Unraveling the Determinants of Transportation Carbon Emissions in China

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SEPTEMBER 2025

KOAY, LIM TRANSPORT CARBON EMISSION IN CHINA BFE (HONS) SEPTEMBER 2025

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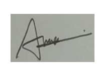
1	KOAY ZHI QI	21ABB06410	
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Date: 26 September 2025

ACKNOWLEDGEMENT

First of all, we would like to take this opportunity to express our sincere gratitude to everyone who contributed directly or indirectly to the completion of this study, whethe. We would like to special thank Universiti Tunku Abdul Rahman (UTAR) for providing the chances to conduct this Final Year Project titled Unraveling the Determinants of Transportation Carbon Emissions in China.

Besides, we would also like to extend our heartfelt appreciation to our beloved project supervisor, Ms. Kalai Vani a/p Kalimuthu for her exceptional guidance, patience and experiences contribution throughout the project. Her strong expertise in the field of economics and her openness in sharing knowledge have been invaluable to the overall learning journey. Throughout the project, Ms. Kalai demonstrated remarkable dedication, patiently clarifying our confusions and offering thoughtful feedback that significantly enhanced our work. Thus, we are truly grateful for her mentorship which not only fostered our personal growth but also ensured the successful completion of our project.

In addition, we would like to express our deepest appreciation to Prof. Dr Lau Lin Sea as our project examiner and for providing constructive advice on the shortcomings of our study. Prof. Lau’s thorough evaluation, thoughtful suggestions and valuable recommendations has played a significant role in refining and strengthening our work. Therefore, we are truly grateful for Prof. Lau’s dedication and support throughout this process.

Last but not least, we would like to extend our heartfelt thanks to all group members for their commitment, perseverance and teamwork in overcoming challenges and striving together to produce a quality research project. We are also sincerely grateful to our family members and friends for their unwavering support and encouragement which greatly contributed to the successful completion of this study.

PREFACE

Transportation plays a fundamental role in promoting economic growth, social connectivity and industrial development. However, it has also emerged as one of the major contributors to the global carbon emissions resulting in environment dedication. This environmental consequences of transport emissions extend beyond rising global temperatures to encompass deteriorating air quality, public health concerns and long-term threats to ecological sustainability. These challenges make transportation carbon emissions an increasingly critical issue that demand policy attention.

China, as the world's largest carbon dioxide emitter, represents a highly significant case for study. The rapid pace of economic expansion and urbanization has spurred an unprecedented demand for mobility, resulting in a surge in private car ownership, freight activity and reliance on fossil fuels. While transportation has contributed substantially to China's economic transformation, it has simultaneously escalated environmental pressures, posing difficulties for the nation's transition toward sustainable development. The growing tension between economic growth and environmental sustainability underscores the need to examine the key drivers of transportation-related carbon emission with the Chinese context.

This study specifically focuses on three major determinants of transportation carbon emission including urbanization, GDP per capita and renewable energy consumption. By examining their influence over nearly four decades, the research aims to uncover how demographic shifts, economic growth and the transition toward clearer energy sources interact to shape emission trends. Through this investigation, the study seeks to provide empirical evidence and valuable insights that may guide policymakers in designing effective strategies to reduce transportation emission while supporting China's sustainable development and long-term carbon neutrality goals.

ABSTRACT

China is the world's largest carbon dioxide emitter and has recorded the fastest transportation growth rate among the top-emitting countries. The rapid expansion of its economies and urbanization have significantly increased the demand for transport services, leading to a surge in private car ownership and overall transport activity, thereby contributing to rising carbon emissions. This study investigates how explanatory variables such as urbanization, GDP per capita and renewable energy influence the transportation carbon emission, with particular focus on existence of the Environmental Kuznets Curve (EKC) hypothesis in China over the 38-year period from 1985 to 2023. Data for all variables were collected from the World Bank and Our World in Data. The study employs the Autoregressive Distributed Lag (ARDL) approach to examine the long-run relationship with robustness checks conducted using such as Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS) and Canonical Cointegration Regression (CCR). The empirical results showing that GDP per capita has significantly negative long-run relationship with transport carbon emission, indicating that the EKC hypothesis does not hold for China's transport sector. Urbanization is found to be positively associated with emissions whereas renewable energy consumption shows a significant negative effect. All these results provide critical policy implications toward policymakers to achieve China's dual carbon goals of peaking emissions by 2023 and reaching carbon neutrality by 2060.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
B2V	Building-to-Vehicle
CCR	Canonical Cointegrating Regression
CO_2	Carbon Dioxide
COVID-19	Coronavirus Disease
CUSUM	Cumulative Sum
CUSUMSQ	Cumulative Sum of Squares
DOLS	Dynamic Ordinary Least Squares
ECM	Error Correction Model
ECT	Error Correction Term
EKC	Environmental Kuznets Curve
EVs	Electric vehicles
FMOLS	Fully Modified Ordinary Least Squares
GDP	Gross domestic product
GHG	Green House Gas
HFCVs	Hydrogen Fuel Cell Vehicles
IPCC	Intergovernmental Panel on Climate Change
JB	Jarque-Bera
KPSS	Kwiatkowski-Phillips-Schmidt-Shin

LM	Lagrange Multiplier
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
SDGs	Sustainable Development Goals
TCE	Transportation Carbon Emissions
V2B	Vehicle-to-Building

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Chapter 1: Research overview

1.0 Introduction

This chapter provides an overview of the research, including the research background, research topic, research questions, research objectives, and significance of study. This study's main goal is to investigate the factors that influence China's transportation-related carbon emissions.

1.1 Research Background

Transportation, as the fundamental force for economic development, is highly energy-intensive and has become one of the fastest-growing contributors to climate change, as highlighted by the IPCC's fifth assessment report (Grazi & van den Bergh, 2008; Stanley et al., 2011; Liu et al., 2022). In a globalized economy, the sector's economic activities and opportunities are closely tied to the movement of people and goods. A well-developed transportation system is strongly correlated with increased economic development, which is reflected in higher output, job creation, and rising income levels. However, these economic benefits often come at a significant environmental cost, particularly through the escalation of GHG emissions (Go et al., 2020). Currently, GHG emissions have increased across multiple sectors, with the energy sector being the largest contributor *(Appendix 1.1)*. Within the energy sector, transportation is the second-largest emitter, responsible for 13.7 of total GHG output (Ge et al., 2024).

Globally, the transport sector plays a crucial role in daily activities around the world which contributes about 20% of global CO_2 emissions, with road transport accounting for the largest proportion. 75% of transport-related emissions in 2018 came from road transport, with passenger cars accounting for 45.1% and freight trucks for 29.4%. *(Appendix 1.2)* (Ritchie, 2020). Evidence from Wei et al. (2021) further indicates that private vehicles emit nearly three times more CO_2 per capita than public transport, emphasizing the disproportionate contribution to environmental degradation. Transport emissions are projected to triple by 2050 with urbanization accelerating and private vehicle ownership rising, thereby intensifying climate change. In addition to harming the ecosystem, vehicle-related air pollution poses serious health concerns to the general public, which is why an estimated 3.7 million premature deaths occurred globally in 2012 (Lindau, 2015). Taken together, this highlights two critical challenges facing the transport sector such as high energy consumption and substantial CO_2 emissions. Nevertheless, transportation remains indispensable for sustaining economic growth (Wei et al., 2021).

At the core of these challenges lies the sector's dependence on fossil fuel combustion, primarily gasoline and diesel, which releases not only CO_2 but also other potent greenhouse gases, including methane (CH_4), nitrous oxide (N_2O), and hydrofluorocarbons (HFCs) (United States Environmental Protection Agency, 2024). In the world's seven largest transport-emitting economies[1], transport energy demand continues to be predominantly met by fossil fuels, highlighting the transport sector's persistent dependence (Solaymani, 2019). According to Igini (2025), the energy-hungry world consumed 1.5% more fossil fuels in 2023 than the year before, with oil accounting for roughly one-third of total global energy use. This record level of consumption was largely driven by rising demand, more than half originated from Global South, where energy needs are expanding at nearly twice the global rate. Given that transportation represents one of the largest consumers of oil, it further intensifies global carbon emissions (Liu et al., 2022).

While South Asia and Sub-Saharan Africa contribute very little to the world total, upper-middle-income and high-income countries are the main producers of transport emissions (Wang & Ge, 2019). Since the implementation of the 'Reform and Opening-up' policy, China has experienced unprecedented economic growth driven by the development of its extensive transportation infrastructure, includes the world's largest highway and railway networks (Xu & Xu, 2021). However, this rapid development has fueled surging energy demand in the transportation sector, leading to transport-related CO_2 emissions grow at faster rates than other industries (Xie et al., 2019). Thus,

[1] Seven largest transport-emitting economies include United States, China, India, Russia, Japan, Brazil and Canada (Solaymani, 2019).

identifying key drivers of transport-related CO_2 emissions is crucial for developing targeted strategies to reduce carbon emissions and meet China's climate commitments under the 2015 Paris Agreement (Liu et al., 2021).

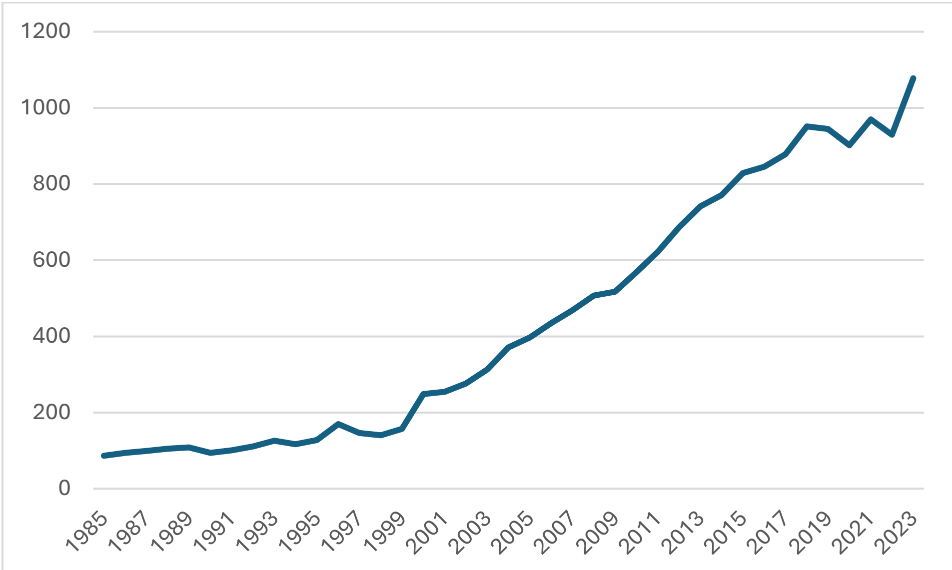

Figure 1.1 Carbon dioxide (CO_2) emissions from Transport (Energy) in China (Mt CO_2e)

Source: World Bank Data

As observed in Figure 1.1, China's transport carbon emission has increased over 30 years from 1985 to 2023. In 2023, China has reached over 1000 Mt of the transport emissions.

China, as part of the Global South and the world's largest carbon dioxide (CO_2) emitter, contributed 31.9% of global emissions in 2020 (Zhou et al., 2013; Hu et al., 2024). This surge in emissions is largely driven by accelerated urbanization and growing motorization, especially in major cities such as Beijing (Wang & Liu, 2015). As the demand for transport services continues to rise, carbon emissions from the sector are also escalating (Xu & Xu, 2021). In 2020, road transport accounted for 81.1% of China's total transport-related carbon emissions, making it a key sector for achieving transport decarbonization (Loo et al., 2023). These trends pose significant obstacles in achieve the China's "dual carbon" goals[2] (Cao & Liu, 2023). In response, China has made major strides in expanding both its renewable energy sector and transportation infrastructure in recent years, positioning itself as a global leader in renewable energy development. A strong renewable energy industry not only mitigates the broader impacts of climate change but also supports the transition to electric vehicles by providing clean power, therefore reducing the dependence on fossil fuels (Ding & Liu, 2023). However, although renewables energy now makes up half of China's installed power capacity, a recent rise in approvals for new coal plants and the fact that more than 70% of electricity still comes from fossil fuels. It indicates that the actual renewable energy usage is falling short of its capacity *(Appendix 1.3)*. Therefore, while renewable energy holds strong prospects, unlocking its full potential will require significant and transformative reforms (Hilton, 2024).

