EXPLORING THE MODERATING ROLE OF GREEN INVESTMENT IN CHINA'S ENERGY PRODUCTION FOR ECOLOGICAL FOOTPRINT REDUCTION

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

(4) The word count of this research report is 12370 words.

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DEDICATION

We dedicate this project to all those who have guided, supported, and inspired us throughout this journey:

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PREFACE

In recent decades, China's unprecedented economic growth has been powered overwhelmingly by fossil fuels, leaving it with the world's largest ecological footprint and mounting pressure to reconcile prosperity with planetary limits. At the same time, the country has injected record sums into green finance—through green bonds, credit programs and pollution-treatment investments—in an effort to accelerate its transition toward cleaner energy. Yet questions remain about how, and to what extent, this influx of green capital actually changes the environmental impact of both renewable and non-renewable energy production.

This study explores whether green investment acts as a true "game-changer" in China's energy mix—magnifying the benefits of renewable sources and softening the costs of fossil fuels—to bring the nation closer to a sustainable development path. Drawing on time-series data from 1990 to 2022, we first test the Environmental Kuznets Curve hypothesis for China's ecological footprint and then introduce interaction terms between green investment and energy outputs to capture any moderating effects.

By shedding light on the real-world interplay between policy-driven green finance and energy-sector emissions, our findings aim to inform policymakers and investors alike: pinpointing which forms of green investment deliver the greatest environmental dividends and guiding more effective strategies for curbing China's ecological footprint as its economy continues to expand.

ABSTRACT

This study investigates how green investment (GI) moderates the relationship between China's energy production—both renewable (RE) and non-renewable (NRE)—and its ecological footprint (EFP) over the period 1990–2022. Drawing on annual data from the Global Footprint Network, International Energy Agency, and CEIC, we employ an autoregressive distributed lag (ARDL) bounds-testing framework to test for cointegration and estimate both long- and short-run dynamics. Our findings confirm a stable long-run relationship among EFP, energy production, GI, GDP, GDP^2, and population density. While GI and RE individually exhibit paradoxical positive effects on EFP—reflecting implementation costs and land-use impacts—the interaction term (REGI) significantly reduces EFP, supporting GI's role as a moderator in expediting ecological benefits from renewable energy deployment. These results underscore the importance of policy measures that simultaneously scale green finance and renewable capacity, such as targeted subsidies, carbon pricing, and technology incentives, to maximize ecological gains and guide China's transition toward sustainable energy production.

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EFP	Ecological Footprint
RE	Renewable Energy Production
NRE	Non-Renewable Energy Production
GI	Green Investment
GDP	Gross Domestic Product
PD	Population Density
REGI	Interaction term between Green Investment and Renewable Energy
NREGI	Interaction term between Green Investment and Non-renewable Energy
EKC	Environmental Kuznets Curve
ARDL	Autoregressive Distributive Lag

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Chapter 1: Introduction

1.1 Research Background

Amid the growing environmental concern, the pressure of human activity such as development, deforestation, consumption and so on and the growing demand for natural resources has crossed the limit of the Earth's capacity to sustainably meet these ongoing needs to maintain their living. The concept of ecological footprint has arisen as a crucial indicator for understanding and measuring human activity's impact on the environment (Raihan et al., 2022a; Jie et al.,2023). It measures the availability of the Earth's productive land and water areas used to support the human lifestyle by taking into account cropland, grazing land, fishing ground, built-up land forest area, and carbon demand on land (Global Footprint Network, 2024). Wackernagel and Rees (1996) have taken into account water and soil pollution in addition to air pollution to develop a more comprehensive environmental pollution indicator, hence, the ecological footprint indicator has emerged. For instance, water is one of the major resources that are declining significantly. Even though 70% of the Earth's planet is water, only a mere 2.5% of the 70% is fresh water and can be used (The World Counts, 2024a). Food and Agriculture Organization of the United Nations (2013) also predicted that by 2025, it is expected that 1.8billion people will be living in countries or regions with "absolute" water scarcity, and about two-thirds of the global population could live under the "stress" condition of water scarcity.

Additionally, natural resources such as fossil fuels are being exhausted at a concerning pace. The worldwide proven oil reserves amounted to 1723 billion barrels by the end of the year 2021, showing a decrease of 2 billion barrels compared to 2019 (The British Petroleum Statistical Review of World Energy, 2021). The worldwide resources-to-production ratio indicates that oil reserves were only sufficient to sustain an average of 51 years of current production. Ecological footprint is a comprehensive indicator of human activities' impact on ecosystems that is gaining traction in sustainable development globally (Ji et al., 2020; Yilanci

& Pata, 2020). Thus, when the ecological footprint index is relatively high, it indicates that the supply of natural resources is having bigger difficulty in meeting the demand for natural resources. Also, the ecological footprint also measures the extent to which human resource consumption exceeds environmental boundaries (Yilanci & Pata, 2020).

Since 1971, the global ecological footprint has been growing at a rapid pace, reaching a staggering 1.71 Earths by 2022 and it is expected to grow continuosly (Global Footprint Network, 2024). This trend indicated that the global demand for resources and waste absorption now exceeds the Earth's capacity by 1.71 times, highlighting that people live beyond the Earth's capacity. The global trend of ecological footprint varies significantly across countries and areas. High-income countries tend to exhibit a relatively high ecological footprint in comparison to low-and-medium-income countries (Moinuddin & Olsen, 2024). For example, high and upper-middle-income countries like China, the US, Russia, Brazil, and Japan often constitute the largest ecological footprints in the world. For instance, the latest data of ecological footprint of China is 2.4 of Earth. China leads with a staggering 5.1 billion global hectares, followed by the US with 2.6 billion, Russia with 848 million, Brazil with 551 million, and Japan with 553 million global hectares (Global Footprint Network, 2024).

Economic development which is significant throughout human development history has contributed to the global ecological footprint (Castro, 2005; Bertoletti et al., 2022). The carbon footprint is the main component of the global ecological footprint with the constitution of 60% of humanity's overall Ecological Footprint and is the most rapidly growing component. (Global Footprint Network, 2024). During the industrial development process, intensive exploitation and utilization of natural resources have led to widespread environmental pollution and ecological degradation on a global scale. For example, China, the United States, and India are leading contributors to global carbon dioxide (CO_2) emissions from fossil fuel combustion with 10, 648.54Mt, 4 549.259Mt, and 279.007 Mt respectively (International Energy Agency, 2024).

Energy combustion is one of the necessary cornerstones of economics and industrial development which leads to emerging CO_2 emissions (U.S. Department of Energy, 1999). Besides, the International Energy Agency (2023) also emphasizes that global CO_2 emissions as a result of energy combustion and industrial activities increased by 0.9%, equivalent to 321 million metric tons, reaching a record high of 36.8 gigatons. In 2023, the CO_2 emissions grew again by another 1.1%, mainly due to the economic recovery and rise in fossil fuel consumption and production from the COVID-19 pandemic. Consequently, because of these increased emissions, the world has experienced a significant global climate change. McKinesy and Company's report by Nivard et al. (2023), highlighted that over more than half a year, from July 1 to January 1, the global average temperature exceeds the 1.5 °C threshold on 182 out of 184 days. This increase in the temperature is mostly caused by a short-term El Niño effect, which has pushed 2023's global warming to a critical 1.48°C above the pre-industrial levels

Not only that, urbanization process also contributes a significant portion of the total global ecological footprint as this process requires a large area of productive land or built-in land to convert into a built environment. On a national scale, urbanization has a limited impact on land cover, but it still leaves a substantial ecological footprint. Even a small-scale urban development can significantly impact the stream ecosystem (US Environmental Protection Agency, 2024). The world loses nearly 6 million hectares of forest land on average due to deforestation. In light of this, it can be described as losing a piece of land size equivalent to Portugal in every two years and alarmingly, a staggering 95% of this destruction happens in tropical regions (Ritchie, 2021). Besides, the global forest area in million hectares has been steadily decreasing, reaching an emerging low from the original 4.24 billion hectares in 1990 to of 4.05 billion hectares in 2021 (Salas, 2024). that urban land usage is expected to expand with approximately 1.2 million square kilometres of underdeveloped land to be added to the global by 2030 (World Bank Group, 2023).

This urbanization causes permanent destruction and fragmentation of habitats. For example, deforestation and fragmentation of forest lands lead to the deterioration and damage of forest interior habitat. The International Union for Conservation of Nature's Red List report (2021) remarked that 28% of the global species are classified as being at risk of extinction. Certain social animals namely, amphibians (41%), sharks (31%), and corals (33%) have been recognized as being significantly exposed to extinction risks observed since 1990 due to excessive development.

Thus, this heightened alert on environmental damages elevates the importance of renewable energy production. Green energy aims to reduce the ecological footprint by lowering carbon emissions and minimising air and water pollution. According to the International Renewable Energy Agency (2024), renewable energy provides over 90% of necessary reductions in energy-related carbon emissions. The share of renewable energy in global electricity production has been showing an escalating trend over the last 10 decades. In 2020, the proportion of renewable energy in electricity production plunged to approximately 29%, reflecting an increment from 27% in 2019. The shares of renewable energy in electricity production globally have further expanded by 10% in 2021, the fastest year-on-year growth since the 1970s (International Energy Agency, 2021). Moreover, renewable energy capacity has also noticed growth further propelled by supportive policies and growing public awareness. For example, in 2022, several key policies have been announced concerning clean energy, particularly REPowerEU in the European Union, the Inflation Reduction Act (IRA), in the United States, and China's 14th Five-Year Plan for renewable energy has promoted the acceleration in renewable energy adoptions (International Energy Agency, 2024). However, it is still a global challenge to balance rapid economic development with environmental stability, as most countries depend on fossil fuels as a major element to meet growing energy demands. According to Ritchie and Rosado (2024), over 70% of the global energy demand is sufficed by non-renewable primary energy sources such as oil, coal, natural gas, and nuclear, which constitute 29.78%, 24.87%, 21.89%, and 3.72%, respectively.

1.2 Problem Statement

China's rapid industrialization is coupled with a high environmental cost particularly affecting its land and water resources. To elaborate, ever since China has opened its economy in 1978 and does international trading, its economy has been growing at an average of gha every year (World Bank, 2024). Consequently, China has the greatest ecological footprint among all countries in the world which amounts to 5.3 billion gha. It has a biocapacity of 1.3 billion hectares, making it the second-largest in the world after Brazil (World Population Review, 2024). However, because of its high population, China has a total ecological deficit of 4 billion gha and a per-capita biocapacity reserve of -2.79 in 2017. In 2013, China's per capita ecological footprint peaked at 3.43gha per person, dropping to 3.26gha per person by 2016. Hence, it is crucial to examine the factors that impact ecological sustainability in China.

Besides, China has an ambitious commitment to global climate goals to balance its energy production with sustainable development. For instance, China is one of the first few that ratify the Paris Agreement and its president, Xi Jinping had pledged to peak carbon emissions in 2030 and has an ambitious target to reach carbon neutrality by 2060 (Liu et al., 2023). However, China is still the world's largest energy production country with 3,190 Mtoe of energy production (Enerdata, 2024). As a result, China's substantial energy production made it the world's top emitter of greenhouse gases, generating over a quarter of the world's annual greenhouse gas emissions, significantly contributing to climate change which could subsequently lead to ecology degradation and ultimately worsen the ecological footprint across the country over time (Andrew et al.,2021).

China's energy landscape is critical in its environmental challenges. A report stated that China was the top energy producer and consumer in the world. In 2022, China's energy production experienced a notable increase of over 6%, with growth observed across various energy sources, including renewable energy. Despite the increasing emphasis on renewable energy, it still constitutes a minor component of China's energy mix (U.S Energy Information Administration, 2023). Moreover, the total CO_2 emissions from electricity generation in China had increased from 2,439.9 million tons of CO_2 in 1991 to 9,974.3 million tons in 2020, and this trend is expected to upward growth (Li et al., 2024). Looking ahead, another report on

China's carbon emission showed that the situation appears even more concerning as China likewise holds the record for the highest cumulative carbon emissions globally, contributing 22% of the world's total emissions between 1990 and 2020 (China Power Team, 2023).

The validity of the Environmental Kuznets Curve (EKC) is particularly crucial for understanding the trajectory of environmental degradation in rapidly developing countries like China. Consecutively, a study conducted on China using data between 1960 and 2020, showed that energy diversification stands valid in the EKC hypothesis in reducing carbon emissions (Zahra & Fatima, 2024). If the EKC hypothesis stands valid for China, this would prove the country has yet to reach its critical point, or rather, green investment is not valid in the EKC hypothesis for the country. As a result, fossil fuel production (and consumption) has increased the death toll and social costs of the country. As a result, annual fatality in China reaches around 2 million people who have died from air pollution (World Health Organisation, 2024); another study showed that that around 100,000 people have died from water pollution each year in China (Buntaine et al., 2021).

In contrast to China, several major economies have already made notable strides in reducing their carbon emissions. For example, the United States, which stands as another trade giant on the global stage next to China, is already witnessing decreasing carbon emissions, coming to a total of less than half of China's emissions at less than 5 million kilotons in 2020. The third biggest carbon emitter in the world, India, had also witnessed a decreasing carbon emissions trend, reaching less than a quarter of China's carbon emission, at 2.2 million kilotons in the same year. Amidst this urgent situation, one of the surfacing solutions is through the effective application of green investment and employing higher levels of renewable energy production (World Bank, 2023).

Despite the many benefits of utilizing renewable energy production to promote environmental conservation, there are challenges to resisting its adoption in China. According to Chen et al. (2023), China's economy remains heavily dependent on traditional energy sources. For example, the country's coal industry remains deeply entrenched in its economic growth. In 2022, 61% of China's total energy supply still came from coal, next to it are oil at 17.9% and natural gas at 7.8% (International Energy Agency, 2024). In response to mounting climate challenges and difficulties in adopting renewable energy production, China has launched the green financial policy under the '1+N' framework, a strategic approach aimed at enhancing its green financial sector and accelerating its efforts to peak carbon emissions by 2030. The emergence of the green investment market provides some excellent options that are growing rapidly in China such as green bonds, recorded at 440.1 billion yuan in 2021 (Climate Bonds Initiative, 2022); green credit, recorded at 15.9 trillion yuan in 2021 (Statista, 2024). However, despite numerous green incentives, the country has struggled to curb its growing energy demand and consequent emissions. In China, the green bond market is still in the early stage, indicating that the green bond market is not mature enough to ensure comprehensive and full reporting on the allocation of the proceeds (Escalanate et al., 2020).

1.3 Research Questions

1. Is the EKC still valid for China after considering the role of green investment in renewable energy production?
2. Is the EKC still valid for China after considering the role of green investment in non-renewable energy production?
3. Does green investment play a moderator role in influencing the impact of renewable energy production on the ecological footprint in China?
4. Does green investment play a moderator role in influencing the impact of non-renewable energy production on the ecological footprint in China?

1.4 Research Objectives

1. To examine the validity of the EKC hypothesis for China, after considering the role of green investment in renewable energy production.
2. To examine the validity of the EKC hypothesis for China, after considering the role of green investment in non-renewable energy production.
3. To examine whether green investment acts as a moderator in influencing the impact of renewable energy production on the ecological footprint in China.

4. To examine whether green investment acts as a moderator in influencing the impact of non-renewable energy production on the ecological footprint in China.

