_1, β_2, β_3, and β_4 capture the impact of economic output, urban agglomeration, construction industry, and CO_2e on non-renewable energy utilization, respectively; γ_1, γ_2, γ_3, and γ_4 capture the impact of non-renewable energy utilization, economic output, construction industry, and CO_2e on urban agglomeration, respectively; θ_1, θ_2, θ_3, and θ_4 capture the impact of non-renewable energy utilization, urban agglomeration, economic output, and CO_2e on the construction industry, respectively; and, $\varnothing_1$, $\varnothing_2$, $\varnothing_3$, and $\varnothing_4$ capture the influence of non-renewable energy utilization, urban agglomeration, construction industry, and economic output on CO_2e, respectively. As Equations (7)–(11) are in logarithmic form, the coefficients of their respective regressors indicate the elasticity coefficients, capturing the responsiveness of each regressand to changes recorded in the regressors of the stated equations.

2.3. Analytical Strategies

Estimating the five-way links that exist between the construction industry, urban agglomeration, utilization of non-renewable energy sources, CO_2e, and economic output requires the employment of five structural modeling equations. An advanced panel approach known as the heterogeneous FMOLS technique, proposed by Peter Pedroni [34], was used in this work. Using the heterogeneous FMOLS, as opposed to one of the alternatives, has the following advantages: the typical longitudinal data approaches in practice to solve endogeneity issues are only effective in a stationary state of variables. This is because these techniques depend on the assumption that the mean and variance of the variables would remain constant over time. While the conventional FMOLS technique by Phillips [41] was applicable to cointegrated panels, it failed to incorporate the heterogeneity aspect of modern panel data econometrics. However, the heterogeneous FMOLS deals with this dilemma even in a non-stationary framework. As a result, it gives concrete results in the presence of non-stationary and cross-section dependency (CSD) features within heterogeneous cointegrated panels. Following Pedroni [34], the log-linearized form Equations (7)–(11) that need to be estimated using heterogeneous FMOLS may be expressed as:

$$ln\widetilde{ECO}_{i,t} = \alpha_{i1} ln\widetilde{PCP}_{i,t} + \alpha_{i2} ln\widetilde{EUT}_{i,t} + \alpha_{i3} lnUBA_{i,t} + \alpha_{i4} lnCNI_{i,t} + \alpha_{i5} lnCO_{2e_{i,t}} + e_{i,t,1} \quad (12)$$

$$ln\widetilde{EUT}_{i,t} = \beta_{i1} ln\widetilde{ECO}_{i,t} + \beta_{i2} lnUBA_{i,t} + \beta_{i3} lnCNI_{i,t} + \beta_{i4} lnCO_{2e_{i,t}} + e_{i,t,2} \quad (13)$$

$$lnUBA_{i,t} = \gamma_{i1} ln\widetilde{EUT}_{i,t} + \gamma_{i2} ln\widetilde{ECO}_{i,t} + \gamma_{i3} lnCNI_{i,t} + \gamma_{i4} lnCO_{2e_{i,t}} + e_{i,t,3} \quad (14)$$

$$lnCNI_{i,t} = \theta_{i1} ln\widetilde{EUT}_{i,t} + \theta_{i2} lnUBA_{i,t} + \theta_{i3} ln\widetilde{ECO}_{i,t} + \theta_{i4} lnCO_{2e_{i,t}} + e_{i,t,4} \quad (15)$$

$$lnCO_{2e_{i,t}} = \xi_{i1} ln\widetilde{EUT}_{i,t} + \xi_{i2} lnUBA_{i,t} + \xi_{i3} lnCNI_{i,t} + \xi_{i4} ln\widetilde{ECO}_{i,t} + e_{i,t,5} \quad (16)$$

Before applying the heterogeneous FMOLS technique, testing the assumptions of heterogenous and cointegrated panels becomes inevitable. In this context, this study applies the slope heterogeneity testing approach by Pesaran and Yamagata [42]. The following expressions are employed to estimate the statistical score of slope heterogeneity:

$$\widetilde{\Delta} = \sqrt{N}(N^{-1}\widetilde{S} - k/2q) \sim \chi^2{}_k \quad (17)$$

$$\widetilde{\Delta}_{adj} = \sqrt{N}(N^{-1}\widetilde{S} - k/v(T,k)) \sim N(0,1) \quad (18)$$

where N is the demonstration of provincial divisions, S is indicative of Swamy's statistical component from [43], k is the representation of stimulus variables, and $v(T,k)$ is the depiction of error terms. Where Equations (17) and (18) estimate parameters for large and small panels, respectively. This study utilized both expressions to test the null hypothesis of slope homogeneity.

