

DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS IN ENGLISH
ECONOMICS IN ENGLISH PROGRAM
MASTER'S THESIS

**DETERMINANTS OF ENERGY INTENSITY: A PANEL
DATA ANALYSIS**

Samet ŞİMŞEK

SUPERVISOR
Assoc. Prof. İstemi BERK

2025

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DECLARATION

I hereby declare that this master thesis titled as “Determinants of Energy Intensity: A Panel Data Analysis” has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

24.4.2025

Samet ŞİMŞEK



ABSTRACT

Master's Thesis

Determinants of Energy Intensity: A Panel Data Analysis

Samet ŞİMŞEK

Dokuz Eylül University

Graduate School of Social Sciences

Department of Economics in English

Economics in English Program

This thesis investigates the determinants of energy intensity through panel data analysis conducted across different country groups. Energy intensity, defined as the amount of energy required to produce a unit of GDP, is a critical measure in understanding the relationship between economic growth and energy use. The study aims to identify the key factors that influence energy intensity and to examine the specific effects of technological progress on both nonrenewable and renewable energy sources. By disaggregating total energy use into these two categories, the study provides a deeper understanding of the drivers of energy intensity. The findings offer valuable guidance for policymakers seeking to promote sustainable economic development and to decouple economic growth from resource use. The motivation for this study aligns with the objectives of the European Green Deal and broader global efforts to address climate change.

Keywords: Energy Intensity, Energy Efficiency, Total Factor Productivity, Panel Data Analysis, Technological Progress, Renewable Energy Intensity, Non-Renewable Energy Intensity, Sustainable Economic Development

ÖZET

Yüksek Lisans Tezi

Enerji Yoğunluğunun Belirleyicileri: Bir Panel Veri Analizi

Samet ŞİMŞEK

Dokuz Eylül Üniversitesi

Sosyal Bilimler Enstitüsü

İngilizce İktisat Anabilim Dalı

İngilizce İktisat Programı

Bu tez, farklı ülke gruplarında enerji yoğunluğunun belirleyicilerini panel veri analizi yöntemiyle incelemektedir. Enerji yoğunluğu, bir birim GSYİH üretmek için gerekli olan enerji miktarı olarak tanımlanır ve ekonomik büyüme ile enerji kullanımı arasındaki ilişkiyi anlamada önemli bir göstergedir. Çalışmanın amacı, enerji yoğunluğunu etkileyen temel faktörleri belirlemek ve teknolojik ilerlemenin hem yenilenemeyen hem de yenilenebilir enerji kaynakları üzerindeki etkilerini değerlendirmektir. Toplam enerji kullanımı bu iki kategoriye ayrılarak analiz edilmiş, böylece enerji yoğunluğunun belirleyicilerine dair daha derinlemesine bir bakış sunulmuştur. Elde edilen bulgular, sürdürülebilir ekonomik kalkınmayı teşvik etmek ve ekonomik büyümeyi kaynak kullanımından ayırmak isteyen politika yapıcılar için değerli bilgiler sunmaktadır. Bu çalışmanın motivasyonu, Avrupa Yeşil Mutabakatı'nın hedefleri ve küresel iklim değişikliğiyle mücadele çabalarıyla örtüşmektedir.

Anahtar Kelimeler: Enerji Yoğunluğu, Enerji Verimliliği, Toplam Faktör Verimliliği, Panel Veri Analizi, Teknolojik İlerleme, Yenilenebilir Enerji Yoğunluğu, Yenilenemeyen Enerji Yoğunluğu, Sürdürülebilir Ekonomik Kalkınma

DETERMINANTS OF ENERGY INTENSITY: A PANEL DATA ANALYSIS

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ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AMG	Augmented Mean Group
ARDL	Autoregressive Distributed Lag
CCEMG	Common Correlated Effects Mean Group
ECM	Error Correction Term
EI	Energy intensity
EU	European Union
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
IDA	Index Decomposition Analysis
IEA	International Energy Agency
IPS	Im-Pesaran-Shin
IRR	Internal Rate of Return
LAC	Latin America and the Caribbean
LLC	Levin-Lin-Chu
MG	Mean Group
OLS	Ordinary Least Squares
PMG	Pooled Mean Group
PPPs	Purchasing Power Parities
SBC	Schwarz Bayesian Criterion
SDA	Structural Decomposition Analysis
SDGs	Sustainable Development Goals
TFP	Total Factor Productivity
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change

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INTRODUCTION

The adoption of the Paris Agreement (2015) and the endorsement of the Sustainable Development Goals (SDGs) by the United Nations (UN) in the same year marked a significant shift in global climate policy. The Paris Agreement is a good starting point as it recognizes the urgent need to limit global temperature increases to below 1.5°C above pre-industrial levels; the SDGs, however, approach sustainable development from a broader perspective and incorporate environmental, economic, and social goals. Collectively, these efforts have created a solid international framework aimed at pushing nations toward innovative, environment-sustaining policies—policies aimed at the mitigation of the adverse impacts brought about by climate change.

The EU, as a leader in these global efforts, has responded with the European Green Deal, which is a comprehensive plan to fight climate change. This plan was announced in 2019 and was officially launched in 2021 with the goal of making the EU a climate-neutral region by 2050. The Green Deal comprises crucial changes with regard to the reduction of greenhouse gas emissions, promotion of circular economy solutions, sustainable agriculture, and acceleration of the shift to renewable energy. Moreover, it has an impact not only within the European Union through the encouragement of sustainable methods of production but also outside the EU, as it calls on trade partners to respect the standards of environmentally friendly production, thus paving the way for the international diffusion of sustainable practices.

On the international stage, agreements like the Kyoto Protocol (1997) and the United Nations Framework Convention on Climate Change (1992) have supported the goals set by the Paris Agreement (2015). Through these accords, nations have concurred to constrain carbon emissions and enhance energy efficiency. The European Green Deal is also a key policy package aimed at reducing energy intensity, defined as the amount of energy needed to produce one unit of Gross Domestic Product (GDP), as one of the means of mitigating carbon emissions. International agreements of this sort are necessary for helping countries integrate

sustainable methods into their national policies so that a harmonious balance can be reached between economic development and environmental protection.

About 73 percent of the world's current anthropogenic CO₂ emissions come from the energy sector, essentially because of the heavy dependency on fossil fuels (International Energy Agency (IEA), 2021). Therefore, a shift towards renewable energy sources and a reduction in energy intensity are among the integral parts of any strategy for sustainable development. Reduction in energy intensity is especially significant for developing countries as it helps minimize the environmental cost linked to economic growth. Energy intensity also acts as a significant indicator of the energy efficiency of an economy, that is, how effectively an economy uses available energy resources to obtain economic output.

In this context, the decoupling of resources becomes increasingly important for the achievement of sustainable development. Resource decoupling has been defined as a loosening relationship between economic growth and natural resources to reduce the environmental consequence of economic activities. Energy intensity decline represents the use of less energy for achieving the exact value of output; hence, it is one of the key tools for sustainable development. In this context, energy intensity is a key factor in global efforts to reduce carbon emissions and preserve natural resources.

The primary objective of this thesis is to conduct an empirical examination of the determinants influencing energy intensity among different classifications of countries through the application of panel data analysis. In investigating the elements that contribute to energy intensity, this study seeks to enhance comprehension of the ways in which technological advancements affect both renewable and nonrenewable energy resources. A special focus is placed on reducing the share and intensity of nonrenewable energy, given its significant impact on carbon emissions. This study will offer some insights helpful to policymakers following goals of efficiency in energy, transitioning from fossil fuels to renewable energy, and sustainable growth paths.

Aligning with the objectives of the European Green Deal and global action on climate, this study contributes to the already existing discussion on sustainable development by identifying a set of drivers that impact energy intensity. This way, it

helps the establishment of practical policy recommendations that are able to respond to climate change and foster resource-efficient economic growth.



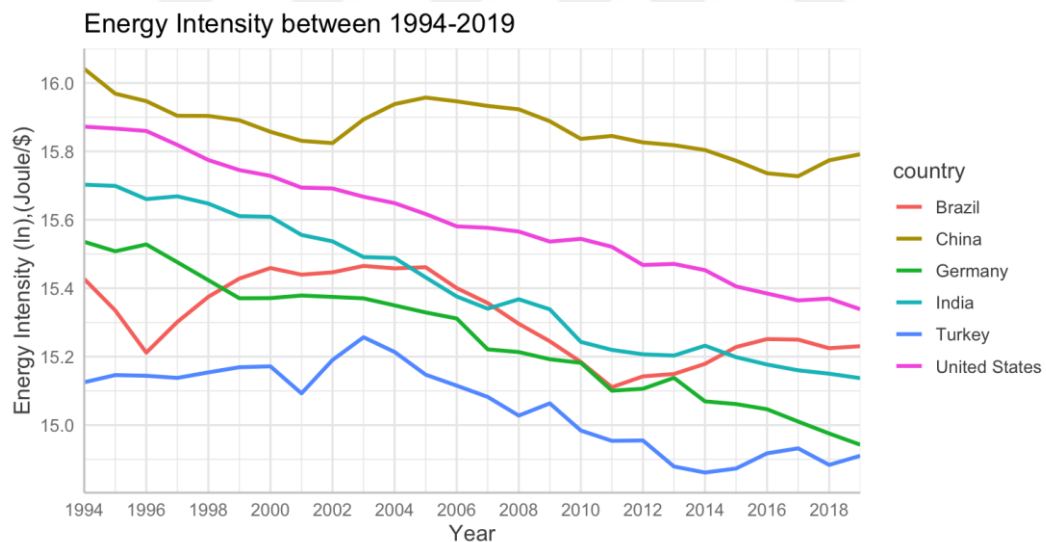
CHAPTER ONE

BACKGROUND

1.1. ENERGY INTENSITY

Energy intensity (EI) is a fundamental indicator used to assess the energy efficiency of an economy (International Energy Agency (IEA), 2021). In general, EI refers to the amount of energy used to produce one unit of GDP and is typically measured in kilograms of oil equivalent (kgOE) or gigajoules (GJ) (Guan et al., 2008). Lower energy intensity indicates that an economy can generate more output with less energy, thus demonstrating improved resource efficiency. This is crucial for achieving sustainable economic growth. Reducing energy intensity helps countries lower their carbon emissions and advance their environmental sustainability goals.

Figure 1: Energy Intensity Over the Years for Selected Countries



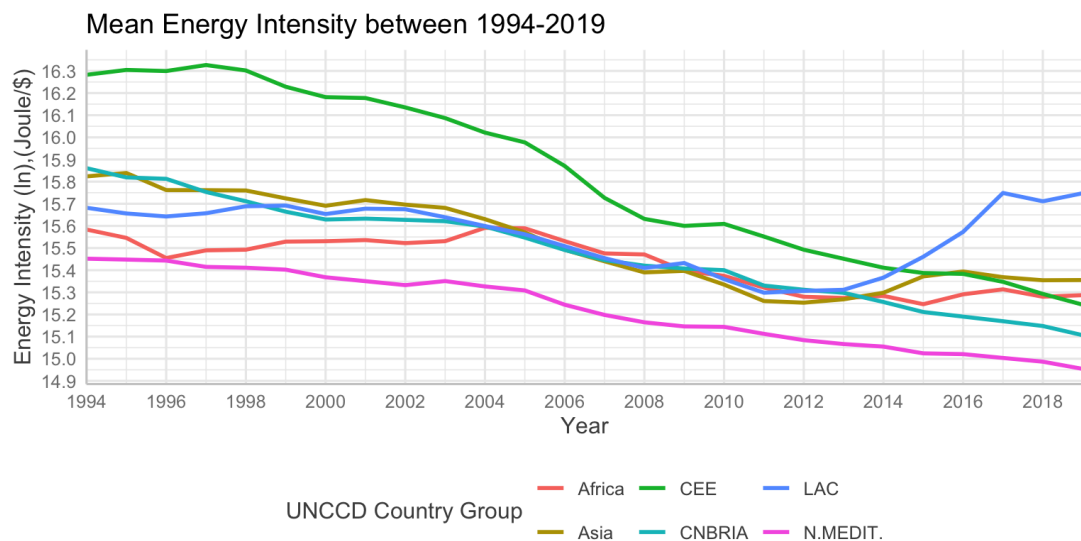
Source: Created by the author.

Figure 1 shows the trends in energy intensity, measured as energy use per unit of GDP (natural logarithmic scale), for China, the United States, Germany, Brazil, and Turkey between 1994 and 2019. Across all five countries, there is a clear downward trend indicating a general reduction in the amount of energy required to

produce economic output. In 1994, China had the highest energy intensity; it has improved significantly since then, but by 2019, it still had the highest levels within the group. The United States also showed a steady decline in energy intensity, which reflects an incremental shift to less energy-intensive sectors and technological progress. Over the entire period under review, Germany consistently had the lowest energy intensity. Brazil and Turkey, although originating from comparable standings, display more gradual reductions, with Turkey attaining a marginally lower energy intensity by the conclusion of the timeframe. These patterns illustrate the varying economic frameworks, industrial strategies, and energy consumption behaviors among countries.

Over the last three decades, a decline in energy intensity has been observed. In fact, from 1990 to 2019, energy intensity globally fell by about 25% at an average annual rate of improvement of 1%. Most of this downward trend has been propelled by technology and energy efficiency policy, with more significant use of cleaner energy technologies. Meanwhile, notwithstanding this overall trend, many countries and regions still exhibit very high levels of energy intensity. The economies with heavy dependence on fossil fuels face considerable challenges in trying to reduce their energy intensities, posing a serious threat to environmental sustainability.

Figure 2: Mean Energy Intensity Over the Years For UNCCD Country Groups



Source: Created by the author.

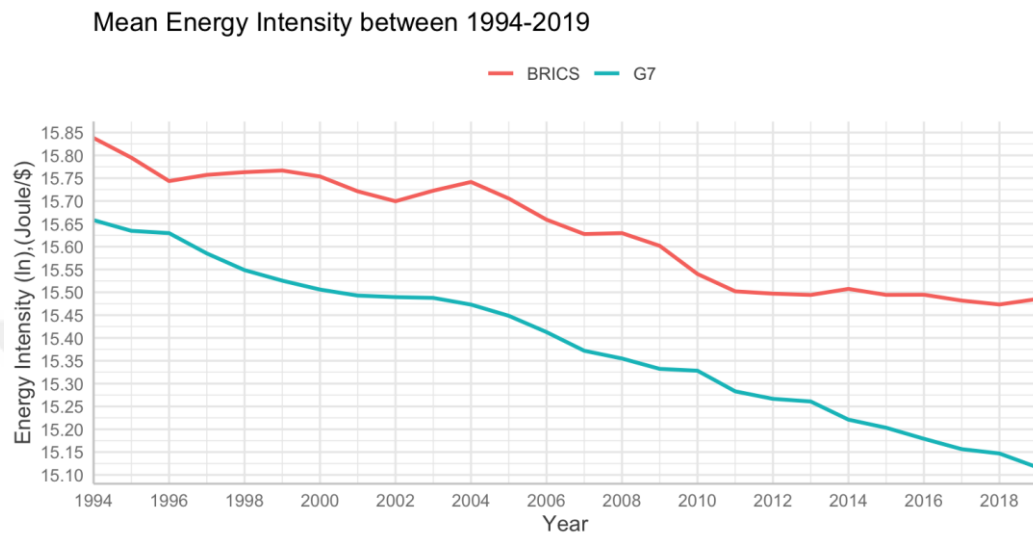
Figure 2 presents energy intensity trends for UNCCD country groups between 1994 and 2019. Overall, all regions show a declining trend and indicate a shift toward less energy-intensive economic structures. The CEE (Central and Eastern Europe) group starts with the highest energy intensity in 1994 but experiences a substantial and consistent decline over the years. In contrast, Asia and CNBRIA (Countries Not Belonging to a Regional Implementation Annex) exhibit moderate reductions and maintain relatively similar trajectories throughout the period. The Africa and Latin America and the Caribbean (LAC) groups show slower improvements in energy intensity compared to others, which may be due to potential challenges in transitioning to less energy-intensive production. The N.MEDIT and Asia have the lowest levels of energy intensity toward the end of the period, reflecting either an already advanced structure of their economies or more powerful policies regarding energy optimization. At the same time, steep rises in the LAC region around 2014 clearly point to a divergence from the general trend of decline observable across the world. They may indicate temporary changes in either the economic structure or energy utilization patterns over recent years.

Reducing energy intensity has become a central strategy for many countries in their efforts to combat climate change. International agreements like the European Green Deal, Kyoto Protocol, and the UNFCCC encourage nations to decrease energy intensity as a means of reducing carbon emissions. For example, the European Union (EU) has set a target to achieve a 32.5% improvement in energy efficiency by 2030 (European Union, 2018). In many countries, all that is not so easy; there are operational obstacles to reach these targets. Thus, the idea of understanding the determinants of energy intensity becomes very essential for designing efficient policy interventions.

The study therefore looks at the determinants of energy intensity separately for renewable and non-renewable sources of energy. Though expected and welcome, the strides being made in increasing the share of renewable energy are not very challenging; the crucial challenge remains the reduction of both the share and intensity of non-renewable sources of energy. This is because nonrenewable sources, such as coal and oil, are major contributors to carbon emissions and environmental degradation. For example, rapidly growing economies like Turkey and India face

significant challenges in reducing their reliance on nonrenewable sources, yet are investing heavily in renewables to meet sustainable growth targets.

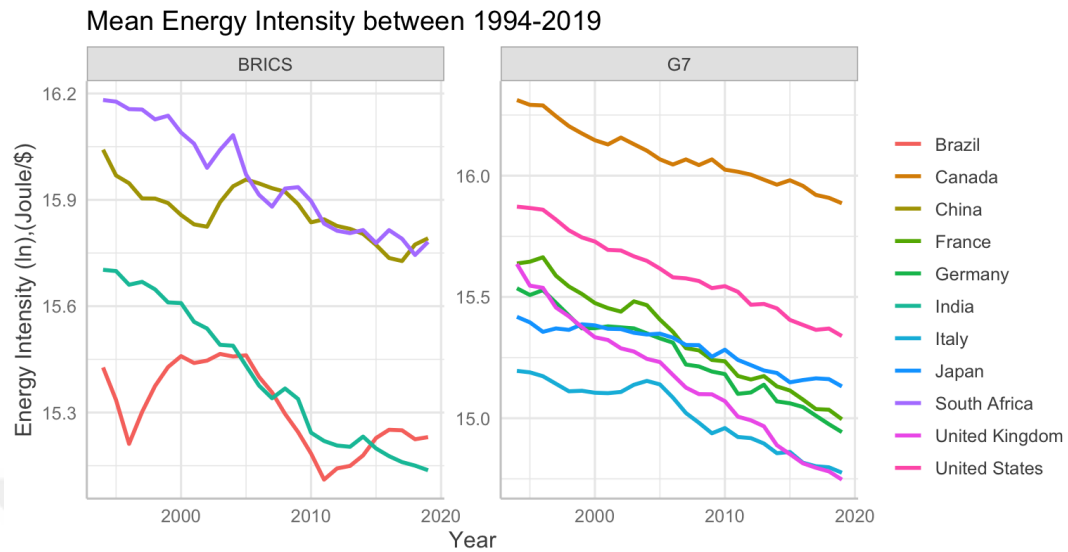
Figure 3: Mean Energy Intensity Over the Years for BRICS and G7 Countries



Source: Created by the author.

