Impact of Energy consumption and Economic policy uncertainty on Ecological footprint: Evidence from BRICS countries.

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Acronyms

AMG	Augmented Mean Group
ADF	Augmented Dickey-Fuller
BRICS	Brazil, Russia, India, China, and South Africa
CCEMG	Common Correlated Effects Mean Group
C02	Carbon dioxide
CS-ARDL	Cross-Sectional Autoregressive Distributive Lag
DSUR	Dynamic Seemingly Unrelated Regression
EC	Energy Consumption
EFP	Ecological Footprint
EPU	Economic Policy Uncertainty
EKC	Environmental Kuznets Curve
GDP	Gross Domestic Product per capita
GDP	Gross Domestic Product per capita
GLO	Degree of Globalization
HYDRO	Hydro Energy Consumption
IPAT	"Integrated Population, Affluence and Technology" effect model
NREC	Non-Renewable Energy Consumption
REC	Renewable Energy Consumption
SOLAR	Solar Energy Consumption
STRIPAT	"Stochastic Impacts by Regression on Population, Affluence, and Technology" model
WIND	Wind Energy Consumption

Abstract

In the past years, a growing concern has been directed towards global environmental quality and the energy required to sustain economic growth. A crucial element in current literature is the influence of economic policy uncertainty (EPU) and on Ecological Footprint (EFP). Given the significant global influence of the BRICS (Brazil, Russia, India, China, and South Africa) group, examining it through their lens will benefit the international context. Therefore, this study utilized AMG and CCEMG methodologies to investigate the impact of energy consumption (EC) and EPU on the EFP in BRICS countries. This study enriches the current literature further by disaggregating EC into REC (Renewable Energy Consumption) and NREC (Non-renewable Energy Consumption) and subsequently looking at the consequences of individual renewable energy sources on the EFP. The study presents empirical findings that show panel and country-specific results and demonstrate that EC and NREC increase EFPs. In contrast, only China's REC positively impacted the environment. EPU has significantly negatively affected the EFP when considering individual REC. This study recommends policymakers accelerate the transition to a sustainable future by considerably increasing support for additional investments and subsidies to the widespread adoption of renewable energy as a primary source to diminish environmental decay.

Chapter One: Introduction

1.1 Problem Statement

EC plays a crucial role in a country's road to development (Ndlovu & Inglesi-Lotz, 2020; Rehman & Rashid, 2017). In recent years, an economy cannot thrive without consuming energy, let alone the people of that economy, as the amount and type of energy a country consumes determines the quality of that nation (Hagens, 2020). Every country strives towards sustainable economic growth, and energy is required for that growth to occur (Kongbuama et al., 2021).

As the world moves towards a more technologically reliant economy, higher energy levels are also required to drive growth (Li et al., 2023). EC and economic development are connected (Ndlovu & Inglesi-Lotz, 2020). According to Shahbaz et al. (2017), the contribution of a diverse range of industries to the GDP is proportional to their EC. To continue the progress of industrialization and maintain efficiency, the manufacturing, technological, transportation, and agriculture industries require increasingly higher levels of energy to function (Shahbaz et al., 2017).

The great industrial revolution of the 1800s and the developments of the 19th century were primarily powered by non-renewable sources of energy from natural resources such as coal, which was generally more cost-effective (Hagens, 2020). However, due to the recent evidence of climate change devastations, countries are pivoting towards renewable and sustainable energy sources, which previously had a more significant cost implication but are becoming more competitive. (Kleinnij et al., 2022, Ndlovu & Inglesi-Lotz, 2020).

The emerging group of countries of "Brazil, Russia, India, China, and South Africa" (BRICS) are critical players in the energy sphere as they account for "40%" and "25% of the world's coal and gas reserves" (The Department of Trade Industry and Competition, 2023) respectively, making them highly dependent on non-renewable energies. Their significant individual and combined contribution to "global atmospheric greenhouse emissions" (Chapungu, 2022) makes BRICS a critical change agent in combating global warming. After the Paris Agreement of 2015 and the 2021 Conference of Parties, BRICS countries collectively aligned their goals to reduce their emissions to "net zero" (Chapungu et al., 2022) by 2050.

Transitioning to renewable energy sources (Solar, Wind, and Hydro) would play a significant role in achieving a net zero emission by 2050. Because each renewable energy impacts the environment to various degrees and the aim of "Sustainable Development Goal" (SDG) 12 entails ensuring "sustainable consumption and production patterns" (United Nations, 2023), prioritizing the utilization of the cleanest renewable energy will aid in creating a sustainable planet. Fortunately, the current economic, agroecological, and political environment is very conducive to the development of these energy types within the BRICS (Department of Trade Industry and Competition, 2023). Despite the potential negative impacts in the short run (i.e. stranded assets and unemployment concerns), renewable energies have large policy support in the long run with the potential to lead to steady, sustainable growth and reduced cost (Ndlovu & Inglesi-Lotz, 2020). In BRICS, these short-term negative impacts – employment displacement, high initial cost, and political instability (Hoang et al., (2021) - create economic policy uncertainties (EPU), which could inhibit the diffusion of such technologies due to EPU's ability to forecast the reduction in investment, production, and employment.

This raises concerns about the environmental implications of EPU (H. Li et al., 2023) in BRICS countries. According to Chu & Le (2022), trade conditions become optimal amongst the BRICS countries when EPU diminishes, leading members to focus on investment and renewable energy development. However, when EPU increases, trade uncertainty rises, redirecting countries to focus on the leading trade that emphasizes their development goals (Chu & Le, 2022) at the detriment of the environment (S. T. Hassan et al., 2022). This demonstrates the importance of the intersectionality between the main topics, EPU, EC and EFP. Moreover, because each renewable energy source impacts the environment to a different degree, it is vital to understand the environmental implications of EPU under the heterogeneous impacts of different renewable energy sources in BRICS.

Given the stated problem, the paper aims to answer the questions below for the purpose of this study:

i. How do EC and EPU influence the EFP in the BRICS countries?
ii. What is the relationship between the REC and NREC patterns and the EFP of the BRICS countries?

1.2 Research Objectives

The main objective is to determine the drivers of the EFP in BRICS countries. The specific objectives are to:

1. Characterize the homogeneous and heterogeneous impacts of EC and EPU on EFP.
2. Estimate the homogeneous and heterogeneous impacts of both REC and NREC patterns on the EFP of the BRICS countries.

1.3 Justification for the research.

Several studies explore the EFP and energy nexus, such as Akadiri et al. (2022), Kongbuamai et al. (2021), Li et al. (2023), Adedoyin et al. (2020), Alola et al. (2019), Destek et al. (2019), Adekoya et al., (2022), Nathaniel et al. (2021) and Ulucak et al. (2020). Adedoyin et al. (2020) looked at economic expansion's role in the relationship between EC and EFP. Alola et al. (2019) evaluated the impact that fertility rates and trade policies have on the relationship between EC and EFP. In contrast, Nathaniel et al. (2021) concentrated on the link of human capital in relation to the impact that EC has on EFP.

However, very few of the existing studies have looked at the importance of EPU and, even more importantly, considered the heterogeneous nature of the impact. In the context of BRICS, Kongbuamai et al. (2021) examined economic policy's role in EC on EFP. Similarly, Li et al. (2023) considered the role of EPU when looking at the effects of REC and NREC on the EFP. Given the important implications that EPU has on business risk and energy investment decisions, neglecting it amounts to omitted variable bias, hence confounding the relationship between EFP and EC. A prior study done by Adedoyin et al. (2021) indicates that if EPU is high, the governments and businesses, including those in BRICS countries, tend to lean towards NREC due to their reduced faith in the policy landscape and focus mainly on their primary trade activities, which are in oil and gas. Conversely, when EPU is low, governments and businesses become risk-seeking and increase their investment in REC. This study contributes to the causal claim between EFP and EC, taking into account the role of EPU in BRICS. The current study is different from Li et al. and others that have looked at similar questions in the following way:

The current study investigates the relationship between EFP, EC and EPU on both panel and country-specific basis. The latter addresses concerns of heterogeneity bias, which is highly possible in such study. Addressing heterogeneity concerns enables a detailed insight into the nuances and peculiarities of a member country's energy patterns, thus allowing for more targeted economic policy initiatives. This is particularly important in the BRICS panel since each country, though developing are at different stages, have differing energy and developmental needs.

Therefore, this study's findings will have an affect the government and businesses in BRICS countries. It could inform policy directions on economic strategy, EC, and environmental degradation, particularly with reference to EPU, where knowledge is currently scant. It will particularly be useful in informing energy and climate policies that accommodate uncertainty in the respective BRICS countries. Thus, it will contribute to the debate surrounding the implemention of radical policy reforms to mitigate the adverse effects that non-renewable energy has on the environment, which directly impacts the living standard of its citizens.

Furthermore, the outcome could guide the international climate commitment target of BRICS countries as they clamour for greener energy solutions heightens by the day. In addition, it will expand the limited research on the relationship between REC, NREC and EPU on EFP. The study further looks at the relationship between individuals' renewable energy and EPU on EFP. This will allow for a comprehensive study of EC impact on the degradation of the planet since BRICS countries have been making greater steps towards renewable energy with the formation of the BRICS Energy Research Platform (BERP), aimed at promoting renewable energy development (BRICS, 2021). This study will, therefore, be relevant in the global landscape as they are international players. Thus, it will contribute to a shift from the regime of wholesome policies to one that accounts for the heterogeneities in the energy sector.

Finally, insights from this study will also be beneficial to businesses operating in BRICS member states in their strategic decision-making and investment initiatives while opening up avenues for sustainable operations. It will offer a clear long-term perspective on climate and energy policies, which will be good for the government, business planning, investment decisions and market expansions, amongst others. Although the outcome of this research would have direct implications for BRICS countries, other nations and businesses could also acquire helpful insight from it.

1.4 Layout of the Research

The research is divided into five chapters. First there is the introduction in chapter one. Chapter two will discuss the trend of the variables of BRICS countries. The third chapter provides a review of the literature. The fourth chapter looks at the framework and data description. Chapter five focuses on the discussion and interpretation of the results. Chapter Six concludes the study concludes with policy suggestions.