Building on the global trends, the case of China is particularly significant. Despite extensive research on emission trends, only a few studies have systematically examined the macro-level determinants of transport-related CO_2 emissions in China, such as urbanization, income levels, and renewable energy consumption. Although China has adopted various emission reduction measures, these efforts have not effectively addressed the underlying drivers of emissions. Thus, the significance of China's transport industry cannot be overstated, as it has been a central driver of the nation's rapid economic expansion during its urbanization and industrialization process. As the world's leading manufacturing hub and most populous country, China's rapid development has been accompanied by the rapid evolution of its modern transportation systems, which play a vital role in facilitating economic growth (Lin & Benjamin, 2017). Determining carbon emission factors in transportation sector is therefore crucial, as studies indicate that transportation is poised to become the largest contributor to carbon emissions, thereby accelerating global warming (Lim & Lee, 2012).

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[2] President Xi unveiled China's "dual carbon" ambitions at the UN General Assembly in September 2020, with the goal of reaching carbon neutrality by 2060 and peaking carbon emissions by 2030 (Huld, 2023).

1.2 Research Problem

Transportation is one of the largest energy consumers and direct sources of CO_2 emissions, making it a key sector in achieving climate mitigation goals. As the expansion of population and economy, along with the increasing complexity of the structures, it has resulted in a significant rise in transportation demand and energy consumption, leading to substantial carbon emissions (Sun et al., 2020). Between 1990 and 2018, China has experienced substantial growth in both urban population and construction land area which increase fossil fuel consumption (Zheng et al., 2022). Evidence from the Oxford Institute of Energy Studies (2022) further reinforce that, over 235 million people in China have moved from rural to urban areas in the last decade. By 2021, seven cities including Shanghai, Beijing, Shenzhen, Chongqing, Guangzhou, Chengdu, and Tianjin, each had a population exceeding 10 million, while 14 other cities had populations ranging from 5 to 10 million. This large-scale of urban relocation underscores that about 75% of China's population, which equivalent to more than 1 billion people, are projected to reside in urban areas by 2030. As a result, a higher mobile population correlates with more vehicles on the road, driving greater energy consumption and higher CO_2 emissions in the transport sector (Li et al., 2016).

In addition, the evolution of urban transport networks has a significant impact on how locals commute. In China, the expansion of car-centric road infrastructure has led to continuous growth in urban road networks, which in turn encourages greater private car ownership and contributes to rising carbon emissions from daily commuting (Yang et al., 2024). Evidence from Lu et al. (2022) show that private car ownership jumped from 65 million in 2010 to 244 million in 2020, an annual growth rate of 14.14%. As a result, China's transport sector's carbon emissions increased significantly from 248 Mt in 2000 to 950 Mt in 2020, making up 9% of the nation's overall emissions. By 2021, the number of vehicles in China had surpassed 300 million, nearly double the total from a decade earlier (Qian, 2024). In 2023, China had maintained its position as the world's largest vehicle market for over a decade and surpassed the U.S. in vehicle ownership by 2020 (Chen et al., 2024). This rapid rise in car ownership has made the China's transportation sector one of the fastest-growing sources of emissions. Although China was the second-largest transport CO_2 emitter (11% of global transport emissions), behind U.S. (21%) (Xue & Liu, 2023). It has experienced the fastest growth among all sectors since 2010, continuing to rise until 2019 before temporarily declining in 2020 due to travel restrictions caused by the COVID-19 pandemic (World Bank, 2024). Overall, China recorded the fastest growth rate in transport emissions among the top emitters between 1990 and 2022 *(Appendix 1.4)* (Wang & Ge, 2019; Li et al., 2023).

China's urbanization, driven by energy-intensive industrial growth, has fueled infrastructure development, raised energy demand, and expanded freight transport to support goods movement, all of which have significantly increased transport demand and emissions (Lv et al., 2018). About 1.308 billion tonnes of greenhouse gases were released by urban transportation vehicles in 2021, including trucks, buses, cars, and ships. This amount is almost equal to the total transportation emissions of the United Kingdom and European countries (Qian, 2024). Economic growth has led to a rising demand for transportation vehicles, posing significant threats to sustainable long-term development. For example, the construction of roads, railways, and airports consumes a growing number of resources including land, technology, and energy. It is driven by urbanization, industrialization, and economic externalities. These activities both directly and indirectly reduce green spaces and contribute to the release of greenhouse gases (Hussain et al., 2022).

Apart from that, one of the main factors influencing the increase in transportation-related carbon emissions is GDP per capita. As income rises, people's living standards improve, so does consumer demand for goods. Since the logistics sector heavily depends on transportation, this further drives up CO_2 emissions (Li et al., 2016). Additionally, the growing demand for tourism-related travel significantly contributes to increased emissions. Consequently, emissions from transport rose from 12.96 million tons in 2001 to 42.17 million tons in 2019 (Gu et al., 2024). Looking ahead, forecasts suggest that as transportation demand continues to increase and without strict regulatory measures, car ownership could rise dramatically by 2050 compared to 2015 levels, surpassing that of OECD nations. Consequently, addressing road transport emissions remains a complex challenge for China’s ambitious ‘dual carbon’ goals (Liu & Zhou, 2025).

Last but not least, renewable energy comes from geothermal, hydro, wind, solar, and biofuel sources. To lessen the adverse effects of climate change, greenhouse gas emissions and reliance on fossil fuels must be reduced. As a result, this approach can indirectly help lower carbon emissions within the transportation industry (Cui et al., 2025). Ding and Liu (2023) noted that China's potential for sustainable growth and carbon neutrality has been strengthened by its technological and renewable energy breakthroughs. However, a key concern is whether the growing share of renewable energy, particularly in transportation, will be sufficient for China’s net-zero goal by 2060. Moreover, Ahmed and Khan (2024) emphasized that China has made significant investments in renewable energy, especially solar and wind, and will lead the world in new installations by 2020. Despite this, debates persist regarding the slow pace of China’s low-carbon transition. Rising energy demand is expected to prolong reliance on fossil fuels, challenging emission reduction targets. Additionally, while the adoption of electric vehicles (EVs) is widely promoted as a strategy to reduce transport-related emissions, the environmental benefits are largely dependent on the energy mix used for electricity generation. Zhao et al. (2023) indicated that, to date, the fact that more than half of China's electricity is still produced by burning fossil fuels highlights the country's energy structure's present shortcomings.

Not only that, although China has introduced numerous policies to foster the growth of its electric vehicle (EV) market, evidence from the International Council on Clean Transportation (ICCT) indicates that current measures such as the stringent 2025 fuel consumption standards for passenger vehicles and fuel efficiency standards for medium and heavy commercial vehicles (MHCVs) remain insufficient. Under a “Low Ambition” pathway, emissions would decline temporarily before rising again, while even under a “High Ambition” pathway, additional measures after 2035 are required to meet the 2060 net-zero target *(Appendix 1.5)* (Callahan, 2022). As a result, fully ‘decoupling’ transportation development from carbon emissions remains a major obstacle. The *Digital Travel Helps Carbon Neutrality* report further highlights this challenge, noting that in China, the transportation sector's high energy dependence and structural limitations make achieving carbon peaking and neutrality goals more difficult than in other industries (Sun et al., 2023).

1.3 Research Questions

1) What is the impact of urban expansion on the transport carbon emissions in China?
2) What is the relationship between GDP per capita and transport carbon emissions in China under the EKC hypothesis?
3) What is the impact of renewable energy consumption on the transport carbon emissions in China?

1.4 Research Objectives

1.4.1 General Objective

This study's main objective is to investigate the relationship between China's transport carbon emissions and urbanization, GDP per capita, and renewable energy usage. Additionally, this study aims to investigate the relationship between independent variables and transportation carbon emissions in the context of China's changing economic environment and to give a better understanding of how these drivers have contributed to emissions over time.

1.4.2 Specifics Objective

1) To examine the impact of urbanization on the transport-related CO_2 emissions in China.

2) To examine the existence of the EKC hypothesis between GDP per capita and transport carbon emissions in China.

3) To examine the impact of renewable energy consumption on transport-related carbon emissions in China

1.5 Research Significance

As the world's largest automotive markets and one of its fastest-growing economies, China is also a major contributor to global transport emissions. This study holds significant academic and practical value by examines the key determinants of transportation-related carbon emissions in China, focusing on urbanization, GDP per capita, and renewable energy consumption using a time series approach over a 30-year period.

Academically, this study contributes to existing literature by examining how various factors influence China's transport sector emissions over time, offering insights into whether these key variables have positive or negative effect on carbon emissions. Furthermore, this study provides a valuable theoretical contribution by applying the Environmental Kuznets Curve (EKC) hypothesis to transportation emissions in China, specifically assessing the relationship between GDP per capita and carbon emissions (Aslam et al., 2021). This study also employed robustness checks using FMOLS, DOLS and CCR methods which distinguish from previous research. The result of these alternative cointegration techniques confirmed the significant of variable and showed consistency in the size of coefficients, thereby reinforcing the validity of the findings.

On a practical level, the findings offer direct implications for policymakers by identifying the most influential drivers of TCE, thereby supporting efforts to balance economic growth with environmental sustainability. China's ambitious goal of reaching carbon peak by 2030 and carbon neutrality by 2060, which is in line with international frameworks for climate action, such as the Sustainable Development Goals (SDGs) of the United Nations, especially SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action), makes this especially important. It also yields significant co-benefits, such as improved air quality, reduced respiratory diseases, and enhanced urban livability through decreased traffic congestion. As the world's largest carbon emitter, China's experience in mitigating TCE can serve as a valuable reference for other developing and urbanizing economies. Therefore, this study not only contributes to the academic discourse on sustainable development but also offers actionable insights for advancing long-term economic prosperity.

Chapter 2: Literature Review

2.0 Introduction

Previous studies have highlighted key factors influencing transport CO_2 emissions, and the theoretical insights derived from these studies form the foundation of our research framework. This chapter discusses three primary determinants such as urbanization, GDP per capita, and renewable energy consumption and their relationship with transport sector CO_2 emissions (TCE).

2.1 Theories Reviewed

2.1.1 Environmental Kuznets Curve (EKC) Hypothesis

Grossman and Krueger (1995) first suggested the Environmental Kuznets Curve (EKC) theory, which depicts an inverse U-shaped relationship between environmental deterioration and wealth. This shows that the environmental quality declines initially and then improve as income increases.

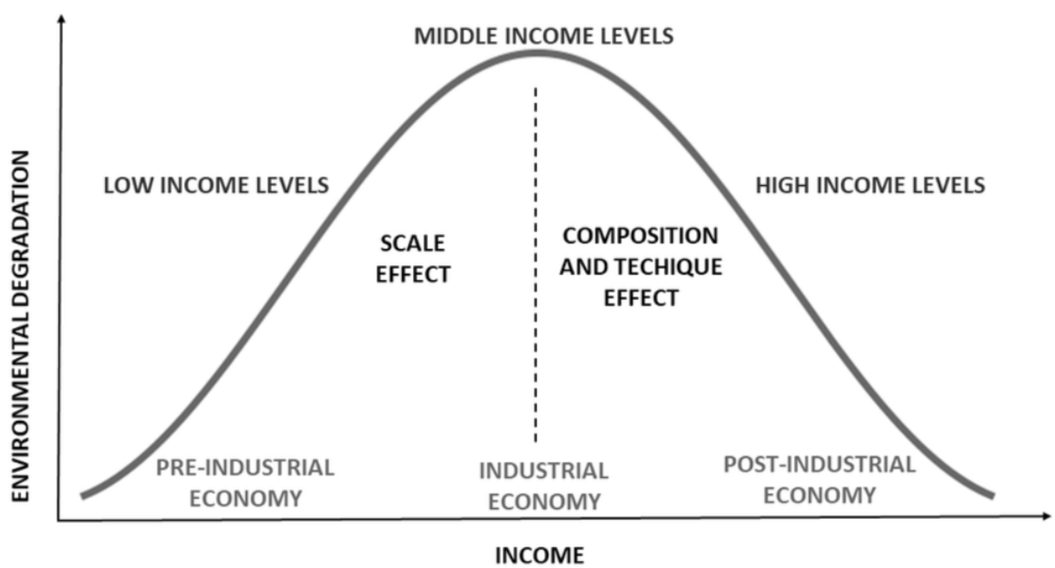

Figure 2.1: Environmental Kuznets Curve from Mitic, Kresoja, and Minović (2019)

The early stage of economic development, the turning point, and the advanced stage are the three stages that make up the Environmental Kuznets Curve (EKC). In the initial stage, economic growth relies heavily on resource consumption, resulting in a sharp rise in environmental degradation. The turning point occurs when income reaches a certain threshold, prompting a shift in the pollution trend. This leads to the final stage, where environmental degradation begins to decline. After the turning point, this relationship becomes less direct, reflecting the close relationship between growth and emissions in the early phase. This is because higher wealth encourages the adoption of clean technology and innovation in the later phase (Leal & Marques, 2022).

