

# **Green Growth Transition and Carbon Neutrality in G7 Countries**

## **Abstract**

This study investigates the impact of green growth, carbon tax, and energy efficiency towards the goal of carbon neutrality in G7 countries. This study uses a multi-dimensional green growth index instead of traditional GDP in the analysis and investigates the validity of the Environmental Kuznets Curve hypothesis. The quantile regression is used for estimation with the data from 1990-2021. Our study finds that green growth has a significant U-shaped relationship with carbon emissions, indicating that when green growth increases, the rate of carbon emissions continues to decline at a faster rate up to a threshold level and then starts to increase thereafter. Secondly, carbon tax, energy efficiency and research and development expenditures (research innovations) are determinants that help achieve carbon neutrality. Therefore, when developing policies related to reducing carbon emissions, policymakers should consider the non-linear relationship between carbon emissions and green growth.

**Key Words: Green Growth, Carbon Neutrality, Environmental Kuznets Curve, Climate Change, G7 Countries**

## 1 Introduction

Eradicating carbon emissions has become a complex problem due to the complicated and interrelated balance between economic, social and environmental objectives and sustainability. The challenge for policymakers is to design policies and regulations that can successfully reduce carbon and other GHG (Greenhouse gases) emissions without compromising economic growth and development, that is, SDG 13 - “Climate Action”. SDG 13 urges us to take urgent measures to combat “Climate Change” and its footprint. According to the United Nations, the global ecosystems are on the verge of crossing a climate threshold, which may potentially lead to far-reaching environmental crises. The world will exceed 1.5°C by 2035 and faces a 2.5 °C warming by 2100, if this “Climate Change” continues at the current rate as today. This existing “Climate Urgency” requires rapid and sustainable solutions for GHG emissions reductions by 43% by 2030 and to net-zero emissions or carbon neutrality by 2050.

The United Nations warns that the 2030 Sustainable Development Goals (SDGs) agenda will become an unfulfilled promise for the world that might have been, unless targeted and transformative action is taken. G7, as a group of developed countries, hold a disproportionate impact on global carbon emissions, thus requires the implementation of sustainable policies to steer the world away from “Climate Calamity” and towards a sustainable and resilient future. Finding solutions and policy recommendations that can quantify the economic impact of environmental sustainability remains a major challenge in the G7 countries (Zheng et al., 2023). G7 is a group of seven major industrialized advanced economies with significant socio-economic and environmental policies; these countries are Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States of America. Due to rapid globalization, economic growth and industrialization, these seven developed countries face a challenging task in implementing policies to reduce carbon emissions while maintaining or even accelerating economic growth and development (Chaudhry et al., 2020).

Carbon neutrality has become a significant goal to achieve the environmental objectives (UN, 2020) and can be achieved by various means, including an increase in innovation investment (Chen et al., 2023), increasing energy efficiency (Adebayo & Ullah, 2024) and implementing green growth-promoting strategies (Zahra & Fatima, 2024). As per the Paris Agreement, the eradication of carbon emissions is a significant objective of SDG 13 (Sustainable Development Goal - 13), which revolves around reducing the global temperature by 1.5°C (Zahra & Fatima, 2024). To reduce the global temperature level by 1.5°C by 2050, carbon emissions need to be reduced by 45% in 2030 from the 2010 level to achieve the target of carbon neutrality

(Commission, 2017; UN, 2020). In summary, achieving the target of carbon neutrality is significant for zero net carbon emissions, which can directly support economic, social and environmental goals.

The concept of economic growth should not be measured through financial gains only (Elkington, 1997), but it should be a comprehensive concept to include the social and environmental impact of economic expansion. The importance of SDGs by UN, which aims to achieve the target of “Low Carbon Economy”, “Resilient Society”, “Ecosystem Health” and “Sustainable Economic Growth”, should be considered to calculate the impact of economic activities regarded as “Green Growth”. One of the major instruments that helps to achieve sustainable and environmentally friendly growth and development is known as "green growth". It is important to achieve a win-win status in terms of environment and economic growth, so that economic growth should not be achieved at the cost of the environment. To integrate the environmental objectives into economic policies, green growth supports cleaner technologies (Chien et al., 2021), efficient use of energy sources (Sandberg et al., 2019) and economic policies to reduce the carbon footprint, which not only help to accelerate economic goals but also align with achieving carbon neutrality.

Towards carbon neutrality, promoting green growth strategies, enhancing energy efficiency, production innovation, and structuring a carbon tax mechanism are crucial strategies. Green growth accelerates sustainable development without compromising environmental objectives (Dong & Ullah, 2023). Energy efficiency promotes resource conservation and waste reduction (Jahanger et al., 2023). Carbon tax or carbon pricing imposes monetary restrictions on the industrial sector and individuals to reduce carbon footprints by costing carbon emissions, and thus helps to achieve carbon neutrality. Figure 1 shows the percentage share of carbon emissions by G7 countries (22%) versus the rest of the world (78%).

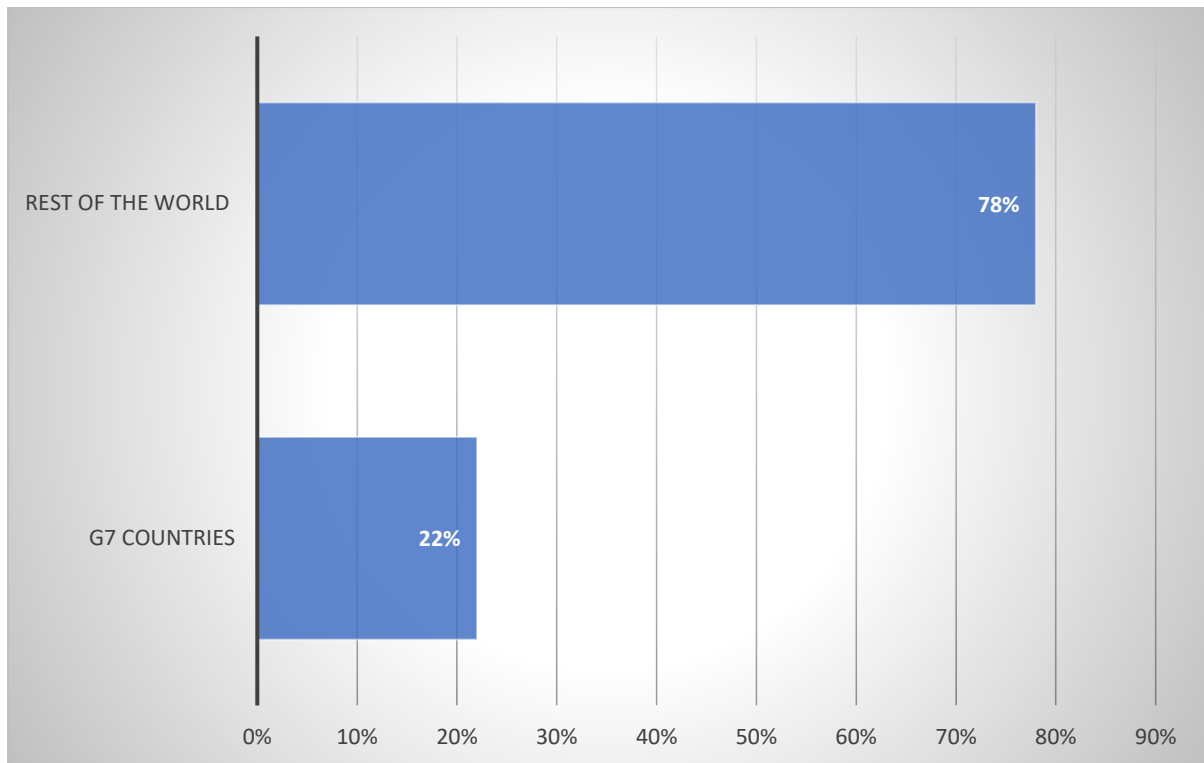


Figure 1: Percentage share of carbon emissions of G7 countries vs the Rest of the world

(Source: British Petroleum; 2020)

The process followed to produce the same or even higher level of output, by strengthening the technological innovations, and the use of lesser energy and minimum energy waste, is called “Energy Efficiency”, which helps to reduce carbon emissions (Javid & Khan, 2020). However, the severity of its impact depends on other economic policies, such as technological innovations and renewable energy transitions (Akram et al., 2020). Although energy efficiency is significant to achieve the carbon neutrality commitments by G7 countries, the implementation to achieve an energy-efficient system is slow (Altın, 2024a). Energy efficiency is measured as GDP per unit of energy use (constant 2021 PPP \$ per kg of oil equivalent). Figure 2 illustrates the energy efficiency of each G7 country between time of 1990 and 2021. These statistics show the disparity in energy efficiency practices among these major industrialized G7 countries.

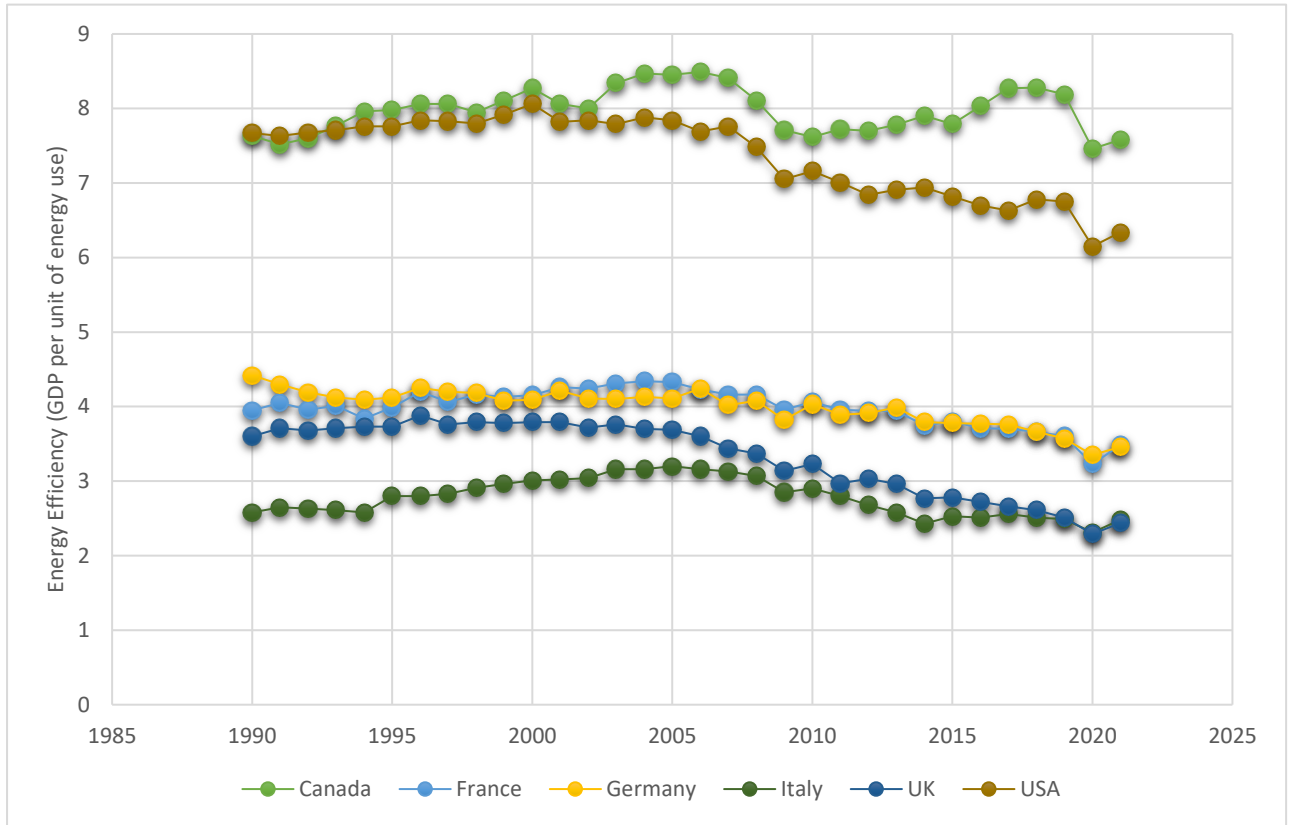


Figure 2: Energy efficiency, 1990-2021, G7 countries (Source: OECD, 2021)

Carbon tax is an economic mechanism to impose a price on carbon emissions to accelerate the pace towards the goal of carbon neutrality. On the one hand, a carbon tax is a type of Pigovian tax, which is imposed to correct economic failures determined by negative externalities. By making carbon emissions costly, the carbon tax enhances sustainable economic practices and encourages a renewable energy transition (Kinoshita, 2024). On the other hand, a carbon tax increases the cost of production, allowing producers to divert this cost to consumers, which will reduce the demand for carbon-intensive goods and services (Zhang et al., 2023). However, there are certain challenges associated with encouraging a carbon tax as a financial tool to control carbon emissions that can disproportionately affect low and middle-income individuals by increasing the cost of living (Fremstad & Paul, 2019). To achieve carbon neutrality, G7 countries actively design and impose carbon tax policies as a part of their comprehensive strategy for achieving environmental sustainability. These carbon tax policies significantly reduce carbon emissions if they are integrated and applied with the appropriate combination of green energy transition and green growth strategies (Doğan et al., 2022). Figure 3 presents a scatterplot of carbon tax vs carbon emissions in the G7 countries.