1.5 Significance of Study

If the study confirms the validity of the EKC hypothesis after considering the role of green investment in renewable and non-renewable energy production, the government will stand to benefit. This insight would empower the government to craft targeted policies that leverage economic growth to drive environmental improvements. For example, if green investment magnifies the positive impact of renewable energy production, the government could introduce and scale up green investments in key sectors, such as green energy and manufacturing, to accelerate the green energy transition to a lower ecological footprint as China's economy grows. Such policies might include tax incentives for renewable energy projects, subsidies for green technology adoption, and stricter environmental regulations encouraging industries to innovate and reduce their emissions. Conversely, if the green investment minimizes the negative consequences of non-renewable energy production, the government could reinforce the environmental restriction on the non-renewable energy production by the industries. The Chinese government could also restructure their carbon pricing mechanism, such as introducing a more comprehensive carbon tax.

If the expected finding shows that renewable energy production impacts ecological footprint and green investment plays a moderating role, it would be useful for government agencies to know how green investments may enforce the positive effects of renewable energy production. For example, the government can design concrete actions, which may include offering incentives to producers of renewable energy or allocating money to encourage private capital investment in green technologies that minimize the human impact on the environment. When the government provides incentives to invest in renewable energy sources such as solar, wind and hydropower, it becomes financially possible for energy producers to transition from non-renewable energy sources to renewable types. This flow of funds into cleaner energy projects means that the carbon intensity of energy produced in the country reduces, thus reducing the ecological footprint.

On the other hand, if the finding indicates that non-renewable energy production affects the ecological footprint and green investment plays a moderating role, there would be a different implication. For example, if green investment mitigates the negative impact of non-renewable energy production on ecological footprint, the government may enhance the efficiency of non-renewable production and slow down the investment in energy transition. This makes logical sense in the short run too because China is still mainly dependent on non-renewable energy sources to produce power. Such initiative may direct movement to R&D efforts to increase the efficiency of non-renewable energy production and installations of activated carbon filters in energy stations such as coal plants to reduce carbon footprint.

Chapter 2: Literature Review

2.1 Green Investment and Ecological Footprint

As the world takes an urgent stance to transition towards sustainable development, environmental regulations have become a vital tool to encourage industries to adopt greener practices and technologies. Porter's hypothesis states that strict environmental regulations stimulate the demand for more green investment toward efficient production and using greener technologies (Porter & Linde, 1995). Testa et al. (2011) conducted a study in the building and construction sector in the EU region and they concluded that a stringent environmental policy has pushed more investments toward innovative products and improved business performance.

China's proactive environmental policies have shown promising results, especially in the reduction of air pollutants. Placing this in mind for China which launched its "war on pollution" in January 2014, the country was able to minimize its particulate pollution by almost 30 percent. Additionally, more than half of the world's reduction of particulate pollution in five years between 2013-2018 came from China (Greenstone & Fan, 2020). Following the Paris Agreement, China has pumped abundant resources and supportive policies that have grown its prime example in green energy production, which is solar. According to Li and Huang (2020), China has decreased its solar installation cost by 80% since 2014 and is accounting for one-third of the world's global solar power in 2017. This has majorly contributed to China's ability to decarbonize its energy system, which in turn reduce the global ecological footprint (Lu et al., 2021).

Alternatively, ecological can also be reduced when green investment has been directed to promote circular economy practices. For instance, Mazzucchelli et al. (2022) who conducted a study on 404 large-sized Italian manufacturing firms, found that firms that adopted circular practices by following the 3R concept have effectively reduced their environmental impact. Moreover, green investment could also be injected into producing recycling technologies that could reduce resource extraction. Take phosphorous for example, which is a limited yet essential resource, Seyhan et al. (2012) proved that recycling can postpone its depletion cost and maintain a low consumption forever. Huangfu et al. (2024) pointed out that this could be advantageous for China, knowing it is the biggest white phosphorous producer in the world and is urgently seeking green transformation for this substance.

China's transition toward a circular economy has been demonstrated by its efforts to integrate sustainability into its industrial field. For example, Guiyang, one of the most resource-dependent cities that heavily relies on resource mining and processing, has majorly depleted its natural resources causing huge environmental degradation. Nevertheless, in a study where the city has taken the sustainable approach of using an industrial symbiosis strategy (waste of one company becomes raw materials for another company) has shown successful resource saving and, decrease in waste and CO_2 emission (Li et al., 2015). Aside from that, China had also approved the National Demonstration Eco-Industrial Parks and has since involved around 90 industrial parks in the change to play a crucial role in circular cities to spur industrial innovation and achieve ecological advancement (Bleischwitz et al., 2022).

Despite the advantages of green investment, several studies pointed out the potential drawbacks, such as the unintended consequences of increased green investment. This can be illustrated as the rebound effect. Berkhout et al. (2000) concluded that when the energy efficiency gains from technological innovation drive the price lower, it would inflict a higher level of consumption; A. Greening et al. (2000) conducted on residential data from the United States also reviewed the rebound effect and saw an offset in environmental benefits when energy becomes more efficient; Lin and Liu (2015) conducted research on both China's rural and urban residential buildings concluded that urban areas consume more energy and, thus, greater rebound effect. China could have conserved 20% of electricity consumption in residential buildings had they had the appropriate energy and pricing policies.

The nature of human behavior can be another caveat that leads to an unsuccessful implementation of green investment. While the rebound effect is one unintended consequence that arises from green investment, there are also grounds to discuss the potential green paradox effect. Sinn (2012) argued that green investment may indirectly increase in fossil fuel consumption temporarily from future anticipation of a potential restriction or taxes on carbon emissions and it must be accompanied by simultaneous policies on carbon pricing to offset this paradoxical effect. He called this the Green Paradox effect. Ecological footprint could increase globally; Jensen et al. (2015) observed that a failure in the U.S. carbon cap could have a spillover effect and leak to world markets, making changes to carbon emissions outside of the country. Wei et al. (2022) mentioned that China does not have a carbon tax at the moment although many have advocated this idea, because it would place a heavy burden on companies, consecutively the economy, and its people's income. However, the anticipation of lower demand in the future could cause an increase in energy supply and consumption (Lai et al., 2022).

Conversely, effective planning is key to maximizing the benefit of green investments, ensuring are directed towards relevant projects that contribute positively to environmental sustainability. To illustrate the opposite, Zhang et al. (2021) have pointed out that inappropriately managed green investment causes a positively correlated relationship between green investment and ecological footprint. To elaborate, China has taken steps to promote its energy security by employing bioenergy. However, growing these energy crops would deepen the problem of deforestation and displace the high-quality land available for food crops. Nevertheless, biofuel crops have great cultivation in non-grain-producing areas, but they require careful strategies and utilization for these crops (Cao et al., 2022).

2.2 Renewable Energy Production on Ecological Footprint

In response to increasing environmental degradation and the urgent need to shift from carbon-intensive practices, renewable energy has emerged as a critical instrument for reducing the ecological footprint and fostering sustainable development. Scholars have broadly examined the relationship between renewable energy and ecological footprint, with consistent findings that the adoption of renewable energy can significantly reduce environmental pressures. Pata (2021), employed the Fourier cointegration ARDL test on data from BRICS countries spanning 1971 to 2016, the study found that renewable energy consumption plays a key role in minimizing environmental pressure. Li et al. (2023), who employed quantile regressions and pairwise causality analysis using an updated and extensive dataset from 1988 to 2021 in China, they found that enhancing and investing in renewable energy usage effectively reduces ecological footprint across different quantiles.

In China, which is the largest emitter of CO_2 globally, the government has made vast investments in renewable energy technologies to mitigate the nation's ecological impact. The aggressive expansion of solar and wind capacity has helped China reduce the carbon intensity of its energy system. China contributed to nearly half of global renewable energy capacity additions in 2022, with solar photovoltaics and wind power being the leading sectors. This transition has played a vital role in improving air quality, reducing land degradation caused by coal mining, and lessening dependency on polluting fossil fuels. For instance, Gao et al. (2021) used the life cycle assessment and found that while wind power is the most effective in reducing ecological footprint. They also found that solar photovoltaic power reduces emissions and increases biomass power to contribute to lowering CO_2 emissions. Sharif et al. (2021) also found that solar energy significantly contributes to reducing ecological footprint scores in China, with the strongest impact observed at higher levels of solar energy use and lower levels of ecological footprint using quantile-on-quantile (QQ) regression. Besides, Nan et al. (2022) employed a vector autoregressive model from 2000 to 2019, and the findings reveal that renewable energy such as photovoltaic, wind energy, and biomass energy exerts a long-term negative effect on the ecological footprint.

Despite the consensus on its benefits, the impact of renewable energy on ecological footprint is not universally positive unless supported by appropriate factors. For instance, Li et al. (2022) employed threshold panel regression model using data from 120 countries spanning the past 20 years found that renewable energy reduces ecological footprint and supports economic growth, but its effectiveness varies with the level of urbanization and income group, showing stronger environmental benefits after urbanization crosses certain thresholds and in regions with better energy efficiency and development conditions. Besides. Azimi and Rahman (2024), who employed the same model in the context of 74 developing countries from 2000 to 2022. They found that renewable energy could reduce ecological footprint by lowering environmental degradation, but its effectiveness depends on achieving certain thresholds in fiscal capacity, human development, institutional quality, and population density.

2.3 Non-Renewable Energy Production on Ecological Footprint

Recently, there has been growing traction in studying natural resources and ecological footprints (Danish et al., 2020; Abbasi et al., 2021; Jahanger et al., 2022). Human activities are the main driving force behind environmental degradation. CO_2 are used as indicator to represent environmental degradation, which serves as a proxy for the ecological footprint (Shabir et al., 2021; Akpanke et al., 2024). The ecological footprint index included a different dimension of factors such as cropland, forest area, carbon demand on land, fishing grounds, grazing land, and built-up land (Alvarado et al. 2022). Azam et al. (2023) revealed that the ecological footprint has expanded dramatically in recent years, primarily due to the production of produce excessive waste and pollution by human activities that encompass energy production. World Energy and Climate Statistics – Yearbook (2024), claims that energy production means the quantity of natural resources extracted for energy production. Danish et al. (2020) posited that economic development boosts the industrialization process, which in turn leads to greater extraction of natural resources. The extraction and exploitation of natural resources increase at the same rate as income, resulting in a decline in biocapacity and, ultimately, an increase in the ecological footprint. Humanity is depleting scarce resources that have surpassed the Earth's ability to regenerate them while also producing waste that exceeds the planet's natural capacity to dispose of them (Akif and Sinha, 2020; Danish et al., 2020; Nathaniel, 2020). When these carbon-based resources such as fossil fuel, coal, and natural gases, are combusted, they emit a significant amount of carbon emission, which heavily depletes the atmosphere (Zhao et al., 2021; Hanif et al., 2019; Zhao et al., 2022). Moreover, they have concluded that the CO_2 emissions are closely related to energy consumption patterns and economic growth by using the autoregressive distributed lag model in Indonesia (Yahya et al., 2023; Idroes et al., 2023). Sharma and Kautish (2020) also examined how electricity generation from oil and coal affects CO_2 emissions, focusing on India from 1976 to 2016. They concluded that both types of power plants significantly contribute to environmental degradation by releasing greenhouse gases.

Liu et al. (2020) noted that high-emitting industries production for steel, cement, chemical and other industries in China that are heavily reliant on fossil fuel energy for their production process are the major contributors to greenhouse gas emissions, as a significant amount of CO_2 was produced during the process in 2019. Lin and Jia (2020) further analysed how coal-based electricity in China impacts energy, economy, and the environment. In China, coal is heavily used for heating during winter. However, combusting coal directly for heat, instead of converting it into electricity, also produces even higher levels of CO_2 emissions, bringing more harmful impacts to the environment. Though generating electricity from coal releases relatively less CO_2 than burning coal directly for heat, the electricity generation from coal is not far less polluting as it generates millions of BTUs of energy output, emitting significant CO_2. In this way, while coal-based electricity is used as a tool for controlling emissions, it also remains a major source of CO_2 pollution. Zhang et al., (2023) reconfirmed that electricity production from fossil fuel and CO_2 emissions are positively correlated, which generally harms the environmental balance and degrades the natural resources. However, they also found that coal-fired plants are the most destructive, as coal combustion releases the highest amount of CO_2 emissions among all fossil fuels such as oil and nuclear.

Besides that, there are several studies that focused on the non-renewable energy in the environmental aspect. The increased of reliance on non-renewable energy significantly reduced environmental sustainability, thereby leading to the urgent requirement for the strategies in using renewable energy (Sherif et al. 2022; Khan et al., 2019; Hassan et al., 2019; Dehdar et al., 2023; Chu et al., 2023; Zhang et al., 2022). Furthermore, Xu et al. (2022) underlined the importance of monitoring non-renewable energy production to reduce the ecological footprint and discourage rent-seeking behavior and uncertain economic policies. By effectively strategizing and overseeing non-renewable energy production, resource extraction can be done responsibly with respect for the environment. Hence, it can reduce the ecological footprint.

2.4 Moderator Role of Green Investment Toward Ecological Footprint

Numerous studies have revealed that those regions and countries with more green investment have a lower ecological impact, even as they grow economically. Such a trend suggests that green investment is not only an additional component of economic growth, but also a factor that can shape growth in a more sustainable manner. For instance, Danish et al. (2020), who employed fully modified ordinary least square and dynamic ordinary least square estimators on BRICS economies for the period from 1992 to 2016. They found that the function of green investment reduces the ecological footprint, implying that green investment has a positive contribution to environmental quality. Besides, Suki et al. (2022) also discussed how technology innovations, a proxy for green investment, play a significant role in sustaining the environmental integrity of sustainable development in Malaysia during the period from 1971 to 2017. Bergougui (2024) also found that green technology reduces ecological footprint, from 1990 to 2021 in Algeria.

The moderating function of green investment on the relationship between research and development (R&D) expenditure and ecological footprint is based on the endogenous growth theory proposed by Romer (1989). The theory considers the key economic growth determinants lie within innovations, human capital, and knowledge. In this case, green investment directs the financial resources towards funding the R&D process, enabling the constant creation of technological innovation that maintain the long-term economic growth and reduce the ecological footprint. For instance, the expenditure on R&D contributes positively to the reduction of CO_2 emissions in the EU-15 and the US (Fernandez et al., 2018). In addition, Alvarado et al. (2021) analysed a sample of 77 countries and investigated how R&D spending contributes towards the reduction of ecological footprint over the time frame of 1996–2016. They concluded that R&D expenditure has a negative relationship with ecological footprint. The outcomes of investment in environment-related technologies in a sustainable environment, Khan et al. (2022) discussed the conditions in Canada, they established that this investment in Canada helped in combating environmental deterioration. Furthermore, Li and Xu, (2023) used the annual data in BRICS countries from 1990 to 2020. They authors concluded that green investment positively influences the fiscal policy on ecological footprint from 1990 to 2018.

Technological innovation is another crucial pathway through which green investment plays a moderating role in reducing the ecological footprint. Green investment plays a role in fostering technological innovation by providing the necessary financial resources and incentives for research, experimentation, and commercialization of eco-friendly technologies. For instance, Xu et al. (2022) discussed the adoption of energy-efficient technologies in industries significantly lower non-renewable energy use and reduce the ecological footprint in Turkey using the yearly dataset spanning from 1980 to 2019. Ahmad et al. (2021) showed that technology innovation moderates the effects of ecological footprint in G-7 countries over 1980 to 2016. Besides, Hosan et al. (2020) analysed that the technological innovation has facilitated the improvement of ecological footprint using environmental quality as proxy in Asian countries of 1985 to 2014 and found a strong inverse relationship between technology innovation and ecological footprint. Satrovic et al. (2024) also found consistent result with Jahanger et al. (2022) in the case of green investment serves as moderating function towards ecological footprint.