Moreover, to test the assumption of whether the panels are cointegrated, this study applied an error-correction-based approach to cointegration devised by Westerlund [44]. This approach accounts for both CSD and slope heterogeneity. It evaluates the null hypothesis of no cointegration against the alternative hypothesis of cointegration. Under this approach, two kinds of statistical measures are estimated: panel-based (P_t, P_a) and group-based (G_t, G_a). In addition, this study utilized Kao cointegration [45] for robustness testing of the outcomes of the Westerlund cointegration.

In order to verify that the estimated parameters make sense, this study employed a heterogeneous causality test proposed by Dumitrescu and Hurlin [46]. This testing approach evaluates the null hypothesis of homogenous non-causality against the alternative hypothesis of heterogeneous causality among the data under analysis.

3. Results

3.1. Basic Analysis

It is appropriate to evaluate the time series and cross-sectional property of panel data before utilizing the primary estimate technique. This may be done by dividing the data into sections at regular intervals. The selection of an estimating method, or the decision to go with one, is a very important step. When used in situations with cross-sectional dependency, traditional unit root tests might provide results that aren't entirely accurate. Therefore, before testing for the stationary feature, CSD has been assessed by utilizing the technique described in Pesaran [47]. According to the findings of the tests, each of the series is reliant on its cross-sectional counterpart. As a consequence of this, the second-generation cross-sectionally adjusted Im–Pesaran–Shin (CSIPS) testing technique of stationarity [48] since it produces accurate results despite the existence of CSD. The results of the tests indicated that all series, with the exception of economic production, were not level-stationary. In addition, after the initial difference, all of the series became immobile. It demonstrated the existence of cross-sectional dependency as well as a unit root in the longitudinal data, which can be seen in Table 2. The heterogeneous FMOLS estimator is used in order to estimate the contents of all four panels of panel data in order to address this particular circumstance.

Table 3 records the results of the slope heterogeneity analysis. In this regard, the significant parameters verified the rejection of null hypotheses of slope homogeneity, authenticating the slope heterogeneity in all the panels.

Table 2. Results of CSD and CSIPS testing approaches.

Samples	Regressors	CSD	CSIPS (@level)	CSIPS (1st Differenced)
Whole country	ECO	42.71 ***	−2.372 **	−2.957 ***
	EUT	23.48 ***	−1.375	−3.183 ***
	UBA	48.28 ***	−1.183	−3.673 ***
	CNI	17.28 ***	−1.203	−2.758 ***
	CO_2e	45.10 ***	−1.048	−3.102 ***
	PCP	33.08 ***	−1.684	−3.463 ***
China's eastern part	ECO	42.00 ***	−2.528 ***	2.775 ***
	EUT	19.77 ***	−1.291	−3.164 ***
	UBA	29.04 ***	−1.068	−3.274 ***
	CNI	57.39 ***	−1.003	−3.684 ***
	CO_2e	11.74 ***	−1.281	−3.293 ***
	PCP	18.92 ***	−1.773	−2.995 ***
China's central part	ECO	24.27 ***	−2.625 ***	−4.001 ***
	EUT	18.02 ***	−1.056	−2.972 ***
	UBA	35.62 ***	−1.689	−3.294 ***
	CNI	57.38 ***	−1.572	−3.683 ***
	CO_2e	27.40 ***	−1.583	−4.192 ***
	PCP	12.58 ***	−1.009	−4.394 ***
China's western part	ECO	10.37 ***	−2.119 *	−3.694 ***
	EUT	34.69 ***	−1.184	−2.996 ***
	UBA	15.47 ***	−1.927	−3.2945 ***
	CNI	35.11 ***	−1.483	−2.845 ***
	CO_2e	12.65 ***	−1.524	−2.365 ***
	PCP	55.48 ***	−1.293	−3.078 ***

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 3. Results of slope heterogeneity.

Sample	Test	Stat.	Prob.	Sample	Test	Stat.	Prob.
Whole country	$\widetilde{\Delta}$	5.10	0.000 ***	China's eastern part	$\widetilde{\Delta}$	5.99	0.000 ***
	$\widetilde{\Delta}_{adj}$	4.92	0.000 ***		$\widetilde{\Delta}_{adj}$	4.81	0.000 ***
China's central part	$\widetilde{\Delta}$	6.03	0.000 ***	China's western part	$\widetilde{\Delta}$	5.72	0.000 ***
	$\widetilde{\Delta}_{adj}$	4.76	0.000 ***		$\widetilde{\Delta}_{adj}$	6.25	0.000 ***

Notes: *** $p < 0.01$; $\widetilde{\Delta}$ and $\widetilde{\Delta}_{adj}$ indicate the test types; Stat. and Prob. are the depictions of statistics and probability.

