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# Analysis of Renewable Energy, Foreign Direct Investment, and CO, Relationship: Evidence from France, Germany, and Italy

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#### ABSTRACT

Transitions to renewable energy sources have begun in several countries in an effort to decrease the impact of solid fossil waste. The paper examines the connection between renewable energy consumption, FDI, and  $CO_2$  emissions using econometric analysis of data from France, Germany, and Italy. The purpose of this research is to examine the correlation between the use of renewable energy sources, FDI,  $CO_2$  emissions from energy sources, and GDP growth in France, Germany, and Italy from 1971 to 2021. The data is analysed using many different tests, including those for stationarity, Granger causality, and the Toda-Yamamoto method. According to the findings, the utilisation of renewable energy sources is a driving factor in cutting  $CO_2$  emissions in France, whereas in Italy, emissions are the result of foreign direct investment. In Germany and Italy, the lack of a correlation between consumption of renewable energy, FDI, and  $CO_2$  emissions over the long term suggests that renewable energy does not play a significant role in driving economic development in those countries. Our results add to the existing body of knowledge and imply that investments in renewable energy are crucial to achieving sustainable development. Governments should take action to mitigate the negative effects of FDI on the environment and promote investments in renewable energy.

Keywords: Renewable Energy, Foreign Direct Investment, CO<sub>2</sub> Emissions, Sustainable Development, Energy Consumption, Environmental Policy JEL Classifications: Q32; Q43

# **1. INTRODUCTION**

Foreign direct investment (FDI) can help cut  $CO_2$  emissions in different ways, depending on the type and sector of the investment. FDI can make it easier to create and use technologies that are good for the environment, which can help cut down on greenhouse gas emissions. For example, if you invest in renewable energy sources, you use less fossil fuels and emit less  $CO_2$ . However, FDI can also increase environmental impacts in some cases. For example, the location of an investment or the nature of its activities may increase the use of environmental resources or increase polluting emissions. Therefore, the environmental impacts of FDI depend on factors such as the nature of the investment, its sector, and environmental regulations. While it is possible for FDI to reduce  $CO_2$  emissions, its realisation depends on the nature of the investment and how it is implemented. Investors should evaluate their investments by considering environmental factors and adopting environmentally friendly practises.

Renewable energy sources like solar, wind, and water power release less carbon dioxide  $(CO_2)$  into the atmosphere than fossil fuels. The greenhouse effect is caused by greenhouse gases that are given off when fossil fuels are burned. This is one of the main reasons why the climate is changing. Renewable energy resources are obtained from natural resources such as solar, wind, hydroelectric, geothermal, and biomass, and no harmful emissions are released into the atmosphere during the use of these resources. Therefore, the use of renewable energy sources is an important tool to reduce greenhouse gas emissions and combat climate change.

There is no hard rule, but foreign direct investment is likely to lead to more use of renewable energy. The renewable energy sector is

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a rapidly growing sector in most countries, and countries have many reasons to diversify their energy sources and increase their energy security by investing in this field. The entry of foreign direct investment into the renewable energy sector can help the sector grow. Investments can finance the infrastructure necessary for the generation, distribution, storage, and management of renewable energy resources, thereby accelerating the growth of the renewable energy sector. However, there is no conclusive evidence that these investments will increase countries' use of renewable energy. The growth of the renewable energy sector depends on many factors, such as environmental policies and the cost of energy resources. It should be noted that foreign direct investment may accelerate the growth of the sector, but it may not be sufficient on its own to increase the use of renewable energy.

# **2. LITERATURE REVIEW**

In recent years, there has been a lot of interest in the question of whether or not the usage of renewable energy sources contributes to long-term economic development. The literature on the subject of energy use and economic development is rich. There is still a lot to learn about environmental pollution, and researchers routinely put the Environmental Kuznets Curve (EKC) hypothesis to the test to see whether economic development correlates with pollution. The EKC hypothesis, first proposed by Grossman and Krueger (1991) and subsequently studied by Shafik and Bandyopadhyay (1992), holds that environmental contamination increases as economies develop. Still, it declines after reaching a particular income threshold, ultimately leading to decreased environmental damage and economic growth. As societies transitioned from an agrarian to an industrial society, there was a surge in economic activity that resulted in the employment of technologies that deplete natural resources and pollute the environment. However, in later stages of economic development, with the shift from industrial to service sectors and the emergence of environmental awareness, societies have exhibited a greater emphasis on investing income towards environmental improvement (Cialani, 2007).

Carbon emissions are the most significant environmental pollution indicator; yet, there is no agreement on the validity of the EKC hypothesis since study results vary depending on country development level, study methodology, study era, and other factors (Aslan et al., 2018; Naz et al., 2019; Ridzuan et al., 2020; Ongan et al., 2020).

There exists a diversity of perspectives regarding the nature of the relationship between openness and carbon emissions. Research by Shahbaz et al. (2017) examining 105 high-, middle-, and low-income countries during the period of 1980-2014, Jebli and Youssef (2017) analyzing Tunisia from 1980-2011, Chen and Lei (2018) studying 30 countries from 1980-2014, and Tachie et al. (2020) observing 18 European Union countries from 1971 to 2019, all suggest that an increase in the openness ratio results in a rise in carbon emissions. Conversely, Al-Mulali and Öztürk (2016) found that for 27 developed countries during 1990-2012, Sinha et al. (2017) for the N-11 countries during 1994-2014, Sinha and Shahbaz (2018) for India from 1971 to 2015, and Amin et al. (2018) for India from 1971-2015 and Amin et al. (2017) for India in the N-11 countries during the same period, indicate that greater

openness does not necessarily lead to increased carbon emissions. Ahmadov and Memmedova (2016) examined the importance of commitments and identified the importance of high commitment.

Jalil and Mahmud (2009) study highlighted that although the degree of openness in China during the 1975-2005 timeframe had a positive impact on carbon emissions, this effect was not statistically significant. Other experts hold the view that to accurately assess the relationship between energy consumption and environmental pollution, it is crucial to distinguish between renewable and non-renewable energy sources (Chiu and Chang, 2009; Sulaiman et al., 2013). By doing so, a more nuanced understanding can be achieved in terms of the impact of energy consumption on the environment. Such insights are important for policymakers and stakeholders seeking to address the challenges posed by climate change and environmental degradation.

While Bölük and Mert's (2014) research revealed that both renewable and non-renewable energy consumption led to environmental damage in European Union (EU) countries between 1980 and 2008. However, López-Menéndez et al. (2014) arrived at a different conclusion based on their analysis of data from 1996 to 2010, finding that renewable energy consumption actually improved environmental quality in EU countries during that time period. These divergent results suggest that the relationship between energy consumption and environmental impact is complex and context-dependent, and underscores the importance of considering a range of factors when assessing the environmental effects of energy consumption.

In addition, between 1980 and 2012, renewable energy usage in Kenya decreased carbon emissions, but non-renewable energy consumption and openness were linked to environmental damage, as found by Al-Mulali et al. (2016). This underscores the need of distinguishing between the environmental implications of various energy sources. Policymakers and other stakeholders may use the research' results to promote sustainable economic development and reduce the negative environmental impacts of energy usage.