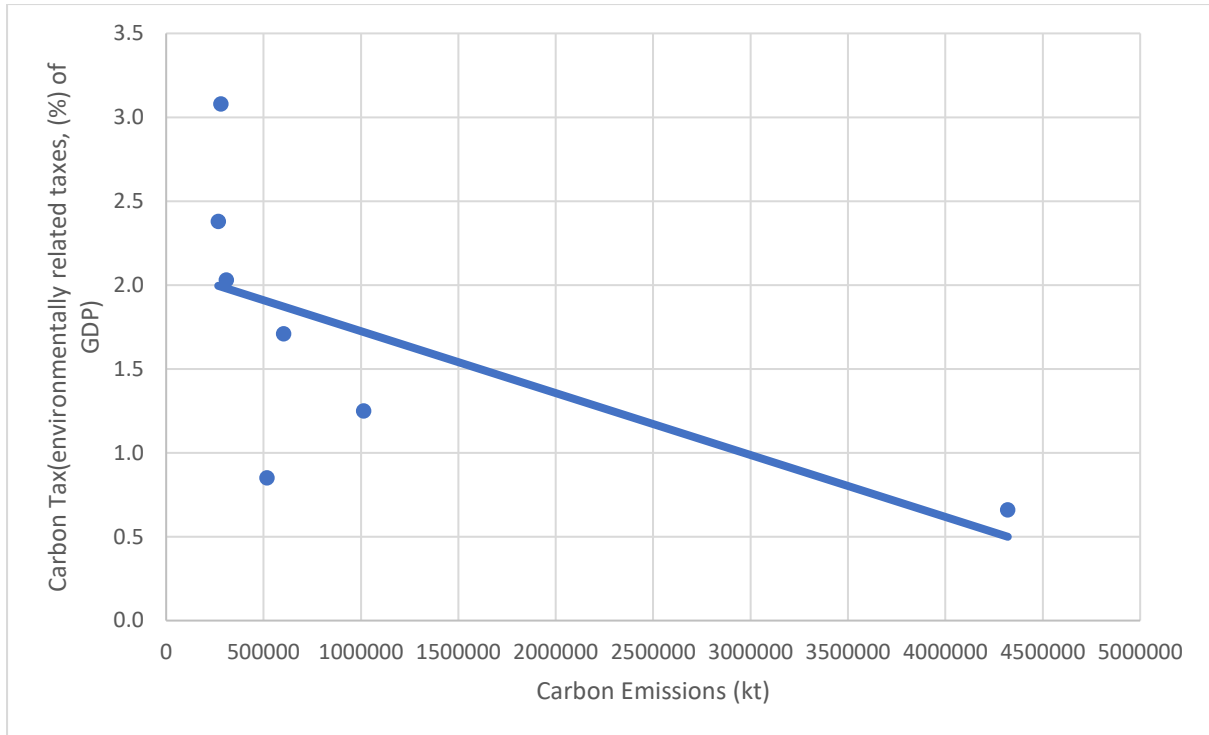


Figure 3: Carbon tax vs carbon emissions, G7 countries

A carbon tax is a financial cost imposed on carbon emissions to encourage industries and consumers to reduce fossil fuel consumption and increase cleaner alternative investments. This economic strategy encourages energy efficiency to directly reduce energy consumption by lowering operational costs. Increasing energy efficiency leads to a decrease in carbon emissions (Li et al., 2022) by reducing the amount of energy required for production and consumption. In conclusion, the carbon tax enhances the pattern of energy efficiency and reduces carbon emissions and supports environmental goals (Ma et al., 2023).

To achieve the carbon neutrality target, understanding how economic strategies can play their significant role in reducing carbon emissions is crucial. The existing literature exhibits many determinants of carbon emissions, but the importance of green growth strategies to achieve the target of carbon neutrality in G7 countries has been ignored. Considering this, there are certain research gaps that need to be further investigated to provide policy recommendations and action plans to achieve economic and environmental objectives.

This study focuses on the critical interaction of economic and environmental objectives on carbon emissions by investigating the validity of the green growth concept, energy efficiency and carbon tax in efforts to achieve the target of carbon neutrality in G7 economies. Examining the G7 economies is crucial because, as an informal group of highly industrialised economies,

they could have the potential to take decisive action against environmental problems and set an example for the rest of the world. The research gaps, along with the novelty and primary contributions are outlined below:

- (1) Carbon emissions is influenced by numerous factors, but economic growth emerges as the foremost determinant. However, there is limited literature that explains the concept of green economic growth as a new emerging trend. Most of the studies have assumed a single factor, such as green finance, green investment, and multifactor productivity, as a proxy of green growth (see, for example, Hao et al. (2021), Koondhar et al. (2021) J. Zhao et al. (2023) and determine their impact towards the target of carbon neutrality. Few other studies have examined the spatial effect of green growth in diminishing carbon emissions. However, there is a need to incorporate multiple factors into the green growth framework by considering green growth as a multidimensional phenomenon. In the literature, a number of SDGs in relation to green economic growth have been proposed by the United Nations (UN, 2022) such as low carbon economy, resilient society, eco system, healthy and sustainable economic growth have been ignored in the analysis of green growth as a determinant of carbon emissions. This is an important research gap that cannot be ignored. In view of this, we construct a new green growth index that combines different interrelated indicators as a proxy for green growth to determine its importance in achieving the target of carbon neutrality.
- (2) In addition, the validity of the Environmental Kuznets Curve (EKC) hypothesis has been investigated in different countries under different scenarios, but those studies have presented contradictory results. In view of this, the current study investigates the validity of EKC with reference to the newly constructed multi-dimensional green growth index towards the target of carbon. As a result, this study will provide clear insight into the impact of green growth strategies to achieve the carbon neutrality target in G7 countries.
- (3) The novelty of this paper extends further to its methodological approach, as it employs the method of moment quantile regression as a robust analytical tool to analyze the non-linear impact of green growth with reference to the EKC hypothesis and linear impact of R&D expenditures, energy efficiency and carbon policy towards the carbon neutrality target in G7 countries. This approach allows for a clearer comprehension of the relationship by estimating the conditional quantile functions of carbon emissions, thereby capturing potential heterogeneity and nonlinearities in the data. By utilising

moment quantile regression, this study also aims to uncover the distributional effects of independent variables on carbon emissions, providing insights into how different quantiles of carbon emissions respond to changes in exogenous variables. This methodological innovation enhances the analytical rigour of the study and offers a more comprehensive assessment of the impact of green growth, energy efficiency, carbon policy and R&D expenditures to achieve the target of carbon neutrality. Furthermore, to increase the robustness of our analysis, this research study employs bootstrap quantile regression as a supplementary test to validate the output calculated from the method of moment quantile regression. Bootstrap quantile regression offers a powerful resampling technique that addresses potential issues of data heterogeneity and model uncertainty, particularly in the context of analyzing complex relationships such as the one between assumed exogenous variables and carbon neutrality. The combination of these two methodologies provides a robust framework for examining the distributional impact of green growth, energy efficiency, carbon policy, R&D expenditures, and to check the validity of EKC, to achieve the target of carbon neutrality and offers valuable insights for policymakers and stakeholders involved in crafting sustainable energy policies.

## **2 Literature Review**

The environmental and climate change issues have been at the forefront and vital for global agendas in recent years. In response to the increasing threats posed by carbon emissions and environmental degradation, the concept of carbon neutrality has emerged as a vital strategy for combating climate change and preserving ecological balance. Governments and organizations worldwide have ambitious pledges to achieve net-zero emissions within the coming decades. Yet, despite these resolute commitments, the pathway to realizing a net-zero energy landscape by 2050 remains ambiguous and complex. It necessitates a holistic approach that harmonizes economic prosperity with environmental objectives. This literature review attempts to interconnect threads to link environmental targets and green growth objectives.

### **2.1 Green Growth and Carbon Neutrality**

In the literature, the term “Green Growth” tends to refer to accelerating economic growth and development, while verifying that natural resources and environmental services continue to enhance human wellbeing (Zahra et al., 2025). The relationship between economic growth and carbon emissions has been investigated by many researchers for various countries, especially

with reference to Environmental Kuznets Curve (EKC), but these studies have presented contradictory results in different scenarios and in different regions and countries (Akadiri et al., 2021; Long et al., 2023; Pata et al., 2023; Wang et al., 2023). Some studies have found economic growth to be a positive determinant of carbon emissions, and others have found the exact opposite results. On the other hand, a number of studies have also found a nonlinear relationship between economic growth and carbon emissions (Ongan et al., 2021; Selvanathan, Jayasinghe, Selvanathan, et al., 2023). These conflicting results about the role of economic growth in environmental sustainability have extended researchers' attention towards green growth instead of traditional economic growth. Green growth is not only helpful for environmental sustainability but also has the ability to defend the environment from negative externalities (Ahmed et al., 2022). Green growth aims to decouple economic growth from resource depletion and environmental degradation, promoting resource efficiency, innovation, and investments in low-carbon technologies and infrastructure (Loiseau et al., 2016; Sohail et al., 2022).

Green growth can have a different impact on carbon emissions depending on different economic and social factors, and promoting green growth practices contributes to achieving the carbon neutrality target (Liang & Luo, 2023). **The relationship between green growth and carbon emissions is complex. By way of illustration, (Akther et al., 2024; Zahra et al., 2025) exhibit how the impact of green growth on carbon emissions varies from country to country, and depends on different factors such as economic growth and development stages of a country, advancement in technology, energy mix and resource utilization.**

Carbon tax and cleaner energy transition can play a crucial role in combination with green growth to achieve the carbon neutrality target. Mamman and Sohag (2023) explored the importance of green growth in achieving carbon neutrality by using data from 1999 to 2019 for OECD countries. They found a dynamic but inverse relationship between green growth and carbon emissions, suggesting that green growth can have a long-term impact on carbon neutrality and suggested that strategies such as carbon taxes and cleaner energy transitions are not enough to achieve the target of carbon neutrality.

The relationship between green growth and carbon emissions is not always linear, it can be non-linear as well. Hao et al. (2021) analyse the role of green growth on carbon emissions for the G7 countries using the data for the period 1991 to 2017 by applying the Cross-Sectionally Augmented Autoregressive Distributed Lags (CS-ARDL) model and conclude that the

relationship between green growth and carbon emissions is non-linear. Similarly, (Zahra & Fatima, 2024; Zahra et al., 2025) observed an “inverted U-shaped” or “U-shaped” relationship between green growth and carbon emissions depending on the different economic and social determinants.

The concept of green growth is based on the assumption that an absolute decoupling of GDP growth from resource utilization and carbon emissions is practical and feasible (Solow, 1973), but Hickel and Kallis (2020) recommended that it is exceedingly doubtful that complete decoupling from CO<sub>2</sub> emissions would occur at a fast enough rate to stop global warming even under optimistic policy conditions. By examining the relevant studies on historical trends and model-based projections, Hickel and Kallis (2020) concluded that resource use and carbon emissions do not support green growth theory. This study concluded that absolute decoupling from carbon emissions to accelerate the green growth with a fast enough rate to achieve carbon neutrality and to prevent global warming of over 1.5 Celsius is not supported by any empirical evidence.

As there is a contradiction in the literature about the role of green growth in reducing carbon emissions, J. Zhao et al. (2023) suggested that the impact of green growth on carbon emissions is complex, with green growth not always leading to significant emission reductions. Similarly, Lin and Ullah (2023) emphasised the importance of prioritising green growth and innovation to address energy efficiency and carbon emissions reduction. However, the study also noted that there are many challenges in achieving this goal. While many studies reported that green growth is often a solution to reduce carbon emissions, the empirical evidence on its effectiveness is mixed. Some research studies prove green growth is a negative determinant of carbon emissions, while some others do not recommend promoting green growth to reduce carbon emissions and to achieve environmental targets.

## **2.2 Research and Development (R&D) Expenditures and Carbon Neutrality**

R&D expenditures are a multifaceted concept that may impact carbon emissions to achieve the environmental targets in different ways depending on different regions, economic conditions and economic stability (Han et al., 2023). The relationship between R&D expenditures is complex and bidirectional (Petrović & Lobanov, 2020). The magnitude of this relationship depends on various determinants, for example, the type of R&D expenditures, different stages of economic development of an economy and the sectors where these expenditures are utilized (Tao et al., 2023).

R&D expenditures play a significant role in reducing carbon emissions, particularly through the promotion of cleaner technologies and sustainable practices. Various studies have highlighted the positive effects of R&D investments on reducing carbon emissions. For example, Adedoyin, Alola, et al. (2020) investigated a negative relationship between R&D expenditures and carbon emissions in sixteen EU economies. Ibrahim and Ajide (2021) applied the PMG estimation technique in G7 countries for the period between 1990 and 2019, and it was found that R&D expenditures are a negative determinant of carbon emissions, and it is helpful to promote them in order to achieve environmental targets. Similarly, Fernández et al. (2018) for fifteen EU economies by applying the OLS method, Alam et al. (2019) for G6 countries by applying PMS and 2sls and Shao et al. (2021) by applying FMOSL and DOLS for the USA, found that R&D expenditures reduce carbon emissions and help to reduce environmental degradation.

The literature presents a contradictory perspective on the relationship between R&D expenditures and carbon emissions, with some studies indicating a positive impact on reducing emissions while others suggest a negative effect. For instance, while certain analyses highlight that increased R&D spending can lead to technological advancements that lower carbon emissions, others point out that high per capita R&D expenditures may hinder the decoupling of economic growth from carbon emissions in specific contexts and thus increase the environmental degradation (Chen & Lee, 2020; Sinha et al., 2020).

The contradiction in the literature about the direction of the relationship between these two highlights that the quantity of R&D expenditures matters, along with its direction and application. When R&D expenditures are utilized in carbon incentive sectors or industries without a special concentration of carbon reduction, it may ultimately increase carbon emissions through accelerated economic growth and development. (Li & Jiang, 2020) exhibits the important differences in how R&D expenditures affect carbon emissions while comparing developed vs developing economies. This study found that the decoupling status of economic development from carbon emission in developed countries (USA, Japan and Germany) is far better and more stable than in developing countries (China, Russia and India). This suggests that the effectiveness of R&D expenditures in reducing carbon emissions depends on the economic development of a country, existing technological infrastructure and implementation of environmental policy.