Figure 3 shows the comparison of the average energy between BRICS and G7 countries from 1994 to 2019. Both groups depict a consistent decline, which reflects a fall in energy intensity over the years. The G7 has consistently maintained a much lower energy intensity than that of BRICS due to high share of services sector, more advanced economic structures, and higher emphasis on energy efficiency and technological innovation. While BRICS improves, it reflects a slower pace of decline, probably because of ongoing industrialization and higher reliance on energy-intensive activities in the emerging economies. Notably, the gap between the two groups widens over time, particularly after 2006, which points to the growing divergence in energy efficiency advancements between developed and emerging economies. This divergence underscores the challenges faced by BRICS in transitioning toward less energy-intensive economic systems compared to G7 economies.

Figure 4: Mean Energy Intensity Over the Years for BRICS and G7 Countries



Source: Created by the author.

Figure 4 compares energy intensity between BRICS and G7 economies from 1994 to 2019. Among BRICS countries, China always occupied the top position with the highest energy intensity, signaling its energy-intensive industrialization process, though it is seen to improve significantly with time. India and South Africa also show descending trends, the former with more significant declines after 2000. Brazil has maintained relatively low levels of energy intensity, though with lesser fluctuation. G7 countries are much behind in terms of energy intensity due to the high share of services sector and higher energy efficiency. Canada starts with the highest energy intensity value in G7 but improves steadily; Japan and Germany hold the two lowest values throughout this period. The United States and the United Kingdom also record considerable declines due to the shift towards service-based economies and policies encouraging energy efficiency. These include the fact that the widening of the gap reflects a difference in the levels of energy per economic output by the two economies. In contrast, the benefit of a mature economy has already been developed with workouts of standards relating to energy saving within G7's economies.

As global energy usage and GDP continue to grow, reducing energy intensity has become a key strategy for decoupling economic growth from natural resource

consumption. Resource decoupling refers to reducing the number of resources used per unit of economic activity, thus promoting sustainable economic growth. In this context, energy intensity is a critical measure for achieving carbon emission reductions and conserving natural resources.

1.2. LITERATURE REVIEW

Energy intensity refers to the amount of energy used per unit of value added (GDP) in an economy and is a critical indicator in terms of both economic efficiency and environmental sustainability (Metcalf, 2008; Rühl et al., 2012). High energy intensity necessitates greater energy consumption to achieve the same level of output, which, in turn, increases dependence on fossil fuels and exacerbates greenhouse gas emissions (Stern, 2012). Consequently, reducing EI has become a priority goal in the context of many countries' climate policies (e.g., the European Green Deal, the Paris Agreement) and sustainable development strategies. The study of energy intensity is becoming more critical in addressing the dual challenges of sustainable development and climate change. As global commitments to reduce carbon emissions intensify, understanding the drivers of energy intensity provides valuable insights into formulating adequate energy and economic policies.

In the literature, factors influencing EI are commonly examined along two primary dimensions: structural change (structural effect) and efficiency/technological advancement (efficiency/technological effect) (Ang, 2006; Metcalf, 2008; Song & Zheng, 2012). Further to these two, a significant proportion of the work focuses on other dimensions related to energy price, foreign investment, openness in trade, institutional structure, and urbanization in addition to intra-sector and inter-sector dynamics.

Energy intensity became a prominent area of research following the oil crises of the 1970s. These crises, triggered by the rapid rise in oil prices, increased concerns about energy efficiency and supply security, which led to significant changes in energy usage and production structures across various countries (Motamen & Schaller, 1985). Kraft and Kraft (1978) conducted one of the early analyses based on U.S. economic data from 1947 to 1974 and found one-way causality from GNP to

energy consumption, indicating the driving effects of economic activities on energy demand. Similarly, Jorgenson (1988) focused on the U.S. manufacturing sector from 1958–1979 and concluded that rising energy prices during the 1970s suppressed productivity growth and constrained labor efficiency.

During this period, energy intensity exhibited an increasing trend in many economies (Casler & Hannon, 1989; Hannesson, 2002; Proops, 1984), though a subsequent decline was observed in most cases following the crisis. Greening et al. (1998) analyzed ten developed countries from 1971–1991 and reported significant reductions in energy intensity, with a 61.7% decrease in Japan and a 37.5% decrease in Norway. Similarly, Sun (1998) found a 26.2% decline in energy intensity among OECD countries between 1973 and 1990. More recent studies by Liddle (2012) and Wang (2013) have confirmed this downward trend in energy intensity across advanced economies. These findings collectively show the substantial potential for energy savings that still exists (Velthuisen, 1993; Worrell et al., 2018).

Two primary decomposition methods are frequently employed to explain the decline in energy intensity: Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA) (Ang, 2004; Hoekstra & Van den Bergh, 2003; Wing, 2008). IDA is a flexible approach for disaggregating energy intensity at the macro or sectoral level into technological (or efficiency) and structural components using time-series data, while SDA relies on input-output tables, allowing for the tracking of indirect demand effects (Garbaccio et al., 1999; Lin & Polenske, 1995).

The efficiency effect, in general, is analyzed along with the structural effect, that is, the change in the sectoral composition of the economy, in the literature, for further information about the energy intensity decline (Fisher-Vanden et al., 2004; Huang, 1993; Sinton & Levine, 1994; Zhang, 2003). Some of them, such as Mulder and De Groot (2012) reported that structural changes decreased the energy intensity by around 25% of the OECD countries. However, the efficiency effect accounted for the lion's share of the tiny effect. Contrarily, Voigt et al. (2014) reported that the efficiency effect dominated in many countries, while the structural change dominated in some countries. As mentioned Metcalf (2008), the energy prices or macroeconomic factors generally omitted in the IDA/SDA methodologies are considered variables. The analysis of energy intensity will be holistic and complete.

In the literature, in addition to the efficiency and structural effects, numerous variables—such as economic growth, energy prices, foreign investment, trade openness, institutional quality, urbanization, and export diversification—are highlighted as influential factors in energy intensity (Samargandi, 2019; Song & Zheng, 2012). The relationship between growth and energy intensity, which began with Kraft and Kraft (1978), has since become a widely discussed topic enriched by contributions from researchers like Sadorsky (2013) and Ang (2008). Rapidly growing economies often face high energy demand at certain stages, while transitions to the service sector or technological advancements tend to lower energy intensity (Kose, 2019). Until now, literature has discussed impacts within the context of efficiency and structural effects. However, significantly fewer have been discussed within a comparative, cross-country framework analyzing interlinkages between TFP and the renewable-non-renewable energy mix. This study aims to fill that gap by exploring such dynamics both for developed and developing economies.

Energy prices, examined in studies by Hang and Tu (2007) and Metcalf (2008), exert downward pressure on energy intensity, with increases in oil or coal prices encouraging shifts toward more efficient technologies (Antonietti & Fontini, 2019; Wang et al., 2019). Foreign direct investment (FDI) and technology transfer are identified as key factors in reducing energy intensity in developing countries, as highlighted by Mielnik and Goldemberg (2002) and Fisher-Vanden et al. (2004). Moreover, trade openness and export diversification play significant roles in transforming production models and shaping energy consumption patterns (Gozgor & Can, 2016; Shahbaz et al., 2019). This is again supported by the works of Sun et al. (2019), who concluded that institutions rank as one of the primary determinants in shaping energy policies. Besides, the influence of urbanization on energy demand goes through positive and negative channels, as evidenced by several empirical results in the literature, among them (Jones, 1991; Ma, 2015; Sadorsky, 2013).

Additionally, the distinction between renewable and non-renewable energy sources is a focal point in contemporary research on energy intensity. Studies like Wu (2012) argue that coal-dominated economies exhibit higher energy intensity and, consequently, increased carbon emissions. In contrast, Saygin et al. (2015) suggest that an increasing share of renewable energy improves both energy security and

efficiency. Clean energy infrastructure, particularly in electricity generation and distribution, has been shown to effectively reduce energy intensity (Dogan & Karay, 2019). Thus, the type of energy source used closely influences energy intensity and greenhouse gas emissions. Technological advancements further contribute by enabling more effective utilization of renewable energy technologies, thereby reducing both energy intensity and carbon emissions (Fisher-Vanden et al., 2004; Ma & Stern, 2008; Voigt et al., 2014).

The relationship between Total Factor Productivity (TFP) and energy intensity is often regarded as a concrete expression of the "efficiency effect" in the literature (Stern, 2012). Studies such as Haider and Ganaie (2017) demonstrate that higher TFP enhances energy efficiency, although rebound effects may occur in specific sectors. Nonetheless, at the macro level, productivity improvements driven by technological progress are consistently found to contribute to reductions in energy intensity (Ma & Stern, 2008; Sinton & Levine, 1994). In developing economies, improved access to technology through channels like R&D and FDI accelerates efficiency gains, thereby reducing energy intensity (Fisher-Vanden et al., 2004; Mielnik & Goldemberg, 2002). Institutional structures and price signals are also frequently highlighted as critical factors in this process (CHANG et al., 2018; Metcalf, 2008; Sun et al., 2019).

Methodologically, studies on energy intensity often focus on decomposition analyses (IDA/SDA) and econometric models. IDA enables the disaggregation of technological and structural effects at the panel or time-series level, while SDA employs input-output tables to reflect sectoral relationships at a more micro level (Ang, 2004; Haas & Kempa, 2018; Lin & Polenske, 1995). Panel data regressions, however, including dynamic approaches like panel ARDL, have been suggested as complementary approaches in the case of a possible omission of important variables in IDA and SDA (Mohammadi & Parvaresh, 2014; Song & Zheng, 2012; Tugcu et al., 2012). Thus, efficiency effects, structural shifts, prices, institutional factors, trade, and urbanization should be combined in a multidimensional way while analyzing energy intensity. While IDA and SDA bring substantial knowledge on structural and efficiency effects, most of the recent studies within the existing approaches fail to take the macro-scale and institutional aspects into consideration.

This study adopts a dynamic panel data approach, such as Panel ARDL, to capture both short- and long-term impacts of productivity and energy mix on energy intensity, offering a more holistic understanding of the determinants.

The prevailing trend in the literature suggests that energy intensity has visibly declined in many economies since the 1970s. However, the extent to which this decline stems from technology-driven efficiency improvements versus intersectoral structural shifts varies across countries and period (Mulder & De Groot, 2012; Voigt et al., 2014). Energy prices and the mix of renewable and non-renewable energy sources further influence these dynamics. Nonetheless, comprehensive studies examining the relationship between TFP and energy intensity alongside the renewable-nonrenewable energy distinction remain limited, representing a gap in the literature (Ma & Stern, 2008; Metcalf, 2008).

This thesis tries to fill the gap by analyzing the determinants of energy intensity across different country groups, such as Annex I/non-Annex I. Concretely, this thesis aims to conduct an empirical analysis of the unique impacts of both productivity-technology change or TFP and the renewable-nonrenewable energy mix on energy intensity. This effort, therefore, underlines how technology-driven energy policy improvements are essential and contribute toward enriching the "efficiency effect" perspective in the literature. Given the differing sectoral structures and institutional environments of developed and developing economies, the findings are expected to provide valuable insights for policymakers, demonstrating how sustainable growth policies based on productivity improvements can reduce energy intensity. The analysis will also explore the contributions of renewable energy and the influence of macroeconomic factors within a comprehensive framework.

CHAPTER TWO

METHODOLOGY

2.1. RESEARCH QUESTION

This study seeks to empirically investigate the determinants of energy intensity across various country groups, with a particular focus on technological progress and the distinct impacts it has on renewable and non-renewable energy intensity. Energy intensity, defined as the amount of energy consumed per unit of GDP, is a critical measure of an economy's energy efficiency and its alignment with sustainability objectives. Decomposing energy intensity between renewable and non-renewable components is considered an integral part of this contribution because of the possibility of providing a more precise view of how technological changes are interacting with energy consumption at the energy source level. This decomposition is significant for evaluating how advancements in technology can reduce reliance on carbon-intensive non-renewable energy while promoting greater efficiency in renewable energy systems.

The following primary research questions guide this study. The first research question investigates the key determinants that influence energy intensity across different country groups. It aims to identify the macroeconomic and technological factors influencing variations in energy intensity across country groups, both Annex I and non-Annex I countries, as well as an 'all countries' group. This means that this study shall address issues of variations in energy efficiency for different levels of economic development, technological capability, and policy environments in diverse national contexts.

The second research question examines how technological progress affects energy intensity differently for renewable versus nonrenewable energy sources. This question focuses on the role of technological advancements in shaping energy intensity, with particular emphasis on the distinct effects on renewable and nonrenewable energy sources. The decomposition of energy intensity into these two categories allows for an assessment of how technological innovation influences energy efficiency within each sector. It is expected that technological progress will reduce nonrenewable energy intensity more significantly, while renewable energy

systems will also benefit, albeit at a different rate due to varying levels of adoption and infrastructure development.

Energy intensity should, therefore, be analyzed between groups of countries at similar levels of technological development. A country at any given level of technological development will tend to have similar effects of technological progress to other countries at the same level. If countries are too far from one another in technological maturity, the resulting trend in energy intensity may even go in opposite directions. Such a comparison will develop an in-depth understanding of the determinants of energy intensity within different economic contexts that may also enable specific policy recommendations. In the process of technological development, countries will face changing impacts on energy intensity that need consideration in formulating sustainable energy policies.

2.2. VARIABLES AND DATA

This study examines the determinants of energy intensity using a comprehensive panel dataset covering 67 countries from 1994 to 2019. In this connection, the paper categorizes these 67 countries into three different groups: Annex I, Non-Annex I, and all 67 countries. The analysis has taken a balanced panel, although some countries have been excluded from the analysis either because of data constraints or because they are being identified as outliers. However, the sample of 67 countries is adequate for empirical analysis and covers the major developed and developing countries that can represent the real energy intensity dynamics of both groups.

The dependent variable in this study is energy intensity, which is analyzed in three forms: total energy intensity, renewable energy intensity, and nonrenewable energy intensity. These variables are calculated by dividing total energy consumption, renewable energy consumption, and nonrenewable energy consumption by GDP, with all values adjusted for differences in purchasing power. Energy consumption data is sourced from the Energy Institute's 2024 Statistical Review of World Energy, which provides reliable and comprehensive data on global energy markets. The consumption data for total, renewable, and nonrenewable

energy is measured in joules. The GDP figures used in this analysis come from the Penn World Table (PWT) and represent real GDP at chained purchasing power parities (PPPs), expressed in millions of 2017 US dollars. This real GDP measure, adjusted for inflation and converted to a common currency, allows for cross-country comparability. To facilitate the statistical analysis, the natural logarithms of the energy intensity variables are calculated, transforming the data into more manageable and interpretable forms.

A central independent variable in this study is TFP, which is also sourced from the Penn World Table. TFP is defined as the level of productivity at current PPPs, with the United States set as the benchmark (USA = 1). On a logical basis and for the objective of the present paper, this variable has emerged as critical amongst the other contributors to the dimensions of energy efficiency and the leap of technology in various countries.

Crude oil prices are another important determinant, as they influence both energy usage patterns and the adoption of energy-efficient technologies. The data on crude oil prices is obtained from the World Bank, and to account for differences in the price levels across countries, these prices are adjusted by dividing them by the price level of the household consumption index for each country (with the United States set to 1 for the year 2017). The natural logarithm of the adjusted crude oil prices is used in the analysis to account for non-linear effects and to facilitate statistical modeling.

Urbanization is included as a key variable, reflecting the proportion of a country's population residing in urban areas. This measure is relevant as urbanization is often associated with changes in energy demand patterns, including increased energy usage but also greater potential for energy efficiency through infrastructure development. The data on urbanization is sourced from the World Bank.

Human capital, as measured by the Human Capital Index (which considers years of schooling and returns to education), is included to capture the role of education and workforce quality in shaping energy usage patterns. The Human Capital Index data is derived from the Penn World Table, and its natural logarithm is applied to standardize the variable.

The real internal rate of return (IRR), a measure of the real return on capital investments, is also considered as a determinant of energy intensity. The IRR influences capital allocation decisions, including those related to the adoption of energy-efficient technologies.

Finally, the average depreciation rate of capital (δ) is incorporated to reflect how the rate of capital depreciation influences investment choices, particularly in terms of energy-intensive technologies. Nevertheless, the δ may most probably determine decisions in a reflection of the need for capital replacement and of the propensity for countries' economies to move towards more up-to-date technologies.

Data for these variables were collected from reputed institutions such as the Energy Institute, Penn World Table, and the World Bank in order to make sure that the dataset is reliable and accurate. This study uses data for 67 countries ranging from 1994 to 2019, and the dataset offers a balanced panel for empirical analysis. The varied countries that were selected had a great difference in economic structure and technological and policy environments, hence offering an opportunity to capture all factors affecting energy intensity under different challenges from various perspectives.

2.3. EMPIRICAL STRATEGY

To study the effect of TFP on EI, we follow a four-step process. First, we examine whether cross-sectional dependence exists, as this is a common issue in cross-country studies. Second, we address the potential presence of unit roots by applying panel unit root tests to ensure the variables are stationary. In the third step, we investigate whether the variables share a long-term equilibrium relationship by performing panel cointegration tests. As a final step, we implement the ARDL framework enhanced by advanced estimators such as the Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) to address cross-country heterogeneity and correlations.

To investigate short- and long-term relationships, we employ the Panel ARDL methodology, introduced by Pesaran and Smith (1995) and Pesaran et al.

(1997). This approach is well-suited for panel data with extended periods but requires careful testing for stationarity due to the potential presence of unit roots. Therefore, prior to estimating the ARDL model, we must check for the order of integration for each series and the cointegration test, which will ensure long-run equilibrium. These steps lay the platform for practical applicability of the ARDL technique. For this analysis, we construct a balanced panel dataset for the selected countries, which spans 26 years of observations, to ensure consistency and robustness in the results.