In order to make the estimation of long-run parameters permissible, this study applies cointegration testing. The findings of Westerlund and Kao's approaches are documented in Table 4. The outcomes revealed the group-based as well as panel-based statistic to be significant (at a 1% level of significance) for all the study panels, thus allowing the rejection of the null hypothesis (i.e., non-cointegration). Furthermore, the statistical outcomes from the Kao test are also consistent with these outcomes. Therefore, it implies that economic output, non-renewable energy utilization, urban agglomeration, construction industry, and CO_2e have a long-run equilibrium association, which makes it legitimate to estimate the long-run parameters.

Table 4. Results of panel cointegration.

Test	Stat.	Whole Country	China's Eastern Part	China's Central Part	China's Western Part
Westerlund	G_t	−7.538 ***	−5.379 ***	−4.027 ***	−6.384 ***
		[0.000]	[0.000]	[0.004]	[0.005]
	G_a	−5.375 ***	−5.886 ***	−4.274 ***	−7.336 ***
		[0.000]	[0.001]	[0.003]	[0.000]
	P_t	−6.059 ***	−7.291 ***	−7.572 ***	−6.803 ***
		[0.000]	[0.000]	[0.000]	[0.001]
	P_a	−5.483 ***	−6.118 ***	−6.894 ***	−8.075 ***
		[0.000]	[0.000]	[0.000]	[0.000]
Kao	t-ratio	−3.978 ***	−3.486 ***	−3.931 ***	−3.299 ***
		[0.000]	[0.000]	[0.000]	[0.004]

Notes: *** $p < 0.01$; Stat. is indicative of statistic; Brackets [ ] enclose the p values.

3.2. Main Analysis

Table 5 shows the estimation outcomes of the five models under analysis based on the heterogeneous FMOLS technique. Herein, the findings of all the modeling specifications in this section have been interpreted and discussed.

Table 5. Analytical findings for the long run based on the heterogeneous FMOLS technique.

Regressors	Whole Country	China's Eastern Part	China's Central Part	China's Western Part
Model 1: Regressand: Economic output				
Non-renewable energy utilization	0.193 **	0.199 ***	0.191 ***	0.179 **
Urban agglomeration	0.198 **	0.205 ***	0.180	−0.156 ***
Construction industry	0.201 ***	0.211*	0.200 **	0.175 ***
CO_2e	−0.267 ***	−0.232 ***	−0.213 ***	−0.136 ***
Physical capital	0.510 ***	0.534 ***	0.479 *	0.361 **
Model 2: Regressand: Non-renewable energy utilization				
Economic output	0.476 ***	0.487 ***	0.463 *	0.396 **
Urban agglomeration	0.243 ***	0.255 **	0.231 ***	0.147 **
Construction industry	0.290 **	0.302 **	0.268 **	0.204 ***
CO_2e	0.301	0.325	0.243	0.191
Model 3: Regressand: Urban agglomeration				
Economic output	1.102 ***	1.391 **	1.218 ***	1.012 ***
Construction industry	0.172 ***	0.158 ***	0.174 ***	0.186 **
Non-renewable energy utilization	0.258	0.299	0.214	0.142
CO_2e	0.287	0.281	0.229	0.118
Model 4: Regressand: Construction industry				
Urban agglomeration	0.128 ***	0.134 **	0.117 **	0.095 ***
Economic output	0.164 **	0.175 ***	0.162 ***	0.140 **
Non-renewable energy utilization	0.224	0.235	0.176	0.089
CO_2e	0.197	0.206	0.155	0.117
Model 5: Regressand: CO_2e				
Non-renewable energy utilization	0.401 ***	0.415 **	0.396 **	0.325 ***
Urban agglomeration	0.137 ***	0.144 *	0.131 **	0.101 *
Construction industry	0.284 ***	0.291 ***	0.272 ***	0.245 **
Economic output	−1.568 ***	−1.681 ***	−1.492 **	1.107 ***