According to Muhammad et al. (2020) study, the EKC hypothesis is supported by the results for high- and upper-middle-income countries, but not for low- and lower-middle-income ones. This suggests that only wealthier nations have reached the income level needed to reduce emissions through development, while lower-income countries remain focused on industrialization and economic growth, with less emphasis on environmental concerns.

Xu and Lin (2015) confirmed the transportation industry has an EKC relationship, with urbanization having an inverted U-shaped impact. This is due to significant population movement during the early stages and increased adoption of cleaner urban rail systems and hybrid vehicles in the later stages. Guo et al. (2022) and Oladunni, Olanrewaju, and Lee (2024) found that GDP and transportation-related carbon emissions have an inverse U-shaped relationship. Using ARDL model, Saqib et al. (2022) analyzed the EKC for E-7 countries (1995–2019), determining that using renewable energy lowers emissions later on. A rise in renewable energy consumption lowers transportation-related CO_2 emissions by approximately 12%, confirming the EKC hypothesis Amin et al. (2020).

However, Azlina et al. (2014), Gill, Viswanathan, and Hassan (2018) and Htike et al. (2021) find a significant positive relationship between GDP and CO_2 emissions, but the squared GDP term is statistically insignificant, supported by Alshehry and Belloumi (2017) finding in Saudi Arabia. It means the data do not support EKC pattern or inverted-U relationship in the short and long run. Shabir et al. (2022) show that the

EKC relationship between income and CO_2 emissions is valid only in Singapore, while in Indonesia, Malaysia, the Philippines, and Thailand, income growth leads to increased CO_2 emissions. Jebli and Youssef (2015) found no long-run support for the inverted U-shaped EKC in Tunisia, indicating the country has not reached the necessary GDP per capita level. Pablo-Romero et al. (2017), analyzing panel data from 27 EU countries between 1995 and 2009, found no evidence that the income threshold for reduced emissions had been met, suggesting the absence of the expected EKC turning point. Same goes to Al-Mulali et al. (2015), Du et al. (2012) and S. Wang et al. (2011) that the EKC hypothesis was not validated in their studies.

2.1.2 Energy Transition Theory

Energy transition is essentially the process of making major adjustments to the key energy system components to move toward a new energy service structure. According to Yang et al. (2024), this shift includes a complicated and multifaceted system that includes energy production, storage, transmission, and consumption in addition to technology, management techniques, and concerns about energy security, geopolitics, and governance. Many countries are prioritizing the shift to cleaner, renewable energy sources in their policies. Due to growing skepticism regarding the viability and public acceptance of alternative strategies for attaining low-carbon growth, such as nuclear energy and carbon capture and storage, the focus on renewables has recently increased (Berkhout et al., 2012). Transitions to more sustainable patterns of economic evolution are viewed as structural changes occurring across decadal time periods, similar to processes of economic development (Berkhout et al., 2009).

The shift to cleaner energy in transportation is viewed as a practical approach to achieving decarbonization in the sector. Adoption of zero- and low-emission vehicle technologies will help to reduce the dependent on fossil fuels. Electric, hydrogen, and biofuel-powered vehicles are at the forefront of this movement. Electrifying transport is seen as the key technological solution with considerable potential to lower pollution and decrease dependence on fossil fuels (Raslavičius et al., 2015). In regions where direct electrification is not possible, renewable electricity-based fuels help meet transport demand. Globally, renewable energy potential is sufficient to support even rapid growth in the sector. The shift improves energy efficiency through better engines, electric motors, and cleaner power sources (Bogdanov et al., 2024).

High energy consumption, especially from fossil fuels, greatly increases CO_2 emissions. To address this, developed countries should lead the shift toward renewable energy sources. Both developed and developing nations need to embrace innovative technologies to lessen the environmental impact of energy use. The adoption of electric and hybrid vehicles can substantially lower CO2 emissions, potentially achieving reductions of up to 45% over time (Ahmad et al., 2024).

2.2 Empirical Review

2.2.1 Urbanization and Transportation Carbon Emissions

The relationship between urbanization and CO_2 emissions has been widely examined, with many studies generally suggesting that urbanization increases transport-related CO_2 emissions, especially due to higher energy consumption in transportation demands. For instance, Xu and Lin (2015) investigated China's transportation sector using a Vector Autoregressive (VAR) model and discovered that urbanisation raises CO_2 emissions over the long and short terms, mostly as a result of intra-city movements and rural-to-urban migration. Similarly, Ali et al. (2017) applied the ARDL approach to study Pakistan and found that a 1% increase in urbanization led to a 0.84% rise in CO_2 emissions, mainly due to the poor public transport. This short-term effect was unidirectional, with urbanization directly causing higher emissions. Another study by Awan et al. (2022) verified that urbanization considerably raises TCE by employing a rigorous quantile methodology to analyze panel data from 33 high-income countries between 1996 and 2014. Xie et al. (2017) further support this relationship, showing that urbanization increases transport carbon emissions through large-scale infrastructure development. Using the STIRPAT model on 283 cities from 2003 to 2013, they found a significant impact in large cities but not in smaller ones.

In contrast to studies emphasizing one-way causality, other research has identified bidirectional relationships between urbanization and CO_2 emissions. Bekhet and Othman (2017) conducted a study in Malaysia and found a long-run bidirectional relationship between urbanization and CO_2 emissions in Malaysia, confirming the EKC hypothesis whereas emissions rise in early urbanization but decline as development stabilize. Similarly, Shafique et al. (2021), analyzing data from 10 high-emission Asian economies (1995–2017), found that urbanization significantly increased vehicle numbers, thereby raising CO_2 emissions. They also observed that rising emissions influenced urban development, indicating a bidirectional relationship.

On the other hand, some studies have found either no significant impact or a weaker negative impact of urbanization on transport CO_2 emissions, especially in developed countries. Amin et al. (2020) investigated the European transportation industry using dynamic OLS estimation and ordinary least squares (OLS). Their results indicated that urbanization does not have a significant impact on CO_2 emissions in these countries. Similarly, Wang et al. (2021) employed a dynamic panel ARDL model to study OECD high-income countries and found that the benefits of urbanization slightly outweighed its energy consumption impacts. This led to a small reduction in CO_2 emissions, with their study concluding that urbanization in these countries had a weak negative impact on carbon emissions.

In summary, the relationship between urbanization and transportation carbon emissions is complex and varies across countries. Generally, urbanization tends to increase transport-related CO_2 emissions, especially in developing nations. While several studies demonstrate a bidirectional relationship where emissions also affect urban development patterns. In contrast, the impact of urbanization on emissions may be weaker or even negative in developed countries.

2.2.2 GDP per capita and Transportation Carbon Emissions

GDP per capita is widely recognized as a key driver of transportation sector carbon emissions (TCE). For instance, Xu and Xu (2021) found that TCE is significantly and favorably impacted by GDP per capita, suggesting that as regional economies expand and individual income levels rise, transportation activities intensify, thereby leading to increased CO_2 emissions. In line with this, Cao et al. (2024) and Dalde et al. (2025) reported that higher income levels typically result in increased private vehicle ownership and greater transport demand, both of which contribute to rising emissions. Likewise, Wang et al. (2018), focusing on China's passenger and freight transport sectors between 1990 and 2015, also observed that economic growth accelerates CO_2 emissions in both areas. Moreover, Lv et al. (2018) emphasized significant regional disparities in freight transport emissions across China, further reinforcing the view that economic development can exacerbate transport-related carbon outputs in unequal ways. Alshehry and Belloumi (2017) using ARDL approach and their results indicate per capita GDP continues to exert a significant and positive influence on transport-related CO_2 emissions, thereby negatively impacting environmental quality in the country.

In contrast, Asumadu-Sarkodie and Owusu (2016) found that in Rwanda, a 1% rise in GDP per capita led to a 1.45% reduction in carbon emissions in the long run, lending support to the EKC hypothesis. According to Kasperowicz (2015), over time, there is a negative correlation between GDP and CO2 emissions, as advancements in low-carbon technologies allow for maintaining the same level of production with reduced emissions. Go et al. (2020) studies in Malaysia found that The GDP per capita coefficient was negatively significant, indicating that rising income levels will likely result in falling transportation-related CO2 emissions.

In short, most studies show that higher GDP per capita increases transport-related CO_2 emissions due to higher vehicle ownership and transport demand. However, in some countries, long-term economic growth supported by technological advancements can help reduce emissions, consistent with the EKC hypothesis.

2.2.3 Renewable energy consumption and Transportation Carbon Emissions

Electric vehicles (EVs) may be powered sustainably by renewable energy sources including wind, solar, and hydroelectric power, which also helps to lower CO2 emissions associated with transportation. Liu et al. (2022) suggested that alternative fuels and sustainable transport modes can lower emissions in the transport sector. Similarly, Zaman et al. (2021) and Kwilinski et al. (2024) found that higher renewable energy consumption has a significant negative correlation with transport CO_2 emissions, indicating that increased renewable energy use helps lower transport-related emissions. This result is consistent with that of Maji and Adamu (2021), who used the OLS method to establish an inverse link between carbon emissions and the use of renewable energy in Nigeria's transport sector from 1989 to 2019.

Advanced renewable technologies, including EVs, hydrogen fuel cell vehicles (HFCVs), and biofuel-powered vehicles, have also been developed to support emission (Zeng et al., 2022). Alnour (2022) further highlights the negative correlation between Turkey's transportation-based emissions and renewable energy consumption between 1990 Q1 and 2014 Q1, indicating that boosting the usage of biofuels and renewable energy sources can greatly lower CO2 emissions associated with transportation. In Ethiopia, Desta et al. (2022) highlighted the success of a biofuel program using cane molasses-based ethanol and jatropha biodiesel, which reduced fossil fuel use and greenhouse gas emissions.

However, several studies present a more nuanced or limited impact of renewable energy consumption on transport CO_2 emissions. Neves et al. (2017) argued that while the use of renewable fuels helps reduce emissions in both the short and long run, the significance level of this effect is relatively lower. This is further supported by Solaymani (2022) examined the transport sector in Malaysia from 1978 to 2018 using the ARDL and found short-term emission increases due to low renewable energy use, and long-term effects that were negative but statistically insignificant, indicating that its usage remains insufficient to effectively reduce CO_2 emissions in this sector.

Summary, many studies support that increased renewable energy consumption helps reduce transportation CO_2 emissions, especially using EVs and biofuels. However, some research highlights that the impact may be limited or statistically weak in certain countries due to low consumption rates or insufficient renewable energy use in the transport sector.

2.3 Conceptual Framework

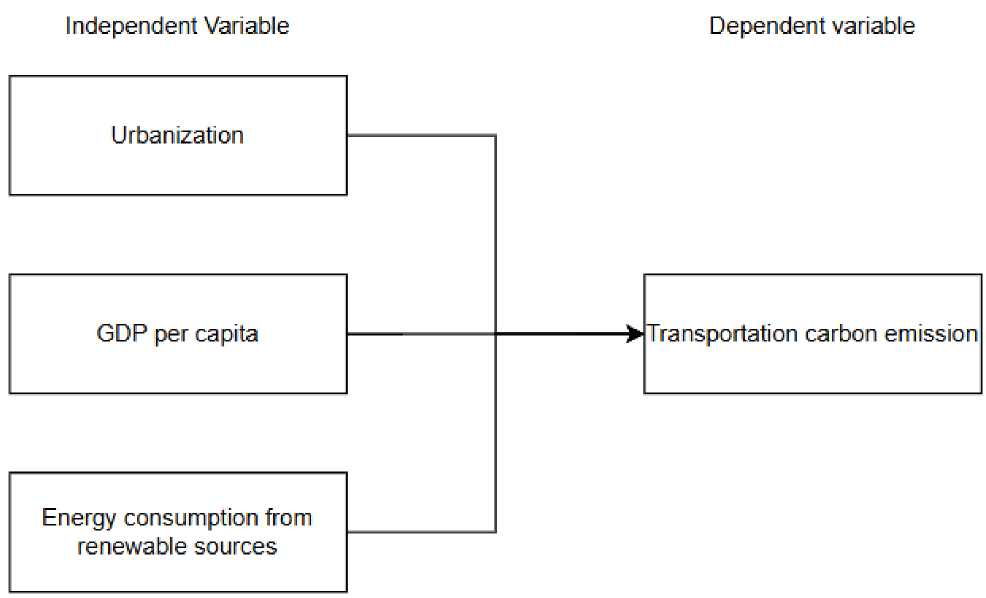

Figure 2.2: Conceptual Research Framework

In this research, Figure 2.2 explains how the explanatory variables like urbanization, GDP per capita, and energy consumption from renewable sources influence transportation carbon emissions in China.