In order to ascertain the stationarity of the variables and determine their integration orders, we apply two popular unit root tests. The first test, Levin-Lin-Chu (LLC), introduced by Levin et al. (2002), assumes a common unit root process across all panels. The second test, Im-Pesaran-Shin (IPS), developed by Im et al. (2003), allows for individual unit root processes for each panel. By employing both tests, we aim to verify whether the variables are integrated of order zero ($I(0)$) or order one ($I(1)$).

The LLC test assumes that the autoregressive coefficients are identical across all panel units, which ensures a homogeneous structure across the dataset. To control for the null hypothesis, it evaluates the pooled t-statistic derived from the following hypothesis framework:

$$\begin{aligned} H_0: \beta_1 &= \beta = 0 \\ H_1: B_i &< 0, \forall i \end{aligned} \quad (1)$$

The null hypothesis asserts that all series within the panel exhibit a unit root, while the alternative hypothesis assumes that all panel members are stationary. By pooling the data, the test creates a unified framework to assess whether non-stationarity exists across the dataset.

The mathematical representation of the LLC test for N cross-sectional units and T time periods can be expressed as in Equation 2:

$$\Delta y_{i,t} = \alpha_i + \rho y_{i,t-1} + \sum_{z=1}^{p_i} \beta_{i,z} \Delta y_{i,t-z} + \varepsilon_{i,t} \quad (2)$$

where, $\Delta y_{i,t}$ denotes the first difference of the dependent variable, and α_i captures the individual effects of each panel unit. The lagged terms, $\beta_{i,z}$, account for autocorrelation within the series, and $\varepsilon_{i,t}$ denotes the error term. The individual effects, under the null hypothesis, are assumed to equal zero, which indicate non-

stationarity across the panel. This framework enables the LLC test to estimate a common autoregressive coefficient by pooling data across all units. It should be noted that while it simplifies estimation, it may over-restrict panels with substantial heterogeneity. In such cases, alternative tests that allow for unit-specific dynamics, such as the IPS test, may provide more flexibility in capturing variation within the dataset.

In equation 2, the parameter p_i determines the optimal number of lags but is not directly observable. To address this limitation, Levin et al. (2002) propose a three-step method for implementing the LLC unit root test. First, they run separate augmented Dickey-Fuller (ADF) regressions on each cross-sectional unit to isolate the individual dynamics of each series. Next, two orthogonalized residuals are generated to remove any interference from serial correlation and to refine the model. Then, the ratio of long-run to short-run standard deviations for innovation terms is calculated for each unit. Finally, the pooled t -statistic is computed by combining the information across all units, which enables the test to evaluate whether a unit root is present in the data, as detailed in Levin et al. (2002).

While the LLC test assumes homogeneity in autoregressive coefficients across all units, this approach may not fully account for variability in panels with diverse structures. The IPS test, introduced by Im et al. (2003), extends the LLC approach by allowing heterogeneity in unit root processes across individual panel units. Unlike the LLC test, which assumes that all panel units share identical autoregressive coefficients, the IPS method permits each unit to follow its own dynamic process. This flexibility makes the IPS test particularly suitable for datasets with diverse cross-sectional behaviors.

To evaluate stationarity, the IPS test calculates the average of the ADF t -statistics derived from individual unit-specific regressions. The test statistic is computed as the mean of these individual t -statistics (Equation 3):

$$\bar{t} = \frac{1}{N} \sum_{i=1}^N t_{iT} \quad (3)$$

where t_{iT} represents the ADF t -statistic for each cross-sectional unit. Under the null, all the units are considered to contain a unit root. That contrasts with the alternative one implying that some units can be stationary though others are not. In such a way,

while the IPS method provides a more flexible framework by allowing heterogeneity across the panel through averaging individual test results, it captures the differences in unit-specific dynamics and makes it a powerful alternative to the homogenous assumptions imposed by the LLC test.

When there is cross-sectional dependence among the panel units, first-generation unit root tests, such as LLC and IPS, may produce biased outcomes. To overcome this limitation, second-generation unit root tests introduced by Pesaran (2007) are utilized. These advanced tests consider both cross-sectional dependence and heterogeneity, which makes them more reliable for datasets where interactions exist between units. In practice, the augmented ADF and augmented IPS (CIPS) procedures are employed to evaluate the stationarity of the variables.

Pesaran's method incorporates cross-sectional averages into the testing procedure. The CADF statistic is calculated using the augmented ADF regression, which can be expressed as:

$$y_{i,t} = (1 - \phi_i)\mu_i + \phi_i y_{i,t-1} + u_{i,t}, \quad u_{i,t} = \gamma_i f_t + \epsilon_{i,t} \quad (4)$$

where $y_{i,t}$ denotes the variable being tested, f_t captures unobserved common factors, and $\epsilon_{i,t}$ represents the idiosyncratic error. By reorganizing this equation, Pesaran (2007) derives the Equation 5:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \epsilon_{i,t} \quad (5)$$

where $\Delta y_{i,t}$ refers to the first-differenced variable, while α_i , β_i , and γ_i represent the coefficients for individual effects, lagged terms, and common factors.

The null hypothesis for the test assumes the presence of a unit root in all panel units, stated as:

$$H_0: \beta_i = 0, \forall i \quad (6)$$

On the other hand, the alternative hypothesis allows some panel units to be stationary while others remain non-stationary:

$$H_A: \begin{cases} \beta_i < 0, & \forall i = 1, 2, \dots, N_1, \\ \beta_i = 0, & \forall i = N_1 + 1, \dots, N. \end{cases} \quad (7)$$

Using the CADF and CIPS tests, we aim to capture both the individual dynamics of each unit and the interdependencies across the panel, in order to accurately assess stationarity.

Pesaran (2007) extends the CADF framework by proposing a test of unit root hypothesis based on the t-ratio of the OLS estimate for the lagged variable in the CADF regression (Equation 8).

$$\Delta y_{i,t} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \epsilon_{i,t} \quad (8)$$

In Equation 8, \bar{y}_{t-1} and $\Delta \bar{y}_t$ are cross-sectional averages of the lagged variable and its first difference, respectively, while $\epsilon_{i,t}$ represents the error term. The CADF test statistics are calculated as the simple average of the t-ratios from this regression, using information criteria such as Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC) to select the optimal lag length. The window width is determined based on the Bartlett Kernel function, defined as $4\left(\frac{T}{100}\right)^{2/9}$, where T is the number of observations.

The test further incorporates critical values provided by Pesaran (2007) for different scenarios, including cases with no intercept or trend, intercept only, and both intercept and trend. These adjustments ensure robustness across varying model specifications.

The augmented IPS (CIPS) test builds upon the CADF framework by averaging the individual CADF test statistics across all panel units. The test statistic for CIPS is given by:

$$\text{CIPS}(N, T) = \frac{1}{N} \sum_{i=1}^N t_i(N, T) \quad (9)$$

where $t_i(N, T)$ is the cross-sectional CADF statistic for each panel unit. For datasets with small T or when $T > N$, a truncated version of the CIPS statistic, denoted as $\text{CIPS}^*(N, T)$, is utilized to improve test reliability.

In analyses spanning multiple countries, the error terms frequently demonstrate cross-sectional dependence resulting from common shocks or unobserved global factors. Testing for such dependence is crucial, as it affects the validity of the results. The Breusch-Pagan LM test is a commonly used method for identifying cross-sectional dependence, but it is only valid when the time dimension (T) exceeds the number of cross-sectional units (N).

For cases where $N > T$, as in this study, alternative tests are applied. These include Pesaran's (2004) cross-sectional dependence (CD) test, Friedman's (1937)

test, and Frees' (1995) statistic (Frees, 1995). The general model used for these tests is written as:

$$y_{i,t} = \alpha_i + \beta' x_{i,t} + \epsilon_{i,t} \quad (10)$$

where $y_{i,t}$ is the dependent variable, $x_{i,t}$ includes independent and control variables, and $\epsilon_{i,t}$ denotes the error term. The null hypothesis assumes that $\epsilon_{i,t}$ is independent and identically distributed across all panel units. The alternative hypothesis, however, allows for correlation between the error terms across units. This framework ensures that cross-sectional dependence is adequately accounted for, strengthening the validity of subsequent analyses.

Before we implement the panel ARDL approach, we must carry out two preliminary tests so that the variables are suitable for this approach. First, regarding the presence of unit roots, we derive the stationarity properties of the variables, and secondly, investigate the presence of cointegration in order to derive whether there exists a long-run equilibrium relationship among the variables.

First, we check whether the series are related in the long run. Its presence guarantees that the variables are integrated and that further steps of the analysis would be warranted. The estimation of the long-run coefficients in the panel ARDL framework will then be obtained. In testing the cointegration among the variables, we will apply the ECM-based panel cointegration test put forward by Westerlund (2007), which offers some crucial improvements on earlier studies. Its key advantage is related to the fact that heterogeneity combined with cross-sectional dependence is considered explicitly in Westerlund's approach, making it more appropriate for a dataset which may possibly have various unit behaviors.

The ECM designed for cointegration analysis builds upon the fundamental linkage between dependent and independent variables, allowing the model to return to equilibrium whenever a short-run deviation occurs. The general form of the ECM equation is given in Equation 11.

$$\Delta y_{i,t} = \delta_t' d_t + \alpha_i (y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{i,j} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{i,j} \Delta x_{i,t-j} + \epsilon_{i,t} \quad (11)$$

In Equation 11, d_t represents deterministic components, where $d_t = 0$ implies no constant or trend, $d_t = 1$ incorporates a constant, and $d_t = (1, t)$ accounts for both constant and trend terms. For our study the dependent variable,

$y_{i,t}$, corresponds to measures of energy intensity (total, renewable and nonrenewable energy intensity), while $x_{i,t}$ represents explanatory variables, including controls.

The adjustment speed back to equilibrium is captured by α_i , with $\alpha_i < 0$ indicating cointegration between variables. If $\alpha_i = 0$, the model fails to correct deviations, which implies the absence of cointegration. The null hypothesis (H_0) assumes no cointegration, while the alternative hypothesis is tested using group and panel tests, as proposed by Westerlund (2007). These tests are defined as follows:

$$H_0: \alpha_i = 0, \forall i$$

$$H_A^G: \exists i \ni \alpha_i < 0 \quad (12)$$

$$H_0: \alpha_i < 0, \forall i$$

Westerlund's cointegration framework is advantageous due to its ability to handle cross-sectional dependence and heterogeneous dynamics. By rejecting the null hypothesis, the results confirm that at least some panel members exhibit long-term equilibrium relationships.

Following the confirmation of cointegration, the Panel ARDL approach is employed to estimate both short-run and long-run coefficients. The ARDL model offers flexibility by accommodating variables integrated at different orders, $I(0)$ or $I(1)$, and allows for dynamic lag structures. This makes the method particularly effective for analyzing datasets with diverse unit-specific characteristics and interdependencies.

For panels without cross-sectional dependence, two estimators are widely utilized within the Panel ARDL framework to assess long-term relationships: the Pooled Mean Group (PMG) estimator, introduced by Pesaran et al. (1997), and the Mean Group (MG) estimator, developed by Pesaran and Smith (1995). The MG estimator allows for full heterogeneity by averaging coefficients derived from individual time-series regressions across panel units. Conversely, the PMG estimator assumes that the long-run coefficients remain consistent across all units, while short-run dynamics are permitted to vary. This distinction makes the PMG estimator suitable when the underlying assumption of long-run homogeneity holds.

However, when the long-run coefficients are indeed homogeneous, the PMG estimator is preferred because of its efficiency by combining pooled information in order to increase precision. On the contrary, when such an assumption of

homogeneity is violated, the PMG estimator loses its consistency, and the MG estimator produces valid and unbiased estimates under heterogeneous conditions. The variance in these estimators can effectively be judged by the Hausman test, which compares relative efficiency between PMG and MG estimates to identify which model fits best to the data.

The general specification of the Panel ARDL model, for which optimal lag lengths are chosen based on criteria such as the AIC or Schwarz Bayesian Criterion SBC, is given below by Equation 13.

$$y_{i,t} = \sum_{j=1}^p \lambda_{i,j} y_{i,t-j} + \sum_{j=1}^q \delta_{i,j} x_{i,t-j} + \mu_i + \epsilon_{i,t} \quad (13)$$

Here $\lambda_{i,j}$, and $\delta_{i,j}$ correspond to the lagged dependent and independent variables, respectively. The term μ_i denotes group-specific effects, $\epsilon_{i,t}$ accounts for the error term. By incorporating lagged variables, this framework captures both short-run dynamics and long-run relationships effectively.

By allowing for both homogeneity and heterogeneity through the joint use of PMG and MG estimators, Panel ARDL modeling is thus capable of fully capturing the dynamics in the panel data. The variance in these estimators can, in turn, be effectively gauged from the Hausman test, which thus identifies which model fits best to the data for relative efficiency between the PMG and MG estimates.

The error correction term in the Panel ARDL model integrates the dynamic relationships in the panel further. The ECT, in simple terms, is the speed of adjustment toward the long-run equilibrium after its short-run deviations. Equation 14 shows the general form of the model.

$$\Delta y_{i,t} = \phi_i (y_{i,t-1} - \theta'_i x_{i,t}) + \sum_{j=1}^{p-1} \lambda_{i,j} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{i,j}^* \Delta x_{i,t-j} + \mu_i + \epsilon_{i,t} \quad (14)$$

Here, ϕ_i captures the speed at which the system returns to equilibrium, with $\phi_i < 0$ indicating that the model adjusts back to equilibrium over time. The term θ'_i represents the long-run coefficients, while $\lambda_{i,j}$ and $\delta_{i,j}^*$ are short-run coefficients for lagged dependent and independent variables, respectively. The group-specific effects are denoted by μ_i , and $\epsilon_{i,t}$ represents the error term.

The presence of cointegration in the panel is determined through the error correction term. If $\phi_i = 0$, the model indicates no adjustment toward equilibrium, which suggests the absence of a long-run relationship.

The Hausman test is employed to evaluate the homogeneity of the long-run coefficients. Under the null hypothesis of homogeneity, both the PMG and MG estimators are consistent, but the PMG estimator is more efficient. If the null hypothesis is rejected, the MG estimator is preferred for its robustness under heterogeneous conditions.

Applications of the Panel ARDL model give scope for certain sector-specific or variable-specific dynamic analysis. Sector-specific lags and adjustments are thus introduced to capture the dynamic relationship underlying the sectoral aspects in production and value-added metrics, as per the nature and character of the data. Such lag structures would then be optimized on model selection criteria such as AIC or SBC to effectively capture the model under consideration both in the short run and the long run.

Thus, the error correction term and flexibility in the lag structure allow the Panel ARDL modeling framework to comprehensively explore dynamic adjustments within panel datasets so that oscillations in the short term and relationships in equilibrium in the long term are well captured to enhance the robustness and reliability of the analysis.

When cross-sectional dependence is present in panel data, second-generation estimators are necessary to address both heterogeneity and interdependence across units. The PMG estimator is unsuitable in such scenarios, as it assumes homogeneity in long-run coefficients, leading to biased estimates when the data exhibits cross-sectional dependence. To overcome this limitation, the MG estimator, introduced by Pesaran and Smith (1995), is used. Unlike PMG, the MG estimator averages coefficients obtained from individual regressions, allowing for full heterogeneity across panel units.

To further address the challenges posed by cross-sectional dependence and heterogeneity, advanced methods such as the CCEMG and AMG estimators are employed. CCEMG accounts for unobserved factors that influence all units in the panel, while AMG extends this approach by incorporating dynamic interactions

among units. Both estimators rely on standard Ordinary Least Squares (OLS) techniques to compute coefficients, ensuring robust estimation under heterogeneous conditions.

The general specification for these models is given as:

$$y_{i,t} = \alpha + \beta x_{i,t} + \theta z_{k,i,t} + u_{i,t} \quad (15)$$

where the error term is defined as:

$$u_{i,t} = \mu_i + \lambda_i f_t + \epsilon_{i,t} \quad (16)$$

In this representation, $y_{i,t}$ is the dependent variable, reflecting key metrics such as energy intensity for different energy sources. The term $x_{i,t}$ includes the independent variables, while $z_{k,i,t}$ represents control variables relevant to the analysis. The error term $u_{i,t}$ is composed of μ_i , which captures individual-specific effects; $\lambda_i f_t$, accounting for unobserved common factors; and $\epsilon_{i,t}$, representing the idiosyncratic error component.

This methodology thereby does consider cross-sectional dependence and heterogeneity issues with the inclusion of estimators like CCEMG and AMG in its design to present more reliable and accurate results related to panel data model estimations.

Proposed by Pesaran (2006), the CCEMG estimator and the AMG estimator developed by Eberhardt and Teal (2010) represent sophisticated approaches aimed at dealing with cross-sectional dependence and varied slope coefficients. The CCEMG method extends the traditional MG framework by performing group-specific OLS regressions and incorporating cross-sectional averages of dependent as well as independent variables. In this framework, the unobservable common factors are treated as nuisance parameters, focusing the analysis solely on the variables of interest.

Positioned as an alternative to CCEMG, the AMG estimator advances the framework by explicitly capturing the shared dynamic processes among units. Implemented in three distinct phases, this approach first applies first-difference OLS to a pooled regression model—including year dummies to account for temporal effects—to estimate the common dynamic component. Secondly, the estimated dynamic process is incorporated into group-specific regressions to refine the results. Lastly, in the third phase, the parameters obtained from each group-specific

regression are averaged across all units, mirroring the methodology employed in MG and CCEMG estimators.

The CCEMG estimator proxies unobserved common factors with cross-sectional averages, while the AMG estimator explicitly models such dynamics; therefore, this approach has greater flexibility and precision in modeling cross-sectional dependence and slope heterogeneity.

2.4. RESULTS

2.4.1. Data 1: All 67 Countries

Table 1: Descriptive Statistics

Variable	Observation	Mean	Standard Deviation	Minimum Value	Maximum Value
ln_ei	1,742	15.492	0.539	14.043	19.615
ln_rei	1,742	11.971	3.080	0.000	18.237
ln_nei	1,742	15.337	0.584	13.758	19.324
ctfp	1,742	0.759	0.226	0.055	1.526
ln_crude_prices	1,742	4.357	0.664	0.787	5.977
urbanization	1,742	0.713	0.171	0.182	1.000
lnhc	1,742	1.049	0.193	0.342	1.471
irr	1,742	0.109	0.065	0.010	0.483
delta	1,742	0.043	0.010	0.021	0.087

Source: Created by the author.