Chapter 2: Trend Analysis

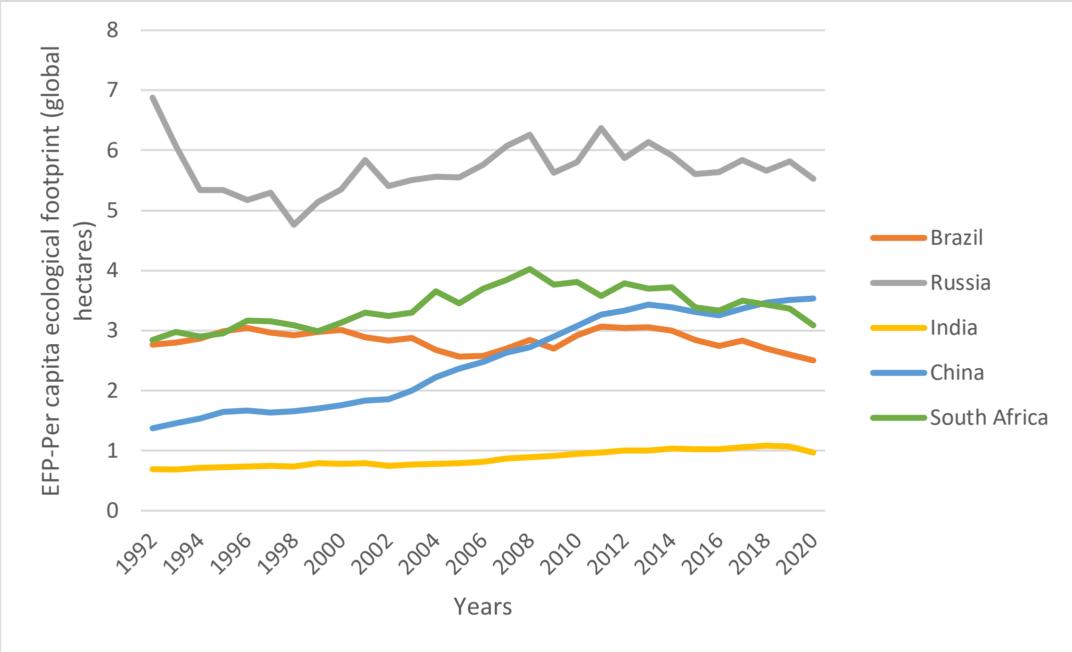
2.1 Ecological Footprint

A key metric for measuring environmental degradation is the EFP of the concerned area or country (Global Footprint Network, 2023). Using EFP encompasses all impacts on the natural environment, ranging from agricultural land to carbon dioxide emissions (Li et al.,2023). (Global Footprint Network, 2023)

According to Global Footprint Network (2019), EFP measures the demand and supply of natural resources as carbon dioxide emissions do not account for other types of pollution (soil and water). The development of EFP came from the growing worldwide awareness of the need to limit consumption in relation to the productivity of the earth. Therefore, EFP looks at how much waste we produce compared to how many resources are available to consume. EFP addresses this phenomenon by comparing the potential of the earth to produce to what the world consumes each year (Sahoo, 2021). Consequently, it implies that the rate of consumption must be less than the productive capacity of the earth for us to live sustainably on this planet. (Global Footprint Network, 2023)

Graph 1 shows the trend over time of how much waste the countries produced compared to how many resources are available to consume. In terms of the BRICS countries, they have varying levels of EFP, with Russia having a relatively higher EFP than the rest of the group, averaging around six global hectares per capita.

Russia's EFP has the largest variation. The country's EFP has decreased from approximately 7 to around 5.5 global hectares per capita. This is the result of the increase in their use of renewable energy. India is shown to have the lowest EFP, averaging one global hectare per capita from 1992 to 2020. China had the largest increase in its EFP, from approximately 1.5 global hectares per capita in 1992 to having the second largest EFP in the group. China's EFP increases with the growth of its economy.

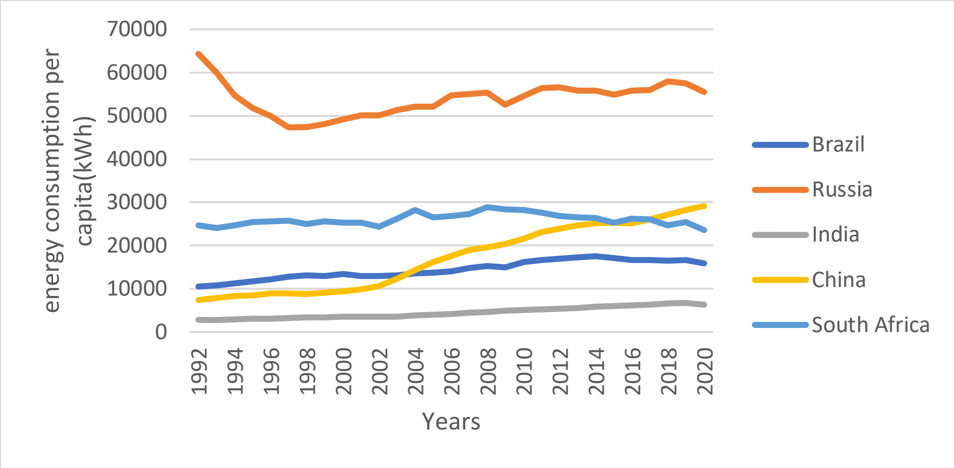


<u>Graph 1:EFP of BRICS countries</u>
Source: Global Footprint Network (2023)

2.2 Energy Consumption of BRICS Countries

Graph 2 shows EC over time for the BRICS countries. It shows that Russia has the largest EC per capita over time, followed by China, South Africa, Brazil, and then India. Russia's EC has decreased over time from a per capita of approximately 64000kWh to approximately 55000kWh.

Similar to Russia; South Africa, Brazil, and India all reduced their EC around 2020, resulting from the global lockdown that was in response to the COVID pandemic. In contrast, the opposite occurred in China, which had increased EC. Around 2002, there was an exponential increase in China's EC, which was attributed to the country's change in production structure (Zhang & Lahr, 2014).

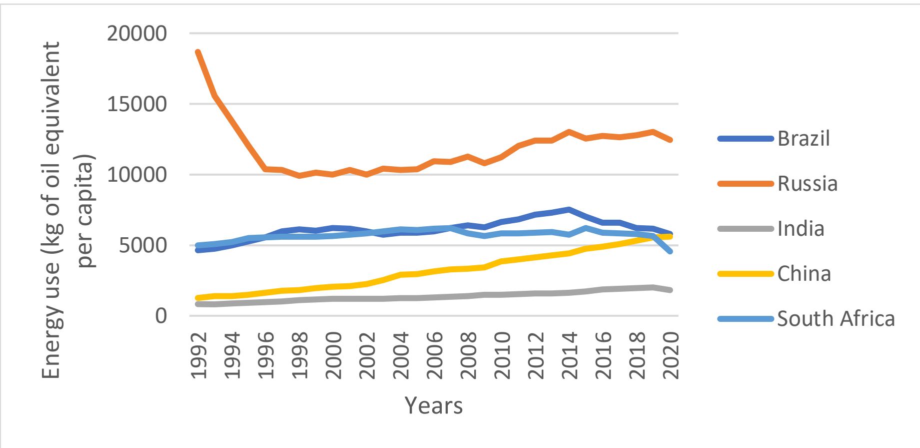


Graph 2: EC of BRICS countries

Source: Our World Data (2023)

2.3 Non-Renewable Energy Consumption of BRICS Countries

Looking at Graph 3 shows the NREC of the BRICS countries over time. Comparing Graphs 2 and 3, it is evident that NREC follows the same trajectory as EC. This is because a significant amount of energy is consumed by oil production, the primary non-renewable energy source. The noticeable difference is that Brazil, China, and South Africa follow Russia, with the highest NREC. This indicates that South Africa, even though the country comes second in EC consumes one of the lowest amounts of non-renewable energy. This demonstrates their diversified energy source and reduced reliance on non-renewable energy.



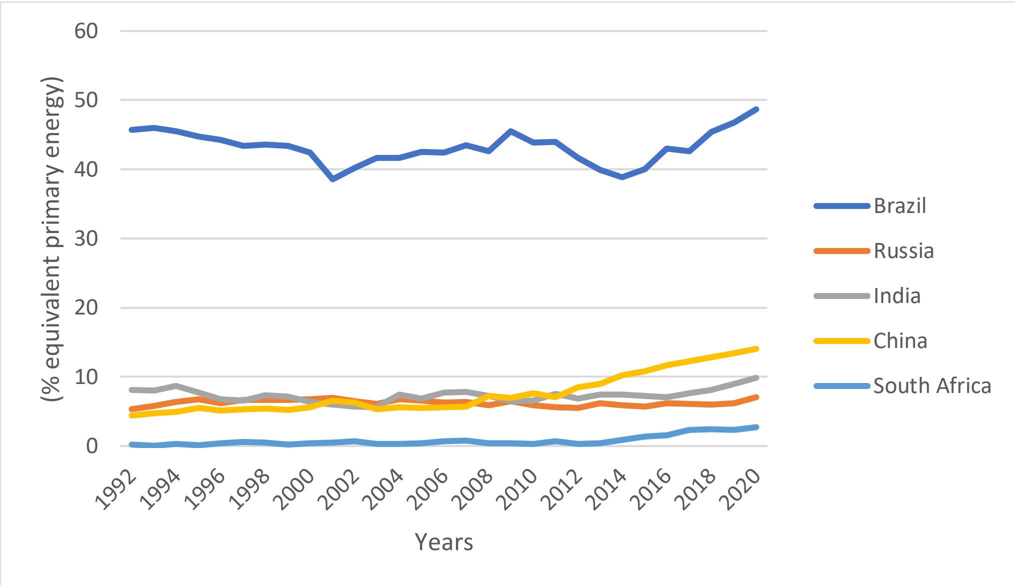
Graph 3: Non-renewable Consumption of BRICS countries

Source: Our World Data (2023)

2.4 Renewable Energy Consumption of BRICS Countries

Graph 4 shows the REC of the BRICS countries over time. As depicted in the graph below, Brazil has the highest percentage (40% to 50%) of renewable energy compared to the group. Besides Brazil's relatively high consumption of non-renewable energy compared to the other BRICS countries (Graph 3), their EC makeup, as depicted in Graph 4, is also exceedingly higher than the rest of the BRICS nations.

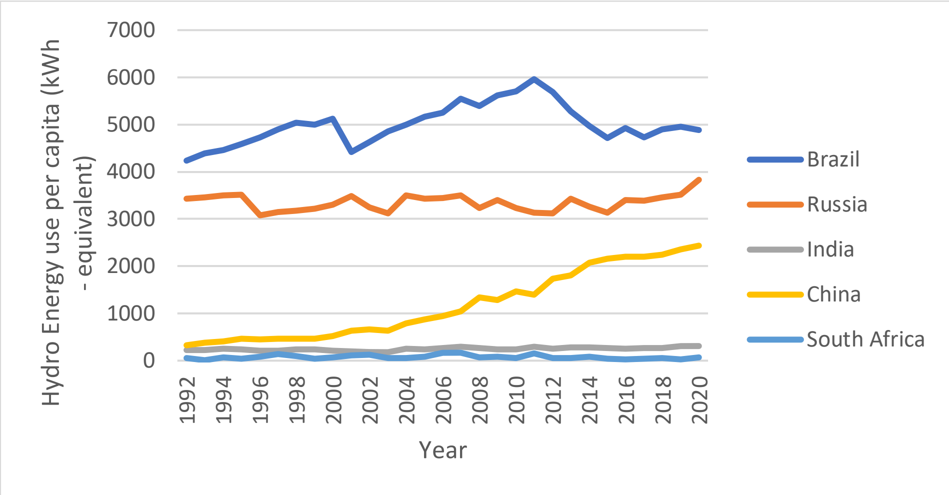
Following Brazil are China, India, Russia, and then South Africa. The rest of the countries use a significantly less renewable energy percentage of their total EC. Though in recent years all the countries' use of renewable energy has increased, with Brazil having the steepest incline. This shows the reliance on renewable energy has strengthened.