From 1950 to 1992, Soytas and Sari (2003) analysed the correlation between energy use and GDP growth for the Group of Seven and 10 emerging market nations. The findings showed that the connection between energy use and GDP development varied among the nations analysed. In particular, Italy showed a long-term causal association between economic development and energy consumption, whereas the same was true for West Germany, Japan, and France. Nevertheless, in the United States, the United Kingdom, and Canada, no significant long-term correlation was found between the two factors. These results highlight the need to account for differences in economic, social, and political settings when investigating the link between energy use and economic development across countries. Insights like this may help policymakers craft energy policies that support long-term economic development while reducing unintended consequences for the environment.

The research of Soytas and Sari (2006) went beyond that of their predecessors by analysing data on G-7 nations' energy use

and economic development from 1960 to 2004. Significantly, a production function framework was used, which allowed for the analysis of energy consumption and economic development to take into account other factors, such as capital stock and labour. The findings suggested that the connection between energy use and GDP growth was context and period dependent. Japan, the UK, Italy, and Germany all showed a positive correlation between economic growth and energy use in the near term. In contrast, researchers in the United States and Canada found evidence of a causal link between energy use and economic development. For France, we discovered no short-term correlations worth mentioning. Energy consumption and GDP growth were shown to be positively and negatively correlated over the long term for Japan, the UK, Italy, and Canada. Yet, in both France and the United States, higher energy consumption was associated with faster economic expansion. In contrast, Germany's increasing energy consumption was directly related to its expanding economy. Our results provide light on the intricate web of causality that connects energy use and GDP growth, and they emphasise the need of country-specific policy interventions. Sustainable development strategies may benefit from a deeper knowledge of the elements that drive economic growth and energy consumption, which is made possible via the use of a production function framework.

The purpose of Mutascu (2016) research was to learn more about the connection between energy use and GDP growth in the G-7 nations between 1970 and 2012. The findings showed that the connection between energy use and GDP development is not uniform across nations. In particular, we see a positive and negative correlation between economic growth and energy consumption in Germany and France, and a causal association in the United States, Canada, and Japan. Italy and the UK were not determined to have any meaningful correlation. It seems that the intricate interaction of economic, social, and environmental elements that are unique to each nation is responsible for the varying conclusions drawn from research that investigate the connection between energy consumption and economic development in the G-7. Similarly, research comparing renewable energy use with GDP growth in the G-7 nations have shown contradictory findings. These results highlight the need for policy interventions to be adapted to the particular circumstances of each nation, taking into consideration the many factors that contribute to and hinder the development of the economy. Overall, Mutascu's results add to the expanding body of literature on the connection between energy use and economic growth, underscoring the necessity for more investigation and policy development in this crucial area of sustainable progress.

Between 1980 and 2009, researchers Tugcu et al. (2012) looked at the possible long-term link and causality between renewable and non-renewable energy use and economic development in the G-7 countries. While investigating the connection between RE use and GDP growth, the researchers used both the conventional production function and the enhanced production function. The research indicated that in Canada, the United States, France, and Italy, there was no causal association between the use of renewable energy and economic development when the enhanced production function was used. We found a positive and negative correlation between renewable energy use and GDP growth in England and Japan, but only a positive correlation in Germany. Yet, when the traditional production function was used, a positive and negative correlation between renewable energy usage and GDP growth was seen across all nations. As a whole, the research sheds light on the intricate web of causes and effects that binds the use of renewable energy sources to economic expansion, showing how the connection changes and evolves depending on the production function used.

Throughout the years 1990-2013, Chang et al. (2015) looked at the link between the use of renewable energy and economic growth. Findings showed that in Italy, the United States, the United Kingdom, and Germany, there was no correlation between GDP growth and the use of renewable energy sources. Yet, in countries like Japan, Canada, and France, researchers have shown a link between renewable energy use and economic growth. Studies examining the link between renewable energy use and economic development are most common at the group or regional level, but there are also studies that focus on a particular nation. Payne (2009), for instance, looked studied the connection between renewable and non-renewable energy usage and GDP growth in the US from 1949 to 2006. Consumption of renewable energy was shown to have a positive and statistically significant effect on economic growth, whereas use of non-renewable energy had no such effect. The findings of these research give important information that might aid policymakers and stakeholders in their pursuit of long-term, environmentally responsible and socially equitable economic growth.

No correlation was found between the usage of renewable energy and GDP growth in the United States between 1973 Q1 and 2019 Q4 in a research by Çevik et al. (2021). This study's results contribute to the expanding body of literature studying the connection between renewable energy use and economic development, and they provide insight on the nuanced nature of that connection and its susceptibility to change depending on external factors and historical epoch. Pegkas (2020) looked at the connection between the use of renewable energy sources, the use of non-renewable energy sources, and GDP growth in Greece. The research looked at data from 1990 to 2016 and found there to be a persistent connection between the factors. Nonetheless, it was determined that the use of non-renewable energy contributed more to growth than the usage of renewable energy. These results highlight the need of tailoring energy policy to the distinct economic and social circumstances of each country. The studies' findings, taken as a whole, stress the need for further investigation and policy innovation into the pros and cons of renewable energy adoption and long-term economic expansion.

Apergis and Payne (2010) investigated the correlation between renewable energy usage and GDP development in 13 Eurasian nations between 1992 and 2007. Given the short-and long-term nature of the study's findings, it's clear that efforts to promote energy policy and development should take into account the connection between renewable energy use and economic growth. Apergis and Payne (2011) conducted research on the connection between the use of renewable energy sources, the use of nonrenewable energy sources, and economic development in both developed and developing nations. The research looked at the years 1980-2008 and found that in both developed and developing nations, non-renewable energy usage had a positive and negative effect on economic development. Yet, it was observed that the use of renewable energy had a favourable effect on economic development both in the short and long term, and that this effect was unidirectional.

These results highlight the need for a well-rounded strategy to energy policy and development that considers not only the diverse economic and social circumstances of different nations, but also the intricate relationship between renewable and nonrenewable energy sources and their effect on economic expansion. Sustainable and equitable economic growth may be achieved, along with urgent environmental and energy security concerns, if policymakers and stakeholders use a holistic and evidence-based approach.

Nine OECD nations, including Japan, Germany, Italy, the United Kingdom, the United States, France, Denmark, Portugal, and Spain, were included in Hung-Pin (2014) research, which looked at the short- and long-term link between renewable energy usage and economic growth. The research looked at data from 1982 to 2011 and discovered a correlation between the use of renewable energy and GDP growth in the United States, the United Kingdom, Italy, and Germany. Yet, neither France nor Spain were shown to have a lasting connection with one another. These results highlight the need to analyse the link between renewable energy consumption and economic development while taking into account each country's specific economic and energy circumstances. The link between renewable energy usage and economic development may be moderated by a number of different factors, including legislative frameworks, market circumstances, social and cultural aspects. Sustainable and equitable economic growth may be achieved, along with urgent environmental and energy security concerns, provided policymakers use a holistic and context-specific approach to energy policy and development.