As the striving toward emission reduction targets, the appropriate use of R&D expenditures represents one of the important determinants available. By understanding the nuanced relationship between R&D expenditures and carbon emissions, policymakers can maximize the emission-reducing potential of their investments while simultaneously driving economic growth and social development.

### **2.3 Energy Efficiency and Carbon Neutrality**

Energy efficiency is a determinant in attaining sustainable growth and development. Despite an increase in renewable energy, around 80% of the world's energy needs are met by fossil fuels like oil and natural gas (Shah et al., 2024), while about 50% of the global electricity demand is met by coal (Liu et al., 2017). This has increased the attention of researchers to find out different ways to improve energy-efficient systems so that maximum output can be derived from the minimum possible energy consumption. Patterson (1996) was the first to introduce the concept of energy efficiency, which means “to utilise the minimum possible resources for the production of the same or even higher level.” Therefore, when less energy is consumed to perform the same tasks or to produce the same level of production, less carbon is emitted from energy-related consumption and production activities (Pashchenko, 2024). The recent literature emphasizes that energy efficiency has the capability to reduce carbon emissions directly and indirectly, thus helping economies to achieve the target of carbon neutrality (Altın, 2024b).

Energy efficiency is an important determinant in reducing carbon emissions by optimising the use of energy. To reduce energy consumption without compromising energy output and economic growth, energy-efficient technologies can help reduce carbon emissions and achieve the carbon neutrality target. Combining renewable energy resources with energy-efficient production techniques will result in the reduction of carbon emissions, as dependence on renewable energy reduces dependence on fossil fuels (Hasanov et al., 2024). Similarly, Hou et al. (2024) suggested that energy-efficient technologies in the industrial sector reduce the carbon footprint in industry, as these energy-efficient innovations are significant to achieve the environmental targets and carbon neutrality. Environmental policies such as carbon taxes and renewable energy transitions have played a significant role in enhancing energy efficiency to reduce carbon emissions globally, but their effectiveness varies from region to region and also depends on the economic condition of the country or region (Rabhi et al., 2024). Qing et al. (2023) by applying MMQR for BRICS economies, Mirza et al. (2022) for developing countries, Lei et al. (2022) for China by applying the ARDL model and Hassan et al. (2022)

for OECD countries, investigated the negative relationship between energy efficiency and carbon emissions.

Thus, the existing literature review shows a significant and negative relationship between energy efficiency improvements and carbon emissions reductions. This evidence shows that energy efficiency represents one of the most cost-effective tools to reduce carbon emissions and to make “Climate Action” an achievable goal.

## **2.4 Carbon Tax and Carbon Neutrality**

The concept of carbon tax dates back to the early twentieth century, after Arthur Pigou introduced the idea of externality for the first time (Pigou, 1920), pointing to a cost or benefit that is caused by an act which is not provoked by the producer of that act. For example, an increase in energy consumption for accelerating the production process is a negative externality for climate change, as it can thus increase carbon emissions. In this situation, the social marginal cost of carbon-intensive production sustained by a society is significantly greater than the private marginal cost of production by a producer firm. This situation results in market failure, in which the optimal market production exceeds the optimal social cost or quantity. Thus Pigou (1920) suggests that a tax on such market activity should be imposed by the policymakers to correct this market failure, where the social cost or damage of a production activity is greater than the benefits of the production process of a firm. This concept of tax is called Pigovian tax, and “Carbon Tax” is a form of Pigovian tax.

A carbon tax is a financial cost that is imposed on the carbon emissions of fossil fuels to reduce greenhouse gas emissions by making carbon emissions more costly (Xu et al., 2023). In other words, a carbon tax can broadly be defined as a price control mechanism that attributes the external cost of carbon emissions by applying an economic cost or price to carbon emissions to reduce their level in favour of environmental objectives (Pan et al., 2024).

The impact of carbon tax has been widely investigated as a policy tool to reduce greenhouse gas emissions (Nong et al., 2021). It is a cost of carbon emissions or carbon footprint, which encourages industrial and consumption sectors to reduce their carbon footprints. Macaluso et al. (2018) determine that a carbon tax is a strategy to increase the cost of carbon emissions and has the capacity to shift the production process towards renewable energy consumption. A comprehensive analysis of this research indicates that carbon taxes effectively reduce carbon emissions through a combination of renewable energy transition, energy efficiency, and switching economic activity from fossil fuel-based industries. This transition is effective in

reducing the use of fossil fuels, increasing green investment, especially in cleaner energy heads, and promoting energy efficiency (Pretis, 2022) and increase the green energy consumption. The effectiveness of carbon taxes not only depends on government policies but also on international policies. A coordinated global approach to carbon pricing could enhance the effectiveness of individual country carbon tax policies, which ensures that carbon emissions are reduced at the global level (Zahra & Badeeb, 2022; Zahra, Khan, & Nouman, 2022). In summary, the carbon tax is an effective economic policy to reduce carbon emissions. As its success is observed across various industries and countries, it promotes both environmental sustainability and economic resilience.

In conclusion, the carbon tax is an effective strategy to reduce carbon emissions, but there is heterogeneity in the magnitude of this carbon reduction mechanism, its economic impact, technological effects and other aspects (Pan et al., 2024).

### **3 Theoretical Framework and Methodology**

This research study investigates the impact of green growth (Economic Policies), research and development (R&D) expenditures (technological advancement), carbon tax (environmental stability), and energy efficiency (technological-economic advancement) on achieving carbon neutrality and Figure 4 illustrates how the objectives of this research study are interrelated. As the core of this framework lies in the concept of green growth, which emphasises the efficient and sustainable use of resources, the protection of natural capital, the development of a green economy, and the inclusion of social dimensions. Green growth serves as a foundational element that contributes to the goal of carbon neutrality by fostering environmentally sustainable economic development. Key drivers supporting carbon neutrality include energy efficiency, which enhances the effectiveness of energy use, reducing waste and emissions; R&D expenditures, which promote the innovation of low-carbon technologies; and the carbon tax, which incentivises emission reductions by internalising the environmental costs of carbon-intensive activities.

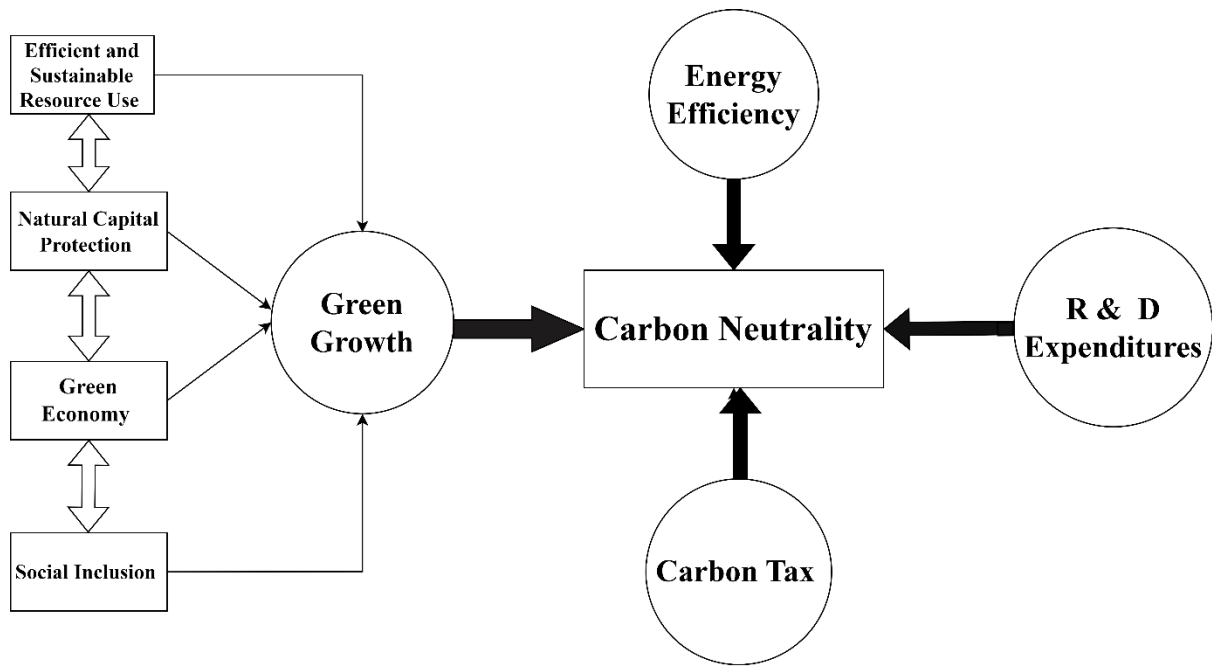


Figure 4: Graphical Presentation of the Objectives of the Study

On the other hand, the “Triple Bottom Line Approach” (TBL) provides the theoretical framework to select the proxy of green growth variables. This approach is proposed by Elkington (1997), is a holistic approach that takes into account the social, economic and environmental perspectives of development. Elkington (1997) emphasizes that growth should not be solely measured by financial gains, but it should also consider social and environmental impact. This approach revolves around three interconnected dimensions, which are the economic aspect (Profit), the social aspect (People) and the environmental aspect (Planet), also known as the Three P's approach (Profit People, Planet). Building on the framework established by Zahra and Fatima (2024), the Eco-Efficiency Domain has been identified as a focal area for the selection of green growth indicators. These indicators align with those designated by the OECD as key metrics of green growth. Within this domain, the green growth index is further subdivided into five primary indicators, which include carbon productivity, energy productivity, Renewable energy supply share, development of environmental-related technologies and environmentally adjusted multifactor productivity growth. **Figure 5 exhibits the interconnection of all indicators related to the “three P’s” (Planet, Profit and People), which are applied to calculate the green growth index through a Venn diagram.**

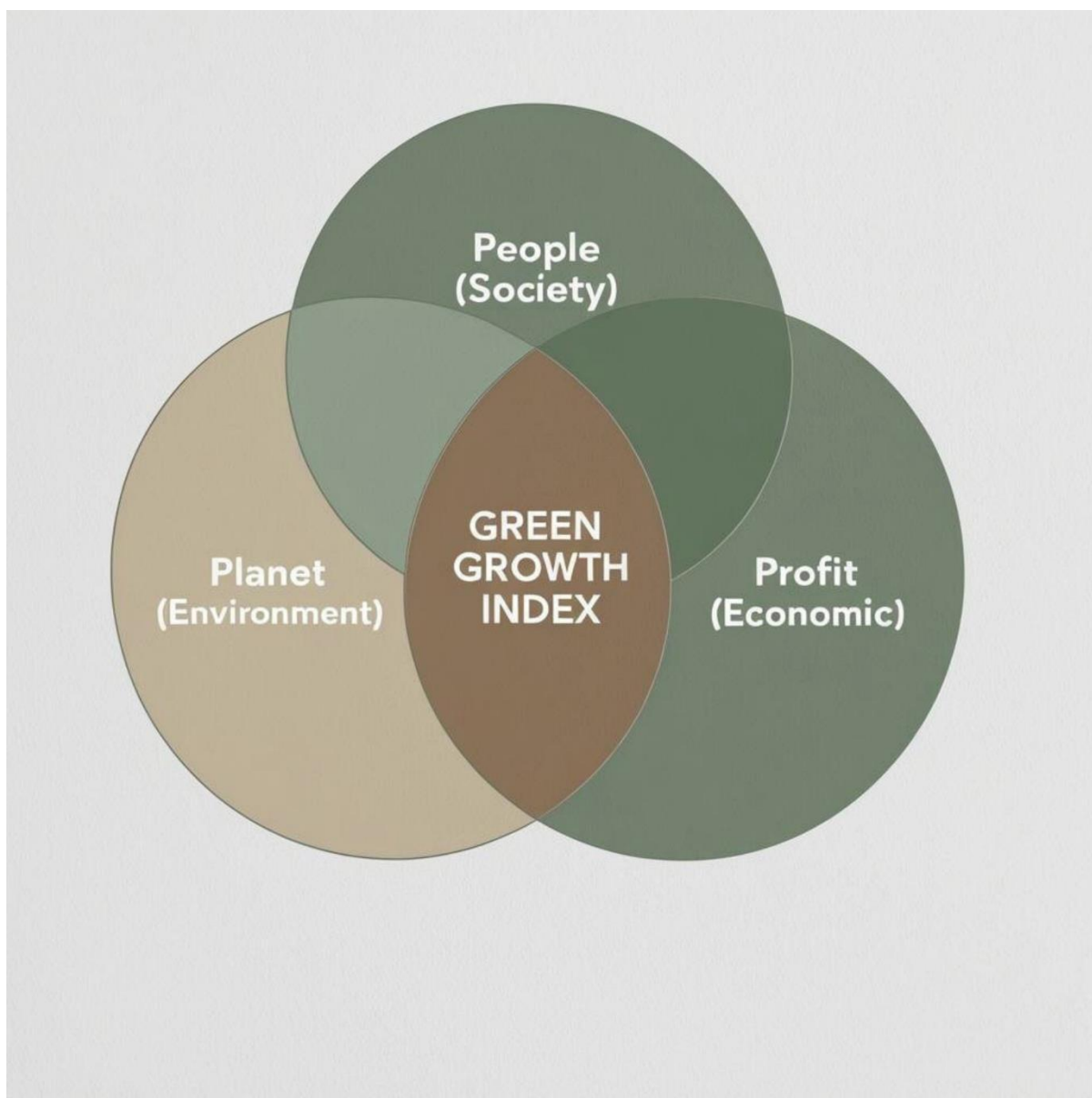


Figure 5: Green Growth Index Conceptual Framework through the Three P's Approach

Table 1 shows the main indicators of the Eco-Efficiency domain as components of the green growth index.