Graph 4: Renewable Consumption of BRICS countries
Source: Our World Data (2023)

2.5 Hydro Energy Consumption of BRICS countries

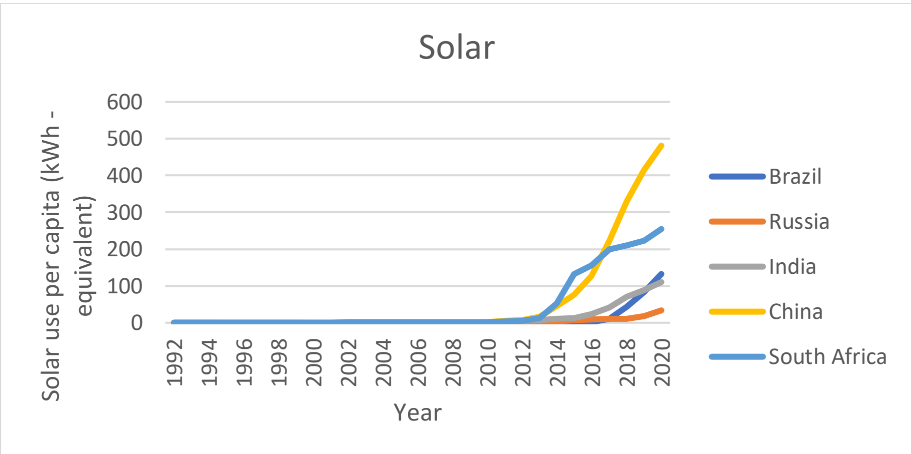
Graph 5 depicts the individual Hydro Energy Consumption for the BRICS countries from 1992 to 2020. As depicted in the graph below, Brazil uses the most hydro energy, averaging around 5000 kWh per capita. This follows Graph 4, which shows that Brazil consumes the greatest quantity of renewable energy among the group. Followed by Russia, China, India, and then South Africa. Russia's use of hydro EC has been the most consistent within the BRICS group staying within the 3000 kWh to 4000 kWh per capita threshold over 28 years. This is due to the country's effort to utilize its hydro energy source to its full potential. In contrast, China experienced the largest growth in its hydro EC, starting from approximately 0kWh in 1992 and continuing to approximately 2400 kWh in 2020. Both South Africa and India's use of hydro energy has been minimal as their consumption remains around 0 kWh for the period of this study.



Graph 5: Hydro EC of BRICS countries
Source: Our World Data (2023)

2.6 Solar Energy Consumption of BRICS Countries

Graph 5 illustrates the individual REC of solar for the BRICS countries over 28 years. China has the highest solar EC, followed by South Africa, Brazil, India, and then Russia. The order can be attributed to the individual countries' climate, as Russia's atmospheric condition is not as conducive to solar EC as China's. Following the trend of the other graphs, China's growth in their solar energy usage is steeper than the rest of the countries.



Graph 6: Solar EC of BRICS countries
Source: Our World Data (2023)

Chapter 3: Literature review

3.1 Theoretical Literature

The majority of the theory around this area of study is based on the Environmental Kuznets Curve (EKC) hypothesis, which was proposed by Simon Kuznets in 1995 and looks at the relationship between economic growth and environmental degradation (Kuznets 1995). The curve is shaped as an inverted U-shape (Kongbuamai et al., 2021). The curve is inverted U-shaped because initially, there is a positive relationship between environmental degradation and income, and as the income levels rise, the relationship evolves towards a negative relationship (Kongbuamai et al., 2021). The theory suggests that during earlier stages of development, rapid industrialization results in overconsumption of natural resources, that translates in a positive relationship between environmental degradation and economic growth (Huang et al., 2021). During this stage the country prioritizes economic growth over the quality of the environment (Mahmood et al., 2023). The environmental damage is high at the early stage as inefficient technology is used to exploit the natural resource available (Mao et al., 2013). As the economy advances and the industrialisation process reaches the final stages, natural resources becomes scarce, service based industries start to expand and technology advancements result in a decline in environmental degradation (Huang et al., 2021). The above fosters environmental public awareness resulting in the use of innovative environmental management techniques that promotes environmental improvements (Mao et al., 2013).

Even though this theory is widely used for understanding economic growth and environmental degradation, and literature has shown that there is a positive relationship between economic growth and EC (Hagens, 2020; Li et al.,2023 Kongbuamai et al., 2021), the theory does not have a theoretical framework therefore "Stochastic Impacts by Regression on Population, Affluence, and Technology" (STIRPAT) model is used as the theoretical framework (X. Li et al., 2023). The model employed current literature to investigate the impact on the EFP (Huang et al., 2021; X. Li et al., 2023; Yang et al., 2021). STIRPAT was modified by Dietz and Rosa (1997) as the extended model of "Integrated Population, Affluence and Technology effect" (IPAT) model which is used to analyse the influence of different elements on the environment (Adom et al., 2018). The IPAT model has had some strong limitations as it was limited to a linear relationship between the variables(X. Li et al., 2023). STRIPAT, accounts for the limitations of the model by providing flexibility in its structure, allowing for non-linear relationships and accounting for the stochastic aspect (Adom et al., 2018; X. Li et al., 2023).

3.2 Empirical Literature

3.2.1 Energy Consumption and Environmental Degradation (BRICS)

Literature reveals that investigation into REC and NREC on EFP has been done using single country and panel analysis. A recent study by Li et al. (2023) on EC and EPU in the BRICS nations concluded that REC enhances the EFP, while the reverse was the case with non-renewable sources. In arriving at their conclusion, the researchers acknowledged the limitation of focusing on the whole function of EC, which may have misled the EFP metrics.

They, therefore, highlighted the need for a detailed analysis of the individual components of renewable sources on the EFP "to better understand their specific contribution to environmental improvement" (Li et al., 2023), which this study aims to achieve. Like in the global scenario, Nathaniel et al. (2021) found within the BRICS context that the data showed opposing impacts on EFP, with renewable energy being negative and non-renewable energy being positive (Ulucak et al., 2020; Wang, 2021). Akadiri et al. (2022) in the Chinese context found that both REC and NREC affect EFP positively. The contradictions stem from the fact that biomass, which contributes the highest proportion of renewable energy in China, increases the EFP through the burning of natural resources. As such, the conclusions are varied. However, it may be that without biomass, the REC pattern would have followed a trajectory similar to the outcome of the studies in the previous paragraph.

In China, Wei et al., (2021) arrived at a contrary outcome from their review of the REC on EPU; their wavelength analysis revealed a significant relationship in the short run, while in the long run, it was not significant.

Methodologically, different studies have applied varying methods to study the nexus between EFP and EC. Supporting Akadiri et al. (2022) findings in the BRICS setting, Kongbuamai et al. (2021) employed the "Dynamic Seemingly Unrelated Regression (DSUR)" method on the BRICS countries and found that regardless of the energy source, degradation increased with consumption. Li et al. (2023) investigated the BRICS countries' context by making use of the Cross-Sectional Autoregressive Distributive Lag (CS-ARDL) using a panel analysis and observed that renewable energy sources reduced greenhouse gases and, therefore, the EFP. Akadiri et al. (2022) used a quantile-on-quantile (QQ) analysis in the Chinese context. Wei et al., (2021) used the wavelength analysis.

The current study veers from the previous studies (Li et al.,.2023; Nathaniel et al., 2021 and Kongbuamai et al.,2021) in the following ways. First, this study utilized AMG and CCEMG methodologies. Second, in terms of data, we employ longitudinal data covering a more extended range of 28 years from 1992, which allows for a more robust trend analysis. Third, this study provides country-specific and panel-level analysis of the BRICS group.

3.2.2 Economic Policy Uncertainty and Environmental Degradation.

In current literature, the impact EPU has on the environment is of importance and is explored heavily. According to Baker et al. (2016), EPU is based on the frequency of media coverage that relates to policy-related economic uncertainty fluctuation. The policy uncertainty is related to stock prices and investment volatility. It has the ability to forecast the reduction in investment, production and employment (Baker et al., 2016). Therefore resulting in firms and investors operating in a risk averse mindset by retaining more cash which reduces the quantity and quality of their investments. The uncertainty can even lead to investors delaying their investments decisions. (Al-Thaqeb & Algharabali, 2019)

The relationship between EPU and EFP is essential in understanding the impact of the economic climate and the economic policy-centred decisions the government and businesses make on the environment of their countries. Due to the connection between the quality of the environment and the economic policies which influence the climate of the country (Iqbal et al., 2023). According to Korley et al. (2023), EPU refers to the frequent volatility surrounding economic policy decisions, which range from fiscal to monetary policy and their impact on businesses and countries.

The literature has mixed findings surrounding the economic impact on the environment (Li et al.,2023; Shouchang et al., 2023). The majority of the literature indicates that EPU has a positive impact on environmental degradation, which means that EPU increases the levels of EFP (Anser et al., 2021; Shabir et al., 2022; H. Su et al., 2022).

Using the CS-ARDL model, Li et al. (2023) found that EPU enhances the EFP along with NREC in the long run. Therefore, it shows that EPU has a negative impact on the protection of the environment. Esmaeili et al. (2022) further supported this by showing EPU increased environmental degradation in the long run but also found evidence that EPU reduced EFP in the short run.

Wei et al. (2021) investigated the type of energy production on EPU using the wavelet co-movement analysis and found that in China, energy production and EPU showed positive cointegration.

Jiang et al. (2023) investigated the impact of EPU on green growth using panel quantile regression and found that EPU is detrimental to green growth, which is consistent with the literature. To go along with the impact EPU has on the environment, looking at its effects on CO2 using the ARDL approach in Iqbal et al. (2023), EPU has a significant increase in CO2, which corroborates the prevailing notion that EPU has a detrimental effect on the environment.

While investigating if EPU and geopolitical risk result in environmental degradation, Anser et al. (2021) found a very significant relationship using EFP as a proxy for environmental degradation. This conclusion is further emphasized by Su et al. (2022), who looked at a more holistic view by considering the political, social and environmental spheres and found that in a panel study of 137 countries, EPU can impact activities related to the protection of the environment.

Su et al. (2022) further established that the development of a country could impact the country's uncertainty in economic policy. Factors such as the level of globalization have a migrating effect on EPU. This is important when looking at a group like BRICS, and how their trade relations can reduce environmental damage, which is why this paper added it as a variable in the study. The literature shows the importance of EPU when investigating environmental damage.

Chapter 4. Theoretical Framework and Methodology

4.1 Theoretical Framework

Theoretically, environmental impact (I) according to Cherlew (2001), can be decomposed into population factors (P), affluence factors (A) and technological factors (T). This is depicted in equation 1 below:

$$I = P * A * T \tag{1}$$

However, the description of environmental impact by Cherlew (2001) has been described as being deterministic and rigid. In response to this, Yorke et al. (2003) recommends a more flexible framework by controlling for both observed and unobserved factors. The main intuition of the model proposed by Yorke et al. (2003) popularised as the STIRPAT model is that environmental impact factors go beyond population, affluence and technological factors. Particularly, in the context of this study, this is true, as uncertainty in economic policy as well as the energy mix composition are critical factors when explaining environmental impact. Based on the recommendation of Yorke et al. (2003), the IPAT model is extended to include a stochastic random term (ε), to capture both observed and unobserved factors.

$$I = P * A * T * \varepsilon \tag{1.1}$$

4.2 Model Specification

Empirically, different indicators have been used to capture environmental impact. In this study, EFP (EFP) is preferred to other indicators such as carbon dioxide emissions due to the comprehensive nature of the measure (Adedoyin et al., 2021; Li et al., 2023). Following other studies, and popularised in the EKC argument, affluence is captured in this study to reflect the real gross domestic product. However, because these economies differ in size significantly, to aid comparison, we deflate real gross domestic product by the population size to get the real gross domestic product per capita (RGDPp). This translates equation 2 into 3.

$$I = GDP/P * T * \varepsilon \tag{2}$$

Technology could mean different things such as inputs, quality of political institutions, and knowledge transfer and spillover (Adom et al., 2018). As inputs, technology could reflect the type of energy input used in the production process, and this has serious implications on the environment (Yang et al., 2021). Therefore, we include EC and the different categories of EC (i.e. REC and NREC) as a driver of environmental impact. Understanding the ecological or environmental impact of different energy sources is critical in designing climate related policies (Kongbuamai et al., 2021). Moreover, the BRICS countries currently have significant investments in non-renewable energy but have taken steps to move to renewable energy (BRICS, 2021). Therefore, understanding how these different energy sources' impact on the environment is critical to BRICS's net zero emission target by 2050 (Chapungu et al., 2022). Also, technology could reflect the quality of the political environment as unfavourable environments drive incentives to innovate downwards. Regarding this, we include geopolitical risk (GEO) to capture the quality of political environment (S. Li et al., 2022). Next, technology could reflect knowledge spillover and transfer. Through globalisation, countries get opportunities to experience technological transfer (i.e., soft and hard) and even imitate advanced technologies. Therefore, we include an index of globalisation (GLO) to capture technological spillovers(S. Li et al., 2022). Lastly, technological innovation is impeded in an environment with high uncertainty in economy policy. Both GLO and GEO have proven to have a significant influence on environmental degradation, and excluding the variables will amount to omitted variable bias (Adekoya et al., 2022). In addition, we include EPU to address the fact that uncertain economic policy can hinder technological transfer. EPU influences the level of confidence the government and investors have in renewable energy; the greater the uncertainty, the less likely they are to invest in renewable energy (Adedoyin et al., 2021).