Renewable energy investment, particularly in wind and solar technologies, has a positive impact on ecological footprint by reducing dependence on carbon-intensive energy sources and minimizing environmental impacts. Green investment, as moderator function, shifts energy production towards cleaner alternatives, resulting in lower greenhouse gas emissions and less strain on natural resources. For example, Zhang et al. (2022) revealed how the application of technology innovation negates the impact of urbanisation on the environment in the course of 1990–2018 in the BRICS countries, suggesting that technology innovation further reducing the deterioration of the environment. Moreover, Haldar and Sethi (2022) indicated that technological innovation reduces environmental pressure and enhances environmental quality. Raihan et al. (2022) also found that technological advancement helps initiate improvements in the ecology in Bangladesh for the period of 1990–2019.

The above literature review revealed that green investment acts as a moderator towards ecological footprint. Therefore, we propose the two hypotheses as follows:

Hypothesis 1: Green investment moderates the impact of renewable energy production on ecological footprint.

Hypothesis 2: Green investment moderates the impact of non-renewable energy production on ecological footprint.

2.5 Environmental Kuznets Curve (EKC) Hypothesis for Ecological Footprint

The Environmental Kuznets Curve (EKC) Hypothesis was first introduced by Grossman and Krueger in the year 1991 (Shahbaz et al., 2019). In EKC, it suggests that when a country develops economically, its environmental condition will tend to worsen at the early stage. However, as the economy expands, there is an increasing awareness among households and the government regarding environmental concerns. Consequently, measures are taken to address these issues, ultimately reducing environmental degradation (Prasad, 2024). In simple words, as economic growth, environmental damage tends to increase. However, after reaching the curtain threshold level, this movement of trend reverses, and environmental degradation starts to decline. This relationship can be illustrated as an inverted- U-shaped curve.

The relationship between pollution and income is influenced by three key factors: scale, composition, and technical. Firstly, the scale effect indicates that when the production level rises, it tends to drive up the pollution level. While the composition effect reflects a sectoral transformation in economies. For instance, during the sectoral transformation like agricultural to industry, the environment tends to degrade along with this transformation. While the technical effect is illustrated when the economy evolves again from the industry sector to services, pollution typically reduces after reaching certain maximum level of industry growth and environment at the stage of industry economies.

In earlier studies, there are numerous researchers studied the cause of environmental degradation by using CO_2 emissions as a proxy for environmental degradation and they have shown there is a correlation between these two variables (Chaabouni, Zghidi, Mbarek, 2016; Shahbaz, Jamel et al., 2016). However, CO_2 emissions provide very limited insight into the extent of environmental degradation because it is limited to the measurement of air quality. Hence, there has been a notable movement in scholarly focus toward using ecological footprint as another proxy for environmental degradation due to its comprehensiveness and extensive dimension (Aydin et al., 2019; Destek & Sarkodie, 2019; Wang & Dong, 2019).

The past studies on ecological footprint and economic growth shown a mixture result as compared with CO_2 emission. A study by Al-Mulahi et al. (2015), who have explored the EKC hypothesis across 93 different countries using panel data with ecological footprint as the dependent variable. In their studies, they found that the EKC is valid for high and middle-income countries, but it does not hold for lower middle and low-income countries. Similarly, Ozturk et al. (2016) also found a coincide result to Al-Mulahi et. al(2015) by testing the correlation between ecological footprint, tourism GDP, foreign trade volume, urban population, and energy consumption across 144 countries from 1988 to 2008 with the time-series generalized method of moment and stochastic generalized method of moment.

Moreover, researchers have shown that economic growth has an inverted U-shaped effect on ecological footprint. For instance, Asıcı and Acar (2016a) analysed the relationship between ecological footprint, biocapacity, GDP, trade openness, population, industry share, ecological regulation, and energy by using the

FE econometric method in 116 countries. Charfeddine and Mrabet (2017) used a panel analysis test for 15 MENA countries for the period from 1995 to 2007 on ecological footprint, GDP, energy usage, urbanization, fertility and life expectancy. Ulucak and Bilgili (2018) explored the correlation between GDP and ecological footprint across 45 low, middle, and high-income nations from 1961 to 2013 by using the second-generation panel data methods. Destek and Sarkodie (2019) discovered the casual relationship between ecological footprint, GDP, energy consumption, and financial development of 11 newly industrialized countries between the sample period 1977-2013. Lee and Chen's study (2020) on 123 countries spanning from 1992-2016 by using a quantile regression approach. This means that, after a certain level of development, the concern about Earth's resources has been apparent by people and thus, the ecological footprint has dropped eventually.

While numerous researchers likewise have shown the opposite result of EKC with ecological footprint. For instance, Bagliani et al. (2008) analyzed ecological footprint data from 141 countries in the year 2001 by utilizing both the Ordinary Least Squares and Weighted Least Squares methods as well as nonparametric regression analysis to examine linear, quadratic, and cubic relationships. Their findings indicate EKC relationship does not emerge when the ecological footprint is used as the dependent variable. Instead, they found that environmental stress tends to rise as income per capital increases. Besides, Wang et al. (2013), observed that both income levels and biocapacity play a significant role in affecting the ecological footprint. Similarly, Uddin et al. (2017) discovered that economic growth as measured by real income is positively correlated with ecological footprint. In other words, the income levels and the ecological footprint tend to move in the same direction. Also, Alola et al. (2022) conducted an analysis of the dynamics of ecological footprint for the period from 1971 to 2016 and they revealed that economic growth are positively correlated with ecological footprint.

In Qatar, Charfeddine (2017) further supported that the concept of ecological footprint is comprehensive. The author discovered a U-shaped relationship between GDP and ecological footprint, implying that when GDP increases, EP initially decreases before bouncing back. Destek and Shinha (2020) have examined the validity of the EKC across twenty-four OECD countries during the period from 1980 to 2014. Their result revealed that EKC did not hold for these countries, and they found evidence of a U-shaped relationship between economic growth and ecological footprint. Bagliani et al. (2008) have concluded that EKC hypothesis is invalid because by changing the localization of supply, environmental damage is shifted away from wealthier countries, suggesting that the changes in production often linked to the EKC, can occur not only through advancement in technology and changes in consumption but also through relocating supply chains in other regions.

The above literature review revealed the dynamic result of the EKC hypothesis in different countries with different periods. Therefore, we propose the hypothesis as follows:

Hypothesis 3: Green investment has a significant inverted U-shaped effect on the relationship between economic growth and the ecological footprint in China.

Chapter 3: Data and Methodology

3.1 Description and Source of Data

The ecological footprint is quantified by calculating the ecological footprint global hectare (gha) per person, using the data obtained from the Global Footprint Network. The ecological footprint consists of a more comprehensive measurement that is calculated by measuring the build-up land, CO_2 emission, cropland, fishing grounds, forest products, and grazing land. For the measurement of green investment (GI), we used another extensively utilized proxy, namely investment in industrial pollution treatment using the unit measurement of RMB billion. The data for this measurement was obtained from the Committee of Electronic Information and Communication.

Renewable energy production (RE) is measured by gigawatt hours (GWh). While non-renewable energy production (NRE) is assessed using terajoule (TJ), which is equivalent to 1 trillion joules. Both of these data are obtained from the International Energy Agency. Besides, gross domestic production (GDP) is measured by the GDP per capita in constant local currency units (LCU), which is obtained from World Bank Data. The measurement of population density (PD) which is quantified by people per sq. km of land area. The data for this measurement was obtained from World Bank Data.

The sample period for data collected spans from 1990 to 2022 in China. In order to reduce multicollinearity and heteroscedasticity in the regression models, natural logarithm transformation is applied to all variables. This approach helps stabilize variance, reduce the scale of the data, and enhance the interpretability of the coefficients, ultimately leading to more robust and reliable results in the analysis.

3.2 Model Specification

To determine the impact of independent variables (energy production and green investment) and control variables (economic growth and FDI) on ecological footprint, we need to construct an appropriate benchmark model for these variables. Based on the studies by Ansari (2022) and Zia et al. (2021), we establish the 2 frameworks to separate into two types of energy production (renewable energy and non-renewable) as shown in the following specification:

$$lnEFP_t = \mathrm{f}\,(lnRE_t,\ lnGI_t,\ lnGDP_t, lnGDP_t^2,\ lnPD) \tag{1}$$

$$lnEFP_t = \mathrm{f}\,(lnNRE_t,\ lnGI_t,\ lnGDP_t, lnGDP_t^2,\ lnPD) \tag{2}$$

where t represents years (i= 1,2,3…Y).

The newly developed method for empirical evaluation is presented in Equations (3) and (4):

$$lnEFP_{t=}\beta_0 + \beta_1 lnRE_t + \beta_2 lnGI_t + \beta_3 lnGDP_t + \beta_4 lnGDP_t^2 + \beta_5 lnPD_t + \varepsilon_t \tag{3}$$

$$lnEFP_{t=}\beta_0 + \beta_1 lnNRE_t + \beta_2 lnGI_t + \beta_3 lnGDP_t + \beta_4 lnGDP_t^2 + \beta_5 lnPD_t + \varepsilon_t \tag{4}$$

where ε_t refers to random errors. β_0 means the constant term. $\beta_{1\ldots5}$ represented expected coefficients.

When $\beta_{1\ldots5}$ are negative values, it indicates that variables have a negative impact on the ecological footprint. In simple terms, the indicators can help reduce the ecological footprint if the coefficients are negative.

3.3 Methodology

3.3.1 The ARDL Bounds Testing Approach

The autoregressive distributive lag (ARDL) bound testing approach is used to estimate the long-run relationship between the variables and to test whether the variables are integrated I(1) or I(0). By applying the correct lag length, we are also able to deal with the endogeneity problem as well as serial correlation. Moreover, it is also an accurate estimation technique used in small finite samples while producing short-run and long-run estimates at the same time. Because of these benefits, ARDL is the best econometric model for estimating both long-run and short-run estimates of our variables. The ARDL model for our selected variables is shown in Equation (5) and Equation (6), to separate between the independent variables, renewable energy production and non-renewable energy production:

$$\triangle LogEFP_t = \theta_0 + \lambda_1 LogRE_{t-1} + \lambda_2 LogGF_{t-1} + \lambda_3 LogGDP_{t-1} + \lambda_4 Log(GDP^2)_{t-1} + \lambda_5 LogPD_{t-1} + \Sigma\pi_1 \triangle LogRE_{t-I} + \Sigma\pi_2 \triangle LogGF_{t-I} + \Sigma\pi_3 \triangle LogGDP_{t-I} + \Sigma\pi_4 \triangle Log(GDP^2)_{t-I} + \Sigma\pi_5 \triangle LogPD_{t-I} + ECT_{t-1} + \mu \quad (5)$$

$$\triangle LogEFP_t = \theta_0 + \lambda_1 LogNRE_{t-1} + \lambda_2 LogGF_{t-1} + \lambda_3 LogGDP_{t-1} + \lambda_4 Log(GDP^2)_{t-1} + \lambda_5 LogPD_{t-1} + \Sigma\pi_1 \triangle LogNRE_{t-I} + \Sigma\pi_2 \triangle LogGF_{t-I} + \Sigma\pi_3 \triangle LogGDP_{t-I} + \Sigma\pi_4 \triangle Log(GDP^2)_{t-I} + \Sigma\pi_5 \triangle LogPD_{t-I} + ECT_{t-1} + \mu \quad (6)$$

where $\triangle$ is the first difference operator, λ represents the long-run coefficients, θ is the short-run coefficients, and μ is the error term.

The joint null hypothesis that signifies no cointegration relationship is H0: $\pi_1 \neq \pi_2 \neq \pi_3 \neq \pi_4 \neq \pi_5 \neq 0$. The alternative hypothesis of a cointegration relationship is H1: $\pi_1 = \pi_2 = \pi_3 = \pi_4 = \pi_5 = 0$. The ARDL method begins with testing the hypothesis of no cointegration using an F statistic. ARDL also has upper bound and lower bound values for the F statistic where if it exceeds the upper bound values signifies cointegration, and if below the lower bound signifies no cointegration. The results are unsuitable if the F statistic lies between the upper and lower bounds. After testing the existence of cointegration is to estimate both short and long run dynamics. A few tests will also be utilized to check the model's reliability and validity.

To test Hypothesis 1 of this study, we explore deeper into how green investment influences the relationship we are examining as a moderating factor. Researchers commonly evaluate the effect of a moderator by incorporating an interaction term between the moderator and the explanatory variables in their baseline regression model. Subsequently, they assess the moderating effect by observing the coefficient of the interaction term to determine its impact on the relationship between the explanatory variable and the outcome (Yang et al., 2022). Thus, this paper investigates how the variable of GI and its interaction with EP affect the moderating role of green investment. It examines how green investment moderates the impact of energy production on ecological footprint. The structure of Equations 7 and 8 are as follows to separate the independent variables, renewable energy production, and non-renewable energy production:

$$\ln\ EFP_{t=}\beta_0 + \beta_1 lnRE + \beta_2 lnGI_t + \beta_3 ln(GI * RE)_t + \beta_4 lnGDP_t + \beta_5 lnGDP_t^2 + \beta_6 lnPD_t + \mu_t \quad (7)$$

$$\ln\ EFP_{t=}\beta_0 + \beta_1 lnNRE + \beta_2 lnGI_t + \beta_3 ln(GI * NRE)_t + \beta_4 lnGDP_t + \beta_5 lnGDP_t^2 + \beta_6 lnPD_t + \mu_t \quad (8)$$

To validate EKC, we have used the baseline equation by focusing on the GDP and GDP^2 to capture the non-linear relationship. To separate between renewable energy production and non-renewable energy production, we used Equation (9) and Equation (10), respectively. Both represent the Environmental Kuznet Curve hypothesis equation in which GDP and GDP^2, are evaluated in the following possible outcomes (Lee, 2021).

$$lnEFP_{t=}\beta_0 + \beta_1 lnRE_t + \beta_2 lnGI_t + \beta_3 lnGDP_t + \beta_4 lnGDP_t^2 + \beta_5 lnPD_t + \varepsilon_t \quad (9)$$

$$lnEFP_{t=}\beta_0 + \beta_1 lnNRE_t + \beta_2 lnGI_t + \beta_3 lnGDP_t + \beta_4 lnGDP_t^2 + \beta_5 lnPD_t + \varepsilon_t \quad (10)$$

The correlation between economic development (GDP) and the ecological footprint can be different depending on the coefficients by GDP and its square term in the model. When both coefficients for GDP and GDP squared are equal to zero ($\beta 3 = \beta 4 = 0$), it implies that there is no statistically significant link between GDP and ecological footprint, indicating a flat association. Conversely, if the coefficient of GDP is positive ($\beta 3 > 0$) and the squared term is zero ($\beta 4 = 0$), it indicates that the ecological footprint increases in a monotonic manner with GDP, demonstrating a persistent positive correlation between economic growth and the ecological footprint.