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

3.2.1. Model of Economic Output

The urban agglomeration demonstrated highly dramatic and fascinating behavior in terms of the difference in its influence on economic output throughout all parts of China in the model of economic output (see Table 5). It had a negative effect on economic output in the less developed China's western part. It also put forward a neutral effect in moderately developed areas, i.e., China's central part. Finally, in the case of China's eastern part, which is the most established one, its effect was observed to be positive. This phenomenon is known as the effect of urban agglomeration. As entities (countries/regions) evolve, the role of urban agglomeration in economic output shifts from detrimental to neutrality to favorable conditions. The second is the positive and statistically significant impact of the construction industry and physical capital on the economic output of each panel, with the highest magnitudes of elasticity for China's eastern part and the lowest for China's western part. The term "industrial expansion effect" refers to the phenomenon wherein the growth of an industry results in a more significant and beneficial contribution to overall economic output. This phenomenon holds true for the construction industry. Non-renewable energy utilization elasticities are positive and statistically meaningful, with the highest magnitude for China's eastern part and the lowest for China's western part. However, CO_2e was negative and statistically significant for economic output, with strong effects in the case of China's eastern part and less for China's western part.

3.2.2. Model of Non-Renewable Energy Utilization

Turning to the model of energy utilization, the non-renewable energy utilization was, for all the panels, impacted positively by economic output, urban agglomeration, and the construction industry. The magnitude is the highest for China's eastern part and the lowest for China's western part. Despite the geographical variations, more crucial results were obtained in urban agglomeration. In more advanced areas, such as China's eastern parts, a rising urban agglomeration is expected to increase non-renewable energy utilization substantially more than that in less developed areas, such as China's western part. Besides, the parameter estimate of CO_2e shows its insignificant contribution to the non-renewable energy utilization of all panels.

3.2.3. Model of Urban Agglomeration

In the model of urban agglomeration, a positive and statistically significant impact of economic output is experienced on urban agglomeration, demonstrating a relatively stronger impact for China's eastern part and a relatively weaker effect on China's western part. In terms of the different impacts across regions, the case of construction industry is very unusual. The positive and statistically significant impacts on urban agglomeration have been demonstrated, with a greater impact on China's western parts and less on China's eastern parts. Compared to the more job-saturated zones, such as China's eastern parts, a boost in the construction industry is expected to promote rapid urban agglomeration in an area with fewer jobs. It can be entitled as the effect of work saturation. Moreover, the statistically insignificant impact on urban agglomeration was expressed by non-renewable energy utilization and CO_2e.

3.2.4. Model of Construction Industry

The model of the construction industry shows statistically significant and positive contributions of urban agglomeration and economic output. The impact is strong for China's eastern part, while China's central and China's western parts, respectively, depict a less strong impact. It is the demonstration of the rapid construction industry progress of increasing urban agglomeration and economic growth at a high level of development as contrasted to a low level of development. This is the case because high levels of development are more advanced. In addition, the neutral effect of non-renewable energy utilization and CO_2e on the construction industry was revealed.

3.2.5. Model of CO_2e

The model of CO_2e revealed positive and statistically significant contributions of non-renewable energy utilization, urban agglomeration, and the construction industry to CO_2e. Energy utilization has contributed significantly in this respect to CO_2e, with stronger impacts for the whole country and China's eastern part, while weaker impacts are achieved for China's western part. The construction industry's influence is dominant in China's eastern part as the construction industry is less developed in China's central part and China's western part. However, for the whole country, China's eastern part, and China's central part, the economic output revealed a negatively significant impact on those emissions, while a positive effect was experienced for China's western part. Thus, economic output promotes CO_2e for less-developed regions, such as China's western part. While, economic output significantly mitigates CO_2e for most developed regions such as China's eastern part. The increased growth is expected to increase CO_2e for the less developed regions due to composition and structure effects in place, whereas the CO_2e is expected to decrease for the more developed regions in response to an enhanced economic output in the face of technique effect in place, which is called the environmental Kuznets Curve (EKC) theory, consistent with the previous studies [49–51].

3.2.6. Diagnostic Checks

In order to validate the credibility of estimated results, several diagnostic checks are applied (see Table 6). To begin with, the coefficients of determination scores are more than 80% for all of the models and for all data samples. This means at least 80% of the variations in regressand are captured by the regressors included in the respective models, depicting the goodness of fit (GoF) of these models. Next, the significant probability scores of χ^2 also demonstrate the GoF of the considered models. After that, the analysis of residuals of the estimated models declared those residuals free from the unit root and CSD concerns, as indicated by CSIPS and CSD tests, respectively. The diagnostic checks signal the credibility of the estimated models.

Table 6. Results of diagnostic checks.