Seven European OECD countries-Italy, Germany, Spain, Turkey, Poland, the United Kingdom, and the Netherlands-were included in a research by Li and Leung (2021) that looked at the correlation between renewable energy usage and GDP growth. Using a production function framework, the research looked at how the use of renewable energy affected GDP growth from 1985 to 2018. The results imply that in these nations, there is no Granger causation between the use of renewable energy and economic development. Whereas the findings suggest no such thing as a causal link between the use of renewable energy and economic expansion, other factors, such as regulatory frameworks, market circumstances, and technology advances, may have a major impact on the nature of that link. The importance of renewable energy in driving economic growth while mitigating environmental repercussions is only expected to expand as governments work to achieve sustainable development objectives and climate targets. Researchers and policymakers may better promote sustainable development and a more fair and prosperous future by delving further into the interconnected web of links between renewable energy usage, economic growth, and other variables.

Cho et al. (2015) research set out to find out whether and how using renewable energy sources contributed to economic development in both high- and low-income nations. Thirty-one OECD countries stood in for developed nations, while the other 49 were non-OECD nations standing in for the less developed nations. The study's findings point to a two-way causal relationship between economic development and renewable energy use in industrialised nations. For the less developed nations in the research, however, the link is one-sided, flowing from renewable energy usage to economic development. These results are helpful in elucidating the multifaceted connection between renewable energy usage and economic expansion across several regional groupings of countries.

Menegaki (2011) looked at 27 European nations from 1997 to 2007 and analysed the correlation between their usage of renewable energy and their GDP growth. Granger causality was tested using strict econometric techniques, and the study's findings showed no significant association between the use of renewable energy and economic expansion. This indicates that there may be no causal relationship between the promotion of renewable energy consumption policies and economic development in these nations. More research may be required to corroborate these results in various circumstances, but for now, it's crucial to highlight that the study only evaluated a certain time period and geographical location.

Saad and Taleb (2018) examined the connection between the use of renewable energy and GDP growth in 12 EU member states between 1990 and 2014. The research discovered a short-term unidirectional association between economic growth and usage of renewable energy, but a long-term bidirectional relationship. The research elucidates the necessity of considering both the shortterm and long-term consequences of the link between renewable energy use and economic development in the European Union.

Jebli et al. (2015) investigated the relationships between per capita CO2 emissions, GDP, renewable and non-renewable energy consumption and economic growth for Tunisia with data from the period 1980–2009.

Koengkan and Fuinhas (2020) analysed the five Mercosur countries-Argentina, Brazil, Paraguay, Venezuela, and Uruguayfrom 1980 to 2014 to determine the correlation between renewable energy usage, non-renewable energy consumption, and economic development. The research revealed a positive and negative correlation between renewable and non-renewable energy consumption and GDP growth, suggesting that all types of energy contribute equally to economic development in the nations studied. The results stress the need of a sustainable energy mix for regional economic development.

Kizilbay (2017) looked at the BRIC nations from 1990 to 2006 to see whether there was a correlation between the use of renewable energy sources and economic development. The results show that there is a long- and short-term, two-way causal relationship between economic expansion and renewable energy. This indicates that in the BRIC nations, a rise in the use of renewable energy sources encourages economic development and vice versa. The research concludes that renewable energy sources may serve as a driver of long-term economic development in these nations.

Uçak (2010) performed an in-depth investigation on the connection between the generation of renewable energy and economic development in OECD countries from 1980 to 2007. His research points to a favourable and robust connection between renewable energy generation and long-term economic expansion. Additionally, the research found that renewable energy and economic development have a mutually reinforcing connection, showing the presence of a bidirectional causation between these two factors. Insights into the potential of renewable energy as a driver of economic development in OECD nations are provided by Uçak's study, which also emphasises the need of maintaining investment and governmental support for this industry.

Apergis and Payne's (2010) study of 20 OECD nations from 1985 to 2005 found a positive correlation between the use of renewable energy sources and GDP growth. They did this by calculating a long-term link between the two, and when they found an elasticity coefficient of 0.76 for renewable energy use, they had strong evidence for a two-way causation between GDP growth and RE usage. This result highlights the significance of renewable energy as a driver of long-term economic development in industrialised nations. The study's solid research design and thorough analysis make it an indispensable resource for academics, politicians, and businesspeople studying the relationship between renewable energy and economic growth.

Using data for Middle Eastern and North African nations from 1988 to 2010, Akay et al. (2015) performed a comprehensive research of the correlation between renewable energy usage, real GDP, and per capita  $CO_2$  emissions. A substantial two-way causal relationship between economic expansion and use of renewable energy sources was found in their investigation. Yet, the researchers exhausted all avenues without success in establishing a cointegration link between the variables. These results not only add to what is already known about the relationship between renewable energy use and economic growth, but also have substantial implications for those working to advance sustainable development in the area.

Apergis and Payne (2012) looked studied the correlation between the use of renewable energy sources and GDP growth in six countries throughout the Americas from 1990 to 2007. Their research found a two-way causal link between renewable energy usage and economic development, with evidence of strong cointegration between the variables. Our findings add significantly to the continuing conversation about achieving long-term economic development in the Americas.

Sebri and Ben-Salha (2014) also analysed the BRICS nations in depth between 1971 and 2010, focusing on renewable energy usage, real GDP, carbon dioxide emissions, and openness. Cointegration was discovered among the variables, suggesting they have a similar long-run equilibrium. Yet, their research showed that there is a two-way connection between economic expansion and the use of renewable energy, highlighting the need of implementing policies that encourage long-term growth in the economy. In conclusion, the results shed light on the intricate relationship between renewable energy use, economic expansion, and ecological viability.

Inglesi-Lotz (2016) performed a comprehensive research among 34 randomly chosen OECD nations between 1990 and 2010 to investigate the correlation between renewable energy usage and GDP growth. The study discovered a cointegration connection between the series and a calculated elasticity coefficient of 0.15 for renewable energy. These results provide useful information for policymakers in the OECD who are working to advance sustainable development by suggesting that the two variables share a long-term equilibrium.

Chen et al. (2019) investigated the relationships between renewable energy production and foreign trade, per capita carbon dioxide (CO2) emissions, gross domestic product (GDP), renewable, gross domestic product (GDP) for China, covering the period 1980-2014.

Similarly, Salim et al. (2014) tested the cointegration connection between economic development and usage of renewable energy from 1980 to 2012. Their analysis included data from 29 nations. Their research showed that the variables were significantly cointegrated, pointing to a long-term equilibrium connection. Also, their examination of cause and effect revealed that there was a unidirectional relationship between renewable energy usage and GDP. The research also assessed the elasticity coefficient for renewable energy to be 0.101, which sheds light on the strength of the link between renewable energy usage and economic expansion. In sum, these findings might be useful for policymakers and other stakeholders interested in implementing renewable energy policies to foster long-term economic development.