2.4 Research Gap

Most existing studies focus on urbanization and GDP per capita, often in combination with other macroeconomic variables (Xu & Lin, 2015; Aslam et al., 2021; Xu & Xu, 2021). However, relatively few studies especially in the context of China's transportation industry, have included renewable energy consumption as a variable in creating a comprehensive framework. This omission limits understanding of how renewable energy consumption influences transport-related carbon emissions. In order to close this gap and offer China more thorough views, our study incorporates renewable energy use into the framework.

Chapter 3: Methodology

3.0 Introduction

The research methodology refers to the set of processes used to address the research problem in this study. A wide range of information from the empirical review in Chapter 2 is utilized to support the construction of the econometric model presented in this chapter. The chosen econometric model will be covered in Chapter 3, along with the steps for empirical testing and diagnostic tests to guarantee the model's accuracy and dependability.

3.1 Data Description

The relationship between the explanatory and response variables is examined using the data. In this study, the dependent variable is transportation carbon emissions, whereby urbanization, GDP per capita and renewable energy consumption are the independent variables.

Table 3.1: Variables and Proxy

Variables	**Variable Description and Measurement**	**Unit Measurements**	**Sources**
Transportation Carbon Emissions	Carbon dioxide (CO_2) emissions from Transport Energy	metric tons per capita	World Bank
Urbanization	Urban population	Number of people	World Bank
GDP per capita	GDP per capita (constant 2015 US$)	Constant 2015 US$ per person	World Bank

Renewable Energy Consumption	Share of primary energy consumption from renewable sources	% equivalent primary energy	Our world in data

3.1.1 Definition of Variables

3.1.1.1. Transport Carbon Emissions (DV)

Transportation carbon emission (TCE) refers to the release of CO_2 and other greenhouse gases produced by different types of transportation, typically during the vehicle operation phase. Commonly associated with energy-consuming travel activities, TCE can be applied to anything from individual trips to the entire transportation sector. Its measurement is usually focused on the mobility process and emphasize direct emissions resulting from fuel consumption. TCE, as an indicator linked to different transportation activities, is present across numerous branches of the transport sector, such as road traffic, international shipping, aviation, and railway systems (Ling et al., 2024).

3.1.1.2. Urbanization (IV)

Urbanization is fundamentally defined as the process of population concentration, occurring through the multiplication of urban centers and the growth in size of existing ones (Tisdale, 1942). Williamson (1988) expands this definition by describing urbanization as a demographic and economic transformation, where population and labor shift from rural to urban areas due to population pressures and economic opportunities. This process is a key aspect of development, driven by technological progress, industrialization, and supportive policy environments.

3.1.1.3. GDP per capita (IV)

Economic growth is typically measured by the rise in a nation's gross domestic product (GDP), which serves as an official indicator of economic progress. GDP reflects the total monetary or market value of all final goods and services produced within a country over a specific time frame. Meanwhile, GDP per capita represents the average economic output generated per individual in that country (Adam & Alzuman, 2024). GDP per capita plays a crucial role in the economy as it reflects the outcome of a country's economic activities over the course of a year. Beyond that, it serves as a key indicator of development and well-being. It is also used to assess sustainable economic growth and evaluate a nation's self-sufficiency based on the income levels of its population (Juliannisa & Artino, 2022).

3.1.1.4. Renewable Energy Consumption (IV)

Daniel Ciolkosz[3] highlights that renewable energy comes from natural sources like sunlight, wind, water, geothermal heat, and biomass that replenish faster than they are used. Unlike fossil fuels, these sources are sustainable and environmentally friendly. He emphasizes that transitioning to renewable energy is crucial for addressing climate change, energy security, and growing population demands (Ernst et al., 2023). Furthermore, ongoing advancements in renewable energy technologies are focused on improving energy conversion efficiency, ensuring that these sources can meet the ever-expanding energy needs (Ang et al., 2022).

[3] Dr. Ciolkosz, an associate research professor at Penn State, supports bioenergy development and energy efficiency for Pennsylvania farms and co-leads the university's renewable energy extension program (*West Virginia University*, n.d.).

3.2 Econometric Model

An econometric model is proposed in this study to investigate the relationship between China's transportation carbon emissions and three important explanatory variables. In this analysis, CO_2 emissions from transport energy (measured in metric tons per capita) serve as a proxy for Transport Carbon Emissions (TCE). The dataset spans the period from 1985 to 2023.

Transport Carbon Emission = f (Urbanization, GDP, GDP^2, Renewable Energy Consumption)

Model 1

$$lnTCE_t = \beta_0 + \beta_1 lnURB_t + \beta_2 lnGDP_t + \beta_3 (lnGDP^2)_t + \beta_4 lnREN_t + \mu_t$$

Where:

TCE_t = Transport Carbon Emissions (metric tons per capita) at time t

URB_t = Urban population at time t

GDP_t = GDP per capita (constant US$) at time t

${GDP_t}^2$ = GDP per capita squared (to test EKC) at time t

REN_t = Share of primary energy consumption from renewable sources (% equivalent primary energy) at time t

β_0 = Slope intercept

$\beta_1, \beta_2, \beta_3, \beta_4$ = Coefficients of the explanatory variables

ln = Natural logarithm

μ_t = Error term at time t

t = 1985, 1986, 1987,…, 2023

This study's model was developed as illustrated above. All dependent and explanatory variables are transformed into their natural logarithmic forms to examine the nature of their relationships and to assess their long-run effects on transport carbon emissions (TCE) in China. Additionally, In order to standardize data fluctuation for improved comparability over time and to make testing the Environmental Kuznets Curve (EKC) hypothesis easier, the natural logarithm of GDP per capita is also squared.

According to the preceding model, adjustments to the coefficient could affect the two variables relationship, making it either positive or negative.. In line with our expectations, the signs for β_1 is positive, consistent with the findings of Ali et al. (2017). Similarly, β_2 is also expected to be positive indicating that an increase in GDP will lead to a further increase in TCE, as supported by Xu and Xu (2021). In contrast, β_3 is expected to have a negative sign, while β_4 is also likely to be negative, as support by the result of Maji & Adamu, (2021).

3.3 Emprical Testing Procedures

3.3.1 Unit Root Test

The unit root test is used as the initial stage in this study to assess the variables' integration order and stationarity. This is crucial as regression results may be spurious if the t-statistics are unusually large, the R-squared is significantly higher than the Durbin-Watson statistics, or the outcomes contradict economic theory or common sense. These signs suggest that the model may be unreliable due to non-stationary data or autocorrelation (Phillips, 1987). As highlighted by Zivot and Wang (2003), When analysing trending data, unit root testing aids in deciding whether time-trend regression or first differencing should be used. For I(0) series, time-trend regression works well, however for I(1) series, the first difference is used. This stage guarantees accurate model formulation and permits the exploration of long-term relationships using co-integration approaches if variables are I(1). The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test and the Augmented Dickey-Fuller (ADF) unit root test are used to evaluate the stationarity of the variables in our study model.

3.3.1.1 Augmented Dickey-Fuller (ADF) Test

Augmented Dickey-Fuller Test (ADF) is a standard method for detecting unit roots and assessing the stationarity of the time series data, which is essential to avoid spurious results when applying Ordinary Least Squares (OLS) regression. It also serves as a key step in testing for cointegration between variables (Dickey & Fuller, 1979). By including lagged values of the dependent variable, the ADF test improves upon the basic Dickey-Fuller test, allowing it to detect serial correlation and handle more complex time series structures. To ensure reliable results, the appropriate lag length is typically selected using model selection criteria such as Akaike's Information Criterion (AIC) to eliminate residual autocorrelation (Otero & Baum, 2018). The null hypothesis states that unit root exists in the variables (non-stationary) while the alternative hypothesis is the variable unit root does not exist (stationary).

H_0: Unit root exists

H_A: Unit root does not exist

The ADF test's decision rules specify that if the p-value is less than the significance level at 1%, 5%, or 10%, the null hypothesis should be rejected; if not, the null hypothesis should not be rejected. If the null hypothesis is rejected, the variables are said to be stationary; if it is not rejected, the variables are said to be non-stationary.

3.3.1.2 Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test

According to Kwiatkowski et al. (1992), a statistical technique known as the KPSS test is used to compare the alternative hypothesis of a unit root with the null hypothesis of a time series being stationary around a constant mean or a deterministic trend. It depicts the series as the product of a random walk, a deterministic trend, and a stationary error term; stationarity is assumed when the random walk's variance is zero.

H_0: Unit root does not exist

H_A: Unit root exists

3.3.2 Model Estimation

3.3.2.1 Autoregressive Distributed Lag (ARDL) Model Bounds Cointegration Test

The ARDL Bounds Cointegration Test, developed by Pesaran et al. (2001), used to determine the existence of a long run relationship between a dependent variable and independent variables, regardless of whether the underlying variables are stationary at level (1(0)), first difference (1(1)), or a mix of both. The test is based on estimating an unrestricted error correction model (ECM) and performing a Wald or F-test on the joint significance of the lagged level variables. Murthy and Okunade (2016) stated that a key strength of the ARDL Bounds testing approach lies in its ability to estimate long-run economic relationships without the need to pre-test the time series data for unit roots as long as none of (I(2)) within the cointegration framework. The ARDL coefficient estimates remain highly reliable, even when applied to small sample sizes. However, despite not requiring all variables to be integrated of order one (I(1)), the method becomes invalid if any of the variables are found to be integrated of order two (I(2)).

H_0: The cointegration relationship between DV and IV does not exist.

H_A: The cointegration relationship between DV and IV exist

The calculated F-statistics are compared with two sets of critical value constraints to determine cointegration. The lower bound assumes that all variables are I(0), whereas the higher bound assumes that all variables are I(1). There is no long-run relationship if the F-statistics fall below the lower bound, a long-run relationship if it exceeds the upper bound, and an inconclusive conclusion if it falls between the boundaries.

ARDL Bound Cointegration Test Model:

$$\Delta lnTCE_t = \alpha_0 + \alpha_1 lnTCE_{t-1} + \alpha_2 lnURB_{t-1} + \alpha_3 lnGDP_{t-1} + \alpha_4 \ln (GDP^2)_{t-1} + \alpha_5 lnREN_{t-1} + \sum_{i=1}^{q} \beta_1 \Delta lnTCE_{t-i} + \sum_{i=1}^{q} \beta_2 \Delta lnURB_{t-i} + \sum_{i=1}^{q} \beta_3 \Delta lnGDP_{t-i} + \sum_{i=1}^{q} \beta_4 \Delta \ln (GDP)^2{}_{t-i} + \sum_{i=1}^{q} \beta_5 \Delta lnREN_{t-i} + \mu_t$$

3.3.2.2 Error Correction Model (ECM)

The Error Correction Model (ECM) will be used to analyse cointegration between variables after the ARDL Bounds Test. According to Banerjee et al. (1998), ECM uses an autoregressive distributed lag (ARDL) model as its foundation and emphasizes the coefficient of the lagged dependent variable. The ECM captures the equilibrium connection between variables throughout the long term as well as the short-term dynamics. Regressors rectify departures from the long-run path in the situation of cointegration by adjusting the dependent variable's lagged level. Because it does not impose potentially invalid common-factor restrictions, the test is beneficial. Additionally, the t-ratio form has better power qualities, particularly when the long-run and short-run coefficients diverge. The t-statistics of the lagged level term in the ECM are usually used to do the test. If this coefficient is notably negative, it indicates that the system returns to equilibrium after a shock, confirming the existence of a long-term link. The ECM test does not rely on nuisance parameters but is sensitive to the number of regressors.

ECM Model is expressed as below:

$$\Delta lnTCE_t = \alpha_0 + \alpha_1 lnTCE_{t-1} + \alpha_2 lnURB_{t-1} + \alpha_3 lnGDP_{t-1} + \alpha_4 \ln{(GDP^2)}_{t-1} + \alpha_5 lnREN_{t-1} + \sum_{i=1}^{q} \beta_1 \Delta lnTCE_{t-i} + \sum_{i=1}^{q} \beta_2 \Delta lnURB_{t-i} + \sum_{i=1}^{q} \beta_3 \Delta lnGDP_{t-i} + \sum_{i=1}^{q} \beta_4 \Delta \ln{(GDP)^2}_{t-i} + \sum_{i=1}^{q} \beta_5 \Delta lnREN_{t-i} + \theta ECM_{t-1} + \mu_t$$

3.4 Diagnostic Checking

Diagnostic checking involving statistical tests to ensure that the estimated model accurately reflects the behavior of the observed data. According to BEGGS (1988), even well-fitting models can yield misleading inferences if underlying assumptions are violated. Therefore, to detect potential econometric issues and ensure reliability, this study will conduct several diagnostic tests, such as the Jarque-Bera Test, the Breusch-Godfrey Serial Correlation LM Test, the Autoregressive Conditional Heteroskedasticity (ARCH) Test, the CUSUM, and the CUSUMSQ Test. To find and evaluate whether the model has any econometric issues, these tests will be carried out using EViews 12.