Items	Whole Country	China's Eastern Part	China's Central Part	China's Western Part
Model 1: Regressand: Economic output				
R^2	0.923	0.851	0.874	0.909
χ^2 [prob.]	11.1 [0.02]	12.3 [0.04]	11.1 [0.02]	10.0 [0.05]
CSD (AACC)	0.399	0.478	0.512	0.598
CSD [prob.]	−0.6 [0.49]	−1.1 [0.12]	−1.0 [0.11]	−0.8 [0.34]
CSIPS	−2.947 **	−2.995 **	−3.694 ***	−2.827 **
RMSER	0.010	0.002	0.006	0.001
Model 2: Regressand: Non-renewable energy utilization				
R^2	0.910	0.946	0.835	0.807
χ^2 [prob.]	8.1 [0.06]	11.2 [0.01]	8.9 [0.04]	7.4 [0.05]
CSD (AACC)	0.475	0.501	0.418	0.490
CSD [prob.]	−0.8 [0.38]	−1.1 [0.22]	−1.6 [0.10]	−1.03 [0.25]
CSIPS	−3.185 **	−2.996 ***	−3.471 *	−3.152 ***
RMSER	0.020	0.014	0.000	0.000
Model 3: Regressand: Urban agglomeration				
R^2	0.886	0.928	0.916	0.793
χ^2 [prob.]	11.7 [0.04]	13.3 [0.01]	12.8 [0.01]	15.4 [0.00]
CSD (AACC)	0.536	0.485	0.493	0.557
CSD [prob.]	−0.6 [0.20]	−0.9 [0.17]	0.8 [0.39]	−1.2 [0.19]
CSIPS	−2.851 ***	−2.692 ***	−2.951 ***	−3.844 **
RMSER	0.050	0.000	0.002	0.018
Model 4: Regressand: Construction industry				
R^2	0.922	0.959	0.908	0.813
χ^2 [prob.]	14.6 [0.00]	13.1 [0.01]	14.4 [0.00]	11.5 [0.01]
CSD (AACC)	0.492	0.523	0.578	0.511
CSD [prob.]	−0.8 [0.38]	−0.7 [0.41]	0.5 [0.52]	−1.0 [0.29]
CSIPS	−3.250 *	−3.481 *	−2.697 ***	−3.602 **
RMSER	0.001	0.038	0.003	0.005
Model 5: Regressand: CO_2e				
R^2	0.935	0.927	0.862	0.807
χ^2 [prob.]	11.1 [0.03]	9.5 [0.05]	10.1 [0.04]	8.9 [0.03]
CSD (AACC)	0.569	0.601	0.618	0.503
CSD [prob.]	−0.7 [0.41]	−1.0 [0.29]	1.5 [0.18]	0.6 [0.44]
CSIPS	−2.780 ***	−2.997 ***	−3.471 **	−5.002 ***
RMSER	0.021	0.000	0.019	0.003
T	17	17	17	17
N	30	11	8	11
n	510	187	136	187

Notes: where χ^2 [prob.] stands for Chi-squared score with probability score within bracket [ ]; R^2 is the coefficient of determination of the estimated models; CSD (AACC) is the CSD test-based average absolute correlation coefficient; CSD [prob.] indicates the CSD statistical score and its associated probability scores in bracket [ ]; CSIPS provides the statistical score of the CSIPS test; RMSER stands for the root mean square error; T indicates the time dimension of panel data; N indicates the cross-sectional dimension of panel data; n represents the number of observations. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

3.3. Heterogeneous Causality Analysis

Table A1 (see Appendix A) records the results of heterogeneous causality by Dumitrescu and Hurlin [46] to provide the direction of causal association among the study variables. The statistical outcomes reveal the existence of the following causal connections: (a) economic output established a bilateral causality with non-renewable energy utilization, urban agglomeration, construction industry, and physical capital for the samples of the whole country, China's eastern part, and China's western part. (b) Economic openness set up a unilateral causality with urban agglomeration for China's central part. (c) The construction industry yielded a bilateral link with urban agglomeration across all data samples. (d) The urban agglomeration and construction industry unfolded a unilateral link with non-renewable energy utilization and CO_2e for all data samples. (e) Non-renewable energy utilization revealed a unilateral connection with CO_2e for all samples under analysis. Notably, these findings are consistent with the main estimation analysis of this study, implying that the results obtained in the parametric estimations are logical and valid.