Conversely, if the coefficient of GDP is negative ($\beta 3 < 0$) and the squared term is insignificant ($\beta 4 = 0$), it suggests a consistent downward trend, where rising GDP is associated with a lower ecological footprint score. When the coefficient of GDP is positive ($\beta 3 > 0$) and the squared term is negative ($\beta 4 < 0$), the relationship exhibits an inverted U-shaped pattern. This implies that the economic growth rate first increases with GDP but eventually declines after reaching a maximum point. Lastly, when GDP has a negative coefficient ($\beta 3 < 0$) and the squared term is positive ($\beta 4 > 0$), it results in a U-shaped relationship. This means that ecological footprint initially decreases with GDP but then increases again over a certain threshold.

Chapter 4: Results and Discussion

4.1 Preliminary Analysis

In this study, we analyze data collected from 1990 to 2022 with 33 observations. The purpose of conducting this descriptive analysis is to study the fundamental properties of the selected variables for our study. This analysis is to provide an overview of our data's central tendency, dispersion, and overall distribution. The descriptive statistics of the variables EFP, RE, NRE, GI, GDP, and PD are summarised in Table 4.1 and reveal variability across the data.

Table 4.1: Preliminary Analysis

	Mean	Standard Deviation	Max	Min	Kurtosis	Skewness	JB-Test
EFP	2.4915	0.8309	3.62	1.35	-1.3498	-0.0044	3.7443
RE	819519.4848	781109.9921	2733262	125165	-0.0009	1.0953	6.0482*
NRE	65134663.1818	28762959.3204	114726060	28030674	-1.6013	0.0879	3.3219
GI	37231.5900	26478.1873	99765.1087	4544.65	0.5629	02.3665	2.2946
GDP	33688.5620	23639.8347	80163.8500	6275.8968	-1.0289	0.5863	3.2540
PD	138.5950	8.9083	150.4398	120.9153	2.0308	-0.3612	2.0092

Note: *LNEFP denotes ecological footprint (Gha Per Person). LNRE denotes renewable energy production (Kilowatt-Hour). LNNRE denotes non-renewable energy production (terajoules). LNGI denotes green investment (RMB million). LNGDP and LNPD denote GDP constant local currency and population density respectively (GDP per Capita & People Per Sq. Km of Land Area).*

For ecological footprint (EFP), the mean ecological footprint of 2.4915 indicates that each person in China would need approximately 2.4915 hectares of productive land and water to sustain their life. Throughout the sample period, the ecological footprint has shown an upward trend, rising from a minimum point of 1.35 in 1990 to a maximum point of 3.62 in 2022. This mean value is found to exceed the Earth's total biocapacity of approximately 1.7 Earth, suggesting that the population in the country consumes more resources and generates waste than what the planet can sustainably support for a person. The standard deviation of ecological footprint is 0.8309 which varies moderately around the mean. This suggests that the people across China have similar access to resources such as productive land, water, energy, food and so on.

Renewable energy production (RE) shows a mean of 819519.4848 kilowatt-hour (KWh). The mean indicates that China has generated 819519.4848kWh of electricity by using renewable energy. The standard deviation of RE is 781109.9921KWh which indicates a significant variability in using renewable energy to produce energy across China, reflecting that the use of renewable energy to produce electricity is not prevalent enough across China. However, renewable energy production has risen from 125165 KWh to 2733262 KWh, reflecting that China has slowly focused on delivering clean energy.

Besides, non-renewable Energy (NRE) exhibits a mean of 65134663.1818terajoules (tj) which represents the average energy production from non-renewable sources (coal, oil, natural gas and nuclear) across the country. The non-renewable energy production in China also shows an upward trend, varying from 28030674tj to 114726060tj throughout the timespan from 1990 to 2022. This massive mean value reflects China's status as one of the world's biggest countries that heavily rely on producing and consuming non-renewable energy. Whereas the standard deviation of 28762959.3204tj suggests that there is huge variability in producing non-renewable energy. A high standard deviation implies that energy production is widely spread along the range, which means there is a fluctuation in producing non-renewable energy across the country.

The mean of green investment (GI) is 37231.5900RMB million, indicating the average investment that China has invested in industrial pollution treatment. The standard deviation is RMB 26478.1873 million, which means that the green investment tends to deviate from the mean by RMB 26.48 billion on average. This standard deviation value suggests that there is huge variability in green investment across China. However, the green investment depicts an upward trend, increasing from 4544.65RMB to 99765.1087RMB over the years, which suggests that China has been gradually prioritizing medicating the pollution issue through substantial financial investment.

For the control variables gross domestic product (GDP) and population density (PD), the descriptive analysis for these variables also reveals a substantial variability across the country. The average of GDP is RMB 33688.5620, which represents economic output per capita in China and the standard deviation is RMB 23,639.8347which signifies a substantial disparity in the economic activity across each population in China. For PD, the mean value is 138.5950km of land area, which shows China has a relatively high population density given its large land area. The standard deviation of this variable is 8.9083km of land which implies that there is a low variation of population across the land in China.

Lastly, based on our preliminary analysis, the JB test statistic indicates the non-rejection of the null-hypothesis of normal distribution. However, there is an exceptional in RE where its test statistic (6.048223) indicates the variable RE is not normally distributed, suggesting an exponential growth in RE which could be attributable to China's Energy Policy 2012 where the Chinese government's strong initiative to develop new and renewable energy (Information Office of the State Council, 2012).

4.2 Unit Root Test

Table 4.2: Augmented Dickey-Fuller Unit Root Test

ADF	Constant without trend		Constant with trend	
	Level	First Difference	Level	First Difference
LNEFP	1.5050 (8)	-2.9305(8)*	1.4945(8)	-3.1455(8)
LNRE	0.9385(1)	-6.6830(1)***	-2.4150(1)	-6.7673(1)***
LNNRE	-0.9571(1)	-2.9481(1)*	-2.0141(1)	-2.949(1)
LNGI	-2.300(8)	-3.9905(8)**	0.32217(8)	-4.618(8)**
LNGDP	-1.506(3)	-1.3380(3)*	0.8713(3)	-3.4541(3)**
LNPD	-2.0894(7)	-0.3833(7)	-0.5693(7)	-3.8319(7)**

*Note: LNEFP denotes ecological footprint. LNRE denotes renewable energy production. LNNRE denotes non-renewable energy production. LNGI denotes green investment. LNGDP and LNPD denotes GDP constant local currency and population density respectively. All these variables are expressed in logarithm form. ***, **, * denote as significance level at 1%, 5%, 10% respectively. Figure in parentheses () represents the lag length used.*

We establish a robust regression models that capture the long-run relationship between the variables. One of the key assumptions in the regression analysis is that the variable must be non-stationary over the sample period, meaning that the statistical properties of the time series do not change over time. The non-stationary data can lead to spurious regression problems, and potentially provide misleading results in our study. To minimize this concern, we implement the augmented Dickey-Fuller unit root test to examine the stationarity of the variables. By using the auxiliary model with constant term and without trend, the results of the unit root test indicate that the null hypothesis of the unit root for each variable failed to be rejected in the level form. However, we can reject the null hypothesis of unit root when variables are in the first difference form. This finding demonstrates that the variables are integrated in the first-order process and similar findings are obtained by using a model with constant terms and trends.

4.3 ARDL Bounds Testing

We further examine the existence of the long-run relationship between ecological footprint and RE, NRE and the interaction terms between REGI and NREGI which are represented as Models 1, 2, 3 and 4 respectively. The calculated F-statistic for each model and its associated critical values at 1%, 5%, and 10% as shown in Table 4.3.

Table 4.3: Bounds Testing

	Model Function	*F-Statistic*	*Significance Level*	*I(0)*	*I(1)*
Model 1	EFP= f (RE, GI, GDP, GDP^2, PD)	6.9567	1%	4.134	5.761
			5%	2.91	4.193
			10%	2.407	3.517
Model 2	EFP= f (NRE, GI, GDP, GDP^2, PD)	4.6952	1%	4.134	5.761
			5%	2.91	4.193
			10%	2.407	3.517
Model 3	EFP= f (RE, GI, GDP, GDP^2, PD, REGI)	12.4722	1%	3.976	5.691
			5%	2.794	4.148
			10%	2.334	3.515
Model 4	EFP= f (NRE, GI, GDP, GDP^2, PD, NREGI)	4.2902	1%	3.976	5.691
			5%	2.794	4.148
			10%	2.334	3.515

Note: f denotes as function of the model

For Model 1, the estimated F-statistic of 6.9567 is found to be above the upper bound, I(1), and is greater than the critical values at all significance levels, 3.517, 4.193, and 5.761. Hence, the null hypothesis of no cointegration is rejected, suggesting that there is a long-run relationship between the ecological footprint, renewable energy production, economic growth (GDP and GDP^2), and population density. With Model 2, also a similar finding of rejecting the null hypothesis. Its calculated F-statistic is equal to 4.6952, which is above the upper bound and is greater than the critical value at 5% and 10% only. This rejection of the null hypothesis also suggests a long-run relationship between ecological footprint, non-renewable energy production, economic growth, and population density.

On the other hand, the F-statistics for Model 3 and Model 4 are 12.4722 and 4.2902, respectively. Moreover, the F-statistics of Model 3 and Model 4 are statistically significant in rejecting the null hypothesis of no cointegration at a 1% significance level, with critical values 5.691, respectively. To illustrate, this means that both models are cointegrated, whereby there is a long-run relationship between ecological footprint, renewable energy production, green investment, economic growth, population density, and the interaction term between renewable energy production and green investment (REGI) in Model 3. As for the case of Model 4, it suggests that there is a long-run relationship between the interaction term, NREGI, with the variables such as non-renewable energy production, green investment, economic growth, and population density.

4.4 Long Run Estimation

Table 4.4**:** The results of long-run estimates for examining the moderator role of green investment

	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	17.2709** (6.8698)	9.1572* (4.5483)	12.4196** (5.3615)	8.8760* (4.3947)
RE	0.0957 (0.1539)	-	0.7998* (0.4026)	-
NRE	-	0.2472** (0.0935)	-	0.3604 (0.4776)
GDP	3.3894*** (1.1399)	2.5338*** (0.6313)	2.4970** (1.0935)	2.3751*** (0.5515)
GDP^2	-0.1246** (0.0594)	-0.0883*** (0.0242)	-0.0777 (0.0565)	-0.0787*** (0.0230)
GI	0.0426 (0.0392)	0.0401** (0.0148)	0.9888** (0.4640)	0.2958 (0.9640)
PD	-8.0088** (1.3190)	-6.0254*** (1.3523)	-8.1213*** (1.2804)	-6.2520** (1.9449)
REGI	-	-	-0.0701** (0.0336)	-
NREGI	-	-	-	-0.0143 (0.0527)
ECT	-0.5588*** (0.0713)	-0.6394*** (0.0993)	-0.5880*** (0.0518)	-0.6717*** (0.0993)
Jacque-Bera test	0.9253 [0.6263]	1.1915 [0.5511]	0.1283 [0.9378]	1.0550 [0.5901]
ARCH test	1.1003 [0.3029]	0.0231 [0.8802]	0.0130 [0.9107]	0.5067 [0.4823]
LM test	0.8053 [0.3792]	0.0967 [0.7588]	4.3554** [0.0482]	0.5237 [0.4776]
CUSUM Test	Stable	Stable	Stable	Stable

*Notes: LNEFP denotes ecological footprint. LNRE denotes renewable energy production. LNNRE denotes non-renewable energy production. LNGI denotes green investment. All these variables are expressed in natural logarithms. ***, **, * denote significant at 1%, 5%, and 10% levels, respectively. Standard errors are reported in ( ). P-values are reported in [ ]. Stable denotes coefficients that have cumulative deviation that stays within the expected range in the CUSUM test.*

After proving the existence of the cointegration between the variables, we establish the long-run model estimation as shown in Table 4.3. The results of Table 4.3 show that all models are adequate. For example, we have performed: The Jacque-Bera test to validate the normal distribution of our models; the ARCH test which aims to check the absence of heteroscedasticity problem; the Error Correction Term (ECT) test to see whether the error terms are correlated to one another; the LM test to test the absence of serial correlation problem; and CUSUM test to ensure the stability of our data. Of these, all of the findings show the non-rejection of the null hypothesis of each diagnostic test, and the CUSUM test suggests that the data are all stable (the cumulative sum line lies between the upper and lower control limits). As a result, all of our models are adequate. However, the exception lies with Model 2, which has passed all but the LM test; it rejected the null hypothesis of the LM test at a 5% significance level.

Beginning with Models 1 and 2, which are our basic models that help examine the dynamics of renewable energy on ecological footprint and non-renewable on ecological footprint, respectively. Other than that, these two models are also among the four that test the validity of the EKC Hypothesis in China after considering the existence of GI. In Model 1, all control variables coefficients are statistically significant at a 5% level, except for GDP, which is statistically significant at a 1% level. To clarify, we can say that every 1% increase in GDP in China cause an approximate 3.39% increase in the country's ecological footprint. In comparison, for every 1% increase in PD, there would be an approximate 8.01% decrease in the country's ecological footprint. Moreover, the GDP exhibits a significantly positive coefficient while GDP-squared (GDP^2) shows a significantly negative coefficient, signalling an inverted U-shape curve that proves the validity of the EKC Hypothesis in China, after considering the existence of GI. Despite the existence of the EKC Hypothesis, the findings in Model 1 serve no useful meaning as the core variables are all statistically insignificant at 1%, 5%, and 10% levels without RE interacting with GI. There is no relationship in reducing ecological footprint after exceeding the threshold point for such a case. The variable, RE itself is not significant to reduce the ecological footprint in the context of China. Thus, the findings from Model 1 concludes that it is not practical in explaining the relationship between GI, RE, and ecological footprint in China and are unable to answer our hypothesis 3.

For Model 2, all variables, including the core independent variables, non-renewable energy and green investment, tend to be at least statistically significant at the 5% level, while all control variables are significant at a 1% significance level. The findings in Model 3 indicate that with every 1% increase in non-renewable energy, the ecological footprint in China increases by approximately 0.25%. For every 1% increase in GI, the ecological footprint tends to increase by approximately 0.04% in China. Furthermore, Model 3 shows a positive coefficient for GDP and a negative coefficient for GDP-squared, proving the validity of the EKC Hypothesis held in China and can answer our hypothesis 3. Consequently, this finding proves that Model 3 is appropriate for testing the relationship between GI, non-renewable energy, and ecological footprint in China. The EKC Hypothesis in Model 3 is proven to be valid because China's energy production mix is mainly dominated by non-renewable energy. The findings suggest that over time, China eventually raised awareness that this continuous energy combustion is adversely contributing to its ecological footprint. Thus, the Chinese government gradually implemented a series of measures like strict control on non-renewable energy and strategic GI to ease the transition of cleaner energy to conserve the environment. For example, China has implemented its 15th 5-year plan to decrease energy production via coal (Oxford Institute for Energy Studies, 2022); China has strongly promoted its "1+N" framework to encourage green investment growth within the country (Climate Bonds Initiative, 2022). Therefore, this finding hints that non-renewable energy, after reaching its maximum level, eventually dropped in the later years as China started to be concerned about the impact of environmental issues. Additionally, GI, independently in the face of non-renewable energy, which is the dominant energy mix in China, is not able to improve ecological footprint but deteriorates it instead. The explanation that GI has no interacting relationship with China's non-renewable energy, suggests that it not only has a negative effect from non-renewable energy, but GI also individually carries forward the drawback from green project implementations that aggravates ecological footprint in China.