Above are the descriptive statistics of key variables that have been used in analyzing energy intensity across 67 countries and 26 years from 1994 to 2019. Summary statistics pertaining to all variables in the underlying dataset comprising

1,742 observations are shown in Table 1 above. These statistics give a preliminary understanding of the distribution of data and an idea about the characteristics of the variables under consideration.

First, the dependent variables are \ln_{ei} , \ln_{rei} , and \ln_{nei} , representing total energy intensity, renewable energy intensity, and nonrenewable energy intensity, respectively. Their distribution is relatively dense around the mean of 15.49, 11.97, and 15.34, respectively. Their standard deviations are around 0.54, 3.08, and 0.58, respectively. These data contain some variability, with the deviation being particularly significant in the renewable energy intensity variable. This variation in these energy intensities is quite widespread across different countries, as can be seen from the minimum and maximum values that these variables take: the maximum value of total energy intensity is 19.61, while the minimum value of renewable energy intensity goes down to approximately 0.

The average total factor productivity level at current PPPs (ctfp) is 0.76, with a standard deviation of 0.23. This suggests that most of the countries included in this sample are at a middle level of technological development. However, some outliers have a very low or very high level of TFP.

Crude oil price (\ln_{crude_prices}) is positively skewed. It could be that the prices which countries in the sample face vary within a wide range given its mean value is 4.36, minimum of 0.79 and a maximum of 5.98.

The mean value of urbanization variable stands at 0.71. That means approximately 71% of the population, on average, lives in the cities of those countries. It means highly urbanized countries, but overall minimum of 0.18 and a maximum of 1 implies that there are variations across countries in their urbanization rates.

The human capital (\ln_{hc}) and the real internal rate of return (\ln_{irr}) are less dispersed with means of 1.05 and 0.11, respectively. The minimum and maximum values of human capital imply that in some countries, it is low, while in others, it is high because they have very well-educated labor forces. The \ln_{irr} ranges between 0.01 and 0.48, indicating divergence across countries in the productivity of capital.

Finally, the delta variable, has a mean value of 0.04 with a minimum and maximum of 0.02 and 0.09, respectively, and thus reasonably moderate variation in capital depreciation across countries.

When one embarks on analyzing the distribution of such variables, several patterns emerge. Evidently, energy intensity measures, \ln_{ei} , \ln_{rei} , and \ln_{nei} are all right-skewed, especially for renewable energy intensity, \ln_{rei} , where a minimum value of 0 indicates that a substantial fraction of the sample countries have practically no renewable energy use compared to their total energy usage. This could also mean that while energy intensity generally might be normally distributed, once renewable energy intensity is added as another measure, it is skewed owing to the congregation of low values in countries which are still making their transition toward renewable energy sources.

Variables such as $ctfp$ and \ln_{crude_prices} are much closer to normal, although they do also represent some degree of skewness; the latter, $ctfp$, is somewhat positively skewed because several countries have very high levels of total factor productivity. This sort of characteristic is typical for this data set since it is large and variable across countries with extremely divergent stages of economic and technological development.

In general, the descriptive statistics outlined the characteristics of this dataset.

Table 2: Tests for Cross-Sectional Dependence and Slope Heterogeneity

Dependent Variable	\ln_{ei}		\ln_{rei}		\ln_{nei}	
	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects
Pesaran's CD	157.426*** (0.0000)	158.831*** 0.0000	1.601 0.1095	1.595 0.1106	168.263*** 0.0000	169.116*** 0.0000
Frees' test	37.046 (0.0996)*** (0.1297)** (0.1870)*	37.151 (0.0996)*** (0.1297)** (0.1870)*	13.696 (0.0996)*** (0.1297)** (0.1870)*	13.782 (0.0996)*** (0.1297)** (0.1870)*	36.966 (0.0996)*** (0.1297)** (0.1870)*	37.009 (0.0996)*** (0.1297)** (0.1870)*
Friedman's test	1082.884*** (0.0000)	1093.411*** 0.0000	35.200 0.9993	34.802 0.9994	1163.744*** 0.0000	1167.297*** 0.0000

Note 1: In all three tests (Pesaran's CD, Frees' test, and Friedman's test), the null hypothesis assumes cross-sectional independence.

Note 2: The optimal lag and lead lengths (both set to 1) are chosen according to the Akaike Information Criterion (AIC), and the optimal Bartlett kernel window width is specified as 3.

Note 3: The values in parentheses indicate p-values derived from (a) Pesaran (2004) and (c) Friedman's (1937) statistics. Significance Levels: The symbols ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively.

Source: Created by the author.

Results of the tests for cross-sectional dependence and slope heterogeneity that will help us decide on the appropriate econometric models for the study of energy intensity are reported in Table 2. These are all inclusive of the degree of cross-sectional dependence and slope heterogeneity within the framework of countries in the sample—Pesaran's CD test, Frees' test, and Friedman's test.

The Cross-Sectional Dependence test results by Pesaran (2004), indicate that all three dependent variables, \ln_{ei} , \ln_{rei} , and \ln_{nei} , are characterized by significant cross-sectional dependence using the Fixed-Effects and Random-Effects regressions. More specifically, the test statistics computed from \ln_{ei} (157.426), \ln_{rei} (1.601), and \ln_{nei} (168.263) are statistically significant at the 1% level, given that the p-values are 0.000, except \ln_{rei} . Therefore, such results confirm a substantial degree of cross-sectional dependence across the countries in the sample, implying that the measures of energy intensity are interrelated across countries. In this respect, the countries' patterns of energy usage are likely to depend on the same global or regional factors that involve changes in technology or international economic linkages.

That is based on heterogeneity in the slopes across the cross-sections. The test has produced very mixed evidence for slope heterogeneity: the \ln_{ei} and \ln_{nei} test statistics were 37.046 and 36.966, at 10%, correspondingly close to 0.100 probability values; the \ln_{rei} had much weaker evidence with test statistics of 13.696 and 13.782 and yielded higher probabilities, 0.1870 and 0.1297, correspondingly. Therefore, the case of renewable energy intensity allows one to accept the assumption of homogeneity across slopes more reasonably than in the case of total and non-renewable energy intensity, where there is some dispersion across country-specific effects.

Friedman test tests the overall heterogeneity in slope coefficients, which is very significant for both total and non-renewable energy intensities as dependent

variables. The test statistics on \ln_ei 1082.884 and \ln_nei 1163.744 are all significant at 1%, respectively, while the value of p-value is 0.0000. On the other hand, the test statistic for renewable energy intensity, \ln_rei , is very low, the value being 35.200 whereas the respective p-value is 0.999 that shows there is no heterogeneity. As a result, it can be said that due to heterogeneity, countries are significantly different from each other in their determinants of energy intensity particularly for the case of total and non-renewable energy intensity, whereas renewable energy intensity can have homogeneous effects among the nations.

Table 3: Second-Generation Unit Root Tests (Pesaran, 2007)

Variables	CIPS (levels)	CIPS I(1)	CIPS I(2)
\ln_ei	-2.143**	-4.649***	-
\ln_rei	-2.086**	-4.828***	-
\ln_nei	-2.142**	-4.637***	-
ctfp	-1.068	-3.830***	-
$\ln_crude_p\sim s$	-1.771	-4.085***	-
urbanization	-1.257	-1.542	-4.057***
lnhc	-1.740	-2.252***	-
irr	-1.426	-4.258***	-
delta	-2.795***	-	-

Note: The CIPS tests operate under the null hypothesis that each series is non-stationary. Significance Levels: The symbols ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively

Source: Created by the author.

The results from Pesaran (2007) second-generation unit root tests provide important insights into the stationarity properties of the variables used in this study. In particular, the tests help determine whether the variables are stationary at their levels or whether they need to be differenced. The CIPS test results indicate that most of the variables in the model are integrated of order 1 (I(1)), meaning that they become stationary after first differencing.

For the energy intensity variables—total energy intensity (\ln_ei), renewable energy intensity (\ln_rei), and nonrenewable energy intensity (\ln_nei)—the results show that all three variables are non-stationary at their levels, with CIPS values of -2.143, -2.086, and -2.142, respectively. However, these variables become stationary at the first difference (I(1)) at the 1% significance level, with CIPS values of -4.649,

-4.828, and -4.637, respectively. This suggests that these variables exhibit unit roots in their levels but are integrated of order 1. As a result, further analysis should be conducted using the first-differenced data for these variables to avoid the risk of spurious results.

The variable for total factor productivity (ctfp) shows a CIPS value of -1.068 at levels, which is not statistically significant, indicating that total factor productivity is non-stationary at the level. However, after first differencing, the series becomes stationary at the 1% significance level, with a CIPS value of -3.830. This indicates that total factor productivity is integrated of order 1 (I(1)) and requires first differencing for stationarity.

Crude oil prices, represented by \ln_crude_prices , also exhibit non-stationarity at the level (CIPS value of -1.771), but become stationary in the first difference with a CIPS value of -4.085 at the 1% significance level. This suggests that crude oil prices are integrated of order 1 (I(1)) and confirms that the first-differenced data should be used in regression models to ensure stationarity.

Urbanization, as measured by the proportion of the population living in urban areas, shows a CIPS value of -1.257 in levels, which is not significant, and remains non-stationary in the first difference (CIPS value of -1.542). However, it becomes stationary at the 1% significance level in the second differences (CIPS value of -4.057). This indicates that urbanization is integrated of order 2 (I(2)), meaning it requires second differencing to achieve stationarity.

The human capital variable ($\ln hc$) is similarly non-stationary in levels (CIPS value of -1.740), but it becomes stationary in the first differences at the 1% significance level (CIPS value of -2.252), indicating that it is integrated of order 1 (I(1)).

The real IRR shows a CIPS value of -1.426 in levels, suggesting that it is non-stationary. However, it becomes stationary in the first difference at the 1% significance level (CIPS value of -4.258), indicating that the variable is also integrated of order 1 (I(1)).

Finally, the depreciation rate of capital (δ) is stationary in levels, with a CIPS value of -2.795. This indicates that it is integrated of order 0 (I(0)), meaning that it does not require differencing for stationarity.

Table 4: Panel Cointegration Tests (Westerlund, 2007)

Dependent Variable	ln_ei		ln_rei		ln_nei	
	Value	p-value	Value	p-value	Value	p-value
$G\tau$	-3.474	0.000	-3.198	0.000	-3.388	0.000
$G\alpha$	-25.734	0.000	-19.154	0.000	-24.466	0.000
$P\tau$	-23.199	0.000	-16.603	0.790	-23.056	0.000
$P\alpha$	-18.036	0.000	-10.244	0.038	-18.156	0.000

*** and ** represent significance at 1%, 5%.

Source: Created by the author.

In the context of the panel cointegration tests, one of the key independent variables under consideration is TFP, denoted as $ctfp$. TFP is a crucial variable because it reflects the technological advancement and efficiency improvements within an economy, which are central to understanding variations in energy intensity across countries.

The $ctfp$ variable shows significant results in the Westerlund panel cointegration tests, particularly for the total energy intensity (ln_ei) and nonrenewable energy intensity (ln_nei) models, where all test statistics ($G\tau$, $G\alpha$, $P\tau$, $P\alpha$) reject the null hypothesis of no cointegration at the 1% significance level. This suggests that TFP is strongly linked with energy intensity measures in the long run, highlighting that improvements in productivity and technological progress contribute to changes in energy usage patterns.

For total energy intensity (ln_ei), the results indicate that technological progress, as measured by TFP, is part of the long-term equilibrium relationship between energy consumption and macroeconomic factors. This suggests that increases in TFP, which represent improvements in efficiency and technology, are associated with reductions in total energy intensity over time. The presence of a stable, long-term relationship between TFP and total energy intensity underscores the role of technological innovation in decoupling economic growth from energy consumption.

Similarly, for nonrenewable energy intensity (\ln_nei), the rejection of the null hypothesis of no cointegration further reinforces the idea that technological advancements captured by TFP are significantly related to reductions in nonrenewable energy use in the long run. As economies advance technologically, they are expected to rely less on energy-intensive, carbon-heavy sources of energy, such as coal and oil, thus reducing nonrenewable energy intensity. This relationship between TFP and nonrenewable energy intensity supports the notion that technological progress is key to driving a transition away from fossil fuels towards more sustainable energy sources.

For renewable energy intensity (\ln_rei), the evidence is slightly weaker. While the $G\tau$, and $G\alpha$ statistics indicate cointegration at the 1% level, the $P\tau$ statistic fails to reject the null hypothesis of no cointegration, suggesting that the relationship between TFP and renewable energy intensity may not be as strong or stable as with total and nonrenewable energy intensity. However, the significant result in the test indicates that there is still some long-term relationship, albeit with less robustness compared to the other two energy intensity measures.

In summary, TFP plays a critical role in explaining the long-run dynamics of energy intensity, particularly for total and nonrenewable energy intensity. The strong evidence of cointegration with these variables suggests that technological progress is a key factor in driving improvements in energy efficiency and promoting the transition towards less energy-intensive and more sustainable economic systems. These findings highlight the importance of fostering technological advancements and productivity growth as part of energy policy strategies aimed at reducing energy intensity and achieving sustainability goals.

Table 5: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	\ln_ei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ctfp$	-0.846*** (0.122)	-0.745*** (0.090)	-0.634*** (0.114)	-0.722*** (0.146)	-0.782*** (0.164)	-0.642*** (0.965)	-0.440*** (0.103)
\ln_crude_prices		-0.044					-0.016

	(0.040)		(0.039)
urbanization	-3.765		-5.975
	(3.365)		(5.939)
lnhc		-0.400	-0.056
		(1.227)	(2.781)
irr		-0.516	-0.623
		(0.592)	(0.389)
delta			-16.605***
			(4.527)
			(6.364)

Source: Created by the author.

The results presented in Table 5 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is total energy intensity (\ln_ei). The coefficient of total factor productivity ($ctfp$) consistently displays a negative and statistically significant relationship with energy intensity across all estimated models, underscoring the importance of technological progress in enhancing energy efficiency.

In the first model, where $ctfp$ is the sole explanatory variable, the coefficient is -0.846 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.846% reduction in total energy intensity.

In the second model, which introduces the variable for crude oil prices (\ln_crude_prices), the $ctfp$ coefficient slightly decreases to -0.745, remaining statistically significant at the 1% level. However, the coefficient for crude oil prices itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the third model, with the addition of urbanization as a control variable, the negative impact of $ctfp$ remains significant at the 1% level, with a coefficient value of -0.634. However, the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fourth model includes human capital (\lnhc) as an explanatory variable. Here, $ctfp$ continues to exhibit a statistically significant coefficient at the 1% level, equal to -0.722. However, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fifth model incorporates the internal rate of return (irr) into the analysis. The negative impact of ctfp persists, with a coefficient of -0.782, statistically significant at the 1% level. However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the sixth model, the depreciation rate of capital (δ) is introduced. The ctfp coefficient continues to be statistically significant at the 1% level (-0.642), although slightly reduced compared to previous models. Notably, δ shows a strong negative and statistically significant relationship at the 1% level.

In the seventh and final model, where all variables are included simultaneously, the ctfp coefficient remains negative with the coefficient of -0.440 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.440% reduction in total energy intensity. The capital depreciation rate (δ) continues to display a statistically significant negative relationship at the 10% significance level, suggesting that higher capital depreciation rates contribute meaningfully to reductions in energy intensity. However, other variables, including crude oil prices, urbanization, human capital, and internal rate of return, remain statistically insignificant in this comprehensive model specification.

In summary, the results from the Panel ARDL-CCEMG estimator consistently affirm that total factor productivity significantly reduces total energy intensity across various model specifications. Additionally, the depreciation rate of capital emerges as an influential factor in reducing energy intensity in specific model specifications. Conversely, crude oil prices, urbanization, human capital, and internal rate of return do not exhibit statistically significant impacts in this analysis. These findings highlight the central role of technological progress, reflected through total factor productivity, in driving sustainable reductions in energy intensity.

Table 6: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	ln_rei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.303 (0.485)	0.197 (0.669)	-0.410 (0.894)	-1.105*** (0.388)	-0.665* (0.400)	-0.229 (0.643)	0.108 (0.601)
ln_crude_prices		0.083 (0.369)					0.027 (0.179)
urbanization			-16.753 (16.874)				23.786 (75.116)
lnhc				-15.055 (12.295)			-19.161 (25.559)
irr					0.353 (1.867)		-1.646 (4.360)
delta						-34.749** (14.897)	-44.524* (23.493)

Source: Created by the author.

The results presented in Table 6 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is renewable energy intensity (ln_rei). The coefficient of total factor productivity (ctfp) displays varying significance across different model specifications.

In the first model, where ctfp is the sole explanatory variable, the coefficient is -0.303 and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the second model, which introduces the variable for crude oil prices (ln_crude_prices), the coefficient for ctfp becomes positive (0.197) but remains statistically insignificant. However, the coefficient for crude oil prices itself is also statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the third model, with the addition of urbanization as a control variable, the ctfp coefficient returns negative (-0.410) but remains statistically insignificant. Similarly, the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The fourth model includes human capital (lnhc) as an explanatory variable. Here, ctfp exhibits a statistically significant negative coefficient at the 1% level, equal to -1.105, indicating that a one-unit increase in total factor productivity is associated with a 1.105% reduction in renewable energy intensity. However, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The fifth model incorporates the internal rate of return (irr) into the analysis. The negative impact of ctfp persists, with a coefficient of -0.665, statistically significant at the 10% level. However, the coefficient for the internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the sixth model, the depreciation rate of capital (δ) is introduced. The ctfp coefficient is negative (-0.229) but statistically insignificant. Notably, δ shows a statistically significant negative relationship at the 5% level.

In the seventh and final model, where all variables are included simultaneously, the coefficient for ctfp turns positive (0.108) and remains statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context. The capital depreciation rate (δ) continues to display a statistically significant negative relationship at the 10% significance level, suggesting that higher capital depreciation rates contribute meaningfully to reductions in renewable energy intensity. However, other variables, including crude oil prices, urbanization, human capital, and internal rate of return, remain statistically insignificant in this comprehensive model specification.

In summary, the results from the Panel ARDL-CCEMG estimator provide limited evidence for the role of total factor productivity in influencing renewable energy intensity, with statistically significant effects observed only in specific model specifications. The depreciation rate of capital emerges as a consistent determinant, exerting significant negative effects on renewable energy intensity in certain contexts. Conversely, crude oil prices, urbanization, human capital, and internal rate of return do not demonstrate statistically significant impacts.