3.4.1 Jarque-Bera Test

Large datasets can benefit greatly from the parametric Jarque-Bera test, which determines if a dataset has a normal distribution. It is predicted on two essential metrics that characterise a distribution's shape: kurtosis, which represents the data's peakedness, and skewness, which denotes asymmetry. The skewness of a normal distribution is zero, while its kurtosis is three (Jarque & Bera, 1980). The test evaluates how much the sample's skewness and kurtosis deviate from the values expected under a normal distribution. Normality is important in statistical analysis, as many statistical methods assume data are normally distributed, and violations can lead to inaccurate and misleading results (Jarque & Bera, 1987). In the JB test, the null hypothesis assumes normality of the error term, while the alternative assumes non-normality. If the test yields a significant result, we reject the null hypothesis and come to the conclusion that the data is not normally distributed. If the finding is not significant, we cannot reject the null hypothesis and infer that the data is normally distributed.

H_0: Normally distribution exists in error terms

H_A: Normally distribution does not exist in error terms

3.4.2 Breusch-Godfrey Serial Correlation LM Test

Breusch (1978) stated that if the error terms in a linear model are autocorrelated, the ordinary least squares (OLS) estimate of the coefficient parameters remain unbiased but are no longer efficient. However, in dynamic models where lagged dependent variables are included as regressors, OLS estimates become biased and typically inconsistent. Therefore, when estimating dynamic models using OLS, it is crucial to conduct tests for autocorrelation. Rois et al. (2012) also mentioned that the Breusch-Godfrey (BG) test is the most suitable method for detecting higher-order autocorrelation, especially when the model includes stochastic regressors like lagged dependent variables. The alternative hypothesis makes the assumption that autocorrelation exists, whereas the null hypothesis makes the assumption that it does not. The presence of autocorrelation in the data is indicated if the test produces a significant result. If the result is not significant, we conclude that the data does not exhibit autocorrelation.

H_0: No autocorrelation exists.

H_A: Autocorrelation exists.

3.4.3 Autoregressive Conditional Heteroskedasticity (ARCH) Test

Heteroscedasticity occurs when the error components in a regression model exhibit non-constant variance across observations. In the presence of heteroscedasticity, the Ordinary Least Squares (OLS) estimator is consistent, but it becomes inefficient and produces statistical inferences that are not reliable. Engle (1982) introduced the ARCH test to examine time-varying variance by modeling the conditional variance of errors as a function of past squared residuals. The ARCH test is specifically suited for time series data, as it examines volatility patterns that depend on historical error behavior.

H_0: No heteroscedasticity exists

H_A: Heteroscedasticity exists

3.4.4 CUSUM and CUSUMSQ Test

Brown et al. (1975) developed the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) to determine if the regression connection is stable over time. According to Nica et al. (2024), the CUSUM test is mainly used to identify gradual shifts or drifts in the mean level of a process or time series over time, particularly highlighting changes in the regression coefficients. It works by calculating the cumulative sum of residual deviations from the model's mean. The difference between the actual and expected values is added up at each time point. The CUSUMSQ test, on the other hand, is intended to identify abrupt or noteworthy shifts in a data series' variance. Compared to the CUSUM test, it is better at detecting sudden changes in structure. The CUSUMSQ plot plots the cumulative sum of the squared residuals against a reference boundary; a large deviation from this line may suggest a structural break. The parameters of the model appear to be stable over time if the points on the CUSUM and CUSUMSQ plots stay inside the lines at the 5% significance level.

3.5 Robustness Checking

3.5.1 Fully Modified Ordinary Least Squares (FMOLS)

Phillips and Hansen (1990) developed FMOLS as an estimation technique to correct biases in cointegrated systems by making non-parametric adjustments that account for both serial correlation and endogeneity. This approach uses long-run covariance estimates to modify the dependent variable and/or regressors, thereby producing asymptotically unbiased and efficient estimates. By addressing these issues without sacrificing a substantial degree of freedom, FMOLS is particularly suitable for small-sample time series analysis and is widely used for obtaining reliable long-run parameter estimates in cointegration studies.

H_0: The independent variable has no significant long-run effect.

H_1: The independent variable has a significant long-run effect.

3.5.2 Dynamic Ordinary Least Squares (DOLS)

Stock and Watson (1993) has introduced DOLS as a parametric technique in cointegration analysis to correct simultaneity bias and serial correlation in the residuals. It eliminates endogeneity and takes higher-order integrated variables into account by adding leads and lags of the regressors' first differences to the cointegration equation. By simulating these extra variables, DOLS removes the link between the error term and the regressors, allowing for an accurate and impartial estimate using ordinary least squares. A critical aspect of applying DOLS is selecting the optimal number of leads and lags, as too few may leave bias uncorrected while too many can reduce estimation efficiency.

3.5.3 Canonical Cointegrating Regression (CCR)

According to Park (1992), CCR is a transformation-based methodology that provides efficient estimation and standard inference in cointegrated systems. To eliminate correlation between the error term and the regressors, stationary components and long-run covariance estimations are used to adjust both the dependent and independent variables. This transformation preserves the original cointegrating relationships while allowing ordinary least squares (OLS) to be applied to the adjusted variables to obtain efficient estimates.

Chapter 4: Data Analysis

4.0 Introduction

This chapter will use E-view 12 to perform diagnostic checks and investigate the relationship between transportation carbon emissions and all independent factors. After that, we will perform and analyze the result of tests.

4.1 Unit Root Test

Table 4.1.1: The values of the Dickey-Fuller test

	ADF			
	Intercept		Trend and intercept	
	Level	1^{st} Difference	Level	1^{st} Difference
$lnTCE_t$	-0.4736(5)	-6.1173(0)***	-1.8736(0)	-6.0314(0)***
$lnGDP_t$	-2.7164(1)*	-4.8009(1)***	-4.5200(0)***	-4.2387(5)**
$lnGDP^2_t$	-2.1527(1)	-4.8301(1)***	-2.5210(0)	-7.2391(1)***
REN_t	2.3703(0)	-5.8866(0)***	-0.4447(0)	-7.4462(0)***

Notes: *, **, *** shows significant at the 10%, 5%, and 1% significance level respectively. The figure in parentheses is the lag chosen in the Schwarz information criteria (SIC). The bandwidth utilized is Newey-West Bandwidth. The Bartlett Kernel is employed in the Spectral estimation technique.

Table 4.1.1 displays the ADF unit root test results for lnTCE, lnGDP, lnGDP2, and REN. lnGDP is stationary at the level of the intercept and the trend and intercept. lnTCE, lnGDP2, and REN are stationary at the first difference between the intercept and the trend and intercept. In conclusion, the variables are either stationary at level form I(0) or first difference I(1).

Table 4.1.2: The values of the Kwiatkowski-Phillips-Schmidt-Shin test

	KPSS			
	Intercept		Trend and intercept	
	Level	1^{st} Difference	Level	1^{st} Difference
$\ln URB_t$	0.7576(5)***	0.7130(5)**	0.2032(5)**	0.1975(4)**

Notes: *, **, *** shows significant at the 10%, 5%, and 1% significance level respectively. The figure in parentheses is the lag chosen in the Schwarz information criteria (SIC). The bandwidth utilized is Newey-West Bandwidth. The Bartlett Kernel is employed in the Spectral estimation technique.

Table 4.1.2 displays the findings of the Kwiatkowski-Phillips-Schmidt-Shin unit root test for lnURB. lnURB is stationary at the level of trend and intercept, as well as at the first difference between intercept and trend and intercept. The variable is either stationary at level form I(0) or at first difference I(1), so we may use the ARDL model.

4.2 Model Estimation

4.2.1 ARDL Cointegration Bounds Test

Table 4.2.1: The ARDL Bounds Test Result

Bounds testing approach to co-integration

	F(LNTCE, LNGDP, LNGDP^2, LNURB, REN)	
Optimal lags	(2, 2, 1, 1, 0)	
F-statistics	4.7054***	
Critical values (k=4, T=37)		
Significance level (%)	**Lower bounds I(0)**	**Upper bounds I(1)**
1	3.29	4.37
5	2.56	3.49
10	2.2	3.09

Remarks: ***, ** and * show the null hypothesis reject at significance level 1%, 5% and 10% respectively.

The ARDL Cointegration Bounds Test is used to analyze the long-term connection between the independent and dependent variables. If the F-statistic is more than the upper bound I(1), it indicates a long-run association; if it is less than the lower bound I(0), it indicates no long-run relationship; and if it falls in the middle of the bounds, it is considered inconclusive. The findings demonstrated that, at the 1% significance level, the F-statistic (4.7054) is higher than the upper bound I(1) (4.37). As a result, we reject the null hypothesis and conclude that the dependent and independent variables have a lasting association.

Table 4.2.1.1: The Long Run Coefficient Result

Variables	Coefficient	Standard Error	t-statistic	P-value
$lnGDP_t$	-2.5919***	0.2745	-9.4417	0.0000
$lnGDP^2_t$	0.1488***	0.0285	5.2133	0.0000
$lnURB_t$	3.8966***	0.8239	4.7295	0.0001
REN_t	-0.0418***	0.0130	-3.2200	0.0034
C	-61.9534***	15.5665	-3.9799	0.0005

Remarks: ***, ** and * show the null hypothesis reject at significance level 1%, 5% and 10% respectively.

Table 4.2.1.1 shows that at the 1% significance level, the P-value of lnGDP (0.0000) is less than (0.01) indicating negatively significant. Therefore, there is a long-run relationship between the transport carbon emissions and GDP per capita. This indicates that if the GDP per capita increases by 1%, the transport carbon emissions will decrease by -2.5919%. The result is consistent with Asumadu-Sarkodie and Owusu (2016) study in Rwanda, GDP per capita leads to a decrease in carbon emissions in the long run. Similar with Kasperowicz (2015) study result indicated that in the long run, the relationship between GDP and CO2 emissions is negative, as advancements in low-carbon technologies allow for maintaining the same level of production with reduced emissions.

At the significance level of 1%, the $lnGDP^2$ P-value (0.0000) is less than (0.01), indicating positive significance. It shows that there are substantial long-term relationships between GDP^2 and carbon emissions from transportation. The coefficient of the $\ln GDP^2$ is positive, which means it does not follow the inverted U-shaped pattern of the EKC hypothesis. However, its positive coefficient would indicate that the environmental degradation follows a U-shaped pattern in relative to the GDP per capita. It is still consistent with Alshehry and Belloumi (2017), Al-Mulali et al. (2015), Du et al. (2012) and S. Wang et al. (2011) studies, where the EKC hypothesis does not validated.

At the significance level of 1%, the lnURB's P-value (0.0001) is less than its positive significance value (0.01). Hence, there is a long-run relationship between urbanization and transport carbon emissions. If the urban population increases by 1%, the transport carbon emissions will increase by 3.8966%. The result is consistent with the study by Xu and Lin (2015), Ali et al. (2017), Awan et al. (2022) and Xie et al. (2017), the result showed the urbanization leads to an increase in carbon emissions.

At the 1% significance level, the REN's P-value (0.0034) is smaller than its negative significance (0.01). There is a long-run relationship between renewable energy consumption and transport carbon emissions, which means that if renewable energy consumption increases by 1%, the transport carbon emissions will decrease by -0.0418%. The result is aligned with the study by Zaman et al. (2021), Kwilinski et al. (2024) and Maji and Adamu (2021), where higher renewable energy consumption has a significant negative correlation with transport CO_2 emissions, indicating that increased renewable energy use helps lower transport-related emissions.

4.2.2 Error Correction Model

Table 4.2.2: The ECM Result

Variables	GDP, GDP^2, URB, REN
ECT_{t-1} Coefficient	-1.4382***
Standard Error	0.2479
t-statistic	-5.8019
P-value	0.0000

Remarks: ***, ** and * show the null hypothesis reject at significance level 1%, 5% and 10% respectively.

According to Table 4.2.2, the ECT coefficients are statistically significant, with a P-value (0.0000) of less than 0.01 at 1% significance level. The ECT coefficient is -1.4382 which exceeds the range of 0 and -1. The value of -1.4382 implies that 143.82% of deviations from the long-run equilibrium are adjusted in the next period. The magnitude of the coefficient (-1.4382) is quite high, might indicate that it is overshooting. The results are consistent with Bekhet and Othman (2017), Rahman and Kashem (2017), Kwakwa et al. (2022) and Qodirov et al. (2024). This may be due to the new energy vehicle boom led by government policies and technological advancement.