Moving on with the results in Model 3 and Model 4 were mainly used to test for the moderating effect of GI on ecological footprint in China. Both models show a rather unorthodox result. Beginning with Model 2, all variables are statistically significant except for GDP^2. The finding in Model 2 renders the EKC hypothesis invalid in China after considering GI and REGI. Putting this aside, all core variables such as GI, RE, and most importantly, REGI, are at least significant at a 10% significance level, except for GI and REGI, which are both significant at a 5% significance level. This result is in contrast to the opposite result of Model 1, where its core variables are all insignificant in the absence of an interaction term. This finding means that for every 1% increase in GI and RE in China, the ecological footprint of the country increases by approximately 0.99% and 0.80%, respectively. This is unusual because it goes against what we hypothesize which suggests that GI and RE tend to reduce ecological footprint. However, when green investment and renewable energy interact (REGI), it becomes viable to reduce ecological footprint by roughly 0.07%. This finding supports our hypothesis 1.

Even though the EKC hypothesis is invalid in this context, it does not preclude that GI, after interacting with RE, could contribute to a long-term reduction in ecological footprint over time. The reason behind the invalid of EKC with the consideration of green investment is that the concept of GI is still immature and emerging in China. Therefore, in our sample period, GI may not be significant enough to boost the adoption of green activities like shifting to RE. China's RE adoption has not been substantial enough to counteract the damage caused by the extreme energy production from non-renewable energy sources, particularly coal. Hence, this exemplified the non-existence of an inverted U-shaped EKC curve. Unlike in Model 1, where both RE and GI are insignificant, they started to produce a meaningful relationship after the inclusion of the interaction term REGI in Model 2. This finding provides useful insights that suggest that GI has always been interacting with RE in China. This significant interaction demonstrates that GI tends to act as a moderator role in reducing ecological footprint, however, GI and RE tend to contribute to impacts that increase ecological footprint.

GI's negative impact on ecological footprint reflects our expectations in the literature review, which suggests that GI might increase ecological footprint based on the rebound effect and the Green Paradox. GI, which funds the initial stages of implementing RE projects may have a substantial negative impact on the environment that outweighs its ecological protection benefits. For example, China's share in global solar photovoltaic supply has exceeded 80% and has one of the highest outputs of solar panels in the world (IEA, 2024). The mining process of precious metals used in the production of solar panels utilizes non-renewable energy, which not only releases greenhouse gases but also causes soil, water, and air pollution. Consequently, increasing the number of solar panel facilities in China may displace wildlife and recreation land, which further decreases the ecological footprint. Depending on the type of solar panels, it could also either demand a high level of electricity fuelled by coal burning to produce or release extremely harmful materials.

However, after the momentum from GI, which rapidly implements RE projects, RE which serves as a variable effect on ecological footprint in China, displays a paradoxical result in our study. RE supposedly has close to zero greenhouse gas emissions and is not reducing the ecological footprint, but is doing the opposite and worsening it. Recalling back, RE may not have an impact on the carbon element of ecological footprint, nevertheless, it may cause other consequences to the environment. One reason is to the immobility of RE infrastructures. Since RE projects such as wind farms, mega-dams, and solar panel facilities in China have already displaced much land that could otherwise be habitats for its broad bio-ecosystems, the monetary costs of restoring the landscape may not be justified by its benefits. When facing the impossibility of a perfect scenario, between saving wildlife lands or sacrificing them to expedite the clean energy transition, China may have chosen the latter just like how it did with mass deforestation. Although they may not contribute much to the carbon element accounted for in the ecological footprint, the RE infrastructures continuously worsen the local ecological systems during their indefinite tenure in occupying those lands. Despite the negative impact of RE and GI, the redeeming point is that the interaction term of REGI can successfully reduce ecological footprint. Although having a relatively smaller magnitude in comparison, the size of future observations will grow exponentially. To roughly simulate the future outcome, we take the latest observation sourced for this research, the year 2022 as shown in Table 4.5.

Table 4.5: Simulation of Partial Extraction from Model 3

Year 2022						
RE Coefficient	RE Obs	GI Coefficient	GI Obs	REGI Coefficient	REGI Obs (GI*RE)	Partial effect on EFP
0.7998	14.8210	0.9888	10.2601	-0.0701	152.0656	11.3393
Scenario 1 (**double** RE Obs, **double** GI Obs)						
0.7998	**29.6420**	0.9888	**20.5203**	-0.0701	**608.2627**	1.3589
Scenario 2 (**triple** RE Obs, **triple** GI Obs)						
0.7998	**44.4630**	0.9888	**30.7803**	-0.0701	**1368.5845**	-29.9407

**Obs stands for observation after logarithmic transformation.*

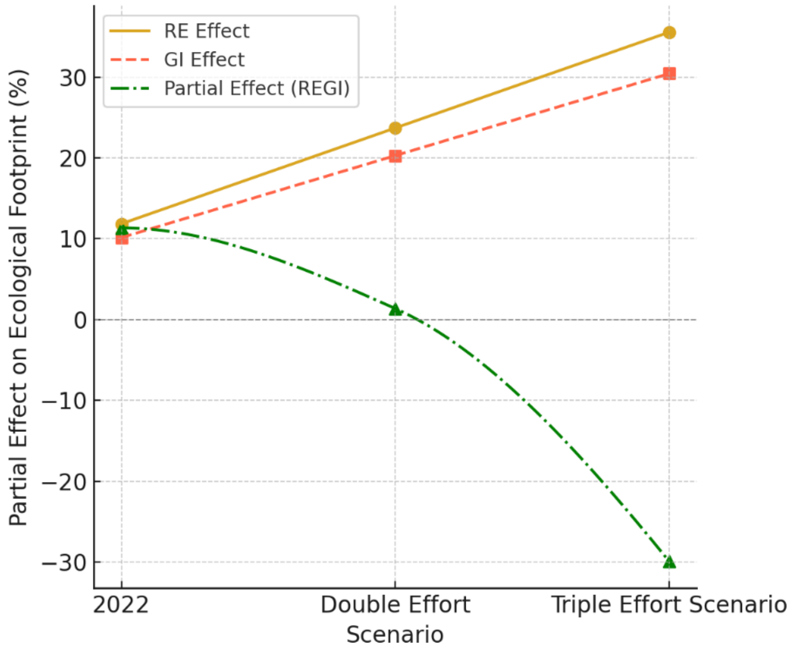

Figure 1: Simulation of Partial Extraction from Model 3

Based on Table 4.5 and Figure 1, we can roughly estimate that the moderating effect of GI tends to overtake the individually negative impact of RE and GI on ecological footprint, ultimately improving ecological footprint in China. Thus, encouraging a higher level of effort not only towards growing the GI and RE markets but also ensuring there is constant interaction between the two concurrently.

On the other hand, Model 4 also presents a contradictory, unexpected result compared to Model 3. In Model 4, all core variables such as GI, non-renewable energy, and NREGI are all statistically insignificant even at the 10% level. Demonstrating that with the inclusion of the interaction term NREGI, the model becomes an impractical design that does not support our hypothesis 2 and does not assist in explaining the relationship between its core variables and ecological footprint in China. By nature, the GI would not be interacting with non-renewable energy. This insignificant interaction term implies that the funds from GI will be channelled toward RE production, such as solar and wind, which produce near-zero emissions, rather than being allocated to enhance the non-renewable energy production, which would only marginally increase carbon emissions. Since GI's funds are not majorly channelled toward non-renewable energy in China, with the inclusion of the interaction term NREGI in Model 4, the relationship between all core variables is nullified because they are non-existent. Therefore, GI does not play the moderator role as shown in Model 4. Moreover, the EKC Hypothesis in this case holds but is not applicable as all the core variables, non-renewable energy, green investment and the interaction between green investment and non-renewable energy (NREGI) are statistically insignificant.

Table 4.6: Summary of Findings

	EKC Hypothesis	GI play as a moderator role
Model 1	Valid	-
Model 2	Valid	Yes
Model 3	Invalid	-
Model 4	Valid	No

Chapter 5: Conclusion

5.1 Main Findings

The results from ARDL have provided four main findings related to our research objectives. To help answer research questions 1 and 2 in testing the validity of the EKC Hypothesis after considering green investment, we have utilized basic models 1 and 2. Model 1 consists of green investment and renewable energy production as its core variables; Model 2 consists of green investment and non-renewable energy production as its core variables. The EKC hypothesis does not hold in Model 1. However, it does hold when considering green investment and non-renewable energy production in Model 2.

To answer research questions 3 and 4 to test the presence of the moderating effect of green investment on energy production as well as the validity of the EKC Hypothesis, we have used Models 3 and 4. Model 3 consists of basic core variables and the inclusion of interaction between green investment and renewable energy production; Model 4 consists of all basic core variables as well as interaction terms between green investment and non-renewable energy. Based on our findings, green investment acts as a moderator role in reducing the ecological footprint in Model 3, however, it has no moderating effect in Model 4. Aside from that, Model 3 does not hold the EKC Hypothesis. In Model 4, however, the EKC Hypothesis does hold. Refer to Table 5.1 below for the summary of our findings.

5.2 Recommendations and Policy Implications

In the absence of interaction between green investment and renewable energy production, our study does not suggest that the scaling up of renewable energy production over time can reduce the ecological footprint in China. Our study reaffirms that green investment does not channel into non-renewable energy production. Instead, it has to interact with renewable energy production to impact reducing ecological footprint directly. The validity of the EKC Hypothesis with the inclusion of non-renewable energy suggests that China, a major producer of electricity in the world via non-renewable resources, is more conscious of reducing its emissions to reduce its ecological footprint. This heightened level of awareness is reflected in their continuous intention to grow the green investment market as well as scaling up renewable energy production.

China cannot completely abandon non-renewable energy production in the short run which would mean a huge brake to its economic development. Moreover, China promised to peak carbon emissions in 2030, as in the Paris Agreement. Our study suggests that the motivation to grow the momentum for energy transition is justified in China. Funds that were originally allocated for non-renewable energy production, such as petroleum subsidies and non-renewable energy R&D efforts, can now be slowly channelled towards growing the green investment market. Consequently, green investment funds have a broad way of utilizing them to increase renewable energy production. For example, increasing its current scale or green innovation for renewable energy technology that produces power more efficiently. Despite potential hazards to the ecological footprint in the short run, with these initiatives from green investment which supports renewable energy production, China potentially becomes one of the first few countries to become carbon neutral in the world before 2060, following the Paris Agreement. Eventually, to reflect the core significance of our study, such policies can potentially reduce the ecological footprint in China.

5.3 Limitations and Recommendations Future Studies

There are some limitations in our study such as the sampling method. We have utilized national data instead of provincial data in China, which provides a general preview of the current issues regarding the emergence of green investment and energy production in China. However, each province may have different initiatives for green investment. Depending on the different approaches taken by each province on green policies, the results could drastically change. For example, Jiangsu province focuses on clean energy industries like solar, while Mongolia prioritizes wind as the green method of producing energy. Conversely, Guangdong, Shandong, and Yunnan provinces aim to stimulate investment in environmental protection and industrial development. Since China's renewable sources are located in areas that may be far from urban centres where energy demand is highest, this presents a geographic mismatch which poses logistical and technical challenges in transmitting power over long distances reliably.

Additionally, we have not tested the green investment's mediating effect on energy production in China due to statistical limitations. Suppose green investment plays a mediator role in non-renewable energy production by minimizing its magnitude to increase the ecological footprint. In that case, policymakers are encouraged to solely grow green investments to diminish the ecological footprint in China. On the other hand, if it plays the mediator role in increasing the assumed positive impact of renewable energy production on ecological footprint, then this phenomenon will also inspire the Chinese government to amass more green funds to preserve its ecological environment.

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Appendix 1 : Descriptive Analysis for Dependent Variable, Ecological Footprint

Series: DEPENDENT_VARIABLE_ECOLO
Sample 1990 2022
Observations 33

Mean	2.491515
Median	2.480000
Maximum	3.620000
Minimum	1.350000
Std. Dev.	0.830896
Skewness	-0.004413
Kurtosis	1.349839
Jarque-Bera	3.744275
Probability	0.153795

Appendix 2 : Descriptive Analysis for Independent Variable, Renewable Energy

Series: SERIES11
Sample 1990 2022
Observations 33

Mean	819519.5
Median	446882.0
Maximum	2733262.
Minimum	125165.0
Std. Dev.	781110.0
Skewness	1.044904
Kurtosis	2.822779
Jarque-Bera	6.048223
Probability	0.048601

Appendix 3: Descriptive Analysis for Independent Variable, Non-Renewable Energy

Series: SERIES06
Sample 1990 2022
Observations 33

Mean	65134663
Median	66251735
Maximum	1.15e+08
Minimum	28030674
Std. Dev.	28762959
Skewness	0.083803
Kurtosis	1.454739
Jarque-Bera	3.321896
Probability	0.189959

Appendix 4: Descriptive Analysis for Green Investment

Series: MEDIATOR_MODERATOR_GREEI
Sample 1990 2022
Observations 33

Mean	37231.59
Median	33523.64
Maximum	99765.11
Minimum	4544.650
Std. Dev.	26478.19
Skewness	0.562925
Kurtosis	2.366535
Jarque-Bera	2.294625
Probability	0.317489

Appendix 5: Descriptive Analysis for control variable, GDP

Series: GDP__CONSTANT_LCU_	
Sample 1990 2022	
Observations 33	
Mean	33688.56
Median	26356.20
Maximum	80163.85
Minimum	6275.897
Std. Dev.	23639.83
Skewness	0.559351
Kurtosis	1.944055
Jarque-Bera	3.253959
Probability	0.196522

Appendix 6: Descriptive Analysis for control variable, population density

Series: POPULATION_DENSITY	
Sample 1 33	
Observations 33	
Mean	138.5950
Median	139.6453
Maximum	150.4398
Minimum	120.9155
Std. Dev.	8.908311
Skewness	-0.361178
Kurtosis	2.030755
Jarque-Bera	2.009197
Probability	0.366192

Appendix 7: Augmented Dickey-Fuller Test on EFP

Appendix 7.1 Level form constant without trend

Null Hypothesis: LN_EFP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.504984	0.5179
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_EFP)
Method: Least Squares
Date: 04/11/25 Time: 01:39
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_EFP(-1)	-0.020246	0.013453	-1.504984	0.1435
D(LN_EFP(-1))	0.528026	0.148892	3.546380	0.0014
C	0.032729	0.013768	2.377127	0.0245

R-squared	0.372062	Mean dependent var	0.031818
Adjusted R-squared	0.327209	S.D. dependent var	0.030462
S.E. of regression	0.024986	Akaike info criterion	-4.449242
Sum squared resid	0.017480	Schwarz criterion	-4.310469
Log likelihood	71.96325	Hannan-Quinn criter.	-4.404006
F-statistic	8.295199	Durbin-Watson stat	1.823493
Prob(F-statistic)	0.001482		

Appendix 7.2 Level form constant with trend

Null Hypothesis: LN_EFP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.494450	0.8098
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_EFP)
Method: Least Squares
Date: 04/11/25 Time: 01:41
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_EFP(-1)	-0.095849	0.064137	-1.494450	0.1467
D(LN_EFP(-1))	0.603994	0.160592	3.761052	0.0008
C	0.045044	0.017058	2.640660	0.0136
@TREND("1990")	0.002954	0.002451	1.205156	0.2386

