IMPLICATIONS OF ELECTRICITY SUPPLY SHOCKS AND TECHNOLOGICAL ADVANCEMENT ON TOTAL FACTOR PRODUCTIVITY: A CASE OF SOUTH AFRICA

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DECLARATION

I declare that the dissertation titled **“IMPLICATIONS OF ELECTRICITY SUPPLY SHOCKS AND TECHNOLOGICAL ADVANCEMENT ON TOTAL FACTOR PRODUCTIVITY: A CASE OF SOUTH AFRICA”** is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references and that this work has not been submitted before for any other degree at any other institution.

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ABSTRACT

This study investigated the implications of electricity supply shocks and technological advancement on total factor productivity in South Africa. To represent electricity supply shocks, electricity production and electricity prices were used. Meanwhile, research and development, patents, and investment in information and communication technology were considered for technological advancement. The study employed the Autoregressive Distributed Lag (ARDL) approach to examine the implications of electricity production, electricity prices, R&D, patents, and investment in ICT on TFP in South Africa from 1999 to 2022. Descriptive statistics confirmed the normal distribution of variables, and correlation analysis revealed a positive correlation between electricity production, R&D, patents, and TFP, with a negative correlation between investment in ICT and electricity prices. The ARDL long-run results revealed a positive relationship between electricity production and TFP, whereas electricity prices have a negative relationship with TFP. R&D and investment in ICT have a negative relationship with TFP, whereas patents positively affect TFP.

The Granger Causality test revealed a two-way causal relationship between total factor productivity and electricity production. A one-way causal link exists between electricity prices, total factor productivity, and electricity prices and electricity production in South Africa, highlighting their pivotal role in driving productivity. The Impulse Response Function illustrated the short-term positive impact of electricity production on TFP, followed by a long-term negative trend. Conversely, electricity prices consistently negatively influenced TFP throughout the same period. Given these findings, the South African government should prioritise policies supporting low electricity prices, renewable energy development, and transparent pricing mechanisms to enhance TFP and electricity production. Promoting R&D, innovation, and investment in ICT is crucial for sustained economic growth. Aligning policies with these drivers while addressing negative factors is a key for South Africa's productivity and energy transition goals.

KEY CONCEPTS: Total Factor Productivity, Electricity Production, Electricity Prices, Research & Development, Patents, Investment in ICT, South Africa, ARDL

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ACRONYMS

4IR	Fourth Industrial Revolution
ADF	Augmented-Dickey Fuller
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
ECM	Error Correction Model
ECT	Error Correction Term
EJETP	Eskom Just Energy Transition Project
EP	Electricity Prices
EPP	Electricity Pricing Policy
EPRO	Electricity Production
FPE	Final Prediction Error
GDP	Gross Domestic Product
GWh	Gigawatt hour
HQC	Hannan-Quinn Information Criteria
HSRC	Human Sciences Research Council
IMF	International Monetary Fund
INV_ICT	Investment in Information and Communications Technology
IRF	Impulse Response Function
JB	Jarque-Bera
LM	Lagrange Multiplier
NDP	National Development Plan
NERSA	National Energy Regulator of South Africa
OECD	Organisation for Economic Co-operation and Development
PAT	Patents
PP	Phillips-Perron

R&D	Research and Development
SARB	South African Reserve Bank
SIC	Schwarz Information Criteria
SITA	State Information Technology Agency
SMMEs	Small Medium and Micro Enterprises
Stats SA	Statistics South Africa
TFP	Total Factor Productivity
VAR	Vector Autoregression
VD	Variance Decomposition

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CHAPTER 1
ORIENTATION TO THE STUDY

1.1 INTRODUCTION AND BACKGROUND

Total Factor Productivity (TFP) is considered a substantial contributor to the advancement of economic growth (Eita & Pedro, 2021). Evidence shows that TFP in South Africa has been low compared to international standards (OECD, 2022). Productivity South Africa has noted a decrease in the manufacturing sector's contribution to the GDP growth during the past two decades. The industry contributes roughly 13% of GDP and is a significant driver of service demand, productivity growth, and employment (Productivity SA, 2022). The TFP, which is determined by how quickly technology advances, will determine how rapidly the economy grows in the long run, as indicated by the rise in the production rate per individual. TFP is commonly known as the 'Solow residual' and is used to calculate TFP (Zeng, Xianfan & Wenxian, 2022). Indicators of output growth other than input growth alone include the Solow residual. The Solow residual is extensively employed as an indicator of product development due to technological advancement. Solow (1956) identified elements that, over time, enable economic growth. Therefore, gaining a comprehensive understanding of the drivers behind TFP, such as technological innovation and the availability of electricity, becomes crucial. This understanding is a cornerstone for optimising TFP and fostering accelerated economic growth (Eita & Pedro, 2021).

Accelerating economic growth is the government's and policymakers' primary goal in any economy. The studies conducted by Kahn, Sithole and Buchana (2022), Milindi and Inglesi-Lotz (2023), and Kreuser and Newman (2018) have likely recognised TFP as a significant factor impacting economic growth in South Africa. TFP improvements assisted nations in moving from middle-income to high-income groups (Kim & Park, 2018). According to the OECD (2022), South Africa has faced persistent challenges in achieving robust economic growth throughout its history. The GDP per capita of South Africa already fell in 2019 compared to 2008, while the country's GDP grew by an average of 1.1% from 2009 to 2019. Deteriorating infrastructure, inadequate telecommunications networks, and poor investment contribute to slow economic growth, which is explained mainly by diminishing productivity (OECD, 2022).

Technology and electricity both contribute significantly to the improvement of human life. Another economic growth driver is electricity. Applications for it include anything from communication and transportation to production. In the modern production process, electricity is acknowledged as a crucial and self-sufficient production factor (Yakubu & Bala, 2015). Power deficit issues are prevalent in many developing nations. Electricity is essential in the South African industry for companies that extract non-ferrous metals and for the soap and pharmaceutical sectors (Takentsi, Sibanda & Hosu, 2021). The ability to produce products and services and a nation’s potential for economic growth are significantly impacted by the availability of energy (Mpatane, 2015). Inglesi-Lotz (2022) asserts that the 1990s saw most of South Africa's population without access to power due to insufficient grid infrastructure. Power interruptions negatively affect South Africa's economy, impacting industries, services, and households (Punt, 2008). Expanding the electricity sector would increase manufacturing output, enhancing overall productivity, and highlighting a positive correlation between the electricity supply and manufacturing output (Mpatane, 2015).

According to StatsSA (2023), South Africa's primary electricity provider, Eskom Holdings SOC Ltd (Eskom), has experienced issues with liquidity and profitability, especially in the middle of the 2000s. It then became essential for Eskom to source funds, and it was allocated R21.9 billion (roughly US$1.5 billion) from the national budget in 2022. A decrease in electricity supply accompanied the issues of liquidity and profitability. StatsSA (2023) noted that in January 2023, electricity production fell by 8.0% annually.

Due to insufficient electricity supply, South Africa's growth has been hindered for an extended period. According to the World Bank (2023), continuous scheduled power cuts, also known as load shedding, began in 2007 and dramatically escalated, reaching more than nine hours of power outages daily in 2022. The consequential severe electricity shortage has disrupted economic growth and increased operational costs for businesses, given their dependence on expensive diesel generators. Other facilities, including water, information technology, and service delivery, have also been impacted. Due to the COVID-19 pandemic and limited structural growth, economic issues have been more challenging. Although South Africa's GDP has returned to the pre-pandemic levels, the employment rate has not increased. The number of work chances decreased by nearly five hundred thousand by the end of 2022 compared to the end of 2019, disproportionately affecting women and young people. As load shedding and shortages in transportation worsened, mining output decreased, but manufacturing output remained constant. Local trade and service industries, including finance, transportation, and personal services, became the key drivers of economic growth. The labour market remained unsteady (World Bank, 2023).

An economic disaster has recently resulted from the inconsistent electricity supply and rising costs. It currently acts as an impediment to income generation and economic development. South African businesses are experiencing enormous losses. In the final quarter of 2021, load shedding increased, with stage 2 ensuring at least two hours per day without power and, for some, four hours. When you multiply that by six days, running even the most fundamental aspects of businesses becomes economically impossible. Electricity blackouts affect production output in South Africa, resulting in businesses to reduce production (Sithole, 2022).

According to the IMF (2022), South Africa needs to draw private sector involvement in the electricity market to regain energy security and rectify Eskom's operational and financial shortcomings. If strictly enforced, the conditions imposed on Eskom's debt relief operation should significantly enhance the company's functioning and secure its long-term survival. Additionally, it is imperative to stop the accumulation of municipal debt owed to Eskom and establish fully cost-reflective mechanisms for determining electricity tariffs, which are vital for Eskom's operational sustainability. Additionally, long-term agreements have been made between the governments of Germany, the European Union, the UK, the USA, and France, along with the government of South Africa, to support the country's decarbonisation initiatives. The Partnership's objective is to help South Africa attain its ambitious emissions reduction targets as stated in its updated Nationally Determined Contribution, primarily focusing on accelerating the decarbonisation of the country's economy, particularly in the electricity sector (European Commission, 2021).

Technology has been commonly recognised as a significant driver of economic progress, playing a crucial role in shaping total factor productivity (Chou, Chuang & Shao, 2014; Jorgenson, 2001; Stiroh, 2002). When technology is incorporated into a labour or capital-intensive process, it becomes more effective. For instance, using robots in manufacturing could increase productivity and output. In December 2019, South Africa established the Centre for the Fourth Industrial Revolution (4IR) to support industry transformation in various industries and changes in government to uphold strong and resilient technology governance regulations (World Economic Forum, 2019). The Centre uses frameworks to promote awareness and capitalise on advanced technologies. According to the United Nations (2021), reverse engineering can help South Africa encourage manufacturing and the adoption of cutting-edge technology. Another potential alternative for South Africa is to create Research & Development (R&D) and technology collaborations with countries at the cutting edge of 4IR technology.

The potential for technological advancements to boost labour productivity lies in their ability to raise the ICT capital ratio to labour ratio. This can lead to higher output through capital deepening, where the production increases without changing the amount of capital and labour employed, and by improving the techniques or organization of capital and labour interaction. In addition, these innovations can also contribute to an increase in total factor productivity (Paul, Marcello & Laura, 2001). R&D is also one indicator of the intensity of technological change. According to Haider, Kunst, and Wirl (2020), R&D is a significant driver of technological progress and innovation, with multiple studies drawing a connection between R&D and productivity. Notably, Venturini (2015) and Coe and Helpman (1995) discovered that ICT capital, particularly R&D, has a significant impact on the repercussions of TFP, distinct from the productivity spillovers stemming from R&D conducted in the underlying technological fields. According to Kumo (2017), investment in R&D can also spur TFP growth.

The Cardona (2013) survey found that several studies have reported a strong and positive association between ICT and productivity. Lehr and Lichtenberg (1998) also discovered a comparable effect for federal agencies. Another proxy for technology is patents. Jackob (2020) states that an extensive international patent stock substantially fosters economic growth. Additionally, combined with knowledge spillovers facilitated by imports, it has contributed significantly to driving total factor productivity growth and promoting convergence among the OECD countries for the past 120 years. When examining factors like human capital and capital stock, it has been found that patent stock has a more pronounced effect on economic progress. The influence of patents on the GDP and growth of private enterprises is twice as significant as that of public enterprises (Chang, McLean, Zhang & Zhang, 2018).

Understanding the drivers of total factor productivity is crucial for informing corporate and industry association initiatives to increase productivity levels in manufacturing enterprises and policymaking to promote growth. It has come to the government's attention, and perhaps the private sector's attention, to improve the electricity challenge and enhance the country's technological advancement. Investigating and examining the implications of technology advancements and electricity supply shocks affecting total factor productivity became essential. According to Milanzi (2021), efficiency and technological progress are identified as the primary components of TFP across various economic sectors. The study will consider these factors to determine whether electricity supply shocks and technology advancements influence South Africa's overall productivity performance.

1.2 STATEMENT OF THE PROBLEM

The South African economy continues to be hampered by a persistently low rate of productivity growth and the detrimental impact of the war between Ukraine and Russia on consumer spending due to the increase in prices for food and energy (OECD, 2022). South Africa has the lowest productivity growth rate among emerging economies. Low productivity performance in South Africa reflects the skills shortage, high cost of doing business, and lack of competition in many markets (OECD, 2018). Stagnant productivity growth, such as labour productivity and total factor productivity, notably of the Small, Medium, and Micro-enterprises (SMMEs) within the production/industry sectors, is hindering the attempts to enhance the competitiveness and economic growth of South Africa (OECD, 2022). According to Productivity SA (2022), the significance of productivity growth cannot be denied as it is the most effective means to secure long-term competitiveness, sustainable business prosperity, and overall economic growth. Furthermore, a comprehensive and integrated approach is essential in addressing critical issues such as unemployment, poverty, inequality, and exclusion. Productivity South Africa also observed that during the past 20 years, the manufacturing sector's contribution to the GDP growth has decreased. The industry, which contributed roughly 13% of GDP in 2022, was a significant driver of demand for services, productivity growth, and employment (Productivity SA, 2022).

According to Cahu, Fall, and Fialho (2022), South Africa has witnessed a persistent decrease in productivity growth over ten years, leading to a slowdown in improving living standards. Low productivity is first caused by inadequate transportation and telecommunications infrastructure. Secondly, the regulatory environment frequently creates barriers to firm admission, exit, and expansion and is not always conducive to business. This has resulted in decreased levels of private investment, particularly in corporate R&D, when coupled with insufficient competition in significant areas. Finally, the educational and healthcare systems have failed to equip workers across the nation with the necessary skills effectively. According to Cahu et al. (2022), public investment must be made in South Africa to be more effective, mainly through improving the selection process for major infrastructure projects. Growing innovative companies would be possible in a more pro-competitive corporate environment (Cahu et al., 2022).

Abisoye (2022) argues that technology and electrical shortages impact South Africa's production, forcing businesses to reduce output. Without technology and the necessary energy supplies, particularly electricity in under-developed nations, the world today cannot develop. Many governments consider the absence of dependable electricity in the developing world a significant barrier to corporate productivity (Fried & Lagakos, 2020). One of the most important types of energy is electricity, and as time and technology advance, so does its use. For businesses, an electricity supply is a crucial component of production (Jack, 2022).

According to the OECD (2022) survey, businesses in South Africa are experiencing many blackouts because of years of declining energy supplies. Power shortages are still the main barrier to economic growth. The survey indicated that the division of Eskom into distinct entities for distribution, transmission, and generation, as well as removing regulatory barriers to market entrance, would allow more producers to enter the market. This increased competition would enhance the electricity supply and result in price reductions.

1.3 RESEARCH AIM AND OBJECTIVES

The study used proxies to assess the impact of electricity supply shocks and technological advancement on TFP. To represent electricity supply shocks, electricity production and electricity prices were used. For technological advancement, research and development, patents, and investment in information and communication technology were considered.

1.3.1 Aim

The study aims to examine the implications of electricity supply shocks and technological advancement on TFP in South Africa for 1999 – 2022.

1.3.2 Objectives

The study aims to achieve the following objectives:

- To examine the impact of electricity production and electricity prices on total factor productivity.
- To analyse the influence of technological advancement on total factor productivity.
- To determine the causal relationship between electricity production, electricity prices, R&D, patents, investment in ICT, and total factor productivity.
- To estimate the behaviour of productivity emanating from shocks in electricity production, electricity prices, R&D, patents, and investment in ICT for the near future.

1.4 RESEARCH QUESTIONS

- Is there any impact of electricity production and prices on total factor productivity?
- What is the analysed influence of technological advancement on total factor productivity?
- What is the causality among electricity production and prices, R&D, patents, investment in ICT, and total factor productivity?
- What is the anticipated behaviour of total factor productivity resulting from shocks in electricity production, electricity prices, R&D, patents, and investment in ICT for the near future?

1.5 DEFINITION OF CONCEPTS

- Total Factor Productivity:

Total factor productivity reflects the share of output that cannot be accounted for solely by the number of inputs used in the production process. Haider, Kunst, and Wirl (2020) highlighted that TFP constitutes the element of economic growth that cannot be explained by the accumulation of either capital or labour alone. Economists consider TFP the primary catalyst for national economic growth, with higher TFPs associated with accelerated growth rates. To determine TFP, it is essential to measure vital elements, including real labour, real capital stock, real output, and possibly additional inputs (Milindi & Inglezi-Lotz, 2023). In this study, TFP is the dependent variable (y-variable), and its data is sourced from the Federal Reserve Bank of Saint Louis.

- Electricity supply shocks:

Fischer (1995) defines a supply shock as an unanticipated event that disrupts the supply of a product or commodity, resulting in a rapid change in its price. When faced with a negative supply shock, there is a decline in output accompanied by price increases. Conversely, a positive supply shock leads to increased production and lower prices. Any natural disaster or other unforeseen incident that interferes with electricity production would be a suitable illustration of this. The electricity supply shocks used in the study are electricity supply and prices. According to Nicholas and Michael (2018), the quality and stability of the power supply are, nevertheless, dependent on shocks caused by either external factors, such as human activity (nuclear accidents) or natural calamities (draughts, earthquakes). Electricity prices continue to rise as a result of electrical supply shocks. Additionally, supply-side electricity distortions, such as those caused by electricity supply shocks, result in widespread blackouts and power supply interruptions that affect the operation of the entire economy (Nicholas & Michael, 2018).

The proxies for electricity supply shocks are electricity production and electricity prices, and they are defined as follows:

- Electricity Production:

Electricity production generates electricity from various sources such as coal, natural gas, renewable resources, and nuclear energy. It involves converting energy from these sources into electricity. Fossil fuels, widely employed for electricity generation globally, are a significant source of greenhouse gas emissions and atmospheric pollutants (Annette & Tim, 2022). Electric generators convert mechanical energy to electrical energy. The supply/production of electricity has been a clear example of monopoly markets for a long time (Joan & Elisa, 2021). Eskom serves as the primary electricity provider in South Africa.

- Electricity Prices:

Electricity pricing can vary widely by country or locality within a country and depends on many factors. Tariffs imposed by Eskom on its customers, including municipalities, significantly contribute to electricity prices in South Africa. As stated in the Eskom Report (2023), the National Energy Regulator of South Africa (NERSA) determines the nature of tariff increase that applies to both direct customer tariff charges and the tariffs imposed by Eskom on local municipalities. In South Africa, municipalities are crucial to ensuring the supply of electricity. The process involves municipalities procuring electricity from Eskom and redistributing it to various entities, including households, companies, and educational institutions. It is vital to pay close attention to how much electricity costs per unit at your specific address because, as was previously indicated, different regions of the nation and suppliers offer varying rates.

- Technological advances:

According to Kesici (2015), technological advances are one of the primary indicators of economic growth. Technological advancements encompass the entire framework of knowledge, organization, and techniques essential for manufacturing processes, and they serve as an additional metric for measuring economic growth. By harnessing technology, it becomes feasible to enhance production outputs while maintaining the same level of inputs across various manufacturing processes (Kesici, 2015). The purpose of technology is to enable more effective technology usage by both organizations and individuals, lowering costs and boosting productivity (Younus, 2021).

To ensure robustness and consider the broad scope of technology, this study utilised three primary proxies to represent technological advancements: R&D, patents, and investment in ICT. These indicators have been selected as reliable measures to capture and represent technological advances within the study, and they are defined as follows:

- Research & Development:

According to Haider, Kunst, and Wirl (2020), R&D is a primary driver of innovation and technological advancement. R&D encompasses a range of innovative activities corporations and governments conduct to develop new products or services and enhance existing ones. It measures the financial investment directed towards implementing diverse R&D initiatives within a given country (Apostol et al., 2022). R&D is a crucial component that propels technological development since it produces new information, which advances energy production and processes.