Table 7: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	ln_nei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.812*** (0.129)	-0.709*** (0.097)	-0.595*** (0.124)	-0.658*** (0.150)	-0.722*** (0.170)	-0.661*** (0.095)	-0.456*** (0.106)
ln_crude_prices		-0.076* (0.041)					-0.040 (0.037)
urbanization			-4.273 (3.557)				-4.529 (5.366)
lnhc				0.360 (1.338)			1.514 (3.143)
irr					-0.750 (0.603)		-0.698* (0.423)
delta						13.879*** (5.221)	-3.880 (6.825)

Source: Created by the author.

The results presented in Table 7 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is nonrenewable energy intensity (ln_nei). The coefficient of total factor productivity (ctfp) consistently demonstrates a negative and statistically significant relationship with nonrenewable energy intensity across all models, highlighting the role of technological progress in reducing nonrenewable energy consumption.

In the first model, where ctfp is the only explanatory variable, the coefficient is -0.812 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.812% reduction in nonrenewable energy intensity.

In the second model, which introduces crude oil prices (ln_crude_prices), the ctfp coefficient remains significant at the 1% level with a slightly reduced magnitude (-0.709). The coefficient for crude oil prices is statistically significant at the 10% level, suggesting limited evidence for its negative effect on nonrenewable energy intensity.

In the third model, with urbanization added as a control variable, the ctfp coefficient is -0.595, statistically significant at the 1% level. However, the coefficient

for urbanization itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The fourth model includes human capital ($\ln hc$) as an explanatory variable. Here, $ctfp$ continues to exhibit a statistically significant coefficient at the 1% level (-0.658). However, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The fifth model incorporates the internal rate of return (irr) variable. The $ctfp$ coefficient remains statistically significant at the 1% level with a value of -0.722. However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the sixth model, with the inclusion of capital depreciation rate (δ), the negative and statistically significant coefficient of $ctfp$ persists at the 1% level (-0.661). Notably, δ displays a statistically significant positive relationship at the 1% significance level.

In the seventh and final model, where all variables are included simultaneously, the $ctfp$ coefficient remains statistically significant at the 1% level, although its magnitude decreases to -0.456, indicating that a one-unit increase in total factor productivity is associated with a 0.456% reduction in nonrenewable energy intensity. Additionally, the coefficient for internal rate of return becomes statistically significant at the 10% level, exhibiting a negative relationship with nonrenewable energy intensity. However, other variables, including crude oil prices, urbanization, human capital, and δ remain statistically insignificant in this comprehensive model specification.

In summary, the results from the Panel ARDL-CCEMG estimator strongly indicate that total factor productivity significantly reduces nonrenewable energy intensity across various model specifications. The internal rate of return and capital depreciation rate emerge as significant determinants in specific contexts. Conversely, crude oil prices, urbanization, and human capital consistently fail to show statistically significant effects on nonrenewable energy intensity. These findings

emphasize the critical role of technological progress, as reflected through total factor productivity, in effectively decreasing nonrenewable energy intensity.

Table 8: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_ei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.637*** (0.123)	-0.820*** (0.100)	-0.667*** (0.118)	-0.592*** (0.122)	-0.644*** (0.170)	-0.553*** (0.105)	-0.453*** (0.104)
ln_crude_prices		-0.239*** (0.026)					-0.134*** (0.027)
urbanization			-4.427* (2.383)				-2.060 (2.380)
lnhc				-1.352*** (0.490)			-1.056 (0.678)
irr					-0.491 (0.495)		-0.577 (0.359)
delta						-16.323*** (5.129)	-16.455*** (4.438)
Common	0.987** (0.092)	1.037*** (0.088)	0.712*** (0.121)	0.672*** (0.116)	0.961*** (0.084)	1.031*** (0.139)	0.489*** (0.100)

Source: Created by the author.

The results presented in Table 8 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is total energy intensity (ln_ei). The coefficient of total factor productivity (ctfp) consistently exhibits a negative and statistically significant relationship with energy intensity across all estimated models, highlighting the importance of technological progress in enhancing energy efficiency.

In the first model, where ctfp is the sole explanatory variable, the coefficient is -0.637 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.637% reduction in total energy intensity.

In the second model, which introduces the variable for crude oil prices (ln_crude_prices), the ctfp coefficient becomes slightly stronger (-0.820), remaining statistically significant at the 1% level. Additionally, the coefficient for crude oil

prices itself is negative and statistically significant at the 1% level, indicating clear evidence that higher crude oil prices contribute to reductions in total energy intensity.

In the third model, with urbanization added as a control variable, the negative impact of ctfp remains significant at the 1% level, with a coefficient value of -0.667. The coefficient for urbanization itself is negative and statistically significant at the 10% level, providing evidence that increased urbanization contributes modestly to reductions in total energy intensity.

The fourth model introduces human capital (lnhc) as an explanatory variable. Here, ctfp continues to exhibit a statistically significant negative coefficient at the 1% level (-0.592). Additionally, the coefficient for human capital itself is negative and statistically significant at the 1% level, suggesting strong evidence that increases in human capital reduce total energy intensity.

The fifth model incorporates the internal rate of return (irr). The negative effect of ctfp persists (-0.644) and remains statistically significant at the 1% level. However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the sixth model, with the depreciation rate of capital (delta) added, the ctfp coefficient continues to display a significant negative relationship (-0.553) at the 1% level. Delta itself shows a strong negative and statistically significant relationship at the 1% level, highlighting its important role in reducing total energy intensity.

In the seventh and final model, where all variables are included simultaneously, the ctfp coefficient remains negative and statistically significant at the 1% level (-0.453), indicating that a one-unit increase in total factor productivity is associated with a 0.453% reduction in total energy intensity. Crude oil prices and capital depreciation rates also exhibit statistically significant negative relationships at the 1% level, further affirming their relevance in reducing energy intensity. However, urbanization, human capital, and internal rate of return do not demonstrate statistically significant impacts in this comprehensive model specification.

Finally, the Common dynamic process term is included in each model, consistently demonstrating statistical significance. In model 7, the coefficient of the Common dynamic process (0.489***) confirms the stability and consistency of the relationships observed over time across countries.

In summary, the Panel ARDL-AMG estimator results robustly indicate that total factor productivity significantly reduces total energy intensity across all model specifications. Crude oil prices, urbanization, human capital, and capital depreciation rate also emerge as significant determinants in certain contexts. Conversely, the internal rate of return consistently lacks statistically significant effects. These findings reinforce the central role of technological progress, represented by total factor productivity, in effectively driving sustainable reductions in energy intensity.

Table 9: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_rei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	0.119 (0.850)	-0.198 (0.445)	-0.045 (0.772)	-1.051*** (0.390)	-0.064 (0.891)	0.167 (0.698)	0.156 (0.692)
ln_crude_prices		-0.063 (0.100)					-0.121 (0.095)
urbanization			-14.478 (10.310)				-6.715 (17.731)
lnhc				2.526 (1.770)			-1.955 (3.090)
irr					0.185 (2.438)		-0.679 (1.594)
delta						-29.089** (14.695)	-45.098** (17.852)
Common dynamic process	1.032*** (0.363)	0.946*** (0.301)	0.954*** (0.315)	1.028*** (0.362)	1.093*** (0.349)	1.045*** (0.287)	1.012*** (0.387)

Source: Created by the author.

The results presented in Table 9 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is renewable energy intensity (ln_rei). The coefficient of total factor productivity (ctfp) displays limited significance across various models, providing mixed evidence for its influence on renewable energy intensity.

In the first model, where ctfp is the sole explanatory variable, the coefficient is positive (0.119) and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the second model, which introduces crude oil prices (\ln_crude_prices), the $ctfp$ coefficient turns negative (-0.198) but remains statistically insignificant. Additionally, the coefficient for crude oil prices itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the third model, with urbanization as an added variable, the coefficient for $ctfp$ remains negative (-0.045) but statistically insignificant. Similarly, the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The fourth model includes human capital ($\ln hc$) as an explanatory variable. Here, $ctfp$ exhibits a statistically significant negative coefficient at the 1% level (-1.051), indicating that a one-unit increase in total factor productivity is associated with a 1.051% reduction in renewable energy intensity. However, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The fifth model introduces the internal rate of return (irr) into the analysis. The coefficient for $ctfp$ turns insignificant (-0.064), indicating limited evidence for its effect on renewable energy intensity. Additionally, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the sixth model, the depreciation rate of capital (δ) is added. The $ctfp$ coefficient becomes positive (0.167) but statistically insignificant. However, δ displays a strong negative and statistically significant relationship at the 5% level, indicating its relevance in reducing renewable energy intensity.

In the seventh and final model, where all variables are included simultaneously, the $ctfp$ coefficient remains positive (0.156) and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity. Nevertheless, the depreciation rate of capital (δ) continues to show a statistically significant negative relationship at the 5% level, highlighting its robust role in decreasing renewable energy intensity. Other variables, including crude oil prices, urbanization, human capital, and internal rate of return, remain statistically insignificant.

Finally, the Common dynamic process term is included in each model and consistently exhibits statistical significance. In model 7, the coefficient of the Common dynamic process (1.012***) further supports the stability and consistency of the relationships observed over time across countries.

In summary, the results from the Panel ARDL-AMG estimator provide limited and mixed evidence regarding the role of total factor productivity in influencing renewable energy intensity, with significant results appearing only in a specific model. The capital depreciation rate consistently emerges as an influential determinant in reducing renewable energy intensity. Conversely, crude oil prices, urbanization, human capital, and internal rate of return do not display statistically significant impacts in this analysis.

Table 10: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_nei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.591*** (0.131)	-0.789*** (0.111)	-0.636*** (0.128)	-0.540*** (0.128)	-0.571*** (0.180)	-0.573*** (0.112)	-0.440*** (0.120)
ln_crude_prices		-0.255*** (0.026)					-0.152*** (0.028)
urbanization			-4.885** (2.488)				-1.871 (2.576)
lnhc				-0.877 (0.541)			-0.949 (0.652)
irr					-1.005* (0.545)		-0.843** (0.356)
delta						-11.992* (6.164)	-13.602*** (5.119)
Common dynamic process	0.983*** (0.086)	1.015*** (0.082)	0.723*** (0.117)	0.728*** (0.098)	0.975*** (0.079)	1.067*** (0.128)	0.540*** (0.099)

Source: Created by the author.

The results presented in Table 10 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is nonrenewable energy intensity (ln_nei). The coefficient of total factor productivity (ctfp) consistently exhibits a negative and statistically significant relationship with nonrenewable energy intensity across all

estimated models, highlighting the critical role of technological progress in reducing nonrenewable energy consumption.

In the first model, where *ctfp* is the sole explanatory variable, the coefficient is -0.591 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.591% reduction in nonrenewable energy intensity.

In the second model, which includes crude oil prices (*ln_crude_prices*), the negative impact of *ctfp* strengthens to -0.789, remaining statistically significant at the 1% level. Additionally, the coefficient for crude oil prices itself is negative and statistically significant at the 1% level, indicating clear evidence that higher crude oil prices contribute to reductions in nonrenewable energy intensity.

In the third model, urbanization is added as a control variable, and the coefficient for *ctfp* remains statistically significant at the 1% level (-0.636). Urbanization itself also demonstrates a statistically significant negative relationship at the 5% level, providing evidence that increased urbanization contributes meaningfully to reductions in nonrenewable energy intensity.

The fourth model incorporates human capital (*lnhc*) as an explanatory variable. Here, the negative impact of *ctfp* persists, with a coefficient of -0.540, statistically significant at the 1% level. However, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the fifth model, the internal rate of return (*irr*) is introduced. The *ctfp* coefficient remains statistically significant at the 1% level (-0.571). Additionally, the coefficient for the internal rate of return itself is negative and statistically significant at the 10% level, providing modest evidence for its role in reducing nonrenewable energy intensity.

The sixth model adds the depreciation rate of capital (*delta*), and the *ctfp* coefficient remains negative and statistically significant at the 1% level (-0.573). The *delta* coefficient is negative and statistically significant at the 10% level, supporting its role in reducing nonrenewable energy intensity.

In the seventh and final model, which includes all variables simultaneously, the *ctfp* coefficient is statistically significant at the 1% level (-0.440), indicating that

a one-unit increase in total factor productivity is associated with a 0.440% reduction in nonrenewable energy intensity. Moreover, crude oil prices, internal rate of return, and capital depreciation rate (δ) exhibit statistically significant negative relationships, further affirming their relevance in reducing nonrenewable energy intensity. However, urbanization and human capital remain statistically insignificant in this comprehensive model specification.

Finally, the Common dynamic process term is included in each model and consistently exhibits statistical significance. In model 7, the coefficient of the Common dynamic process (0.540***) further confirms the stability and consistency of the relationships observed over time across countries.

In summary, the Panel ARDL-AMG estimator results robustly confirm that total factor productivity significantly reduces nonrenewable energy intensity across various model specifications. Crude oil prices, urbanization, internal rate of return, and capital depreciation rate also emerge as influential determinants in specific contexts. Conversely, human capital does not display statistically significant effects in this analysis. These findings strongly emphasize the critical role of technological progress, represented by total factor productivity, in effectively driving reductions in nonrenewable energy intensity.

2.4.2. Data 2: Annex I

Table 11: Descriptive Statistics

Variable	Observation	Mean	Standard Deviation	Minimum Value	Maximum Value
ln_ei	988	15.477	0.449	14.115	16.985
ln_rei	988	12.748	1.918	0.000	16.316
ln_nei	988	15.284	0.486	13.917	16.957
ctfp	988	0.825	0.203	0.259	1.491
ln_crude_prices	988	4.166	0.588	2.611	5.833
urbanization	988	0.734	0.115	0.504	0.980
lnhc	988	1.147	0.124	0.612	1.348
Irr	988	0.084	0.049	0.010	0.368

delta	988	0.040	0.008	0.021	0.073
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Source: Created by the author.

Table 11 summarizes the descriptive statistics for key variables in the sample of Annex 1 countries. The dataset includes 988 observations across all variables.

The dependent variables \ln_ei (total energy intensity), \ln_rei (renewable energy intensity), and \ln_nei (nonrenewable energy intensity) exhibit relatively stable distributions. The mean of \ln_ei is 15.477, with a standard deviation of 0.449, suggesting moderate variation in total energy intensity across Annex 1 countries. \ln_rei has a mean of 12.748, with a higher standard deviation of 1.918, reflecting greater variability in renewable energy intensity. In contrast, \ln_nei has a mean of 15.284, with a standard deviation of 0.486, indicating relatively consistent nonrenewable energy intensity values.

The $ctfp$ (total factor productivity) variable, with a mean of 0.826 and a standard deviation of 0.203, shows a moderate level of technological progress across Annex 1 countries, ranging from 0.259 to 1.491.

The \ln_crude_prices (crude oil prices) variable has a mean of 4.166 and a standard deviation of 0.588, indicating some fluctuation in crude oil prices across countries. The urbanization variable has a mean of 0.734, showing that the average Annex 1 country has a significant proportion of its population living in urban areas, with values ranging from 0.504 to 0.980.

The human capital index ($\ln hc$) has a mean of 1.147, showing good levels of human capital, with a relatively low standard deviation of 0.124.

The real IRR has a mean of 0.084 and a standard deviation of 0.049, suggesting that the rate of return on capital varies across Annex 1 countries. The δ (depreciation rate of capital) has a mean of 0.040, with a standard deviation of 0.008, indicating some variation in the depreciation rate across countries.

Table 12: Tests for Cross-Sectional Dependence and Slope Heterogeneity

Dependent Variable	ln_ei		ln_rei		ln_nei	
	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects
Pesaran's CD	116.263*** (0.0000)	116.616*** 0.0000	-0.126 0.8995	0.209 0.8346	127.808*** 0.0000	128.776*** 0.0000
Frees' test	31.750 (0.0996)*** (0.1297)** (0.1870)*	31.822 (0.0996)*** (0.1297)** (0.1870)*	11.589 (0.0996)*** (0.1297)** (0.1870)*	12.498 (0.0996)*** (0.1297)** (0.1870)*	32.131 0.0996*** 0.1297** 0.1870*	32.456 (0.0996)*** (0.1297)** (0.1870)*
Friedman's test	818.255*** (0.0000)	819.087*** 0.0000	23.465 0.9591	26.271 0.9055	893.717*** 0.0000	898.169*** 0.0000

Note 1: In all three tests (Pesaran's CD, Frees' test, and Friedman's test), the null hypothesis assumes cross-sectional independence.
Note 2: The optimal lag and lead lengths (both set to 1) are chosen according to the Akaike Information Criterion (AIC), and the optimal Bartlett kernel window width is specified as 3.
Note 3: The values in parentheses indicate p-values derived from (a) Pesaran (2004) and (c) Friedman's (1937) statistics.
Significance Levels: The symbols ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively.

Source: Created by the author.

The results of the cross-sectional dependence and slope heterogeneity tests for ln_ei (total energy intensity), ln_rei (renewable energy intensity), and ln_nei (nonrenewable energy intensity) are presented using Pesaran's CD test, Frees' test, and Friedman's test.

For ln_ei and ln_rei, the CD test statistics are significant at the 1% level (116.263 and 116.616, respectively), indicating strong evidence of cross-sectional dependence. This means that the energy intensity measures across countries are correlated, which suggests that global or regional factors may influence energy usage patterns. For ln_nei, the CD test statistic is also significant (127.808), further supporting the presence of cross-sectional dependence.

The results of Frees' test also suggest significant heterogeneity across countries for ln_ei and ln_rei with test statistics of 31.750 and 31.822 for Fixed and Random Effects models, respectively, both significant at the 1% level. For ln_nei, the Frees' test statistic is 32.131 and significant at the 1% level, indicating that there is variation in the slope coefficients across countries.

The results of Friedman’s test for all three dependent variables (ln_ei, ln_rei, ln_nei) are highly significant, with test statistics of 818.255 for ln_ei, 23.465 for ln_rei, and 893.717 for ln_nei, all significant at the 1% level. This suggests that there is strong evidence of heterogeneity in the slope coefficients, meaning that the relationships between the variables differ across countries.

Table 13: Second-Generation Unit Root Tests Pesaran (2007)

Variables	CIPS (levels)	CIPS I(1)	CIPS I(2)
ln_ei	-2.427***	-	-
ln_rei	-2.349***	-	-
ln_nei	-2.379***	-	-
ctfp	-1.394	-4.139***	-
ln_crude_prices	-2.093*	-4.637***	-
urbanization	-0.832	-1.534	-4.202***
lnhc	-1.095	-2.299***	-
irr	-1.524	-4.486***	-
delta	-2.326***	-	-

Note: The CIPS tests operate under the null hypothesis that each series is non-stationary. Significance Levels: The symbols ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively

Source: Created by the author.