Table 1: Indicators of Green Growth Index

Domain of Green Growth Index	Indicators of the Green Growth Index	Description
D: Eco-Efficiency Domain	I1: Carbon productivity	Production-based CO <sub>2</sub> productivity, GDP per unit of energy-related CO <sub>2</sub> emissions.
	I2: Energy Productivity	GDP per unit of total energy supply (TES).
	I3: Share of Renewable Energy Supply	Share of renewable energy supply as % of total energy supply (TES).
	I4: Development of environmental-related technologies	Development of environmentally related technologies as % of all technologies.

	15: Environmentally adjusted multifactor productivity growth	Environmentally adjusted multifactor productivity growth.
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The weights associated with each indicator to be used in the construction of this index are calculated through Principal Component Analysis (PCA). PCA is a technique used to simplify the complexity of high-dimensional data. There are many techniques that are good for interpreting large and multiple indicator datasets, but PCA is widely known because it has the ability to reduce the dimensionality of the data in a more comprehensive way and keep the important information of the data as intact as possible (Wold et al., 1987). PCA will determine the principal component that will explain most of the variations in the indicators in the form of eigenvalues. While constructing a green growth index through PCA, weights will be assigned based on these eigenvalues according to the relative importance of each of the selected indicators. This technique is applied to closely inspect the internal correlation between different indicators, as it also handles the problem of multicollinearity (Jayasinghe et al., 2021; Zahra, Khan, Gupta, et al., 2022).

Similarly, in this sphere, the importance of the SDGs by the UN in 2015 cannot be ignored, which aims to achieve targets of a low-carbon economy, a resilient society, ecosystem health and sustainable economic growth. **By incorporating the Three P's approach with the framework**

of the SDGs by the UN, Figure 6 represents the graphical framework of calculating the green growth index.

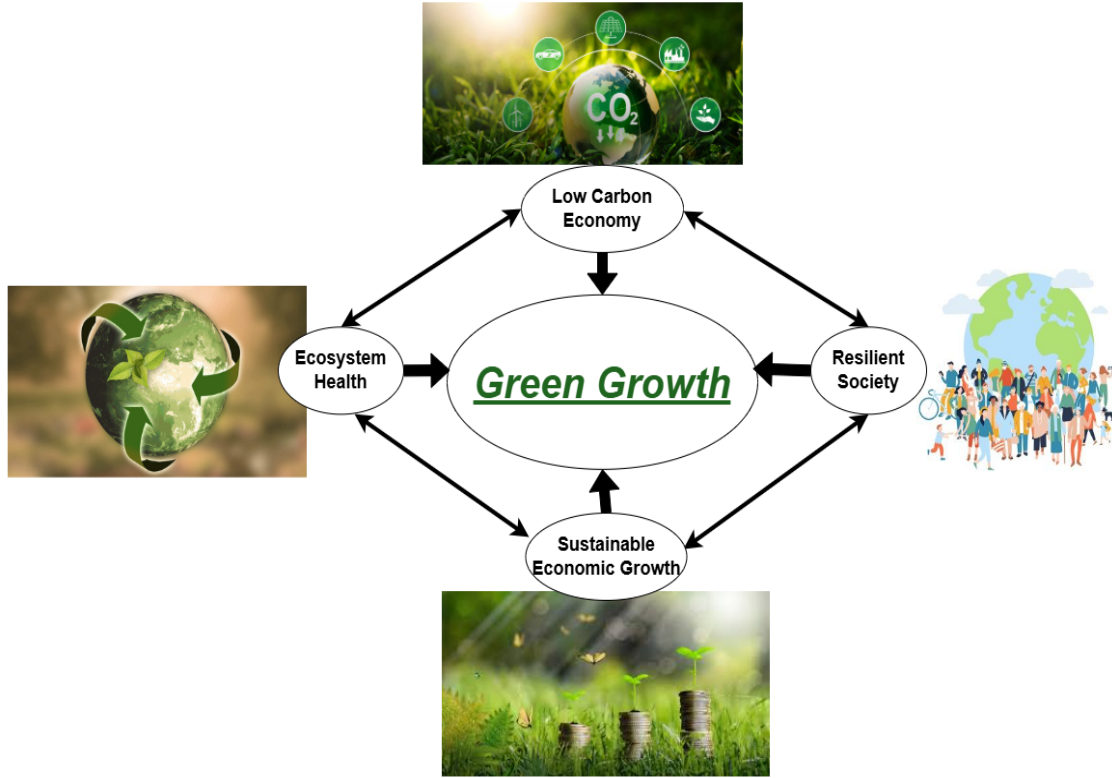


Figure 6: Interconnection of Green Growth Index Variables (SDGs and Three P's Approach)

Based on this theoretical background and literature review, this study proposes carbon neutrality (CN) as a function of Green Growth Index (GGI), R&D expenditures (RDE), Energy Efficiency (EE), and Carbon Tax (CT).

$$CN = f(GGI, RDE, EE, CT) \quad (1)$$

We specify the functional form for equation (1) similar to a Cobb-Douglas production function in the following form:

$$CN = e^{\beta_0} GGI^{\beta_1} RDE^{\beta_2} EE^{\beta_3} CT^{\beta_4} e^{\mu} \quad (2)$$

We linearize the above function by taking the natural logarithm of both sides of equation (2), with country  $i$  and time  $t$  subscripts added to give:

$$lCN_{it} = \beta_0 + \beta_1 lGGI_{it} + \beta_2 lRDE_{it} + \beta_3 lEE_{it} + \beta_4 lCT_{it} + \mu_{it}, \quad (3)$$

where  $l$  refers to the natural logarithm of the variable,  $\beta_0$  represents the intercept of the model;  $\beta_i$ 's ( $i=1,2,3,4$ ) are the parameters of the model variables; and  $\mu_{it}$  is the stochastic disturbance term.

The literature review presented above also reveals the possibility of non-linear relationships, also known as the EKC hypothesis, between carbon neutrality and green growth index, therefore, a non-linear relationship of the following form (an extended non-linear version of model (3) is used for the empirical estimation:

$$lCN_{it} = \beta_0 + \beta_{11} lGGI_{it} + \beta_{12} (lGGI_{it})^2 + \beta_2 lRDE_{it} + \beta_3 lEE_{it} + \beta_4 lCT_{it} + \mu_{it} \quad (4)$$

The conflicting role of economic growth in environmental sustainability has extended researchers' attention towards green growth instead of traditional economic growth. Green growth refers to fostering economic growth and development while ensuring that natural assets continue to provide resources and environmental services on which economic, social, amenity, and environmental objectives rely (Amara & Qiao, 2023; Peng et al., 2023). It aims to reduce carbon emissions and environmental degradation while promoting sustainable economic progress. Economic growth initially leads to an increase in carbon emissions, but as economies mature and transition to a green economy, carbon emissions tend to decrease (Peng et al., 2023). However, economic growth still relies heavily on fossil fuels, which increases carbon emissions (Zheng et al., 2023). The concept of green growth is based on the assumption that an absolute decoupling of GDP growth from resource utilisation and carbon emissions is practical and feasible (Solow, 1973), but Hickel and Kallis (2020) argued that it is exceedingly doubtful that complete decoupling from carbon emissions would occur at a fast enough rate to stop global warming even under optimistic policy conditions. Therefore, this study considers that the transition towards green growth from focusing on traditional economic growth may have a U-shaped relationship with carbon emissions, which does not support the validity of the EKC hypothesis with reference to green growth. This implies that when green growth increases, the rate of carbon emissions continues to decline up to a threshold point and starts increasing thereafter. Thus, given as  $\beta_{11} = \frac{\partial CN_{it}}{\partial GGI_{it}} < 0$  and  $\beta_{12} = \frac{\partial^2 CN_{it}}{\partial GGI_{it}^2} > 0$ .

R&D expenditures facilitate the development and adoption of clean technologies, renewable energy sources, and energy-efficient processes, which are essential for transitioning towards a

low-carbon economy and achieving net-zero emissions. The importance of R&D expenditures in increasing technological and innovative advancement cannot be ignored for reducing carbon emissions and helping to achieve the carbon neutrality target (Zhang et al., 2022). Thus, one would expect a negative impact of R&D expenditures on carbon emissions, and it is hypothesized as a helpful determinant to achieve the carbon neutrality target. This means that  $\beta_2 = \frac{\partial CN_{it}}{\partial RDE_{it}} < 0$ . It is implied that R&D expenditures can lead to improved energy efficiency, which in turn reduces nonrenewable energy consumption and carbon emissions (Altın, 2024a). An increase in energy efficiency leads to a reduction in energy consumption and lower carbon emissions. As energy efficiency increases, energy demand decreases, which in turn encourages the use of renewable energy sources and facilitates the transition to a low-carbon energy system and helps to achieve the target of carbon neutrality (Akram et al., 2020). Power plants primarily use fossil fuels, releasing greenhouse gases like carbon dioxide, which contributes to global warming. However, there are a number of environmental benefits to energy efficiency. It reduces carbon emissions both directly through the burning of fossil fuels and indirectly through power generation (Zheng et al., 2023). Given the arguments above, one would expect that  $\beta_3 = \frac{\partial CN_{it}}{\partial EE_{it}} < 0$ . Implementing a carbon tax leads to reductions in carbon emissions (Pretis, 2022), however the evidence of their impact on aggregate emissions is mixed. The magnitude of emission reductions depends on the level of the carbon tax, its coverage and implementation, and sectoral differences in emission responses (Du et al., 2022; Siriwardana et al., 2011). Although the magnitude of carbon emissions by implementing the carbon tax is mixed (Nong et al., 2021) but the existing literature elaborates the negative impact of carbon tax implementation on carbon emissions (Ding et al., 2019). Therefore, one would expect  $\beta_4 = \frac{\partial CN_{it}}{\partial CT_{it}} < 0$ .

For the past few decades, particularly over the last three decades, environmental degradation and climate change have been the most addressed challenges. Examining G7 economies is crucial because, as an informal group of highly industrialized economies, they could have the potential to take decisive action against these pressing problems and set an example for the rest of the world.

Considering the non-linear relationships between independent and dependent variables by taking the whole distribution into account, quantile regression analysis is one of the recommended techniques in the literature (Uribe et al., 2020). The quantile regression equips

the researchers to empirically determine the relationship between a set of exogenous variables not only at the centre but also alongside the entire conditional distribution of the dependent variable (Le Cook & Manning, 2013; Uribe et al., 2020). Quantile regression is a technique to identify the factor that influences the magnitude of the response at points of the data that are far from the central value and that are not necessarily found in symmetric positions with respect to the mean. Method of Moment Quantile Regression (MMQR) is an extension to quantile regression that incorporates the conditions under which it is impossible to estimate regression quantiles by estimating conditional means. It provides an additional technique to quantile regression estimators that allows the quantile regression estimation in situations where otherwise that would be difficult or impossible (Machado & Silva, 2019). Unlike traditional OLS regression, which only estimates the mean values, MMQR allows us to explore the conditional distribution of the dependent variable at different quantiles. MMQR has the advantage of utilising methods that are exclusively applicable in estimating conditional means, such as eliminating individual effects in the model, while also providing insights into how the regressors impact the entire conditional distribution. These informational gains are perhaps the most attractive feature of the quantile regression (Machado & Silva, 2019). Quantile regression via moments or method of moment quantile regression shows the variations among low, moderate and high impact of assumed determinants on carbon emissions, thus enhancing the understanding of what triggers the heterogeneous response, and which determinant is a valuable factor for the policy makers.

The robustness of the models is analyzed with Bootstrap Quantiles Regression (BSQR). However, the MMQR technique effectively predicts values at certain locations and scales by presenting quantile values. The Bootstrap Quantile Regression (BSQR) technique concentrates on determining the reliability of the model. The empirical analysis of this study is carried out at two levels: (1) pooling the data across seven countries and estimating a panel MMQR, and (2) using individual country data and estimating the MMQR model for each of the seven countries separately. The single country analysis will provide an in-depth analysis of the relationship between dependent and independent variables under consideration in each country separately, which is very useful for policy decision making at the individual country level (Selvanathan, Jayasinghe, & A. Selvanathan, 2023).

## 4 Data Source, Empirical Results and Discussion

We use annual time series data for the G7 countries during the period of 2010–2022. The period from 2010 to 2022 was chosen for this study based on the availability of consistent and reliable data for the key variables across the countries included in the analysis. This timeframe also coincides with significant global policy shifts towards sustainability and carbon neutrality, as many countries introduced more rigorous environmental policies and green technological innovations during this period. Additionally, the 2010–2022 span ensures consistency in data availability, as earlier years had notable gaps or less reliable data, especially for green growth, which would have compromised the robustness of the analysis. Table 2 shows the variables and their description used in this study.

Table 2: The Description of Data

Variable Type	Symbols	Variable Name	Description / Proxy Indicators
Dependent Variable	CN	Carbon Neutrality	CO <sub>2</sub> emissions measured in kt.
Independent Variable	GGI	Green Growth Index	An Index Calculated through PCA by following the Eco-Efficiency Domain.
Nonlinear Term	(GGI) <sup>2</sup>	Test for Curvature	The Square of Green Growth Index
Control Variables	RDE	Research and Development Expenditures	Environmentally related government R&D budget, (% total government R&D)
	EE	Energy Efficiency	Energy intensity (TES per capita)
	CT	Carbon Tax	Environmentally related taxes, (% GDP)

### 4.1 Panel Estimation

One of the prerequisites to perform panel data analysis is to investigate the heterogeneity and cross-sectional dependence in the data, as the choice to select the unit root tests depends on whether cross-sectional dependence is present in the data or not. As there are many socio-economic, financial and political differences among the selected countries, this may affect the panel or cross-sectional data. Therefore, it is important to check the heterogeneity and cross-sectional dependence among the variables before the panel data analysis. Pesaran and Yamagata (2008) test outcomes ( $\Delta = 11.39$  with p-value 0 and  $\Delta \text{ Adj} = 12.89$  with p-value 0) indicate that there is support for the alternate hypothesis of heterogeneity, indicating the presence of heterogeneous effects in the model.