R-squared	0.404116	Mean dependent var	0.031818
Adjusted R-squared	0.337907	S.D. dependent var	0.030462
S.E. of regression	0.024786	Akaike info criterion	-4.437122
Sum squared resid	0.016588	Schwarz criterion	-4.252091
Log likelihood	72.77538	Hannan-Quinn criter.	-4.376806
F-statistic	6.103618	Durbin-Watson stat	1.895145
Prob(F-statistic)	0.002618		

Appendix 7.3 first difference constant without trend

Null Hypothesis: D(LN_EFP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.930543	0.0533
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_EFP,2)
Method: Least Squares
Date: 04/11/25 Time: 01:42
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LN_EFP(-1))	-0.441646	0.150705	-2.930543	0.0065
C	0.014404	0.006566	2.193826	0.0364

R-squared	0.228479	Mean dependent var	0.000630
Adjusted R-squared	0.201875	S.D. dependent var	0.028571
S.E. of regression	0.025525	Akaike info criterion	-4.435971
Sum squared resid	0.018894	Schwarz criterion	-4.343456
Log likelihood	70.75756	Hannan-Quinn criter.	-4.405814
F-statistic	8.588080	Durbin-Watson stat	1.772428
Prob(F-statistic)	0.006535		

Appendix 7.4 first difference constant with trend

Null Hypothesis: D(LN_EFP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.145499	0.1140
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_EFP,2)
Method: Least Squares
Date: 04/11/25 Time: 01:43
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LN_EFP(-1))	-0.481932	0.153213	-3.145499	0.0039
C	0.026351	0.011851	2.223574	0.0344
@TREND("1990")	-0.000629	0.000521	-1.206830	0.2376

R-squared	0.266626	Mean dependent var	0.000630
Adjusted R-squared	0.214242	S.D. dependent var	0.028571
S.E. of regression	0.025327	Akaike info criterion	-4.422163
Sum squared resid	0.017960	Schwarz criterion	-4.283390
Log likelihood	71.54353	Hannan-Quinn criter.	-4.376927
F-statistic	5.089845	Durbin-Watson stat	1.800196
Prob(F-statistic)	0.013018		

Appendix 8: Augmented Dickey-Fuller Test on RE

Appendix 8.1 level from constant without trend

Null Hypothesis: LNRENEWABLE__ENERGY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.938489	0.9948
Test critical values:	1% level	-3.653730	
	5% level	-2.957110	
	10% level	-2.617434	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNRENEWABLE__ENERGY)
Method: Least Squares
Date: 04/11/25 Time: 01:44
Sample (adjusted): 1991 2022
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNRENEWABLE__ENERGY(-1)	0.012153	0.012949	0.938489	0.3555
C	-0.063195	0.170041	-0.371647	0.7128

R-squared	0.028521	Mean dependent var	0.095960
Adjusted R-squared	-0.003861	S.D. dependent var	0.070084
S.E. of regression	0.070219	Akaike info criterion	-2.413934
Sum squared resid	0.147921	Schwarz criterion	-2.322325
Log likelihood	40.62294	Hannan-Quinn criter.	-2.383568
F-statistic	0.880762	Durbin-Watson stat	2.358561
Prob(F-statistic)	0.355488		

Appendix 8.2 Level from constant with trend

Null Hypothesis: LNRENEWABLE__ENERGY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.414693	0.3655
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNRENEWABLE__ENERGY)
Method: Least Squares
Date: 04/11/25 Time: 01:47
Sample (adjusted): 1991 2022
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNRENEWABLE__ENERGY(-1)	-0.224811	0.093101	-2.414693	0.0223
C	2.630905	1.061372	2.478778	0.0192
@TREND("1990")	0.024805	0.009666	2.566235	0.0157

R-squared	0.208306	Mean dependent var	0.095960
Adjusted R-squared	0.153706	S.D. dependent var	0.070084
S.E. of regression	0.064473	Akaike info criterion	-2.556078
Sum squared resid	0.120547	Schwarz criterion	-2.418665
Log likelihood	43.89725	Hannan-Quinn criter.	-2.510530
F-statistic	3.815154	Durbin-Watson stat	2.255622
Prob(F-statistic)	0.033813		

Appendix 8.3 First difference constant without trend

Null Hypothesis: D(LNRENEWABLE__ENERGY) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.682959	0.0000
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNRENEWABLE__ENERGY,2)
Method: Least Squares
Date: 04/11/25 Time: 01:48
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNRENEWABLE__ENERGY(-...	-1.171107	0.175238	-6.682959	0.0000
C	0.115917	0.020844	5.561208	0.0000

R-squared	0.606310	Mean dependent var	0.003362
Adjusted R-squared	0.592734	S.D. dependent var	0.107141
S.E. of regression	0.068375	Akaike info criterion	-2.465289
Sum squared resid	0.135578	Schwarz criterion	-2.372774
Log likelihood	40.21198	Hannan-Quinn criter.	-2.435131
F-statistic	44.66194	Durbin-Watson stat	2.086836
Prob(F-statistic)	0.000000		

Appendix 8.4 First difference constant with trend

Null Hypothesis: D(LNRENEWABLE__ENERGY) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.767267	0.0000
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNRENEWABLE__ENERGY,2)
Method: Least Squares
Date: 04/11/25 Time: 01:48
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNRENEWABLE__ENERGY(-...	-1.216976	0.179833	-6.767267	0.0000
C	0.094468	0.028754	3.285419	0.0027
@TREND("1990")	0.001521	0.001409	1.079483	0.2896

R-squared	0.622039	Mean dependent var	0.003362
Adjusted R-squared	0.595042	S.D. dependent var	0.107141
S.E. of regression	0.068181	Akaike info criterion	-2.441547
Sum squared resid	0.130161	Schwarz criterion	-2.302774
Log likelihood	40.84398	Hannan-Quinn criter.	-2.396311
F-statistic	23.04089	Durbin-Watson stat	2.082091
Prob(F-statistic)	0.000001		

Appendix 9: Augmented Dickey-Fuller Test on NRE

Appendix 9.1 Level from constant without trend

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.957074	0.7558
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNNONRENEWABLE_ENERGY)
Method: Least Squares
Date: 04/11/25 Time: 01:50
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNNONRENEWABLE_ENERGY(-1)	-0.014017	0.014646	-0.957074	0.3467
D(LNNONRENEWABLE_ENERGY(-...	0.544900	0.152802	3.566046	0.0013
C	0.272194	0.262392	1.037357	0.3084

R-squared	0.331972	Mean dependent var	0.045267
Adjusted R-squared	0.284256	S.D. dependent var	0.044072
S.E. of regression	0.037286	Akaike info criterion	-3.648655
Sum squared resid	0.038926	Schwarz criterion	-3.509882
Log likelihood	59.55416	Hannan-Quinn criter.	-3.603419
F-statistic	6.957217	Durbin-Watson stat	1.861450
Prob(F-statistic)	0.003525		

Appendix 9.2 Level from constant with trend

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.014093	0.5711
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNNONRENEWABLE_ENERGY)
Method: Least Squares
Date: 04/11/25 Time: 01:50
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNNONRENEWABLE_ENERGY(-1)	-0.123858	0.061495	-2.014093	0.0541
D(LNNONRENEWABLE_ENERGY(-...	0.620447	0.152396	4.071296	0.0004
C	2.135064	1.046105	2.040966	0.0511
@TREND("1990")	0.005798	0.003160	1.834782	0.0776

R-squared	0.406030	Mean dependent var	0.045267
Adjusted R-squared	0.340033	S.D. dependent var	0.044072
S.E. of regression	0.035803	Akaike info criterion	-3.701640
Sum squared resid	0.034611	Schwarz criterion	-3.516609
Log likelihood	61.37542	Hannan-Quinn criter.	-3.641325
F-statistic	6.152281	Durbin-Watson stat	2.007184
Prob(F-statistic)	0.002512		

Appendix 9.3 First difference constant without trend

Null Hypothesis: D(LNNONRENEWABLE_ENERGY) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.948148	0.0513
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNNONRENEWABLE_ENERGY,2)
Method: Least Squares
Date: 04/11/25 Time: 01:51
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNNONRENEWABLE_ENERGY(-...	-0.449501	0.152469	-2.948148	0.0063
C	0.021228	0.009436	2.249674	0.0322

R-squared	0.230597	Mean dependent var	0.001600
Adjusted R-squared	0.204066	S.D. dependent var	0.041732
S.E. of regression	0.037232	Akaike info criterion	-3.680981
Sum squared resid	0.040199	Schwarz criterion	-3.588466
Log likelihood	59.05521	Hannan-Quinn criter.	-3.650823
F-statistic	8.691579	Durbin-Watson stat	1.839275
Prob(F-statistic)	0.006256		

Appendix 9.4 First difference constant with trend

Null Hypothesis: D(LNNONRENEWABLE_ENERGY) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.948909	0.1620
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNNONRENEWABLE_ENERGY,2)
Method: Least Squares
Date: 04/11/25 Time: 01:52
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNNONRENEWABLE_ENERGY(-...	-0.457698	0.155209	-2.948909	0.0064
C	0.028352	0.016641	1.703768	0.0995
@TREND("1990")	-0.000398	0.000761	-0.522890	0.6052

R-squared	0.238038	Mean dependent var	0.001600
Adjusted R-squared	0.183612	S.D. dependent var	0.041732
S.E. of regression	0.037707	Akaike info criterion	-3.626182
Sum squared resid	0.039811	Schwarz criterion	-3.487409
Log likelihood	59.20583	Hannan-Quinn criter.	-3.580946
F-statistic	4.373614	Durbin-Watson stat	1.843399
Prob(F-statistic)	0.022237		

Appendix 10: Augmented Dickey-Fuller Test on GI

Appendix 10.1 Level from constant without trend

Null Hypothesis: GREENINVSETMENT has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.300020	0.1781
Test critical values:	1% level	-3.653730	
	5% level	-2.957110	
	10% level	-2.617434	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GREENINVSETMENT)
Method: Least Squares
Date: 04/11/25 Time: 01:53
Sample (adjusted): 1991 2022
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GREENINVSETMENT(-1)	-0.091880	0.039948	-2.300020	0.0286
C	0.994634	0.409032	2.431678	0.0212

R-squared	0.149903	Mean dependent var	0.057451
Adjusted R-squared	0.121566	S.D. dependent var	0.215719
S.E. of regression	0.202182	Akaike info criterion	-0.298835
Sum squared resid	1.226327	Schwarz criterion	-0.207227
Log likelihood	6.781365	Hannan-Quinn criter.	-0.268470
F-statistic	5.290090	Durbin-Watson stat	1.475491
Prob(F-statistic)	0.028580		

Appendix 10.2 Level from constant without trend

Null Hypothesis: GREENINVSETMENT has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.322177	0.9979
Test critical values:	1% level	-4.273277	
	5% level	-3.557759	
	10% level	-3.212361	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GREENINVSETMENT)
Method: Least Squares
Date: 04/11/25 Time: 01:54
Sample (adjusted): 1991 2022
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GREENINVSETMENT(-1)	0.029687	0.092146	0.322177	0.7496
C	-0.030565	0.809770	-0.037745	0.9701
@TREND("1990")	-0.013018	0.008929	-1.457934	0.1556

R-squared	0.207956	Mean dependent var	0.057451
Adjusted R-squared	0.153333	S.D. dependent var	0.215719
S.E. of regression	0.198493	Akaike info criterion	-0.307069
Sum squared resid	1.142581	Schwarz criterion	-0.169656
Log likelihood	7.913107	Hannan-Quinn criter.	-0.261521
F-statistic	3.807070	Durbin-Watson stat	1.783187
Prob(F-statistic)	0.034030		

Appendix 10.3 First Difference constant without trend

Null Hypothesis: D(GREENINVSETMENT) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.990048	0.0044
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GREENINVSETMENT,2)
Method: Least Squares
Date: 04/11/25 Time: 01:54
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GREENINVSETMENT(-1))	-0.709064	0.177708	-3.990048	0.0004
C	0.031734	0.039384	0.805744	0.4269

R-squared	0.354415	Mean dependent var	-0.013973
Adjusted R-squared	0.332153	S.D. dependent var	0.256728
S.E. of regression	0.209803	Akaike info criterion	-0.222958
Sum squared resid	1.276497	Schwarz criterion	-0.130443
Log likelihood	5.455855	Hannan-Quinn criter.	-0.192801
F-statistic	15.92048	Durbin-Watson stat	1.963306
Prob(F-statistic)	0.000411		

Appendix 10.4 First Difference constant with trend

Null Hypothesis: D(GREENINVSETMENT) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=8)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.617999	0.0045
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GREENINVSETMENT,2)
Method: Least Squares
Date: 04/11/25 Time: 01:55
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GREENINVSETMENT(-1))	-0.864774	0.187262	-4.617999	0.0001
C	0.189741	0.088923	2.133764	0.0418
@TREND("1990")	-0.008704	0.004439	-1.960633	0.0599

R-squared	0.432347	Mean dependent var	-0.013973
Adjusted R-squared	0.391800	S.D. dependent var	0.256728
S.E. of regression	0.200214	Akaike info criterion	-0.287089
Sum squared resid	1.122404	Schwarz criterion	-0.148316
Log likelihood	7.449885	Hannan-Quinn criter.	-0.241853
F-statistic	10.66296	Durbin-Watson stat	1.912953
Prob(F-statistic)	0.000361		

Appendix 11: Augmented Dickey-Fuller Test on GDP

Appendix 11.1 Level from constant without trend

Null Hypothesis: LNGDP has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.506134	0.5169
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNGDP)
Method: Least Squares
Date: 04/11/25 Time: 01:58
Sample (adjusted): 1993 2022
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP(-1)	-0.008215	0.005455	-1.506134	0.1441
D(LNGDP(-1))	0.359647	0.193962	1.854217	0.0751
D(LNGDP(-2))	0.264910	0.187472	1.413065	0.1695
C	0.111357	0.066023	1.686622	0.1036

R-squared	0.539599	Mean dependent var	0.078389
Adjusted R-squared	0.486476	S.D. dependent var	0.023730
S.E. of regression	0.017005	Akaike info criterion	-5.187056
Sum squared resid	0.007518	Schwarz criterion	-5.000230
Log likelihood	81.80584	Hannan-Quinn criter.	-5.127289
F-statistic	10.15751	Durbin-Watson stat	2.003417
Prob(F-statistic)	0.000132		

Appendix 11.2 Level from constant with trend

Null Hypothesis: LNGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.871343	0.9465
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNGDP)
Method: Least Squares
Date: 04/11/25 Time: 01:58
Sample (adjusted): 1993 2022
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNGDP(-1)	-0.063230	0.072566	-0.871343	0.3919
D(LNGDP(-1))	0.365164	0.195689	1.866041	0.0738
D(LNGDP(-2))	0.378118	0.240614	1.571469	0.1286
C	0.580234	0.620268	0.935456	0.3585
@TREND("1990")	0.004714	0.006200	0.760318	0.4542

R-squared	0.550004	Mean dependent var	0.078389
Adjusted R-squared	0.478005	S.D. dependent var	0.023730
S.E. of regression	0.017145	Akaike info criterion	-5.143250
Sum squared resid	0.007348	Schwarz criterion	-4.909717
Log likelihood	82.14874	Hannan-Quinn criter.	-5.068540
F-statistic	7.639027	Durbin-Watson stat	1.992633
Prob(F-statistic)	0.000364		

