Journal of Emerging Markets and Management | Volume 01 | Issue 01 | June 2025

Journal of Emerging Markets and Management
https://journals.zycentre.com/jemm

ARTICLE

Investigating the Determinants of Carbon Emissions Using the Granger Causality Test: Evidence from China's Main Sectors

Chuwei Zhang , ***Paul Anthony MariaDas*** , ***Yamunah Vaicondam***

School of Business & Law, Taylor's University, Subang Jaya, Selangor 47500, Malaysia

ABSTRACT

This study attempts to investigate the key determinants of carbon emissions across China's major sectors, including transportation, real estate, and industrial sector, throughout the period between 2004 and 2023. Then examine their causal relationship to develop a carbon emission reduction framework. The Auto-Regressive Distributed Lag (ARDL) model and Granger causality test were utilized for analysis. In the long-term, EC and FDI negatively affect CE, while IT positively affects that. In the short-term, CE are positively influenced by FDI and PG, while negatively impacted by EG and EC. Besides, the impacts of these determinants on carbon emissions vary across sectors. Moreover, the analysis reveals bidirectional causality between CE and EG, CE and FDI, and CE and IT, while unidirectional causal relationship is observed with EC driving CE. The finding also reveals that the policies should prioritize low-carbon transitions by integrating sustainability into economic planning and infrastructure development in the "the Five-Year Plans". This study provides critical policy-relevant insights to guide policymakers in designing effective strategies for carbon emission mitigation. It introduces an innovative sector-specific analysis that identifies key opportunities across different sectors. Additionally, the study proposes a structured policy framework to systematically support China's carbon goals. By bridging research and practical implementation, this work contributes both theoretically and empirically to the advancement of sustainable development.

Keywords: Carbon Emission; Economic Growth; Foreign Direct Investment; ARDL; The Granger Causality Test; Carbon Peak and Carbon Neutrality; Policy

*CORRESPONDING AUTHOR:
Chuwei Zhang, School of Business & Law, Taylor's University, Subang Jaya, Selangor 47500, Malaysia; Email: zhangchuwei1276@163.com

ARTICLE INFO
Received: 15 April 2025 | Revised: 5 June 2025 | Accepted: 10 June 2025 | Published Online: 17 June 2025
DOI: https://doi.org/10.63385/jemm.v1i1.55

CITATION
Zhang, C., MariaDas, P.A., Vaicondam, Y., 2025. Investigating the Determinants of Carbon Emissions Using the Granger Causality Test: Evidence from China's Main Sectors. Journal of Emerging Markets and Management. 1(1): 26–40. DOI: https://doi.org/10.63385/jemm.v1i1.55

1. Introduction

Climate change represents a critical global environmental challenge that is increasingly capturing widespread attention. As fossil fuel combustion and cement manufacture are the principal concern in efforts to address climate change, the carbon dioxide emitted in this process became increasingly important for global countries [1]. China has become the leading emitter of carbon dioxide globally since 2007 [2–4]. Due to the rapid expansion of export production, China has emerged as the fourth-largest economic entity and the important exporter ranked third in size in the world [5]. In December 2009, at the Copenhagen Climate Conference, China made a formal commitment to lower the carbon intensity, measured by emissions generated per unit of GDP, by 40% to 45%, relative to 2005 levels, aiming for this reduction by 2020. This pledge marked a significant step in China's climate policy framework. Subsequently, in China's 12th Five-Year Plan, it reaffirmed its commitment to reducing emissions intensity, setting a target of a 17% reduction by 2015, compared to 2010 levels. Additionally, the plan introduced a goal to raise the percentage of non-fossil fuel energy within the country's overall energy mix, aiming for a contribution of 11.4% by 2015. These commitments highlighted China's sustained efforts to align economic growth with environmental sustainability [6]. Then, the country undertook a commitment in 13th Five-Year Plan, to cut its carbon intensity by 18% by 2020, in relation to 2015 levels [7]. In 2015, at the Paris Climate Conference China made a significant international pledge to decrease greenhouse gas emissions, which is "Carbon peak" by 2030 and "carbon neutrality" by 2060. This commitment was made as part of the broader Paris Agreement, in which nations collectively committed to limiting temperature globally increase to below 2°C, restricting it to no more than 1.5°C. Additionally, the goal of China by 2030 was set with an increased share of green energy [8]. Then China's government had set a target to achieve carbon neutrality by 2060, and to peak emissions before 2030 during the 75th session of the United Nations General Assembly. As outlined in the 14th Five-Year Plan, China reaffirmed its commitment alongside strengthening its efforts to decarbonize its economy. The plan set more detailed objectives, such as a 13.5% reduction in carbon intensity by 2025, relative to 2020 levels. The plan also targeted a substantial rise in the contribution of renewable energy sources aiming for them to represent 20% of total energy consumption, including solar, hydro, wind, and nuclear [9].

However, achieving these short-term and long-term targets face crucial challenges, including industrial structure adjustment, technical progress, and regional development particularly in provinces that are heavily dependent on energy consumption [10,11]. Fossil fuel consumption remains the dominant source of energy in many sectors. Given China's ongoing urbanization and industrialization processes, it is imperative to restructure the industrial framework, particularly in energy-intensive industries, such as transport, real estate and industry. The three sectors are the primary sources of carbon emissions that account for more than 80% totally in each year [12] and are three of five sectors that used to trace global greenhouse gas [13]. Thus, these three sectors are more important than others in the examination of driving forces for China's carbon emissions due to their contribution, which is 38%, 18%, and 28% respectively, and they are primary targets for climate policies. While others are less important, such as service sector that only indirect emission and already captured in industry sector, and agriculture that policies exist but are less centralized. The targets can be achieved by integrating advanced technologies into infrastructure development, and the adjustment of industrial structure. Then, the "1 + N" policy framework was introduced as a central guiding document ("1") alongside a series of detailed, sector-specific policies, guidelines, and action plans ("N") to facilitate China's attainment of its carbon-related objectives: "Carbon Peak" and "Carbon Neutrality" [14,15]. The primary document outlines China's strategic commitments for each stage with 2025, 2030 and 2060 respectively. Before 2030, traditional energy is projected to contribute around 25% of the nation's main energy structure, apart from that, carbon intensity is projected to decline by over 65%, in comparison to 2005 levels. Furthermore, the policy emphasizes the target for achieving carbon neutrality by 2060, with share of non-fossil energy expected to exceed 80% before that year [16]. The policy was designed to address three key areas: transforming the energy structure, controlling environmental pollution, and reducing carbon emissions [15]. Thus, the effectiveness can be examined by the level of carbon emission and non-fossil energy consumption within the energy composition. In 2024, non-fossil energy accounts for approximately 18.9% in the nation's primary energy consumption, with expectations to reach nearly 20% by 2025, aligning with the target for that year [17]. In this context, investigating the driving forces for China's carbon emissions is significant to enhance the effectiveness of current policies.