To test whether there is a possibility of cross-sectional dependence in the data, Breusch-Pagan LM, Pesaran Scaled LM, Bias-Corrected Scaled LM and Pesaran CD tests are applied to check the cross-sectional dependence in the data. Table 3 presents the cross-sectional dependence test

results. The null hypothesis of the test is  $H_0$ : time series is cross-sectionally independent and  $H_A$ , the time series is cross-sectionally dependent. The cross-sectional dependence test results in Table 3 indicate that there is no support for the variables to be cross-sectionally independent, revealing that selected variables are cross-sectionally dependent and interrelated to each other (Selvanathan, Jayasinghe, & A. Selvanathan, 2023).

Table 3: Cross-Sectional Dependence Tests

Variables	Tests			
	Breusch-Pagan LM	Pesaran Scaled LM	Bias-Corrected Scaled LM	Pesaran CD
<i>ICN</i>	274.73*** (0.0)	39.15*** (0.0)	39.04*** (0.0)	10.19*** (0.0)
<i>IGGI</i>	457.34*** (0.0)	67.33*** (0.0)	67.23*** (0.0)	21.22*** (0.0)
<i>IGGI<sup>2</sup></i>	425.169*** (0.0)	62.37*** (0.0)	62.25*** (0.0)	19.84*** (0.0)
<i>IRDE</i>	148.46*** (0.0)	19.67*** (0.0)	19.54*** (0.0)	0.08 (0.93)
<i>IEE</i>	387.70 *** (0.0)	56.58*** (0.0)	56.47*** (0.0)	18.81 *** (0.0)
<i>ICT</i>	246.34*** (0.0)	34.77*** (0.0)	34.66*** (0.0)	11.04*** (0.0)

\*\*\*, \*\*, \*represent 1%, 5% and 10% level of significance, respectively (values in parentheses are probability values)

As selected variables are cross-sectionally dependent, the second-generation panel unit root tests, such as CIPS and CADF tests, are employed to check the panel unit roots among the variables. The panel unit root test results presented in Table 4 indicate that all the variables except green growth and the square of green growth have a unit root at the level and are stationary in their first difference. Analysis of the model without checking the order of integration may lead to the spurious estimation of coefficients (Granger & Newbold, 1974). Therefore, in the next step, we test the cointegration or long-run relationship between dependent and independent variables.

Table 4: Second Generation Unit Root Tests

Variables	CIPS		CADF		Level of Integration
	Level	1 <sup>st</sup> Difference	Level	1 <sup>st</sup> Difference	
$lCN_{it}$	-1.83	-5.5***	-1.82	2.98***	I (1)
$lGGI_{it}$	-4.44***	--	-3.32***	--	I (0)
$lGGI_{it}^2$	-3.86***	--	-2.76***	--	I (0)
$lRDE_{it}$	-2.3	-5.64***	-1.70	-2.98***	I (1)
$lEE_{it}$	-1.81	-5.88***	-1.14	-2.96***	I (1)
$lCT_{it}$	-1.47	-4.91*	-1.72	-2.59**	I (1)

\*\*\*, \*\*, \*represent 1%, 5% and 10% levels of significance, respectively

Table 5 presents the Kao (1999) Panel cointegration test to check the long-run association in the model. The null hypothesis of this test is about no cointegration between the variables in the panel data against the alternative hypothesis about the presence of cointegration. The results confirm the acceptance of the alternative hypothesis, which depicts that a long-run relationship exists, supporting the evidence of cointegration at the 1% level of significance.

Table 5: Panel Cointegration Test

Kao Panel Cointegration Test		
	Statistics	P-value
Modified Dickey-Fuller t	-4.51***	0.0
Dickey Fuller t	-3.91***	0.0
Augmented Dickey Fuller t	-2.76***	0.0
Unadjusted Modified Dickey-Fuller t	-6.35***	0.0
Unadjusted Dickey-Fuller t	-4.38***	0.0

\*\*\*represent 1% level of significance respectively

### Panel Estimation Results

Table 6 presents the results of MMQR in four quantiles,  $Q_{0.25}$ ,  $Q_{0.50}$ ,  $Q_{0.75}$ ,  $Q_{0.90}$  and also depicts the significance of location and scale of the respective independent variables. Location estimates in column 2 of the table show the central tendency, such as the mean of the data, while scale estimates in column 3 show the variability or dispersion to analyse how independent variables influence both central tendency and dispersion of carbon neutrality in different quantiles of the model. Thus, each significant coefficient estimate of location indicates that the respective independent variable in column 1 has a significant impact on the central tendency of the dependent variable at that particular quantile. The significant coefficient

estimate of scale indicates the influence on the variability or dispersion of the corresponding independent variables in column 1 (Machado & Santos Silva, 2019).

Table 6: Panel Estimation Results - MMQR

Variables (1)	Location (2)	Scale (3)	Q <sub>0.25</sub> (4)	Q <sub>0.50</sub> (5)	Q <sub>0.75</sub> (6)	Q <sub>0.90</sub> (7)
$lGGI_{it}$	-0.58*** (0.0)	0.08* (0.06)	-0.65*** (0.0)	-0.60*** (0.0)	-0.51*** (0.0)	-0.46*** (0.0)
$lGGI_{it}^2$	0.12 (0.17)	-0.11** (0.03)	0.21** (0.02)	0.15* (0.09)	0.14 (0.89)	-0.07 (0.60)
Turning Points	2.42	0.36	1.55	2.00	1.82	-3.29
$lRDE_{it}$	-0.40*** (0.0)	-0.04 (0.24)	-0.36*** (0.0)	-0.39*** (0.0)	-0.43*** (0.0)	-0.45*** (0.0)
$lEE_{it}$	-0.93*** (0.0)	0.25*** (0.01)	-1.14*** (0.0)	-0.99*** (0.0)	-0.70*** (0.0)	-0.52*** (0.03)
$lCT_{it}$	-1.64*** (0.0)	0.15** (0.05)	-1.76*** (0.0)	-1.67*** (0.0)	-1.49*** (0.0)	-1.39*** (0.0)
Constant	7.22*** (0.0)	-0.05 (0.54)	7.27*** (0.0)	7.23*** (0.0)	7.17*** (0.0)	7.14*** (0.0)

\*\*\*, \*\*, \*represent 1%, 5% and 10% level of significance respectively (p-values are in parentheses).

The positive coefficients associated with  $lGGI_{it}^2$  reported in Table 6 indicates that green growth (GGI) has a U-shaped relationship with carbon emissions in the first three quantiles (significant in the first two quantiles). Such a nonlinear relationship between green growth and carbon emissions is also supported by existing literature (see, for example, Hao et al. (2021), Dong et al. (2022), Gu et al. (2023), Zahra and Fatima (2024)). The U-shape non-linear relationship combined with negative lGGI coefficient also means that with each unit increase in green growth, the carbon emissions will decline at a decreasing rate up to turning points and starts increasing after surpassing threshold turning points of 1.55 units (in log value) in Q<sub>25</sub>, 2.00 units (in log value) in Q<sub>50</sub> and 1.82 units (in log value) in Q<sub>75</sub> respectively. There are certain studies, for example, Hickel and Kallis (2020), that do not recommend promoting green growth to reduce carbon emissions. Such studies recommend that governments should consider alternative approaches to reduce carbon emissions rather than relying on green growth

concepts, as this is probably an unwise goal to focus on. The concept of green growth based on the assumption that an absolute decoupling of GDP growth from resource utilization and carbon emissions is practical and feasible (Solow, 1973), but Hickel and Kallis (2020) recommended that it is exceedingly doubtful that complete decoupling from carbon emissions would occur at a fast enough rate to stop global warming even under optimistic policy conditions. The majority of studies in the existing literature support this positive association between green growth and carbon emissions, see, for example, Gazheli et al. (2016), X. Zhao et al. (2023) and Mikayilov et al. (2018). Thus, the impact of green growth on carbon emissions is complex, with green growth not always leading to significant emission reduction (J. Zhao et al., 2023).

On the other hand, Hao et al. (2021) Supports the negative impact of green growth on carbon emissions and suggests promoting green growth to achieve the target of carbon neutrality in the long run. This study investigated the inverted U-shaped relationship between green growth and carbon emissions, which is also in line with the results of  $Q_{0.90}$ . These results are supported by some of the previous literature see, for example, Lee (2011) and Jouvét and de Perthuis (2013).

Thus, the U-shaped relationship between green growth and carbon emissions is supported by certain reasons. Firstly, an increase in carbon productivity (Liu et al., 2023), energy productivity (Zahra & Badeeb, 2022), renewable energy supply, and adoption of environmentally related technologies and enhancement in environmentally adjusted multifactor productivity (Zahra et al., 2025), facilitates decoupling economic growth from carbon emissions at first stage. Thus, the initial stage of investment in renewable energy and resource efficiency reduces carbon emissions. However, after surpassing the threshold, the relationship between the green growth index and carbon emissions becomes positive, and with every unit increase in the green growth index, the carbon emissions also increase. “Scale Effect” is the possible reason for this positive association between them, as green growth may lead to higher demand for energy resources, which ultimately leads to an increase in carbon emissions, even if the relative efficiency of economic growth is improving (Zhang, 2012). Another possible reason for this positive relationship between green growth and carbon emission after a threshold level is “Rebound Effect”, where efficiency gains lower the effective cost of energy services, leading to an increase in energy demand that offsets environmental benefits and increases the carbon emissions (Li, 2021). Therefore, the observed U-shaped curve highlights a critical insight: while green growth can effectively reduce emissions in the initial

phase, it does not guarantee that it will achieve the target of carbon neutrality if environmental objectives are not addressed in the long run without addressing deeper structural and infrastructure issues. Policymakers must recognise the turning point as an important insight to shift focus from only promoting green growth towards ensuring that economic growth remains environmentally sustainable.

Another important determinant of carbon emissions is R&D expenditure, and results show that this is a negative and significant determinant of carbon emissions in all four quantiles. Thus, an increase in R&D expenditure will help to achieve the target of carbon neutrality in G7 countries. These results are also in line with existing literature (see, for example, Ibrahim and Ajide (2021), Adedoyin, Alola, et al. (2020), Bilgili et al. (2024), Mamkhezri and Khezri (2024).

Research and development (R&D) expenditures are increasingly viewed as critical tools in the global fight against climate change. The effectiveness of R&D in reducing emissions highlights its potential as a policy tool for addressing climate change while maintaining economic growth. However, this negative relationship is not universal across all contexts and measurement approaches. Some analyses reveal that the significant impact of R&D expenditures on emissions may vary across different quantiles of the distribution (Han et al., 2023). This suggests that to reduce carbon emissions, the effects of R&D may be different at certain thresholds or within specific economic contexts, rather than demonstrating a uniform impact across all scenarios. The variability in these findings underscores the complex and conditional nature of the relationship between R&D and emissions. R&D expenditures in the renewable energy sector have a significant impact on reducing carbon emissions and improving the quality of the environment.(Hailemariam et al., 2022). This targeted approach to R&D allows for the development of cleaner energy alternatives and more efficient technologies that directly address emission sources (Adedoyin, Bekun, et al., 2020). R&D expenditures influence carbon emissions through several different procedures. A primary pathway is through improvements in energy efficiency, as research enables the development of technologies and processes that achieve the same output with reduced energy inputs (Zahra et al., 2025). This process is particularly related to green innovation, which has been shown to decrease carbon emissions significantly by enhancing energy efficiency at the enterprise level (Xie & Wang, 2024).

The source of R&D expenditures also influences its environmental impact (Zafar et al., 2019). The total spending on R&D is not sufficient to reduce carbon emissions if they are not applied

in a targeted approach with a specific focus on energy-efficient innovations, technologies and green technologies (Dzator & Acheampong, 2020). This finding has important implications for policy making, which suggests that governments should not merely increase overall budget R&D expenditures but allocate resources to environmental technologies decisively.

As energy efficiency is considered a vital tool to diminish carbon emissions and to achieve the target of carbon neutrality and other environmental objectives (Bakaloglou & Belaïd, 2022; Belaïd, 2024). Although through energy efficiency, an economy can increase the level of economic output with minimal possible use of energy required, which can reduce the carbon intensity and reduce the cost of energy (Belaïd et al., 2021; Belaid et al., 2020). Table 5 results also show that energy efficiency reduces carbon emissions in all four quantiles. This outcome is in line with the existing literature (see, for example, Qing et al. (2023) , Li et al. (2022), Mirza et al. (2022), Akram et al. (2020), Lei et al. (2022).

G7 countries pursue their collective commitment to achieve net-zero emissions by 2050 (Ullah et al., 2025), energy efficiency has emerged as a significant determinant for carbon reduction (Li et al., 2022). An increase in energy efficiency can reduce over 70% or decline in demand of oil and a 50% decrease in gas consumption by 2030, which is aligned with the efforts towards carbon neutrality by 2050 (IEA, 2024). Accelerated energy efficiency can operate to achieve the carbon neutrality target in two ways. First, it reduces the demand for energy and fossil fuels through improvements in energy technologies and green practices (Zahra & Fatima, 2024). Secondly, it supports a transition from fossil fuels to renewable energy (Bilgili et al., 2024). As G7 countries are trying to triple the green energy capacity to support the renewable energy transition, measures towards energy efficiency can help to manage the demand for fossil fuels, reduce the cost of the production process and ensure their stability. Energy efficiency represents a powerful but currently underutilized tool for reducing carbon emissions across G7 nations. To meet their climate commitments, including the goal of net-zero emissions by 2050, these countries must accelerate efficiency improvements across all sectors of their economies.