- Patents:

According to WIPO (2020), a patent is a special right granted by the state to its owner, protecting their invention and granting them the authority to use and exploit it while prohibiting unauthorised usage by others. Patents serve as valuable indicators of technological advancement since they often stem from intensive research efforts that yield advancements in products or techniques, thus contributing value to industries and facilitating economic expansion. In contrast to R&D investments, which represent inputs that have the potential to generate new products or patents, patents serve as concrete proof of output or the realization of a final product (Milindi & Inglesi-Lotz, 2023).

- Investment in ICT:

Investment in ICT refers to the procurement of equipment and computer software utilised in production for a period exceeding one year. The ICT sector encompasses manufacturing and services industries that primarily produce or facilitate information processing and communication through electronic means, encompassing transmission and display. As an indicator, ICT investment is expressed as a proportion of the overall non-residential gross fixed capital formation (OECD, 2017). The ICT industry supports increased productivity, output, and technology advancement. There are numerous methods to analyse its effects: directly by looking at its contribution to production, employment, or productivity growth; or indirectly by looking at it as a source of technical development that influences other aspects of the economy, for example (OECD, 2023).

1.6 ETHICAL CONSIDERATIONS

This study used secondary data, and all relevant sources were acknowledged and cited. It was conducted according to ethics and guidelines. This thesis is free of plagiarism and does not include any data, images, graphs, or other information that has not been specifically cited as coming from another source.

1.7 SIGNIFICANCE OF THE STUDY

Although it is widely acknowledged that the increase in TFP is a crucial factor driving economic growth, there is a noticeable gap in the literature concerning the link between electricity supply, technological advancements, and TFP, particularly in South Africa and other nations. The literature on the link between electricity supply, technological advancements, and TPF is somewhat scant. There is a gap in the body of evidence supporting how factors such as electricity supply and prices, R&D, patents, and investment in ICT affect total factor productivity. The empirical literature examines a variety of nations and approaches to investigate the implications of independent variables on total factor productivity, which serves as the dependent variable. The impact of technology and electricity supply where TFP as a dependent variable was the subject of very little research in South Africa such as Kahn, Sithole, and Buchana (2022), Milindi and Inglesi-Lotz (2023), Lefophane and Kalaba (2022), Kreuser and Newman (2018), and Mpatane (2015). Looking at the existing literature, it appears that not many studies specifically addressed the implications of electricity supply shocks and technological advancements on TFP in South Africa.

The existing body of literature suggests that this study will contribute as the pioneering study to explore the implications of electricity supply shocks of electricity supply and prices and technological advancements of investments in R&D, patents, and Investment in ICT on TFP in South Africa. Moreover, it appears as if no research has been done in South Africa to examine how changes in electricity supply shocks and technological advances impact productivity. The study will be distinctive since it will use the ARDL methodology to analyse data from 1999 to 2022. The chosen period is also unique because it is notable for weak productivity growth and electricity crises in South Africa. Since TFP measures long-term economic growth, it is imperative to investigate and understand how changes in electricity supply shocks and technological advancements impact the country's productivity. Considering this, the study will contribute to the research gap on these issues and open the door to further investigation of the variables influencing TFP.

1.8 STRUCTURE OF THE STUDY

The dissertation unfolds in a structured manner across six chapters, each contributing uniquely to the study's depth and findings. Chapter 1 serves as the foundational anchor, offering the study's orientation and setting the context for subsequent explorations. Chapter 2 plays a pivotal role by meticulously reviewing and analysing critical trends in South Africa, including total factor productivity, real GDP, electricity production, electricity prices, R&D, patents, and investment in ICT, providing a comprehensive framework for the study.

Moving forward, Chapter 3 assumes significance by delving into theoretical frameworks and empirical literature. Here, it examines the theories surrounding total factor productivity, electricity supply shocks, and technological advances and synthesises findings from diverse sources, offering a nuanced understanding rooted in theoretical constructs and empirical evidence.

Chapter 4 lays out the methodology employed in the study, focusing specifically on the Autoregressive Distributed Lag approach. This chapter elucidates the tools and techniques used to analyse the data.

Chapter 5 represents the research findings and interpretation of findings derived from the econometrics tests conducted in the study. These findings validate or challenge existing hypotheses, offering insights into the relationships and dynamics between the variables under study.

Finally, Chapter 6 concludes the dissertation by presenting conclusions drawn from the research findings and offering policy recommendations based on these conclusions. It consolidates the study's essence, providing actionable insights and implications.

CHAPTER 2

ANALYSIS OF MACROECONOMIC VARIABLES

2.1 INTRODUCTION

This chapter undertakes a crucial analysis of the macroeconomic variables, aiming to provide a comprehensive understanding of South Africa's economy. It delves into the driving forces behind the economy and offers policy perspectives for each variable. The analysis commences with a focus on total factor productivity and South African GDP trends, encompassing electricity production, electricity prices, research and development, patents, and investment in ICT. While the study models are limited by data availability, the latest information forms the basis of the country analysis. This chapter present a detailed account of the trends and performance of each variable in South Africa from 1999 to 2022.

2.2 TOTAL FACTOR PRODUCTIVITY AND GDP PERFORMANCE TRAJECTORY

The decline in South Africa's productivity growth over the past ten years is hampering progress in enhancing living standards (OECD, 2022). The Productivity SA report (2020) highlighted a concerning trend: a decrease in the manufacturing sector's contribution to GDP growth over the past twenty years. This sector, constituting roughly 13% of the GDP, holds vital importance for employment and productivity advancement while also driving demand in the service sector. Recognizing its pivotal role, prioritizing the manufacturing sector is imperative to combat the persistent threat of unemployment that undermines our societal stability (Productivity SA, 2022).

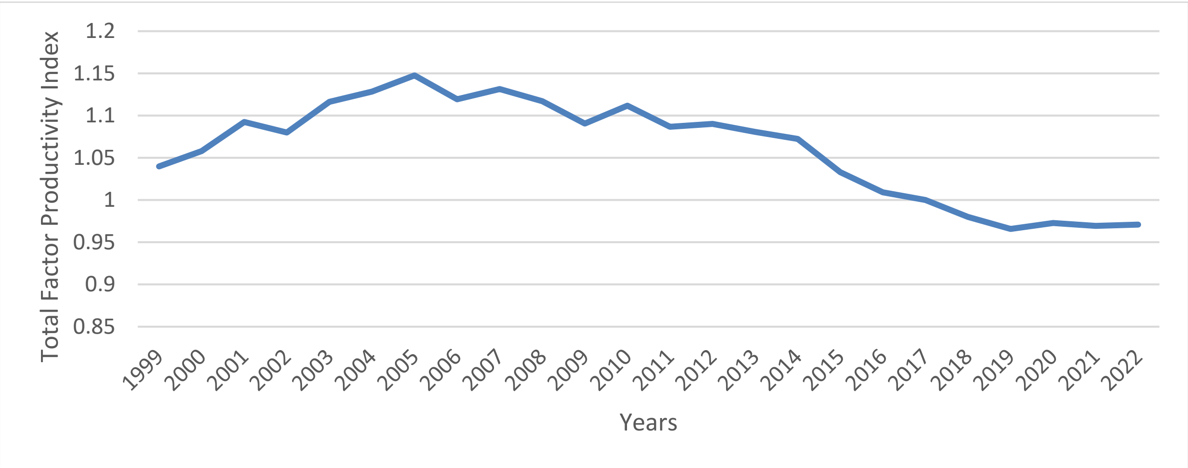

Figure 2.1: The trajectory of total factor productivity from 1999 to 2022.

Source: Author’s computation

Figure 2.1 presents South Africa's TFP trends. The data reveals a peak in TFP around an index of 1.14 in 2005, followed by a consistent decline in 2006. Notably, from 2015, there was a significant decline in TFP, starting at an index of 1.07 and further decreasing to 1.03 in the same year. This downward trajectory persisted beyond 2015, with a notable slowdown in TFP growth in 2019, marked by an index of 0.96. Several factors could have contributed to this slowdown, including policy stagnation, increased drought occurrences, labour challenges, and escalating production costs within South Africa. The TFP remained at a low index for the past eight years, from 2015 to 2022, as depicted in Figure 2.1. This continual decline in productivity directly influences the country's GDP or overall economic output. The low productivity figures in South Africa suggest that resources must optimise their skills and competencies to their fullest potential, increasing companies' resourcing costs (OECD, 2018).

Low productivity growth stalls South Africa’s competitiveness. A decline in productivity growth, specifically in total factor productivity and labour productivity, especially among SMMEs within the productive sectors, poses a significant obstacle to enhancing South Africa's economic growth and competitiveness (Productivity SA, 2022). Inefficient infrastructure in transport and telecommunications contributes to low productivity. Additionally, the regulatory environment is not consistently conducive to business and frequently poses challenges for firms regarding entry, exit, and expansion. Coupled with a lack of competition in crucial sectors, these factors have diminished private investment levels, especially in business R&D (OECD, 2022). The reduced productivity performance in South Africa results from a shortage of skills, high business operating costs, and a lack of competition in various markets within South Africa (OECD, 2018).

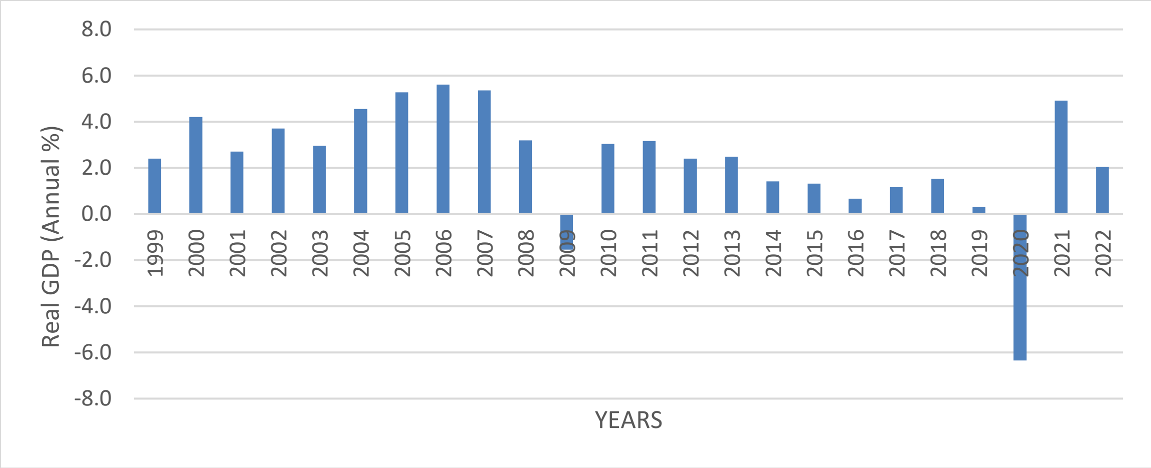

Figure 2.2: Trends of Real GDP from 1999 to 2022

Source: Author’s computation

Figure 2.2 illustrates South Africa's GDP trajectory, highlighting notable fluctuations. 2009, the nation faced an economic downturn, marking a notable negative GDP of -1.5%. Over the past five years, from 2016, South Africa encountered two consecutive technical recessions, resulting in remarkably low GDP growth rates. The GDP stood at a modest 0.7% in 2016 and further declined to 0.3% in 2019, signifying subdued economic expansion during these periods. 2020 witnessed a severe contraction, with the country's GDP plunging to -6.3%, a consequence primarily attributed to the stringent COVID-19 lockdown measures. However, a positive turn emerged in 2021, highlighting a notable upsurge as South Africa experienced a peak GDP of 4.9%. Undoubtedly, metrics such as total factor productivity and the GDP growth rate substantially influence a nation's economic well-being and the quality of life for its citizens.

A negative GDP in South Africa can profoundly impact the economy. It signifies a contraction in the country's overall economic output, reflecting reduced production, lower income levels, and decreased consumption. This downturn can lead to increased unemployment rates, reduced investment, and constrained government revenue. Addressing a negative GDP often requires policy interventions to stimulate economic activity, job creation, and foster an environment conducive to sustainable growth.

2.3 THE ANALYSIS OF ELECTRICITY PRODUCTION AND PRICE TRENDS IN SOUTH AFRICA

Persistent electricity shortages remain the primary obstacle to economic activity, adversely affecting businesses due to an escalation in power cuts following several years of declining energy production and supply (OECD, 2022). While power cuts are a harsh reality for numerous Sub-Saharan African nations, the ongoing electricity shortages in South Africa and their associated economic repercussions have gained widespread attention. For several years, Eskom, South Africa's state-owned utility responsible for over 90% of the nation's electricity supply, has been implementing scheduled power outages. However, during December 2019 and the initial period of January 2020, these outages escalated to a daily occurrence. According to the Council for Scientific and Industrial Research (CSIR), 2019 marked the most severe year of power cuts in South Africa, with blackouts persisting for a cumulative duration of 530 hours and stage 6 load shedding being introduced.

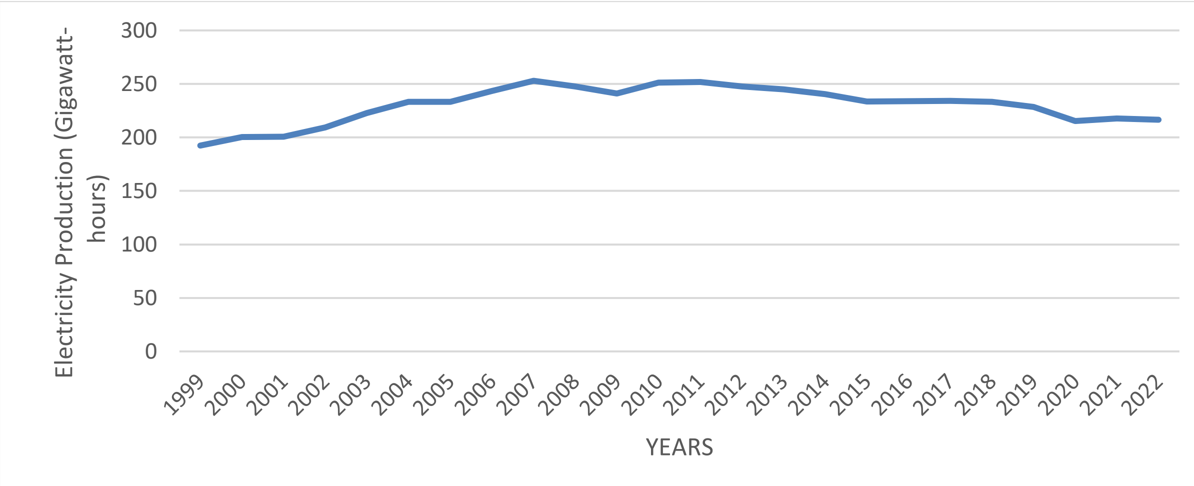

Figure 2.3: Trends of electricity production from 1999 to 2022

Source: Author's computation

Figure 2.3 shows South Africa's electricity generation capacity improved from 1999 to 2007. After that, there was a slight downward trend in 2009 and a slight uptrend in 2011. Since 2011, electricity production has declined steadily to 2022, approximately a 0.56% decline in the electricity produced in 2022 compared with 2021. The production decreased from 217650 GWh (gigawatt-hours) in 2021 to 216421 GWh in 2022, which shows that electricity production does not meet demand.

Several studies revealed that the ongoing energy crisis, signified by the persistent power cut episodes, has significant adverse effects on production and overall economic confidence (Morema et al., 2019; Mpini, Walter & Makrelov, 2019; Goldberg, 2015). According to the Oxford Policy Management Report (2020), consistent electricity supply leads to high operational expenses and improved business productivity and profitability. The power interruptions in South Africa have led to significant sales losses for businesses across various sectors, including retail, services, manufacturing, and industry. In response to the request of the Government of South Africa, the World Bank Group approved the Eskom Just Energy Transition Project (EJETP), a project with funding of $497 million in November 2022. This project supports the South African public energy utility.

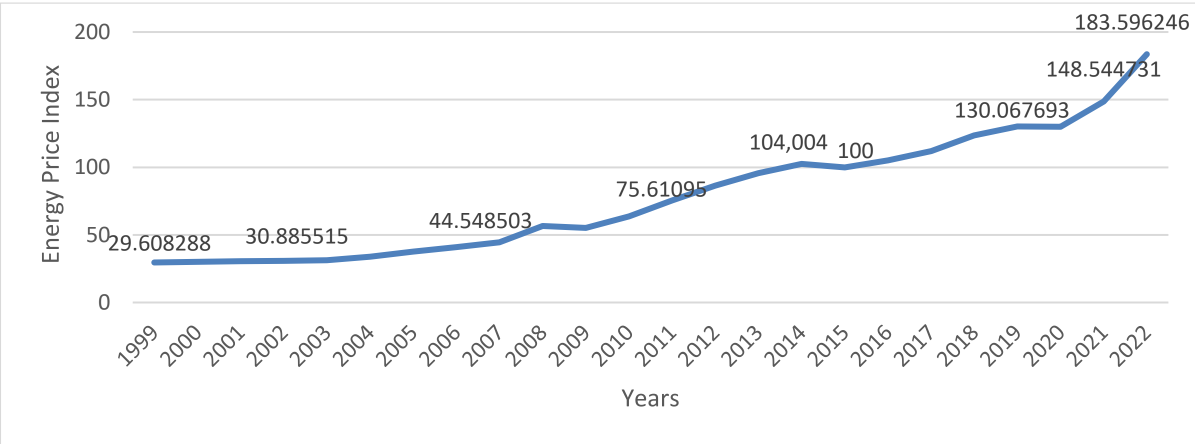

Figure 2.4: Trends of energy prices from 1999 to 2022

Source: Author's computation

Figure 2.4 illustrates a consistent upward trend in South African energy prices spanning 1999 to 2022. In 1999, the energy prices index was recorded at 29.6. Over subsequent intervals, this index gradually increased, reaching 30.8 in 2002, escalating to 44.5 by 2007, and notably surging to 75.6 in 2011. In subsequent years, they reflected significant spikes in energy prices, with the index rising to 104 in 2014 and maintaining stability at 100 in 2015, indicating strength in energy prices. However, by 2019, the index climbed to 130.0, marking a 30% hike in energy prices. This increase intensified in 2021, with the index peaking at 148.5, representing a 40% surge compared to 2019. By 2022, the index surged to 183.5, nearly doubling the 2015 price levels and highlighting the substantial burden of excessively high energy costs consumers face.

This increase in electricity prices has been linked to the ongoing energy crisis, marked by widespread national blackouts. Load shedding has not only impacted electricity availability but has also contributed to escalated electricity tariffs within the economy. The National Energy Regulator of South Africa, created under the provisions of the National Energy Regulator Act of 2004, is responsible for overseeing the electricity, piped gas, and petroleum sectors in South Africa. Additionally, it is tasked with collecting levies from individuals who hold ownership of petroleum and gas. South Africa's Electricity Pricing Policy (EPP) also regulates South African electricity prices.

2.4 THE ANALYSIS OF R&D TRENDS IN SOUTH AFRICA

According to the Human Sciences Research Council (2022), research and development include creating new products and maintaining or enhancing existing products, processes, or services represented by entities like Eskom. Over the past decade, the R&D patterns observed in South Africa have raised economic concerns despite hopeful signs in the public sector's R&D activities. The predominant trend is the decline in R&D spending, particularly within the business sector, over the last ten years. During the 2011/12 fiscal year, the business sector's share of R&D exceeded 50%. Subsequently, it consistently dropped below this threshold, reaching approximately 40% in 2019/20. This decline implies a significant reduction in R&D expenditure by businesses (HSRC, 2022).