The results from Pesaran’s (2007) second-generation unit root tests for Annex 1 countries provide insight into the stationarity properties of the key variables in the analysis. For the dependent variables, ln_ei (total energy intensity), ln_rei (renewable energy intensity), and ln_nei (nonrenewable energy intensity), all show significant negative CIPS values at levels, indicating that these variables are stationary at the level.

Regarding the explanatory variables, total factor productivity (ctfp) is non-stationary at levels (-1.394) but becomes stationary at the first difference (-4.139*), suggesting it is integrated of order 1 (I(1)). Similarly, crude oil prices (ln_crude_prices) show non-stationarity at levels (-2.093*) but are stationary at first differences (-4.637*), implying they are also I(1). The variable urbanization is non-stationary at levels (-0.832) but becomes stationary at second differences (-4.202*), indicating it is I(2).

However, lnhc is not stationary at levels (-1.095) and becomes stationary at first differences (-2.299*), making it I(1). Real IRR also shows non-stationarity at

levels (-1.524) but becomes stationary at first differences (-4.486*), indicating it is I(1). Finally, the depreciation rate of capital (δ) is stationary at levels (-2.326*), suggesting it is I(0).

Table 14: Panel Cointegration Tests (Westerlund, 2007)

Dependent Variable	ln_ei		ln_rei		ln_nei	
	Value	p-value	Value	p-value	Value	p-value
G τ	-3.617	0.000	-3.544	0.000	-3.458	0.000
G α	-33.407	0.000	-21.539	0.000	-30.561	0.000
P τ	-15.951	0.000	-14.860	0.016	-15.776	0.001
P α	-19.567	0.000	-12.628	0.000	-19.961	0.000

*** and ** represent significance at 1%, 5%.

Source: Created by the author.

The results of the Westerlund (2007) Panel Cointegration Tests indicate significant evidence of cointegration for all three dependent variables, ln_ei, ln_rei, and ln_nei, as shown by the test statistics G τ , G α , P τ , and P α .

For ln_ei (Total Energy Intensity), the G τ statistic is -3.617 with a p-value of 0.000, indicating strong evidence of cointegration. Similarly, the G α statistic is -33.407, with a p-value of 0.000, reinforcing this conclusion. The P τ statistic is -15.951 (p-value 0.000), and P α is -19.567 (p-value 0.000), both showing significant cointegration at the 1% level.

For ln_rei (Renewable Energy Intensity), the G τ statistic is -3.544 (p-value 0.000), and the G α statistic is -21.539 (p-value 0.000), both indicating strong evidence of cointegration. The P τ statistic is -14.860 (p-value 0.016), which is significant at the 5% level, and the P α statistic is -12.628 (p-value 0.000), significant at the 1% level.

For ln_nei (Nonrenewable Energy Intensity), the G τ statistic is -3.458 (p-value 0.000), and the G α statistic is -30.561 (p-value 0.000), both strongly indicating cointegration. The P τ statistic is -15.776 (p-value 0.001), and the P α statistic is -19.961 (p-value 0.000), both significant at the 1% level.

The results from the Westerlund panel cointegration tests confirm that there is strong evidence of a long-term equilibrium relationship between energy intensity measures (\ln_ei , \ln_rei , \ln_nei) and their explanatory variables across the countries in the sample. All test statistics for $G\tau$, $G\alpha$, $P\tau$, and $P\alpha$ are significant at the 1% or 5% level, suggesting stable, long-run relationships among the variables.

Table 15: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	\ln_ei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.505*** (0.079)	-0.529*** (0.090)	-0.461*** (0.081)	-0.431*** (0.088)	-0.369*** (0.109)	-0.479*** (0.077)	-0.209 (0.163)
\ln_crude_prices		0.004 (0.050)					-0.080 (0.091)
urbanization			4.089 (3.911)				-2.080 (5.248)
$\ln hc$				-0.432 (1.342)			-5.198 (4.440)
irr					-0.673 (0.656)		-0.744 (0.583)
delta						-8.376 (9.069)	-6.619 (13.388)

Source: Created by the author.

The results presented in Table 15 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is total energy intensity (\ln_ei). The coefficient of total factor productivity (ctfp) displays a consistently negative and statistically significant relationship with energy intensity across the first six model specifications, underscoring the role of technological progress in improving energy efficiency.

In the first model, where ctfp is the sole explanatory variable, the coefficient is -0.505 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.505% reduction in total energy intensity.

In the second model, with crude oil prices (\ln_crude_prices) introduced as a control variable, the coefficient for $ctfp$ remains statistically significant at the 1% level, with a slightly increased magnitude of -0.529. However, the coefficient for crude oil prices itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the third model, urbanization is added as a control variable. The $ctfp$ coefficient decreases slightly to -0.461, remaining statistically significant at the 1% level. However, the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fourth model incorporates human capital ($\ln hc$). The coefficient for $ctfp$ is -0.431 and remains statistically significant at the 1% level. However, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fifth model introduces the internal rate of return (irr). The coefficient of $ctfp$ is -0.369, statistically significant at the 1% level. However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the sixth model, the depreciation rate of capital (δ) is added. The coefficient for $ctfp$ remains negative and statistically significant at the 1% level (-0.479). However, the coefficient for δ is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the seventh and final model, where all explanatory variables are included simultaneously, the coefficient for $ctfp$ becomes statistically insignificant (-0.209), indicating limited evidence for its effect on total energy intensity in the full model specification. Similarly, the coefficients for crude oil prices, urbanization, human capital, internal rate of return, and capital depreciation rate are all statistically insignificant in this model.

In summary, the results of the Panel ARDL-CCEMG estimator reveal that total factor productivity significantly reduces total energy intensity across most model specifications, emphasizing the importance of technological progress. However, this effect becomes statistically insignificant in the full model with all controls. Other explanatory variables—including crude oil prices, urbanization,

human capital, internal rate of return, and depreciation—do not exhibit statistically significant effects in this analysis.

Table 16: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	ln_rei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.238 (0.661)	-0.643 (0.565)	0.457 (0.969)	0.071 (1.011)	-0.893* (0.531)	0.645 (0.792)	-0.280 (0.436)
ln_crude_prices		0.599 (0.469)					0.520 (0.690)
urbanization			-10.056 (20.417)				49.839 (47.257)
lnhc				-22.670 (22.377)			-51.905** (20.739)
irr					-4.032 (3.477)		3.285 (2.945)
delta						8.587 (29.734)	-38.219 (32.617)

Source: Created by the author.

The results presented in Table 16 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is renewable energy intensity (ln_rei). The coefficient of total factor productivity (ctfp) displays inconsistent patterns across model specifications, providing limited evidence for its role in influencing renewable energy intensity.

In the first model, where ctfp is the only explanatory variable, the coefficient is -0.238 and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the second model, with crude oil prices (ln_crude_prices) introduced as a control variable, the coefficient for ctfp becomes more negative (-0.643) but remains statistically insignificant. Additionally, the coefficient for crude oil prices itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the third model, which adds urbanization as a control variable, the coefficient for ctfp turns positive (0.457) and remains statistically insignificant. The coefficient for urbanization itself is also statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The fourth model includes human capital (lnhc) as a control variable. The ctfp coefficient remains statistically insignificant (0.071). Similarly, the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the fifth model, which incorporates the internal rate of return (irr), the coefficient for ctfp becomes negative (-0.893) and statistically significant at the 10% level, suggesting that a one-unit increase in total factor productivity is associated with a 0.893% reduction in renewable energy intensity. However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the sixth model, the depreciation rate of capital (δ) is introduced. The coefficient for ctfp turns positive (0.645) but remains statistically insignificant. Similarly, δ is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the seventh and final model, where all variables are included simultaneously, the coefficient for ctfp becomes negative again (-0.280) but is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this full model specification. The coefficient for human capital, however, becomes statistically significant at the 5% level and negative (-51.905), indicating that an increase in human capital significantly reduces renewable energy intensity. All other variables, including crude oil prices, urbanization, internal rate of return, and δ , remain statistically insignificant in this comprehensive model.

In summary, the results from the Panel ARDL-CCEMG estimator provide limited and inconsistent evidence for the effect of total factor productivity on renewable energy intensity. While ctfp shows significance in one specification, its effect is not robust across models. Human capital emerges as a significant determinant in the full model, suggesting a potential channel through which

renewable energy efficiency can be improved. Other explanatory variables do not exhibit statistically significant effects in this analysis.

Table 17: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	ln_nei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.470*** (0.096)	-0.470*** (0.084)	-0.423*** (0.097)	-0.355*** (0.097)	-0.296*** (0.108)	-0.407*** (0.089)	-0.261* (0.153)
ln_crude_prices		-0.011 (0.042)					-0.116 (0.075)
urbanization			2.682 (3.981)				-1.032 (6.507)
lnhc				0.990 (1.436)			-2.936 (4.790)
irr					-1.140 (0.717)		-0.784 (0.587)
delta						-8.659 (8.964)	-0.056 (12.552)

Source: Created by the author.

The results presented in Table 17 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is nonrenewable energy intensity (ln_nei). The coefficient of total factor productivity (ctfp) consistently displays a negative and statistically significant relationship with nonrenewable energy intensity across all models, reinforcing the central role of technological progress in reducing the reliance on nonrenewable energy sources.

In the first model, where ctfp is the only explanatory variable, the coefficient is -0.470 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.470% reduction in nonrenewable energy intensity.

In the second model, crude oil prices (ln_crude_prices) are added as a control variable. The ctfp coefficient remains unchanged at -0.470 and statistically significant at the 1% level. However, the coefficient for crude oil prices itself is

statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the third model, which incorporates urbanization, the *ctfp* coefficient remains statistically significant at the 1% level (-0.423). However, the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The fourth model includes human capital (*lnhc*) as an additional control variable. The coefficient for *ctfp* remains negative and statistically significant at the 1% level (-0.355). However, the coefficient for human capital is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the fifth model, the internal rate of return (*irr*) is included. The *ctfp* coefficient remains negative and statistically significant at the 1% level (-0.296). However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the sixth model, the depreciation rate of capital (*delta*) is added. The coefficient for *ctfp* remains statistically significant at the 1% level (-0.407), while the coefficient for *delta* is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the seventh and final model, where all control variables are included simultaneously, the coefficient for *ctfp* is -0.261 and statistically significant at the 10% level, indicating that a one-unit increase in total factor productivity is associated with a 0.261% reduction in nonrenewable energy intensity. All other variables, including crude oil prices, urbanization, human capital, internal rate of return, and capital depreciation rate, are statistically insignificant in this comprehensive specification.

In summary, the Panel ARDL-CCEMG estimator results confirm that total factor productivity significantly reduces nonrenewable energy intensity across all model specifications, although its magnitude and significance decrease in the full model. Other explanatory variables—including crude oil prices, urbanization, human capital, internal rate of return, and capital depreciation—do not show statistically

significant effects, highlighting the robust and central role of technological progress in reducing nonrenewable energy use.

Table 18: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_ei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.497*** (0.092)	-0.485*** (0.092)	-0.404*** (0.091)	-0.461*** (0.087)	-0.415*** (0.110)	-0.542*** (0.089)	-0.0392*** (0.118)
ln_crude_prices		0.048*** (0.015)					0.011 (0.013)
urbanization			0.268 (2.795)				-2.389 (3.102)
lnhc				-0.999* (0.550)			-0.705 (0.798)
irr					0.207 (0.472)		0.261 (0.505)
delta						-9.523** (3.932)	-7.652 (5.442)
Common	0.954*** (0.077)	0.975*** (0.076)	0.977*** (0.115)	0.883*** (0.130)	0.928*** (0.074)	1.043*** (0.109)	0.954*** (0.142)

Source: Created by the author.

The results presented in Table 18 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is total energy intensity (ln_ei). The coefficient of total factor productivity (ctfp) consistently exhibits a negative and statistically significant relationship with energy intensity across all model specifications, highlighting the vital role of technological progress in reducing energy intensity.

In the first model, where ctfp is the only explanatory variable, the coefficient is -0.497 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.497% reduction in total energy intensity.

In the second model, which includes crude oil prices (ln_crude_prices) as a control variable, the coefficient for ctfp remains statistically significant at the 1% level (-0.485). The coefficient for crude oil prices is positive and statistically

significant at the 1% level, suggesting that higher oil prices are associated with increased energy intensity.

In the third model, urbanization is added. The coefficient for ctfp remains statistically significant at the 1% level (-0.404), while the coefficient for urbanization is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fourth model incorporates human capital (lnhc). The ctfp coefficient remains negative and statistically significant at the 1% level (-0.461). Human capital shows a statistically significant negative effect at the 10% level, suggesting that increases in human capital are associated with reductions in total energy intensity.

In the fifth model, the internal rate of return (irr) is included. The coefficient for ctfp is -0.415 and remains statistically significant at the 1% level. However, the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The sixth model introduces the depreciation rate of capital (delta). The coefficient for ctfp becomes slightly stronger at -0.542 and is statistically significant at the 1% level. Additionally, delta has a statistically significant negative coefficient at the 5% level, indicating that higher capital depreciation is associated with lower energy intensity.

In the seventh and final model, where all explanatory variables are included simultaneously, the coefficient for ctfp remains statistically significant at the 1% level (-0.392), indicating that a one-unit increase in total factor productivity is associated with a 0.392% reduction in total energy intensity. Other variables, including crude oil prices, urbanization, human capital, internal rate of return, and capital depreciation, are statistically insignificant in this comprehensive model.

Finally, the Common dynamic process term is included in each model and consistently demonstrates statistical significance. In model 7, the coefficient of the Common dynamic process (0.954***) further supports the stability and consistency of the relationships observed over time across countries.

In summary, the Panel ARDL-AMG estimator results strongly confirm that total factor productivity significantly reduces total energy intensity across all model specifications. Human capital and capital depreciation rate also emerge as relevant

determinants in specific models. Conversely, crude oil prices, urbanization, and internal rate of return generally do not exhibit statistically significant effects in this analysis. These findings emphasize the consistent role of technological progress in promoting energy efficiency.

Table 19: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_rei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.048 (0.785)	-0.102 (0.648)	0.122 (0.868)	-0.324 (0.813)	-0.244 (0.699)	0.550 (1.206)	0.834 (1.303)
ln_crude_prices		0.368* (0.214)					0.340** (0.161)
urbanization			-6.086 (9.091)				-14.729 (14.727)
lnhc				9.248** (3.920)			5.018 (3.629)
irr					0.213 (2.363)		-0.420 (1.656)
delta						-19.965 (21.484)	-42.104 (27.655)
Common	0.952** (0.461)	0.918** (0.371)	0.510* (0.263)	1.073** (0.525)	1.005** (0.436)	0.912** (0.371)	0.895*** (0.332)

Source: Created by the author.

The results presented in Table 19 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is renewable energy intensity (ln_rei). The coefficient of total factor productivity (ctfp) does not exhibit a consistent or statistically significant relationship across the models, indicating limited evidence for its effect on renewable energy intensity in this context.

In the first model, where ctfp is the only explanatory variable, the coefficient is -0.048 and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the second model, with crude oil prices (\ln_crude_prices) introduced, the coefficient for $ctfp$ remains statistically insignificant (-0.102). However, crude oil prices exhibit a statistically significant and positive relationship at the 10% level, indicating that higher oil prices are associated with increased renewable energy intensity.

In the third model, which includes urbanization, the $ctfp$ coefficient becomes positive (0.122) but remains statistically insignificant. The coefficient for urbanization is also statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The fourth model incorporates human capital ($\ln hc$). The coefficient for $ctfp$ is -0.324 and statistically insignificant. However, human capital becomes statistically significant at the 5% level, with a coefficient of 9.248, suggesting that improvements in human capital are associated with higher renewable energy intensity.

In the fifth model, which includes the internal rate of return (irr), the coefficient for $ctfp$ remains statistically insignificant (-0.244). The coefficient for irr is also statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

The sixth model adds the depreciation rate of capital (δ). The $ctfp$ coefficient turns positive (0.550) and remains statistically insignificant. Similarly, δ does not exhibit a statistically significant effect on renewable energy intensity in this context.

In the seventh and final model, where all control variables are included simultaneously, the coefficient for $ctfp$ becomes more strongly positive (0.834) but remains statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in the full specification. Crude oil prices remain statistically significant at the 5% level, with a positive coefficient of 0.340, suggesting that higher oil prices are associated with increased renewable energy intensity. All other control variables are statistically insignificant in this comprehensive model.

Finally, the Common dynamic process term is included in each model and consistently demonstrates statistical significance. In model 7, the coefficient of the

Common dynamic process (0.895***) further supports the stability and consistency of the relationships observed over time across countries.

In summary, the Panel ARDL-AMG estimator results provide limited and inconsistent evidence for the effect of total factor productivity on renewable energy intensity. Crude oil prices and human capital emerge as statistically significant factors in certain models, while other control variables, including urbanization, internal rate of return, and capital depreciation, do not exhibit statistically significant effects. These findings suggest that, within the context of renewable energy use, total factor productivity may not be a primary determinant.

Table 20: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_nei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.488*** (0.101)	-0.512*** (0.103)	-0.388*** (0.085)	-0.450*** (0.084)	-0.391*** (0.116)	-0.534*** (0.108)	-0.370*** (0.111)
ln_crude_prices		-0.000 (0.015)					-0.025** (0.011)
urbanization			-0.307 (2.377)				-3.635 (3.114)
lnhc				-0.723 (0.519)			-0.436 (0.760)
irr					-0.568 (0.492)		-0.470 (0.474)
delta						-8.851** (4.402)	-10.777* (5.730)
Common dynamic process	0.941*** (0.062)	0.962*** (0.068)	0.937*** (0.091)	0.922*** (0.086)	0.923*** (0.062)	0.999*** (0.081)	0.937*** (0.108)

Source: Created by the author.

The results presented in Table 20 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is nonrenewable energy intensity (ln_nei). The coefficient of total factor productivity (ctfp) consistently exhibits a negative and statistically significant relationship with nonrenewable energy intensity across all

model specifications, underscoring the importance of technological progress in reducing nonrenewable energy use.

In the first model, where *ctfp* is the only explanatory variable, the coefficient is -0.488 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.488% reduction in nonrenewable energy intensity.