Tiwari (2011) performed a thorough causality test using data from 16 European Union member nations covering the period from 1965 to 2009, including their gross domestic product, renewable energy sources, non-renewable energy sources, and  $CO_2$  emissions. The study's findings of a strong bidirectional causal association between economic development and use of renewable energy shed light on the intricate interaction of these factors within the setting of the European Union.

Ucan et al. (2014) made an important contribution to the field by using a comprehensive dataset that included real GDP, renewable energy consumption, non-renewable energy consumption,  $CO_2$  emission, real gross fixed capital formation, and energy technology R&D indicators for EU member states between 1990 and 2011. Many econometric methods were used, including the Panel Cointegration Test, Panel FMOLS, Vector Error Correction Model, and Granger Causality tests. The analysis indicated that the use of renewable energy was causally related to economic development, notwithstanding the existence of cointegration. In light of these results, it is clear that encouraging renewable energy consumption is crucial to the European Union's long-term economic development.

Similar research was conducted by Farhani and Shahbaz (2014), who analysed the years 1980-2009 to see how the adoption of renewable energy affected economic development in Middle

Eastern and North African nations. They achieved this by contrasting the per capita use of fossil fuels with that of renewable energy sources, as well as the actual GDP and  $CO_2$  emissions of each country. Although the research did reveal evidence of cointegration between renewable energy usage and GDP growth, no statistically significant causal association was discovered. These results suggest the need for more study in this area to determine effective techniques for fostering sustainable development and have significant policy implications for the region. In his research, Filiz Baştürk (2021) looked at the G-7 nations from 1990 to 2017 to see whether there was a correlation between the use of renewable energy and economic development. The analysis concluded that there is no correlation between the use of renewable energy and GDP growth in the G-7.

In Muradzadə (2022) study, she discussed the importance of the Trans-Anatolian Natural Gas Pipeline Project (TANAP) between Turkey and Azerbaijan in Azerbaijan and its impact on Turkey's economy and energy policies.

Humbatova et al. (2020) establish the presence of positive relationships between GDP, electric energy consumption, and GDP growth in different sectors of the economy in Azerbaijan. These findings contribute to a better understanding of the dynamics between economic growth and energy consumption in the country. As a recommendation, the authors suggest the importance of conserving electric energy, likely in consideration of the positive correlation between electric energy consumption and GDP growth.

Efeoğlu (2022) conducted a study to investigate the impact of industrialization, renewable energy, energy consumption, and financial development on  $CO_2$  emissions in the E7 countries between 1989 and 2016, within the framework of the Environmental Kuznets Curve (EKC) concept. The results of the research revealed that higher GDP per capita, industrialization, and energy consumption were associated with increased  $CO_2$ emissions in the E7 nations. However, the square of GDP per capita, adoption of renewable energy sources, and financial development were found to decrease emissions, which aligns with the EKC hypothesis.

This study by Muradzadə (2022) examines the role of energy in trade relations between Azerbaijan and Turkey. The research was conducted to evaluate the size, interaction and importance of energy trade between the two countries. The study was carried out on the basis of current data and literature analysis.

Suleymanli et al. (2022) provide valuable insights into the relationship between fuel price changes and fuel demand in Turkey. Their findings indicate that fluctuations in exchange rates and gasoline costs have a significant impact on fuel consumption. Moreover, the study highlights the positive association between expenses connected to car sales and rental charges with fuel costs.

Sarkhanov (2022), in her study, reveals the strong effect of oil prices on the Azerbaijani economy, emphasizing the relationship between fluctuations in oil prices and basic economic indicators such as GDP and oil production.

Muradzadə (2022) study focuses on Russia's oil and gas industries, aiming to shed light on how global oil prices impact the country's key economic metrics. The research also addresses the concept of the Dutch disease, which refers to the potential adverse effects that natural resource wealth, such as oil and gas, can have on a country's economy.

he authors of the Tutar et al. (2022) study highlight the significance of energy dependency in the modern, interconnected world. They emphasise the potential for conflict between nations coming from conflicting energy plans, notably over access to energy resources, and they bring this threat to our attention.

The study that was conducted by Sarkhanov and Muradzada (2022) offers a detailed analysis of the function that the energy resources of the Gulf Basin play in the context of the energy security of the EU. In spite of the fact that the Gulf area is recognised in the article as a significant contributor to the world's energy supply, it urges readers to diversify their energy sources and work together in order to mitigate the dangers that come with over-reliance on the region's natural resources. The authors underline the role that renewable energy sources play in lowering this reliance and emphasise the need of continuing efforts to promote renewable energy and energy efficiency within the EU. They also note the importance of reducing this dependency as quickly as possible. In conclusion, the paper emphasises the significance of communication and collaboration between the governments of the Gulf and the European Union in order to guarantee a reliable and long-term supply of energy.

# **3. DATA SET AND MODEL SPECIALTY**

# 3.1. Data Set

The purpose of this research was to examine the potential longterm relationship between renewable energy consumption, carbon dioxide emissions, and FDI in France, Germany, and Italy. The study included information collected annually from 1971 through 2021. The study's variables and data sources are shown in Table 1. The natural logarithm of each variable was utilised to aid in the analysis for each nation.

# 3.2. Methodology

This section describes the steps the researchers took to find the best model for capturing the relationship between energy prices and market indexes. If all variables are deemed stable, a conventional time

#### Table 1: Variables used in analysis

Variables	Acronyms	Resource
Renewable energy consumption in Italy	RCI	<b>BP</b> Statistical
Renewable energy	RCF	Review of
consumption in France		World Energy-
Renewable energy	RCG	all data,
consumption in Germany		1965-2021
Carbon dioxide in Italy	CO2I	
Carbon dioxide in France	CO2F	
Carbon dioxide in Germany	CO2G	
Foreign Direct Investment in Italy	FDIITA	World Bank
Foreign Direct Investment in France	FDIFRA	2023
Foreign Direct Investment in Germany	FDIG	

series analysis can be performed. However, if any of the variables exhibit non-stationary behaviour, a cointegration analysis, vector error correction (VEC), or vector autoregressive (VAR) model may be more appropriate. Therefore, the initial step is to perform tests to assess stationarity. Following stationarity checks, the section goes on to describe the VAR model and Granger causality test.

#### 3.2.1. Stationarity tests

Time series data is highly valuable, and the property of stationarity is crucial to drawing accurate conclusions. Analysing nonstationary data may result in misleading findings. However, the absence of stationarity does not necessarily imply erroneous regression results from the correlation between variables. If the variables are cointegrated in level form, the regression results will exhibit long-term equilibrium correlations between them. Various methods can be employed to test for the stationarity of variables. One such method is the unit root test, which examines if the variables are stationary. If the variables have a unit root, it indicates they are non-stationary. In this study, the Augmented Dickey-Fuller (ADF) test was used as an extension of the Dickey-Fuller test. According to Syzdykova and Azretbergenova (2021), the standard Dickey-Fuller test requires the use of three equations, which are as follows:

$$\Delta y_t = \beta 1 * yt - 1 + \varepsilon t$$
  

$$\Delta y_t = \beta 0 + \beta_1 * yt - 1 + \varepsilon t$$
  

$$\Delta y_t = \beta 0 + \beta_1 * yt - 1 + \beta_2 * Trend + \varepsilon t$$

In all three tests, the hypothesis is as follows:

H0:  $\beta 1 = 0$  The variable is not stationary since it has a unit root. H1:  $\beta 1 < 0$  There is no changing value in the variable, hence it is considered stationary.