The last assumed determinant of carbon emissions in this study is carbon tax. Results show that the carbon tax also reduces carbon emissions across all four quantiles. Implementing a carbon tax leads to reductions in carbon emissions (Pretis, 2022), the evidence of impact and its magnitude on aggregate emissions is mixed (Nong et al., 2021). The magnitude of emission reductions depends on the level of the carbon tax, its coverage and implementation, and sectoral

differences in emission responses (Du et al., 2022; Siriwardana et al., 2011) and thus this reduction in carbon emissions leads to a reduction in carbon emissions.

The effectiveness of environmental taxes in reducing carbon emissions across G7 countries can be explained through multiple reinforcing mechanisms. Carbon pricing, implemented either through direct carbon taxes or emissions trading systems (ETS), has become a cornerstone policy tool in G7 climate strategies, creating economic incentives that discourage carbon-intensive activities while encouraging low-carbon alternatives (Doğan et al., 2022). The G7 “Clean Energy Economy Action Plan” further reinforces these effects by coordinating policy approaches that incentivise partners to achieve green growth transitions of their economies, creating a unified framework where environmental taxes can most effectively reduce carbon emissions through both direct economic policies and indirect green innovation strategies.

The implementation strategies of carbon taxes vary across G7 members but consistently demonstrate effectiveness in emissions reduction. This integrated approach has brought the G7 to the forefront of climate policy development, with their collective commitment to net-zero emissions or carbon neutrality targets by 2050 providing a framework for strengthening carbon and other environmental tax measures.

### Bootstrap Quantile Regression

Bootstrap Quantile Regression (BSQR) is applied to check the robustness of the MMQR estimated results presented in Table 6. Table 7 presents the outcomes of the BSQR estimation results. A comparison of Table 7 BSQR results with the corresponding MMQR coefficient estimates of Table 6 confirms that the MMQR results are reliable and robust.

Table 7:BSQR Test Results of Robustness

Variables	Q <sub>0.25</sub>	Q <sub>0.50</sub>	Q <sub>0.75</sub>	Q <sub>0.90</sub>
$lGGI_{it}$	-0.66*** (0.0)	-0.64*** (0.0)	-0.23*** (0.0)	-0.20*** (0.0)
$lGGI_{it}^2$	0.29*** (0.0)	0.24** (0.04)	-0.09 (0.36)	-0.05 (0.5)
$lrDE_{it}$	-0.29*** (0.0)	-0.36*** (0.0)	-0.22*** (0.0)	-0.12** (0.02)
$lEE_{it}$	-1.12*** (0.0)	-1.19*** (0.0)	0.52 (0.12)	0.88*** (0.0)

$lCT_{it}$	-1.80*** (0.0)	-1.75*** (0.0)	-1.11*** (0.0)	-1.02*** (0.0)
Constant	7.22*** (0.0)	7.37*** (0.0)	6.20*** (0.0)	5.91*** (0.0)

\*\*\*, \*\*, \*represent 1%,5% and 10% level of significance respectively

## 4.2 Individual Country Analysis

Individual country estimation results have been presented in this section for each of the seven countries separately. ADF (Dickey & Fuller, 1981), and PP (Phillips & Perron, 1988) is employed to check the stationarity of the individual country's variables, which are presented in Table 8.

Table 8: Unit Root Tests for Individual Country

Canada					
Variables	ADF		PP		Interpretation
	t-stats	P-value	t-stats	P-value	
$ICN$	-2.53	0.12	-1.52	0.52	
$\Delta ICN$	-5.20***	0.00	-6.62***	0.00	I (1)
$IGG$	-1.87	0.34	-1.81	0.37	
$\Delta IGG$	-6.36***	0.00	-6.65***	0.00	I (1)
$IGG^2$	-1.52	0.52	-1.45	0.45	
$\Delta IGG^2$	-5.99***	0.00	-6.03***	0.00	I (1)
$IRDE$	-2.86*	0.06	-3.18***	0.03	I (0)
$IEE$	-2.96**	0.05	-2.19	0.21	
$\Delta IEE$	-4.50***	0.00	-4.45***	0.00	I (1)
$ICT$	0.63	0.98	0.84	0.99	
$\Delta ICT$	-4.66***	0.00	-4.62***	0.00	I (1)
France					

	t-stats	P-value	t-stats	P-value	Interpretation
<i>ICN</i>	-0.155	0.93	-0.99	0.75	
$\Delta ICN$	-7.11	0.00	-7.31	0.00	I (1)
<i>IGG</i>	-0.59	0.85	-2.22	0.93	
$\Delta IGG$	-7.62***	0.00	-7.92***	0.00	I (1)
$IGG^2$	-0.31	0.92	0.04	0.96	
$\Delta IGG^2$	-6.68***	0.00	-6.91	0.00	I (1)
<i>IRDE</i>	-3.24**	0.03	-3.23**	0.02	I (0)
<i>IEE</i>	1.00	0.99	-0.32	0.92	
$\Delta IEE$	-7.78***	0.00	-7.59	0.00	I (1)
<i>ICT</i>	-1.85	0.35	-1.85	0.35	
$\Delta ICT$	-5.39***	0.0	-5.39***	0.00	I (1)
<b>Germany</b>					
	t-stats	P-value	t-stats	P-value	Interpretation
<i>ICN</i>	-1.58	0.48	-1.52	0.52	
$\Delta ICN$	-4.85***	0.0	-4.74***	0.0	I (1)
<i>IGG</i>	-1.56	0.48	-1.52	0.51	
$\Delta IGG$	-4.84***	0.0	-4.75***	0.0	I (1)
$IGG^2$	-1.56	0.49	-1.52	0.51	
$\Delta IGG^2$	-4.85***	0.0	-4.74	0.0	I (1)
<i>IRDE</i>	-1.57	0.49	-1.52	0.51	
$\Delta IRDE$	-4.85***	0.0	-4.74	0.0	I (1)
<i>IEE</i>	0.73	0.9	-0.38	0.89	
$\Delta IEE$	-8.59	0.0	-8.83	0.0	I (1)
<i>ICT</i>	-1.02	0.73	-1.14	0.68	

$\Delta ICT$	-5.22***	0.0	-5.31***	0.0	I (1)
<b>Italy</b>					
	t-stats	P-value	t-stats	P-value	Interpretation
$ICN$	-0.89	0.78	-0.86	0.78	
$\Delta ICN$	-4.85***	0.0	-4.93***	0.0	I (1)
$IGG$	-1.16	0.67	-0.85	0.79	
$\Delta IGG$	-4.72***	0.0	-11.91***	0.0	I (1)
$IGG^2$	-1.03	0.73	-0.68	0.84	
$\Delta IGG^2$	-4.86***	0.0	-10.71	0.0	I (1)
$IRDE$	-3.35**	0.02	-3.35**	0.02	I (0)
$IEE$	-0.86	0.79	-1.02	0.73	
$\Delta IEE$	-5.35***	0.0	-5.46***	0.0	I (1)
$ICT$	-1.68	0.43	-1.94	0.31	
$\Delta ICT$	-5.27***	0.0	-5.29***	0.0	I (1)
<b>Japan</b>					
	t-stats	P-value	t-stats	P-value	Interpretation
$ICN$	-2.71	0.10	-2.72	0.10	
$\Delta ICN$	-4.21***	0.0	-3.28***	0.02	I (1)
$IGG$	-0.04	0.95	-2.27	0.19	
$\Delta IGG$	-7.27***	0.0	-15.03	0.0	I (1)
$IGG^2$	-0.12	0.94	-2.12	0.23	
$\Delta IGG^2$	-7.49***	0.0	-15.76	0.0	I (1)
$IRDE$	0.15	0.96	-0.83	0.79	
$\Delta IRDE$	-2.84*	0.06	-6.16***	0.0	I (1)
$IEE$	-0.001	0.95	-0.39	0.89	

$\Delta IEE$	-5.66***	0.0	-5.69***	0.0	I (1)
$ICT$	-0.25	0.92	-0.12	0.94	
$\Delta ICT$	-5.87***	0.0	-5.89	0.0	I (1)
<b>UK</b>					
	t-stats	P-value	t-stats	P-value	Interpretation
$ICN$	0.85	0.99	-0.35	0.91	
$\Delta ICN$	-6.42***	0.0	-6.52***	0.0	I (1)
$IGG$	-0.48	0.89	-4.77	0.88	
$\Delta IGG$	-5.38***	0.0	-5.93***	0.0	I (1)
$IGG^2$	0.34	0.97	0.75	0.99	
$\Delta IGG^2$	-5.41***	0.0	-6.12	0.0	I (1)
$IRDE$	-2.34	0.16	-2.43	0.14	
$\Delta IRDE$	-4.10***	0.0	-3.96***	0.0	I (1)
$IEE$	2.32	0.99	1.22	0.99	
$\Delta IEE$	-7.14***	0.0	-6.95***	0.0	I (1)
$ICT$	-1.70	0.43	-1.74	0.40	
$\Delta ICT$	-5.04***	0.0	-4.93***	0.0	I (1)
<b>USA</b>					
	t-stats	P-value	t-stats	P-value	Interpretation
$ICN$	-0.75	0.82	-0.88	0.78	
$\Delta ICN$	-7.07***	0.0	-5.59	0.0	I (1)
$IGG$	-1.40	0.57	-1.22	0.65	
$\Delta IGG$	-4.34***	0.0	-8.39***	0.0	I (1)
$IGG^2$	-3.12**	0.03	-3.12**	0.03	I (0)
$IRDE$	0.81	0.99	0.13	0.96	

$\Delta IRDE$	-6.04***	0.0	-6.34***	0.0	I (1)
$IEE$	0.122	0.96	0.35	0.98	
$\Delta IEE$	-5.04***	0.0	-6.32	0.0	I (1)
$ICT$	0.74	0.99	0.80	0.99	
$\Delta ICT$	-5.21***	0.0	-5.21	0.0	I (1)

\*\*\*, \*\*, \*represent 1%, 5% and 10% levels of significance respectively

Table 8 exhibits that all variables are stationary in first difference for all countries except R&D expenditures in Canada, France and Italy, which are stationary at the level, along with the square term of green growth in the USA. As most of the variables are stationary in all countries, this paves the way to investigate the cointegration or long-run relationship among the variables. Table 9 shows the outcomes of the F-Bound Cointegration Test at 1%, 5% and 10% levels of significance. It is determined that in Canada, France, Italy and the UK, the variables are cointegrated, thus inferring the long run relationships among dependent and independent variables. On the other hand, in Germany and Japan, no cointegration is found, thus inferring that there is no long-run relationship between dependent and independent variables in these two countries.

Table 9: F-Bound Cointegration Test

Countries	F-Statistics	10% Sig level		5% Sig level		1% Sig level		Interpretation
		L <sub>0</sub>	L <sub>1</sub>	L <sub>0</sub>	L <sub>1</sub>	L <sub>0</sub>	L <sub>1</sub>	
Canada	8.55***	2.41	3.52	2.91	4.19	4.13	5.76	Cointegrated
France	4.94**	2.41	3.51	2.91	4.19	4.13	5.76	Cointegrated
Germany	1.12	2.41	3.51	2.91	4.19	4.13	5.76	No Cointegration
Italy	5.15**	2.41	3.52	2.91	4.19	4.13	5.76	Cointegrated
Japan	2.10	2.41	3.52	2.91	4.19	4.13	5.76	No cointegration
The UK	6.47***	2.41	3.52	2.91	4.19	4.13	5.76	Cointegrated
The US	3.40**	2.41	3.00	2.91	3.38	4.13	5.76	Cointegrated

\*\*\*, \*\*, \*represent 1%, 5% and 10% level of significance respectively (L<sub>0</sub> represents lower bound critical value and L<sub>1</sub> represents upper bound critical value)

## Robustness Check

Table 10 presents the MMQR and BSQR results at the individual country level, for Canada, France, Germany, Italy, Japan, the UK and the USA. The table is organized to show detailed statistical outcomes for each country, allowing for a comparative analysis across different

quantiles by applying both techniques that are MMQR and BSQR. Columns (2) through (7) provide the estimated quantile coefficients by method of MMQR as primary results and columns (8) through (11) provide the estimated quantile coefficients by method of BSQR for the test of robustness, which illustrates how the dependent variable responds to changes in the independent variable at different points in the distribution. The turning points of these models (indicating where the relationship between the variables changes direction) are also specified. This detailed presentation helps in understanding the impacts and variations in the relationship between dependent and independent variables across different quantiles for each country studied. Figures 7 to 13 show the graphical presentation of the quantile process for quadratic models in all G7 countries individually, which shows the quantile coefficient trends of the determinants of the carbon emissions over a period of time.