In the second model, which introduces crude oil prices (*ln_crude_prices*), the *ctfp* coefficient becomes slightly stronger at -0.512 and remains statistically significant at the 1% level. However, the coefficient for crude oil prices is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the third model, which adds urbanization, the *ctfp* coefficient remains statistically significant at the 1% level (-0.388), while the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The fourth model incorporates human capital (*lnhc*). The *ctfp* coefficient is -0.450 and statistically significant at the 1% level. However, the coefficient for human capital is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the fifth model, the internal rate of return (*irr*) is introduced. The coefficient for *ctfp* remains negative and statistically significant at the 1% level (-0.391), while the coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The sixth model introduces the depreciation rate of capital (*delta*). The coefficient for *ctfp* remains statistically significant at the 1% level (-0.534), and the coefficient for *delta* is statistically significant at the 5% level, indicating that a higher depreciation rate is associated with a reduction in nonrenewable energy intensity.

In the seventh and final model, where all variables are included simultaneously, the coefficient for *ctfp* remains statistically significant at the 1% level (-0.370), indicating that a one-unit increase in total factor productivity is associated with a 0.370% reduction in nonrenewable energy intensity. Crude oil

prices and capital depreciation rate (δ) also exhibit statistically significant negative coefficients at the 5% and 10% levels, respectively, confirming their relevance in reducing nonrenewable energy intensity. Other variables, including urbanization, human capital, and internal rate of return, remain statistically insignificant in this comprehensive model.

Finally, the Common dynamic process term is included in each model and consistently demonstrates statistical significance. In model 7, the coefficient of the Common dynamic process (0.937***) further supports the stability and consistency of the relationships observed over time across countries.

In summary, the Panel ARDL-AMG estimator results robustly confirm that total factor productivity significantly reduces nonrenewable energy intensity across all model specifications. Crude oil prices and capital depreciation rate also emerge as significant determinants in specific models. Conversely, urbanization, human capital, and internal rate of return do not demonstrate statistically significant effects. These findings reaffirm the essential role of technological progress in driving sustainable reductions in nonrenewable energy use.

2.4.3. Data 3: Non-Annex I

Table 21: Descriptive Statistics

Variable	Observatio n	Mean	Standard Deviation	Minimum Value	Maximum Value
ln_ei	754	15.511	0.637	14.043	19.615
ln_rei	754	10.953	3.910	0.000	18.237
ln_nei	754	15.406	0.687	13.758	19.324
ctfp	754	0.673	0.225	0.055	1.526
ln_crude_prices	754	4.608	0.674	0.787	5.977
urbanization	754	0.686	0.221	0.182	1.000
lnhc	754	0.920	0.190	0.342	1.471

Irr	754	0.141	0.070	0.010	0.483
delta	754	0.047	0.011	0.026	0.087

Source: Created by the author.

In this section, we examine the descriptive statistics for the non-Annex I countries subset of the data, consisting of 754 observations. The variables presented here include energy intensity measures, technological factors, and economic indicators that will be used in subsequent analyses.

For total energy intensity (\ln_ei), the mean value is 15.511 with a standard deviation of 0.637, indicating a relatively narrow spread around the mean compared to other countries. The minimum value is 14.043, and the maximum is 19.615, showing the variation in energy intensity levels across these countries.

The mean for renewable energy intensity (\ln_rei) is 10.953, with a larger standard deviation of 3.910, suggesting more significant variation in the adoption of renewable energy technologies. The minimum value of 0 indicates that some countries still rely heavily on nonrenewable sources, while the maximum value is 18.237, showing substantial renewable energy adoption in the highest-performing countries.

For nonrenewable energy intensity (\ln_nei), the mean is 15.406, with a standard deviation of 0.687, indicating that non-Annex I countries generally have higher reliance on nonrenewable energy sources. The minimum value is 13.758, and the maximum is 19.324, showing a range that suggests significant reliance on nonrenewable sources in the majority of countries.

Total factor productivity ($ctfp$) has a mean of 0.673 and a standard deviation of 0.225, suggesting a moderate level of technological development across these countries, with some variation. The minimum value is 0.055, indicating countries with low technological development, while the maximum value is 1.526, suggesting the presence of highly productive economies in the sample.

The crude oil prices (\ln_crude_prices) have a mean of 4.608, with a standard deviation of 0.674, reflecting significant price volatility in the global oil market. The minimum value is 0.7870754, and the maximum is 5.977, indicating wide price fluctuations over the period under consideration.

The urbanization rate has a mean of 0.686, with a standard deviation of 0.221, showing moderate urbanization across non-Annex I countries. The minimum value of 0.182 suggests that some countries have low urbanization, while the maximum value of 1 indicates a high level of urbanization in some nations.

Human capital (lnhc) has a mean value of 0.920, with a standard deviation of 0.190, indicating moderate human capital levels across these countries. The minimum value is 0.342, suggesting some countries have low educational attainment, while the maximum value is 1.471, reflecting countries with higher levels of human capital.

The real IRR has a mean value of 0.141, with a standard deviation of 0.070, suggesting moderate returns on investments across non-Annex I countries. The minimum value is 0.010, while the maximum is 0.483, showing variability in economic returns across the sample.

Finally, capital depreciation rate (delta) has a mean value of 0.047, with a standard deviation of 0.011, indicating a moderate rate of depreciation. The minimum value is 0.026, and the maximum is 0.087, showing that countries in the sample experience varying rates of capital turnover.

The descriptive statistics for the non-Annex I countries provide an overview of the energy intensity, technological, and economic conditions in these nations. The variables show considerable variation, particularly in areas such as renewable energy intensity, and crude oil prices, reflecting the diverse economic and technological development of these countries. These variations will be important in understanding the determinants of energy intensity and the role of technological progress in these nations.

Table 22: Tests for Cross-Sectional Dependence and Slope Heterogeneity

Dependent Variable	ln_ei		ln_rei		ln_nei	
	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects
Pesaran's CD	33.432*** (0.0000)	34.411*** 0.0000	8.957*** 0.0000	9.104*** 0.0000	31.612*** 0.0000	32.586*** 0.0000
Frees' test	8.004 (0.0996)*** (0.1297)**	8.263 (0.0996)*** (0.1297)**	5.127 (0.0996)*** (0.1297)**	5.121 (0.0996)*** (0.1297)**	7.441 0.0996*** 0.1297**	7.732 (0.0996)*** (0.1297)**

	(0.1870)*	(0.1870)*	(0.1870)*	(0.1870)*	0.1870*	(0.1870)*
Friedman's test	251.258*** (0.0000)	259.261*** 0.0000	76.198*** 0.0000	78.000*** 0.0000	241.545*** 0.0000	249.193*** 0.0000

Note 1: In all three tests (Pesaran's CD, Frees' test, and Friedman's test), the null hypothesis assumes cross-sectional independence.

Note 2: The optimal lag and lead lengths (both set to 1) are chosen according to the Akaike Information Criterion (AIC), and the optimal Bartlett kernel window width is specified as 3.

Note 3: The values in parentheses indicate p-values derived from (a) Pesaran (2004) and (c) Friedman's (1937) statistics.

Significance Levels: The symbols ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively.

Source: Created by the author.

The results from the Cross-Sectional Dependence and Slope Heterogeneity Tests provide evidence of cross-sectional dependence in the data for all three dependent variables (ln_ei, ln_rei, and ln_nei).

Pesaran's CD test shows significant cross-sectional dependence for all models across the three variables, with p-values of 0.000 in all cases, indicating that the null hypothesis of cross-sectional independence is rejected at the 1% level. The Frees' test shows significance at the 5% level in most models for ln_ei and ln_rei, with p-values ranging from 0.100 to 0.130. For ln_nei, the test shows significance with p-values around 0.0996, also indicating evidence of cross-sectional dependence. The Friedman's test also rejects the null hypothesis of cross-sectional independence with p-values of 0.000 for all models in all three variables, confirming significant cross-sectional dependence.

The tests indicate significant cross-sectional dependence across all models for ln_ei, ln_rei, and ln_nei. This suggests that the error terms in the models are correlated across countries, implying the need to account for this dependence when modeling the relationships between energy intensity and explanatory variables.

Table 23: Second-Generation Unit Root Tests (Pesaran, 2007)

Variables	CIPS (levels)	CIPS I(1)	CIPS I(2)
ln_ei	-1.739	-4.260***	-
ln_rei	-1.897	-4.374***	-
ln_nei	-1.719	-4.377***	-
ctfp	-1.437	-4.046***	-
ln_crude_p~s	-1.776	-4.073***	-
urbanization	-1.502	-1.266	-2.814***
lnhc	-2.476***	-	-
irr	-1.432	-4.176***	-
delta	-2.564***	-	-

Note: The CIPS tests operate under the null hypothesis that each series is non-stationary.

Significance Levels: The symbols ***, **, * represent significance at the 1%, 5%, and 10% levels,

respectively

Source: Created by the author.

The results from the Pesaran (2007) Second-Generation Unit Root Tests indicate that most of the variables are non-stationary at the levels but become stationary at I(1), which is the first difference. This includes key variables such as \ln_ei (total energy intensity), \ln_rei (renewable energy intensity), \ln_nei (nonrenewable energy intensity), $ctfp$ (total factor productivity), \ln_crude_prices (crude oil prices), IRR , and δ (capital depreciation rate). The only exception is urbanization, which is stationary at I(2). These findings suggest that most variables in the dataset are integrated of order 1 (I(1)), which is important for the subsequent panel data analysis.

Table 24: Panel Cointegration Tests (Westerlund, 2007)

Dependent Variable	\ln_ei		\ln_rei		\ln_nei	
	Value	p-value	Value	p-value	Value	p-value
$G\tau$	-3.286	0.000	-2.745	0.005	-3.296	0.000
$G\alpha$	-15.679	0.001	-16.028	0.000	-16.480	0.000
$P\tau$	-15.986	0.000	-9.515	0.985	-16.003	0.000
$P\alpha$	-17.514	0.000	-8.703	0.590	-17.521	0.000

*** and ** represent significance at 1%, 5%.

Source: Created by the author.

The Westerlund (2007) Panel Cointegration Tests provide insights into the long-run relationships between $ctfp$ (total factor productivity) and the energy intensity variables.

For \ln_ei (total energy intensity) and \ln_nei (nonrenewable energy intensity), all four test statistics ($G\tau$, $G\alpha$, $P\tau$, $P\alpha$) are statistically significant at the 1% level, with p-values of 0.000. This suggests a strong long-term cointegrating relationship

between *ctfp* and these two energy intensity measures, implying that *ctfp* (technological progress) plays a significant role in reducing energy intensity over time.

However, for *ln_rei* (renewable energy intensity), the test results are mixed. While $G\tau$ and $G\alpha$ are significant at the 1% level, the $P\tau$ test is insignificant ($p = 0.985$), and $P\alpha$ is also insignificant at the 5% level ($p = 0.590$). This indicates that the long-run relationship between *ctfp* and renewable energy intensity is weaker compared to total and nonrenewable energy intensity, although there is still some evidence of cointegration.

The cointegration results suggest that *ctfp* is strongly related to *ln_ei* and *ln_nei* in the long run, highlighting the importance of technological progress in reducing total and nonrenewable energy intensity. The relationship with *ln_rei* is less robust, suggesting that technological progress may have a weaker influence on renewable energy intensity in the long term.

Table 25: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	<i>ln_ei</i>						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ctfp</i>	-0.980*** (0.286)	-0.792*** (0.196)	-0.692*** (0.181)	-0.847*** (0.183)	-0.930** (0.369)	-0.590*** (0.147)	-0.591*** (0.175)
<i>ln_crude_prices</i>		-0.139* (0.073)					0.010 (0.064)
<i>urbanization</i>			-9.712 (8.054)				11.661 (12.842)
<i>lnhc</i>				2.602 (2.428)			-0.167 (1.839)
<i>irr</i>					0.225 (0.884)		-0.734 (0.465)
<i>delta</i>						-17.393 (12.013)	-12.544** (6.050)

Source: Created by the author.

The results presented in Table 25 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is total energy intensity (*ln_ei*).

The coefficient of total factor productivity (ctfp) consistently shows a negative and statistically significant relationship with energy intensity across all model specifications, emphasizing the crucial role of technological progress in reducing total energy intensity.

In the first model, where ctfp is the only explanatory variable, the coefficient is -0.980 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.980% reduction in total energy intensity.

In the second model, crude oil prices (ln_crude_prices) are introduced as a control variable. The coefficient for ctfp remains negative and statistically significant at the 1% level (-0.792). Crude oil prices are also statistically significant at the 10% level, with a negative coefficient, suggesting that higher oil prices contribute to reductions in total energy intensity.

In the third model, urbanization is included. The coefficient for ctfp remains statistically significant at the 1% level (-0.692). However, the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fourth model incorporates human capital (lnhc). The coefficient for ctfp remains statistically significant at the 1% level (-0.847), while the coefficient for human capital itself is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the fifth model, the internal rate of return (irr) is introduced. The coefficient for ctfp remains statistically significant at the 5% level (-0.930). However, the coefficient for internal rate of return is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the sixth model, capital depreciation (delta) is included. The coefficient for ctfp remains statistically significant at the 1% level (-0.590), while delta is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the seventh and final model, where all control variables are included simultaneously, the coefficient for ctfp remains statistically significant at the 1% level (-0.591), indicating that a one-unit increase in total factor productivity is

associated with a 0.591% reduction in total energy intensity. Capital depreciation (delta) also emerges as a statistically significant factor at the 5% level, with a negative effect. All other variables—including crude oil prices, urbanization, human capital, and internal rate of return—are statistically insignificant in this comprehensive specification.

In summary, the Panel ARDL-CCEMG estimator results robustly confirm that total factor productivity significantly reduces total energy intensity across all model specifications. Additionally, capital depreciation appears to be a relevant factor in specific models. Conversely, other variables such as crude oil prices, urbanization, human capital, and internal rate of return do not consistently demonstrate statistically significant effects. These findings reinforce the central role of technological advancement in promoting energy efficiency.

Table 26: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	ln_rei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-1.265 (0.826)	-0.699 (0.572)	-1.229 (0.761)	-1.321* (0.675)	-1.057 (0.700)	0.016 (0.509)	-0.763 (0.984)
ln_crude_prices		0.749** (0.296)					0.111 (0.368)
urbanization			25.692 (67.848)				-11.328 (186.104)
lnhc				-4.834 (6.135)			-5.572 (15.830)
irr					-1.471 (1.976)		-0.936 (4.332)
delta						-44.905** (18.279)	-69.881 (47.545)

Source: Created by the author.

The results presented in Table 26 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is renewable energy intensity (ln_rei). The coefficient of total factor productivity (ctfp) varies in sign and

significance across model specifications, providing limited and inconsistent evidence for its role in determining renewable energy intensity.

In the first model, where *ctfp* is the only explanatory variable, the coefficient is -1.265 and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the second model, crude oil prices (*ln_crude_prices*) are introduced. The coefficient for *ctfp* remains statistically insignificant (-0.699), while the coefficient for crude oil prices is positive and statistically significant at the 5% level (0.749), suggesting that higher oil prices are associated with increased renewable energy intensity.

In the third model, urbanization is added. The coefficient for *ctfp* remains statistically insignificant (-1.229), and urbanization itself also fails to show statistical significance, indicating limited evidence for its effect on renewable energy intensity in this context.

The fourth model incorporates human capital (*lnhc*). The coefficient for *ctfp* becomes -1.321 and is statistically significant at the 10% level, indicating that a one-unit increase in total factor productivity is associated with a 1.321% reduction in renewable energy intensity. However, the coefficient for human capital is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the fifth model, which includes the internal rate of return (*irr*), the coefficient for *ctfp* is -1.057 and statistically insignificant. The coefficient for internal rate of return is also statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the sixth model, the depreciation rate of capital (*delta*) is introduced. The coefficient for *ctfp* turns positive (0.016) and statistically insignificant. However, the coefficient for *delta* is statistically significant at the 5% level, with a negative sign, suggesting that higher capital depreciation is associated with reductions in renewable energy intensity.

In the seventh and final model, where all explanatory variables are included simultaneously, the coefficient for *ctfp* is -0.763 and statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in the full

model. The coefficient for capital depreciation remains negative but is statistically insignificant. All other variables, including crude oil prices, urbanization, human capital, and internal rate of return, are also statistically insignificant in this comprehensive specification.

In summary, the Panel ARDL-CCEMG estimator results offer limited support for the effect of total factor productivity on renewable energy intensity, with statistical significance emerging only in one model. Crude oil prices and capital depreciation rate appear to influence renewable energy intensity under specific model specifications, while other explanatory variables—urbanization, human capital, and internal rate of return—do not demonstrate statistically significant effects. These findings suggest that the relationship between technological progress and renewable energy use is less robust than for total or nonrenewable energy intensity.

Table 27: Panel ARDL Estimates (CCEMG Approach)

Dependent Variable	ln_nei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.984*** (0.300)	-0.852*** (0.213)	-0.642*** (0.199)	-0.833*** (0.186)	-0.950** (0.383)	-0.550*** (0.157)	-0.553*** (0.209)
ln_crude_prices		-0.133* (0.077)					0.015 (0.066)
urbanization			-8.679 (8.973)				8.697 (12.173)
lnhc				2.924 (2.535)			-1.691 (2.109)
irr					0.055 (0.934)		-0.749 (0.484)
delta						-12.066 (13.010)	-2.607 (7.359)

Source: Created by the author.

The results presented in Table 27 are obtained using the Panel ARDL-CCEMG estimator, where the dependent variable is nonrenewable energy intensity (ln_nei). The coefficient of total factor productivity (ctfp) consistently displays a

negative and statistically significant relationship with nonrenewable energy intensity across all model specifications, highlighting the central role of technological advancement in promoting reductions in nonrenewable energy intensity.

In the first model, where *ctfp* is the only explanatory variable, the coefficient is -0.984 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.984% reduction in nonrenewable energy intensity.

In the second model, crude oil prices (*ln_crude_prices*) are introduced. The coefficient for *ctfp* remains negative and statistically significant at the 1% level (-0.852). Crude oil prices are also statistically significant at the 10% level, with a negative coefficient, suggesting that rising oil prices contribute to reductions in nonrenewable energy intensity.