Scholars explored various driving factors of carbon emission in previous studies, among which energy consumption has been widely identified as the primary contributor. Besides, balancing economic development with emissions reduction was a prominent subject of scholarly investigation, with a variety of empirical investigations and numerous theoretical explorations [18]. This relationship was also explored by Mardani et al. [19], noting that while economic growth has improved living standards in many countries, it has contributed to a rise in carbon emissions and the depletion of natural resources. Beyond assessing China's carbon emissions in the context of economic growth, it is equally imperative to account for the influence of energy consumption. This is because China's rapid economic expansion has been strongly linked to high energy consumption, resulting in significant greenhouse gas emissions, particularly carbon dioxide [20]. As a result, the Chinese government faces substantial pressure to reduce carbon emissions with the reduction on its energy consumption. Meanwhile, this pressure is further exacerbated by the growing energy demand driven by rapid economic growth, which has likely been a major factor contributing to the rise in carbon emissions and energy consumption over the last thirty years [21]. Additionally, foreign direct investment is a key factor driving economic growth, alongside its interaction with carbon emissions. And it has become a main determinant to China's economic growth since China's economic reforms initiated in 1978 [22]. As many companies participate in the global allocation of investment and numerous countries actively promote foreign investment to drive economic growth, economic development has become increasingly globalized. However, this phenomenon is accompanied by environmental challenges that cannot be overlooked [23]. Except that, international trade is a vital element in fostering economic expansion and plays an essential part in promoting overall economic progress. China's WTO accession in 2001 marked a pivotal turning point, triggering exponential growth in both import and export volumes [24]. As a result, China has emerged as one of the largest nations in global foreign trade. This expansion in foreign trade has not only fostered economic growth but has also led to a substantial rise in China's energy consumption [25]. They also observed that China's rapid economic and population growth has transformed the country into the top emitter of carbon dioxide and the leading energy consumer globally. Therefore, population growth must also be considered when exploring the determinants of China's carbon emissions. This determinant was also examined by Rehman et al. [26], who underscored the essential role of agriculture in mitigating climate change. They argued that agricultural initiatives are essential to meeting the growing global demand for food and fiber, particularly considering the increasing population.

The association between carbon emissions and their affecting factors remains unclear, although numerous studies have investigated these factors affecting carbon emissions. What effects do these determinants have on carbon emissions, whether positive or negative? Additionally, whether causal relationships exist among these factors or not? While China's economic expansion and growing energy demand have precipitated a substantial increase in carbon emissions, empirical analysis reveals that demographic factors have exerted statistically negligible influence on emission levels within the Chinese context [27]. In contrast, their negative relationship was demonstrated by Rehman et al. [26]. An opposite relationship was also identified by Zhang et al. for carbon emissions and energy consumption, which is negative, although this varies regionally [16]. Additionally, regional differences in the economic growth-emission relationship are observed only in five provinces of China, where energy-intensive industries constitute a significant portion of the overall industrial sector [22]. A bidirectional causality was also found by Mardani et al. after conducting a thorough examination of the relationship between these two, that carbon emissions are influenced by fluctuations in economic growth, with increases or decreases in economic growth corresponding to higher or lower levels of carbon emissions [19]. Conversely, potential reductions in emissions were found to negatively affect economic growth. However, no such causal relationship was identified between these two [18]. Furthermore, foreign direct investment has a positive association with carbon emissions, while international trade is negatively associated with that [9]. This relationship was also examined by Wang and Zhang [24], who found that their relationship is negative. In contrast, Hao and Liu argued that the impact of foreign trade on carbon emissions, whether direct or indirect, is negligible or insignificant [28]. To address these gaps, the Granger causality tests are applied to establish directional relationships. After that, this study conducts a panel regression model to quantify emission determinants across China's key sectors, including transportation, real estate, and industrial sectors, with the employment of panel estimations using panel data during the period from 2004 to 2023. The historical trend of each variable during the investigated period are presented in **Figure 1**.

The findings derived from this research can provide relevant information from a policy perspective, so that policymakers can design effective policies to effectively control carbon emissions and achieve China's 2060 carbon-neutral vision. Besides, the findings will help identify tipping points for environmental quality improvement, and how to reach the target for carbon emissions reduction by reorienting affected macroeconomic factors in China's sectors of transport, real estate and industry.

This paper is structured as follows: the second section provides a comprehensive review of the relevant literature. Next, the primary model employed in the research is described in sequence, along with the data sources utilized. Then presents the empirical results and interpretation of the findings, followed by a thorough discussion. Finally, Section 5 provides a conclusion, including the key findings and recommendations.

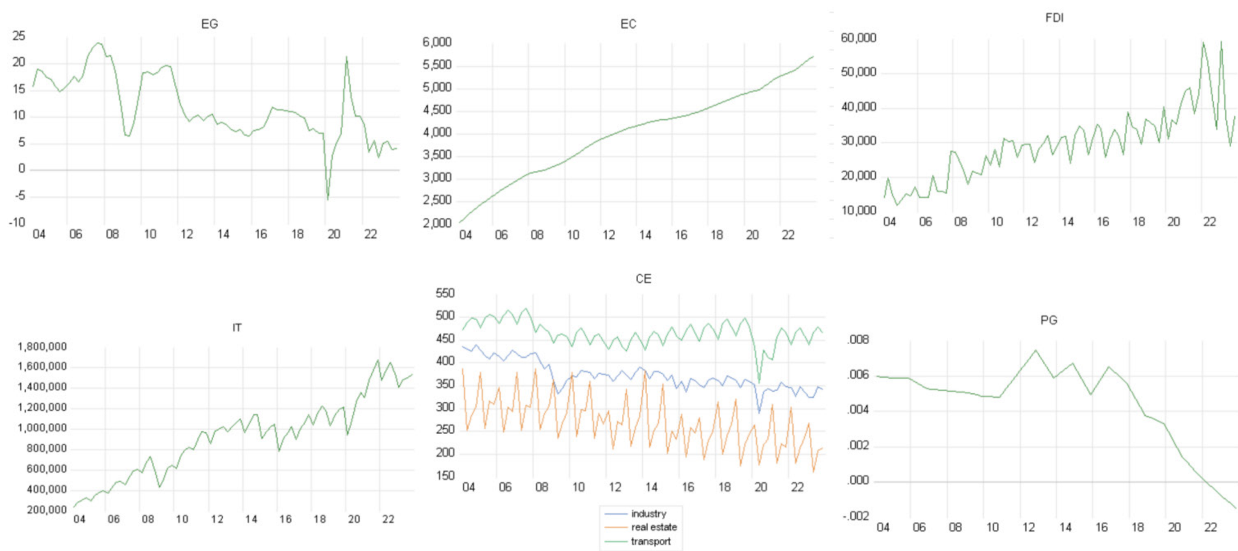

Figure 1. Historical Trend for Each Variable.