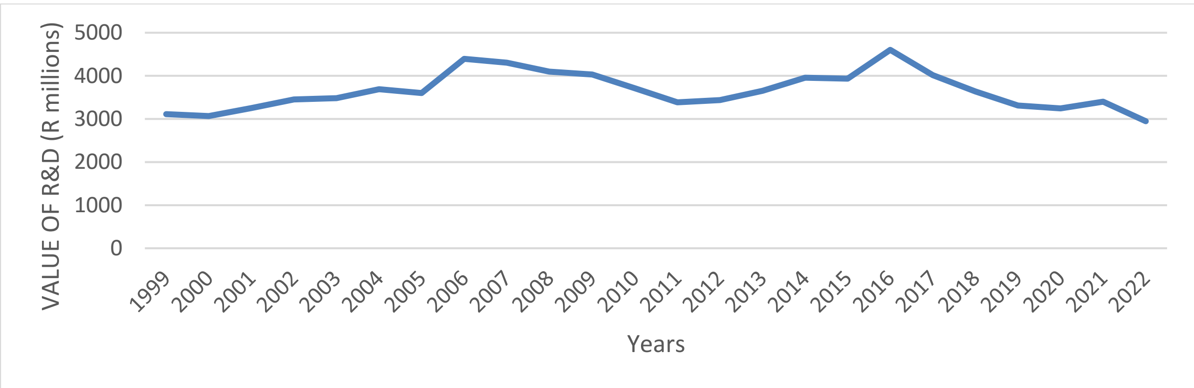

Figure 2.5: Trends of Research and development from 1999 to 2022

Source: Author’s computation

Figure 2.5 illustrates the trend analysis of South Africa’s R&D. It reveals a consistent upward trajectory in R&D expenditure since 2002, peaking notably in 2006 at R4393 million and again in 2016 at R4603 million. However, a significant shift occurred in 2017, witnessing a decrease from R4603 million in 2016 to R4017 million in 2017, marking a 13% decline. This decline persisted into 2022, with R&D investment further dropping to R2947 million, a 13% decrease from the 2021 figure of R3403 million.

According to HSRC (2022), South Africa requires additional R&D initiatives to attract and retain researchers and R&D staff. The HSRC study findings indicated that there is a chance to increase R&D expenditure in the manufacturing sector rather than exporting South Africa's raw resources to be converted into goods overseas. The study results also revealed that South Africa performs R & D at a different level than developed countries. Compared to other countries, most inventions developed in South Africa are not unique but are based on adapting or copying technologies from abroad (HSRC, 2022).

2.5 THE ANALYSIS OF PATENTS TRENDS IN SOUTH AFRICA

Patent applications refer to applications filed globally using the Patent Cooperation Treaty process or with a national patent office. These applications seek exclusive rights for an invention, whether a product or a process, which introduces a novel approach to accomplishing a task or presents an innovative technical solution to a problem (Trading Economics, 2023). A patent grants the inventor exclusive rights for a specified duration, typically 20 years. South African patent applications, including actual values, historical data, forecasts, and projections, were obtained from the World Bank in November 2023. The regulation of South African patents falls under the jurisdiction of the Patents Act, 57 of 1978. As the Department of Trade, Industry, and Competition states, the Patents Act of 1978 aims to facilitate the registration and issuance of patent letters for inventions and related matters.

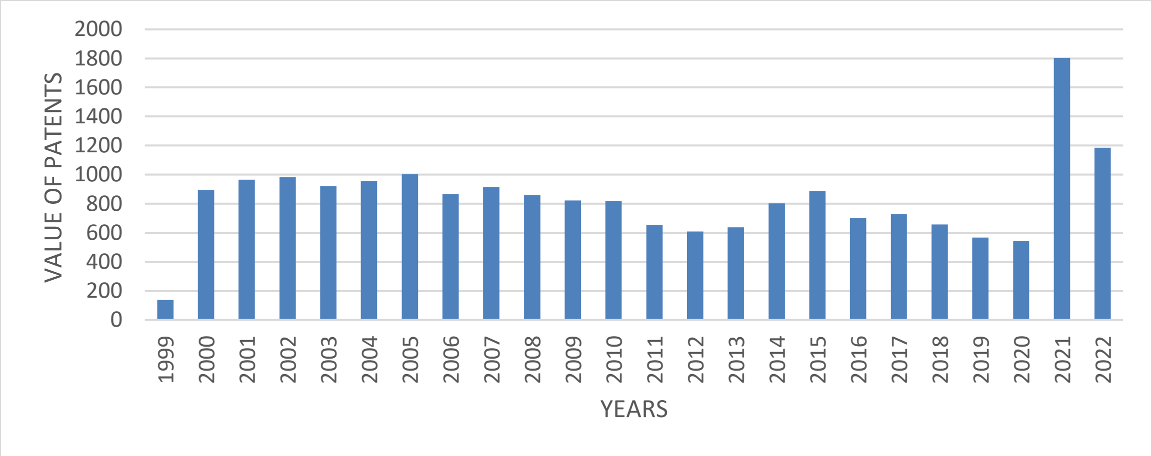

Figure 2.6: Trends of patent applications for residents from 1999 to 2022

Source: Author's computation

Figure 2.6 illustrates that the number of patents granted to South African residents decreased from 2016 to 2020. It was also worse in 1999 because the number of patent applications for South African residents was 138, but after 2000, it started increasing until 2005. According to the Department of Planning, Monitoring and Evaluation report (2022), a reduction in the number of patents granted is commonly seen as a sign of reduced investment in R&D. This is a matter of significant concern considering the emphasis placed by the National Development Plan (NDP) on the pivotal role of R&D in enhancing South Africa's global competitiveness, particularly in the context of the Fourth Industrial Revolution. However, patents granted to South African residents rose significantly in 2021, to 1804 from 542 in 2020 (an increase of 70%). In 2022, patents granted to South African residents declined to 1186 (a decrease of 34%).

A decrease in patent applications by South African residents could signal a slowdown in innovation and R&D within the country. This might suggest reduced investment in innovative ideas, inventions, and technological advancements. This decline could further negatively impact economic growth by limiting innovation-driven sectors, job creation, and overall productivity in the South African economy.

2.6 THE ANALYSIS OF INVESTMENT IN ICT TRENDS IN SOUTH AFRICA

According to the International Trade Administration (2023), South Africa has one of the largest ICT markets in Africa, showcasing excellence in security software, mobile software, and electronic banking services. This sector significantly contributes to the country's GDP, attracting major global players like IBM, Cisco, Unisys, AWS, Microsoft, Intel, Systems Application Protocol (SAP), Dell, Novell, and Compaq, who have established subsidiaries in South Africa. While the public sector drives IT spending, current conditions foresee short-term reductions to offset the escalating debt from economic challenges and the impact of COVID-19. The South African government leverages ICT for socio-economic justice and inclusion, improves competitiveness and prepares for the 4th Industrial Revolution. The State Information Technology Agency (SITA) oversees tenders for public sector IT (International Trade Administration, 2023).

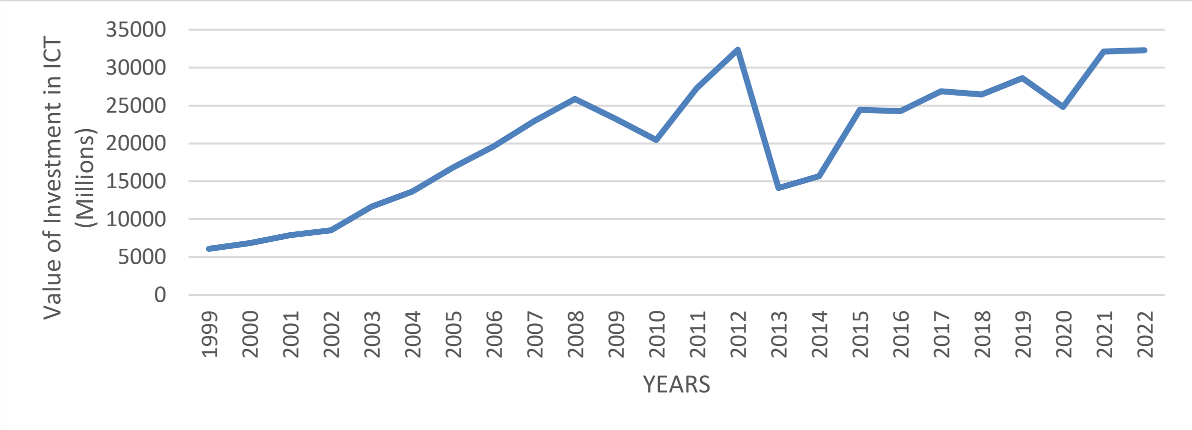

Figure 2.7: The investment in ICT trends from 1999 to 2022

Source: Author's computation

Figure 2.7 illustrates a noteworthy pattern in South Africa's ICT investment between 1999 and 2022. Initially, the country's investment in ICT displayed a pronounced upward trajectory, starting at R6095 million in 1999 and steadily rising. However, this trend reversed course by 2009, witnessing a decline in ICT investment to R23,266 million from R25,862 million in 2008. In contrast, there was a significant surge in patents granted to South African residents in 2012, escalating to R32,367 million from R27,302 million in 2011, marking a notable 19% increase. Since 2012, ICT investment has peaked and remained at that point. Subsequent years, specifically 2021 and 2022, recorded investment figures of R32,139 million and R32,305 million, respectively, signifying a marginal increase of 0.52%. Despite this increase, the growth rate appears relatively modest over the past few years.

A decrease in investment in ICT adversely affects the South African economy by potentially limiting innovation, hindering technological progress, and limiting competitiveness. This decline may affect total factor productivity, job creation, and the country's ability to adapt to the digital era, potentially weakening its global economic standing.

2.7 SUMMARY

In summary, Chapter 2 sheds light on South Africa's real GDP and overall productivity while considering the impacts of electricity supply shocks and technological advancements from 1999 to 2022. The analysis delved into the performance of electricity production and prices, R&D, patents, and investment in ICT as determinants of TFP. Notably, the observed trends in these variables revealed fluctuations, indicating a potential interdependence among them. Furthermore, the chapter presented an overview of South Africa's macroeconomic landscape, specifically focusing on the association between electricity supply shocks, technology advances, and their influence on total factor productivity. By examining the performance of these macroeconomic variables, this chapter sheds light on the complex relationship shaping South Africa's economic trajectory. Finally, the observed trends highlighted the significant role played by electricity production and prices and technological advancements proxies in influencing South Africa's TFP over the examined period.

CHAPTER 3
LITERATURE REVIEW

3.1 INTRODUCTION

The literature review comprises two main sections. The theoretical literature section discusses the theories that explain the implications of electricity supply shocks and technological advancements on total factor productivity. In contrast, the empirical literature subsection examined the literature on electricity supply shocks, technological advancement, and total factor productivity.

3.2 THEORETICAL FRAMEWORK

This study's literature and relevant theories demonstrated a clear link between total factor productivity, electricity supply shocks, and technology advancements. This connection is substantiated by pertinent theories, including the production theories, such as the Cobb-Douglas Production theory, and growth theories, such as the Endogenous Growth theory, which additionally encompasses the AK and innovation-based theories.

3.2.1 Cobb-Douglas Production Theory

The Cobb-Douglas production theory is a popular economic theory that explains how an economy produces goods and services by analysing the connection of inputs and outputs in a production process. Between 1927 and 1947, Charles Cobb and Paul Douglas developed and validated the Cobb–Douglas form through analysis of statistical evidence. Douglas stated that the foundational structure of the model had been earlier formulated by Philip Wicksteed in 1894. Cobb and Douglas (1928) examined its applicability in modelling the growth of the American economy from 1899 to 1922 in their study. They employed data from the manufacturing sector in the United States spanning from 1899 to 1922 to introduce the Cobb-Douglas production function. This concept has been extensively applied in economic theory for many years (Smirniv & Wang, 2021). The authors calculated and presented the index figures for fixed capital, the total count of production workers, and physical production in manufacturing using logarithmic expressions (Smirniv & Wang, 2021). They determined that the production curve was roughly one-fourth of the way between the curves depicting the corresponding alterations in labour and capital. As a result, Cobb and Douglas adopted the function previously employed by Wicksteed and Wicksell, as follows:

$$Y = f(L, K) = AL^k K^{1-k} \ldots\ldots (3.1)$$

In equation 3.1, the variables $Y, L,$ and K denotes production, labour, and capital, whereas A represents total factor productivity. The authors used the least squares method to determine the value of $K = \frac{3}{4}$ of the estimated Y values accurately represented the actual production values.

Cobb and Douglas (1928) put forward the idea that the quantity of labour and physical capital invested is a crucial factor in determining the level of production output. The defining characteristics of the Cobb-Douglas production function include linearity and homogeneity, with a degree of one. This functional form effectively incorporates labour and capital inputs to explain the output. The methodology employed in this context aligns with the approaches presented by Islam (1995), reiterated in the works of Lee, Pesaran, and Smith (1997); and Barossi-Filho, Silva, and Diniz (2003). Estimating the parameters of aggregate production functions holds significant importance in contemporary research addressing topics such as growth, technological change, productivity, and labour.

Mpatane (2015) asserts that the most accurate indicators of production output are labour input and capital expenditure. According to Lee et al. (1997) and Barossi-Filho et al., (2003), production output is predominantly influenced by labour and capital. The authors' conceptualisation of production encompassed measuring its monetary value, encompassing all manufactured products within a specific year. They defined labour as the cumulative count of individuals involved in work for one hour during the same time frame. On the other hand, capital encompassed the collective monetary worth of structures, machinery, and other relevant assets. The equation representing the Cobb-Douglas Production Function is modelled in the following form:

$$Y = f(L, K) = AL^{\beta} K^{\propto} \ldots\ldots (3.2)$$

Equation 3.2 describes how a change in total factor productivity reflects an efficiency or technological advancement enhancement. The effect of alterations in labour or physical capital on output is captured by the output elasticity denoted by the Greek symbols α and β. The Cobb-Douglas production function incorporates critical elements of capital input, TFP, labour input, and technology. It offers an explanatory framework to understand how these factors are interconnected and influence one another.

Based on the assumptions of the Cobb-Douglas production function, if either labour or capital is absent, production output would be reduced. As a result of machinery that has been shown to generate more items than when done by people, a loss in labour does not necessarily imply a decrease in productivity. Additionally, it is assumed that doubling the amount of labour or capital will lead to a proportional doubling of industrial output. In the context of this function, it is postulated that there are constant returns to scale, indicating that when inputs are expanded, the output also expands proportionally. However, it is essential to note that such perfect scalability is not attainable in the real world. Even doubling capital may not lead to a doubling of output. Other elements, such as electricity, are necessary for the machines to run continuously. Insufficient utilization of machinery may occur due to intermittent electrical supply, load-shedding, and brownouts, leading to lower production output than expected (Mpatane, 2015).

However, it has been determined that the Cobb-Douglas production function's second assumption, which suggests constant proportions of labour and capital to total output, does not hold. This is because labour and capital can be interchanged in the production process of a single good, rendering this premise inaccurate. Certain products may rely more on labour while others rely more on machinery. With the rapid advancement of technology, businesses now utilise cutting-edge machinery and equipment to manufacture their products. These modern technologies have the advantage of being operated by a minimal workforce of just two or three individuals, decreasing the overall labour requirement (Mpatane, 2015).

Felipe and McCombie (2020) examined the Cobb-Douglas production function, which allows us to analyse the association between various inputs, including labour, capital, and energy, and the output, particularly in electricity production. TFP in this model represents the unexplained portion of the output, indicating the influence of factors beyond the measured inputs. Additionally, the coefficients assigned to these inputs provide insights into their contributions to electricity production. Moreover, the model can account for input costs, including energy price, affecting the overall cost structure of production. Therefore, fluctuations in energy prices can influence production costs and potentially impact electricity output levels. Furthermore, including R&D as an input in the Cobb-Douglas model acknowledges that R&D investments can enhance TFP by improving technology and knowledge. As R&D expenditures increase, the coefficient for R&D within the production function is valuable for estimating its effects on output and productivity.

3.2.2 Endogenous Growth Theory

The second theory pertinent to this study is the endogenous growth theory. It places significant importance on technological progress as a primary driver of economic growth. The proposed endogenous growth theory has its roots in Abramowitz (1952) and later received substantial contributions from Lucas (1988). However, much of the work in this field is commonly associated with Romer, as evidenced by his influential contributions in 1983, 1986, 1990b, 1994, and 2018. This dissertation adopts a theoretical framework aligned with the endogenous growth theory proposed by Samuel and Lionel (2013). The importance of employing an accurate growth model specification to achieve robust estimation results is emphasised by Mabangu and Inglesi-Lotz (2022); and Samuel and Lionel (2013). During the 1980s, Paul Romer introduced the endogenous growth theory, which sets itself apart from the Cobb-Douglas production theory by emphasizing technological advancements as the primary catalyst for economic growth (Eita & Pedro, 2021). This theory emphasises the crucial role that the accumulation of physical and human assets plays in determining the economy's growth and acknowledges the significance of human capital in fostering economic development (Lucas, 1990). The endogenous growth theory posits that economic growth is driven by internal dynamics, including improving factors, technological progress, and generating innovative ideas (Howitt, 2010).

The distinction between endogenous growth theory and the Cobb-Douglas production theory lies in their respective emphasis. Endogenous growth theory places significant importance on technological progress as a primary driver of economic growth. In contrast, the Cobb-Douglas production theory centres around the role of physical capital and labour inputs in economic growth (Eita & Pedro, 2021). According to the theory, economic growth is driven by endogenous factors, including investments in human capital and research and development, in contrast to the traditional growth models that primarily rely on exogenous factors (Lucas, 1990). R&D is an essential indicator of technological progress. Economic growth models, such as endogenous growth theory, emphasise the role of R&D in boosting productivity and economic development. Increased R&D spending can lead to technological advancements that improve TFP. Empirical evidence has supported this, showing that technology, research, and development can lead to sustained economic growth. According to Howitt (2010), the phrase valid and accurately represents the critical differences between endogenous growth theory and the Cobb-Douglas production theory.

In the long run, the growth rate of output per person, which is the primary indicator of economic growth, is contingent upon the total factor productivity growth rate. This growth rate of total factor productivity, in turn, is shaped by the pace at which technological advancements occur (Howitt, 2010). The correlation among these variables highlights that sustained economic growth is closely tied to technological advancements, which drive productivity and efficiency improvements. By emphasizing the role of technological progress, it is recognised for its crucial contribution to long-term economic growth and development. Romer (1994) noted that the model posits economic growth as an inherent outcome of economic activity rather than being impacted by external factors. According to Romer (1994), the endogenous growth model emphasises how the economy behaves. Evaluating technical advancements or productivity within the industry or firm is a complementary approach (Takentsi, Sibanda & Hosu, 2022).

Endogenous growth economists argue that higher investments in human capital and promoting accelerated innovation exert a direct influence on the growth of productivity. Therefore, they advocate for promoting institutions, both in the public and private sectors, that facilitate innovation initiatives and offer incentives to individuals and businesses to foster creativity. These measures include funding support for R&D activities and protecting intellectual property rights. Institutions, technical advancement, total factor production, and other factors were all considered exogenous factors (Takentsi, Sibanda & Hosu, 2022). The empirical foundation for endogenous growth theory is rooted in R&D to TFP analysis, highlighting a strong correlation between R&D and TFP growth (Sekaiwa & Maredza, 2018).