Table 10: Primary Results (MMQR) and Robustness Test (BSQR)

Canada										
	MMQR						BSQR			
Variables (1)	Location (2)	Scale (3)	Q <sub>0.25</sub> (4)	Q <sub>0.50</sub> (5)	Q <sub>0.75</sub> (6)	Q <sub>0.90</sub> (7)	Q <sub>0.25</sub> (8)	Q <sub>0.50</sub> (9)	Q <sub>0.75</sub> (10)	Q <sub>0.90</sub> (11)
$lGGI_i$	-0.053 (0.33)	0.022 (0.45)	-0.075 (0.30)	-0.05 (0.35)	-0.034 (0.48)	-0.03 (0.58)	-0.08 (0.41)	0.01 (0.91)	-0.051 (0.53)	-0.09 (0.32)
$lGGI_i^2$	0.27* (0.07)	-0.022 (0.79)	0.30 (0.15)	0.28 (0.10)	0.26* (0.06)	0.25* (0.07)	0.29 (0.17)	0.13 (0.54)	0.28 (0.19)	0.54** (0.05)
Turning Points	0.10	0.50	0.13	0.09	0.07	0.06	--	--	--	--
$lRDE_i$	0.17*** (0.0)	0.04** (0.02)	0.13*** (0.0)	1.80*** (0.0)	0.20*** (0.0)	0.21*** (0.0)	0.14*** (0.0)	0.20*** (0.0)	0.19*** (0.0)	0.22*** (0.01)
$lEE_i$	0.71*** (0.0)	-0.37*** (0.0)	1.06*** (0.0)	0.64** (0.02)	0.38 (0.13)	0.27 (0.28)	0.99* (0.06)	0.46** (0.04)	0.46** (0.04)	0.61*** (0.0)
$lCT_i$	-0.20*** (0.0)	0.07 (0.83)	-0.20*** (0.01)	-1.96*** (0.0)	0.39*** (0.0)	-0.19*** (0.0)	-0.23*** (0.0)	-0.23*** (0.0)	-0.22*** (0.0)	-0.07 (0.48)
Constant	4.98*** (0.0)	0.32*** (0.01)	4.67*** (0.0)	5.04*** (0.0)	5.30*** (0.0)	5.35*** (0.0)	4.7*** (0.0)	4.7*** (0.0)	5.22*** (0.0)	5.02*** (0.0)
France										
Variables (1)	Location (2)	Scale (3)	Q <sub>0.25</sub> (4)	Q <sub>0.50</sub> (5)	Q <sub>0.75</sub> (6)	Q <sub>0.90</sub> (7)	Q <sub>0.25</sub> (8)	Q <sub>0.50</sub> (9)	Q <sub>0.75</sub> (10)	Q <sub>0.90</sub> (11)
$lGGI_i$	-0.31** (0.02)	-0.07 (0.45)	-0.25*** (0.04)	-0.30** (0.02)	-0.35** (0.04)	-0.45* (0.10)	0.40 (0.12)	-0.23 (0.20)	-0.42* (0.07)	-0.23 (0.24)
$lGGI_i^2$	0.24* (0.07)	0.06 (0.52)	0.20 (0.11)	0.24* (0.07)	0.28* (0.10)	0.37 (0.19)	0.33 (0.18)	0.17 (0.31)	0.36* (0.09)	0.15 (0.40)
Turning Points	0.65	0.58	0.62	0.62	0.62	0.61	--	--	--	--
$lRDE_i$	-0.03*** (0.0)	-0.001 (0.87)	-0.03*** (0.0)	-0.03*** (0.0)	- 0.033*** (0.01)	-0.04 (0.11)	-0.04*** (0.0)	-0.04*** (0.01)	-0.04 (0.18)	-0.05* (0.08)
$lEE_i$	1.18*** (0.0)	-0.09 (0.45)	1.25*** (0.0)	1.18*** (0.0)	1.11*** (0.0)	0.98*** (0.0)	1.44*** (0.0)	1.19 (0.0)	1.33*** (0.0)	1.03*** (0.0)
$lCT_i$	-0.07 (0.43)	-0.04 (0.47)	-0.03 (0.67)	-0.07 (0.45)	-0.10 (0.39)	-0.16 (0.38)	-0.02 (0.89)	-0.11* (0.08)	-0.06 (0.63)	-0.12 (0.25)
Constant	4.96*** (0.0)	0.09 (0.26)	4.88*** (0.0)	4.95*** (0.0)	5.02*** (0.0)	5.16*** (0.0)	4.79*** (0.0)	4.94*** (0.0)	4.88*** (0.0)	5.07 (0.0)
Germany										
Variables (1)	Location (2)	Scale (3)	Q <sub>0.25</sub> (4)	Q <sub>0.50</sub> (5)	Q <sub>0.75</sub> (6)	Q <sub>0.90</sub> (7)	Q <sub>0.25</sub> (8)	Q <sub>0.50</sub> (9)	Q <sub>0.75</sub> (10)	Q <sub>0.90</sub> (11)
$lGGI_i$	-0.05*** (0.0)	0.01 (0.13)	-0.06*** (0.0)	-0.05*** (0.0)	-0.04*** (0.0)	-0.04*** (0.0)	-0.05 (0.58)	-0.36*** (0.0)	-0.03 (0.51)	-0.02 (0.86)
$lGGI_i^2$	0.05 (0.11)	-0.02 (0.31)	0.06* (0.08)	0.05* (0.10)	0.03 (0.32)	0.03 (0.46)	0.08 (0.37)	0.06 (0.13)	-0.02 (0.75)	0.04 (0.80)
Turning Points	0.5	0.25	0.50	0.50	0.67	0.67	--	--	--	--

$IRDE_i$	2.44*** (0.0)	-0.03 (0.53)	0.26*** (0.0)	0.25*** (0.0)	0.22*** (0.0)	0.21*** (0.0)	0.33** (0.02)	0.29*** (0.02)	0.14 (0.16)	0.29* (0.06)
$LEE_i$	1.27*** (0.0)	-0.07 (0.42)	1.32*** (0.0)	1.30*** (0.0)	1.20*** (0.0)	1.20*** (0.0)	1.48*** (0.0)	1.36*** (0.0)	1.09*** (0.0)	1.26*** (0.0)
$ICT_i$	-0.04 (0.39)	0.03 (0.35)	-0.06 (0.29)	-0.04 (0.39)	-0.02 (0.76)	-0.01 (0.91)	-0.36 (0.65)	0.02 (0.75)	-0.03 (0.62)	0.007 (0.95)
Constant	5.04*** (0.0)	0.06 (0.41)	5.01*** (0.0)	5.04*** (0.0)	5.9*** (0.0)	5.11*** (0.0)	4.85*** (0.0)	5.21*** (0.0)	5.21*** (0.0)	5.01*** (0.0)
<b>Italy</b>										
Variables (1)	Location (2)	Scale (3)	$Q_{0.25}$ (4)	$Q_{0.50}$ (5)	$Q_{0.75}$ (6)	$Q_{0.90}$ (7)	$Q_{0.25}$ (8)	$Q_{0.50}$ (9)	$Q_{0.75}$ (10)	$Q_{0.90}$ (11)
$IGGI_i$	0.36 (0.67)	-0.31 (0.67)	0.65** (0.10)	0.35 (0.67)	0.06 (0.97)	-0.21 (0.93)	0.76* (0.07)	0.31 (0.59)	0.04 (0.93)	0.21 (0.72)
$IGGI_i^2$	-0.45 (0.54)	0.27 (0.67)	-0.70** (0.04)	-0.41 (0.54)	-1.89 (0.87)	0.04 (0.98)	-0.78** (0.05)	-0.43 (0.41)	-0.15 (0.65)	-0.28 (0.56)
Turning Points	0.4	0.57	0.46	0.43	0.02	2.62	--	--	--	--
$IRDE_i$	0.03 (0.83)	-0.01 (0.94)	0.03 (0.54)	0.03 (0.84)	0.02 (0.94)	0.01 (0.97)	-0.015 (0.73)	0.04 (0.41)	-0.01 (0.67)	0.02 (0.77)
$LEE_i$	0.93*** (0.0)	-0.13 (0.64)	1.05*** (0.0)	0.90*** (0.0)	0.80 (0.18)	0.69 (0.44)	1.097*** (0.0)	0.76*** (0.0)	0.78*** (0.0)	0.80*** (0.0)
$ICT_i$	-0.09 (0.72)	-0.15 (0.51)	0.05 (0.71)	0.099 (0.68)	-0.24 (0.63)	-0.37 (0.63)	0.035 (0.81)	0.20 (0.40)	-0.30** (0.03)	-0.14 (0.47)
Constant	5.18*** (0.0)	0.23*** (0.0)	4.96 (0.0)	5.18 (0.0)	5.40*** (0.0)	5.59*** (0.0)	4.92*** (0.0)	5.30*** (0.0)	5.43*** (0.0)	5.30*** (0.0)
<b>Japan</b>										
Variables (1)	Location (2)	Scale (3)	$Q_{0.25}$ (4)	$Q_{0.50}$ (5)	$Q_{0.75}$ (6)	$Q_{0.90}$ (7)	$Q_{0.25}$ (8)	$Q_{0.50}$ (9)	$Q_{0.75}$ (10)	$Q_{0.90}$ (11)
$IGGI_i$	0.14 (0.55)	-0.03 (0.81)	0.20 (0.40)	0.15 (0.51)	0.12 (0.72)	0.09 (0.81)	0.07 (0.79)	0.11 (0.82)	-0.7 (0.83)	-0.034 (0.87)
$IGGI_i^2$	-0.15 (0.64)	0.09 (0.57)	-0.23 (0.38)	-0.17 (0.57)	-0.06 (0.88)	-0.02 (0.99)	-0.13 (0.74)	-1.16 (0.80)	0.18 (0.72)	0.079 (0.78)
Turning Points	2.33	0.83	0.43	0.44	1.00	2.25	--	--	--	--
$IRDE_i$	0.07*** (0.01)	-0.01 (0.45)	0.08*** (0.0)	0.07*** (0.0)	0.06* (0.09)	0.051 (0.22)	0.07* (0.09)	0.05 (0.21)	0.04 (0.34)	0.72* (0.07)
$LEE_i$	0.45*** (0.0)	0.004 (0.95)	0.45*** (0.0)	0.45*** (0.0)	0.45*** (0.0)	0.45*** (0.0)	0.43*** (0.0)	0.46*** (0.0)	0.59*** (0.01)	0.42*** (0.03)
$ICT_i$	0.24 (0.21)	-0.08 (0.44)	0.32*** (0.05)	0.26 (0.16)	0.17 (0.51)	0.12 (0.71)	0.27 (0.50)	0.025 (0.94)	0.07 (0.80)	0.06 (0.79)
Constant	5.73*** (0.0)	0.02 (0.59)	5.71*** (0.0)	5.72*** (0.0)	5.75** (0.0)	5.76*** (0.0)	5.75*** (0.0)	5.78*** (0.0)	5.72*** (0.0)	5.83*** (0.0)
<b>UK</b>										
Variables (1)	Location (2)	Scale (3)	$Q_{0.25}$ (4)	$Q_{0.50}$ (5)	$Q_{0.75}$ (6)	$Q_{0.90}$ (7)	$Q_{0.25}$ (8)	$Q_{0.50}$ (9)	$Q_{0.75}$ (10)	$Q_{0.90}$ (11)
$IGGI_i$	0.06	0.00	0.062	0.063	0.063	0.064	-0.03	0.12	0.05	0.05

	(0.15)	(0.97)	(0.11)	(0.13)	(0.27)	(0.32)	(0.82)	(0.22)	(0.41)	(0.39)
$lGGI_i^2$	0.01 (0.94)	-0.02 (0.69)	0.03 (0.77)	0.014 (0.89)	-0.01 (0.93)	-0.021 (0.89)	0.20 (0.42)	-0.08 (0.68)	0.05 (0.78)	0.31 (0.88)
Turning Points	-3.0	0.0	-1.04	-2.25	3.15	1.52	--	--	--	--
$lRDE_i$	-0.02 (0.70)	-0.01 (0.69)	-0.01 (0.82)	-0.014 (0.72)	-0.02 (0.66)	-0.03 (0.65)	-0.012 (0.88)	0.015 (0.85)	-0.053 (0.45)	-0.07 (0.45)
$lEE_i$	1.29*** (0.0)	0.14 (0.27)	1.42*** (0.0)	1.34*** (0.0)	1.15*** (0.0)	1.09*** (0.0)	1.74*** (0.0)	1.21*** (0.01)	1.20*** (0.0)	1.21** (0.02)
$lCT_i$	0.05 (0.70)	0.13** (0.04)	-0.07 (0.54)	0.02 (0.89)	0.18 (0.30)	0.23 (0.21)	-0.30 (0.29)	0.14 (0.65)	0.14 (0.32)	0.07 (0.69)
Constant	4.97*** (0.0)	0.05 (0.56)	4.92*** (0.0)	4.96*** (0.0)	5.01*** (0.0)	5.03*** (0.0)	4.84*** (0.0)	4.97*** (0.0)	5.01*** (0.0)	5.04*** (0.0)
USA										
Variables (1)	Location (2)	Scale (3)	Q <sub>0.25</sub> (4)	Q <sub>0.50</sub> (5)	Q <sub>0.75</sub> (6)	Q <sub>0.90</sub> (7)	Q <sub>0.25</sub> (8)	Q <sub>0.50</sub> (9)	Q <sub>0.75</sub> (10)	Q <sub>0.90</sub> (11)
$lGGI_i$	0.01 (0.47)	0.01 (0.39)	0.004 (0.82)	0.10 (0.47)	0.02 (0.33)	0.02 (0.29)	-0.01 (0.83)	0.033 (0.28)	0.03 (0.44)	0.02 (0.56)
$lGGI_i^2$	0.071*** (0.0)	0.02 (0.26)	0.05* (0.07)	0.07*** (0.01)	0.086*** (0.0)	0.10*** (0.01)	0.05 (0.47)	0.10** (0.05)	0.14* (0.10)	0.11 (0.21)
Turning Points	-0.07	0.02	-0.04	-0.72	-0.12	-0.10	--	--	--	--
$lRDE_i$	0.09*** (0.06)	0.04 (0.17)	0.05 (0.33)	0.092* (0.07)	0.12** (0.03)	0.15** (0.03)	0.07 (0.21)	0.30 (0.66)	0.14 (0.23)	0.12 (0.24)
$lEE_i$	1.91*** (0.0)	-0.21 (0.82)	1.93*** (0.0)	1.91*** (0.0)	1.90*** (0.0)	1.88*** (0.0)	1.91*** (0.0)	2.30*** (0.0)	2.12*** (0.0)	2.30*** (0.0)
$lCT_i$	-0.70*** (0.0)	-0.01 (0.90)	-0.70*** (0.0)	0.71*** (0.0)	-0.71*** (0.0)	0.71*** (0.0)	-0.74*** (0.0)	-0.65*** (0.0)	-0.71*** (0.05)	-0.84** (0.05)
Constant	5.03*** (0.0)	0.03 (0.70)	4.99*** (0.0)	5.07*** (0.0)	5.05*** (0.0)	5.07*** (0.0)	5.02*** (0.0)	4.71*** (0.0)	4.86*** (0.0)	4.71*** (0.0)