Based on the above discussion, the theoretical framework in (2) can be re-casted as equation 3:

$$EFP = RGDP * EC * GE0 * GLO * EPU * \varepsilon \qquad (3)$$

Objective I: Energy Consumption impact on EFP

The aim of the study is to compare the impact of EC (renewable and non-renewable) on EFP. Based on the theoretical framework, the empirical model in this study is specified as (4), which is a modified version of the models estimate Le & Bao, (2020)Le & Bao, (2020) and Adekoya et al, (2022):

$$EFP_{it} = \beta_0 + \beta_1 EC_{it} + \beta_2 EPU_{it} + \beta_3 GDP_{it} + \beta_3 GEO_{it} + \beta_4 GLO_{it} + \varepsilon_{it} \qquad (4),$$

Where β_0 represents the interpret and β_i represent the slope coefficients of the model. Empirically, the nature of the effect of GDP per capita on the environment, since the seminar

EKC paper, has been very contentious, with evidence, no evidence or higher polynomial form of EKC. In this study, we controlled for the squared of real GDP per capita as a de facto variable in all the models we estimate, where the statistical relevance of it will justify it inclusion in the models.

Objective II: Impact of Renewable and Non-Renewable Energy Consumption on EFP

To investigate a sub-objective of the paper, equation 4 is respecified into equations 5 and 6 to capture the effects of both renewable and non-renewable on EFP and individual renewable energy sources (solar, wind, hydro) impact on the EFP of the countries. Again, we include where justified by statistical test the inclusion of the square of real GDP per capita as another control variable in the model.

Equation5: Model 2

$$EFP_{it} = \beta_0 + \beta_1 REC_{it} + \beta_2 NREC_{it} + \beta_3 EPU_{it} + \beta_4 GDP_{it} + \beta_5 GEO_{it} + \beta_6 GLO_{it} + \mu_{it} \quad (5)$$

Equation 6: Model 3

$$EFP_{it} = \beta_0 + \beta_1 SOLAR_{it} + \beta_2 HYDRO_{it} + \beta_3 EPU_t + \beta_4 GDP_{it} + \beta_5 GEO_{it} + \beta_6 GLO_{it} + \mu_{it} \quad (6)$$

Where *SOLAR* and *HYDRO* are the individual renewable energy sources (solar and hydro), respectively. All the expressions are logged.

4.3 Estimation Technique

The above empirical models could exhibit dynamic patterns, with lag values impacting the outcome variable. Such adjustments differentiate short run impacts from long run impacts. Therefore, a cointegration model that delineates short run impacts from long run impacts is appropriate in this context. The two-panel approaches utilized in the estimation of this study are the “Common Correlated Effects Mean Group” (CCEMG) developed by Pesaran (2006) and the “Augmented Mean Group” (AMG) developed by Eberhardt and Teal (2010). Utilizing this method allows this study greater reliability and flexibility of the data, allowing for a deeper understanding of the relationship between the variables of interest. Both approaches follow a two-stage procedure for the estimation process.

Using CCEMG will allow for this study to be able to show how common factors impact the countries (Ahmad et al., 2018). The CCEM estimator specification is as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + \rho_i \bar{x}_{it} + \sigma_i \bar{y}_{it} + c_i f_t + \varepsilon_{it} \qquad 7(a)$$

In equations 7a, the dependent variable are y_{it}, x_{it} represents the regressors. The country specific slope is β_i and the "unobserved common factor with heterogenous factor" (Ahmad et al., 2024) is represented by f_t. $\bar{x}_{it}$ and $\bar{y}_{it}$ have no interpretable meaning as they represent the means of the regressor (independent and dependent) across different cross-sectional units. α_i represents the intercept and ε_{it} represents the error term.(Le & Bao, 2020; Sencer Atasoy, 2017)

The CCEM estimator for the specific models follow:

Model 1:

$$\begin{aligned} EFP_{it} = \alpha_i &+ \beta_1 EC_{it} + \beta_2 EPU_{it} + \beta_3 GDP_{it} + \beta_4 GEO_{it} + \beta_5 GLO_{it} + \rho_1 \overline{EC}_{it} + \rho_2 \overline{EPU}_{it} \\ &+ \rho_3 \overline{GDP}_{it} + \rho_4 \overline{GEO}_{it} + \rho_5 \overline{GLO}_{it} + \sigma_1 \overline{EFP}_{it} + c_i f_t + \varepsilon_{it} \qquad 7(ai) \end{aligned}$$

Model 2:

$$\begin{aligned} EFP_{it} = \alpha_i &+ \beta_1 REC_{it} + \beta_2 NREC_{it} + \beta_3 EPU_{it} + \beta_4 GDP_{it} + \beta_5 GEO_{it} + \beta_6 GLO_{it} \\ &+ \rho_1 \overline{REC}_{it} + \rho_2 \overline{NREC}_{it} + \rho_3 \overline{EPU}_{it} + \rho_4 \overline{GDP}_{it} + \rho_5 \overline{GEO}_{it} + \rho_6 \overline{GLO}_{it} \\ &+ \sigma_1 \overline{EFP}_{it} + c_i f_t + \varepsilon_{it} \qquad 7(aii) \end{aligned}$$

Model 3:

$$\begin{aligned} EFP_{it} = \alpha_i &+ \beta_1 SOLAR_{it} + \beta_2 HYDRO_{it} + \beta_3 EPU_{it} + \beta_4 GDP_{it} + \beta_5 GEO_{it} + \beta_6 GLO_{it} \\ &+ \rho_1 \overline{SOLAR}_{it} + \rho_2 \overline{HYDRO}_{it} + \rho_3 \overline{EPU}_{it} + \rho_4 \overline{GDP}_{it} + \rho_5 \overline{GEO}_{it} + \rho_6 \overline{GLO}_{it} \\ &+ \sigma_1 \overline{EFP}_{it} + c_i f_t + \varepsilon_{it} \qquad 7(aiii) \end{aligned}$$

Equation 7b shows the CCEMG's mean group estimator which controls for heterogeneity of the slope parameters and structural breaks. It is determined by calculating the mean of the coefficients across individual regression, which is shown below. ((Le & Bao, 2020;Adekoya et al., 2022; Sencer Atasoy (2017)):

$$CCEMG = N^{-1} \sum_{i=1}^{N} \widehat{\beta_\iota} \qquad 7(b)$$

Where $\widehat{\beta_\iota}$ is the estimates of the coeffcients for the models (7(ai), 7(aii), 7(aiii))

AMG addresses the problem of heterogeneity by adding individual (country) specific time-invariant variables (Atasoy, 2017). The estimator can distinguish between the effect of observed regressors and the unobserved common factors (Adekoya et al., 2022). The AMG estimator specifications are :

$$\Delta y_{it} = \alpha_i + \beta_i \Delta x_{it} + \rho_i f_t + \sum_{t=2}^{T} \sigma_i \Delta D_t + \varepsilon_{it} \qquad 8(a)$$

The AMG estimator for the specific models follow:

Model 1:

$$\Delta EFP_{it} = \alpha_i + \beta_i \Delta EC_{it} + \beta_i \Delta EPU_{it} + \beta_i \Delta GDP_{it} + \beta_i \Delta GEO_{it} + \beta_i \Delta GLO_{it} + \rho_i f_t + \sum_{t=2}^{T} \sigma_i \Delta D_t + \varepsilon_{it} \qquad 8(ai)$$

Model 2:

$$\Delta EFP_{it} = \alpha_i + \beta_i \Delta REC_{it} + \beta_i \Delta NREC_{it} + \beta_i \Delta EPU_{it} + \beta_i \Delta GDP_{it} + \beta_i \Delta GEO_{it} + \beta_i \Delta GLO_{it} + \rho_i f_t + \sum_{t=2}^{T} \sigma_i \Delta D_t + \varepsilon_{it} \qquad 8(aii)$$

Model 3:

$$\Delta EFP_{it} = \alpha_i + \beta_i \Delta SOLAR_{it} + \beta_i \Delta HYDRO_{it} + \beta_i \Delta EPU_{it} + \beta_i \Delta GDP_{it} + \beta_i \Delta GEO_{it} + \beta_i \Delta GLO_{it} + \rho_i f_t + \sum_{t=2}^{T} \sigma_i \Delta D_t + \varepsilon_{it} \qquad 8(aiii)$$

Within equation 8(ai), 8(aii), and 8(aiii), Δ represents the first difference operator , β_i indicates the country-specific slopes, f_t indicates the "unobserved heterogeneous common factor" and $D_t \sigma_i$ represents "the common dynamic effect parameter" captured by the dummy variable (Le & Bao, 2020; Adekoya et al.: 2022; Sencer Atasoy, 2017).

Below shows the AMG estimator, which is more flexible than the first estimator (Click or tap here to enter text.Adekoya et al., 2022):

$$AMG = N^{-1} \sum_{i=1}^{N} \widehat{\beta_\iota} \qquad 8(b)$$

Where $\widehat{\beta_\iota}$ is the estimates of the coefficients for the models (8(ai), 8(aii), and 8(aiii))

While other "longitudinal data techniques" require stationarity of the variables to overcome endogeneity, AMG and CCEMG are not restricted by stationarity and can handle the endogeneity problem in a non-stationary framework and are able to demonstrate robustness whether there is evidence of cointegration or not (Ahmad et al., 2018). Both CCEMG and AMG allow countries to be independent of each other by addressing cross-sectional dependence and accounting for interdependence amongst the BRICS countries (Adekoya et al., 2022).

This study utilized the following statistical methods in order to utilize the CCEMG and AMG methods:

4.3.1 Cross-sectional dependence tests

To ensure the robustness of results, neglecting the dependency can result in invalid results as a consequence of invalid test statistics (Iheonu et al., 2021); the following cross-sectional tests are employed: Peseran's (2015) cross-sectional dependence test, Friedman'''s (1937) test of cross-sectional independence, and Frees (1995) test of cross-sectional independence.

4.3.2 Panel unit root tests

To evaluate the stationarity of the variables, two generations of panel unit root tests are employed. The first generation unit root test of "Levin, Lin, and Chu test (2002) assumes "cross-sectional independence". While the second generation panel unit root test, the Cross-sectionally Augmented Dickey-Fuller (CADF) and the Cross-sectionally Augmented Im, Pesaran and Shin (CIPS) unit root tests proposed by Pesaran (2007) account for interdependence (Tugcu, 2018). Of the two, the CIPS unit root is preferred as it addresses the "issue of cross-sectional dependence" (Shabir et al., 2022).

4.3.3 Panel cointegration

Following Li et al. (2023) and Shabir et al. (2022), the study examined the cointegration between the variables. The three methods utilized are the “Kao cointegration test” by Kao (1999), the Pedroni cointegration approach by Pedronni (2004), and the Westerlund cointegration test proposed by Westerlund and Edgerton (2007).