2. Literature Review

Given the increasing global focus on mitigating carbon emissions, a significant body of research has examined the contributors to China's carbon emissions. This section synthesizes the direction of their impacts and the causal relationships among these factors, as identified in prior studies.

Alam et al. examined the impacts of energy consumption and population growth on carbon emissions employing the ARDL approach in four countries, including China, using yearly data between 1970 and 2012 [27]. They revealed that China's carbon emissions have risen significantly with an increase in energy consumption. However, the impact of population growth on that was determined to be statistically insignificant. These findings are further explored by Rehman et al. [26], who investigated the relationship among same factors that Alam et al. investigated using time series data between 1970 and 2017 [27]. They employed the vector autoregressive model and Granger causality tests in their analysis and found that carbon emissions are negatively affected by energy consumption in the long run, as well as by population growth. In contrast, population growth maintained a similar negative short-term impact on carbon emissions, whereas energy consumption demonstrated a positive relationship across all examined periods. Moreover, these relationships were demonstrated as a unidirectional association. However, a two-way positive causal long-term relationship between carbon emissions and energy consumption were presented by Wang et al. who employed a panel data model for 30 Chinese provinces over the period 1995–2011 [21]. Additionally, Zhu and Peng presented a different perspective on how carbon emissions and population increase interact, using data on China's population, consumption, and carbon emissions from 1978 to 2008 [29], suggesting that changes in population size were not the primary driver of carbon emissions. Instead, they found a strong correlation between consumption levels and carbon emissions, indicating that consumption, rather than population growth, played a more significant role in influencing carbon emissions during this period. Zhang et al. conducted a comprehensive analysis of the interrelationships among economic growth, energy consumption, and carbon emissions from 1990 to 2021 [30], employing regression analysis complemented by Granger causality tests. They concluded that environmental quality is strongly negatively affected by energy consumption and found that economic growth causes carbon emissions and energy consumption. These casual relationships were also examined in China using data for the period from 1990 to 2012 [18]. In their research, Granger causality tests identified notable causal relationships, more precisely, a unidirectional causal link was identified from energy consumption to carbon emissions, whereas a bidirectional causal relationship was found between economic growth and energy consumption. The findings are consistent with Wang et al. [20], who employed panel cointegration and vector error correction modelling methods based on panel data covering the period from 1995 to 2007 in 28 Chinese provinces, to explore the causal relationships between these three factors. In their study, they found carbon emissions and energy consumption affect each other, just as energy consumption and economic growth exhibit mutual influence. Additionally, they identified that the long-term driving forces for carbon emissions were economic growth and energy consumption; meanwhile, those for energy consumption are carbon emissions and economic growth. Chandran and Tang [31] also performed a Granger causality test for China, which offered robust evidence supporting that economic growth causes carbon emissions. The finding is consistent with the exploration of the relationship between carbon emissions and economic growth, which is based on a review of 175 articles published in 55 international academic journals between 1995 and 2017 [19]. Their study concluded that a bidirectional causality exists between economic growth and carbon emissions, indicating that fluctuations in economic growth led to corresponding increases or decreases in carbon emissions. Consequently, efforts to reduce emissions may potentially have an adverse impact on economic growth.

In addition to previous research summarized above, the impact of international trade and foreign direct investment has also garnered substantial attention from scholars. Hao and Liu revealed that the combined direct and indirect impacts on carbon emissions were negatively affected by foreign direct investment in China [28]. In contrast, they found that the influence on carbon emissions by international trade was statistically insignificant. This finding differs from the research conducted by Liu et al. [32], which suggested that increased international trade leads to a decrease in carbon emissions, while foreign direct investment positively affects that. Liu et al. incorporated international trade, foreign direct investment, and renewable energy consumption as determinants of carbon emissions over the period from 1995 to 2017 [32], using advanced panel methods. Similarly, Wang and Zhang corroborated the findings of Hao and Liu [24,28], suggesting that foreign direct investment affect carbon emissions negatively. Additionally, Pao and Tsai investigated the effect of foreign direct investment and economic growth on carbon emissions for the period from 1980 to 2007 [23], employing a panel cointegration approach. Their causality analysis revealed a strong bidirectional association between foreign direct investment and carbon emissions, and a unidirectional causal impact that runs from economic growth to foreign direct investment. In contrast, Peng et al. found that the causal relationships vary regionally based on Granger causality tests applied to China's province-level data [22]. In detail, foreign direct investment was identified as a directional driver of carbon emission in Guizhou, Henan, Beijing, and Shanxi, while a two-way causality existed between carbon emissions and economic growth in Shanxi; the bidirectional causality between these two variables was observed in other countries. Moreover, they found that the bidirectional causality is present only in Henan, while in other provinces, the unidirectional causality was identified. Wang et al. conducted a comparative analysis by employing of a vector autoregressive model, based on panel data of the eastern, central, and western provinces from 1997 to 2015 [24], to investigate the casualties between carbon emissions and its economic factors in China's provinces. They found that a causality existed among carbon emissions, GDP, and foreign direct investment, with the direction of causality varying across different regions in China. Additionally, according to Chen et al. who found a causality that run from international trade to carbon emissions was identified [25].

More importantly, the effect of macroeconomic factors on carbon emissions differs across sectors which can be seen from previous literature. Wang et al. found that in the transportation sector, economic factors had the largest impact on carbon emissions, specifically, GDP and population were found to drive the increase in carbon emissions in transportation [33]. Additionally, the structure of the transportation sector contributed significantly to the rise in emissions level of carbon dioxide, especially within the freight sector. Besides, Lin and Xu employed a Vector Autoregressive model in the study which analysed the primary factors driving the rise in carbon emissions [34], in the industrial sector of Shanghai. They found that, in the short term, energy efficiency, economic growth, and energy consumption structure affect carbon emissions positively, while urbanization drives in reducing emissions. But energy consumption and its structure are beneficial to mitigate carbon emissions in the long-term, whereas urbanization and energy efficiency result in a rise in carbon emissions. Besides, the most significant contributing factor was the level of economic output in the building sector [35]. Moreover, Beibei et al. found that economic growth targets can result in a decline in energy efficiency and increased energy consumption at the industrial level [36], which enhance the meaningfulness to investigate the determinants for sectors' carbon emissions in China under the target on carbon emission reduction in Five-Year Plan.

Existing research has extensively examined the determinants of carbon emissions, employing methodologies (e.g., ARDL and Vector Autoregressive), econometric model (e.g., EKC), and regional analysis. However, studies focusing on sector-specific relationships remain limited, particularly in the context of China's carbon neutrality goals. While previous work has identified macroeconomic drivers (e.g. GDP, energy intensity) of emissions, few have systematically investigated key drivers and casual linkages using time-series econometrics. This study advances the literature in Granger Causality for sectoral emissions and disaggregated sectoral analysis. Unlike conventional correlation-based analyses, the Granger causality tests are applied to determine the direction and significance of causal relationships between economic, energy, and trade variables and sectoral carbon emissions, which provides stronger evidence for policy targeting by distinguishing between mere associations and predictive causality. Besides, previous studies often treat China's emissions as an aggregate, while this study focuses on high-emission sectors to reveal heterogeneous determinants.