A group of growth theorists grew increasingly pessimistic about popular explanations for how exogenous factors affect long-run growth around the middle of the 1980s. Endogenous growth theorists advocated for a growth model that specifically incorporated the critical determinants of economic growth instead of relying on exogenous factors such as unexplained technological progress. This approach builds upon the seminal research conducted by Kenneth Arrow (1962), Hirofumi Uzawa (1965), and Miguel Sidrauski (1967), who laid the foundation for its development. Within their framework of endogenous growth theory, two models emerged: the AK theory and the Innovation-based theory. These two models are explained as follows:

3.2.2.1 AK Theory

According to Howitt (2010), the AK theory is widely acknowledged as the original formulation of endogenous growth theory. Frankel (1962) developed a preliminary version of the AK theory, proposing that the aggregate production function may exhibit a constant or potentially increasing marginal product of capital. This occurs because as firms accumulate more capital, some of it represents intellectual capital that drives technological progress, counteracting the usual decline in the marginal product of capital. A constant external saving and endogenous growth rates are prerequisites for the simplest endogenous model, the AK theory. It just changes one parameter to simulate technological progress, typically A. The model assumes that the production function maintains a constant rate of return to scale, implying no diminishing returns in the production process. Several arguments have supported this idea, including the positive economic spillovers from capital expenditure and the upward spiral of technological advancements. However, models incorporating agents' decisions on optimal spending, saving, resource allocation to R&D, and technological advancements provide more robust support for the endogenous growth theory. Romer (1986, 1990) integrated imperfect markets and R&D as fundamental components in the growth model. Additionally, Vladimir Pokrovskii, a Russian economist, proposed the quantity theory of endogenous productivity increase. The theory, which allows one to replicate past rates of economic expansion precisely, characterises growth as the outcome of the dynamics of three components, including technological aspects of production equipment.

The production function in the AK model can be seen as a particular instance that fits into the broader framework of the Cobb-Douglas production function:

$Y = AK^{a}L^{1-a}$……………………………………………………………………………. (3.3)

In equation 3.3, Y represents the overall production in an economy, and the Cobb-Douglas function is presented. A represents total factor productivity, K represents capital, L represents labour, and the parameter a measures the output elasticity of capital. When the value of a is equal to $1(a = 1)$ in the production function, it causes the production function to assume a linear relationship with capital, which leads to constant returns to scale. As a result, the formula for this is expressed as follows:

$Y = AK$………………………………………………………………………………… (3.4)

Where A represents a positive constant. Thus, the term ‘AK theory’ is derived. Despite the requirement for arbitrary parameters, this specific version of the theory elucidates that economic growth results from the dynamics inherent in the production components. This feature allows for a precise replication of historical rates of economic growth.

3.2.2.2 Innovation-Based Theory

According to Howitt (2010), the innovation-based growth theory was the phase of endogenous growth theory that came after the AK theory. This recent perspective recognises the differentiation between intellectual capital, which forms the basis for technological progress, and physical and human capital. While physical and human capital is acquired through saving and education, intellectual capital flourishes through innovation. The innovation-based theory can drive TFP improvements, leading to economic growth in the country.

Romer (1990) formulated a particular iteration of the innovation-oriented theory and posited the hypothesis that an increase in the extent of product diversity contributes to overall productivity growth. As per this concept, innovation enhances productivity by generating novel product varieties, even if they do not necessarily exceed existing ones in quality. The theory relies on employing the Dixit-Stiglitz-Ethier production function, where labour and a diverse variety of intermediate products are combined to yield the final output:

$Y = L^{1-\alpha} \int_0^A x(i)^{\propto} di, \quad 0 < \propto < 1$…………………………………………………….. (3.5)

L represents the overall labour supply, which is considered to remain constant. $x(i)$ represents the inflow of intermediate products i while A represents the measure of various available intermediate products. It is reasonable to anticipate that a rise in product diversity, as indicated by A, would enhance productivity by enabling a more balanced allocation of intermediate production across a broader range of activities. This distribution allows each activity to operate at a lower intensity, taking advantage of diminishing returns and resulting in higher production levels for the average good. A different version of innovation-based growth theory is the 'Schumpeterian' theory established by Aghion and Howitt (1992) and Grossman and Helpman (1991).

3.2.3 Endogenous growth theory versus Cobb-Douglas Production theory

In contrast to the Cobb-Douglas Production theory, the Endogenous Growth theory views technical advancements as the primary factor influencing economic growth. Human capital is what drives economic growth (Lucas, 1990). According to Lucas (1990), the two main factors that affect economic growth are human and physical capital accumulation. In endogenous growth models, there has been a consistent emphasis on the importance of R&D in enabling TFP expansion (Romer, 1990; Grossman & Helpman, 1991). Yet, the underlying assumption is that more R&D would encourage the spread of knowledge and innovation, which would then fuel productivity development. Like how higher levels of education strengthen one's capacity to utilise and advance existing technologies, human capital is thought to boost productivity growth (Lucas, 1988).

One of its strongest drawbacks is that empirical data cannot support the Endogenous Growth theory. Unlike the Cobb-Douglas Production theory, which can be reliably quantified, the Endogenous Growth theory has been suspected of being founded on untestable assumptions. This theory emphasises the importance of enhancing a nation's human capital to promote the advancement of modern technologies and effective production methods, consequently stimulating economic growth.

3.3 EMPIRICAL LITERATURE

The following categories are used to group empirical literature on electricity supply shocks, technological advances, and productivity: literature on the impact of electricity production and prices on productivity, literature on technological advances and productivity, causality among energy, technological advances, and productivity, and lastly, forecasting of productivity.

3.3.1 Electricity production, prices, and productivity

Takentsi et al. (2022) investigated the correlation between economic performance and energy prices in South Africa using an ARDL bounds testing approach spanning from 1994 to 2019. Their study findings indicated that electricity prices notably adversely impact economic growth, persisting in the short and long run. Conversely, crude oil prices are positively associated with economic growth throughout the specified time frame. Despite these outcomes, the Granger causality test failed to establish a causal relationship between energy prices and economic growth in South Africa. Instead, it identified a unidirectional causality between labour productivity, gross fixed capital formation, and economic growth.

Gonese, Hompashe, and Sibanda (2019) used a fixed-effect estimator approach to investigate the impact of power costs on South African sectoral output from 1994 to 2015. Their findings revealed that power costs harm South African sectoral output. Moreover, the SUR estimator highlighted sectoral output's diverse reactions to South Africa's electricity price changes. Consequently, significant, and negative responses to these price fluctuations were observed in six sectors.

In Pakistan, Granger, and Zhang (2019) conducted a study on the impact of electricity shortages on manufacturing productivity, employing a survey of four thousand five hundred manufacturing enterprises from 2010 to 2011. Their findings revealed that an additional daily hour of unexpected shortages led to a nearly ten percent decrease in annual revenues. Similarly, a one-hour increase in daily shortages resulted in about a twenty percent reduction in value-added yearly at the firm level, coupled with an increase in the labour share of output. The study also noted a comparatively more minor impact for a similar amount of load-shedding, attributed to predictability and firm adaptation. In contrast, the effects of a comparable level of load-shedding were considerably diminished, possibly owing to the predictability of such events and the ability of businesses to adapt accordingly. Their findings provided compelling evidence that an enhanced and dependable power supply would significantly boost manufacturing productivity in the region.

Alam, Miah, Hammoudeh, and Tiwari (2018) studied the nexus between access to electricity and labour productivity in developing countries using a balanced panel data set of fifty-six developing countries. Their results of the panel cointegration tests provided evidence of the long-run equilibrium association between access to electricity and labour productivity, considering factors such as economic growth, FDI, gross capital formation, and financial development. Their long-term findings indicated a substantial enhancement in labour productivity in developing countries due to improved access to electricity. Additionally, the heterogeneous panel non-causality test results highlight a reciprocal causal connection between electricity access and labour productivity in the short run.

Mpatane (2015) conducted a study using the VECM method to examine how the availability of electricity affected the production of the South African manufacturing industry between 1985 and 2014. The results showed a consistent and favourable relationship between manufacturing production, employment, and supply. These results indicated that maintaining equilibrium in manufactured output depended on the contributions of electricity supply and manufacturing employment. Mpatane (2015) concluded that expanding the electricity sector would increase manufacturing output, underlining the beneficial policy ramifications of the positive correlation between electricity supply and manufacturing output.

Yakubu and Bala (2015) applied the ARDL model to explore the correlation between electricity supply and manufacturing output in Nigeria from 1971 to 2010. Their research findings revealed a consistent association between the variables, supported by a significant and negative error correction term. Short- and long-term analyses demonstrated a positive correlation between manufacturing output and electricity supply, with statistical significance observed primarily in the long run. The study highlighted the policy implication that increasing electricity supply is crucial for enhancing the productive capacity of the manufacturing sector. Notably, this research provided evidence that to achieve Nigeria's economic vision of becoming one of the top twenty industrialised economies globally by 2020, particularly in the manufacturing sector, it is crucial to put in place a steadfast policy that ensures a sufficient and stable increase in electricity supply.

Akiri, Ijuo, Odike, Apochi, and Maria (2015) investigated the link between electricity supply and manufacturing productivity in Nigeria. For their analysis, the researchers employed OLS multiple regression covering the period from 1980-2012. Their results revealed a positive association between electricity generation and supply and manufacturing productivity growth. However, the inadequate and irregular electricity supply significantly impacted the coefficient value, especially within the manufacturing subsector. This inadequacy was attributed to the government's excessive expenditure on non-economic and unproductive sectors. Based on their findings, the study suggested measures to reverse the unfavourable trend, including the prudent utilization of funds allocated for developing the electricity subsector and the continued deregulation of the power industry to enhance competitiveness and ensure sufficient and reliable electricity supply in the country.

3.3.2 Technological advances and productivity

Marire (2023) studied the connection among the composition of R&D fixed capital spending, expressed as the ratio of the private sector to public sector R&D capital expenditure and national total factor productivity. This study utilised South African data from 1965 to 2019 and applied a non-linear distributed lag modelling framework to address non-linearities in the relationship. The results, firstly, indicated a positive impact of the ratio of private sector to public sector R&D capital spending on total factor productivity. Secondly, the configuration of R&D capital spending exhibited substantial asymmetric effects on national total factor productivity, with negative changes outweighing positive changes. Adverse alterations in the structure of R&D capital spending negatively affect total factor productivity, while positive changes yield positive effects. Both in the short-run and the long-run, cumulative multipliers revealed that adverse changes in the structure of R&D capital spending significantly surpass positive changes by a substantial margin.

Milindi and Inglesi-Lotz (2023) conducted a study examining the influence of technology development on carbon emissions in nations of different income levels from 1989 to 2018. Their study encompassed sixty countries evenly distributed across four distinct income groups: high-income, upper-middle-income, lower-middle-income, and lower-income countries. For a comprehensive analysis and account for the broad concept of technology, the researchers employed six distinct indicators to capture various aspects of technological progress. These indicators included patents, total factor productivity, ICT, technology publications, and public R&D expenditure. The study revealed that ICT factors effectively reduced carbon emissions across all income groups. However, the study concluded that R&D expenditure and patents had no significant effect. Interestingly, total factor productivity contributed to higher carbon emissions, while scientific and technological articles were associated with decreased emissions. Overall, the study yielded inconsistent findings across multiple measures and wealth levels of the countries.

Asongu and Odhiambo (2023) conducted a study to explore the significance of IT in influencing the relationship between FDI and TFP dynamics. Their research focused on a panel of twenty-five nations in Sub-Saharan Africa (SSA) between 1980-2014. The study employed the Generalised Method of Moments (GMM) technique for analysis. The empirical findings obtained through the GMM revealed that information technology, particularly mobile phone penetration and internet penetration, played a noteworthy role in moderating the positive influence of FDI on the dynamics of TFP. However, it is worth noting that the estimates related to the growth of real TFP did not meet the criteria of post-estimation diagnostic tests in their study.

Kahn, Sithole and Buchana (2022) conducted a study investigating the effects of technological innovation on productivity in the manufacturing industry in South Africa. Their research employed direct innovation measurements and examined how technological advancements influenced firm productivity. A modified version of the CDM model was used in their analysis, based on a sample of manufacturing companies and data from the Business Innovation Survey (BIS) from 2014 to 2016. The findings of their study revealed a strong correlation between productivity in South African manufacturing businesses and the adoption of new products or processes. Furthermore, their research identified factors associated with a higher likelihood of investing in innovation, such as a more significant proportion of skilled employees, a larger total workforce, and engagement in export activities.

Laddha, Tiwari, Kasperowicz, Bilan, and Streimikiene (2022) conducted a study focusing on technological advancements and their impact on productivity. Their research specifically examined the effects of ICT on labour productivity using a panel data approach. Their study adopted a panel data approach and analysed a wide-ranging dataset of ninety-eight countries. The research covered the period from 2000 to 2015 and encompassed three main country groups: low, middle, and high-income countries. They found a noteworthy influence of telephone and broadband subscriptions on overall labour productivity and the service sector's productivity. Their results strongly suggested that investing in ICT enhances labour productivity. Furthermore, their study emphasised the importance of factors, including the growth rate of Gross Capital Formation and the expansion rates of telephone and broadband subscriptions, in influencing overall labour productivity and productivity within the service sector. Consequently, it emphasised the necessity of investing in capital formation and ICT to foster increased labour productivity.

Fujii, Shinozaki, Kagawa, and Managi (2019) examined the connection between technological advancements and productivity, employing the Determinant Factor Analysis. Their research focused primarily on how ICT capital affected the rise in productivity in the energy sector. Their study focused specifically on three types of ICT: IT capital, communication technology capital, and software capital. Their study used the Luenberger productivity indicator to measure total factor productivity by analysing data from fourteen nations in the energy industry between 2000 and 2014 since it is more reliable than the Malmquist indicator. Their findings revealed that total ICT capital did not significantly impact either capital or material productivity. The energy sector's capital productivity, however, was positively affected by IT and software investments, respectively. In contrast, Fujii et al., (2019) found contrasting results regarding the effect of ICT capital on productivity indicators. Interestingly, their study revealed that specific types of ICT capital have offsetting effects on productivity. Additionally, a notable finding was that the interaction between the proportion of renewable energy and the proportions of ICT capital affects the improvement of capital productivity.

Sekaiwa and Maredza (2018) used the ARDL model to investigate the influence of R&D on total factor productivity in South Africa from 1970 to 2013. The ARDL test findings revealed cointegration between TFP and R&D in all samples. These findings indicate that domestic and foreign R&D efforts have positively impacted the growth of TFP in South Africa. Consequently, their results suggest a valuable policy implication for South African decision-makers, urging them to implement targeted policy measures that promote increased investment in R&D, with a particular emphasis on bolstering domestic R&D initiatives to foster and sustain higher TFP growth in the country.

Kreuser and Newman (2018) explored the TFP of manufacturing firms in South Africa between 2010 and 2013, utilizing firm-level data. The results demonstrated that productivity experienced growth across most subsectors, albeit at varying rates. The study also established a positive relationship between firm size, productivity, and growth rates. Furthermore, a positive correlation was identified between productivity and R&D expenditure, highlighting the crucial role of investing in R&D to foster TFP.

Kumo (2017) investigated the TFP and prospective output growth in South Africa. The study employed an economic growth decomposition exercise to analyse the contributions of numerous factors to growth in the post-apartheid period from 1996 to 2015. The results highlighted the enduring significance of TPF as the primary catalyst for economic development. The study also emphasised that the democratic transition of 1994, which brought about significant political changes and the end of international isolation, played a crucial role in boosting TFP through trade liberalization. Furthermore, implementing improved macroeconomic policies and reforms and establishing solid institutions contributed to rapid TFP gains and increased efficiency during the subsequent decade. Additionally, the study identified that investment in R&D can catalyse TFP growth.

3.3.3 Association between energy, technological advances, and productivity

Asongu and Odhiambo (2023) study revealed a two-way causal connection among energy consumption and the growth of TFP in specific countries. They observed that in Brazil, natural gas consumption influenced TFP growth, while in South Africa, both total non-renewable electricity consumption and coal consumption impacted TFP growth. However, no causal connections were detected between energy consumption and the growth in TFP in India, China, and Russia. These results suggested that non-renewable energy use for BRICS countries can potentially affect economic growth and TFP, with statistically significant effects observed in Brazil and South Africa.

Mabugu and Inglesi-Lotz (2022) examined the association between South Africa's economic growth and the imbalance between electricity supply and demand. They employed a production function framework and utilised a panel data method. Their research covered the period from 1996 to 2015. Their findings demonstrated a reciprocal causal connection between renewable and non-renewable energy sources in South Africa and India, while a contrasting relationship was observed in Brazil.

Moreover, the study revealed a unidirectional causal connection between non-renewable energy and GDP in South Africa and Brazil, non-renewable energy and R&D in Brazil, Russia, and China, and GDP and R&D in Russia, India, and South Africa. It is crucial to acknowledge that the absence of an impact from renewable energy on GDP and R&D does not undermine its potential as a viable option for the future. Instead, it suggested that historically, both the share of renewable energy and total R&D investments have been relatively low, preventing them from exerting significant influence.

Tugcu and Tiwari (2016) examined the causal relationship among energy, technological advances, and productivity using the VECM approach. Their findings highlighted the significance of TFP growth in driving output growth, with variables affecting TFP demonstrating a robust explanatory power for output. Furthermore, the study revealed a unidirectional causality where non-renewable energy influenced GDP in Brazil and South Africa, non-renewable energy influenced R&D in Brazil, Russia, and China, and GDP influenced R&D in Russia, India, and South Africa. It is crucial to acknowledge that the absence of an impact from renewable energy on GDP and R&D does not diminish its potential as a viable option in the future.

Ahmed, Hamid, Mahboob, Rehman, Ali, Senkus, Wysokińska-Senkus, Siemiński, and Skrzypek (2022) conducted a recent study that focused on exploring the causal connection between agricultural insurance, air pollution, and agricultural green TFP in the US. The researchers employed the ARDL method to analyse panel data from all fifty states, covering 2005 to 2019. Their results, determined through the panel Granger causality test, unveiled a unidirectional causal relationship between agricultural insurance, green TFP, and air pollution. Furthermore, air pollution and agricultural green TFP established a one-way causal connection. Based on their outcomes, the authors concluded that enhancing agricultural insurance coverage or reducing air pollution could positively affect agricultural green total factor output. The results of this study carry significant implications for policymakers, agriculture policy stakeholders, and environmental management professionals, offering valuable insights for long-term policy planning and management strategies.

Ladu and Meleddu (2014) conducted a study examining the connection between total factor productivity and energy consumption within the regional contexts of Italy. The main objective of this study was to analyse the long-term association between TFP and energy consumption at the regional level, focusing on the period from 1996 to 2008. In contrast to previous studies, TFP was used to assess economic growth and technological advancements, and the researchers employed the dynamic panel estimation technique. Their results revealed a two-way causality among the Italian regions, indicating that areas with higher TFP tended to allocate more resources towards research activities rather than energy-intensive sectors. This approach allowed for the optimal utilization of limited resources and fostered sustainable growth.

Tugcu (2013) investigated the link between energy consumption and TFP). This study aimed to explore the short-term and long-term relationships between different forms of energy consumption and TFP growth in the Turkish economy from 1970 to 2011. The research employed the ARDL approach and utilised Granger causality analyses following Dolado and Lütkepohl's methodology to achieve this. This study's results revealed cointegration between disaggregated energy consumption and TFP growth, suggesting a long-term association among these variables. Furthermore, the research identified bi-directional causal relationships among the examined variables. These results shed light on the interplay between energy consumption and TFP growth, providing valuable perceptions of the dynamics of the Turkish economy. Notably, Tugcu (2013) found that a higher proportion of renewable energy consumption, compared to other energy sources, positively influenced TFP growth in the Turkish economy. This finding highlights the significance of promoting increased renewable energy consumption as part of the overall energy mix to enhance economic efficiency.