#### 3.2.2. Vector autoregressive model

Due to possible endogeneity difficulties, conventional multilinear models may provide biassed results. The best tool available to deal with these issues is the vector autoregressive (VAR) model. All variables are treated as endogenous in the VAR model, and their interdependencies are evaluated. Each variable in this model is represented by an equation, and the solution includes lagged values of both the dependant and independent variables. The VAR model allows us to analyse the impact of a single variable on several others since the number of equations is proportional to the number of variables. In the VAR model, the two variables are represented by the following systems of equations:

$$Y_{t} = \alpha_{0} + \sum_{i=1}^{m} \beta_{i} Y_{t-1} + \sum_{i=1}^{m} \beta_{i} X_{t-i} + \varepsilon_{t}$$
(1)

$$X_{t} = \alpha_{0} + \sum_{i=1}^{m} \beta_{i} Y_{t-1} + \sum_{i=1}^{m} \beta_{i} X_{t-i} + \varepsilon_{t}$$
(2)

The ideal lag period, denoted by "m" in the aforementioned formulas, must be chosen before doing a VAR analysis. The optimal lag time is determined by the information criteria. Likelihood Ratio (LR), Final Prediction Error (FPE), Hannan-Quinn (HQ), Schwarz (SIC), and Akaike Information Criterion (AIC) were employed in this investigation (AIC). When the information criteria for the model is small, the lag time used is optimum. Therefore, picking the optimal delay time based only on data criteria is impractical. Serial correlation may be difficult to deal with in a VAR model because of the lagged value of the dependant variable. Hence, serial correlation in the VAR model output at that lag should be checked before settling on the best lag length. The proper lag time may be selected after it is known that there is no serial correlation problem.

#### 3.2.3. Vector error correction model, VECM

To examine the short-term fluctuations of the parameters after establishing a long-term relationship between the series, the vector error correction technique is utilized in the VAR model. The error correction model aids in distinguishing the long-term equilibrium of the variables from their short-term dynamics. This is accomplished by introducing an error correction term between the explanatory variables, which reflects the adjustment to the long-term equilibrium through first-order differences of the nonstationary variables (Lebe and Akbaş, 2014:67).

If the variables have a cointegration relationship, VECM can be used to analyse short- and long-term causal links. This approach examines the causation link between variables without regard to whether or not the series are stationary, avoiding information loss about the series. When X and Y variables are treated as dependent variables, VECM models can be defined using the following equations (3) and (4) (Turan, 2018: 205):

$$\Delta lnY_{t} = \alpha_{1} + \sum_{i=1}^{k} \beta_{1i} \Delta X_{t-1} + \sum_{i=1}^{k} \theta_{1i} \Delta Y_{t-1} + \mu VECT_{t-1} + \varepsilon_{1t}$$
(3)  
$$\Delta lnX_{t} = \alpha_{2} + \sum_{i=1}^{k} \beta_{2i} \Delta X_{t-1} + \sum_{i=1}^{k} \theta_{2i} \Delta Y_{t-1} + \mu VECT_{t-1} + \varepsilon_{2t}$$
(4)

The ideal delay length, k, is represented by the error correction term, VECT, in equations (3) and (4). The vector error correction coefficient, denoted by the number before the VECT term, quantifies how quickly the system returns to equilibrium after a shock. The developed VECM model is accurate and the long-term causal link between the variables is genuine if the VECT coefficient is negative, between 0 and 1, and statistically significant. The reliability of the current VECM model may be assessed by diagnostic analysis based on a battery of tests. Autocorrelation, variable variance, and normality tests are some examples of diagnostic tools. An autocorrelation test looks for evidence of serial correlation between the model's residuals up to a certain lag duration. In order to assess autocorrelation, the LM test statistic is used. There is no autocorrelation if the probability value for each delay value is larger than 5%. This demonstrates the validity of the model. The variable variance test is another technique used to evaluate the model's stability.

The Chi-Square distribution provides the basis for the variance transformation test. If the Chi-square test statistic for the model has a probability of more than 1%, then it is accepted that there is no issue with variance. Lastly, multivariate normality should be seen in the residuals of the created VECM model (Mert and Çağlar, 2019: 273). The Jarque-Bera test statistic is used to ensure normality. It is assumed that the model meets the normalcy criteria if the probability of the Jarque-Bera test statistic is larger than 1%. Hence, a robust VECM model will have a VECT coefficient that is negative, between 0 and 1, statistically significant; it will

not have any issues with autocorrelation or variable variance in its residuals; and its residuals will follow the normal distribution (Tayyar, 2021: 273-274).

Nevertheless, it is not clear if the variables utilised are internal or external from the cointegration relationship, which reveals long-term correlations between the variables. Whether the variables are internal or external has a significant impact on the VECM model building process (Sağlam and Yıldırım, 2014: 203). This allows us to perform the weak externality test to each series individually and hence evaluate the model's equation correctness. The Chi-square statistic is the foundation of the weak externality test. The cointegration link between series is broken when the relevant variable is constrained. An endogenous variable is one whose chi-square probability value is less than 1% or 5%, respectively (Tayyar, 2021: 273-274).

#### 3.2.4. Granger causality and Toda-Yamamoto test

Granger Causality Test: In regression analysis, the importance lies in the relationship between the dependant variable and the other factors. Yet, this does not always imply a causal relationship. The presence of a correlation between two variables does not establish causation or the direction of an effect (Gujarati, 2013: 652). Estimating the subsequent regression systems is the Granger causality test (Syzdykova and Azretbergenova, 2021: 51):

$$Y_t = \sum_{i=1}^m \beta_i Y_{t-i} + \sum_{i=0}^n a_i X_{t-i} + \varepsilon i$$
(5)

$$Y_t = \sum_{i=1}^m \gamma_i Y_{t-i} + \sum_{i=0}^n \delta_i X_{t-i} + \varepsilon i$$
(6)

The Granger Causality test makes use of such models to uncover not only the statistical significance of a correlation between variables but also the direction of that connection.

Toda-Yamamoto Test: These models are used in the Granger Causality Test to demonstrate not only the significance but also the direction of the link between variables. Toda-Yamamoto (1995) developed a causality test for establishing a relationship between time series that is often seen as an extension of the Granger causality test. The Toda-Yamamoto causality test is useful when the more common Granger causality test cannot be performed. This is particularly the case with causal-link analysis with variables that lack level-value stationarity.

# **4. EMPIRICAL RESULTS**

#### 4.1. Stationarity Test

The below results present the stationarity analysis under the Augmented Dicky Fuller Test. The variable RCI is stationary at the second difference as the p-value was only significant at level 2. The RCF variable has unit root at all levels, and the RCG variable has unit root as well. These two variables may not be converted into stations.