3. Model

3.1. Model Specification

This study investigates the long-term and short-term relationship by employing a similar approach to that of Alam et al. [27], alongside the causality tests conducted by Pao and Tsai [23], Peng et al. [22], and Chen et al. [25]. The impact on sector-specific carbon emission from its driving factors in China is modelled as follows:

$$CE_{it} = \beta_0 + \beta_1 EG_{it} + \beta_2 EC_{it} + \beta_3 IT_{it} + \beta_4 FDI_{it} + \beta_5 PG_{it} + \epsilon_{it} \quad (1)$$

where i = 1, …, N denotes the sector, t = 1, …, T represents the time period, with ε_{it} assumed to be an error term that is serially uncorrelated. CE, EC, IT and FDI are the variables that represent their natural logarithms of carbon emissions, energy consumption, foreign direct investment, and international trade, respectively. PG and EG represent the reciprocals of population growth and economic growth, such that the signs of β_1 and β_5 can indicate an inverse relationship.

3.2. Panel Unit Root Test

This study employs two such tests: the Augmented Dickey-Fuller (ADF) test and the Im-Pesaran-Shin (IPS) test, introduced by Dickey & Fuller and Im, Pesaran, & Shin [37,38], respectively, to assess the stationary properties of the relevant variables in panel data analysis. The null hypothesis of these tests posits that the variables contain a unit root. The IPS test accounts for heterogeneity across sections and corrects for serial correlation, making it particularly effective in small sample sizes. Besides, the ADF test is also crucial for the validity of econometric models, which is a commonly used statistical method for detecting unit roots in time series data. The ADF test can be adjusted to handle cross-sectional dependence and heterogeneity between entities in panel data.

3.3. Panel Cointegration Tests

To examine whether a long-run relationship exists between the variables, the procedure proposed by Pedroni and Pedroni was employed [39,40]. The Pedroni cointegration tests consist of four statistics from panel cointegration tests, and three statistics from group cointegration tests. The variables are considered cointegrated if the statistics reject the null hypothesis of no cointegration.

The formula for Pedroni cointegration tests is modeled as follows:

$$\mathrm{CE}_{it} = \alpha_{it} + \delta_t + \beta_{1i}\mathrm{EG}_{it} + \beta_{2i}\mathrm{EC}_{it} + \beta_{3i}\mathrm{IT}_{it} + \beta_{4i}\mathrm{FDI}_{it} + \beta_{5i}\mathrm{PG}_{it} + \epsilon_{it} \quad (2)$$

where i represents each sector in China, and i represents the time period. α_{it} and δ_i are the fixed effects for each sector in China and deterministic trends, respectively.

3.4. ARDL Model

To test the long-term and short-term relationships, Panel Autoregressive Distribution Lag (ARDL) is a common approach [41]. The generalized Panel ARDL model is specified as follows:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + \epsilon_t \quad (3)$$

where y_t represents for dependent variable, x_t represents for independent variables, p and q refer to the optimal lags of these variables, respectively, and it is assumed that ε_{it} represents an error term.

Once the cointegration relationship among the variables is established, this model is applied based on the long-run coefficients of the linear ARDL model, which can be estimated as follows:

$$CE = \beta_0 + \sum_{i=1}^{p} \gamma_i\, CE_{t-i} + \sum_{j=0}^{q1} \delta_j\, EG_{t-i} + \sum_{m=0}^{q2} \eta_m\, EC_{t-m} + \sum_{n=0}^{q3} \lambda_n\, \mathrm{FD}I_{t-n} + \sum_{l=0}^{q4} \rho_l\, IT_{t-l} + \sum_{r=0}^{q5} \psi_r\, \mathrm{P}G_{t-r} + \epsilon_t \quad (4)$$

In this process, Akaike Information Criterion (AIC) is employed to determine the optimal lag length for the ARDL model across all variables being studied. Finally, to estimate short run dynamics, the error correction model is shown below:

$$\Delta\, CE = \beta_0 + \sum_{i=1}^{p} \gamma_i\, \Delta\, CE_{t-i} + \sum_{j=0}^{q1} \delta_j\, \Delta\, EG_{t-i} + \sum_{m=0}^{q2} \eta_m\, E\,\Delta\, C_{t-m} + \sum_{n=0}^{q3} \lambda_n\, \Delta\, \mathrm{FD}I_{t-n} + \sum_{l=0}^{q4} \rho_l\, \Delta\, IT_{t-l} + \sum_{r=0}^{q5} \psi_r\, \Delta\, \mathrm{P}G_{t-r} + \upsilon \mathrm{emc}_{t-1} + \epsilon_t \quad (5)$$

3.5. Granger Causality Test

The presence of cointegration suggests that the causality exists in at least one direction. Then the Granger causality test proposed by Dumitrescu and Hurlin [42] is employed to examine the directional causality between multiple time series variables. This methodology is a robust extension of the traditional Granger causality test, which allows for causality testing across heterogeneous panel data, and is especially useful when dealing with cross-sectional dependence and non-stationarity in economic, financial, and social science datasets. The model can be modified as follows:

$$CE_{it} = \alpha_{1i0} + \sum_{x=1}^{p1} \alpha_{i1}^{x} EG_{it-x} + \sum_{x=1}^{p2} \alpha_{i2}^{x} EC_{it-x} + \sum_{x=1}^{p3} \alpha_{i3}^{x} IT_{it-x} + \sum_{x=1}^{p4} \alpha_{i4}^{x} FDI_{it-x} + \sum_{x=1}^{p5} \alpha_{i5}^{x} PG_{it-x} + \epsilon_{1it} \quad (6)$$

$$EG_{it} = \alpha_{1i0} + \sum_{x=1}^{p1} \alpha_{i1}^{x} CE_{it-x} + \sum_{x=1}^{p2} \alpha_{i2}^{x} EC_{it-x} + \sum_{x=1}^{p3} \alpha_{i3}^{x} IT_{it-x} + \sum_{x=1}^{p4} \alpha_{i4}^{x} FDI_{it-x} + \sum_{x=1}^{p5} \alpha_{i5}^{x} PG_{it-x} + \epsilon_{1it} \quad (7)$$

$$EC_{it} = \alpha_{1i0} + \sum_{x=1}^{p1} \alpha_{i1}^{x} EG_{it-x} + \sum_{x=1}^{p2} \alpha_{i2}^{x} CE_{it-x} + \sum_{x=1}^{p3} \alpha_{i3}^{x} IT_{it-x} + \sum_{x=1}^{p4} \alpha_{i4}^{x} FDI_{it-x} + \sum_{x=1}^{p5} \alpha_{i5}^{x} PG_{it-x} + \epsilon_{1it} \tag{8}$$