4. Discussion

A combined consideration of parametric estimation and heterogeneous causality results led to the comprehensive findings to be discussed. At the outset, the causal correlation between the construction industry and non-renewable energy utilization is unidirectionally affirmative for all panels of research. This finding is intuitive in that the construction industry relies heavily on non-renewable energy sources since the transition toward clean energy in China's construction sector is yet at the nascent stage of development [52]. This finding is aligned with Cheng et al. [31] from the Chinese perspective and Arıoğlu Akan et al. [53] in the Turkish context. Furthermore, for all four panels, non-renewable energy utilization has a positive and not vice versa impact on CO_2e. This finding is consistent with several previous studies such as Ahmad and Satrovic [54] in the Organization for Economic Co-operation and Development (OECD) countries, Usman et al. [55] in the top 15 CO_2e emitter economies, and [56] in 34 high-income global economies. Moreover, the bidirectional causal negative relationship is revealed for all samples, except China's western part, between CO_2e and economic output. On the one hand, this finding presents an analogy with the conception of EKC supported by a plethora of previous research [49–51]. On the other hand, similar to this finding, Apergis et al. [57] found that increased CO_2e accelerated healthcare expenditures in the USA, adding a burden to the economy. Therefore, this argument is a viable justification for the adverse impact of CO_2e on economic output. The impact of economic output on non-renewable energy utilization is recorded to be stronger for all panels than its counterpart. It means that energy utilization aggravates economic output, which consequently demonstrates relatively more substantive "*feedback*" on non-renewable energy utilization. The stated influence is relatively more substantial for China's eastern part, whereas China's central part and China's western part are less strong. Initially, growth led to energy utilization and CO_2e, but it is not the same for all panels under analysis. This finding lends credence to the findings of Shahbaz et al. [58] in the case of the United Kingdom and Salari et al. [59] for the state-level analysis of the USA.

Furthermore, the construction industry has contributed to CO_2e, and it is not the same for all the panels. A possible explanation for this outcome is that China's eastern part is at the highest urbanization level across the country [60]. Since more urbanization means constructing more urban infrastructure, leading to a high level of CO_2e driven by the rich construction industry [31]. There were more flexible outcomes for the mutual connection between economic output and urban agglomeration. In the case of the whole country and China's eastern part, a positive bidirectional link is formed between the two factors. A unidirectional positive relationship is observed for China's central part, from growth to urban agglomeration. However, these variables showed bidirectional causal associations with mixed signs for China's western part. A positive causal connection from economic output to urban agglomeration and a negative causal link originating from urban agglomeration to economic output has also been found to exist. It can be explained in a way that, on the one hand, the poorly developed provincial divisions cannot offer employment opportunities to rapidly urbanizing individuals. On the other hand, more people in cities require governments to allocate more resources for the urbanized people, thus increasing the burden on the regional economy. However, moderately developed provincial divisions started accommodating the urban population to urban industrial units, thus reverting and neutralizing the adverse economic effects of rapid urbanization. While the developed provincial divisions focus on planned urbanization as opposed to the poorly developed provinces. It might allow them to reap the economies of scale of available cheap labor for the urban industry, capitalizing on the economic gains of urban economic agglomeration. Finally, for all the study panels, there is a bilateral positive causal association between urban agglomeration and the construction industry. However, the strength of influence of the construction industry is observed to be greater in China's western part and less in China's eastern part. This finding can be explained in the following manner. It has been observed that rural-to-urban migration in China was mainly driven by the motive of finding employment opportunities in the industrial sector [61]. Against this backdrop, increased construction activities demand more labor and induce urban agglomeration further. However, more developed provinces incur saturation in terms of employing new labor due to already available rich urban infrastructure, thus leading to a less aggressive boost in urban agglomeration. On the contrary, less developed provinces have a less saturated construction industry in terms of offering employment opportunities, thus inducing urban agglomeration more aggressively [61].

5. Conclusions

The present study examined and established five-way links between urban agglomeration, the construction industry, non-renewable energy utilization, economic output, and CO_2e through simultaneous equation systems. The stylized concluding remarks based on heterogeneous FMOLS-based data inspection are given as follows:

First, the bidirectional causal link has been found between economic output and energy utilization, economic output and construction industry, economic output and urban agglomeration, and urban agglomeration and construction industry. Nevertheless, a unidirectionally positive causal link has been revealed from the construction industry to energy utilization and CO_2e, and energy utilization and urban agglomerations to CO_2e. A negative causal bidirectional link between economic output and CO_2e is revealed for the under-analysis panels. These findings varied from region-to-region, particularly for the connection between economic prosperity and urban agglomeration, CO_2e and economic output, and construction industry and economic growth. Secondly, the urban agglomeration behavior showed a very intuitive effect on the economic output, which ranged from adverse to neutrality to favorable influence for China's western, central, and eastern parts. In view of the various rates of development in these areas, this result is especially significant. This trend is referred to as the consequence of the urban agglomeration ladder. This means that urban agglomeration will have a positive effect on economic output for the provincial/ city divisions. In addition, provincial/ city divisions have shown the greatest difference in their effects on economic output in projecting the urban agglomeration. Third, the long-term construction industry elasticity estimates showed that its impact on economic output ranged from less to stronger for China's western to central to eastern parts. This means that business development has a greater and more optimistic impact on economic output in rapidly developing regions.