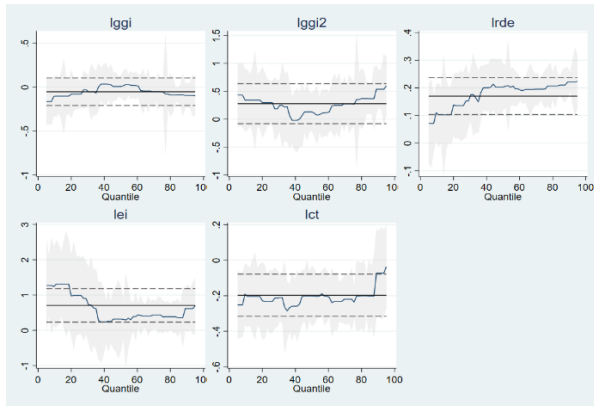


Figure 7: The Graphical Presentation of MMQR Coefficients (Canada)

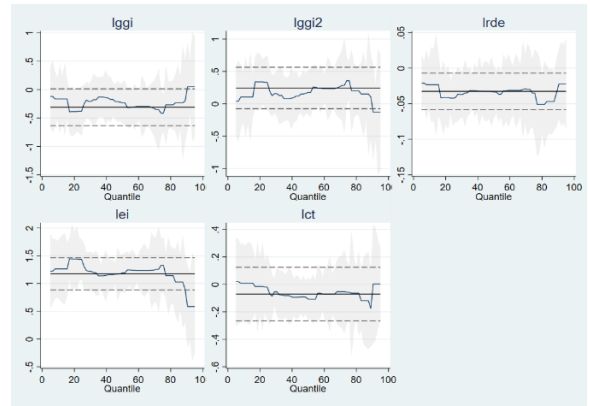


Figure 8: The Graphical Presentation of MMQR Coefficients (France)

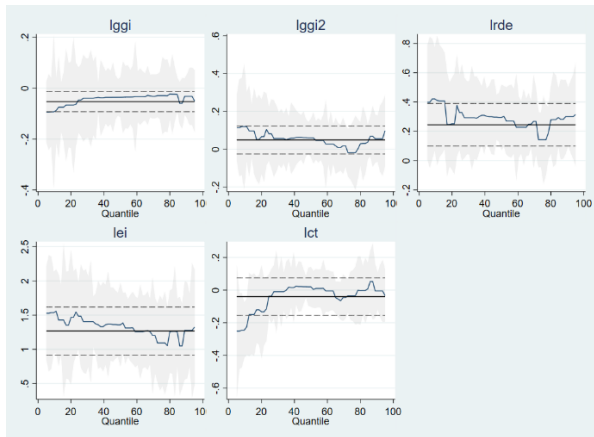


Figure 9: The Graphical Presentation of MMQR Coefficients (Germany)

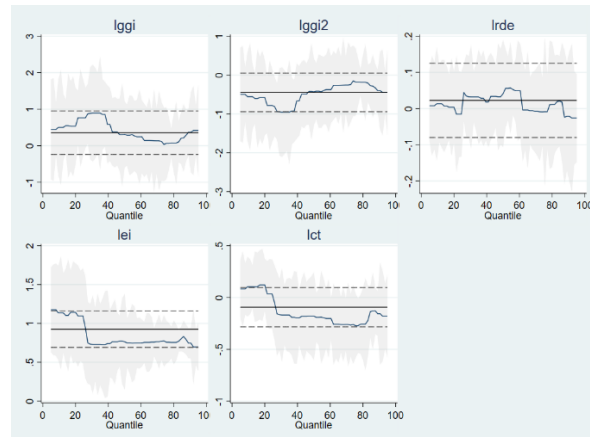


Figure 10: The Graphical Presentation of MMQR Coefficients (Italy)

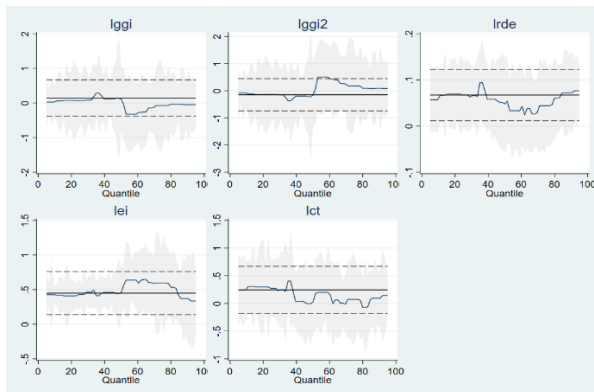


Figure 11: The Graphical Presentation of MMQR Coefficients (Japan)

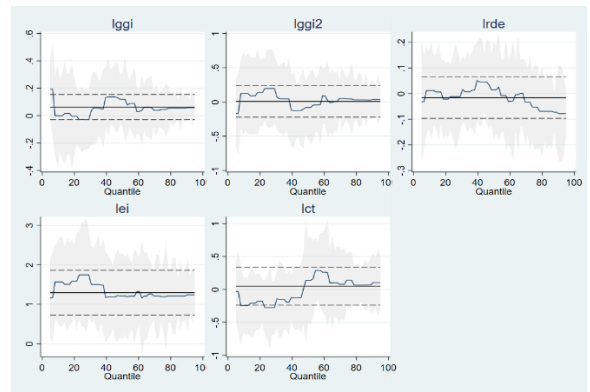


Figure 12: The Graphical Presentation of MMQR Coefficients (the UK)

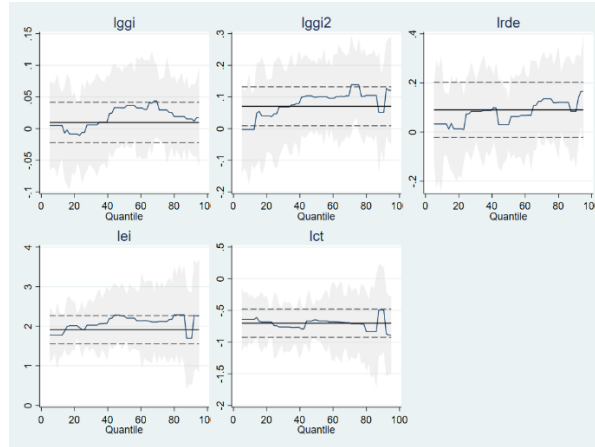


Figure 13: The Graphical Presentation of MMQR Coefficients (the USA)

Table 11: Individual Country Summary Results of EKC Hypothesis Validity

Countries	Inverted U-shaped Relationship				U- shaped Relationship			
	Q0.25	Q0.50	Q0.75	Q0.90	Q0.25	Q0.50	Q0.75	Q0.90
Panel Model	--	--	--	S	S	S	S	--
Canada	--	--	--	--	NS	NS	S	S
France	--	--	--	--	S	S	S	S
Germany	--	--	--	--	S	S	S	S
Italy	S	NS	NS	--	--	--	--	NS
Japan	NS	NS	NS	NS	--	--	--	--
The UK	--	--	NS	NS	NS	NS	--	--
The USA	--	--	--	--	S	S	S	S

Note: NS shows not significant and S shows significant in respective quantiles.

Table 11 presents summary results of Tables 6 and 10, showing the shape of quadratic (either U-shaped or inverted U-shaped) and the significance of the quadratic terms in panel estimation results and individual country results. Results show that GGI has U shaped relationship with carbon emissions in panel model (except last quantile), Canada, France, Germany, the USA, in last quantile of Italy and in the first two quantiles of the UK, while it has inverted U shaped relationship with carbon emissions in Japan, in first three quantiles of Italy, in the last two quantiles of the UK and in the last quantile of the panel model. Table 12 shows the values of the turning points in each quantile for both the panel model and the individual country models. This table shows the turning points both in log form and in level units.

Table 12: Summary Results of Turning Points

Turning Points in Log Form								
Quantiles	Panel Model	Canada	France	Germany	Italy	Japan	UK	USA
Q <sub>0.25</sub>	1.55	0.13	0.63	0.50	0.46	0.43	-1.04	-0.04
Q <sub>0.50</sub>	2.00	0.09	0.63	0.50	0.43	0.44	-2.25	-0.72
Q <sub>0.75</sub>	1.82	0.07	0.63	0.67	0.02	1.00	3.15	-0.12
Q <sub>0.90</sub>	-3.29	0.06	0.61	0.67	2.62	2.25	1.52	-0.10
Turning Points in Level Form								
Quantiles	Panel Model	Canada	France	Germany	Italy	Japan	UK	USA
Q <sub>0.25</sub>	4.70	1.13	1.87	1.65	1.59	1.54	0.36	0.96
Q <sub>0.50</sub>	7.38	1.09	1.87	1.65	1.53	1.55	0.11	0.49
Q <sub>0.75</sub>	6.18	1.07	1.87	1.95	1.02	2.72	23.34	0.89
Q <sub>0.90</sub>	0.04	1.06	1.84	1.95	13.80	9.49	4.59	0.91

## 5 Conclusion and Policy Implications

This study investigates the role of green growth, R&D expenditures, energy efficiency and carbon tax to achieve the target of carbon neutrality in G7 countries. The empirical analysis of this study is carried out at two levels: (1) pooling the data source across the countries and estimating a panel quantile regression, and (2) using individual country data and estimating a quantile regression model for each of the seven countries. The empirical study based on panel data modelling revealed a number of important results. Firstly, green growth has a significant U-shaped relationship with carbon emissions in the first three quantiles, indicating that when green growth increases, the rate of carbon emissions continues to decline up to threshold (turning) points and starts to increase thereafter. Green growth has a significant inverted U-shaped relationship with carbon emissions in the last quantile, showing that when green growth increases, the rate of carbon emissions continues to increase up to the turning point and starts to decline thereafter. Secondly, R&D expenditures, energy efficiency and carbon tax have a

negative relationship with the carbon emissions in all four quantiles, showing that it has the potential to achieve carbon neutrality in G7 countries.

In the early stages of the relationship between the green growth index and carbon emissions, the improvements in renewable energy supply, energy productivity, and eco-efficiency may lead to efficiency gains and diminished carbon emissions, where initial investments in green strategy reduce the carbon emissions effectively (Gafsi & Bakari, 2025). After a threshold point, green growth may lead to diminishing returns due to rebound effects, an increase in production and consumption and mismanagement of technology deployment with the production. In G7 countries, overemphasis on financial development and green technological innovations without the implementation of adequate regulatory measures and strategies can lead to an increase in carbon emissions and technology misuse (Hao et al., 2021; Ruza & Caro-Carretero, 2022). Similarly, green innovation-driven economic growth may also become carbon-intensive in the long run if adequate policy is not adopted to lead the situation towards sustainability and achieve the carbon-neutral targets (Liang et al., 2024).

There are several policy implications from this study. G7 countries, as the most developed countries of the world, should improve green growth strategies and their determinants towards carbon neutrality through appropriate investment allocation and carbon tax policies. Carbon tax not only stimulates green growth but may also lead investors to start investing in green projects. Green investment should be allocated to enhance energy efficiency and renewable energy transitions to curtail the ever-increasing carbon emissions. Additionally, the policies to enhance green trade, green employment, and green technological innovations should be prioritised to enhance the green economy as a major domain of green growth towards carbon neutrality.

More investment is required to remove the financial constraints in the production sector to adopt and improve green technologies, which will further reduce the level of carbon emissions.

The digital economy should be improved in G7 countries for tracking the achievement of environmental objectives, such as smart technologies and energy-efficient services, to improve social, economic and environmental well-being. The use of artificial intelligence (AI) is recommended for biodiversity protection and efficient use of natural resources to enhance green growth and reduce carbon emissions.

Similarly, trade liberalisation plays its important role in stimulating the carbon footprint both in the long run and in the short run (Zahra, Khan, Gupta, et al., 2022). Therefore, strict environmental regulatory policies should be implemented to reduce environmental degradation in selected countries, and steps should be taken to shift the trade paradigm to green trade. G7 countries should also participate in market integration with their trading partners, which is necessary to promote globalisation coupled with environmental sustainability. Renewable energy trade should be promoted to facilitate the trade of renewable energy technologies and products such as solar panels, wind turbines and energy-efficient appliances.

It is recommended to establish an institutional paradigm to monitor the green growth and threshold points at the individual country level to suggest a shift after green growth becomes counterproductive for carbon emissions. It is also important to promote balanced investments across all indicators of green growth, especially in renewable energy supply and green technological innovations. Otherwise, overreliance on any single dimension cannot make green growth a determinant of achieving environmental objectives in the G7 countries (Khan et al., 2025).

## **6 Limitations of the Study**

Despite the insightful findings, this study is subject to several limitations. First, the construction of the Green Growth Index (GGI) involves methodological subjectivity in selecting and weighting indicators, which may influence the robustness of the index across different conditions of the selected countries. Second, the U-shaped relationship identified may be sensitive to the functional form and model specification, raising concerns of potential model misspecification. Third, the analysis is limited to G7 countries, which, while economically advanced, may not reflect the dynamics in developing or emerging economies where green growth trajectories and environmental pressures differ significantly. Fourthly, quantile regression is powerful in capturing heterogeneous effects; it may be more complex to interpret compared to traditional mean regression models. This can make it challenging to communicate the results to policymakers. Quantile regression provides insights across different points of distribution, but the results may not be easily generalizable to the entire population. Different quantiles may show varying effects that could complicate policy recommendations or interpretation. Therefore, the choice of econometric technique can also be used to perform long-run and short-run analysis. Future research studies could explore this approach for a more comprehensive cost-benefit analysis. Finally, the study assumes a uniform threshold effect

across countries, potentially overlooking country-specific institutional, technological, or policy variations that can change the GGI and carbon emissions nexus.

### **Declaration of Competing Interest**

The authors declare that they have no known competing interests that could have appeared to influence the work reported in this paper.

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