$$IT_{it} = \alpha_{1i0} + \sum_{x=1}^{p1} \alpha_{i1}^{x} EG_{it-x} + \sum_{x=1}^{p2} \alpha_{i2}^{x} EC_{it-x} + \sum_{x=1}^{p3} \alpha_{i3}^{x} CE_{it-x} + \sum_{x=1}^{p4} \alpha_{i4}^{x} FDI_{it-x} + \sum_{x=1}^{p5} \alpha_{i5}^{x} PG_{it-x} + \epsilon_{1it} \tag{9}$$

$$FDI_{it} = \alpha_{1i0} + \sum_{x=1}^{p1} \alpha_{i1}^{x} EG_{it-x} + \sum_{x=1}^{p2} \alpha_{i2}^{x} EC_{it-x} + \sum_{x=1}^{p3} \alpha_{i3}^{x} IT_{it-x} + \sum_{x=1}^{p4} \alpha_{i4}^{x} CE_{it-x} + \sum_{x=1}^{p5} \alpha_{i5}^{x} PG_{it-x} + \epsilon_{1it} \tag{10}$$

$$IT_{it} = \alpha_{1i0} + \sum_{x=1}^{p1} \alpha_{i1}^{x} EG_{it-x} + \sum_{x=1}^{p2} \alpha_{i2}^{x} EC_{it-x} + \sum_{x=1}^{p3} \alpha_{i3}^{x} IT_{it-x} + \sum_{x=1}^{p4} \alpha_{i4}^{x} FDI_{it-x} + \sum_{x=1}^{p5} \alpha_{i5}^{x} CE_{it-x} + \epsilon_{1it} \tag{11}$$

where i = 1, …, N represents the sector, t = 1, …, T represents the time period, ε_{it} represent stochastic error terms, and x is the lag length. The variables CE, EC, IT and FDI are the natural logarithms of carbon emissions, energy consumption, foreign direct investment, and international trade, respectively. EG and PG are the reciprocals of economic growth and population growth.

The traditional Granger causality test, proposed by Granger [43], evaluates whether the past values of one variable can improve the predictions of another. However, it is limited to time series data from a single unit or variable and may not account for potential heterogeneity across cross-sectional units. To address this, a panel data extension of the Granger causality test proposed by Dumitrescu and Hurlin [42] relaxes the assumption of homogeneity across the units in the panel. Their methodology allows for causality to differ across individual cross-sectional units, making it more suitable for datasets where the causality relationship may vary from one cross-sectional unit to another.

4. Results and Discussion

4.1. Panel Unit Roots and Panel Cointegration Tests

In the initial step, with the results shown in **Table 1**, IPS test and ADF are performed to evaluate the stationarity of the data across all variables. The results indicate that only EG appear to stationary in the level for the test of ADF. While under the IPS test, at the level with trend, CE and EG are stationary, while EG and IT are stationary at the level without trend. Since all series stationary in their first difference, it means the estimated coefficients from a simple panel regression may not have a meaningful economic interpretation, however, if the variables are identified as non-stationary, they can be transformed by taking their first differences to achieve stationarity. Moreover, although all variables are statistically significant under the ADF test after first-order differencing, IPS test is more suitable for small sample size and panel data. Therefore, each variable is integrated of order one.

Table 1. Panel Unit Root Test Results.

Variables	**Unit root test**			
individual intercept without trends	**IPS**		**ADF**	
	Level	**1st diff.**	**Level**	**1st diff.**
CE	0.76013	−5.07717***	4.74664	39.4954***
EG	−3.46915***	−10.7128***	23.3955***	92.6693***
EC	−1.62140	−3.58890***	1.06904	−24.0954***
FDI	−0.75603	−8.40890***	−6.34086	73.1469***
IT	−1.60562*	−3.58020***	10.2498	24.6173***
PG	7.80309	−11.3913***	4.2E-05	95.9754***
individual intercept with trends	**IPS**		**ADF**	
	Level	**1st diff.**	**Level**	**1st diff.**
CE	−1.53317*	−4.58768***	10.1394	45.2483***
EG	13.8085***	−2.79136***	102.392***	−102.644***
EC	−1.28145	−14.6634***	9.18089	70.1702***
FDI	−0.60149	19.9976***	5.85009	68.8213***
IT	−0.83933	−3.32987***	6.35320	15.6059**
PG	9.88287	−11.0203***	2.1E-07	102.225***

Note: ***, **, and * represent significant levels (1%, 5%, and 10%)

Then the existence of cointegration relationship is determined using testing approach by Pedroni. **Table 2** presents the panel cointegration results between variables as follows:

Table 2 presents the panel cointegration results, six of the seven statistics reject the null hypothesis of no cointegration, while one statistic, the panel v-statistic, does not reject this hypothesis, indicating the cointegration between the variables is absent. It means a cointegration relationship exists, making it reasonable to affirm that a cointegrating relationship exists among the variables.

4.2. Panel Estimation

The panel estimation results are presented in **Table 3**. The results indicate that, under the ARDL model, the short-term coefficient of EG displays a statistically significant positive magnitude. Specifically, since economic growth is expressed reciprocally, it shows a negative short-term effect on carbon emissions. However, no long-term relationship is observed between them. Moreover, economic growth is significant at 5% level in each sector, including transport, real estate, and industry sectors, and positively affects carbon emission in transport and industry sectors while adversely affecting it in the real estate sector. This finding supports the opinion that economic growth affects carbon emissions significantly when viewed from various sectors [36]. The current study also finds that energy consumption is negatively correlated to carbon emissions in both temporal horizons, which can be seen from the results. This is inconsistent with Rehman et al. who found a negative long-term effect on carbon emissions caused by energy consumption [26], while it exerted a positive short-term impact on carbon emissions. Besides, the positive impact on carbon emissions from energy consumption is observed exclusively in the real estate sector, rather than in the industrial sector and transport sector. This finding supports Alam et al. but contradicts the results from Zhang et al., who indicated that carbon emission is significantly negatively affected by energy consumption [27,30].

Table 2. Pedroni Residual Cointegration Test Results.

Alternative hypothesis: common AR coefs. (within-dimension)		
Statistic tests	Statistic	Prob.
Panel v-Statistic	−1.375608	0.9155
Panel rho-Statistic	−8.245818***	0.0000
Panel PP-Statistic	−19.4689***	0.0000
Panel ADF-Statistic	−7.673386***	0.0000
Alternative hypothesis: individual AR coefs. (between-dimension)		
Group rho-Statistic	−4.04149***	0.0000
Group PP-Statistic	−10.41913***	0.0000
Group ADF-Statistic	−4.409478***	0.0000

Note: ***, **, and * represent significant levels (1%, 5%, and 10%)

Table 3. Panel estimation results.