The variable CO2I was stationary at the first difference; this variable has a significant P-value. The other two CO variables are also stationary at the first level, respectively. CO2F is stationary at

the first difference level, just as CO2G is stationary at the first level. FDII was stationary at level because the variables have a significant P-value. The FDIF and FDIG were significant at 1<sup>st</sup> difference.

# 4.2. LM Autocorrelation Test

One way to measure autocorrelation in an LM is to calculate the Pearson correlation coefficient between the predicted probabilities of the current word and the probabilities of the previous work at different lags. A high positive correlation at a particular lag indicates that the LM is relying heavily on the information from the previous work at that lag to predict the current word. Conversely, a negative correlation at a lag indicates that the LM is trying to avoid repeating the same word.

The below results presented in the Table 3 explain the outputs of LM autocorrelation test results at different levels of lag. The results presented below indicates serial correlation in majority lag length levels.

The LM autocorrelation test shows that lag one is very important because it comes after high serial correlation. But lags 2 and 3 are not following the strong serial correlation issue, and as per the lag selection criteria, we can incorporate 3 lags in our VAR analysis. In this study, we have a limited number of observations; therefore, we cannot incorporate long lag lengths.

## 4.3. Johnson's Cointegration Test

The statistical method of Johnson's cointegration is used to find out if 2 time series are cointegrated. Cointegration is the relationship between two non-stationary time series with the same stochastic trend over a long period of time. The Johnson cointegration test

### Table 2: Unit root test

Variable	t-statistic	<b>P-value</b>	Stationary level
RCI	-6.027918	0.0000	2 <sup>nd</sup> Difference
RCF	NA	NA	Non-Stationary at All Levels
RCG	NA	NA	Non-Stationary at All Levels
CO2I	-5.894460	0.0000	1 <sup>st</sup> Difference
CO2F	-7.576601	0.0000	1 <sup>st</sup> Difference
CO2G	-7.978261	0.0000	1 <sup>st</sup> Difference
FDII	-4.668764	0.0004	Level
FDIF	-8.079192	0.0000	1 <sup>st</sup> Difference
FDIG	-3.641477	0.0082	1 <sup>st</sup> Difference

#### Table 3: LM autocorrelation test

VAR RI	ESIDUAL SERIAL CORRELATION	LM TESTS
Lags	LM-Stat	Prob
1	151.8606	0.0000
2	100.3242	0.0717
3	102.7638	0.0517
4	139.4535	0.0001
5	111.3310	0.0143
6	114.0691	0.0091
7	89.67758	0.2386
8	140.8127	0.0000
9	144.9369	0.0000
10	115.0820	0.0077
11	111.1919	0.0147
12	146.7750	0.0000

Probs from Chi-square with 81 df.

#### Table 4: Johnson's cointegration test

	Series: CO2F CO2G CO2 Lags inter	tion: Linear deterministic tre 21 FDIFRA FDIG FDIITA Re val (in first differences): 1–2 Cointegration Rank Test (Tra	CF RCG RCI	
Hypothesized No. of CE (s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0.962441	519.7936	197.3709	0.0001
At most 1*	0.922569	362.2658	159.5297	0.0000
At most 2*	0.855148	239.4643	125.6154	0.0000
At most 3*	0.681977	146.7263	95.75366	0.0000
At most 4*	0.552284	91.73600	69.81889	0.0004
At most 5*	0.429983	53.16334	47.85613	0.0146
At most 6	0.300579	26.18310	29.79707	0.1233
At most 7	0.161520	9.022967	15.49471	0.3633
At most 8	0.011745	0.567076	3.841466	0.4514

Trace test indicates 6 cointegrating eqn (s) at the 0.05 level,\*denotes rejection of the hypothesis at the 0.05 level,\*\*MacKinnon-Haug-Michelis (1999) P-values

#### Table 5: Vector error correction model (VECM)

Statistical terms	CO2F	CO2G	CO2I	FDIFRA	FDIG	FDIITA	RCF	RCG	RCI
R-squared	0.947762	0.984101	0.976261	0.950426	0.738712	0.921703	0.999439	0.999694	0.998725
Adj. R-squared	0.877240	0.962636	0.944214	0.883501	0.385973	0.816003	0.998681	0.999281	0.997004
Sum sq. resids	8789.701	12905.82	2081.763	1.55E+21	3.36E+22	9.49E+20	0.001295	0.008871	0.004274
S.E. equation	20.96390	25.40258	10.20236	8.79E+09	4.10E+10	6.89E+09	0.008047	0.021061	0.014618
F-statistic	13.43926	45.84823	30.46297	14.20137	2.094217	8.719939	1318.584	2421.846	580.2722
Log likelihood	-193.1523	-202.3706	-158.5835	-1146.168	-1220.043	-1134.456	184.3814	138.1980	155.7270
Akaike AIC	9.214679	9.598776	7.774313	48.92365	52.00177	48.43566	-6.515892	-4.591581	-5.321958
Schwarz SC	10.30621	10.69031	8.865847	50.01519	53.09331	49.52720	-5.424358	-3.500047	-4.230424
Mean dependent	378.6937	896.4292	387.6646	2.79E+10	3.97E+10	1.07E+10	0.161875	0.575000	0.213333
S.D. dependent	59.83332	131.4172	43.19532	2.58E+10	5.23E+10	1.61E+10	0.221529	0.785694	0.267059

Determinant resid covariance (dof adj.) 5.82E+54. Determinant resid covariance 2.20E+51.Log likelihood -3450.319, Akaike information criterion 154.2633. Schwarz criterion 164.0871

is based on the Johansen procedure, which uses the concept of eigenvalues and eigenvectors to estimate the number of cointegrating relationships between multiple time series. The test checks to see if the residuals from each time series' regression on a set of cointegrating vectors are stable. The results of Johnson's cointegration test are presented below in Table 4.

As per the above analysis, up to six cointegrated equations were studied. It means that our data supports a long-term relationship; therefore, we can run a vector error correction model in VAR. The results based on VECM are presented in the next section.

# 4.4. Vector Error Correction Model (VECM)

Non-stationary and cointegrated time series may be analysed statistically with the use of a VECM, or vector error correction model. This model is a special case of the Vector Autoregressive (VAR) model in which an error correction factor is used to account for any disruptions in the time series' long-term equilibrium connection. The lagged values of the dependant variables and the lagged values of the error correction term are used to simulate the VECM. When there are disruptions in the equilibrium connection between the dependent variables, the error correction term describes how they are readjusted to return to that state. As our series is cointegrated, we may use the VECM approach to VAR analysis. Table 5 displays the results of our VECM investigation.

The study used three latencies in VECM analysis. As per the above analysis, the CO2F is significantly associated with the RCF, as all lagged variables are highly significant. Furthermore, CO2G is also significantly related to RCG, as all lagged transformations of CO2G are highly significant at the 0.01 level. Moreover, CO2I is significantly related to RCI, as all variables have a p-value near zero. Other variables do not follow any significant relationship.