In the third model, which includes urbanization, the *ctfp* coefficient is -0.642 and remains statistically significant at the 1% level. The coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The fourth model incorporates human capital (*lnhc*). The coefficient for *ctfp* is -0.833 and statistically significant at the 1% level. However, the coefficient for human capital is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the fifth model, the internal rate of return (*irr*) is added. The *ctfp* coefficient remains negative and statistically significant at the 5% level (-0.950). The coefficient for internal rate of return is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The sixth model introduces capital depreciation (*delta*). The *ctfp* coefficient is -0.550 and statistically significant at the 1% level. However, the coefficient for *delta* is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the seventh and final model, where all explanatory variables are included simultaneously, the coefficient for *ctfp* remains statistically significant at the 1% level (-0.553), indicating that a one-unit increase in total factor productivity is associated with a 0.553% reduction in nonrenewable energy intensity. All other

variables—including crude oil prices, urbanization, human capital, internal rate of return, and capital depreciation—are statistically insignificant in this comprehensive model specification.

In summary, the Panel ARDL-CCEMG estimator results robustly confirm that total factor productivity significantly reduces nonrenewable energy intensity across all model specifications. Crude oil prices also appear as a statistically significant determinant in one specification. Other variables—urbanization, human capital, internal rate of return, and capital depreciation—do not show statistically significant effects in this analysis. These findings reaffirm the consistent and dominant role of technological progress in mitigating reliance on nonrenewable energy.

Table 28: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_ei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.848*** (0.248)	-0.900*** (0.197)	-0.894*** (0.235)	-0.933*** (0.173)	-0.821** (0.394)	-0.842*** (0.249)	-0.687*** (0.180)
ln_crude_prices		-0.251*** (0.087)					-0.104** (0.048)
urbanization			-3.721 (3.635)				1.402 (3.530)
lnhc				-0.364 (0.496)			-0.792 (0.756)
irr					0.309 (1.093)		-0.156 (0.527)
delta						-19.133*** (5.774)	-15.082*** (5.244)
Common	0.936*** (0.216)	0.656*** (0.220)	0.575*** (0.165)	0.887*** (0.329)	0.863*** (0.204)	0.621*** (0.236)	0.212 (0.143)

Source: Created by the author.

The results presented in Table 28 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is total energy intensity (ln_ei). The coefficient of total factor productivity (ctfp) consistently exhibits a negative and

statistically significant relationship with energy intensity across all model specifications, underlining the key role of technological progress in total energy intensity.

In the first model, where *ctfp* is the sole explanatory variable, the coefficient is -0.848 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.848% reduction in total energy intensity.

In the second model, which introduces crude oil prices (*ln_crude_prices*), the coefficient for *ctfp* remains statistically significant at the 1% level (-0.900). Crude oil prices are also statistically significant at the 1% level, with a negative coefficient (-0.251), suggesting that rising oil prices contribute to reductions in total energy intensity.

In the third model, urbanization is included. The *ctfp* coefficient remains significant at the 1% level (-0.894), while urbanization is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The fourth model incorporates human capital (*lnhc*). The coefficient for *ctfp* is -0.933 and remains statistically significant at the 1% level. However, the coefficient for human capital is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

In the fifth model, the internal rate of return (*irr*) is added. The coefficient for *ctfp* is -0.821 and statistically significant at the 5% level. However, the coefficient for *irr* is statistically insignificant, indicating limited evidence for its effect on total energy intensity in this context.

The sixth model introduces capital depreciation (*delta*). The *ctfp* coefficient is -0.842 and statistically significant at the 1% level. *Delta* shows a strong and statistically significant negative effect at the 1% level (-19.133), indicating that higher capital depreciation is associated with reduced energy intensity.

In the seventh and final model, where all control variables are included simultaneously, the coefficient for *ctfp* remains statistically significant at the 1% level (-0.687), indicating that a one-unit increase in total factor productivity is associated with a 0.687% reduction in total energy intensity. Crude oil prices and capital depreciation rate also remain statistically significant, while other control

variables—including urbanization, human capital, and internal rate of return—are statistically insignificant in this comprehensive model.

Finally, the Common dynamic process term is included in each model and is statistically significant in all but the final specification. In model 7, the coefficient of the Common dynamic process (0.212) becomes statistically insignificant, though it remains significant in all previous models, generally supporting the stability and time-consistency of the relationships across countries.

In summary, the Panel ARDL-AMG estimator results consistently confirm that total factor productivity significantly reduces total energy intensity across all model specifications. Crude oil prices and capital depreciation also emerge as robust determinants in specific contexts. Conversely, urbanization, human capital, and internal rate of return do not display statistically significant effects. These findings reinforce the foundational role of technological advancement in achieving greater energy efficiency.

Table 29: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_rei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-1.736*	-1.111**	-1.469*	-1.306*	-2.054**	-0.821	-0.483
	(0.945)	(0.558)	(0.841)	(0.696)	(0.949)	(0.567)	(0.853)
ln_crude_prices		-0.132					-0.155
		(0.086)					(0.146)
urbanization			-3.548				50.662
			(13.223)				(32.328)
lnhc				-0.488			-11.340*
				(1.347)			(5.967)
irr					-0.124		0.265
					(1.527)		(1.603)
delta						19.949	-35.460
						(30.849)	(22.856)
Common	0.922**	0.908**	1.029***	0.975***	0.983**	0.906**	1.197**
dynamic process	(0.426)	(0.410)	(0.349)	(0.357)	(0.400)	(0.352)	(0.598)

Source: Created by the author.

The results presented in Table 29 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is renewable energy intensity (\ln_rei). The coefficient of total factor productivity ($ctfp$) shows statistically significant negative effects in several models, though this significance weakens in more comprehensive specifications. These patterns suggest that technological progress may play a conditional role in influencing renewable energy intensity.

In the first model, where $ctfp$ is the only explanatory variable, the coefficient is -1.736 and statistically significant at the 10% level, indicating that a one-unit increase in total factor productivity is associated with a 1.736% reduction in renewable energy intensity.

In the second model, which includes crude oil prices (\ln_crude_prices), the coefficient for $ctfp$ becomes -1.111 and is statistically significant at the 5% level. However, the coefficient for crude oil prices itself is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the third model, urbanization is added. The $ctfp$ coefficient remains statistically significant at the 10% level (-1.469), while urbanization is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity.

The fourth model incorporates human capital ($\ln hc$). The coefficient for $ctfp$ is -1.306 and statistically significant at the 10% level. Human capital itself is statistically insignificant in this model.

In the fifth model, the internal rate of return (irr) is introduced. The coefficient for $ctfp$ is -2.054 and statistically significant at the 5% level. However, the coefficient for irr is statistically insignificant, indicating limited evidence for its effect on renewable energy intensity in this context.

In the sixth model, capital depreciation (δ) is added. The coefficient for $ctfp$ becomes statistically insignificant (-0.821), and the coefficient for δ is also statistically insignificant.

In the seventh and final model, where all explanatory variables are included simultaneously, the coefficient for $ctfp$ becomes further reduced in magnitude and remains statistically insignificant (-0.483), indicating limited evidence for its effect on renewable energy intensity in the full model. Notably, human capital shows a

statistically significant negative effect at the 10% level (-11.340), suggesting that increases in human capital are associated with reductions in renewable energy intensity. All other variables, including crude oil prices, urbanization, internal rate of return, and capital depreciation, are statistically insignificant.

Finally, the Common dynamic process term is included in each model and remains statistically significant throughout. In model 7, the coefficient (1.197**) continues to confirm the stability and consistency of the relationships over time across countries.

In summary, the Panel ARDL-AMG estimator results provide partial evidence that total factor productivity reduces renewable energy intensity. Human capital emerges as a significant factor in the comprehensive model, while crude oil prices, urbanization, internal rate of return, and capital depreciation do not consistently demonstrate statistically significant effects. These findings suggest a more nuanced role for technological progress in the context of renewable energy use.

Table 30: Panel ARDL Estimates (AMG Approach)

Dependent Variable	ln_nei						
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ctfp	-0.827*** (0.260)	-0.929*** (0.216)	-0.941*** (0.247)	-0.961*** (0.181)	-0.824** (0.411)	-0.815*** (0.263)	-0.793*** (0.185)
ln_crude_prices		-0.245*** (0.090)					-0.095* (0.050)
urbanization			-4.200 (3.733)				2.360 (3.881)
lnhc				-0.409 (0.523)			-0.836 (0.813)
irr					0.251 (1.124)		-0.149 (0.588)
delta						-19.143*** (6.022)	-8.913 (6.301)
Common	0.941*** (0.222)	0.629*** (0.225)	0.517*** (0.183)	0.820** (0.324)	0.831*** (0.214)	0.647** (0.270)	0.197 (0.136)

Source: Created by the author.

The results presented in Table 30 are obtained using the Panel ARDL-AMG estimator, where the dependent variable is nonrenewable energy intensity (\ln_{nei}). The coefficient of total factor productivity (ctfp) consistently exhibits a negative and statistically significant relationship with nonrenewable energy intensity across all model specifications, highlighting the robust role of technological progress in nonrenewable energy intensity.

In the first model, where ctfp is the sole explanatory variable, the coefficient is -0.827 and statistically significant at the 1% level, indicating that a one-unit increase in total factor productivity is associated with a 0.827% reduction in nonrenewable energy intensity.

In the second model, which introduces crude oil prices (\ln_{crude_prices}), the ctfp coefficient remains significant at the 1% level (-0.929). Crude oil prices are also statistically significant at the 1% level with a negative sign, suggesting that higher oil prices lead to reductions in nonrenewable energy intensity.

In the third model, where urbanization is added, the coefficient for ctfp remains statistically significant at the 1% level (-0.941), while the coefficient for urbanization itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

The fourth model incorporates human capital (\ln_{hc}). The coefficient for ctfp remains statistically significant at the 1% level (-0.961), while the coefficient for human capital is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the fifth model, internal rate of return (irr) is introduced. The coefficient for ctfp is -0.824 and statistically significant at the 5% level. The coefficient for internal rate of return itself is statistically insignificant, indicating limited evidence for its effect on nonrenewable energy intensity in this context.

In the sixth model, the depreciation rate of capital (δ) is added. The coefficient for ctfp remains statistically significant at the 1% level (-0.815), and the coefficient for δ is also statistically significant at the 1% level (-19.143), suggesting that higher depreciation rates contribute meaningfully to reductions in nonrenewable energy intensity.

In the seventh and final model, where all variables are included simultaneously, the coefficient for *ctfp* remains statistically significant at the 1% level (-0.793), indicating that a one-unit increase in total factor productivity is associated with a 0.793% reduction in nonrenewable energy intensity. Crude oil prices also remain statistically significant at the 10% level. Other variables—including urbanization, human capital, internal rate of return, and capital depreciation—are statistically insignificant in this full specification.

Finally, the Common dynamic process term is included in each model and is statistically significant in all but the final model. In model 7, the coefficient of the Common dynamic process (0.197) is statistically insignificant, while in prior models it consistently confirms the temporal stability of the estimated relationships across countries.

In summary, the Panel ARDL-AMG estimator results confirm that total factor productivity significantly reduces nonrenewable energy intensity across all model specifications. Crude oil prices and capital depreciation also appear as important determinants in specific models. Conversely, urbanization, human capital, and internal rate of return do not demonstrate statistically significant effects. These findings reinforce the role of technological advancement and structural economic factors in achieving lower dependency on nonrenewable energy.

CONCLUSION

This thesis provides a comprehensive panel data analysis on the determinants of energy intensity using a multi-dimensional dataset covering 67 countries, categorized into All Countries, Annex I, and Non-Annex I groups. The empirical framework is based on Panel ARDL estimation techniques (CCEMG and AMG), where total factor productivity (TFP) is the primary explanatory variable, and energy intensity—disaggregated into total, renewable, and nonrenewable forms—is the key dependent outcome.

Across the full dataset, the findings consistently show that TFP exerts a strong, negative, and statistically significant influence on both total and nonrenewable energy intensity, regardless of the estimator employed. This confirms the central role of technological progress in enhancing energy efficiency and facilitating a shift away from carbon-intensive energy systems. However, the impact of TFP on renewable energy intensity is more limited and inconsistent, indicating that the diffusion of productivity-enhancing technologies into renewable energy systems may require additional institutional or infrastructural support.

A closer examination of country groupings reveals meaningful heterogeneity. In Annex I countries, which are typically more technologically advanced and capital-abundant, TFP consistently reduces both total and nonrenewable energy intensity. However, in full models with extensive controls, the magnitude and significance of this relationship tend to diminish—suggesting that other macro-structural factors may mediate the TFP-energy intensity nexus in high-income settings. In Non-Annex I countries, by contrast, the relationship between TFP and energy intensity is particularly robust, even when full models are specified. This may reflect a greater marginal return on productivity-enhancing innovations in developing economies, where energy systems are more inefficient and industrial processes more energy-intensive.

The contrast between total and renewable energy intensity outcomes is particularly noteworthy. While TFP robustly reduces total and nonrenewable energy intensity, its effect on renewable energy intensity is generally weak or statistically insignificant—a result that holds across all estimators and country groupings. Several

explanations may account for this asymmetry. First, improvements in TFP may initially translate into incremental efficiency gains in existing (primarily fossil-based) systems rather than radical shifts toward renewables. Second, the renewable sector may require complementary investments in infrastructure, regulation, and institutional capacity, which are not directly captured by productivity growth. Finally, the adoption of renewables is often driven by policy mandates and subsidies, rather than by endogenous technological progress alone.

These findings have significant policy implications. First, the robust and consistent impact of TFP on nonrenewable and total energy intensity suggests that innovation policies and productivity-enhancing reforms are central to the energy transition. Governments should prioritize R&D investment, support for digitalization, industrial upgrading, and the diffusion of best-available technologies—especially in carbon-intensive sectors. In Non-Annex I countries, where energy inefficiencies are higher, such investments can yield particularly strong returns.

Second, the weak link between TFP and renewable energy intensity implies that productivity growth alone is not sufficient to accelerate the uptake of renewables. This calls for dedicated renewable energy policies, including price-based mechanisms (such as feed-in tariffs or carbon pricing), infrastructure investments, and institutional reforms that lower the entry barriers for clean technologies. These complementary policies can help transform productivity gains into structural energy shifts.

Furthermore, the significance of capital depreciation in many models points to the importance of maintaining and modernizing the capital stock. Investment in energy-efficient equipment, smart grids, and green infrastructure should be considered a core component of national energy strategies. Similarly, the role of crude oil prices in specific specifications suggests that market-based incentives can play an enabling role in altering energy consumption patterns.

While other control variables such as urbanization, human capital, and internal rate of return do not consistently explain variation in energy intensity, they should not be neglected. For instance, human capital shows occasional significance in the context of renewable energy intensity, implying that educational and

institutional capacities may matter more when transitioning to complex, decentralized energy systems.

Nevertheless, this study is not without limitations. A key methodological limitation lies in the way renewable and nonrenewable energy intensities are calculated. In standard energy economics, energy intensity is typically defined as the ratio of energy consumption to GDP. While this approach is conceptually appropriate for total energy intensity, it becomes theoretically less accurate when applied to renewable or nonrenewable sources. Ideally, renewable energy intensity should be measured as the ratio of renewable energy use to the share of GDP generated from renewable sources. However, such disaggregated economic output data is not available internationally. Therefore, like many studies in the literature, this thesis calculates energy intensities using total GDP, which may introduce bias in interpreting the productivity of energy subcategories.

To address this and enrich the empirical and policy relevance of future research, further studies may benefit from applying the current analytical framework to regional classifications defined by the United Nations Convention to Combat Desertification (UNCCD). These include Africa, Asia, Latin America and the Caribbean, the Northern Mediterranean, Central and Eastern Europe and Countries Not Belonging to a Regional Implementation Annex. Since the UNCCD regional annexes are not only ecologically and climatically distinct but also represent different institutional capacities and stages of development, aligning energy intensity analysis with this framework could offer more context-sensitive policy insights. In practice, such a direction would allow researchers to deliver targeted, region-specific recommendations, improving the effectiveness and equity of energy transition strategies. Moreover, integrating energy efficiency studies with land-based sustainability frameworks, such as those promoted by the UNCCD, could enhance global coordination around sustainable development and climate resilience.

In conclusion, this thesis empirically affirms that technological progress, as measured by TFP, is a foundational pillar in reducing energy intensity, particularly in relation to nonrenewable energy use. However, to fully leverage these gains for a sustainable transition, targeted policies must be designed to translate productivity growth into structural energy transformation. This requires a coordinated policy mix

that aligns innovation, investment, regulation, and institutional reform. The insights offered here contribute to the ongoing global discourse on how to decouple economic growth from environmental degradation and support strategic energy planning consistent with the European Green Deal and UN Sustainable Development Goals.



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APPENDIX



APPENDIX 1: Country Groups

Countries and their respective groups are presented in the Table X.

Table X: Country Groups

Country	Region	Country	Region
Argentina	Non-Annex 1	Japan	Annex 1
Australia	Annex 1	Kazakhstan	Non-Annex 1
Austria	Annex 1	South Korea	Non-Annex 1
Belgium	Annex 1	Kuwait	Non-Annex 1
Bulgaria	Annex 1	Sri Lanka	Non-Annex 1
Brazil	Non-Annex 1	Lithuania	Annex 1
Canada	Annex 1	Luxembourg	Annex 1
Switzerland	Annex 1	Latvia	Annex 1
Chile	Non-Annex 1	Morocco	Non-Annex 1
China	Non-Annex 1	Mexico	Non-Annex 1
Colombia	Non-Annex 1	Malaysia	Non-Annex 1
Cyprus	Annex 1	Netherlands	Annex 1
Czech Republic	Annex 1	Norway	Annex 1
Germany	Annex 1	New Zealand	Annex 1
Denmark	Annex 1	Peru	Non-Annex 1
Ecuador	Non-Annex 1	Philippines	Non-Annex 1
Egypt	Non-Annex 1	Poland	Annex 1
Spain	Annex 1	Portugal	Annex 1
Estonia	Annex 1	Qatar	Non-Annex 1
Finland	Annex 1	Romania	Annex 1
France	Annex 1	Russian Federation	Annex 1
United Kingdom	Annex 1	Saudi Arabia	Non-Annex 1
Greece	Annex 1	Singapore	Non-Annex 1
Hong Kong	Non-Annex 1	Slovakia	Annex 1
Croatia	Annex 1	Slovenia	Annex 1
Hungary	Annex 1	Sweden	Annex 1
Indonesia	Non-Annex 1	Thailand	Non-Annex 1
India	Non-Annex 1	Trinidad and Tobago	Non-Annex 1
Ireland	Annex 1	Turkey	Annex 1
Iran	Non-Annex 1	Ukraine	Annex 1
Iraq	Non-Annex 1	United States	Annex 1
Iceland	Annex 1	Venezuela	Non-Annex 1
Israel	Non-Annex 1	South Africa	Non-Annex 1
Italy	Annex 1		