Independent Variables	**Short Run**	**Long Run**	**Transport**	**Real estate**	**Industry**
EG	0.17942***	0.100416	−0.148594**	0.35419**	−0.148594**
EC	−3.662191**	−1.327979**	1.829847	7.748457**	1.829847
FDI	0.160379*	−0.468656***	0.066128*	0.324822***	0.066128*
IT	−0.137333	0.641473***	0.114648*	−0.329564*	0.114648*
PG	−0.00000387**	0.00000322	−3.57E-06	3.81E-07	−3.57E-06

Note: ***, **, and * represent significant levels (1%, 5%, and 10%)

The coefficients associated with foreign direct investment are statistically significant across all estimators, including those evaluating long-term and short-term effects, as well as sectoral impacts. Specifically, foreign direct investment exerts a positive short-term influence on carbon emissions, a relationship that is consistent across all three sectors examined. In contrast, a negative long-term impact on carbon emissions from foreign direct investment is found. The results for the short-term relationship and sectoral effects align with the study by Liu et al. [32], who posit that carbon emissions are affected by foreign direct investment positively. However, these results stand in contrast to the conclusions of Wang and Zhang and Hao and Liu [24,28], who found an inverse relationship between carbon emissions and foreign direct investment. Notably, their findings align with the long-term impact of foreign direct investment observed in current study, indicating a negative effect. Moreover, the finding demonstrates that carbon emission is affected by international trade positively in the long run, as well as transport sector and industrial sector, which is inconsistent with Chen et al. [25], who found that a rise in international trade leads to lower energy consumption. In contrast, their findings align with the adverse relationship between international trade and carbon emissions in real estate sector. These differences may help explain why the short-term effect appears to be statistically insignificant, this result also observed by Hao and Liu [28], who found that the influence of international trade volume was not statistically significant in level of carbon emission. At last, population growth is found to have a significantly positive short-term effect on carbon emissions, with no sector-specific variations observed. This finding contrasts with the results of Rehman et al. [26], who reported that the relationship between carbon emissions and population growth was statistically insignificant for China in both the short and long run. Similarly, Zhu and Peng found that population growth affects carbon emissions insignificantly in China during the period from 1978 to 2008 [29].

4.3. Panel Causality Test

Based on the coefficient value and probability of rejecting null hypothesis, that IV does not cause DV, from Granger causality tests results in **Table 4**, the causality relationships among these variables are presented in **Figure 2**. It shows that the bidirectional relationship exists between EC and EG, EC and FDI, CE and EG, EC and FDI, IT and FDI, CE and FDI, CE and IT. And unidirectional causality is found from EC to CE, from EC to IT, from IT to EG, and from FDI to EG. While no causality is observed between PG and any of other variables, except for EG. The causalities between carbon emissions and their determinants align with the short-term results estimated by the ARDL model on EG, EC and FDI. Specifically, all the investigated determinants are found to cause carbon emissions, apart from population growth. While this test does not reveal the long-term causal relationship or the direction (positive or negative) of the short-term relationship.

Table 4. Results of Granger Causality Tests.

DV	**IV**					
	CE	**EG**	**EC**	**FDI**	**IT**	**PG**
CE		9.5312***	21.0103***	20.6834***	47.2730***	1.2742
EG	6.0134***		9.5593***	15.3640***	12.2313***	2.3836
EC	2.8200	4.6503**		4.2713*	1.4536	1.3388
FDI	19.8561***	1.2878	36.0695***		53.8242***	2.5953
IT	10.8220***	0.0376*	20.2658***	25.8295***		0.9143
PG	0.2596	4.2413*	0.4694	0.3654	1.5483	

The bidirectional relationship between CE and EG is align with the results from Wang et al. [18], while contradicts to Zhang et al. who revealed a unidirectional causality from EG to CE [30]. Besides, the result shows that the relationship between EC and CE is one-way causality, which is from EC to CE, and aligns with the results from Rehman et al. [26], whereas this relationship was examined as two-way by Wang et al. [21]. Moreover, this study does not find causal relationship from PG to CE that demonstrated by Rehman et al. [26]. Additionally, Peng et al. and Pao and Tsai found bidirectional relationship between EC and FDI in China and China's provinces [22,23], which is consistent with the results from current study. Despite Peng et al. also examining the bidirectional relationship between EG and FDI [22], in contrast, the current study finds a one-way relationship from FDI to EG, which is the opposite of Pao and Tsai [23], who identified this one-way relationship as flowing from EG to FDI. Furthermore, the causality between IT and CE is bidirectional, which is inconsistent with the study by Chen et al. [25], who found a unidirectional causality from IT to CE.

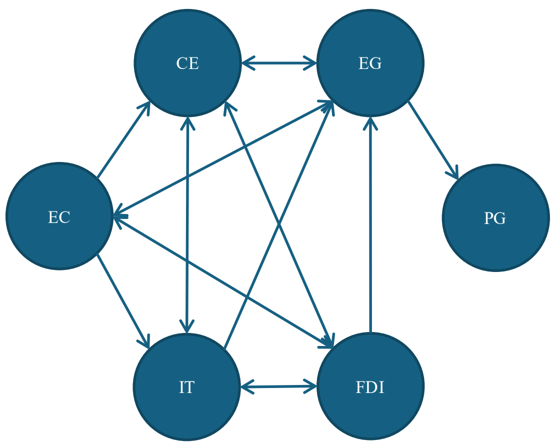

Figure 2. Panel Causality Relations for China.

5. Conclusions

This research investigated the driving forces for China's carbon emissions, using data for a panel of China's main sectors, including transportation, real estate, and industrial sectors, over the period from 2004 to 2023. In this research, the effects of investigated factors on carbon emissions are examined, including economic growth, energy consumption, foreign direct investment, international trade, and population growth. Then, within established model, the causal relationships between these variables are investigated and summarized. The main findings are summarized as follows:

Firstly, EC and FDI negatively affect CE in the long run, while international trade positively affects that. In the short run, all factors statistically significantly affect carbon emissions, except IT. Specifically, CE is positively influenced by FDI and PG, while negatively impacted by EC and EG.

Secondly, PG is not a significant influencing factor in any of the sectors. Furthermore, transport-related carbon emissions are positively influenced by EG, FDI, and IT. However, within the transport sector, EC does not seem to have a substantial impact on CE. In the real estate sector, EC and FDI positively affect carbon emissions, whereas IT and EG exert a negative effect. In contrast, industrial carbon emissions are negatively influenced by IT but positively impacted by FDI and EG.

Lastly, between EC and EG, EC and FDI, CE and EG, EC and FDI, IT and FDI, CE and FDI, and CE and IT, a bidirectional causal relationship is observed. And unidirectional causality is found from EC to CE, from EC to IT, and from IT to EG, and from FDI to EG. Besides, population growth is identified as the sole causal factor for economic growth.