# 4.5. Granger Causality Test

To ascertain whether 1 time series may be used to predict another, statisticians use the Granger causality test. The hypothesis being tested is that the past values of X should include information that helps to anticipate the future values of Y beyond what can be expected from the past values of Y alone. A VAR model containing two or more variables (X and Y) must be estimated before the Granger causality test can be performed; then, the predictive power of the lagged values of X on the lagged values of Y must be evaluated, taking into account the lagged values of Y itself. The test's null hypothesis states that X does not affect Y, which means that we can't learn anything new about Y's future values by looking at its previous values in X. Granger causality test results for this investigation are shown in Table 6.

According to the results of the above analysis, the variable FDII only Granger causes the CO2I because the P-value of the causality analysis is significant. In the above analysis, FDIF is also a granger cause of the CO2I, and FDIF is also a granger cause of the RCF. Only these three analyses were significant, and the remaining analyses do not cause any association. In our case, the majority of variables were non-stationary, and long-term associations were studied. Therefore, the study incorporated Toda Yamamoto causality analysis, as shown below.

# Table 6: Granger causality test

Dependent → Independent	<b>F-Statistic</b>	Prob.
France		
FDIFRA → CO2F	0.24793	0.8623
CO2F → FDIFRA	1.40344	0.2555
$RCF \rightarrow CO2F$	1.74059	0.1737
$CO2F \rightarrow RCF$	0.89135	0.4537
$RCF \rightarrow FDIFRA$	15.2870	8.E-07
FDIFRA → RCF	3.96258	0.0143
Germany		
$FDIG \rightarrow CO2G$	0.69057	0.5630
$CO2G \rightarrow FDIG$	3.40850	0.0263
$RCG \rightarrow CO2G$	1.31455	0.2827
$CO2G \rightarrow RCG$	4.05753	0.0129
$RCG \rightarrow FDIG$	1.91545	0.1422
FDIG → RCG	1.64974	0.1928
Italy		
FDIITA → CO2I	3.70381	0.0190
CO2I → FDIITA	1.37825	0.2629
RCI → CO2I	3.52035	0.0232
CO2I → RCI	2.33636	0.0878
RCI → FDIITA	1.08163	0.3676
FDIITA → RCI	1.62726	0.1978

# Table 7: Toda-Yamamoto causality analysis

VAR Granger causality/block exogeneity wald tests			
	Dependent variable	e: CO2F	
Excluded	<b>Chi-square</b>	df	Prob.
CO2G	12.83542	3	0.0050
CO2I	1.979474	3	0.5767
FDIFRA	1.573401	3	0.6654
FDIG	2.138671	3 3 3	0.5441
FDIITA	0.675074	3	0.8791
RCF	1.836481	3	0.6070
RCG	1.015527	3	0.7975
RCI	2.328250	3	0.5071
All	33.63843	24	0.0913
	Dependent variable	e: CO2G	
Excluded	<b>Chi-square</b>	df	Prob.
CO2F	15.20577	3	0.0016
CO2I	11.05722	3	0.0114
FDIFRA	6.915107	3	0.0747
FDIG	10.35051	3 3 3 3 3	0.0158
FDIITA	3.857033	3	0.2773
RCF	2.751347	3	0.4316
RCG	3.611189	3	0.3066
RCI	3.126779	3	0.3725
All	57.21166	24	0.0002
	Dependent variabl		
Excluded	<b>Chi-square</b>	df	Prob.
CO2F	2.947881	3	0.3997
CO2G	2.676914	3	0.4442
FDIFRA	2.462452	3	0.4821
FDIG	5.226945	3	0.1559
FDIITA	4.592501	3	0.2042
RCF	3.522554	3	0.3178
RCG	3.380004	3	0.3367
RCI	2.562551	3	0.4641
All	43.01266	24	0.0099
	Dependent variable:	FDIFRA	
Excluded	<b>Chi-square</b>	df	Prob.
CO2F	4.619253	3	0.2019
CO2G	15.78459	3	0.0013
			(Contd)