4.3 Diagnostic Checking

4.3.1 Jarque-Bera Test, LM Test and ARCH Test

Table 4.3.1: The Jarque-Bera Test, LM Test and ARCH Test Result

Diagnostic Testing	t-statistic/F-statistic	P-value	Conclusion
Jarque-Bera normality test	4.5982	0.1003	Normally distributed
Serial Correlation LM test	0.6219	0.5454	No autocorrelation exists
ARCH test	0.6235	0.4352	No heteroscedasticity exists

Remarks: ** show the null hypothesis rejected at significance level 5%

The results in Table 4.3.1 reveal that there is no econometric concern. The P-value for the Jarque-Bera normality test is 0.1003, the Serial Correlation LM test is 0.5454, and the ARCH test is 0.4352, all of which surpass the 5% significance level. As a result, we do not reject the null hypothesis and conclude that the model is normally distributed, with no autocorrelation or heteroscedasticity.

4.3.2 CUSUM Test and CUSUM Square Test

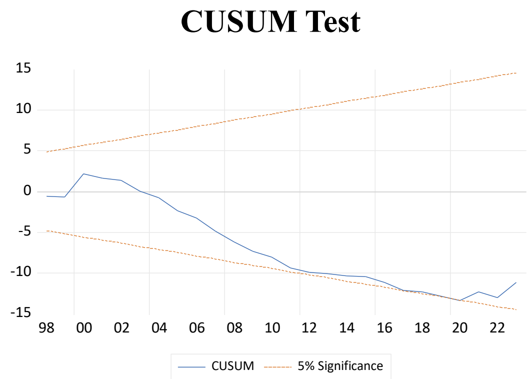

Figure 4.1

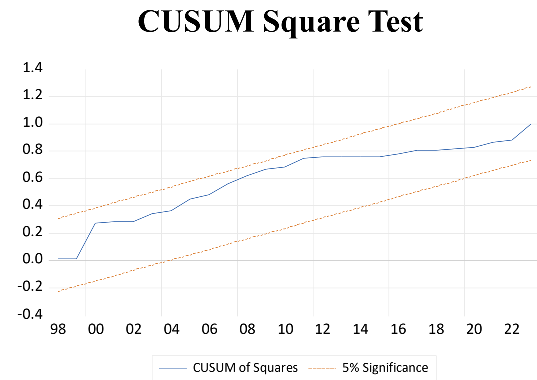

Figure 4.2

CUSUM test and CUSUMSQ tests results are shown in the Figure 4.1 and 4.2 respectively. The model's parameters appear to be stable over time, since both points stayed inside the straight-line boundaries at the 5% significance level.

4.4 Robustness Checking

4.4.1 FMOLS, DOLS and CCR

Table 4.4.1: The FMOLS, DOLS and CCR Result

Variables	FMOLS		
	Coefficient	T-statistic	P-value
lnGDP	-2.3290***	-6.7907	0.0000
$lnGDP^2$	0.1304***	3.6697	0.0009
lnURB	3.9514***	3.4398	0.0016
REN	-0.0862***	-5.4406	0.0000
Constant	-62.8211***	-2.9162	0.0063
	DOLS		
	Coefficient	t-statistic	
lnGDP	-2.2990***	-9.1689	0.0000
$lnGDP^2$	0.1155***	4.6200	0.0002
lnURB	4.7266***	6.4189	0.0000
REN	-0.0310**	-2.6074	0.0173

Constant	-79.1472***	-5.6818	0.0000
	CCR		
	Coefficient	t-statistic	
lnGDP	-2.1603***	-7.4314	0.0000
$lnGDP^2$	0.1281***	3.5654	0.0011
lnURB	3.5331***	3.2900	0.0024
REN	-0.0832***	-5.1564	0.0000
Constant	-55.6222**	-2.7245	0.0102

***, ** and * show the statistical significance at 1%, 5% and 10% levels.

To confirm the result's robustness, FMOLS, DOLS, and CCR are used. Except for the DOLS result, which shows that the energy consumption from renewable sources is only significant at the 5% significance level, the results of FMOLS, DOLS, and CCR verified that all independent variables are significant at the 1% significance level. The coefficients for the GDP per capita and renewable energy consumption are negative. However, the coefficients for the quadratic term of the GDP and urbanization are positive. The results are robust since the FMOLS, DOLS, and CCR coefficient signs match the ARDL Bounds test result.

Chapter 5: Discussion, Conclusion and Implications

5.0 Introduction

The summary of the major findings, policy implications, limitations and recommendations for future research will be discussed in this chapter.

5.1 Summary of Major Findings

The primary objective of the study is to determine what factors affect China's transportation-related carbon emissions. Urbanization, GDP per capita, and the renewable energy consumptions are the explanatory factors. The ARDL Bounds Test for the year 1985–2023 is used to analyze the relationship between the explanatory and response variables.

At a significant level of 1%, GDP per capita is negatively significant. There is a long run negative relationship between GDP per capita and transport carbon emissions, which means if the GDP per capita increases, the transport carbon emission will decrease. The result is consistent with some past studies. According to Asumadu-Sarkodie and Owusu (2016) research in Rwanda, GDP per capita eventually reduces carbon emissions in the long run. Kasperowicz (2015) study result indicated that in the long run, the relationship between GDP and CO2 emissions is negative, as advancements in low-carbon technologies allow for maintaining the same level of production with reduced emissions. Go et al. (2020) studies in Malaysia found that The GDP per capita coefficient was negatively significant, indicating that rising income levels will likely result in falling transportation-related CO2 emissions. The result is most likely due to China rising GDP per capita leads to greater purchasing power for electric vehicles. China electric vehicles market has grown rapidly, reaching over 50% last year (Kaur, 2025). Also, China high economic growth makes it affordable in providing subsidies and expanding infrastructure to support the EV adoption. For example, subsidies and tax exemption on EV and expansion of the renewables charging station. Evidence from Yang (2023) stated that in order to enable EV producers to produce cars, buses, or taxis for individual consumers, China began offering financial subsidies to them in 2009. Between 2009 and 2022, the government spent about 200 billion RMB ($29 billion) on relevant tax breaks and subsidies. The implementation of policy along with people's high income accelerates transport decarbonization. In conclusion, the result showed GDP per capita leads to a decrease in carbon emissions.

Urbanization is positively significant at 1% significance level. Hence, in the long run, urbanization and transport carbon emissions are positively correlated, meaning that as urbanization rises, so will transport carbon emissions. The result aligns with the research conducted by Xu and Lin (2015), due to extensive population movements, urbanization also significantly affects carbon dioxide emissions. In addition to the migration of rural excess labor from rural to urban areas, urbanization also causes large population migration between cities, which raises CO_2 emissions in the transportation sector. Ali et al. (2017) studies found that Pakistan's ongoing urbanization has a negative relationship between CO_2 emissions. Pakistan is another developing nation with a high pace of urbanization growth. According to research by Awan et al. (2022), the percentage of individuals who live in cities has a bigger influence on transportation-related carbon emissions. The need for transport services is expected to grow as urbanization increases. Xie et al. (2017) findings also show a strong and positive correlation between urbanization and carbon emissions. As mentioned by Lv et al. (2018), the result might be due to the China's urbanization is accelerating. The creation of infrastructure is accelerated by urbanization, which raises the need for energy and other bulk products. It also speeds up the movement of goods, which will surely increase the demand for transportation. Urbanization will therefore eventually have an even greater effect on carbon emissions from freight transportation. In conclusion, the result showed urbanization leads to an increase in carbon emissions.

At the 1% significance level, the consumption of renewable energy is negatively significant. Long-term consumption of renewable energy and transportation carbon emissions are negatively correlated, indicating that as renewable energy consumption rises, transportation carbon emissions will fall. The results are in line with a research by Zaman et al. (2021), which discovered that a greater percentage of renewable energy consumption relative to total final energy consumption aids in the reduction of environmental issues by lowering atmospheric CO_2 emissions. Kwilinski et al. (2024) results show that the EU's carbon dioxide emissions related to energy production are declining in tandem with its growing usage of renewable energy. In other words, the quantity of CO_2 released into the atmosphere as a result of energy generation tends to decline when renewable energy sources such as wind, solar, hydro, and geothermal power are more widely used and incorporated into the energy mix. Maji and Adamu (2021) studies found that outcome also demonstrates a negative relationship between transportation-related carbon emissions and the consumption of renewable energy. This implies that using more renewable energy will improve environmental quality and lower carbon emissions from these industries. The result might be due to the China rapidly adoption of renewable energy in vehicles where China is the world largest EV market with proper policy support that has played a crucial role. The usage of fossil fuels like petrol, which release greenhouse gases into the atmosphere, can be greatly decreased by switching to renewable energy. In conclusion, there is a substantial negative association between transportation CO_2 emissions and higher renewable energy consumption, suggesting that using more renewable energy reduces emissions associated with transportation.

The EKC hypothesis states that environmental degradation and per capita income have an inverse U-shaped connection, with environmental quality first decreasing and then increasing as wealth increases. The existence of EKC is tested by including GDP per capita and the GDP per capita quadratic term. If the EKC hypothesis exists, the GDP per capita quadratic term should be negatively significant, and the GDP per capita coefficient should be positively significant.

However, the results of the ARDL Bounds test indicate that the GDP quadratic term is positive and significant, whereas the GDP per capita coefficient is negative and significant. It indicates that the transport carbon emission decreases initially with rising income and then increases again at higher income levels. Therefore, it shows that the EKC hypothesis is not validated in China transport sector. This result is consistent with

Alshehry and Belloumi (2017), research indicates that there is no inverse-U relationship between Saudi Arabia's economic growth and transport CO2 emissions, and the country is still to the left of the EKC's turning point. Jebli and Youssef (2015) study found that in the long run, the inverted U-shaped environmental Kuznets curve (EKC) is unsupported by any data. This indicates that Tunisia has not yet attained the GDP per capita level necessary to obtain an inverted U-shaped EKC. This outcome is expected since developed countries often validate the EKC hypothesis. According to research by Al-Mulali et al. (2015), Vietnam does not follow the EKC theory.

The U-shaped EKC relationship in China might be because of the GDP per capita initially improve efficiency and reduced emissions due to adoption of clean energy technologies like wind, solar and hydrogen. But as both the GDP per capita and urbanization increase further, it might lead to an increase in transport demand, and the growth of the transport demand might be faster than the renewable technology adoption and cause the transport emissions to increase again. This is likely to be true since most of the China renewable energy production still comes from the fossil fuel.

5.2 Policy Implications

5.2.1 Widespread Green Hydrogen Corridor

Since the GDP per capita is negatively affected the transport carbon emissions, China should develop more green hydrogen corridor. Countries with higher GDP per capita can afford large scale green infrastructure projects like hydrogen refueling stations for freight transport which require huge initial costs. Also, people with higher incomes tend to have greater environmental awareness, therefore they will adopt various types of potential clean logistics and transport in the future. Not only that, as GDP per capita increases, people buy more goods as their purchasing power increases. It means that the logistic activity will increase, which increases the transport emissions. Green hydrogen corridors enable wealthier regions to decarbonize freight and long-distance transport, ensure that income growth does not lead to higher emissions.

China now produces more than 50 million tonnes of hydrogen a year, making it the greatest producer in the world. Therefore, China has the largest potential to use hydrogen as its primary energy consumption towards the transportation system in the future. However, fossil fuels, such as coal and natural gas, provide 81% of its hydrogen generation, with 62% and 19% coming from these sources, respectively (Fan et al., 2025). China is currently leveraging its abundant renewable energy resources, for example according to FuelCellsWorks (2024), green hydrogen technology has advanced significantly with Sinopec's opening of its first large-scale research plant for direct hydrogen production from seawater in Qingdao, Shandong Province. As a result, China hydrogen production that rely on fossil fuels could be reduced significantly in the future. Hence, China should implement more comprehensive hydrogen highway system across the nations for the Hydrogen Fuel Cell Vehicles (HFCVs). It encourages people to adopt (HFCVs) as an option other than Electric Vehicles (EV).

China is still in early development of its hydrogen infrastructure for its Hydrogen Fuel Cell Vehicles, where it does not have a wide coverage across the nation. China could build a nation-wide hydrogen corridor for the hydrogen-powered vehicles. As a first move, China has launched its first cross-regional hydrogen trucking corridor in the mid of 2025 with public-private partnerships. According to FuelCellsWorks (2025), In order to connect inland logistics with the Port of Qinzhou, Sinopec has started China's first cross-regional hydrogen trucking corridor, which will stretch 1,150 km across Chongqing, Guizhou, and Guangxi. The route will enhance green logistics and facilitate heavy-duty hydrogen trucking. China can continue to expand the development of the hydrogen corridor towards other larger port like the Port of Shanghai where it is the largest port in China, and eventually towards the large city across the nation.

5.2.2 Widespread Congestion Pricing

Furthermore, car ownership rises when the urban areas expand. Traffic jams and a rise in transportation-related emissions will result from this. The number of commuting and delivery trips rises in tandem with the urban population density. Since the urbanization in China is positively affected the transport carbon emissions, China should implement congestion pricing in the urban cities to reduce the reliance on the private vehicles by the people living in the urban areas.