4.3.4 Slope Homogeneity test

To address the potential of biased results as a result of not accounting for the presence of slope heterogeneity, this study follows Perone (2023). The paper employs the Pesaran and Yamagata (2008) test. The tests null hypothesis is that the slope coefficients are homogenous, while the alternative hypothesis will reject that. The test will account for both heteroskedasticity and autocorrelation.

4.3.5 Causality test

To analyse the direction of causality, whether unidirectional, two way causality or no statistically significant causality between the variables, this study follows Dumitrescu Hurlin, (2012) . This study employs the “Dumitrescu & Hurlin (2012) Granger non-causality test”. Previous studies have indicated that the causality test maintains consistency in the panel with cross-sectional dependence present (Destek & Sarkodie, 2019; Khan et al., 2019).

4.4 Data Description

The annual data was collected from Our World in Data (2023) andThe World Bank Group (2023); and the EFP data was collected from the Global Footprint Network(2023). Meanwhile, the geopolitical risk index and the EPU data were collected from the Matteo Iacoviello website, and the globalization data was collected from the KOF Swiss Economic Institute. The data covers the years 1992 to 2020; the period chosen is based on the availability of information on EFP in Russia and the degree of Globalisation data.

To enhance the reliability and interpretation of the data, the World Uncertainty Index is used as a proxy for EPU as it includes both economic and political factors, which is relevant for a group like BRICS (Li et al., 2023). EPU data was converted from monthly to annual data by adding the monthly values and dividing the sum of monthly values by 12 to obtain the annual average. To shows the relationship between EC (renewable and non-renewable energy) and EFP in the BRICS context, all the data was based on BRICS. All the data series are in logged form to mitigate heteroscedasticity in the results and to facilitate understanding.

Table 1: Data description

Variable	Measurement scale	Notation	Source
Ecological Footprint	Per capita ecological footprint (global hectares)	EFP	Global Footprint Network (https://data.footprintnetwork.org/)
Energy consumption	energy consumption per capita (kWh)	EC	Our World Data (https://ourworldindata.org)
Economic policy uncertainty	World uncertainty index	EPU	Economic Policy Uncertainty Index (http://www.policyuncertainty.com)
Gross Domestic Product per capita	GDP per capita (constant 2015 US$)	GDP	World Data Bank (https://data.worldbank.org)
Renewable energy consumption	Renewable energy consumption (% equivalent primary energy)	REC	Our World Data (https://ourworldindata.org)
Geopolitical risk index	Word count of geopolitics and uncertainty in newspaper stories	GEO	Matteo Iacoviello (https://www.matteoiacoviello.com/gpr_country.htm#country)
Non-renewable energy	Energy use (kg of oil equivalent per capita)	NREC	World Data Bank (https://data.worldbank.org)
Degree of globalization	KOF index of globalization	GLO	KOF Swiss Economic Institute (https://kof.ethz.ch/en/data/kof-time-series-database.html)
Hydro energy consumption	Hydro Energy use per capita (kWh–-equivalent)	HYDRO	Our World Data (https://ourworldindata.org)
Solar energy consumption	Solar use per capita (kWh–- equivalent)	SOLAR	Our World Data (https://ourworldindata.org)
Wind energy consumption	Wind Energy use per capita (kWh–-equivalent)	WIND	Our World Data (https://ourworldindata.org)

Source: authors' computation

Chapter 5. Empirical Results

5.1 Preliminary Results

Table 2 displays the descriptive statistics for each variable. The dependent variable has a relatively moderate standard deviation, with the minimum being -0.377 and the maximum being 1.928. This suggests that the EFP deviates from the mean and that BRICS countries, but the overall deviation is narrow. The EPU (lnEPU) index has the lowest mean at -3.952, while EC (lnEC) has the highest mean value at 9.726. The BRICS EPU is relatively low, indicating that the perceived uncertainty relating to the countries' policies' future is lower than the previous periods. The degree of globalization (lnGLO) has the lowest standard deviation, which indicates that the BRICS countries are generally stable across the countries.

In contrast, the highest standard deviations reside in the two renewable energy sources, indicating a substantially considerable variation in REC across the countries, with Solar EC (LnSolar) having the highest standard deviation at 2.655. Hydro energy has significantly less deviation than Solar energy at 1.678. Hydro has a higher mean of 6.633kWh relative to Solar's mean of 0.176, which shows that Hydro EC is utilized at a higher level than Solar. This suggests that the countries do not consume the same quantity of renewable energy.

Table 2 Descriptive Statistics

	OBS	MEAN	STD. DEV.	MIN	MAX	P1	P99	SKEW.	KURT.
LNEFP	145	.94	.646	-.377	1.928	-.369	1.852	-.652	2.393
LNEC	145	9.726	.871	7.942	11.072	7.946	11	-.376	2.224
LNREC	145	1.782	1.472	-3.168	3.886	-1.966	3.846	-.763	3.508
LNNREC	145	8.377	.786	6.699	9.835	6.709	9.652	-.484	2.166
LNGDP	145	8.309	.836	6.303	9.246	6.329	9.226	-.982	2.645
LNEPU	145	-3.952	.891	-5.406	-2.081	-5.403	-2.081	.089	2.826
LNGLO	145	4.062	.176	3.51	4.279	3.54	4.278	-1.159	3.715
LNGEO	145	-1.823	1.115	-4.01	.132	-3.715	.081	-.059	1.692
LNSOLAR	145	0.176	2.655	-5.777	6.176	-4.894	6.029	.274	2.756
LNHYDRO	145	6.633	1.678	2.318	8.693	3.388	8.648	-.387	1.838
LNWIND	145	2.978	2.736	-2.602	6.757	-2.602	6.757	-.577	2.262

Source: authors' computation

The Pearson's Correlation Coefficient results from Table 3 to Table 5 demonstrate a mixed correlation between the variables ranging from a strong to weak linear relationship between the variables. Table 3 shows the first model (with EC as the main independent variable) with the highest correlation between EFP and energy consumed, which indicates an extremely strong relationship between the variables.

In Table 4, looking at the correlation between EFP and disaggregated EC (REC and NREC, respectively), it is evident that the source of the correlation is the non-renewable energy with the correlation at 0.963 and a significance level of 1% which indicates an extremely strong positive relationship between the two variables. When looking at renewable energy's relationship with EFP, it is evident the relationship is not statistically significant, with a p-value of 0.172, even though there is a weak negative relationship.

When looking at the correlation between GDP and EFP across the models, the connection between GDP and EFP has a strong positive relationship between the variables at 0.902 (model 1, model 2 and model 3). It shows that with a GDP increase, the amount of environmental degradation also tends to increase.

Table 5 shows that individual REC (solar, wind, and hydro) is only one statistically significant at 1% (Wind and hydro). Wind and Solar have a moderate positive relationship between the variables at 0.531, which can be attributed to the fact that wind and solar energy operate as complementary energy sources as Solar peaks in the summer while the wind is stronger during the colder seasons like winter (Q. Hassan et al., 2023). Therefore, because of the complementary nature of wind and solar sources, this paper decided to exclude wind EC from the model in order to avoid confounding variables (Pourhoseingholi et al, (2012).

Table 3 Pearson's Correlation Coefficient: Model 1

MODEL 1	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) L_EFP	1.000					
(2) L_EC	0.978***	1.000				
	(0.000)					
(3) L_EPU	-0.085	-0.109	1.000			
	(0.309)	(0.192)				
(4) L_GDP	0.902***	0.843***	0.073	1.000		
	(0.000)	(0.000)	(0.383)			
(5) L_GLO	0.550***	0.582*	0.118	0.627***	1.000	
	(0.000)	(0.000)	(0.157)	(0.000)		
(6) L_GEO	0.137	0.252**	0.464***	-0.089	0.135	1.000
	(0.101)	(0.002)	(0.000)	(0.286)	(0.106)	

**** p<0.01, ** p<0.05, * p<0.*

Source: authors' computation

Table 4 Pearson's Correlation Coefficient: Model 2

MODEL 2	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1) L_EFP	1.000						
(2) L_REC	-0.114	1.000					
	(0.172)						
(3) L_NREC	0.963***	-0.017	1.000				
	(0.000)	(0.839)					
(4) L_EPU	-0.085	0.648***	-0.129	1.000			
	(0.309)	(0.000)	(0.121)				
(5) L_GDP	0.902***	0.098	0.914***	0.073	1.000		
	(0.000)	(0.240)	(0.000)	(0.383)			
(6) L_GLO	0.550***	0.062	0.580*	0.118	0.627***	1.000	
	(0.000)	(0.458)	(0.000)	(0.157)	(0.000)		
(7) L_GEO	0.137	-0.001	0.055	0.464***	-0.089	0.135	1.000
	(0.101)	(0.986)	(0.511)	(0.000)	(0.286)	(0.106)	

**** p<0.01, ** p<0.05, * p<0.*

Source: authors' computation

Table 5 Pearson's Correlation Coefficient: Model 3

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1) l_EFP	1.000							
(2) l_HydroEC	0.400***	1.000						
	(0.000)							
(3) l_SolarEC	0.345***	0.019	1.000					
	(0.000)	(0.816)						
(4) l_WindEC	-0.238***	-0.078	0.531***	1.000				
	(0.004)	(0.348)	(0.000)					
(5) l_EPU	-0.085	0.609***	0.057	0.371***	1.000			

	(0.309)	(0.000)	(0.495)	(0.000)				
(6) l_GDP	0.902***	0.485***	0.501***	0.031	0.073	1.000		
	(0.000)	(0.000)	(0.000)	(0.707)	(0.383)			
(7) l_GLO	0.550***	0.253***	0.520***	0.312***	0.118	0.627***	1.000	
	(0.000)	(0.002)	(0.000)	(0.000)	(0.157)	(0.000)		
(8) l_GEO	0.137	0.246***	-0.058	-0.053	0.464***	-0.089	0.135	1.000
	(0.101)	(0.003)	(0.487)	(0.526)	(0.000)	(0.286)	(0.106)	

*** p<0.01, ** p<0.05, * p<0.*

Source: authors' computation

5.2 Cross-Sectional Dependence Tests

Table 6 shows the results of the three cross-sectional dependence tests (Peseran's (2015) cross-sectional dependence test, Friedman's (1937) test of cross-sectional independence, and Frees (1995) test of cross-sectional independence) on the three different models. The test shows evidence of cross-sectional dependence across all the tests across all models, with the majority having a 1% level of significance except with the Frees test.

The Frees (1995) test showed evidence of cross-sectional dependence at a 10% significance level for all three models. Peseran's (2015) test showed evidence of cross-sectional dependence at a 1% level of significance for models 1(equation 4) and 2 (equation 5). For all three models, Friedman's (1937) test supports the presence of cross-sectional dependence at a 1% significance level. Models 1 and 2 show the presence of cross-sectional dependence in all three tests, ranging from a 10% to 1% significance level. While in model 3 (equation 6), Peseran's showed no evidence of cross-sectional dependence. The Frees test supports evidence of cross-sectional dependence at a 10% significance level, and Friedman supports it at 1% significance. Therefore we accept the evidence of cross-sectional dependence for all the models.

Table 6: Cross-Sectional Dependence Tests

	MODEL 1		**MODEL 2**		**MODEL 3**	
TEST	Stat	Prob	Stat	Prob	Stat	Prob
PESERAN CD	2.902***	0.004	3.411***	0.001	1.086	0.224
FREES	1.032*	0.089	0.545*	0.089	0.778*	0.089
FRIEDMAN	45.832***	0.000	47.542***	0.000	33.600***	0.000

*** p<0.01, ** p<0.05, * p<0.1*

Source: authors' computation

5.3 Unit Root Test

The results from Table 7 were obtained by comparing the three different unit root tests, Two being second generational unit roots (CADF and CIPS) and the other one being first generation (Levin, Lin and Chu test (2002)). Across all the tests, the dependent variable lnEFP was stationary after the first difference. The LLC test suggests that the majority of the variables are stationary at levels while lnEFP, lnREC, lnEPU, lnGeo, lnHydro and lnSolar are stationary after the first difference. Meanwhile, lnEC, lnNREC, lnGDP, and lnGLO were stationary at different levels.