Hu (2005) conducted a study focusing on how IT investments influence productivity across various industries. By utilizing the Granger causality model and analysing industry-level data spanning three decades, the authors discovered compelling evidence demonstrating a causal relationship between IT investments and productivity at the industry level. The results of their study powerfully revealed that IT investments played a significant role in fostering productivity growth across most industries included in their sample.

Hu and Plant (2001) examined the causal connection between IT investment and firm performance. They argued that it was challenging to establish a reliable causal relationship between IT investment and firm performance based on concurrent data.

Instead, they suggested that inferring causality would be more convincing by assessing the correlation between IT investments in previous years and subsequent firm performance. By employing Granger causality models and analysing three sets of financial data at the firm level, the researchers did not find any significant statistical evidence to support the idea that investments in IT led to enhanced economic performance among the examined firms. Interestingly, the causal models revealed a somewhat unexpected finding, suggesting that improved financial performance in consecutive years might have played a role in the subsequent year's increased IT investment.

3.3.4 The behaviour of productivity emanating from shocks in the predictors

Li, Cifuentes-Faura, Talbi, Sadiq, Mohammed, and Bashir (2023) recently conducted a study investigating Tunisia's energy transition and the dynamic, interconnected effects of biomass energy, technological innovations, and electricity prices. Their research period spanned from 1980 to 2018, and various empirical methodologies such as the ARDL approach, VD, and IRF tests were employed. The results of their study demonstrated that in Tunisia, power prices were significantly correlated with economic expansion, natural gas usage, biomass energy use, and innovations in technology. Based on these outcomes, the study recommends gradually adopting cleaner and more reliable energy alternatives as part of comprehensive economic and environmental policies to transition away from "dirty energy resources."

Lefophane and Kalaba (2022) analysed the industry level to examine the effects of ICT intensity on productivity, employment, and output in South Africa. Their research used VD and IRF tests to forecast the prospective impacts of ICT intensity on the rise in labour productivity, employment, and output. ICT intensity has a considerable effect on growth, according to their analysis of panel vector autoregression, especially in sectors with higher ICT intensity. ICT investments in agro-processing sectors will likely result in enhanced ICT-driven growth. Additionally, based on the TY tests conducted, the study provided empirical evidence supporting a causal connection between ICT intensity and employment growth, particularly in industries with higher levels of ICT intensity. This suggests that increased investment in ICT directly contributes to employment growth within agro-processing industries exhibiting greater ICT intensity. According to their findings from the variance decomposition analysis, both industry groups' development is influenced by ICT intensity. However, the contribution is more substantial in the industry group with higher ICT intensity.

De Santis, Esposito, and Lasinio (2021) investigated the correlation between environmental regulation and productivity in 18 OECD countries from 1990 to 2015. Their study's findings suggested a positive correlation between the implementation of environmental policies and productivity growth. Both market-based and non-market-based policies positively influenced labour and multifactor productivity growth, albeit through some variations. The study also confirmed previous research by demonstrating that countries with high ICT intensity exhibited a more pronounced response of multifactor productivity to stricter environmental policies. These countries benefited from the combined effects of market-based and non-market-based measures. On the other hand, low-ICT-intensive countries showed a comparatively lower impact driven primarily by market-based measures, indicating a differentiated pattern of effects over time. Overall, the study underscores the significance of environmental policies in fostering productivity growth, with ICT intensity influencing the nature and extent of their impact across different countries.

In addition, the De Santis et al. (2021) study also discovered that countries with high ICT intensity demonstrated a more pronounced response of ICT capital to stricter environmental policies, particularly those driven by non-market-based measures. Similarly, the effect of more stringent environmental policies on hourly labour productivity was positive over time, but only in countries with high ICT intensity. The impulse response analysis provided valuable insights into the indirect effects of changes in environmental policy stringency and its various components, revealing that increasing policy stringency leads to an accumulation of ICT capital. Among the policy instruments examined, non-market measures such as standards and R&D subsidies were identified as particularly influential. Their findings shed light on the intricate connection among environmental policies, ICT intensity, and productivity, emphasizing the significance of targeted policy measures for promoting sustainable technological advancements and economic growth.

Khan, Zaman, Khan, and Islam (2017) examined the interconnections among ICT, patent applications, R&D expenditures, and specific growth factors in seven group countries from 1995 to 2013. Their research findings revealed a positive association between high-technology exports and growth factors, indicating their mutually reinforcing relationship. Conversely, residential patent applicants were found to harm per capita GDP and FDI inflows. Furthermore, R&D expenditures negatively correlated with GDP per capita and energy efficiency. In contrast, the involvement of researchers in R&D activities showed a positive influence on per capita GDP and energy efficiency. The researchers highlighted the crucial role of ICT in shaping the future. They emphasised the necessity of robust policies that promote R&D expenditures and innovation to enhance the growth factors in seven group countries, thereby fostering future economic development. These findings underscore the significance of targeted strategies and investments to drive sustainable economic growth and technological advancement in the seven group nations.

3.4 SUMMARY

This chapter delved into the theoretical and empirical literature surrounding TFP within the context of South Africa and in both developing and developed countries. Initially, the study identifies and elucidates the theoretical framework that underpins the connections between the chosen variables. The literature review and relevant theories applied in this study consistently revealed a strong and well-supported relationship between TFP, electricity supply shocks, and technological advancements. This relationship is substantiated by various relevant theories, including production theories such as the Cobb-Douglas Production theory, and growth theories like the Endogenous Growth theory, encompassing the AK and innovation-based theories. Finally, a comprehensive review of empirical literature examining total factor productivity, electricity supply shocks, and technological advancement in South Africa, developing countries, and developed nations is provided in this chapter. There is a gap in the body of evidence supporting how factors such as electricity supply and prices, R&D, patents, and investment in ICT affect total factor productivity. The impact of technology and electricity supply, where TFP was a dependent variable, was the subject of very little research in South Africa. Looking at the existing literature, it appears that not many studies specifically addressed the implications of electricity supply shocks and technological advancements on TFP in South Africa. Considering this, this study serves as a valuable contribution to addressing existing gaps in the current body of literature and will contribute to the research gap on these issues and open the door to further investigation of the variables influencing TFP.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 INTRODUCTION

This chapter is structured into several sub-sections, encompassing essential aspects such as data sources, model specifications, estimation techniques, and a summary. Different estimation techniques, such as lag length criteria, cointegration analysis, ARDL model, Granger causality test, diagnostic and stability tests, variance decomposition, and impulse response function tests, are used to achieve the study's objectives.

4.2 DATA

The study utilised yearly time series data from 1999 to 2022, specifically focusing on South Africa. The study encountered limitations regarding data availability in South Africa, hence the analysis relied on an annual time series dataset spanning 1999 to 2022, a period chosen due to these constraints. The data for TFP and electricity prices were obtained from the Federal Reserve Bank of Saint Louis. R&D and investment in ICT data were obtained from the South African Reserve Bank. Data for patents was obtained from the World Bank Database, while Quantec Easy Data provided data for electricity production. The study period was also chosen because it includes notable weak productivity growth and electricity crises in South Africa.

4.3 MODEL SPECIFICATION

The study examined the implications of electricity supply shocks and technological advances on TFP in South Africa. Electricity production (EPRO) and electricity prices (EP) were selected as proxies to represent electricity supply shocks. For technological advances, proxies, including research and development (R_D), patents (PAT), and investment in Information and Communication Technology (INV_ICT), were considered. The selected electricity supply shock variables are supported by a study conducted by Polemis (2017), which focused on assessing the impact of shocks on the electricity sector's performance in the OECD. Similarly, using the selected proxies for technological advances is based on a study by Milindi and Inglesi-Lots (2023). Consequently, the model is built using six variables. The model's functional form is expressed as follows:

$TFP = f(EPRO, EP, R\_D, PAT, INV\_ICT)$..(4.1)

Where:

TFP = Total Factor Productivity as measured by index

$EPRO$ = Electricity Production as measured by gigawatts-hour

EP = Electricity Prices as measured by the energy prices index

R_D = Research & Development as measured in millions of rand

PAT = Patents as measured by a unit of millions

Inv_ICT = Investment in Information and Communications Technology as measured in millions of rand

ε = Error term

Furthermore, equation 4.1 is the functional form of this model and is transformed into a linear equation. The linear equation representing this model is given by:

$TFP_t = \beta_0 + \beta_1 EPRO_t + \beta_2 EP_t + \beta_3 R\_D_t + \beta_4 PAT_t + \beta_5 Inv\_ICT_t + \varepsilon_t$........................ (4.2)

Furthermore, equation 4.2 is the linear equation transformed into a natural logarithm. Adnan, Chowdhury, and Mallik (2020) explained that the use of logarithms helps to standardise variables, which is why, in this study, all variables were converted to their natural logarithmic form except for total factor productivity as it is already in percentage. This transformation was undertaken to enhance estimation efficiency or achieve standardisation. This is also done to obtain variables' elasticity coefficients and minimise outliers' impact (Mpatane, 2015). The logarithmic equation describing this model is expressed as follows:

$TFP_t = \beta_0 + \beta_1 LEPRO_t + \beta_2 LEP_t + \beta_3 LR\_D_t + \beta_4 LPAT_t + \beta_5 LInv\_ICT_t + \varepsilon_t$..................(4.3)

Where L denotes the logarithm of variables in equation 4.3, t denotes the particular year of the variable, ε denotes an error/random term capturing the effects of any omitted variables in the model, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are the intercept of the variables, β_0 is the constant. TFP denotes Total Factor Productivity, EPRO denotes Electricity

Production, EP denotes Electricity Prices, R&D denotes Research and Development, PAT denotes Patents, and ICT denotes Investment in Information and Communications Technology.

4.4.1 ESTIMATION TECHNIQUES

This subsection presents the tests employed to examine the set model, the Auto Regressive Distributed Lag. Before performing the econometric tests, a preliminary analysis of the trend and variability of the variables was conducted through descriptive statistics and correlation analysis tests. This study relies on descriptive statistics and econometric techniques before estimating the process.

4.4.1 Descriptive Statistics

The first test conducted in this study is the descriptive statistics test. Descriptive analysis was conducted to ascertain the statistical properties of the variables (Epaphra, 2017). Descriptive statistics test encompasses the numerical and graphical methods employed to arrange, present, and analyse data. The type of descriptive statistics utilised to characterise a variable in a sample depends on the chosen level of measurement (Fisher & Marshall, 2009). This test is conducted to calculate the basic properties of all the study variables. It gives a snapshot or a way to describe and summarise the main characteristics of a dataset. These statistics include the mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jarque-Bera, probability, sum square deviation, and the total number of observations of each of the variables involved in the study (Ali, Zubair & Hussain, 2021). The study conducted a descriptive statistical test on the macroeconomic variables utilised in this study.

4.4.2 Correlation Analysis

The correlation analysis test was also conducted for all study variables to find out the interconnection relationship of one variable with another. According to Gogtay & Thatte (2017), correlation analysis is a term utilised to indicate the association between two or more quantitative variables. This test measures the proximity of one linked variable to another and is valuable for investigating the associative connection between independent and dependent variables (Senthilnathan, 2019). Since significant correlation does not imply causality, more econometric tests are required to determine the variables' short- and long-run links (Opeyemi & Paul-Francois, 2019).

The potential for a positive association and a resulting positive correlation coefficient arises when the trend of one variable is positive and closely resembles that of another variable; similarly, if the trend of one variable is positive but nearly opposite to that of another, a negative association may occur, leading to a negative correlation coefficient (Senthilnathan, 2019). The correlation coefficient (R) is a measure that falls within the range -1 and $+1$, denoted as $-1 \leq R \leq +1$ (Gogtay & Thatte, 2017). If the absolute value of the correlation coefficient (|r|) is close to 0 (|r| < 0.3), it suggests a low or weak linear relationship between the variables in the model. If |r| is between 0.3 and 0.7, it indicates a moderate linear relationship between the variables. If |r| is close to 1 (|r| > 0.7), it signifies a robust linear relationship.

Multicollinearity in multiple regression analysis refers to linear relationships among independent variables (Shrestha, 2020). Within a multiple-regression model, when one explanatory variable is essentially identical to another independent variable, resulting in a high correlation coefficient, this condition is termed multicollinearity. Such variables typically convey similar information for predicting the dependent variable, introducing redundancy in the model. Detecting multicollinearity is crucial, and low correlation coefficients between independent variables and the dependent variable suggest its absence. Conversely, high correlation coefficients indicate the presence of multicollinearity, signalling a cautionary note for proceeding with the model. After conducting the correlation analysis test, the study runs the econometric techniques.

4.4.3 Stationarity/Unit Root Test

Before estimating empirical models, examining the stationarity of time series data through a unit root test is crucial. This test allows for an assessment of the specific characteristics of the variables and their degree of integration. It ensures that no variable exhibits I (2) characteristics, which would be inappropriate when employing the ARDL approach for model estimation. Eita and Pedro (2021) emphasise the significance of performing a unit root test to ensure the suitability of variables in the empirical models.

The study utilised the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to examine the stationarity among the selected variables. In econometrics, the ADF and PP tests are frequently used to assess the presence of unit roots in time series data. These tests help determine whether the variables under consideration exhibit non-stationarity. These tests are preferred over other unit root tests because they can handle many models, including autoregressive and autoregressive-moving-average models, and are resilient to many types of serial correlation (Eita & Pedro, 2021). Both tests also permit the insertion of extra covariates into the model, which can increase test power and consider extra causes of data volatility. Another reason for choosing these tests is that they have been extensively studied and validated in the literature, making them widely accepted as standard tests for unit root analysis. The results from these tests are more likely to be reproducible and comparable across studies, making it easier to build on previous research and draw meaningful conclusions. A variable that cannot be stationary at a level can still be stationary at the first or second difference (Mongale, 2018).

4.4.3.1 Augmented Dickey-Fuller Test

The ADF test, developed by Dickey and Fuller (1979), is commonly used to analyse whether an autoregressive model possesses a unit root, indicating non-stationarity (Khan, Teng & Khan, 2019). This test aims to examine whether non-stationarity exists in a time series. This is achieved by comparing the null hypothesis H_0 , which posits non-stationarity, with the alternative hypothesis H_1 , Which asserts stationarity (Valoyi, 2019). The alternative time series is considered stationary when H_0 is rejected. In this context, the ADF test holds significant importance as it helps identify a unit root's existence and assess the time series' stationarity. The regression equation below serves as the basis for the ADF test:

$$\Delta y_t = \alpha y_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-1} + \mu_t \ldots\ldots (4.4)$$

Where μ_tIs the error term, $\Delta y_{t-1} = (y_{t-1} - y_{t-2}),\ \Delta y_{t-2} = (y_{t-2} - y_{t-3})$ and so on.

The null hypothesis (H_0) and alternative hypothesis (H_1). This may be expressed as follows:

$H_0 : \alpha = 0$ (Unit root exists or stationary)

$H_1 : \alpha \neq 0$ (Unit root does not exist or non-stationary)

The ADF assesses the H_0 that y_t is stationary against the H_1 that y_t is non-stationary. It also assesses the significance of y_{t-1}. The test statistic in the ADF test compares the behaviour of a time series to that of a random walk, determining whether it is stationary or has a unit root. By employing the critical value, the calculated test statistic is compared. When the test statistic is below the critical value, it leads to rejecting the null hypothesis, indicating the presence of stationarity. Conversely, if the test statistic surpasses the critical value, the null hypothesis is not rejected, signifying non-stationarity. The ADF test is specifically designed to identify trends in time series and determine if differencing is necessary for stationarity. Rejecting the H_0 suggests that there is already a stationary time series, eliminating the need for differencing. On the other hand, not rejecting the null hypothesis implies non-stationarity, indicating the potential requirement for differencing to remove the trend.

Ratombo (2019) asserts that the ADF results must be considered while choosing the ideal lag time for each model. This will allow the study to optimise the relevant model's log-likelihood function. The model selection process aims to identify the model that exhibits the smallest Schwartz Bayesian Information Criterion (SBIC) to ensure optimal performance. Additionally, the accuracy of the selected model will be validated by cross-referencing the results through the Akaike Information Criterion (AIC).

4.4.3.2 Phillips-Perron Test

Peter, Phillips, and Pierre Perron (1988) introduced the PP test as a distinct unit root test, offering a different approach from the ADF test. In time series analysis, the PP test is commonly employed to assess whether a time series is integrated at order 1 (Ratombo, 2019). The study used the PP test to determine the stationarity of the time series data. Notably, the PP test incorporates a non-parametric correction to effectively handle any correlation in the error terms, enhancing its robustness (Khoza, 2017). Like the ADF test, the PP test assesses whether a time series demonstrates stationarity or non-stationarity because of a unit root. However, the PP test incorporates an automatic correction for serial correlation in the residuals, making it more resilient to several types of serial correlation in the data. The PP test is instrumental when the model's residuals are found to be serially correlated, as failure to account for this correlation appropriately can result in inaccurate conclusions.

As stated by Ratombo (2019), the PP test is an extension of the Dickey-Fuller test, specifically designed to account for the potential existence of higher-order autocorrelation in the test equation. This consideration becomes crucial as it can undermine the validity of the Dickey-Fuller t-test. To address this issue, the PP test introduces a non-parametric correction to the t-test statistic, ensuring its accuracy. Furthermore, the PP test demonstrates robustness by effectively handling unspecified autocorrelation and heteroskedasticity within the disturbance process of the test equation. Like ADF tests, the PP tests also feature an automatic correction to handle autocorrelated residuals properly, thus providing reliable inference. Serial correlation in residuals can cause bias in unit root tests, including the ADF test. The PP test overcomes this bias by employing a modified version of the ADF test that considers the presence of serial correlation. This enhanced robustness allows the PP test to yield more accurate results and reduce the risk of drawing incorrect conclusions regarding the stationarity of the time series. The PP test generally leads to the same conclusions as ADF tests, as suggested by Davidson and MacKinnon (2004).

The following equation provides the test regression for the Phillips-Perron test:

$\Delta y_t = \beta D_t + \pi y_{t-1} + \mu_t$ .... (4.5)

Where μ_t is $I(0)$ and may be heteroskedastic. By altering the test statistics, statistic $t_{n=0}$ and T_n , the PP test adjusts for any serial correlation and heteroskedasticity in the error's μ_t of the test regression, ensuring that the dependent variable does not require additional lags in the presence of serially correlated errors.

The following are the stationarity tests for the Phillips-Perron test:

H_0: y_t is stationary.

H_1: y_t is non-stationary.

The null hypothesis H_0 of the PP test is that the time series y_t is stationary, while the alternative hypothesis H_1 is that it is non-stationary. If the computed test statistic is below the critical value, the null hypothesis is not rejected, indicating the presence of stationarity in the time series. Conversely, if the test statistic exceeds the critical value, the null hypothesis is rejected, suggesting non-stationarity. It is worth noting that although the PP test is a widely utilised unit root test, alternative tests are available for evaluating stationarity in a time series. To ensure the reliability and robustness of the results, it is advisable to employ multiple tests and conduct diagnostic checks in the analysis.

4.4.4 Lag Length Criteria

The study determined the optimal lag length for Vector Autoregressions (VAR) by conducting stationarity or unit root tests (Valoyi, 2019). Before performing the cointegration test, the study estimated the optimal lag duration. This involves evaluating different lag lengths to identify the most suitable one that effectively captures the time series data's characteristics, as Khoza (2017) emphasised. The study itself ascertained the lag length required for the VAR estimation procedure. To aid in lag length selection, diverse options of information criteria are available, such as the Akaike Information Criteria (AIC), Hannan-Quinn Information Criteria (HQC), Schwarz Information Criteria (SIC), and Final Prediction Error (FPE). Still, the study chose to use the Akaike Information Criteria.