According to Green et al. (2020) study, there has been growing concern over air pollution in key cities. Congestion charging provides a way to reduce overall travel miles and standstills, which in turn reduces pollution, since vehicle exhaust accounts for a significant portion of urban pollution. The reductions are significantly greater than what would be predicted if traffic volumes were reduced alone. Additional social advantages resulted from the charge scheme's lowering of the externality caused by traffic. Pollution per mile decreased as a result of shorter stoppages and faster travel times.

For example, Teo (2025) mentioned that prior to places like Stockholm, Sweden, and London, the capital of Britain, Singapore was the first to adopt the upgraded ALS, which is now called the automated Electronic Road Pricing (ERP) system, in 1998. In order to charge drivers to travel specific routes during peak hours, the ERP system uses gantries that integrate a short-range wireless technology with an in-vehicle unit. To detect negligent drivers, gantries are equipped with cameras that can record a car's back license plate. During peak rush hours, this fee serves as a financial deterrent to promote the use of public transportation or alternative routes. In addition to reducing traffic, the ERP offers beneficial knock-on effects like less environmental damage from vehicle emissions and more pedestrian-friendly routes. Khosravani (2025) also highlighted the effect of Singapore’s congestion pricing on urban mobility. The decrease in the number of cars on the road during rush hour was one of the most obvious consequences. This instantaneous decrease in traffic volume eased congestion and enhanced traffic flow in general. By forcing cars to pay for their actual trip expenses, congestion pricing can also have an impact on urban growth by encouraging more economical land use and preventing urban expansion.

According to Menon and Guttikunda (2010), congestion pricing is thought to have promoted non-motorized transport and decreased 20–30% of downtown passenger automobile traffic in London on average. The average speed of traffic rose by at least 15 kph in Singapore. The everyday use of cars in Stockholm immediately decreased by at least 20%. Overall, by implementing congestion pricing in the urban areas, it can encourage people living in urban areas to reduce the usage of vehicles and utilize the public transport system available in the area.

5.2.3 Building-to-Vehicle (B2V) Energy

Moreover, since China renewable energy consumption is negatively affected the transport carbon emissions, China should develop Building-to-Vehicle (B2V) energy system since China has the largest EV market. The B2V system allows the buildings to store excess energy in electric vehicles (EVs) when production is more than the demand, and the energy stored can be used to discharge to the grid. Instead of using the grid electricity from fossil fuels, B2V can use EV batteries as storage.

The electricity infrastructure may face serious challenges because of the electric vehicle industry's explosive growth. For instance, the increasing unregulated demands of EV charging could degrade power quality and place a great deal of strain on utility grid transformers and distribution networks (He et al., 2022). According to Zhou et al. (2019) the vehicle-to-building (V2B) and building-to-vehicle (B2V) interaction can be realized to lessen dependency on the electric grid for both transportation and household use by putting in place a device for managing the bidirectional power flow. B2V can contribute to the development of a more sustainable energy system by promoting the use of renewable energy sources and reducing reliance on fossil fuel-based energy sources, as over 70% of China's electricity still originates from these sources. With B2V technology, an electric car may be charged using the excess photovoltaic production capacity mounted on the building roof. Another efficient way to store electricity is with a charge and discharge electric vehicle (Hou et al., 2022). Utilising the potential of battery storage systems and renewable energy sources, the Smart Energy Management System (SEMS) manages building energy and EV charging. The effective use of available energy resources is maximised by carefully planning EV charging and discharging activities (Lo et al., 2023). This technology is suitable for China to implement since the China have the largest market of Electric Vehicles (EVs), with the sales over 11 million. In 2024, nearly two-thirds of all electric cars sold worldwide were in China, where nearly half of all car sales were electric (International Energy Agency, 2025).

5.3 Limitations and Recommendations

This study on the determinants of transport carbon emissions identified several limitations. Accordingly, several recommendations are proposed to address these limitations and guide future research. First, all of the study's finding might only apply to China's transportation industry and significant in guiding local policymakers. This is because the study's data source originated solely from China. The factors influencing transportation carbon emissions may vary greatly between countries due to each one's unique history, political systems, and economic conditions. Consequently, the results and conclusions of this study may not be directly generalized to other countries. The discussions and implications can only be presented as a reference in other contexts that investigate the determinants of transport carbon emissions. Future researchers are therefore encouraged to conduct comparative studies across multiple countries to evaluate similarities and differences.

Additionally, the limitation of this study is the omission of relevant variables. This study consists of 4 explanatory variables such as urbanization, GDP, GDP^2 and renewable energy consumption. Other potentially important determinants, such as government effectiveness, were excluded in the models due to limitations of data. The reliable data on government effectiveness in China are only available from 1996 onwards, whereas this study employed a 39-year time series dataset. Moreover, urbanization was selected as a more suitable explanatory variable than population because the rate of urbanization has increased significantly over the past decades, while population growth has remained relatively slow due to the implementation of the one-child policy (Lin & Benjamin, 2017). Future researchers can therefore examine by employing panel data covering multiple countries, which would provide sufficient observations. Furthermore, the choice of urbanization over population in this study is context-specific to China and may not be directly applicable to other nations. Therefore, future studies should adapt their variable selection according to the demographic, economic, and policy characteristics of the countries under investigation.

The last research limitation is that the time series data did not include a structural break. China has undergone major legislative changes, the COVID-19 pandemic, and the Global Financial Crisis of 2008–2009 throughout the course of the 39-year period, all of which may have changed the relationship between factors and transportation carbon emissions. However, this study did not include dummy variables to capture such events, which assumes parameter stability for the whole sample period. This omission could bias the ARDL model's short- and long-run estimates, which would ultimately undermine the validity of the findings. Future research could address this limitation by using structural break tests, such as the Zivot Andrews or Perron methods and incorporate dummy variables to improve the robustness of findings.

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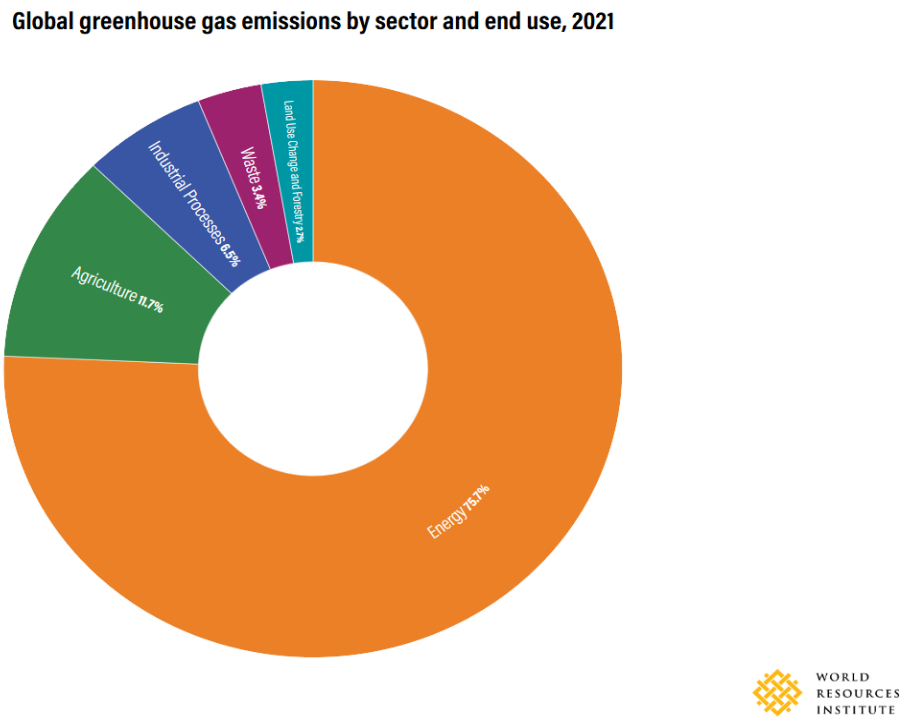
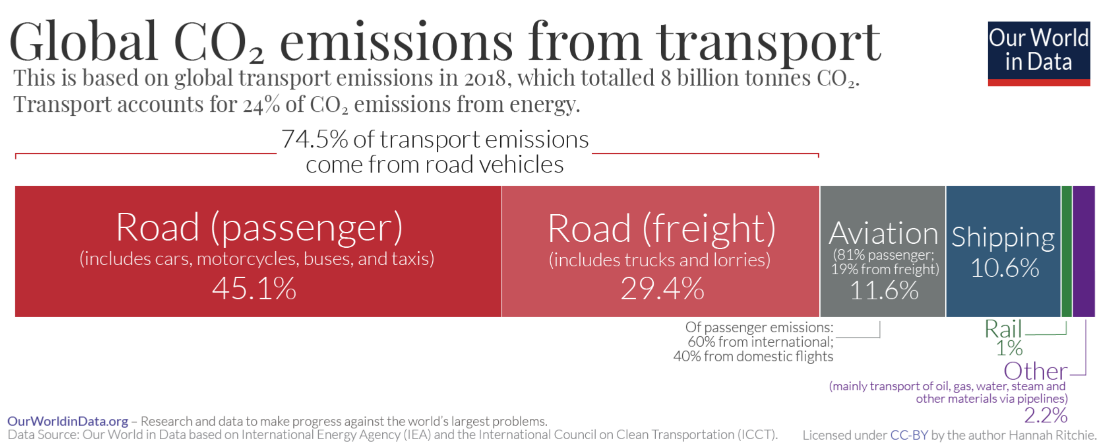
Appendices