Given the above findings, the policies should prioritize low-carbon transitions by integrating sustainability into economic planning and infrastructure development in the "the Five-Year Plans" as it can establish clear targets for emissions reductions across key sectors. Thus, the main recommendations for current economic and environmental policy based on key influence factors in different sectors are as follows: At first, in transport sector, the transportation economic development goals should be set based on local economic structure. Moreover, the polices should be implemented in each sub-sectors of transport sector, including road transport, air transport, and rail transport. And the government also should focus on private vehicles rather than public transportation, such as vehicle purchase tax and public transportation discount. Secondly, in real estate sector, it is suggested to foster the enhancement and efficiency of the real estate market by the purchase restriction policy, to avoid overbuilding. At the same time, the implementation of a real estate tax is essential to conduct, which could avoid excessive investment and speculation. Besides, in this sector, the improvement in the production efficiency of building materials is also significant, as well as incentives for using green materials, and optimization of structural designs are vital for reducing emissions. At last, in the industrial sector, the implementation and development of new technologies should be actively promoted, as they are advantageous in reducing the carbon intensity and improving energy efficiency of industrial processes. Transitioning from carbon-intensive energy sources, such as coal, to more sustainable, low-carbon alternatives, including natural gas, electricity, solar, and nuclear energy, is also critical. What is most important is phasing out subsidies for fossil fuels and introducing incentives for clean energy sources.

Despite its potential contribution to the current literature, it is also meaningful to policymakers and scholars. To policymakers, this study provides relevant information from a policy perspective so that policymakers can design effective policies to control carbon emissions to achieve China's 2060 carbon-neutral vision. And help to identify the causes for increasing carbon emission with better understanding of relationships between carbon emissions and its determinants. Besides, it is also crucial for them when making ecological and environmental protection policies and fiscal strategic decisions. To scholars, this study contributes to the growth of theoretical knowledge by building a research framework for carbon emissions research. Moreover, it explores the macroeconomic determinants of China's carbon emissions, drawing on the most recent data, and fills the current research gap. However, there are limitations related to this study. Due to the limitations of the Granger causality test, which can only assess short-term causal relationships, future research could explore long-term causal relationships through cointegration tests. Additionally, the sectors examined in this study do not encompass all sectors in China, and a more comprehensive sectoral analysis would enhance the robustness and generalizability of the findings. These findings would help policymakers design more targeted strategies to reduce emissions in the short term by focusing on high-impact sub-sectors. Finally, the results of the panel estimation can be used to model and forecast future carbon emissions, thereby enabling an assessment of the likelihood of China's commitment on governance and target of carbon emissions.

Author Contributions

Conceptualization, C.Z.; methodology, C.Z.; validation, C.Z.; formal analysis, C.Z.; investigation, C.Z.; resources, C.Z.; data curation, C.Z.; writing—original draft preparation, C.Z.; writing—review and editing, C.Z.; supervision, P.A.M. and Y.V.; project administration, C.Z. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data collected from China's National Bureau of Statistics can be accessed via the following link: https://data.stats.gov.cn/easyquery.htm?cn=C01.

Acknowledgments

Foremost, I would like to express my sincere gratitude to my co-supervisor, Associate Professor Dr. Paul Anthony MariaDas for their continuous support of my Ph.D. study and research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this proposal. I could not have imagined having better supervisor and mentors for my Ph.D. studies. I thank also my best friend, Mr. Jing Cheng for his technical support and encouragement in completing this study. My thanks also go to the authors whose books and articles have given me inspiration in the writing of this study. Last but not last, I would like to express my special thanks to my parents, whose care and support motivate me to move on and make me want to

be a better parson.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Gregg, J.S., Andres, R.J., Marland, G., 2008. China: Emissions pattern of the world leader in CO2 emissions from fossil fuel consumption and cement production. Geophysical Research Letters. 35(8), L08806. DOI: https://doi.org/10.1029/2007GL032887
[2] Hao, Y., Chen, H., Wei, Y.M., et al., 2016. The influence of climate change on CO2 (carbon dioxide) emissions: an empirical estimation based on Chinese provincial panel data. Journal of Cleaner Production. 131, 667–677. DOI: https://doi.org/10.1016/j.jclepro.2016.04.117
[3] Lin, B., Sun, C., 2010. Evaluating carbon dioxide emissions in international trade of China. Energy Policy. 38(1), 613–621. DOI: https://doi.org/10.1016/j.enpol.2009.10.014
[4] Zhang, D.Y., Huang, T., 2023. Six Charts That Explain China's Carbon Emissions [in Chinese]. World Resources Institute. Available from: https://wri.org.cn/insights/data-viz-6-graphics-ghg-emissions-china (cited 5 June 2025).
[5] Guan, D., Peters, G.P., Weber, C.L., et al., 2009. Journey to world top emitter: An analysis of the driving forces of China's recent CO2 emissions surge. Geophysical Research Letters. 36(4), L04709. DOI: https://doi.org/10.1029/2008GL036540
[6] Lu, Y., Stegman, A., Cai, Y., 2013. Emissions intensity targeting: from China's 12th Five Year Plan to its Copenhagen commitment. Energy Policy. 61, 1164–1177. DOI: https://doi.org/10.1016/j.enpol.2013.06.075
[7] Zhang, C., Su, B., Zhou, K., et al., 2019. Decomposition analysis of China's CO2 emissions (2000–2016) and scenario analysis of its carbon intensity targets in 2020 and 2030. Science of the Total Environment. 668, 432–442. DOI: https://doi.org/10.1016/j.scitotenv.2019.02.406
[8] Zhou, S., Tong, Q., Pan, X., et al., 2021. Research on low-carbon energy transformation of China necessary to achieve the Paris agreement goals: A global perspective. Energy Economics. 95, 105137. DOI: https://doi.org/10.1016/j.eneco.2021.105137
[9] Liu, X., Wang, X., Meng, X., 2023. Carbon Emission Scenario Prediction and Peak Path Selection in China. Energies. 16(5), 2276. DOI: https://doi.org/10.3390/en16052276
[10] Zheng, J., Mi, Z., Coffman, D.M., et al., 2019. Regional development and carbon emissions in China. Energy Economics. 81, 25–36. DOI: https://doi.org/10.1016/j.eneco.2019.03.003
[11] Zhou, X., Zhang, J., Li, J., 2013. Industrial structural transformation and carbon dioxide emissions in China. Energy Policy. 57, 43–51. DOI: https://doi.org/10.1016/j.enpol.2012.07.017
[12] International Energy Agency, 2023. Greenhouse Gas Emissions from Energy Data Explorer. Available from: https://www.iea.org/data-and-statistics/data-tools/greenhouse-gas-emissions-from-energy-data-explorer (cited 5 June 2025).
[13] Lamb, W.F., Wiedmann, T., Pongratz, J., et al., 2021. A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. Environmental Research Letters. 16(7), 073005. DOI: https://doi.org/10.1088/1748-9326/abee4e
[14] Bai, J., Chang, I.S., Zhang, C., et al., 2024. Allocation of CO2 emission target in China under the "1+N" policy: Considering natural carbon sinks and wind-solar-hydropower endowments. Environmental Impact Assessment Review. 106, 107472. DOI: https://doi.org/10.1016/j.eiar.2024.107472
[15] Hu, Y.J., Zhang, R., Wang, H., et al., 2024. Synergizing policies for carbon reduction, energy transition and pollution control: Evidence from Chinese power generation industry. Journal of Cleaner Production. 436, 140460. DOI: https://doi.org/10.1016/j.jclepro.2023.140460
[16] National Development and Reform Commission, 2023. The Achievement of The Third Anniversary of Carbon Peak and Carbon Neutrality. Available from: https://www.ndrc.gov.cn/fggz/hjyzy/stwmjs/202308/t20230817_1359890_ext.html (cited 5 June 2025).
[17] The State Council of the People's Republic of China, 2024. Energy Conservation and Carbon Reduction Action Plan for 2024–2025 [in Chinese]. Available from: https://www.gov.cn/zhengce/zhengceku/202405/content_6954323.htm (cited 1 January 2024).
[18] Wang, S., Li, Q., Fang, C., et al., 2016. The relationship between economic growth, energy consumption, and CO2 emissions: Empirical evidence from China. Science of the Total Environment. 542(A), 360–371. DOI: https://doi.org/10.1016/j.scitotenv.2015.10.027
[19] Mardani, A., Streimikiene, D., Cavallaro, F., et al., 2019. Carbon dioxide (CO2) emissions and economic growth: A systematic review of two decades of research from 1995 to 2017. Science of the Total Environment. 649, 31–49. DOI: https://doi.org/10.1016/j.scitotenv.2018.08.229
[20] Wang, S.S., Zhou, D.Q., Zhou, P., et al., 2011. CO2