Fourth, economic output revealed a very peculiar behavior with regard to its effects on urban agglomeration in different regions, as it ranged between high positive effects for China's western part and lower impacts for China's eastern part. The assumption is that economic output has facilitated swift urban agglomeration, compared to the reverse in less urbanized and less jobs-saturated regions. It is described as the "effect of work saturation". Fifth, the non-renewable energy utilization led to huge CO_2e. The construction industry remains the leading player in this regard, though urban agglomeration is also a giant contributor to CO_2e. Sixth, economic output and the use of resources push one another, but later than before, the consequences of the former dominate. It shows that energy utilization promotes economic output, which in turn has a stronger "feedback" impact on power consumption. China's eastern part is strong, while China's central and western parts are less-to-medium strong. Finally, economic output had a negative impact on CO_2e for the complete sample, China's eastern and central parts, while the effect for China's western part was positive. It means that economic output has reduced CO_2e for the whole country, China's eastern part, and China's central part, while economic output is being fostered in response to CO_2e for China's eastern part. In more developed areas such as China's eastern part, economic output is directed to reduce CO_2e, while for the less developed regions like China's western part, CO_2e is upsurged by economic output.

Based on the empirical findings of this study, the following policies are advised. (i) The negative contribution of urban agglomeration towards economic output for China's western part is an indicator of a lack of jobs in the region. Thus, rural-to-urban migration should also be followed by creating employment in the western part. Furthermore, there have been significant differences in the effect of urban agglomeration on the economic output of Chinese provinces, suggesting that the policies of provinces are better than those of nationwide strategies. (ii) Construction industry expansion has had a strong economic impact for the more developed China's eastern part but a less strong economic impact for China's western part. This suggests that the expansion of the construction industry in China's western part might boost economic output if the development in the region is centered. As China's eastern part is detected as the biggest CO_2e emitter due to non-renewable energy utilization, it is recommended to use efficient energy methods to minimize CO_2e. This process can reduce the difference between the various regions of China. (iii) Energy can be conserved by means of a transport system in two different ways: (a) public transport development in large cities such as Beijing and Shanghai must be aimed at reducing the use of personal vehicles and thus helpful in reducing CO_2e; (b) green energy vehicles that should run on green energy could be promoted, increasing the likelihood of reducing CO_2e [62]. China has already surpassed the existing national emission standards, as stated earlier. Economic output in the developing region, which is China's eastern part, is observed to greatly reduce CO_2e. Nevertheless, in the less developed, China's western part, economic output supported CO_2e. Thus, it could be proposed that CO_2e is anticipated to increase as economic output rises to a certain level of production in less-developed parts of China. Given these conclusions, both developed and developing countries may learn some lessons from the case study of China involving diversified development scales.

Though this study has offered novel contributions to the existing knowledge, there are certain concerns that need attention by future scholars aiming to research in the same domain. Firstly, this study considered varying provincial development levels to provide useful heterogeneous inferences across those local development levels. However, for the generalizability of these findings across global development levels, the follow-up studies should take into account the global panel data to investigate the heterogenous results across different economic development levels globally. Secondly, as CO_2e is not the only indicator responsible for environmental unsustainability, future studies shall benefit from employing a comprehensive indicator such as ecological footprint consumption. Finally, this study has introduced non-renewable energy utilization, which is a potential driver of CO_2e, in the growth modeling. However, the inclusion of renewable energy and environment-related technological innovation could prove critical determinants of both CO_2e and economic output within a Cobb–Douglas production function. Therefore, future studies shall capitalize on the academic value of such inclusions in their growth modeling to deliver useful recommendations for economic and environmental sustainability goals of Sustainable Development.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Results of heterogeneous causality.