The CADF test also revealed that most of the variables were significant at first difference (lnEFP, lnREC, lnGEO, lnHydro lnSolar) at a 1% significance level. While rest of the variables (lnEC lnNREC, lnGDP and lnGLO) except for lnEPU were stationary at levels and at first difference at a 10% level of significance of higher.
From the CIPS test, half of them were stationary at levels (lnEC, lnNREC, lnGDP and lnGLO and lnGEO) while the half were stationary at the first difference(lnEFP, lnREC, lnHydro, lnSolar andlnEPU).

For lnEPU in the CADF test, it showed that EPU was not stationary at levels or the first difference. Fortunately, the CIPS test showed that lnEPU was stationary at a 1% significance level, while in the LLC test, LnEPU was significant at 10%. We conclude that since both LLC and CIPS unit root tests indicate that the EPU variable was stationary, we perform the cointegration test to determine the relationship between the variables in the models.

Table 7: Unit Root Tests

	LLC			**CADF**			**CIPS**		
VARIABLES	Level	1st diff	I(d)	Level	1st diff	I(d)	Level	1st diff	I(d)
(1) LNEFP	-2.292	-3.279***	I(1)	-2.365*	-2.753***	I(1)	-2.356	-4.422***	I(1)
(2) LNEC	-2.772***		I(0)	-3.083***		I(0)	-3.327***		I(0)
(3) LNREC	-2.450	-4.278***	I(1)	-1.396	-3.569***	I(1)	-1.501	-5.013***	I(1)
(4) LNNREC	-2.951***		I(0)	-2.535**	-2.861***	I(0)	-2.332**		I(0)
(5) LNGDP	-1.7319**		I(0)	-2.786***		I(0)	-3.162***		I(0)
(6) LNEPU	-2.005	-2.884*	I(1)	-1.900	-1.575		-1.721	-3.124***	I(1)

(7) LNGLO	-2.642**		I(0)	-2.642***		I(0)	-2.736***		I(0)
(8) L_GEO	-2.344	-4.975***	I(1)	-2.158	-4.968***	I(1)	-2.808***		I(0)
(9) LNHYDRO	-0.849	-4.585***	I(1)	-1.913	-3.852***	I(1)	-1.821	-5.502***	I(1)
(10) LNSOLAR	1.656	-2.736***	I(1)	-1.180	-2.708***	I(1)	-0.776	-4.163***	I(1)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: authors' computation

5.4 Cointegration Tests

Table 8 shows the results from the Kao cointegration test, Pedroni cointegration, and the Westerlund cointegration test. The Pedroni test shows that there is evidence of cointegration in all three models, though the significance varies. For model 1 there is evidence of cointegration amongst the variables at a 5% level with an Augmented Dickey–Fuller (ADF) t-statistics of -2.1915. Model 2 shows the presence of cointegration at a 10% level with an ADF of -1.5985. Lastly, model 3 has the highest significance at 1% with an ADF of -2.6471.

Meanwhile, Westerlund confirms the presence of cointegration amongst all the panels at a 10% level of significance (model 1) and a 5% level of significance (model 2 and model 3). Conversely, in the Kao test, only models 1 and 3 are statistically significant at 5% and 1% respectively. Model 2 shows no evidence of cointegration in all panels. Since Pedroni and Westerlund show evidence of cointegration in all models, this study concludes that cointegration is present. This implies that the independent variables are identified as the 'long run forcing' variables explaining EFP in BRICS.

Table 8: Cointegration Tests

	PEDRONI TEST		**WESTERLUND TEST**		**KAO TEST**	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
MODEL 1	-2.1095**	0.0175	-1.5785*	0.0572	-1.7034**	0.0442
MODEL 2	-1.5985*	0.0550	1.6524**	0.0492	-1.0846	0.1390
MODEL 3	-2.6471***	0.0041	1.8301**	0.0366	-2.5152***	0.0059

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.5 Slope Homogeneity Test

Table 9 shows the results from the slope homogeneity test for all models, which provides valid results even though there is cross-sectional dependence (Perone, 2023). The results show that in all the models (model 1 model 2 and model 3), the slope coefficients are heterogenous at a 1% significance level. Therefore, there is a clear need for all the models to have country-specific estimates in the estimations.

Table 9: Slope Homogeneity Test

	MODEL 1	MODEL 2	MODEL 3
DELTA	6.609***	16.074***	4.424***
ADJUSTED DELTA	7.421***	18.455***	5.199***

*** *p<0.01, ** p<0.05, * p<0.1*
Source: authors' computation

5.6 Model estimation and interpretation.

5.6.1: Model 1 estimation: (Energy Consumption Impact on Ecological Footprint)

Table 10 shows the homogeneous impact of EC on EFP. The table shows that in both AMG and CCEMG estimations EC has a positive and statistically significant effect on EFP, supporting the environmental induced nature of higher EC. According to the estimates, a 1% increase in BRICS group EC results in an increase in EFP of 0.596% in AMG case and 0.509% in CCEMG case. These results are supported by Wang and Dong (2019) and (Nathaniel et al. (2019). As indicated earlier, the energy mix is dominated by fossil fuel-based energies, which are very high in carbon content. Therefore, increasing use of these energy types pose danger to the environment through the high contribution to greenhouse gas emissions.

In terms of the BRICS group, EPU in the AMG model is not statistically significant. The variable is significant in the CCEMG model. A 1% increase in BRICS' EPU increases their EFP by 0.124% at a 10% level of significance. Therefore, the relationship between EPU and EFP is of weak statistical significance in the model. This means that when looking at EC, which includes both REC and NREC, the impact of EPU is not great.

In both estimations, the GDP coefficient is highly significant at 1%. In the AMG model a 1% increase in the BRICS group GDP increases EFP by 0.345%. In CCEMG, a 1% increase in the groups' GDP increases EFP by 0.428.This shows that the economy's growth increases the planet's environmental degradation, thus affirming the conclusions reached by previous scholars (Kongbuama et al., 2021).

The degree of globalization and geopolitical risk index coefficients are significant in the AMG and CCEMG estimation. In terms of Globalization, the AMG estimator shows that at a 5% level of significance, a 1% increase in the globalization of the BRICS group decreases their EFP by 0.421%. Correspondingly, the CCEMG estimator supports the AMG estimator at a 1% level of significance as 1% increase in the GLO of the five countries results in a 0.603 decrease in their EFP. This is supported by S. Li et al. (2022) and Yang et al. (2020)with the reasoning that the technology associated with globalization essentially promotes environmentally friendly.

Looking at the geopolitical risk of the AMG and CCEMG estimators, the coefficient is statistically significant at a 1% significance level. The AMG estimate shows that 1% increase in their geopolitical risk decreases their EFP by 0.015%. This is supported by the CCEMG estimate, which indicates that 1% increase in their geopolitical risk decreases their EFP by 0.021%. The results were consistent with Li et al. (2023) and Su et al. (2021). Therefore, it surprisingly shows that an increase in adverse geopolitical events will not lead to greater environmental degradation. This suggests that implementing the geopolitical risk index creates a standard that negatively affects NREC, resulting in a decreased EFP (H. Li et al., 2023).

Table 10: Model 1 (EC Impact on EFP)–- Panel level

	AMG	**CCEMG**
LNEC	0.596*** (0.000)	0.509*** (0.001)
LNEPU	-0.045 (0.569)	0.124* (0.053)
LNGDP	0.345*** (0.004)	0.428*** (0.000)
LNGLO	-0.421** (0.030)	-0.603*** (0.000)
LNGEO	-0.015*** (0.000)	-0.021*** (0.000)
Constant	-6.024*** (0.000)	0.857 (0.716)

Source: authors' computation

Heterogenous impact of Energy Consumption on Ecological Footprint

The above result assumed a homogenous impact of EC and EPU on EFP, which is a strong assumption. The differing economic structures, energy need requirements, environmental regulations and law, and political and economic institutions are important sources of heterogeneities, which could influence how EFP reacts to EC and EPU differently in each country. Table 11 shows country-specific long run estimations. There is clear evidence of slope heterogeneity amongst the BRICS countries. Though the results of the AMG procedure show that while Brazil, India, China, and South Africa indicate a significant positive relationship between EC and the EFP, the degree of impact varies across these countries in the long run.

Brazil’s EC has the largest impact on its EFP, with a one percent increase in EC; on average, the EFP increases by 1.066%. Therefore, the amount of energy consumed by Brazil results in more environmental degradation.

Meanwhile, India's, South Africa's, and China’s EC has a moderate positive impact on the EFP in the AMG results. In India, a 1% increase in EC results in a 0.659% increase in the EFP, which is at a 1% significance level. China’s EC has the least impact on EFP compared to the rest of the countries with a 0.480% for a 1% increase in EC at a 1% level of significance. Compared to the rest, China has been very aggressive with energy efficiency and renewable energy policies, which might explain the low EFP elasticity concerning EC. Looking at the CCEMG results, only Brazil, India, and China have a significant positive relationship between EC and EFP variables. Like in the AMG results, all the coefficients are positive and highly significant at the 1% level.

However, the CCEMG results differ slightly from AMG. India has the largest impact on its EFP, as 1% increase in EC increases result in a 0.790% increase in EFP in the long run. South Africa EC has the smallest impact on EFP, with a 1% increase in EC resulting in a 0.392 increase. These results confirm that EC increases environmental degradation. The differing degrees of EC on EFP could reflect the diverse energy mix, economic structure, and climate policies.

Table 11 shows that only in Russia and India does EPU have a significant relationship with EFP , according to AMG. While all the variables were not significant in the CCEMG results. A 1% increase in India’s EPU decreases the EFP by approximately 0.088% at a 5% level of significance. A 1% increase in the Russia’s EPU decreases the EFP by approximately 0.278% at a 1% level of significance. Therefore this illustrates that despite the economic uncertainty, the countries’ environmental policies are adequate to mitigate the impact of the uncertainty and reduce the country’s EFP.

Table 11:Model 1(EC on EFP) Country-specific

	AMG					**CCEMG**				
	B	**R**	**I**	**C**	**S**	**B**	**R**	**I**	**C**	**S**
LNEC	1.066***	0.277	0.659***	0.480***	0.499***	0.782***	-0.058	0.790***	0.642***	0.392
	(0.000)	(0.395)	(0.000)	(0.000)	(0.009)	(0.008)	(0.885)	(0.000)	(0.000)	(0.185)
LNEPU	-.0664	-0.278***	-0.088**	-0.009	0.215	0.107	0.140	-0.092	0.158	0.307
	(0.608)	(0.000)	(0.041)	(0.926)	(0.228)	(0.669)	(0.457)	(0.485)	(0.135)	(0.271)
LNGDP	0.003	0.685***	.2378**	.2690***	.5314***	.2992	.5606**	.2158	.3394**	.7244**
	(0.994)	(0.000)	(0.016)	(0.000)	(0.000)	(0.388)	(0.018)	(0.215)	(0.014)	(0.030)
LNGLO	-1.042***	-0.654**	-.2579***	-.2232**	.0724	-.4656	-.9513**	-.3737	-.1973	-1.027**
	(0.000)	(0.027)	(0.000)	(0.019)	(0.266)	(0.575)	(0.042)	(0.114)	(0.595)	(0.015)
LNGEO	-0.012	-.0148	-.0152*	-.0262	-.0053	-.0266	-.0230	-.0378**	-.0184	-.0009
	(0.454)	(0.402)	(0.061)	(0.113)	(0.849)	(0.351)	(0.266)	(0.018)	(0.371)	(0.976)
Constant	-5.181***	-5.703	-6.605***	-5.079***	-7.550***	1.777	6.734	1.005	2.473	-7.702*
	(0.000)	(0.127)	(0.000)	(0.000)	(0.000)	(0.716)	(0.170)	(0.720)	(0.465)	(0.062)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: authors’ computation

5.6.2: Model 2 estimation: (Renewable and Non-renewable Energy Consumption Impact On Ecological Footprint)

The results from Table 12 shows that in both the AMG and CCEMG estimation that the BRICS group’s REC does not have statistical impact on their EFP, even though in the case of AMG the impact is found to be negative. This indicates that their REC is not enough to impact environmental degradation.