Appendix 11.3 First difference constant without trend

Null Hypothesis: D(LNGDP) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.337908	0.5986
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNGDP,2)
Method: Least Squares
Date: 04/11/25 Time: 01:58
Sample (adjusted): 1993 2022
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNGDP(-1))	-0.205348	0.153484	-1.337908	0.1921
D(LNGDP(-1),2)	-0.334018	0.185991	-1.795879	0.0837
C	0.013741	0.012882	1.066667	0.2956

R-squared	0.237543	Mean dependent var	-0.003039
Adjusted R-squared	0.181065	S.D. dependent var	0.019227
S.E. of regression	0.017400	Akaike info criterion	-5.170073
Sum squared resid	0.008174	Schwarz criterion	-5.029954
Log likelihood	80.55110	Hannan-Quinn criter.	-5.125248
F-statistic	4.205914	Durbin-Watson stat	2.065896
Prob(F-statistic)	0.025699		

Appendix 11.4 First difference constant with trend

Null Hypothesis: D(LNGDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.454117	0.0625
Test critical values:	1% level	-4.284580	
	5% level	-3.562882	
	10% level	-3.215267	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNGDP,2)
Method: Least Squares
Date: 04/11/25 Time: 01:59
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNGDP(-1))	-0.591124	0.171136	-3.454117	0.0018
C	0.066273	0.019154	3.460012	0.0017
@TREND("1990")	-0.001160	0.000428	-2.711628	0.0113

R-squared	0.315402	Mean dependent var	-0.001463
Adjusted R-squared	0.266502	S.D. dependent var	0.020840
S.E. of regression	0.017848	Akaike info criterion	-5.122043
Sum squared resid	0.008920	Schwarz criterion	-4.983270
Log likelihood	82.39167	Hannan-Quinn criter.	-5.076807
F-statistic	6.449959	Durbin-Watson stat	1.833371
Prob(F-statistic)	0.004967		

Appendix 12: Augmented Dickey-Fuller Test on PD

Appendix 12.1 Level from constant without trend

Null Hypothesis: POPULATION__DENSITY has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.089474	0.2500
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION__DENSITY)
Method: Least Squares
Date: 04/11/25 Time: 02:02
Sample (adjusted): 1993 2022
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
POPULATION__DENSITY(-1)	-0.008020	0.003838	-2.089474	0.0466
D(POPULATION__DENSITY(-...	1.507246	0.168469	8.946702	0.0000
D(POPULATION__DENSITY(-...	-0.676869	0.160067	-4.228652	0.0003
C	0.040609	0.019478	2.084861	0.0470

R-squared	0.973983	Mean dependent var	0.006828
Adjusted R-squared	0.970981	S.D. dependent var	0.002734
S.E. of regression	0.000466	Akaike info criterion	-12.38235
Sum squared resid	5.64E-06	Schwarz criterion	-12.19552
Log likelihood	189.7352	Hannan-Quinn criter.	-12.32258
F-statistic	324.4469	Durbin-Watson stat	1.950704
Prob(F-statistic)	0.000000		

Appendix 12.2 Level from constant with trend

Null Hypothesis: POPULATION__DENSITY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.569371	0.9737
Test critical values:	1% level	-4.296729	
	5% level	-3.568379	
	10% level	-3.218382	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION__DENSITY)
Method: Least Squares
Date: 04/11/25 Time: 02:02
Sample (adjusted): 1993 2022
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
POPULATION__DENSITY(-1)	-0.008861	0.015562	-0.569371	0.5742
D(POPULATION__DENSITY(-...	1.508210	0.172661	8.735085	0.0000
D(POPULATION__DENSITY(-...	-0.680824	0.177948	-3.825979	0.0008
C	0.044690	0.075782	0.589710	0.5607
@TREND("1990")	4.83E-06	8.66E-05	0.055800	0.9559

R-squared	0.973986	Mean dependent var	0.006828
Adjusted R-squared	0.969824	S.D. dependent var	0.002734
S.E. of regression	0.000475	Akaike info criterion	-12.31581
Sum squared resid	5.64E-06	Schwarz criterion	-12.08227
Log likelihood	189.7371	Hannan-Quinn criter.	-12.24110
F-statistic	234.0060	Durbin-Watson stat	1.953972
Prob(F-statistic)	0.000000		

Appendix 12.3 First difference constant without trend

Null Hypothesis: D(POPULATION__DENSITY) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.383275	0.8998
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION__DENSITY,2)
Method: Least Squares
Date: 04/11/25 Time: 02:03
Sample (adjusted): 1993 2022
Included observations: 30 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(POPULATION__DENSITY(-1))	-0.012916	0.033698	-0.383275	0.7045
D(POPULATION__DENSITY(-1),2)	0.597209	0.164866	3.622378	0.0012
C	-8.67E-05	0.000257	-0.336741	0.7389

R-squared	0.346007	Mean dependent var	-0.000425
Adjusted R-squared	0.297564	S.D. dependent var	0.000589
S.E. of regression	0.000494	Akaike info criterion	-12.29379
Sum squared resid	6.59E-06	Schwarz criterion	-12.15367
Log likelihood	187.4069	Hannan-Quinn criter.	-12.24897
F-statistic	7.142437	Durbin-Watson stat	1.797798
Prob(F-statistic)	0.003238		

Appendix 12.4 First difference constant with trend

Null Hypothesis: D(POPULATION__DENSITY) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 7 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.831894	0.0323
Test critical values:	1% level	-4.394309	
	5% level	-3.612199	
	10% level	-3.243079	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(POPULATION__DENSITY,2)
Method: Least Squares
Date: 04/11/25 Time: 02:03
Sample (adjusted): 1999 2022
Included observations: 24 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(POPULATION__DENSITY(-1))	-0.408998	0.106735	-3.831894	0.0018
D(POPULATION__DENSITY(-1),2)	0.783469	0.183468	4.270340	0.0008
D(POPULATION__DENSITY(-2),2)	-0.036523	0.224092	-0.162984	0.8729
D(POPULATION__DENSITY(-3),2)	0.564029	0.217543	2.592726	0.0213
D(POPULATION__DENSITY(-4),2)	0.025890	0.297288	0.087086	0.9318
D(POPULATION__DENSITY(-5),2)	0.997495	0.313500	3.181804	0.0067
D(POPULATION__DENSITY(-6),2)	-0.442320	0.299025	-1.479206	0.1612
D(POPULATION__DENSITY(-7),2)	0.605952	0.275983	2.195616	0.0455
C	0.005859	0.001532	3.825159	0.0019
@TREND("1990")	-0.000145	3.84E-05	-3.783325	0.0020

R-squared	0.752401	Mean dependent var	-0.000389
Adjusted R-squared	0.593230	S.D. dependent var	0.000623
S.E. of regression	0.000397	Akaike info criterion	-12.53078
Sum squared resid	2.21E-06	Schwarz criterion	-12.03992
Log likelihood	160.3694	Hannan-Quinn criter.	-12.40056
F-statistic	4.727000	Durbin-Watson stat	2.179354
Prob(F-statistic)	0.004953		

Appendix 13 Autoregressive Distributed Lag Bound Testing

Appendix 13.1 Bound Testing on Model 1

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	6.956729	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
Actual Sample Size	32	Finite Sample: n=35		
		10%	2.331	3.417
		5%	2.804	4.013
		1%	3.9	5.419
		Finite Sample: n=30		
		10%	2.407	3.517
		5%	2.91	4.193
		1%	4.134	5.761

Appendix 13.2 Bound Testing on Model 2

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	4.695231	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15
Actual Sample Size	32	Finite Sample: n=35		
		10%	2.331	3.417
		5%	2.804	4.013
		1%	3.9	5.419
		Finite Sample: n=30		
		10%	2.407	3.517
		5%	2.91	4.193
		1%	4.134	5.761

Appendix 13.3 Bound Testing on Model 3

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	12.47219	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99
Actual Sample Size	32		Finite Sample: n=35	
		10%	2.254	3.388
		5%	2.685	3.96
		1%	3.713	5.326
			Finite Sample: n=30	
		10%	2.334	3.515
		5%	2.794	4.148
		1%	3.976	5.691

Appendix 13.4 Bound Testing on Model 4

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	4.290189	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99
Actual Sample Size	32		Finite Sample: n=35	
		10%	2.254	3.388
		5%	2.685	3.96
		1%	3.713	5.326
			Finite Sample: n=30	
		10%	2.334	3.515
		5%	2.794	4.148
		1%	3.976	5.691

Appendix 14 Long Run Estimation on Model 1

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GREENINVSETMENT	0.042611	0.039239	1.085934	0.2888
LNGDP	3.389401	1.139931	2.973340	0.0068
GDP_2	-0.124555	0.059378	-2.097656	0.0471
POPULATION__DENS...	-8.008797	1.319021	-6.071774	0.0000
LNRENEWABLE__EN...	0.095747	0.153913	0.622084	0.5400
C	17.27089	6.869806	2.514029	0.0194

EC = LN_EFP - (0.0426*GREENINVSETMENT + 3.3894*LNGDP -0.1246
*GDP_2 -8.0088*POPULATION__DENSITY + 0.0957
*LNRENEWABLE__ENERGY + 17.2709)

Appendix 14.1 Error Correction Form on Model 1

ARDL Error Correction Regression
Dependent Variable: D(LN_EFP)
Selected Model: ARDL(1, 1, 0, 0, 1, 0)
Case 2: Restricted Constant and No Trend
Date: 04/11/25 Time: 02:47
Sample: 1990 2022
Included observations: 32

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GREENINVSETMENT)	0.055388	0.017340	3.194140	0.0040
D(POPULATION__DE...	-16.13630	2.514540	-6.417196	0.0000
CointEq(-1)*	-0.558849	0.071319	-7.835859	0.0000

R-squared	0.624180	Mean dependent var	0.030824
Adjusted R-squared	0.598262	S.D. dependent var	0.030490
S.E. of regression	0.019325	Akaike info criterion	-4.965745
Sum squared resid	0.010831	Schwarz criterion	-4.828332
Log likelihood	82.45192	Hannan-Quinn criter.	-4.920197
Durbin-Watson stat	1.651345		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	6.956729	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

Appendix 14.2 Jacqaue-Bera Test on Model 1

Series: Residuals
Sample 1991 2022
Observations 32

Mean	2.75e-14
Median	0.002755
Maximum	0.037575
Minimum	-0.043660
Std. Dev.	0.018691
Skewness	-0.408267
Kurtosis	2.835040
Jarque-Bera	0.925254
Probability	0.629627

Appendix 14.3 ARCH Test on Model 1

Heteroskedasticity Test: ARCH

F-statistic	1.100329	Prob. F(1,29)	0.3029
Obs*R-squared	1.133216	Prob. Chi-Square(1)	0.2871

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/11/25 Time: 02:50
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000408	0.000105	3.900343	0.0005
RESID^2(-1)	-0.190904	0.181993	-1.048966	0.3029

R-squared	0.036555	Mean dependent var	0.000344
Adjusted R-squared	0.003333	S.D. dependent var	0.000473
S.E. of regression	0.000472	Akaike info criterion	-12.41753
Sum squared resid	6.46E-06	Schwarz criterion	-12.32502
Log likelihood	194.4717	Hannan-Quinn criter.	-12.38737
F-statistic	1.100329	Durbin-Watson stat	2.000347
Prob(F-statistic)	0.302858		

Appendix 14.4 LM Test on Model 1

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

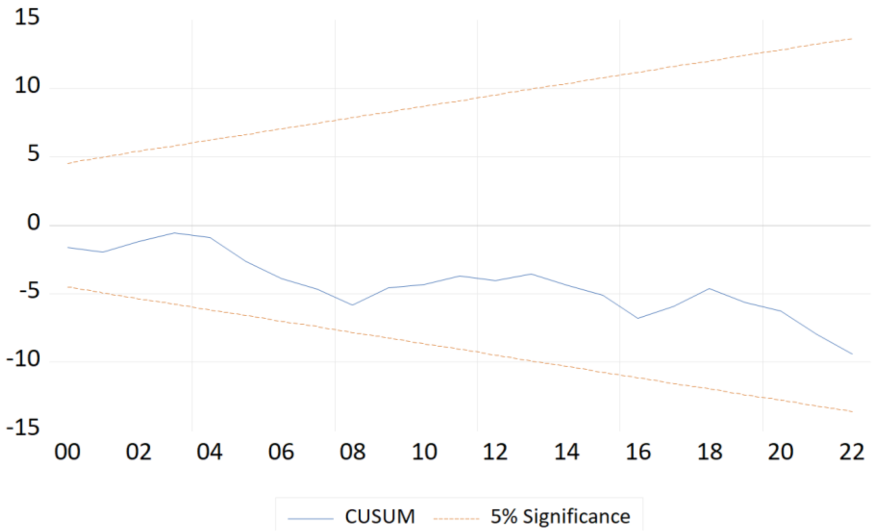
F-statistic	0.805352	Prob. F(1,22)	0.3792
Obs*R-squared	1.130054	Prob. Chi-Square(1)	0.2878

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 04/11/25 Time: 02:50
Sample: 1991 2022
Included observations: 32
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_EFP(-1)	-0.081762	0.189986	-0.430358	0.6711
GREENINVSETMENT	-0.005781	0.026586	-0.217432	0.8299
GREENINVSETMENT(-1)	0.006822	0.026274	0.259647	0.7976
LNGDP	0.243288	0.796359	0.305501	0.7629
GDP_2	-0.007947	0.036024	-0.220594	0.8274
POPULATION__DENSITY	1.190206	5.306084	0.224310	0.8246
POPULATION__DENSITY(-1)	-1.611921	5.284607	-0.305022	0.7632
LNRENEWABLE__ENERGY	-0.005159	0.085732	-0.060178	0.9526
C	0.543069	4.430755	0.122568	0.9036
RESID(-1)	0.240035	0.267474	0.897414	0.3792

R-squared	0.035314	Mean dependent var	2.75E-14
Adjusted R-squared	-0.359330	S.D. dependent var	0.018691
S.E. of regression	0.021792	Akaike info criterion	-4.564198
Sum squared resid	0.010448	Schwarz criterion	-4.106155
Log likelihood	83.02717	Hannan-Quinn criter.	-4.412370
F-statistic	0.089484	Durbin-Watson stat	1.916533
Prob(F-statistic)	0.999615		

Appendix 14.5 CUSUM Test on Model 1



Appendix 15 Long Run Estimation on Model 2

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GREENINVSETMENT	0.040119	0.014819	2.707362	0.0126
LNGDP	2.533765	0.631300	4.013565	0.0005
GDP_2	-0.088254	0.024235	-3.641540	0.0014
POPULATION__DENS...	-6.025443	1.352310	-4.455666	0.0002
LNNONRENEWABLE...	0.247245	0.093545	2.643058	0.0145
C	9.157223	4.548253	2.013349	0.0559

EC = LN_EFP - (0.0401*GREENINVSETMENT + 2.5338*LNGDP -0.0883
*GDP_2 -6.0254*POPULATION__DENSITY + 0.2472
*LNNONRENEWABLE_ENERGY + 9.1572)