			Whole Country			
	ECO→EUT	**EUT→ECO**	**ECO→UBA**	**UBA→ECO**	**ECO→CNI**	**CNI→ECO**
Z-stat. Prob.	7.684 *** 0.000	5.736 ** 0.036	6.280 *** 0.002	8.114 *** 0.000	5.617 ** 0.028	6.146 *** 0.005
	ECO→CO_2e	CO_2e→ECO	ECO→PC	PC→ECO	EUT→UBA	UBA→EUT
Z-stat. Prob.	6.148 *** 0.007	8.319 *** 0.000	5.728 ** 0.026	4.612 * 0.079	3.105 0.261	5.782 ** 0.028
	EUT→CNI	CNI→EUT	EUT→CO_2e	CO_2e→EUT	UBA→CNI	CNI→UBA
Z-stat. Prob.	2.461 0.197	8.015 *** 0.000	6.972 *** 0.003	1.463 0.158	5.128 ** 0.042	5.691 ** 0.029
	UBA→CO_2e	CO_2e→UBA	CNI→CO_2e	CO_2e→CNI		
Z-stat. Prob.	4.764 * 0.071	2.189 0.126	5.693 ** 0.046	1.962 0.402		
			China's eastern part			
	ECO→EUT	EUT→ECO	ECO→UBA	UBA→ECO	ECO→CNI	CNI→ECO
Z-stat. Prob.	8.130 *** 0.000	4.965 ** 0.045	7.336 *** 0.001	5.479 ** 0.048	7.352 *** 0.000	4.181 * 0.075
	ECO→CO_2e	CO_2e→ECO	ECO→PC	PC→ECO	EUT→UBA	UBA→EUT
Z-stat. Prob.	5.957 ** 0.044	4.361 * 0.079	4.173 * 0.076	5.668 ** 0.035	2.917 0.165	7.115 *** 0.002
	EUT→CNI	CNI→EUT	EUT→CO_2e	CO_2e→EUT	UBA→CNI	CNI→UBA
Z-stat. Prob.	1.850 0.215	6.377 *** 0.004	8.164 *** 0.000	2.378 0.225	6.722 *** 0.009	5.137 ** 0.034
	UBA→CO_2e	CO_2e→UBA	CNI→CO_2e	CO_2e→CNI		
Z-stat. Prob.	5.289 ** 0.034	1.335 0.158	6.922 *** 0.006	2.401 0.269		
			China's central part			
	ECO→EUT	EUT→ECO	ECO→UBA	UBA→ECO	ECO→CNI	CNI→ECO
Z-stat. Prob.	3.952 * 0.081	6.739 *** 0.002	8.723 *** 0.000	2.472 0.197	5.691 ** 0.018	6.722 *** 0.004
	ECO→CO_2e	CO_2e→ECO	ECO→PC	PC→ECO	EUT→UBA	UBA→EUT
Z-stat. Prob.	7.226 *** 0.000	5.835 ** 0.031	8.349 *** 0.000	6.815 *** 0.001	2.583 0.207	6.990 *** 0.001
	EUT→CNI	CNI→EUT	EUT→CO_2e	CO_2e→EUT	UBA→CNI	CNI→UBA
Z-stat. Prob.	3.001 0.256	4.960 * 0.058	5.627 ** 0.002	1.390 0.156	4.874 * 0.093	9.226 *** 0.000
	UBA→CO_2e	CO_2e→UBA	CNI→CO_2e	CO_2e→CNI		
Z-stat. Prob.	6.581 *** 0.000	2.794 0.185	7.152 *** 0.002	2.580 0.311		

Table A1. *Cont.*

	Whole Country					
	ECO→EUT	**EUT→ECO**	**ECO→UBA**	**UBA→ECO**	**ECO→CNI**	**CNI→ECO**
	China's western part					
	ECO→EUT	EUT→ECO	ECO→UBA	UBA→ECO	ECO→CNI	CNI→ECO
Z-stat. Prob.	5.880 ** 0.027	3.974 * 0.068	5.916 ** 0.049	7.112 *** 0.003	4.569 * 0.065	5.338 ** 0.032
	ECO→CO_2e	CO_2e→ECO	ECO→PC	PC→ECO	EUT→UBA	UBA→EUT
Z-stat. Prob.	4.971 * 0.049	7.335 *** 0.001	6.993 *** 0.008	4.528 * 0.091	1.947 0.136	5.781 ** 0.015
	EUT→CNI	CNI→EUT	EUT→CO_2e	CO_2e→EUT	UBA→CNI	CNI→UBA
Z-stat. Prob.	2.164 0.135	6.882 *** 0.000	9.356 *** 0.000	2.728 0.189	7.160 *** 0.000	5.238 ** 0.029
	UBA→CO_2e	CO_2e→UBA	CNI→CO_2e	CO_2e→CNI		
Z-stat. Prob.	8.369 *** 0.000	2.157 0.208	8.107 *** 0.005	1.332 0.249		

Notes: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$; Prob. stands for the p values; Z-stat. is indicative of the statistic of heterogeneous causality test.

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