Conversely NREC coefficients are significant in both the AMG and CCEMG estimation at a 1% and 10% level of significance respectively. The AMG estimate shows that 1% increase in their NREC increases their EFP by 0.247%. This is supported by the CCEMG estimator where 1% increase in their NREC increases their EFP by 0.165%. The results suggest that the use of non- renewable energy results in the increased degradation of the environment.

The table shows that EPU does not have a significant relationship with EFP for both estimators as the coefficients are not statistically significant. This shows that the level of their economic uncertainty does not have an impact on environmental degradation. The table shows that in both AMG and CCEMG estimations the GDP and geopolitical risk index coefficients are significant at 1% level of significance. In both estimations when the panels' GDP increases by 1%, the EFP increases by 0.566% (AMG estimation) and 0.662% (CCEMG estimation), respectively. This suggests that economic growth increases environmental degradation. The geopolitical risk index in model 2 follows the results of Table 10 (model 1), where a 1% increase in geopolitical risk leads to a decrease in their EFP by 0.018% and 0.023%, respectively.

While the degree of globalization is only statistically significant in the AMG estimation at a 1% level of significance, the coefficients indicate that a 1% increase in the degree of globalization decreases EFP by 0.505%.

Table 12 Model 2(REC And NREC Impact On EFP): Panel-level

	AMG	**CCEMG**
LNREC	-0.003 (0.964)	0.007 (0.872)
LNNREC	0.247***(0.003)	0.165* (0.070)
LNEPU	0.004 (0.971)	0.137 (0.241)
LNGDP	0.566*** (0.000)	0.662 *** (0.000)
LNGLO	-0.505*** (0.003)	-0.369 (0.129)
LNGEO	-0.018*** (0.000)	-0.023 *** (0.011)
Constant	-3.783*** (0.000)	-3.069 (0.317)

*** *p<0.01*, ** *p<0.05*, * *p<0.1*
Source: authors' computation

Heterogeneous impact of Renewable and Non-renewable Energy Consumption On Ecological Footprint

Looking at model 2, table 13 shows that only China's REC has a significant relationship with EFP in the AMG estimations alone. A 1% increase in the country's REC decreases the EFP by 0.211%, at a 5% significance level in the long run. Compared to other countries in BRICS, China has been very aggressive with the adoption of renewable energy, with stringent policies. This supports this paper's hypothesis that renewable energy helps mitigate the impact of EFP, and from these results, it reduces the level of EFP, too.

However, in the CCEMG estimations, there is no significant relationship between the BRICS countries' NREC and EFP. Brazil and India's NREC is significant at a 5% level of significance in the AMG estimation. Both country-specific estimates of India and Brazil show that NREC contributes to environmental degradation.

Like in the first model, Brazil's NREC has the strongest impact on EFP with a 1% increase in NREC on average, resulting in a 0.545% increase in EFP at a 1% level of significance. Model 2 results are supported by Adedoyin et al. (2020), Kongbuamai et al. (2021) and Li et al. (2023).

In model 2, the relationship between EPU and EFP follows model 1 as only in the AMG estimation is it significant, specifically in Russia. This is attributed to EC being split between REC and NREC, and the majority of the EC is made up of the relationship between EPU and EFP. Like in the first model, a 1% increase in EPU results in a decrease of 0.334% in EFP.

Table 13 Model 2 (REC And NREC Impact On EFP): Country-specific

	AMG					**CCEMG**				
	B	**R**	**I**	**C**	**S**	**B**	**R**	**I**	**C**	**S**
LNREC	0.181	0.018	0.002	-.2108**	-0.004	0.160	-0.007	0.012	-.0897	-0.043
	(0.274)	(0.857)	(0.964)	(0.011)	(0.759)	(0.441)	(0.960)	(0.813)	(0.383)	(0.420)
LNNREC	0.545**	0.106	0.299**	0.146	0.138	0.322	0.297	0.209	0.180	-0.183
	(0.010)	(0.374)	(0.015)	(0.488)	(0.273)	(0.314)	(0.230)	(0.365)	(0.424)	(0.483)
LNEPU	-0.164	-0.334***	0.047	0.160	0.311	-0.131	-0.021	0.023	0.313	0.502
	(0.315)	(0.000)	(0.584)	(0.277)	(0.127)	(0.713)	(0.929)	(0.934)	(0.297)	(0.318)
LNGDP	0.529	0.764***	0.475***	0.519***	0.546***	0.586	0.654***	0.620**	0.259	1.192
	(0.110)	(0.000)	(0.000)	(0.009)	(0.000)	(0.211)	(0.004)	(0.024)	(0.491)	(0.201)
LNGLO	-0.863***	-0.677***	-0.402***	-0.704***	0.118	0.063	-0.111	-0.380	-0.120	-1.300**
	(0.000)	(0.007)	(0.000)	(0.000)	(0.110)	(0.954)	(0.866)	(0.352)	(0.855)	(0.049)
LNGEO	-.0094	-0.010	-0.025**	-0.021	-0.024	-0.056	-0.019	-0.021	-0.004	-0.012
	(0.629)	(0.616)	(0.022)	(0.452)	(0.399)	(0.127)	(0.483)	(0.478)	(0.917)	(0.672)
Constant	-6.232***	-4.531**	-3.788***	-0.858	-3.508**	-7.977**	-5.915	3.445	5.050	-9.949*
	(0.006)	(0.019)	(0.000)	(0.644)	(0.046)	(0.050)	(0.221)	(0.480)	(0.319)	(0.075)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: authors' computation

5.6.3: Model 3 estimation:(Individual Renewable Energy Consumption Impact n Ecological Footprint)

Table 14 depicts model 3, the individual REC impact on EFP at a panel level. From the results, it is evident that neither solar nor hydro EC is statistically significant across the AMG and CCEMG estimations. This shows that on a panel level the consumption of the individual renewable energy sources is not significant enough to impact the level of EFP.

The table shows that EPU's coefficients indicate that a 1% increase in the EPU decreases EFP by 0.188%, at a 1% level of significance. This follows the other models. In both estimations, GDP is statistically significant at a 1% level of significance. Supporting model 1 and model 2 results on the GDP relationship with EFP with a 1% increase in GDP increases EFP by 0.801% and 0.963%, respectively.

On the other hand degree of globalization is only statistically significant in the AMG estimation at a 1% level of significance, the coefficients indicate that a 1% increase in the degree of globalization decreases EFP by 0.465%. This also supports the 2 model results and interpretations.

Table 14 Model 3 (The Individual REC Impact On Ecological Footprint): Panel level

	AMG	**CCEMG**
LNHYDRO	-0.011	0.021
	(0.803)	(0.536)
LNSOLAR	-0.008	0.001
	(0.236)	(0.909)
LNEPU	-0.078	-0.188***
	(0.575)	(0.000)
LNGDP	0.801***	0.963***
	(0.000)	(0.000)
LNGLO	-0.465***	-0.154
	(0.003)	(0.704)
LNGEO	-0.013	-0.015
	(0.241)	(0.270)
Constant	-4.114 ***	-1.299
	(0.008)	(0.579)

*** *p<0.01, ** p<0.05, * p<0.1*
Source: authors' computation

Table 15 depicts model 3, the individual REC impact on EFP at a country-specific level. From the table Hydro EC does not have a statistically significant impact on the EFP in both the estimations. Fortunately that is not the case for solar EC as both the CCEMG and AMG estimations show significant relationships. The AMG estimations show significant coefficients for both China and South Africa at a 5% level of significance. In China a 1% increase in SOLAR decreases China's EFP by 0.028 %. While South Africa's 1% increase in SOLAR resulted in a 0.019 decrease in their EFP. In the CCEMG only India's Solar EC was significant at 10%.This further supports this paper's hypothesis that renewable energy helps mitigate the impact of EFP and reduce environmental damage.

In AMG the EPU follows the same trend as the rest of the models to show the negative relationship between EPU and EFP at a 1% significance level for Brazil Russia and China.

<u>Table 15 Model 3 (The Individual REC Impact On Ecological Footprint): Country-Specific level</u>

	AMG					**CCEMG**				
	B	**R**	**I**	**C**	**S**	**B**	**R**	**I**	**C**	**S**
LNHYDRO	-0.166	0.007	0.003	0.104	-0.002	0.135	-0.013	-0.024	0.061	-0.053
	(0.169)	(0.949)	(0.925)	(0.272)	(0.832)	(0.393)	(0.911)	(0.596)	(0.509)	(0.228)
LNSOLAR	0.007	0.000	0.001	-0.028**	-0.019**	-0.004	-0.007	0.008*	0.032	-0.024
	(0.271)	(0.950)	(0.813)	(0.019)	(0.047)	(0.697)	(0.361)	(0.081)	(0.111)	(0.201)
LNEPU	-0.418***	-0.303***	-0.065	0.376***	0.023	-0.248	-0.139	-0.238	-0.290	-0.025
	(0.000)	(0.000)	(0.446)	(0.002)	(0.923)	(0.490)	(0.517)	(0.292)	(0.246)	(0.947)
LNGDP	1.249***	0.820 ***	0.757***	0.320*	0.860***	0.989***	0.772***	0.966***	0.726***	1.367***
	(0.000)	(0.000)	(0.000)	(0.065)	(0.000)	(0.007)	(0.000)	(0.000)	(0.009)	(0.003)
LNGLO	-0.62 ***	-0.799***	-0.234**	-0.694***	0.020	0.585	-0.821	-0.863**	1.060*	-0.732
	(0.010)	(0.000)	(0.045)	(0.001)	(0.827)	(0.583)	(0.200)	(0.038)	(0.092)	(0.134)
LNGEO	-0.046**	-0.002	-0.016	0.020	-0.019	-0.059 *	-0.015	-0.015	0.029	-0.017
	(0.016)	(0.914)	(0.159)	(0.505)	(0.488)	(0.098)	(0.588)	(0.486)	(0.418)	(0.550)
Constant	-7.810***	-3.404***	-4.634***	1.388	-6.110***	-6.204	3.038	0.040	3.994	-7.363*
	(0.000)	(0.008)	(0.000)	(0.402)	(0.004)	(0.152)	(0.541)	(0.992)	(0.346)	(0.071)

**** p<0.01, ** p<0.05, * p<0.1*
Source: authors' computation

In terms of findings, Li et al (2023) was able to provide evidence that REC reduces as NREC and EPU increases EFP. This paper was able to reiterate that NREC increases environmental degradation on a panel level. Since this paper also expanded to a country specific level, it was able to show that REC positively impacted the environment of China. Considering individual REC, EPU had a negative impact on EFP.