emissions, energy consumption and economic growth in China: A panel data analysis. Energy Policy. 39(9), 4870–4875. DOI: https://doi.org/10.1016/j.enpol.2011.06.032

[21] Wang, S., Fang, C., Guan, X., et al., 2014. Urbanisation, energy consumption, and carbon dioxide emissions in China: A panel data analysis of China's provinces. Applied Energy. 136, 738–749. DOI: https://doi.org/10.1016/j.apenergy.2014.09.059

[22] Peng, H., Tan, X., Li, Y., et al., 2016. Economic Growth, Foreign Direct Investment and CO2 Emissions in China: A Panel Granger Causality Analysis. Sustainability. 8(3), 233. DOI: https://doi.org/10.3390/su8030233

[23] Pao, H.T., Tsai, C.M., 2011. Multivariate Granger causality between CO2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. Energy. 36(1), 685–693. DOI: https://doi.org/10.1016/j.energy.2010.09.041

[24] Wang, Q., Zhang, Q., 2022. Foreign direct investment and carbon emission efficiency: The role of direct and indirect channels. Sustainability. 14(20), 13484. DOI: https://doi.org/10.3390/su142013484

[25] Chen, Y., Wang, Z., Zhong, Z., 2019. CO2 emissions, economic growth, renewable and non-renewable energy production and foreign trade in China. Renewable Energy. 131, 208–216. DOI: https://doi.org/10.1016/j.renene.2018.07.047

[26] Rehman, A., Ma, H., Ahmad, M., et al., 2021. Towards environmental Sustainability: Devolving the influence of carbon dioxide emission to population growth, climate change, Forestry, livestock and crops production in Pakistan. Ecological Indicators. 125, 107460. DOI: https://doi.org/10.1016/j.ecolind.2021.107460

[27] Alam, M.M., Murad, M.W., Noman, A.H.M., et al., 2016. Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecological Indicators. 70, 466–479. DOI: https://doi.org/10.1016/j.ecolind.2016.06.043

[28] Hao, Y., Liu, Y.M., 2015. Has the development of FDI and foreign trade contributed to China's CO2 emissions? An empirical study with provincial panel data. Natural Hazards. 76(2), 1079–1091. DOI: https://doi.org/10.1007/s11069-014-1534-4

[29] Zhu, Q., Peng, X., 2012. The impacts of population change on carbon emissions in China during 1978–2008. Environmental Impact Assessment Review. 36, 1–8. DOI: https://doi.org/10.1016/j.eiar.2012.03.003

[30] Zhang, X., Lau, C.K.M., Li, R., et al., 2024. Determinants of carbon emissions cycles in the G7 countries. Technological Forecasting and Social Change. 201, 123261. DOI: https://doi.org/10.1016/j.techfore.2024.123261

[31] Chandran Govindaraju, V.G.R., Tang, C.F., 2013. The dynamic links between CO2 emissions, economic growth and coal consumption in China and India. Applied Energy. 104, 310–318. DOI: https://doi.org/10.1016/j.apenergy.2012.10.042

[32] Liu, X., Wahab, S., Hussain, M., et al., 2021. China carbon neutrality target: revisiting FDI-trade-innovation nexus with carbon emissions. Journal of Environmental Management. 294, 113043. DOI: https://doi.org/10.1016/j.jenvman.2021.113043

[33] Wang, B., Sun, Y., Chen, Q., et al., 2018. Determinants analysis of carbon dioxide emissions in passenger and freight transportation sectors in China. Structural Change and Economic Dynamics. 47, 127–132. DOI: https://doi.org/10.1016/j.strueco.2018.08.003

[34] Lin, B., Xu, B., 2018. Growth of industrial CO2 emissions in Shanghai city: Evidence from a dynamic vector autoregression analysis. Energy. 151, 167–177. DOI: https://doi.org/10.1016/j.energy.2018.03.052

[35] He, J., Yue, Q., Li, Y., et al., 2020. Driving force analysis of carbon emissions in China's building industry: 2000–2015. Sustainable Cities and Society. 60, 102268. DOI: https://doi.org/10.1016/j.scs.2020.102268

[36] Beibei, S., Guiyim, Z., Nan, L., 2024. Does economic growth targets setting lead to carbon emissions? An empirical study from China. Journal of Environmental Management. 368, 122084. DOI: https://doi.org/10.1016/j.jenvman.2024.122084

[37] Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association. 74(366a), 427–431. DOI: https://doi.org/10.1080/01621459.1979.10482531

[38] Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of Econometrics. 115(1), 53–74. DOI: https://doi.org/10.1016/S0304-4076(03)00092-7

[39] Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics. 61(S1), 653–670. DOI: http://doi.org/10.1111/1468-0084.0610s1653

[40] Pedroni, P., 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econometric Theory. 20(3), 597–625. DOI: https://doi.org/10.1017/S0266466604203073

[41] Nkoro, E., Uko, A.K., 2016. Autoregressive Distributed Lag (ARDL) cointegration technique: applica-

tion and interpretation. Journal of Statistical and Econometric Methods. 5(4), 63–91.
[42] Dumitrescu, E.I., Hurlin, C., 2012. Testing for Granger non-causality in heterogeneous panels. Economic Modelling. 29(4), 1450–1460. DOI: https://doi.org/10.1016/j.econmod.2012.02.014
[43] Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica. 37(3), 424–438. DOI: https://doi.org/10.2307/1912791