Table 7: (Co	ntinued)		
VAR (	Franger causality/block e		l tests
	Dependent variable:		
Excluded CO2I	<b>Chi-square</b> 1.366811	df 2	<b>Prob.</b> 0.7133
FDIG	7.316391	33	0.7133
FDIITA	2.585318	3	0.4601
RCF	7.902252	3	0.0481
RCG	29.58076	3	0.0000
RCI	34.76130	3	0.0000
All	137.6639	24	0.0000
	Dependent variabl		
Excluded CO2F	<b>Chi-square</b> 4.184907	<b>df</b> 3	<b>Prob.</b> 0.2422
CO2G	2.250347	3	0.2422
CO2I	5.106882	3	0.1641
FDIFRA	10.26435	3	0.0164
FDIITA	2.912657	3 3	0.4053
RCF	7.549583	3	0.0563
RCG	5.423878	3	0.1433
RCI	3.486573	3	0.3225
All	33.71487 Dependent variable	24 • EDUTA	0.0899
Excluded	Chi-square	df	Prob.
CO2F	10.41053	3	0.0154
CO2G	2.394160	3	0.4947
CO2I	9.047000	3	0.0287
FDIFRA	16.12856	3	0.0011
FDIG	17.16717	3 3 3 3 3	0.0007
RCF	38.12198	3	0.0000
RCG	134.7690		0.0000
RCI	22.33756 890.2458	3 24	0.0001 0.0000
All	090.2430	24	0.0000
	Dependent variab		
Excluded	Dependent variab Chi-square	le: RCF	
Excluded CO2F	Dependent variab Chi-square 4.257316	le: RCF df	<b>Prob.</b> 0.2350
	Chi-square	le: RCF df 3	Prob.
CO2F CO2G CO2I	Chi-square 4.257316 7.156390 6.542374	le: RCF df 3	<b>Prob.</b> 0.2350 0.0671 0.0880
CO2F CO2G CO2I FDIFRA	Chi-square 4.257316 7.156390 6.542374 14.24020	le: RCF df 3	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026
CO2F CO2G CO2I FDIFRA FDIG	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212	le: RCF df 3 3 3 3 3 3 3	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026 0.0002
CO2F CO2G CO2I FDIFRA FDIG FDIITA	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672	le: RCF df 3 3 3 3 3 3 3 3	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672 12.96890	le: RCF df 3 3 3 3 3 3 3 3 3 3	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0000
CO2F CO2G CO2I FDIFRA FDIG FDIITA	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672	le: RCF df 3 3 3 3 3 3 3 3	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672 12.96890 13.86196	le: RCF df 3 3 3 3 3 3 3 3 3 24	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0000 0.0047 0.0031
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672 12.96890 13.86196 179.4813	le: RCF df 3 3 3 3 3 3 3 3 3 24	<b>Prob.</b> 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0000 0.0047 0.0031
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variable           Chi-square           0.547399	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variable           Chi-square           0.547399           0.670194	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variable           Chi-square           0.547399           0.670194           5.343215	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802           0.1483
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variable           Chi-square           0.547399           0.670194           5.343215	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802           0.1483
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672 12.96890 13.86196 179.4813 Dependent variabl Chi-square 0.547399 0.670194 5.343215 12.75766 12.62783 10.51244 11.45732	le: RCF df 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIFRA FDIG FDIITA RCF RCI	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672 12.96890 13.86196 179.4813 Dependent variabl Chi-square 0.547399 0.670194 5.343215 12.75766 12.62783 10.51244 11.45732 8.253849	le: RCF df 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095 0.0410
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF	Chi-square 4.257316 7.156390 6.542374 14.24020 19.44212 26.13672 12.96890 13.86196 179.4813 Dependent variabl Chi-square 0.547399 0.670194 5.343215 12.75766 12.62783 10.51244 11.45732 8.253849 706.4475	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 24 le: RCG le: RCG	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802           0.1483           0.0052           0.0147           0.0095           0.0410           0.0000
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b>	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square	le: RCF df 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095 0.0410 0.0000 Prob.
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square           4.232586	le: RCF df 3 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 4 le: RCG le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802           0.1483           0.0055           0.0147           0.0095           0.0410           0.0000
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b> CO2F	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square	le: RCF df 3 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 4 le: RCG le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0002 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095 0.0410 0.0000 Prob.
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square           4.232586           4.279705           1.467110           3.836740	le: RCF df 3 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 4 le: RCG le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0002           0.0000           0.0047           0.0031           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802           0.1483           0.0052           0.0147           0.0095           0.0410           0.0000           Prob.           0.2374           0.2328           0.6899           0.2796
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIFRA FDIG	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.75766           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square           4.232586           4.279705           1.467110           3.836740           1.748434	le: RCF df 3 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 4 le: RCG le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob.           0.2350           0.0671           0.0880           0.0026           0.0000           0.0000           0.0047           0.0031           0.0000           0.0047           0.0031           0.0000           Prob.           0.9084           0.8802           0.1483           0.0052           0.0147           0.0095           0.0410           0.0000           Prob.           0.2374           0.2374           0.2374           0.2374           0.2374           0.2374           0.2374           0.2374           0.2374
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIFRA FDIG FDIFRA FDIG FDIFRA FDIG FDIFRA FDIG FDIITA	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.6783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square           4.232586           4.279705           1.467110           3.836740           1.748434           0.707263	le: RCF df 3 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 4 le: RCG le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095 0.0410 0.0000 Prob. 0.2374 0.2328 0.6899 0.2796 0.6262 0.8715
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.62783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square           4.232586           4.279705           1.467110           3.836740           1.748434           0.707263           8.980013	le: RCF df 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.1483 0.0052 0.0055 0.0147 0.0095 0.0147 0.0095 0.0410 0.0000 Prob. 0.2374 0.2328 0.6899 0.2796 0.6262 0.8715 0.0296
CO2F CO2G CO2I FDIFRA FDIG FDIITA RCG RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIITA RCF RCI All <b>Excluded</b> CO2F CO2G CO2I FDIFRA FDIG FDIFRA FDIG FDIFRA FDIG FDIFRA FDIG FDIFRA FDIG FDIITA	Chi-square           4.257316           7.156390           6.542374           14.24020           19.44212           26.13672           12.96890           13.86196           179.4813           Dependent variabl           Chi-square           0.547399           0.670194           5.343215           12.6783           10.51244           11.45732           8.253849           706.4475           Dependent variab           Chi-square           4.232586           4.279705           1.467110           3.836740           1.748434           0.707263	le: RCF df 3 3 3 3 3 3 3 3 3 3 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 4 le: RCG le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 4 24 le: RCG df 3 3 3 3 3 3 3 3 3 3 3 3 3	Prob. 0.2350 0.0671 0.0880 0.0026 0.0000 0.0047 0.0031 0.0000 Prob. 0.9084 0.8802 0.1483 0.0052 0.0055 0.0147 0.0095 0.0410 0.0000 Prob. 0.2374 0.2328 0.6899 0.2796 0.6262 0.8715

#### 4.6. Toda-Yamamoto Test

Granger causality in non-stationary time series may be tested for with the use of the Toda-Yamamoto test. The standard Granger causality test, which requires stationary time series, is extended in this way. By using a VAR model with extra lagged values of the dependent variable(s) and lagged differences of the dependent variable(s) up to a specific order, the Toda-Yamamoto test accounts for non-stationarity. After accounting for the impact of the lagged values, the test examines the significance of the coefficients of the lagged differences, which indicate the influence of the previous values of the dependant variable(s) on the current values. As trends and structural breakdowns are common in economic and financial time series, the Toda-Yamamoto test comes in handy when analysing them. It may be used to uncover underlying causal linkages between variables that non-false stationarity's correlations could otherwise mask. Like every statistical test, the Toda-Yamamoto test involves caveats and assumptions that must be carefully weighed before relying on the results. In particular, the test presupposes a linear relationship between the variables and a well-specified lag structure. The findings must be understood in the context of the economic theory upon which they are based, as well as the presence or absence of additional complicating variables. Table 7 displays the Toda-Yamamotobased findings.

Finally, the study incorporated the Toda-Yamamoto causality analysis to test the causal relationship because our variables are non-stationary at level. The variable CO2F significantly causes the FDIF, as the P-value of Chi-square is 0.0013. CO2I and CO2G do not cause FDIF, as both variables are insignificant. Moreover, RCI, RCF, and RCG are highly significantly causing the FDIF as their p-values of Chi-square were near zero. The variables CO2F and CO2G significantly cause the FDII, as these variables have Chi-square values of 10.41 and 9.04, respectively. Both chi-square values are highly significant, just as P-values are significant. RCF, RCI, and RCG cause the FDII as well as the Chi-square values to be highly significant. We can summarise our finding from the Toda-Yamamoto analysis by saying that the CO2F, RCI, RCF, and RCG significantly cause the FDIF. Moreover, CO2I, CO2F, RCI, RCF, and RCG significantly cause the FDIF.

# **5. CONCLUSION**

The study incorporated three different models for analysis. The models were analysed using vector autoregressive estimation techniques. The variables used in this study were non-stationary at level; therefore, we assume that all variables were stationary at the first difference, and the study incorporates a vector error correction model. Moreover, the study also incorporated a causality analysis. The study initially incorporated the Granger causality test to analyse the causal relationship. But our time series were non-stationary at level; therefore, we incorporated the Toda-Yamamoto causality test. As per the VECM analysis, the variable CO2G is also significantly impacted by the RCG as all lagged transformations of CO2G are highly significant at the 0.01 level, and the variable CO2I is also significantly impacted by the RCI as all variables have a P-value near zero. As the P-value of the causality analysis is significant, the variable FDII

is the only one that causes CO2I. In the above analysis, FDIF is also a granger cause of the CO2I, and FDIF is also a granger cause of the RCF. We can summarise our finding from the Toda-Yamamoto analysis by saying that the CO2F, RCI, RCF, and RCG significantly cause the FDIF. Moreover, CO2I, CO2F, RCI, RCF, and RCG significantly cause the FDII.

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