Appendix 15.1 Error Correction Form on Model 2

ARDL Error Correction Regression
Dependent Variable: D(LN_EFP)
Selected Model: ARDL(1, 0, 0, 1, 0, 1)
Case 2: Restricted Constant and No Trend
Date: 04/11/25 Time: 02:56
Sample: 1990 2022
Included observations: 32

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP_2)	-0.076731	0.012900	-5.948323	0.0000
D(LNNONRENEWABL...	0.541944	0.050633	10.70333	0.0000
CointEq(-1)*	-0.639375	0.099321	-6.437431	0.0000

R-squared	0.872044	Mean dependent var	0.030824
Adjusted R-squared	0.863220	S.D. dependent var	0.030490
S.E. of regression	0.011276	Akaike info criterion	-6.043172
Sum squared resid	0.003687	Schwarz criterion	-5.905760
Log likelihood	99.69076	Hannan-Quinn criter.	-5.997624
Durbin-Watson stat	2.051322		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	4.695231	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

Appendix 15.2 Jacque-Bera Test on Model 2

Series: Residuals	
Sample 1991 2022	
Observations 32	
Mean	3.00e-15
Median	0.001064
Maximum	0.017253
Minimum	-0.020558
Std. Dev.	0.010906
Skewness	-0.204308
Kurtosis	2.147548
Jarque-Bera	1.191522
Probability	0.551143

Appendix 15.3 ARCH Test on Model 2

Heteroskedasticity Test: ARCH

F-statistic	0.023113	Prob. F(1,29)	0.8802
Obs*R-squared	0.024688	Prob. Chi-Square(1)	0.8751

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/11/25 Time: 02:58
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000122	3.10E-05	3.940629	0.0005
RESID^2(-1)	-0.027954	0.183869	-0.152030	0.8802

R-squared	0.000796	Mean dependent var	0.000119
Adjusted R-squared	-0.033659	S.D. dependent var	0.000126
S.E. of regression	0.000128	Akaike info criterion	-15.02959
Sum squared resid	4.74E-07	Schwarz criterion	-14.93707
Log likelihood	234.9586	Hannan-Quinn criter.	-14.99943
F-statistic	0.023113	Durbin-Watson stat	2.020236
Prob(F-statistic)	0.880216		

Appendix 15.4 LM Test on Model 2

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

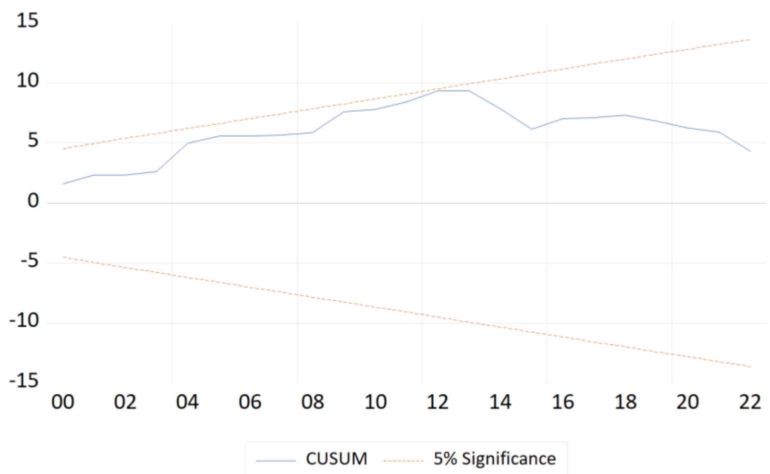
F-statistic	0.096689	Prob. F(1,22)	0.7588
Obs*R-squared	0.140023	Prob. Chi-Square(1)	0.7083

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 04/11/25 Time: 02:59
Sample: 1991 2022
Included observations: 32
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_EFP(-1)	0.032369	0.186081	0.173951	0.8635
GREENINVSETMENT	-0.000392	0.011139	-0.035207	0.9722
LNGDP	-0.047569	0.410771	-0.115805	0.9089
GDP_2	0.002624	0.021364	0.122805	0.9034
GDP_2(-1)	-0.000936	0.009763	-0.095891	0.9245
POPULATION__DENSITY	0.092387	0.943519	0.097918	0.9229
LNNONRENEWABLE_ENERGY	0.006168	0.073554	0.083863	0.9339
LNNONRENEWABLE_ENERGY(-1)	-0.019622	0.122293	-0.160450	0.8740
C	0.068752	2.733207	0.025154	0.9802
RESID(-1)	-0.087071	0.280018	-0.310948	0.7588

R-squared	0.004376	Mean dependent var	3.00E-15
Adjusted R-squared	-0.402925	S.D. dependent var	0.010906
S.E. of regression	0.012918	Akaike info criterion	-5.610058
Sum squared resid	0.003671	Schwarz criterion	-5.152015
Log likelihood	99.76092	Hannan-Quinn criter.	-5.458229
F-statistic	0.010743	Durbin-Watson stat	1.985798
Prob(F-statistic)	1.000000		

Appendix 15.5 CUSUM Test on Model 2



Appendix 16 Long Run Estimation on Model 3

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GREENINVSETMENT	0.988783	0.464016	2.130924	0.0435
LNGDP	2.496958	1.093546	2.283359	0.0316
GDP_2	-0.077707	0.056484	-1.375732	0.1816
POPULATION__DENS...	-8.121313	1.280358	-6.343004	0.0000
LNRENEWABLE__EN...	0.799790	0.402633	1.986399	0.0585
GIRE	-0.070124	0.033628	-2.085269	0.0479
C	12.41962	5.361492	2.316449	0.0294

EC = LN_EFP - (0.9888*GREENINVSETMENT + 2.4970*LNGDP -0.0777
*GDP_2 -8.1213*POPULATION__DENSITY + 0.7998
*LNRENEWABLE__ENERGY -0.0701*GIRE + 12.4196)

Appendix 16.1 Error Correction Form on Model 3

ARDL Error Correction Regression
Dependent Variable: D(LN_EFP)
Selected Model: ARDL(1, 0, 0, 0, 0, 0, 0)
Case 2: Restricted Constant and No Trend
Date: 04/11/25 Time: 03:02
Sample: 1990 2022
Included observations: 32

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CointEq(-1)*	-0.588033	0.051798	-11.35250	0.0000

R-squared	0.601540	Mean dependent var	0.030824
Adjusted R-squared	0.601540	S.D. dependent var	0.030490
S.E. of regression	0.019246	Akaike info criterion	-5.032248
Sum squared resid	0.011483	Schwarz criterion	-4.986444
Log likelihood	81.51597	Hannan-Quinn criter.	-5.017065
Durbin-Watson stat	1.305825		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	12.47219	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Appendix 16.2 Jacque-Bera Test on Model 3

Series: Residuals
Sample 1991 2022
Observations 32

Mean	1.03e-15
Median	0.004219
Maximum	0.046222
Minimum	-0.043116
Std. Dev.	0.019246
Skewness	-0.135419
Kurtosis	2.848665
Jarque-Bera	0.128340
Probability	0.937846

Appendix 16.3 ARCH Test on Model 3

Heteroskedasticity Test: ARCH

F-statistic	0.012791	Prob. F(1,29)	0.9107
Obs*R-squared	0.013667	Prob. Chi-Square(1)	0.9069

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/11/25 Time: 03:05
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000375	0.000114	3.297860	0.0026
RESID^2(-1)	-0.020930	0.185057	-0.113098	0.9107

R-squared	0.000441	Mean dependent var	0.000367
Adjusted R-squared	-0.034027	S.D. dependent var	0.000502
S.E. of regression	0.000510	Akaike info criterion	-12.26161
Sum squared resid	7.55E-06	Schwarz criterion	-12.16909
Log likelihood	192.0550	Hannan-Quinn criter.	-12.23145
F-statistic	0.012791	Durbin-Watson stat	2.013649
Prob(F-statistic)	0.910732		

Appendix 16.4 LM Test on Model 3

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

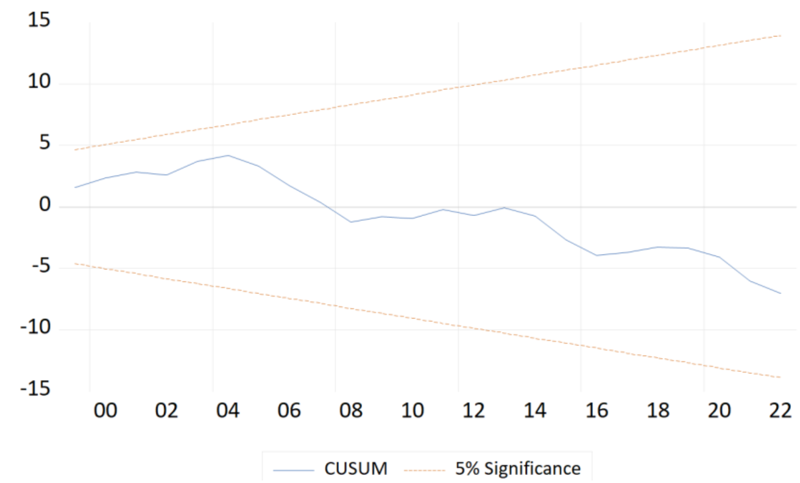
F-statistic	4.355417	Prob. F(1,23)	0.0482
Obs*R-squared	5.094908	Prob. Chi-Square(1)	0.0240

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 04/11/25 Time: 03:05
Sample: 1991 2022
Included observations: 32
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_EFP(-1)	-0.162529	0.173606	-0.936192	0.3589
GREENINVSETMENT	-0.145364	0.221961	-0.654905	0.5190
LNGDP	0.592079	0.747951	0.791601	0.4367
GDP_2	-0.020689	0.034100	-0.606717	0.5500
POPULATION__DENSITY	-0.830855	1.230510	-0.675212	0.5063
LNRENEWABLE__ENERGY	-0.127855	0.195864	-0.652777	0.5204
GIRE	0.010681	0.015903	0.671628	0.5085
C	2.082250	3.875622	0.537269	0.5962
RESID(-1)	0.478017	0.229049	2.086964	0.0482

R-squared	0.159216	Mean dependent var	1.03E-15
Adjusted R-squared	-0.133231	S.D. dependent var	0.019246
S.E. of regression	0.020488	Akaike info criterion	-4.705668
Sum squared resid	0.009655	Schwarz criterion	-4.293430
Log likelihood	84.29069	Hannan-Quinn criter.	-4.569023
F-statistic	0.544427	Durbin-Watson stat	1.978039
Prob(F-statistic)	0.810965		

Appendix 16.5 CUSUM Test on Model 3



Appendix 17 Long Run Estimation on Model 4

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GREENINVSETMENT	0.295810	0.963969	0.306867	0.7620
LNGDP	2.375141	0.551540	4.306377	0.0003
GDP_2	-0.078670	0.023029	-3.416117	0.0026
POPULATION__DENS...	-6.251992	1.944901	-3.214555	0.0042
LNNONRENEWABLE...	0.360387	0.477562	0.754640	0.4588
GINRE	-0.014318	0.052694	-0.271713	0.7885
C	8.876008	4.394695	2.019710	0.0564

EC = LN_EFP - (0.2958*GREENINVSETMENT + 2.3751*LNGDP -0.0787
*GDP_2 -6.2520*POPULATION__DENSITY + 0.3604
*LNNONRENEWABLE_ENERGY -0.0143*GINRE + 8.8760)

Appendix 17.1 Error Correction Form on Model 4

ARDL Error Correction Regression
Dependent Variable: D(LN_EFP)
Selected Model: ARDL(1, 1, 0, 1, 0, 0, 1)
Case 2: Restricted Constant and No Trend
Date: 04/11/25 Time: 03:08
Sample: 1990 2022
Included observations: 32

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GREENINVSETMENT)	-0.474954	0.100958	-4.704445	0.0001
D(GDP_2)	-0.074295	0.012052	-6.164614	0.0000
D(GINRE)	0.028382	0.005529	5.133534	0.0000
CointEq(-1)*	-0.671691	0.099293	-6.764763	0.0000

R-squared	0.885408	Mean dependent var	0.030824
Adjusted R-squared	0.873131	S.D. dependent var	0.030490
S.E. of regression	0.010860	Akaike info criterion	-6.090979
Sum squared resid	0.003302	Schwarz criterion	-5.907762
Log likelihood	101.4557	Hannan-Quinn criter.	-6.030248
Durbin-Watson stat	2.085160		

* p-value incompatible with t-Bounds distribution.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	4.290189	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Appendix 17.2 Jacque-Bera Test on Model 4

Series: Residuals
Sample 1991 2022
Observations 32

Mean	3.89e-15
Median	0.000592
Maximum	0.017021
Minimum	-0.019690
Std. Dev.	0.010321
Skewness	-0.110996
Kurtosis	2.138633
Jarque-Bera	1.054979
Probability	0.590085

Appendix 17.3 ARCH Test on Model 4

Heteroskedasticity Test: ARCH

F-statistic	0.506664	Prob. F(1,29)	0.4823
Obs*R-squared	0.532306	Prob. Chi-Square(1)	0.4656

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/11/25 Time: 03:10
Sample (adjusted): 1992 2022
Included observations: 31 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000119	2.75E-05	4.343224	0.0002
RESID^2(-1)	-0.135323	0.190113	-0.711803	0.4823

R-squared	0.017171	Mean dependent var	0.000106
Adjusted R-squared	-0.016719	S.D. dependent var	0.000112
S.E. of regression	0.000113	Akaike info criterion	-15.27144
Sum squared resid	3.72E-07	Schwarz criterion	-15.17893
Log likelihood	238.7074	Hannan-Quinn criter.	-15.24129
F-statistic	0.506664	Durbin-Watson stat	1.950211
Prob(F-statistic)	0.482274		

Appendix 17.4 LM Test on Model 4

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

F-statistic	0.523727	Prob. F(1,20)	0.4776
Obs*R-squared	0.816580	Prob. Chi-Square(1)	0.3662

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 04/11/25 Time: 03:12
Sample: 1991 2022
Included observations: 32
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_EFP(-1)	0.124987	0.236343	0.528836	0.6027
GREENINVSETMENT	0.213026	0.655210	0.325126	0.7485
GREENINVSETMENT(-1)	0.106384	0.237931	0.447120	0.6596
LNGDP	-0.237501	0.550370	-0.431529	0.6707
GDP_2	0.015582	0.031640	0.492472	0.6277
GDP_2(-1)	-0.004543	0.011328	-0.401024	0.6927
POPULATION__DENSITY	-0.017292	1.042956	-0.016580	0.9869
LNNONRENEWABLE_ENERGY	0.110132	0.337583	0.326238	0.7476
GINRE	-0.011561	0.036053	-0.320660	0.7518
GINRE(-1)	-0.006232	0.013368	-0.466168	0.6461
C	-0.736306	3.352099	-0.219655	0.8284
RESID(-1)	-0.295360	0.408130	-0.723690	0.4776

R-squared	0.025518	Mean dependent var	3.89E-15
Adjusted R-squared	-0.510447	S.D. dependent var	0.010321
S.E. of regression	0.012685	Akaike info criterion	-5.616828
Sum squared resid	0.003218	Schwarz criterion	-5.067177
Log likelihood	101.8693	Hannan-Quinn criter.	-5.434634
F-statistic	0.047612	Durbin-Watson stat	1.985709
Prob(F-statistic)	0.999995		

Appendix 17.5 CUSUM Test on Model 4