4.4.5 Cointegration Analysis

The objective of the cointegration test is to determine whether multiple time series exhibit a long-term relationship or correlation. The study assessed for cointegration to determine and assess the long-term association among the chosen variables. According to Ratombo (2019), the cointegration test determines whether the model contains one or more cointegration vectors. If there is cointegration between the chosen variables in the study, it can be inferred that the variables have a long-term relationship.

Bounds tests are essential in constructing a solid statistical and economic framework for the empirical error correction model. This model integrated both short-term and long-term associations from the variables chosen for analysis. One critical aspect of this process is the cointegration test, which is pivotal in assessing whether the model displays a significant long-term relationship among the variables (Khoza, 2017). Well-known cointegration tests include the Engle-Granger (1987) test, Johansen test, Phillips-Ouliaris test, ARDL cointegration technique, and bound cointegration testing technique. For this study, the ARDL cointegration technique was employed. The general formulation for the equilibrium correction term model can be expressed as follows:

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \cdots + \beta_k x_{kt} + u_t \qquad (4.6)$$

Where both the dependent and independent variables y_t and x_t are lagged by a particular year, representing the values of the variables from the previous years. u_t to be $I(0)$ if the variables $y_t, x_{2t}, \dots\dots x_{kt}$ are cointegrated.

For the cointegration testing, the study used both the ARDL method and the bound cointegration testing approach, which were developed by Pesaran, Shin, and Smith (2001). Incorporating lagged values of the dependent variable for both lagged and current values of explanatory variables is an integral part of these approaches. The initial step in the ARDL model entails assessing the long-run relationship, as Malindini (2017) mentioned. Notably, these techniques eliminate the need for stationarity or unit root tests and are well-suited for analysing variables with different integration orders, including those that are integrated of order zero $I(0)$, integrated of order one $I(1)$, or a combination of both. This approach remains robust even when dealing with small sample sizes and offers an effective method for estimating a single long-run relationship between variables. In cases where variables have different integration orders, and none are integrated into order two, the ARDL bound approach can be employed, as discussed by Adnan, Chowdhury, and Mallik (2020).

The utilization of the ARDL test offers multiple advantages. Firstly, it accommodates series with different integration orders, including stationary $I(0)$, non-stationary $I(1)$, or a combination of both $I(0)$ and $I(1)$. Secondly, it surpasses prior models such as Engle and Granger (1987), Phillips and Hansen (1990), Johansen (1988), and Johansen and Juselius (1990), which necessitate variables to possess equal integration degrees, specifically. $I(1)$. This approach ensures reliable estimates, even with limited sample sizes (Pesaran and Shin, 1998). Thirdly, this approach facilitates the simultaneous estimation of both long- and short-run parameters without losing model information. Fourthly, the ARDL model addresses potential endogeneity among explanatory variables by considering residual correlation, thereby maintaining the validity of ARDL estimations even in the presence of endogeneity (Pesaran et al., 2001). According to Kale and Rath (2017), the estimation accuracy of the ARDL approach remains unaffected by the presence of endogeneity among the explanatory variables.

The ARDL method in cointegration analysis helps identify cointegration vectors, where each selected variable represents a distinct long-run relationship equation. According to Nkro & Uko (2016), if a cointegrating vector is identified, the ARDL approach allows reparameterization into an Error Correction Model (ECM). The existence of a long-run association is determined using the F-statistic (Nkoro & Uko, 2016).

The expression of the ARDL model employed in this study can be summarised as:

$$\Delta TFP_t = \beta_0 + \sum_{i=1}^{m} \beta_1 \Delta TFP_{t-i} + \sum_{i=1}^{m} \beta_2 \Delta LEPRO_{t-i} + \sum_{i=1}^{m} \beta_3 \Delta LEP_{t-i} + \sum_{i=1}^{m} \beta_4 \Delta LR\_D_{t-i} \sum_{i=1}^{m} \beta_5 \Delta LPAT_{t-i}$$
$$+ \sum_{i=1}^{m} \beta_6 \Delta LINV\_ICT_{t-i} + \alpha_1 TFP_{t-1} + \alpha_2 LEPRO + \alpha_3 LEP_{t-1} + \alpha_4 LR\_D_{t-1} + \alpha_5 LPAT_{t-1}$$
$$+ \alpha_6 LINV\_ICT_{t-1} + \mu_{t-1} \dots \dots \dots \dots \dots \dots \dots .. \dots \dots (4.7)$$

In equation 4.7, Δ serves as the first difference operator, m denotes the maximum lag length, i is the number of lags in the model, μ_t is the white noise error term, and β_0 to β_6 denotes the short-run dynamics. Total factor productivity is denoted as TFP, electricity production as EPRO, electricity prices as EP, research and development as R_D, patents as PAT, and investment in ICT as INV_ICT. All variables are expressed in their natural logarithmic form except for TFP, which is presented in index units. The F-statistic of the lagged terms in this equation is employed to assess the long-term equilibrium.

There are two primary steps in the ARDL analysis. In the initial step, researchers analyse whether there is a long-term relationship among variables using bounds tests proposed by Pesaran and Shin (1999); and Pesaran et al. (2001) for larger sample sizes, as well as Narayan et al. (2005) for smaller sample sizes. These tests rely on critical values of lower I (0) and upper I (1). Cointegration is determined based on the computed F-test statistic. The absence of cointegration is indicated if the estimated F-test statistic is below the lower limit, represented by I(0), which means insufficient evidence to reject the null hypothesis. If the computed F-test statistic falls between the upper and lower limits, it is inconclusive when cointegration exists. On the other hand, when the computed F-test statistic surpasses the upper limit, it leads to the rejection of the null hypothesis, indicating the existence of cointegration between the variables. Once cointegration is established, the study can proceed with the Error Correlation Model (ECM) analysis.

The short-run dynamic coefficients of this study are derived from the respective ECM as presented in the following equation:

$$\Delta TFP_t = \beta_0 + \sum_{i=1}^{m} \beta_1 \Delta TFP_{t-i} + \sum_{i=1}^{m} \beta_2 \Delta LEPRO_{t-i} + \sum_{i=1}^{m} \beta_3 \Delta LEP_{t-i} + \sum_{i=1}^{m} \beta_4 \Delta LR\_D_{t-i} \sum_{i=1}^{m} \beta_5 \Delta LPAT_{t-i} + \sum_{i=1}^{m} \beta_6 \Delta LINV\_ICT_{t-i} + \beta_7 ECM_{t-i} + \mu_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4.8)$$

Where β_0 to β_6 are short-run dynamic multipliers, while ECM_{t-i} stands for the error correction term of the model, signifying the speed of adjustment from convergence to equilibrium (Guan, Zhou & Zhang, 2015). Within the model framework, it is expected that the coefficient of the lagged error correction term will exhibit negativity and statistical significance, thereby suggesting the presence of a long-term relationship among the variables. This coefficient captures the adjustment process towards equilibrium, where a negative and significant value of the lagged ECM. ECM_{t-i} indicates a long-term causal link among the variables and implies convergence of the estimated variables in the model (Pedro, 2019).

4.4.6 Granger Causality Test

The Granger Causality test was conducted to determine which variable is causally related to the other. Granger (1981) outlined this method as an approach to decide if X Influences Y by assessing the degree to which past values of Y can account for the current Y value. Additionally, the test examines whether including lagged values of X enhances the explanatory capacity of the model. Granger causality is a statistical concept focused on prediction (Seth, 2007). Typically, this test is conducted within the framework of a linear regression model. It determines whether variable X causes variable Y or vice versa. For example, if the electricity supply causes total factor productivity or vice versa, an electricity supply is considered causal to total factor productivity. The null hypothesis in the test suggests that the lagged values of X do not provide any explanation for the variation in Y, indicating that x_t does not Granger cause y_t in the model (Stephanie, 2016). The Granger causality test is derived from the following equation:

$$y_t = a_1 + \sum_{i=1}^{n} \beta_i \, x_{t-1} \sum_{j=1}^{m} y_j y_{t-j} + e_{1t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(4.9)}$$

$$x_t = a_2 + \sum_{i=1}^{n} \theta_i \, x_{t-i} + \sum_{j=1}^{m} \alpha_j y_{t-j} + e_{2t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(4.10)}$$

The Granger causality test assumes that x_t does not Granger cause y_t. This assumption relies on the notion that the error terms y_t and x_t are uncorrelated white noise. Consequently, the null hypothesis asserts that there is no Granger causality, implying that x does not Granger cause y in the initial regression, and likewise, y does not Granger cause x in the subsequent regression (Milanzi, 2021). If the Granger Causality test reveals a causal relationship among the selected variables, it will then enable the variables to be forecasted and will deploy IRF and Decomposition tests.

4.4.7 Diagnostic Tests

Diagnostic tests were conducted to assess the accuracy and validity of the data acquired and the presence of violations in the classical assumptions (Khoza, 2017). Furthermore, diagnostic testing aims to evaluate the adequacy of a regression model in terms of the included regressors and ensure its correct specification. Conducting various diagnostic tests is essential in every time series modelling. The study employed various residual tests, including the normality test, heteroskedasticity, and autocorrelation. The significance of conducting diagnostic tests within this model was to evaluate the existence of serial correlation/autocorrelation, normality, and heteroscedasticity (Ratombo, 2019). These tests were conducted to verify and ensure the model's goodness of fit.

4.4.7.1 Normality Test

In this study, the Jarque-Bera (JB) test, commonly employed in econometrics to examine normality, was conducted to evaluate the normality of residuals within the model (Gujarati & Porter, 2009). This test serves the purpose of assessing the presence of serial correlation and heteroskedasticity in the model. The serial correlation analysis was conducted to determine any serial correlation within the model, while the heteroskedasticity test aims to detect whether the model exhibits homoscedasticity. If the Probability value exceeds the 5% significance level, the null hypothesis is not rejected, concluding that the model is free from autocorrelation and heteroskedasticity. Valoyi (2019) stated that the sample data exhibits skewness and kurtosis values that align with a normal distribution. The equation representing the JB test statistic is expressed as follows:

$$JB = \frac{N}{6}\left(S^2 + \frac{K^2}{4}\right) \qquad (4.11)$$

Where: S is the sample skewness, K is the sample kurtosis and N is the sample size. The JB test statistic is calculated by combining the sample skewness and kurtosis, adjusting for the sample size. If the residuals adhere to a normal distribution, the test statistic (t-statistic) will conform to a chi-square distribution with 2 degrees of freedom. Consequently, it is possible to compare the t-statistic with the critical values from the chi-square distribution to determine the normality of the residuals. Suppose the calculated t-statistic surpasses the critical value. In that case, the JB test suggests that the residuals do not exhibit a normal distribution, signifying a deviation from the assumptions of classical linear regression models. Conversely, if the t-statistic is lower than the critical value, then the null hypothesis of normality is not rejected, implying that the residuals are normally distributed.

4.4.7.2 Serial Correlation Test

Serial correlation or autocorrelation measures the correlation between a signal and its past observations at different time points. It quantifies the similarity between observations based on the time lag between them. When evaluating serial correlation, the autocorrelation test can be used as an alternative to Q-statistics. Unlike the Durbin-Watson statistic, which applies only to AR (1) errors and requires lagged dependent variables, the Lagrange Multiplier (LM) test can detect higher-order ARMA errors. It can be used regardless of the presence of lagged dependent variables. Hence, it is recommended to use the LM test when investigating potential autocorrelation in the errors, as suggested by Stewart and Gill (1998).

In time series regressions, a common issue arises where the estimated residuals demonstrate a correlation over time. This serial correlation in ordinary least squares (OLS) regressions results in estimates with minor standard errors. This leads to inadequate, biased, and inconsistent results, particularly when including lagged dependent variables in the regression equation (Mongale & Baloyi, 2019). A test for serial correlation is conducted to evaluate whether serial correlation exists in the model. This test determines whether the model exhibits autocorrelation. If the calculated p-value is higher than the specified significance levels (1%, 5%, and 10%), the null hypothesis is not rejected, indicating that the model does not suffer from autocorrelation. Under the null hypothesis, the Lagrange Multiplier test assumes no serial correlation up to a specified lag order. In contrast, the alternative hypothesis implies the presence of serial correlation (Milanzi, 2021).

4.4.7.3 Heteroskedasticity Test

A heteroskedasticity test was also conducted in this study. As Stock and Watson (2012) described, heteroskedasticity occurs when the variance of the regression error term, given the explanatory variables, does not remain constant. The White Heteroskedasticity Test was created by White (1980) to assist in checking for heteroscedasticity in the residuals where least squares estimates are used. These tests can be utilised to examine the residuals of your equation based on various heteroscedasticity criteria. In heteroscedasticity, the ordinary least squares (OLS) estimates remain constant, but the accuracy of conventional estimated standard errors diminishes. In such cases, opting for robust standard errors is a preferable solution to address the issue of heteroscedasticity.

The heteroscedasticity tests available in E-Views come in a variety of forms. The auxiliary regressions from the initial equation are used in each test. The Breusch-Pagan-Godfrey, Harvey, Glejser, ARCH LM Test, and White's Heteroscedasticity Test are the tests that were employed for distinct types of equations, including least squares-estimated equations, two-stage least squares equations, and nonlinear least squares equations. The study used the heteroskedasticity test to determine whether the model is homoscedastic. The null hypothesis is not rejected when the probability value exceeds 1%, 5%, and 10% significance levels. In such cases, it can be concluded that the model does not exhibit heteroscedasticity.

4.4.8 Stability Tests

The stability test was employed to examine whether the model exhibits stability or instability. The CUSUM and CUSUM of Squares were utilised in the study to investigate the stability of the study model. Brown, Durbin, and Evan (1975) developed the CUSUM and CUSUM of Squares tests to assess the parameter stability. These tests aim to demonstrate whether the CUSUM line, indicated by the blue line, lies within the 5% significance level as denoted by the red lines. The CUSUM of squares test will also be run to determine whether the cumulative sum of squares fluctuates within the 5% significance level. If the oscillations of the blue line remain within the boundaries of the two red lines (representing the 5% level of significance), it indicates the stability of the model. These tests were conducted to determine the model's stability and whether any structural breaks became apparent over the observation period (Mulaudzi, 2018).

4.4.9 Variance Decomposition Test

The Variance Decomposition (VD) test was used in this study to determine the relative contributions of each variable concerning the other factors that form the autoregression model. Decomposition of variance or forecast error, a vector autoregression model, is interpreted using variance decomposition once fitted. VD test is a valuable tool that allows us to assess the proportion of changes in a dependent variable attributed to shocks specific to that variable versus shocks affecting other variables in the system. During variance decomposition analysis, it is essential to consider that a shock to the ith variable generates effects on all other variables due to the dynamic features of the VAR model (Mpatane, 2015). By examining variance decomposition, we gain insights into the amount of information contributed by each variable in the autoregression to the behaviour of the other variables. Additionally, it determines the extent to which exogenous shocks to the different variables can explain the variance in forecast error for each variable (Milanzi, 2021).

4.4.10 Impulse Response Function Test

The Impulse Response Function (IRF) test is an essential analytical tool that helps trace one particular function's impact on endogenous variables' existing and potential future values (Molele & Ncanywa, 2019). When using the VAR model in econometric analysis, the IRF test is a crucial step. The IRF's primary goal is to determine whether the variables in the model change in response to a shock caused by a specific variable or a combination of variables (Franz, 2020). The IRF test was conducted in this study to determine how TFP, a dependent variable, responds over time to changes in electricity production and prices, R&D, patents, and Investment in ICT.

4.5 SUMMARY

This chapter has specified the model used to investigate the implications of electricity supply shocks and technological advancement on South Africa's total factor productivity. The variables used in the tests are total factor productivity, electricity production, electricity prices, research and development, and patents and investment in ICT. Initially, descriptive statistics and correlation analysis tests were employed to gauge the statistical behaviour of these variables. Following these tests, such as ADF and PP, ascertain the integration order of the selected variables. Subsequently, the study employed the lag length criteria to aid in determining the best lag that is suitable for this study. The ARDL model was chosen over the other cointegration models because of its capacity to handle any order of integration between I(0) and I(1). The Granger causality test was then used to see whether there were any causal relationships between the variables. Diagnostic and stability tests were undertaken to validate the robustness of the model. Finally, VD and IRF tests were performed to investigate the causality between electricity production, electricity prices, and total factor productivity in South Africa.

CHAPTER 5

DISCUSSION / PRESENTATION / INTERPRETATION OF FINDINGS

5.1. INTRODUCTION

This chapter provides the empirical findings and interpretations of all the tests outlined in the previous chapter. Its structure unfolds orderly, beginning with a presentation of descriptive statistics, followed by correlation analysis, stationarity/unit root tests, and the critical process of lag length selection. Additionally, cointegration tests are conducted to assess long-run relationships, complemented by the Granger causality test to unveil potential causal links between the selected variables. Diagnostic and stability tests further examine the robustness of the analysis. Furthermore, this study incorporates IRF and VD tests, which are crucial in determining the impact of economic shocks. Collectively, these approaches to data analysis provide valuable insights, allowing for a distinct comprehension of the dynamics and connections among the variables under study.

5.2. EMPIRICAL TEST RESULTS

This section presents the empirical findings on the relationship between electricity production, electricity prices, research & development, patents, and investment in ICT on total factor productivity in South Africa. The results are presented as follows.

5.2.1. Descriptive Statistics

Descriptive analysis is a statistical term that determines the statistical behaviour of variables. It includes the mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jarque-Bera, probability, sum square deviation, and total number of observations for each variable examined in this study. Table 5.1 presents the descriptive statistics results for the variables used in this study.

Table 5.1: Descriptive analysis

	TFP	LEPRO	LEP	LR_D	LPAT	LINV_ICT
Mean	1.061	12.343	4.194	8.197	6.647	9.825
Median	1.080	12.361	4.239	8.193	6.734	10.048
Maximum	1.148	12.441	5.213	8.434	7.498	10.385
Minimum	0.966	12.167	3.388	7.989	4.927	8.715
Std. Dev.	0.059	0.079	0.601	0.117	0.448	0.509
Skewness	-0.399	-0.703	-0.025	0.226	-2.189	-0.905
Kurtosis	1.777	2.413	1.566	2.280	10.578	2.605

Jarque-Bera	2.132	2.318	2.060	0.722	76.587	3.431
Probability	0.344	0.314	0.357	0.697	0.000*	0.180
Sum	25.464	296.220	100.657	196.737	159.528	235.801
Sum Sq. Dev.	0.081	0.145	8.299	0.317	4.606	5.954
Observations	24	24	24	24	24	24

Source: Author's computation

Drawing insights from the data presented in Table 5.1, the descriptive statistics indicate notable characteristics of the variables. The Skewness statistic LR_D displays a positive skew, whereas TFP, LEPRO, LEP, LPAT, and LINV_ICT exhibit negative skewness. The prevalence of negative skewness suggests that these variables possess long left tails with values lower than the sample mean. Examining the kurtosis coefficients, TFP, LEPRO, LEP, LR_D, and LINV_ICT are classified as platykurtic, as their values fall below 3.00. This suggests that their distributions have thinner tails compared to a normal distribution. In contrast, LPAT is classified as leptokurtic with a kurtosis coefficient exceeding 3.00, indicating a flatter tail compared to a normal distribution. TFP, LEPRO, and LR_D have a low standard deviation (0.059, 0.079, and 0.117), which indicates that their data are clustered tightly around the mean. LEP, LPAT, and LINV_ICT have high standard deviations (0.601, 0.448, and 0.509), indicating that these variables' data are more spread out.