5.7 Causality Test

Table 17 shows the causality test in the models. The paper utilized the Dumitrescu & Hurlin (2012) Granger non-causality test. The test found a bi-directional causality between EPU and EFP. This is important as it shows that EPU impacts the economic sectors and extends beyond the economy.

Both EC and NREC granger cause GDP, while REC does not granger cause GDP. This can indicate that the level and quality of REC that the group is consuming does not impact the GDP of the country, which is added to the conclusion from the estimations that the level REC is not enough to make an impact.

When considering the causation between REC and EFP and NREC EFP, there is no causality running between the variables. When looking at individual REC (solar and hydro), there is a unidirectional causality that flows from solar to EFP and hydro to EFP, which is statistically significant at 1%. This shows that when looking at REC as a whole there is no sign of causality but when looking at specific renewable energy sources there is evidence of causality.

Table 16: Causality Test

NULL HYPOTHESIS	W STAT	Z BAR STAT	PROB
LNEC-LNEFP	1.8209	-0.2002	0.8413
LNEFP-LNEC	6.2582	4.7608	0.0000***
LNGDP-LNEFP	4.0149	2.2528	0.0243**
LNEFP-LNGDP	7.6981	6.3707	0.0000***
LNREC-LNEFP	3.2266	1.3714	0.1703
LNEFP-LNREC	0.9844	-1.1355	0.2562
LNNREC-LNEFP	1.9290	-0.0794	0.9368
LNEFP-LNNREC	3.1648	1.3023	0.1928
LNEPU-LNEFP	4.2227	2.4850	0.0130**
LNEFP-LNEPU	7.7232	6.3987	0.0000***
LNGLO-LNEFP	4.0784	2.3237	0.0201**
LNEFP-LNGLO	5.6697	4.1028	0.0000***
LNEPU-LNEC	3.1018	1.2318	0.2180
LNEC-LNEPU	11.5118	10.6345	0.0000***
LNGEO-LNEFP	2.5329	0.5958	0.5513
LNEFP-LNGEO	0.9588	-1.1641	0.2444
LNGDP-LNEC	7.1823	5.7940	0.0000***
LNEC-LNGDP	8.0990	6.8189	0.0000***
LNEPU-LNGDP	7.5968	6.2574	0.0000***
LNGDP-LNEPU	6.7894	5.3547	0.0000***

LNGDP-LNREC	3.5802	1.7667	0.0773*
LNREC-LNGDP	2.7741	0.8654	0.3868
LNGDP-LNNREC	5.1141	3.4817	0.0005***
LNNREC-LNGDP	6.1335	4.6213	0.0000***
LNHYDRO-LNEFP	5.9951	4.4666	0.0000***
LNSOLAR-LNEFP	8.3680	7.1197	0.0000***
LNEFP- LNHYDRO	1.0934	-1.0136	0.3108
LNEFP- LNSOLAR	2.2424	0.2710	0.7864

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: authors' computation

Chapter 6: Conclusion and Policy Recommendations

The study investigated the complex relationship between EC, EPU and EFP in BRICS. It further examined the impact of renewable and NREC on EFP. Then, isolating REC, the paper investigated solar and hydro's impact on the EFP. Throughout the investigation, EPU remained the primary independent variable. The study was from 1992 to 2020 and utilized AMG and CCEMG in the investigation.

The empirical results revealed that the EC of the BRICS countries has a positive impact on the degradation of the environment, with Brazil's EC having the most significant impact on its EFP. However, this study does not support the theoretical literature that the BRICS collective has reached the economic level where their EC positively impacts the environment.

When looking at results in terms of REC and NREC on a group, renewable energy does not have an impact on EFP. The country-specific results differ slightly as only China's REC showed evidence of reducing the country's EFP. With China being the most developed of the BRICS group, it is logical to state that they are approaching the income level where its EC starts improving the environmental quality.

EPU's results where diverse on a panel level: model 1 has weak positive significance, while in Model 2 EPU was not significant. On the country-specific level EPU did not increase the EFP but helped mitigate the environmental damage. Now, considering the individual renewable energy source (model 3), EPU has a positive relationship with the EFP on both levels.

The paper contributes to the literature in three ways. The first shows that EC and NREC have a significant impact on the EFP in both a panel and country level. Secondly, REC and individual renewable energy (solar and hydro) did not have a statistical impact on the EFP on a panel level, only at country-specific estimates. Lastly, EPU grows in significance as we disaggregate from total energy to individual renewable energy.

By BRICS continuously increasing the amount of REC, the level of REC will reach a significant level for the suggested effects to be achieved. Through continuous investment in renewable energy, the BRICS countries possess the potential to not only mitigate but lessen the harm to the environment. Their collecting impact can extend outside of their group.(Ndlovu & Inglesi-Lotz, 2020)

The paper shows that both panel specific and country-specific impacts in the panel study, which controlled for heterogeneity and allowed for a greater understanding of how each variable affected the different countries in the BRICS group. This will allow for more effective policy recommendations.

Further research should be done with a focus on China as it showed evidence of the negative impact of REC on EFP. As the BRICS coalition grows with more countries joining, a study can be done to see the impact EC has on a grander scale.
As the BRICS group are important players in the global economy coupled with the countries' economies' continuous growth. It is of great importance that they prioritize a sustainable growth that reduced their EFP.

To achieve sustainable development this paper proposes the following policy recommendation. First an increase in renewable energy investment will enable a significant contribution of a sustainable energy source to the overall energy supply. Secondly, the government of the countries should explore targeted funding and subsidies for businesses that specialize in renewable energy. The promotion of the renewable energy sector would allow the theoretical impact to become a tangible reality.

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Appendix

Appendix A: EC Impact on EFP

Table 16: Model 1 (EC Impact on EFP)–- Panel level

	AMG	CCEMG
LNEC	0.596*** (0.000)	0.509*** (0.001)
LNEPU	-0.045 (0.569)	0.124* (0.053)
LNGDP	0.345*** (0.004)	0.428*** (0.000)
LNGLO	-0.421** (0.030)	-0.603*** (0.000)
LNGEO	-0.015*** (0.000)	-0.021*** (0.000)
Constant	-6.024*** (0.000)	0.857 (0.716)

Table 17:Model 1(EC on EFP) Country-specific

	AMG					CCEMG				
	B	**R**	**I**	**C**	**S**	**B**	**R**	**I**	**C**	**S**
LNEC	1.066***	0.277	0.659***	0.480***	0.499***	0.782***	-0.058	0.790***	0.642***	0.392
	(0.000)	(0.395)	(0.000)	(0.000)	(0.009)	(0.008)	(0.885)	(0.000)	(0.000)	(0.185)
LNEPU	-.0664	-0.278***	-0.088**	-0.009	0.215	0.107	0.140	-0.092	0.158	0.307
	(0.608)	(0.000)	(0.041)	(0.926)	(0.228)	(0.669)	(0.457)	(0.485)	(0.135)	(0.271)
LNGDP	0.003	0.685***	.2378**	.2690***	.5314***	.2992	.5606**	.2158	.3394**	.7244**
	(0.994)	(0.000)	(0.016)	(0.000)	(0.000)	(0.388)	(0.018)	(0.215)	(0.014)	(0.030)
LNGLO	-1.042***	-0.654**	-.2579***	-.2232**	.0724	-.4656	-.9513**	-.3737	-.1973	-1.027**
	(0.000)	(0.027)	(0.000)	(0.019)	(0.266)	(0.575)	(0.042)	(0.114)	(0.595)	(0.015)
LNGEO	-0.012	-.0148	-.0152*	-.0262	-.0053	-.0266	-.0230	-.0378**	-.0184	-.0009
	(0.454)	(0.402)	(0.061)	(0.113)	(0.849)	(0.351)	(0.266)	(0.018)	(0.371)	(0.976)
Constant	-5.181***	-5.703	-6.605***	-5.079***	-7.550***	1.777	6.734	1.005	2.473	-7.702*
	(0.000)	(0.127)	(0.000)	(0.000)	(0.000)	(0.716)	(0.170)	(0.720)	(0.465)	(0.062)

*** p<0.01, ** p<0.05, * p<0.1*

Appendix B: REC and NREC Impact on EFP

Table 18 Model 2(REC and NREC Impact On EFP): Panel-level

	AMG	CCEMG
LNREC	-0.003 (0.964)	0.007 (0.872)
LNNREC	0.247***(0.003)	0.165* (0.070)
LNEPU	0.004 (0.971)	0.137 (0.241)
LNGDP	0.566*** (0.000)	0.662 *** (0.000)
LNGLO	-0.505*** (0.003)	-0.369 (0.129)
LNGEO	-0.018*** (0.000)	-0.023 *** (0.011)
Constant	-3.783*** (0.000)	-3.069 (0.317)

*** p<0.01, ** p<0.05, * p<0.1*

Table 19 Model 2 (REC And NREC Impact On EFP): Country-specific

	AMG					CCEMG				
	B	**R**	**I**	**C**	**S**	**B**	**R**	**I**	**C**	**S**
LNREC	0.181	0.018	0.002	-.2108**	-0.004	0.160	-0.007	0.012	-.0897	-0.043
	(0.274)	(0.857)	(0.964)	(0.011)	(0.759)	(0.441)	(0.960)	(0.813)	(0.383)	(0.420)
LNNREC	0.545**	0.106	0.299**	0.146	0.138	0.322	0.297	0.209	0.180	-0.183
	(0.010)	(0.374)	(0.015)	(0.488)	(0.273)	(0.314)	(0.230)	(0.365)	(0.424)	(0.483)
LNEPU	-0.164	-0.334***	0.047	0.160	0.311	-0.131	-0.021	0.023	0.313	0.502
	(0.315)	(0.000)	(0.584)	(0.277)	(0.127)	(0.713)	(0.929)	(0.934)	(0.297)	(0.318)
LNGDP	0.529	0.764***	0.475***	0.519***	0.546***	0.586	0.654***	0.620**	0.259	1.192
	(0.110)	(0.000)	(0.000)	(0.009)	(0.000)	(0.211)	(0.004)	(0.024)	(0.491)	(0.201)
LNGLO	-0.863***	-0.677***	-0.402***	-0.704***	0.118	0.063	-0.111	-0.380	-0.120	-1.300**
	(0.000)	(0.007)	(0.000)	(0.000)	(0.110)	(0.954)	(0.866)	(0.352)	(0.855)	(0.049)
LNGEO	-.0094	-0.010	-0.025**	-0.021	-0.024	-0.056	-0.019	-0.021	-0.004	-0.012
	(0.629)	(0.616)	(0.022)	(0.452)	(0.399)	(0.127)	(0.483)	(0.478)	(0.917)	(0.672)
Constant	-6.232***	-4.531**	-3.788***	-0.858	-3.508**	-7.977**	-5.915	3.445	5.050	-9.949*
	(0.006)	(0.019)	(0.000)	(0.644)	(0.046)	(0.050)	(0.221)	(0.480)	(0.319)	(0.075)

**** p<0.01, ** p<0.05, * p<0.1*

Appendix C: Individual REC Impact on EFP

Table 20 Model 3 (The Individual REC Impact On Ecological Footprint): Panel level

	AMG	**CCEMG**
LNHYDRO	-0.011	0.021
	(0.803)	(0.536)
LNSOLAR	-0.008	0.001
	(0.236)	(0.909)
LNEPU	-0.078	-0.188***
	(0.575)	(0.000)
LNGDP	0.801***	0.963***
	(0.000)	(0.000)
LNGLO	-0.465***	-0.154
	(0.003)	(0.704)
LNGEO	-0.013	-0.015
	(0.241)	(0.270)
Constant	-4.114 ***	-1.299
	(0.008)	(0.579)

**** p<0.01, ** p<0.05, * p<0.1*