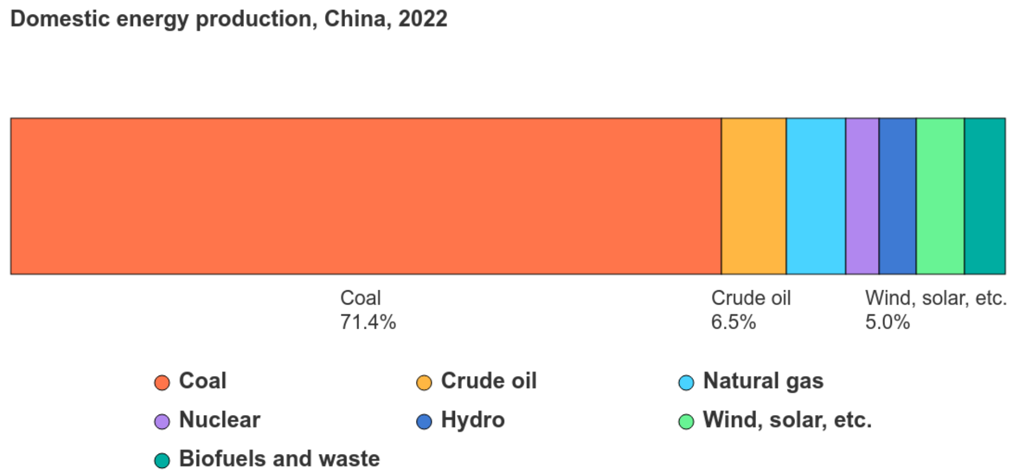
Appendix 1.1



Appendix 1.2

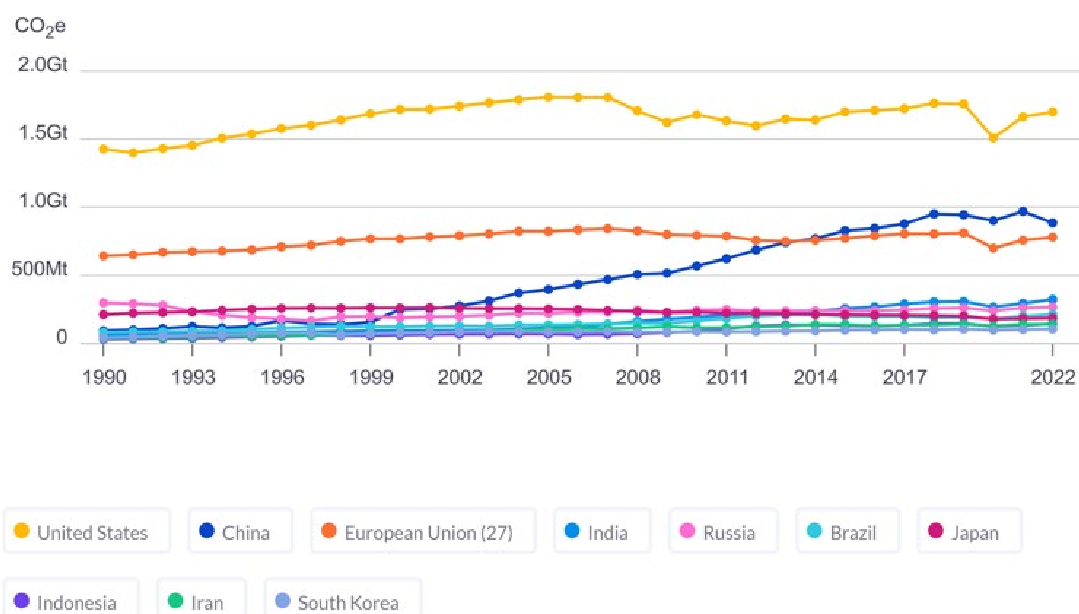


Appendix 1.3

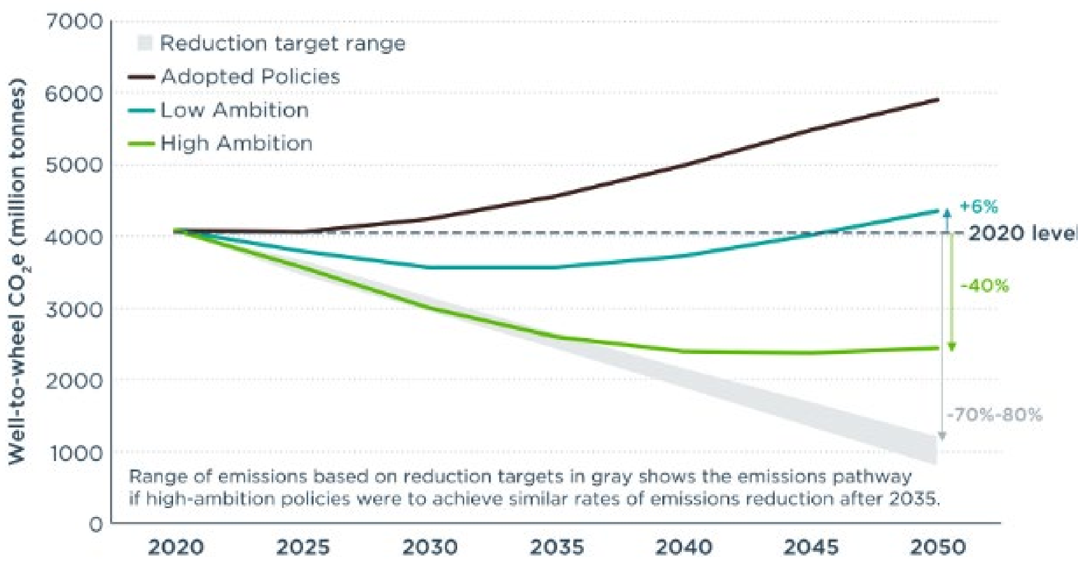


Appendix 1.4

Data source: Climate Watch; Location: Top Emitters; Sectors/Subsectors: Transportation; Gases: CO2; Calculation: Total; Show data by Countries.



Appendix 1.5



Reduction target range
Adopted Policies
Low Ambition
High Ambition
Well-to-wheel CO_2e (million tonnes)
7000
6000
5000
4000
3000
2000
1000
0
2020
2025
2030
2035
2040
2045
2050
+6%
2020 level
-40%
-70%-80%
Range of emissions based on reduction targets in gray shows the emissions pathway
if high-ambition policies were to achieve similar rates of emissions reduction after 2035.

Appendix 4.1.1: Augmented Dickey Fuller Test (ADF)

Level Form: Intercept Without Trend

Null Hypothesis: LNTCE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.511303	0.8779
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

Null Hypothesis: LNGDP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.335991	0.1666
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

Null Hypothesis: LNGDP2 has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.047297	0.2663
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

Null Hypothesis: RENEWABLES EQUIVALENT PRIMARY ENERGY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.488118	1.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

First Difference: Intercept Without Trend

Null Hypothesis: D(LNTCE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.213729	0.0000
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

Null Hypothesis: D(LNGDP) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.527155	0.0009
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

Null Hypothesis: D(LNGDP2) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.142409	0.0026
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

Null Hypothesis: D(RENEWABLES EQUIVALENT PRIMARY ENERGY) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.883648	0.0000
Test critical values:	1% level	-3.621023	
	5% level	-2.943427	
	10% level	-2.610263	

Level Form: Intercept With Trend

Null Hypothesis: LNTCE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.838839	0.6659
Test critical values:	1% level	-4.219126	
	5% level	-3.533083	
	10% level	-3.198312	

Null Hypothesis: LNGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.448869	0.8290
Test critical values:	1% level	-4.226815	
	5% level	-3.536601	
	10% level	-3.200320	

Null Hypothesis: LNGDP2 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.998718	0.9323
Test critical values:	1% level	-4.219126	
	5% level	-3.533083	
	10% level	-3.198312	

Null Hypothesis: RENEWABLES EQUIVALENT PRIMARY ENERGY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.431883	0.9826
Test critical values:	1% level	-4.219126	
	5% level	-3.533083	
	10% level	-3.198312	

First Difference: Intercept With Trend

Null Hypothesis: D(LNTCE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.392137	0.0005
Test critical values:	1% level	-4.234972	
	5% level	-3.540328	
	10% level	-3.202445	

Null Hypothesis: D(LNGDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.631312	0.0406
Test critical values:	1% level	-4.226815	
	5% level	-3.536601	
	10% level	-3.200320	

Null Hypothesis: D(LNGDP2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.688843	0.0358
Test critical values:	1% level	-4.226815	
	5% level	-3.536601	
	10% level	-3.200320	

Null Hypothesis: D(RENEWABLES EQUIVALENT PRIMARY ENERGY) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.558037	0.0000
Test critical values:	1% level	-4.226815	
	5% level	-3.536601	
	10% level	-3.200320	

Appendix 4.1.2: Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test

Level Form: Intercept Without Trend

Null Hypothesis: LNURB is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.757599
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

First Difference: Intercept Without Trend

Null Hypothesis: D(LNURB) is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.712961
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

Level Form: Intercept With Trend

Null Hypothesis: LNURB is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.203234
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

First Difference: Intercept With Trend

Null Hypothesis: D(LNURB) is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.197497
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

Appendix 4.2.1: ARDL Cointegration Bounds Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(LNTCE)
Selected Model: ARDL(2, 2, 1, 1, 0)
Case 2: Restricted Constant and No Trend
Date: 08/20/25 Time: 17:37
Sample: 1985 2023
Included observations: 37

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP	-2.591911	0.274518	-9.441681	0.0000
LNGDP2	0.148802	0.028543	5.213264	0.0000
LNURB	3.896620	0.823900	4.729482	0.0001
RENEWABLES ...	-0.041832	0.012991	-3.220013	0.0034
C	-61.95336	15.56646	-3.979925	0.0005

EC = LNTCE - (-2.5919*LNGDP + 0.1488*LNGDP2 + 3.8966*LNURB
-0.0418*RENEWABLES EQUIVALENT PRIMARY ENERGY -
61.9534)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	4.705422	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	37		Finite Sample: n=40	
		10%	2.427	3.395
		5%	2.893	4
		1%	3.967	5.455
			Finite Sample: n=35	
		10%	2.46	3.46
		5%	2.947	4.088
		1%	4.093	5.532

Appendix 4.2.2: Error Correction Model

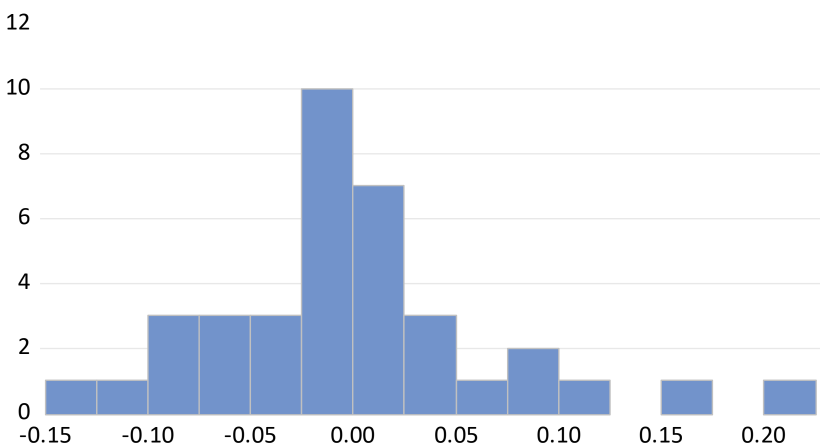
ARDL Error Correction Regression
Dependent Variable: D(LNTCE)
Selected Model: ARDL(2, 2, 1, 1, 0)
Case 2: Restricted Constant and No Trend
Date: 08/20/25   Time: 17:40
Sample: 1985 2023
Included observations: 37

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNTCE(-1))	0.539398	0.165237	3.264386	0.0031
D(LNGDP)	-6.949467	1.263760	-5.499038	0.0000
D(LNGDP(-1))	1.310977	0.402237	3.259220	0.0031
D(LNGDP2)	0.447438	0.080502	5.558071	0.0000
D(LNURB)	31.70529	5.643437	5.618081	0.0000
CointEq(-1)*	-1.438154	0.247877	-5.801884	0.0000

Appendix 4.3: Diagnostic Checking

Appendix 4.3.1.1: Jarque-Bera Test



Series: Residuals
Sample 1987 2023
Observations 37

Mean	-1.34e-14
Median	-0.002380
Maximum	0.200963
Minimum	-0.131894
Std. Dev.	0.069006
Skewness	0.705882
Kurtosis	3.994753
Jarque-Bera	4.598193
Probability	0.100349

Appendix 4.3.1.2: LM Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.621854	Prob. F(2,24)	0.5454
Obs*R-squared	1.822917	Prob. Chi-Square(2)	0.4019

Appendix 4.3.1.3: ARCH Test

Heteroskedasticity Test: ARCH

F-statistic	0.623515	Prob. F(1,34)	0.4352
Obs*R-squared	0.648303	Prob. Chi-Square(1)	0.4207

Appendix 4.4.1:Cointegration (Robustness Checking)

Appendix 4.4.1.1: FMOLS

Dependent Variable: LNTCE
Method: Fully Modified Least Squares (FMOLS)
Date: 08/20/25 Time: 17:43
Sample (adjusted): 1986 2023
Included observations: 38 after adjustments
Cointegrating equation deterministics: C
Long-run covariance estimate (Bartlett kernel, Newey-West fixed
bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP	-2.329039	0.342977	-6.790652	0.0000
LNGDP2	0.130401	0.035535	3.669685	0.0009
LNURB	3.951409	1.148719	3.439839	0.0016
RENEWABLES EQUIVALENT PRI...	-0.086208	0.015845	-5.440615	0.0000
C	-62.82105	21.54211	-2.916198	0.0063

R-squared	0.987846	Mean dependent var	5.787647
Adjusted R-squared	0.986373	S.D. dependent var	0.870573
S.E. of regression	0.101627	Sum squared resid	0.340824
Long-run variance	0.012442		

Appendix 4.4.1.2: DOLS

Dependent Variable: LNTCE
Method: Dynamic Least Squares (DOLS)
Date: 08/20/25 Time: 17:43
Sample (adjusted): 1987 2022
Included observations: 36 after adjustments
Cointegrating equation deterministics: C
Fixed leads and lags specification (lead=1, lag=1)
Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth
= 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP	-2.298951	0.250734	-9.168868	0.0000
LNGDP2	0.115504	0.025001	4.619999	0.0002
LNURB	4.726559	0.736351	6.418893	0.0000
RENEWABLES___EQUIVALENT_PRI...	-0.031012	0.011894	-2.607361	0.0173
C	-79.14719	13.92984	-5.681846	0.0000

R-squared	0.995964	Mean dependent var	5.789001
Adjusted R-squared	0.992566	S.D. dependent var	0.846290
S.E. of regression	0.072968	Sum squared resid	0.101163
Long-run variance	0.001438		

Appendix 4.4.1.3: CCR

Dependent Variable: LNTCE
Method: Canonical Cointegrating Regression (CCR)
Date: 08/20/25 Time: 17:44
Sample (adjusted): 1986 2023
Included observations: 38 after adjustments
Cointegrating equation deterministics: C
Long-run covariance estimate (Bartlett kernel, Newey-West fixed
bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP	-2.160304	0.290698	-7.431433	0.0000
LNGDP2	0.128134	0.035938	3.565414	0.0011
LNURB	3.533094	1.073874	3.290045	0.0024
RENEWABLES EQUIVALENT PRI...	-0.083203	0.016136	-5.156359	0.0000
C	-55.62219	20.41576	-2.724473	0.0102

R-squared	0.987751	Mean dependent var	5.787647
Adjusted R-squared	0.986267	S.D. dependent var	0.870573
S.E. of regression	0.102022	Sum squared resid	0.343480
Long-run variance	0.012442		