The JB test statistic measures goodness of fit, assessing if the skewness and kurtosis of sample data align with those of a normal distribution. This test, which integrates skewness and kurtosis, determines normality (Babatunde, Ibukun & Oyeyemi, 2017). The JB test statistic in Table 5.1 reveals that the LPAT probability value is below the 5% significance level, while TFP, LEPRO, LEP, LR_D, and LINV_ICT exceed this level. Considering these findings, the conclusion drawn is the failure to reject the null hypothesis for TFP, LEPRO, LEP, LR_D, and INV_ICT, as their p-values indicate a statistically insignificant, which suggests that there is a normal distribution. The null hypothesis for LPAT is rejected, as its p-value is statistically significant, suggesting a non-normal distribution for LPAT.

5.2.2. Correlation Analysis

This study also used a correlation test to investigate the correlation between the endogenous variable (TFP) and a group of exogenous variables (LEPRO, LEP, LR_D, LPAT, and INV_ICT). The correlation analysis is crucial as it reveals the relationship between the variables used in this study. The outcomes of this test are presented in Table 5.2 below.

Table 5.2: Correlation analysis

Variable	TFP	LEPRO	LEP	LR_D	LPAT	LINV_ICT
TFP	1.000000					
LEPRO	0.384046	1.000000				
LEP	-0.745813	0.237917	1.000000			
LR_D	0.322831	0.689667	0.010785	1.000000		
LPAT	0.116782	0.202402	0.122143	0.167480	1.000000	
LINV_ICT	-0.348445	0.610386	0.784386	0.309587	0.299578	1.000000

Source: Author's computation

The correlation results in Table 5.2 show that LEPRO, LR_D, and LPAT have low and moderate positive correlations with the dependent variable TFP, respectively, of about 38%, 32%, and 11%, whereas LINV_ICT has a low negative correlation of 35%. LEP is the only variable that exhibits a strong negative correlation of 75% with the dependent variable TFP. Hence, the correlation results suggest that, except for LEP, the independent variables exhibit low correlation coefficients with the dependent variable, signifying the absence of multicollinearity among the variables.

5.2.3. Stationarity/Unit Root Test Results

The ADF and PP tests were employed to measure stationarity among the selected variables. The results of the ADF and PP tests are presented in Table 5.3.

Table 5.3: ADF and PP test results

VARIABLES	**AUGMENTED DICKEY-FULLER (ADF)**			**PHILLIPS PERRON (PP)**			**DECISION**
	NONE	**INTERCEPT**	**INTERCEPT & TREND**	**NONE**	**INTERCEPT**	**INTERCEPT & TREND**	
TFP	-0.703451 (0.4010)	-0.115191 (0.9365)	-2.751328 (0.2273)	-0.636384 (0.4305)	-0.310847 (0.9089)	-2.973152 (0.1603)	Non-Stationary I(0)
△TFP	-2.444132 (0.0173)**	-4.517440 (0.0019)*	-5.314623 (0.0016)*	-4.540930 (0.0001)*	-4.529005 (0.0018)*	-5.281356 (0.0017)*	Stationary I(1)
LEPRO	0.511894 (0.8186)	-2.057730 (0.2621)	-1.803824 (0.6664)	0.409981 (0.7934)	-2.044687 (0.2671)	-1.288681 (0.8651)	Non-Stationary I(0)
△LEPRO	-3.249515 (0.0024)*	-0.829958 (0.7885)	-5.402415 (0.0015)*	-3.233700 (0.0025)*	-3.100437 (0.0413)**	-9.150172 (0.0000)*	Stationary I(1)
LEP	5.520961 (1.0000)	0.771318 (0.9911)	-2.267339 (0.4336)	5.520961 (1.0000)	0.771318 (0.9911)	-2.331612 (0.4021)	Non-Stationary I(0)
△LEP	-0.681683 (0.4095)	-3.671546 (0.0124)**	-3.700286 (0.0440)**	-1.662973 (0.0901)***	-3.645142 (0.0131) **	-3.700286 (0.0440)**	Stationary I(1)

LR_D	-0.153203 (0.6199)	-1.660085 (0.4372)	-1.373936 (0.8413)	-0.152290 (0.6202)	-1.833233 (0.3560)	-1.373936 (0.8413)	Non-Stationary I(0)
△LR_D	-4.209548 (0.0002)*	-4.098977 (0.0048) *	-3.515239 (0.0698)***	-4.210846 (0.0002) *	-4.100154 (0.0048)*	-4.619439 (0.0069) *	Stationary I(1)
LPAT	0.655877 (0.8506)	-7.212264 (0.0000)*	-2.769761 (0.2216)	0.706610 (0.8609)	-6.705965 (0.0000)*	-6.993069 (0.0000)*	Stationary I(0)
LINV_ICT	1.695288 (0.9739)	-2.505076 (0.1284)	-2.401720 (0.3685)	2.567536 (0.9961)	-2.963982 (0.0535)***	-2.120381 (0.5083)	Non-Stationary I(0)
△LINV_ICT	-4.209944 (0.0002)*	-4.806820 (0.0011)*	-5.184749 (0.0023)*	-4.649467 (0.0001)*	-5.480996 (0.0002)*	-8.360063 (0.0000)*	Stationary I(1)

Notes: 0.01* (1%), 0.05** (5%), 0.1*** (10%) significance levels

Source: Author’s computation

Table 5.3 presents the findings from the ADF and PP tests, which assess the existence of unit roots in the variables. The results of the ADF and PP tests for unit root confirm that all variables are stationary at the first difference except for the patent, which is stationary at the level. Therefore, the null hypothesis that TFP, LEXPRO, LEP, LR_D, LPAT & LINV_ICT contain unit roots can be rejected. It can be concluded that the variables are integrated at varying levels, that is, I (0) and I (1), allowing the ARDL model to be employed along with the restriction in the number of observations.

5.2.4. Lag Length Selection

Choosing a suitable lag length is a crucial step in conducting cointegration tests. Careful selection is essential, as the choice of lag length in an ARDL model can significantly impact the outcomes of the bound tests.

Table 5.4: Lag length selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	98.29784	NA	9.15e-12	-8.390713	-8.093155	-8.320617
1	215.2717	159.5097	6.66e-15	-15.75197	-13.66907	-15.26130
2	277.8703	51.21705*	1.49e-15*	-18.17002*	-14.30178*	-17.25878*

Source: Author’s computation

Table 5.4 presents the lag length selection criteria, encompassing LR (sequential modified LR test statistic at a 5% level), FP, AIC, SC, and HQ information criterion. Consequently, the study opted to use two lags, a decision informed by FP, AIC, SC, and HQ criteria, to accommodate the variables under consideration.

Table 5.5: Lag Exclusion Test

Variable	TFP	LEPRO	LEP	LR_D	LPAT	LINV_ICT	Joint
Lag 1	19.43280	29.89323	35.47578	10.79753	7.013339	4.056336	249.3589
	[0.003492]	[4.12e-05]	[3.48e-06]	[0.094839]	[0.319615]	[0.669053]	[0.000000]
Lag 2	28.82065	27.24214	15.51143	5.641801	2.950401	1.218952	200.6647
	[6.58e-05]	[0.000130]	[0.016631]	[0.464486]	[0.815046]	[0.975938]	[0.000000]
Df	6	6	6	6	6	6	36

Source: Author's computation

Table 5.5 illustrates the lag exclusion test results of the variables in this study. The findings presented in Table 5.5 reveal that the combined probability of all the variables falls below the 5% significance level, both at lag 1 and 2. Consequently, in line with the AIC criterion, lag order two is chosen for the study to account for the pertinent variables effectively. Moreover, when considering the AIC information criteria for selecting the optimal ARDL model with a lag of two, the most suitable model configuration is identified as 2, 1, 2, 2, 1, 0. This selection is based on the model's significant explanatory power and precision in representing the data.

5.2.5. Cointegration Test Results

As specified in Chapter 4 of the study, the cointegration tests were performed using the ARDL cointegration technique to determine whether multiple time series exhibit a long-term relationship. The study checked for cointegration to determine and assess the long-term relationship among the chosen variables. Cointegration is determined based on the computed F-test statistic. The null hypothesis is rejected if the computed F-test statistic from the cointegration test exceeds the upper and lower limits, signifying the presence of cointegration among the variables. After running the test, the results of the cointegration tests revealed that all variables chosen exhibit cointegration, demonstrating a long-term relationship between the variables. Table 5.6 presents the cointegration findings for the Bounds test and provides an interpretation following the table.

Table 5.6: Bounds test results.

Test Statistic	Value	k
F-statistic	8.362001	5
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	2.08	3
5%	2.39	3.38
2.5%	2.7	3.73
1%	3.06	4.15

Source: Author's computation

The computed F-statistic is 8.362001, which is above the upper bound at a 5% significance level for both critical bounds. Consequently, the null hypothesis suggesting no cointegration is rejected, establishing evidence for a long-run relationship between the variables and indicating that there is cointegration. The findings of the bound test have given sufficient support for a long-run relationship between TFP and the regressors, suggesting that electricity production, prices, R&D, patents, and investment in ICT all impact TFP growth. The study will then proceed to estimate the long-run coefficients of the model and the Error Correction Model (ECM).

5.2.6. ARDL Results

The summary of ARDL estimates is vital as it presents a concise yet comprehensive snapshot of the model's statistical significance and validity. This summary captures crucial statistical information such as coefficient estimates, standard errors, t-statistics, p-values, and goodness-of-fit measures like R-squared. Table 5.7 presents the overview of ARDL estimates and provides an interpretation of these results, as shown in the table below.

Table 5.7: Summary of ARDL Estimates

Selected Model: ARDL(2, 1, 2, 2, 1, 0)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
TFP(-1)	-0.318465	0.198817	-1.601801	0.1479
TFP(-2)	0.362658	0.165315	2.193741	0.0596
LEPRO	0.097827	0.111999	0.873466	0.4079
LEPRO(-1)	0.608555	0.170972	3.559394	0.0074
LEP	-0.003329	0.049909	-0.066701	0.9485

LEP(-1)	-0.145654	0.049863	-2.921109	0.0193
LEP(-2)	0.055717	0.045388	1.227560	0.2545
LR_D	-0.052844	0.033108	-1.596090	0.1491
LR_D(-1)	-0.058964	0.039708	-1.484959	0.1759
LR_D(-2)	-0.082656	0.032336	-2.556125	0.0339
LPAT	0.037020	0.013235	2.797096	0.0233
LPAT(-1)	0.018384	0.014100	1.303834	0.2286
LINV_ICT	-0.028631	0.011666	-2.454232	0.0397
C	-5.810013	2.189597	-2.653462	0.0291
R-squared	0.994190	Mean dependent var		1.062085
Adjusted R-squared	0.984749	S.D. dependent var		0.061904
S.E. of regression	0.007645	Akaike info criterion		-6.648474
Sum squared resid	0.000468	Schwarz criterion		-5.954174
Log-likelihood	87.13321	Hannan-Quinn criteria.		-6.484918
F-statistic	105.3059	Durbin-Watson stat		2.566059
Prob(F-statistic)	0.000000			

Source: Author's computation

With a Durbin-Watson statistic of approximately 2.57, which tends to be higher than the value of the R-squared of 0.99, it is evident that the model is free from spurious regression and serial correlation issues. Consequently, the following tables illustrate the estimated results for both the long-run and short-run analyses. The R-squared of 0.99 and an adjusted R-squared of 0.98 in Table 5.7 indicate an extremely elevated level of goodness of fit for the model in the study. These metrics signify that approximately 99% of the variance in the dependent variable is explained by the independent variables in the model. The adjusted R-squared considers the number of predictors in the model and slightly adjusts the R-squared to avoid overestimation, resulting in a value of 0.98, which is still remarkably high. This high goodness of fit indicates that the model is robust and dependable in explaining the relationship between TFP and the independent variables in the study.

5.2.7. ARDL Long-Run and ECM Estimates

As specified in Chapter 4, the study employed the ARDL cointegration technique. After using the ARDL approach, the results revealed a long-run association between the chosen variables, as indicated in Table 5.8. The ARDL approach in cointegration analysis helps identify cointegration vectors, where each selected variable represents a distinct long-run relationship equation. According to Nkro and Uko (2016), if a cointegrating vector is determined, the ARDL approach allows reparameterization into an Error Correction Model (ECM). Tables 5.8 and 5.9 present the ARDL long-run and short-run estimates found after running the cointegration test, and they also provide an interpretation following the tables below.

Table 5.8: ARDL Long-Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO	0.739043	0.077417	9.546237	0.0000*
LEP	-0.097579	0.012192	-8.003418	0.0000*
LR_D	-0.203455	0.055665	-3.655017	0.0064*
LPAT	0.057966	0.016305	3.555037	0.0075*
LINV_ICT	-0.029955	0.010649	-2.812949	0.0227*
C	-6.078646	0.967689	-6.281611	0.0002*

Source: Author's computation

Table 5.8 shows the estimated coefficients of the long-run association among the observed variables. These findings illustrate that electricity production positively affects TFP in the long run. This is illustrated by a positive coefficient of 0.739043 and is statistically significant at the 5% level. This suggests that a 1% increase in electricity production ceteris paribus will lead to a 0.739043% rise in total factor productivity. This finding aligns with a previous study conducted by Mpatane (2015), which similarly concluded that expanding the electricity sector has the potential to boost manufacturing output. This emphasises the significant policy implications of the positive correlation between electricity production and manufacturing output, which can enhance the overall productivity rate. A positive relationship between TFP and electricity production aligns with the Cobb-Douglas Production theory. Reliable electricity production plays a vital role in economic development as it enables the adoption of various technologies and enhances productivity. An increase in electricity production can influence the cost structure of businesses and households, potentially leading to increased overall output and fostering economic growth in South Africa. Hence, electricity rationing/load-shedding practices adversely affect the country's productivity outlook.

Electricity prices negatively influence total factor productivity in the long run, as shown by -0.097579. This implies an inverse relationship between electricity prices and total factor productivity over time. The effect of electricity prices is statistically significant at the 1% level. This suggests that a 1% increase in electricity prices ceteris paribus will lead to a -0.097579 decrease in total factor productivity. These findings align with a previous study conducted by Gonese et al., (2019), which demonstrated that electricity prices harm sectoral output, and it also shows that electricity price is a limiting factor to the sectoral production growth in South Africa. This outcome aligns with the theoretical expectations concerning the connection between electricity prices and total factor productivity. This indicates that higher electricity prices lead to a reduction in TFP. This negative relationship between TFP and electricity price is consistent with the Cobb-Douglas Production Function.

R&D negatively influences TFP in the long run, as shown by -0.203455. This implies an inverse relationship between R&D and total factor productivity in the long run. However, the effect of R&D is statistically significant at the 5% level. This suggests that a 1% increase in R&D ceteris paribus will lead to a -0.203455 decrease in TFP. This result aligns with previous studies conducted in South Africa by Sekaiwa and Maredza (2018). However, it deviates from the a priori expectations rooted in the theoretical connections between R&D and TFP. A negative correlation between TFP and R&D contradicts the principles of the Endogenous Growth Theory and the Cobb-Douglas production function. Endogenous growth economists contend that more significant investments in R&D and the promotion of accelerated innovation directly enhance productivity growth, thereby contributing to overall productivity levels in a country. R&D drives technological advancements, fosters innovation, and nurtures human capital development. The Endogenous Growth Theory underscores the significance of R&D in facilitating sustainable economic growth. R&D investments can lead to the discovery and development of recent technologies, ultimately increasing TFP and stimulating economic growth.

The results for the long run using the ARDL model show that patents positively affect total factor productivity in the long run. The effects are statistically significant at the 5 level. This suggests that a 1% increase in patents ceteris paribus will lead to a 0.057966% rise in total factor productivity. This finding aligns with previous research conducted by Ledwaba (2022) and Kahn et al., (2022), which concluded that increased patents can positively impact a country's overall productivity. This result supports the expected relationship between patents and TFP in South Africa, as outlined in economic theory. A positive correlation between TFP and patents is consistent with economic theory, as patents serve as powerful incentives for innovation and the development of recent technologies. They provide inventors and companies with legal protection and exclusive rights for a designated period, encouraging R&D investments that can result in technological advancements. This finding demonstrates that this relationship is consistent with the endogenous growth theory outlined in Chapter 4. The Endogenous growth economists argue that higher investments in human capital and promoting accelerated innovation directly influence the growth of productivity. These measures include funding support for R&D activities and protecting intellectual property rights. Institutions, technical advancement, total factor production, and other factors were all considered exogenous factors (Takentsi et al., 2022). Hence, this finding shows that patents positively affect total factor productivity in the long run, which is in line with the Endogenous growth theory.

In South Africa, the investment in ICT has a long-term negative impact on total factor productivity. The p-value of 0.0227 shows that the effect is statistically significant at 5%. This indicates that for each 1% increase in investment in ICT, there is a corresponding -0.029955 drop in total factor productivity, assuming all other variables remain constant. A negative relationship between TFP and ICT investment is inconsistent with the Cobb-Douglas production function. The Cobb-Douglas production function assumes that the absence of either labour or capital leads to reduced output. However, machinery's efficiency might offset labour loss. It suggests doubling labour or capital results in a proportional output increase, implying constant returns to scale. However, it is essential to note that such perfect scalability is not attainable in the real world. Even doubling capital may not lead to a doubling of output. Other elements, such as electricity, are necessary for the machines to run continuously. Insufficient utilization of machinery may occur due to intermittent electrical supply, load-shedding, and brownouts, leading to lower production output than expected (Mpatane, 2015). Hence, this discrepancy might explain why investment in ICT and TFP in the context of South Africa does not align consistently with the predictions of the Cobb-Douglas production and Endogenous Growth theories. Additionally, Chapter 2's analysis of ICT trends highlights that South Africa has relatively low investment in ICT. The observed downtrend in ICT investment during specific years, notably 2005 and 2017, underlines this trend of decreased investment, as shown in Chapter 2.

Table 5.9 below presents the short-term results derived from the ECM within the framework of the ARDL approach. The error term coefficient is expected to be within the range of 0 to 1, and its probability value should be below the 5% significance level.

Table 5.9: Short-Run Coefficients

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(TFP(-1))	-0.374760	0.125549	-2.984960	0.0175*
D(LEPRO)	0.069884	0.090238	0.774441	0.4609
D(LEP)	0.008290	0.034639	0.239317	0.8169
D(LEP(-1))	-0.048836	0.040397	-1.208900	0.2612
D(LR_D)	-0.037950	0.029091	-1.304520	0.2283
D(LR_D(-1))	0.070548	0.029880	2.361029	0.0459*
D(LPAT)	0.031437	0.008902	3.531608	0.0077*
LINV_ICT	-0.000342	0.000478	-0.715295	0.4948
CointEq(-1)	-0.867607	0.117697	-7.371560	0.0001*

Source: Author's computation

The results of the short-run relationship using the ARDL model in Table 5.9 reveal a positive relationship between patents and total factor productivity. This is evident through a positive coefficient of 0.031437, and this effect is statistically significant, indicated by the probability value of 0.0077. The findings suggest a positive correlation between patents and total factor productivity in South Africa in the short run. The estimated coefficient of 0.031437 for patents implies that ceteris paribus, a 1% increase in patents corresponds to an expected improvement of 0.031437 units in TFP. This interpretation aligns with the principles of Endogenous Growth theory. In this theory, technological progress and innovation are considered essential drivers of economic growth. Patents play a crucial role by incentivizing innovation through legal protection and encouraging firms and individuals to invest in R&D to create recent technologies or improve existing ones. As patents increase, innovation and technological advancements are expected to rise, leading to improvements in TFP. Notably, other variables such as electricity production, electricity prices, R&D, and investment in ICT do not exhibit statistically significant relationships with TFP in the short run. The results of the short run revealed that electricity production has a positive relationship with TFP, and it is statistically insignificant, while electricity prices have an inverse relationship with TFP in the short run, and it is statistically insignificant. R&D and investment in ICT also have an inverse relationship with TFP in the short run.

The Error Correction Term demonstrates an anticipated and statistically significant negative value of -0.867607, as expected, and a statistical significance of 1%, shown by the probability value of 0.0001. This ECT signifies a speed of adjustment towards equilibrium, indicating that the model can rapidly converge at an impressive rate of 86%.

5.2.8. Diagnostic Test Results

Conducting diagnostic tests is essential in every time series modelling. Diagnostic tests are utilised to assess the accuracy and validity of the data acquired and the presence of violations in the classical assumptions (Khoza, 2017). The study conducted various residual tests, which include the normality test, heteroskedasticity, and autocorrelation. The significance of performing diagnostic tests within the model is to evaluate the existence of serial correlation/autocorrelation, normality, and heteroscedasticity (Ratombo, 2019). These tests are conducted to verify and ensure further the model's goodness of fit.

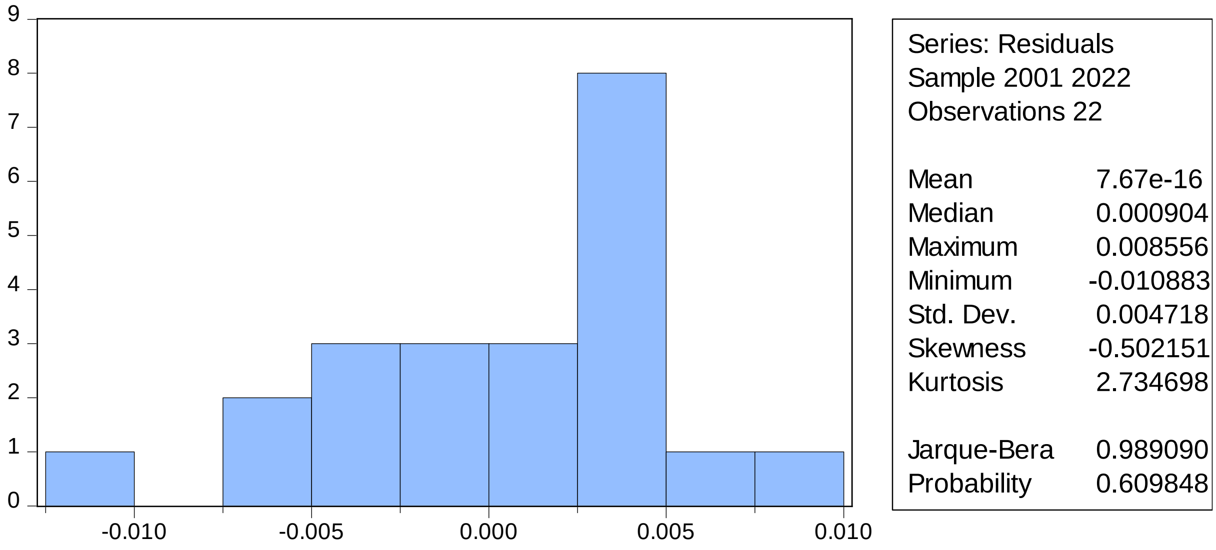

Figure 5.1: Normality Test Results

Source: Author’s computation

The results in Figure 5.1 reveal the JB of 0.989090 and the probability value of 0.609848, higher than the significance level of 5%. Considering this result, the null hypothesis cannot be rejected; thus, the null hypothesis is accepted. This result demonstrates that the model is normally distributed. The residuals are, therefore, normally distributed, as shown by the skewness of -0.502151 and p-value of 0.609848, which is statistically insignificant.

Table 5.10: Diagnostic checks on the error term

Test	**Null hypothesis**	**Test-statistic**	**P-Value**	**Conclusion**
Jarque-Bera	Residuals are normally distributed	0.989090	0.609848	Do not reject H0 as the P-value is greater than a 5% level of significance; hence, the model's residuals are normally distributed.
Breusch-Godfrey Serial Correlation	No Serial Correlation	1.247678	0.3523	Do not reject H0 as the P-value is greater than a 5% level of significance. This indicates the absence of serial correlation.
Heteroskedasticity Test: Breusch-Pagan-Godfrey	No heteroskedasticity	0.879816	0.5982	Do not reject H0 as the P-value value is greater than a 5% level of significance. This suggests that there is no evidence of heteroskedasticity, and instead, we find evidence of homoscedasticity, which is a desirable outcome.
Heteroskedasticity Test: Harvey	No heteroskedasticity	1.028542	0.5032	Do not reject H0 as the P-value is more significant than a 5% level of significance, implying no heteroskedasticity in the model. Instead, there is homoskedasticity, which is desirable.
Heteroskedasticity Test: Glejser	No heteroskedasticity	1.387719	0.3283	Do not reject the null hypothesis since the p-value is more significant than the 5% significance level. This indicates that there is no evidence of heteroskedasticity within the model; instead, there is evidence of homoskedasticity, which is a desirable outcome.
Heteroskedasticity Test: ARCH	No heteroskedasticity	0.184147	0.8335	Do not reject H0 as the P-value is more significant than a 5% level of significance, implying no heteroskedasticity in the model. Instead, there is homoskedasticity, which is desirable.

Source: Author’s computation

Table 5.10 above presents diagnostic test results on the error term. The results are based on the level of significance: 1%, 5%, and 10%. The JB test statistic shows that the residuals of the regression are normally distributed in this study because the p-value of 0.609848 is higher than all the levels of significance (1%, 5%, and 10%). The Breusch-Godfrey Serial Correlation was assessed to check if there is a serial correlation in the model. The p-value is 0.3523, and due to its exceeding all significance levels, the null hypothesis is not rejected, indicating an absence of serial correlation.

A heteroskedasticity test was conducted to detect if the model is homoscedastic or heteroskedastic. The heteroskedasticity test-Breusch-Pagan-Godfrey p-value is 0.5982. Hence, the null hypothesis is not rejected as its p-value is greater than the level of significance 1%, 5%, and 10%, which indicates no evidence of heteroskedasticity within the model. Instead, there is evidence of homoskedasticity, which is a desirable outcome. The Heteroskedasticity Test- Harvey also confirms the null hypothesis of no heteroskedasticity in the model, given the P-value of 0.5032. Hence, the null hypothesis is not rejected as its p-value is greater than 1%, 5%, and 10% levels of significance, implying no heteroskedasticity in the model. Instead, there is desirable homoskedasticity. The Glejser p-value is 0.3283, which indicates failure to reject the null hypothesis as its p-value is greater than all levels of significance, implying no heteroskedasticity in the model. The ARCH p-value is 0.8335, higher than all the significance levels; hence, the null hypothesis is not rejected. These results indicate the actual estimations of the ECM.

5.2.9. Stability Test Results

After examining the diagnostic tests, the next step was determining if the model presented in Chapter 4 was stable using stability tests. The stability tests were performed using the CUSUM and the CUSUM of Squares tests. Brown, Durbin, and Evan (1975) introduced the CUSUM and CUSUM of Squares tests for parameter stability. These tests indicate whether the cumulative sum moves within the critical line. The results of the CUSUM and CUSUM of squares tests are presented in Figures 5.2 and 5.3 below.

CUSUM TEST

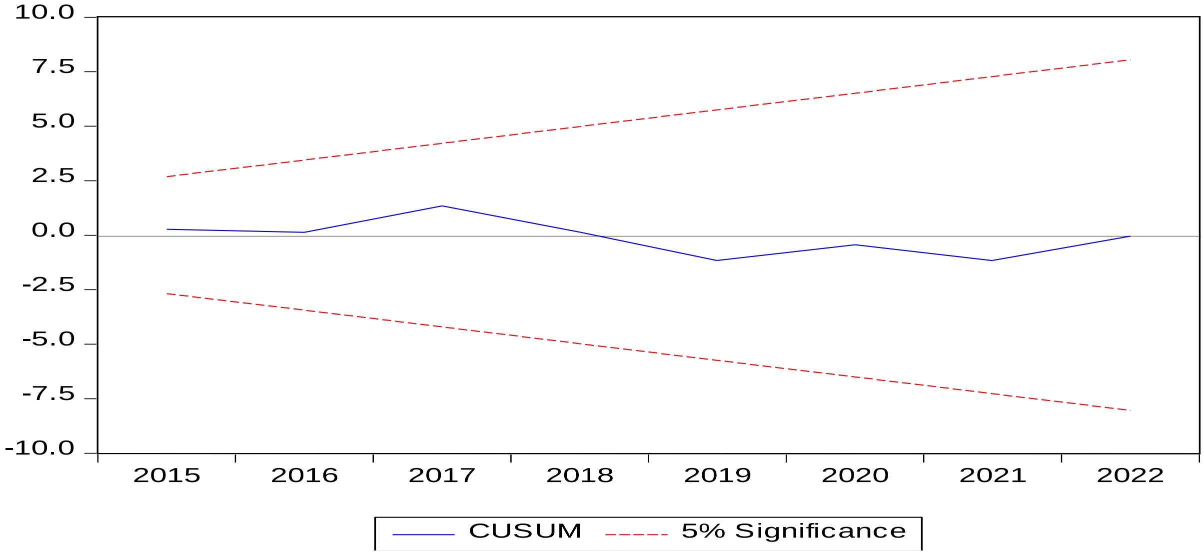

Figure 5.2: CUSUM Test

Source: Author's computation

The results in Figure 5.2 show that the CUSUM line (blue line) fluctuates within the 5% critical line (red line), showing that the model is stable.

CUSUM of squares

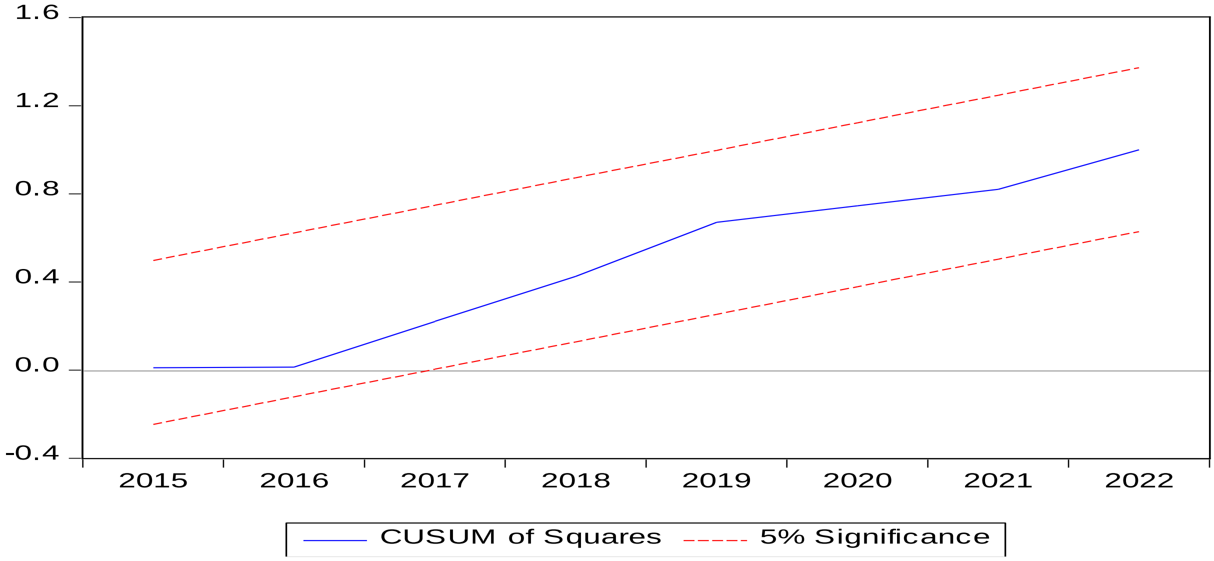

Figure 5.3: CUSUM of Squares Test

Source: Author's computation

The results in Figure 5.3 above show that the CUSUM of the Squares line (blue line) fluctuates within the 5% critical line (red line), demonstrating that the model is stable.

Table 5.11: Ramsey test

	Value	df	Probability
t-statistic	0.247750	7	0.8114
F-statistic	0.061380	(1, 7)	0.8114

Source: Author's computation

Table 5.11 above illustrates the results of the Ramsey test. The t-statistic (0.247750) and F-statistic (0.061380) values are statistically insignificant. In other words, at a 5% significance level, the t-statistic and F-statistic values are higher than the critical values. This suggests that the asymmetric model is likely free from specification errors. Consequently, there is inadequate evidence to reject the null hypothesis, as there are no signs of model misspecification. The failure to reject H0 occurs due to the probability value exceeding 5% significance level, demonstrating that the study model is appropriately specified.

5.2.10. Granger Causality Test

Conducting Granger Causality tests is crucial in determining the causal relationships between variables in a time series context. This test helps ascertain if one variable helps forecast another, establishing potential causal links between them. Additionally, the test examines whether including lagged values of X enhances the model's explanatory capacity. Table 5.12 presents the results of the Granger Causality test and provides an interpretation following the table below.

Table 5.12: Granger Causality Results

Null Hypothesis:	Obs	F-Statistic	Prob.	Decision
LEPRO does not Granger Cause TFP	22	8.16965	0.0033*	Reject the null hypothesis.
TFP does not Granger Cause LEPRO		6.21728	0.0094*	Reject the null hypothesis.
LEP does not Granger Cause TFP	22	9.92260	0.0014*	Reject the null hypothesis.
TFP does not Granger Cause LEP		1.09319	0.3576	Accept null hypothesis
LR_D does not Granger Cause TFP	22	3.44713	0.0554	Accept null hypothesis
TFP does not Granger Cause LR_D		3.02893	0.0750	Accept null hypothesis

LPAT does not Granger Cause TFP	22	1.01713	0.3826	Accept null hypothesis
TFP does not Granger Cause LPAT		1.03707	0.3759	Accept null hypothesis
LINV_ICT does not Granger Cause TFP	22	2.82247	0.0874	Accept null hypothesis
TFP does not Granger Cause LINV_ICT		0.21251	0.8107	Accept null hypothesis
LEP does not Granger Cause LEPRO	22	10.1098	0.0013*	Reject the null hypothesis.
LEPRO does not Granger Cause LEP		2.05438	0.1588	Accept null hypothesis
LR_D does not Granger Cause LEPRO	22	0.77731	0.4753	Accept null hypothesis
LEPRO does not Granger Cause LR_D		0.52471	0.6010	Accept null hypothesis
LPAT does not Granger Cause LEPRO	22	3.42961	0.0561	Accept null hypothesis
LEPRO does not Granger Cause LPAT		2.17666	0.1440	Accept null hypothesis
LINV_ICT does not Granger Cause LEPRO	22	1.73535	0.2062	Accept null hypothesis
LEPRO does not Granger Cause LINV_ICT		0.19380	0.8256	Accept null hypothesis
LR_D does not Granger Cause LEP	22	0.24088	0.7886	Accept null hypothesis
LEP does not Granger Cause LR_D		0.96676	0.4003	Accept null hypothesis
LPAT does not Granger Cause LEP	22	0.99182	0.3914	Accept null hypothesis
LEP does not Granger Cause LPAT		0.94781	0.4071	Accept null hypothesis
LINV_ICT does not Granger Cause LEP	22	3.48564	0.0539	Accept null hypothesis
LEP does not Granger Cause LINV_ICT		0.37344	0.6939	Accept null hypothesis
LPAT does not Granger Cause LR_D	22	0.43300	0.6555	Accept null hypothesis
LR_D does not Granger Cause LPAT		2.41495	0.1194	Accept null hypothesis
LINV_ICT does not Granger Cause LR_D	22	0.66436	0.5275	Accept null hypothesis
LR_D does not Granger Cause LINV_ICT		0.70702	0.5070	Accept null hypothesis
LINV_ICT does not Granger Cause LPAT	22	0.70204	0.5094	Accept null hypothesis
LPAT does not Granger Cause LINV_ICT		0.49182	0.6199	Accept null hypothesis

Notes: 0.01* (1%) significance level

Source: Author's computation

The results in Table 5.12 reveal that the null hypothesis is rejected, and the alternative hypothesis that electricity production Granger causes total factor productivity is accepted. This is due to the probability values of 0.0033 and 0.0094, each falling below the 1% significance level. Electricity production Granger causes total factor productivity, and total factor productivity Granger causes electricity production. In this case, a bi-directional causality exists between total factor productivity and electricity production. An increase in electricity production can lead to higher TFP, indicating that an efficient energy supply contributes to overall productivity growth. Conversely, improvements in TFP could lead to increased demand for electricity or more efficient utilization of energy resources.

Electricity prices, on the other hand, Granger causes total factor productivity, but total factor productivity does not Granger cause electricity prices, as shown in Table 5.12. In this case, electricity prices have a unidirectional causality on total factor productivity since its p-value is 0.0014, which is also significant at 1%. Electricity prices Granger causes electricity production since its p-value is 0.0013, which falls within the 1% significance level. In this case, there is unidirectional causality between electricity prices and production. Higher electricity prices could increase production costs for firms, thereby affecting their productivity levels.

The Granger Causality test has revealed a two-way causal relationship between total factor productivity and electricity production. Additionally, there is a one-way causal link between electricity prices, total factor productivity, and electricity production in South Africa. These findings provide the basis for forecasting these variables.

5.2.11. Variance Decomposition Test Results

The VD and IRF tests were performed to explore the causality detected among electricity production, electricity prices, and total factor productivity in South Africa. The findings from Table 5.12, illustrating the results of the Granger Causality, have proven that only electricity production and electricity prices have a causal effect / innovative information on TFP in South Africa, enabling the variables to be forecasted. Table 5.13 presents the VD results in the model. This technique was used to determine how much of the forecast error variance for the main variables is explained by shocks. The variance decomposition test demonstrates shocks' short-run and long-run effects on the regressed variable. The short run is denoted by period 3, and the long run is represented by period 10 in the table below.

Table 5.13: Variance decomposition of TFP

Variance Decomposition of TFP							
Period	**S.E.**	**TFP**	**LEPRO**	**LEP**	**LR_D**	**LPAT**	**LINV_ICT**
1	0.009791	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.017924	38.66765	16.34570	15.23767	16.57221	9.187875	3.988896
10	0.038954	12.96627	18.38758	18.38758	9.577907	25.19835	6.012437

Source: Author’s computation

The VD test was used to assess how factors such as electricity production, electricity prices, R&D, patents, and investment in ICT contribute to variations in measures of TFP at different time horizons. The variance decomposition results in Table 5.13 revealed an evolving pattern in how these factors influence TFP. In the short term, TFP accounts for 100% of the variation in TFP (own shock) in period one and starts to decrease to 38% in period three and further declines to 12% in the long run, corresponding to period 10. The LEPRO shock accounts begin with a contribution of 16.35% in the short-run (period 3) and steadily increase over time, eventually reaching 18.39% in the long-run (period 10). Likewise, LEP demonstrates a 15.24% influence in period three during the short-run and expands over time to reach 18.39% in the long run, mirroring the behaviour of the LEPRO shock.

5.2.12. Impulse Response Function Results

Figure 5.4 presents the results for the IRF, illustrating the impact of a one standard deviation shock to the residual on the reciprocal reactions among various variables throughout ten periods. The blue line represents the IRF, while the two red lines indicate the 95% confidence intervals. The x-axis represents the time horizon or shock duration, while the y-axis depicts the direction and magnitude of the IRF (De Alwis & Dewasiri, 2021).

Impulse Response Function Test Results

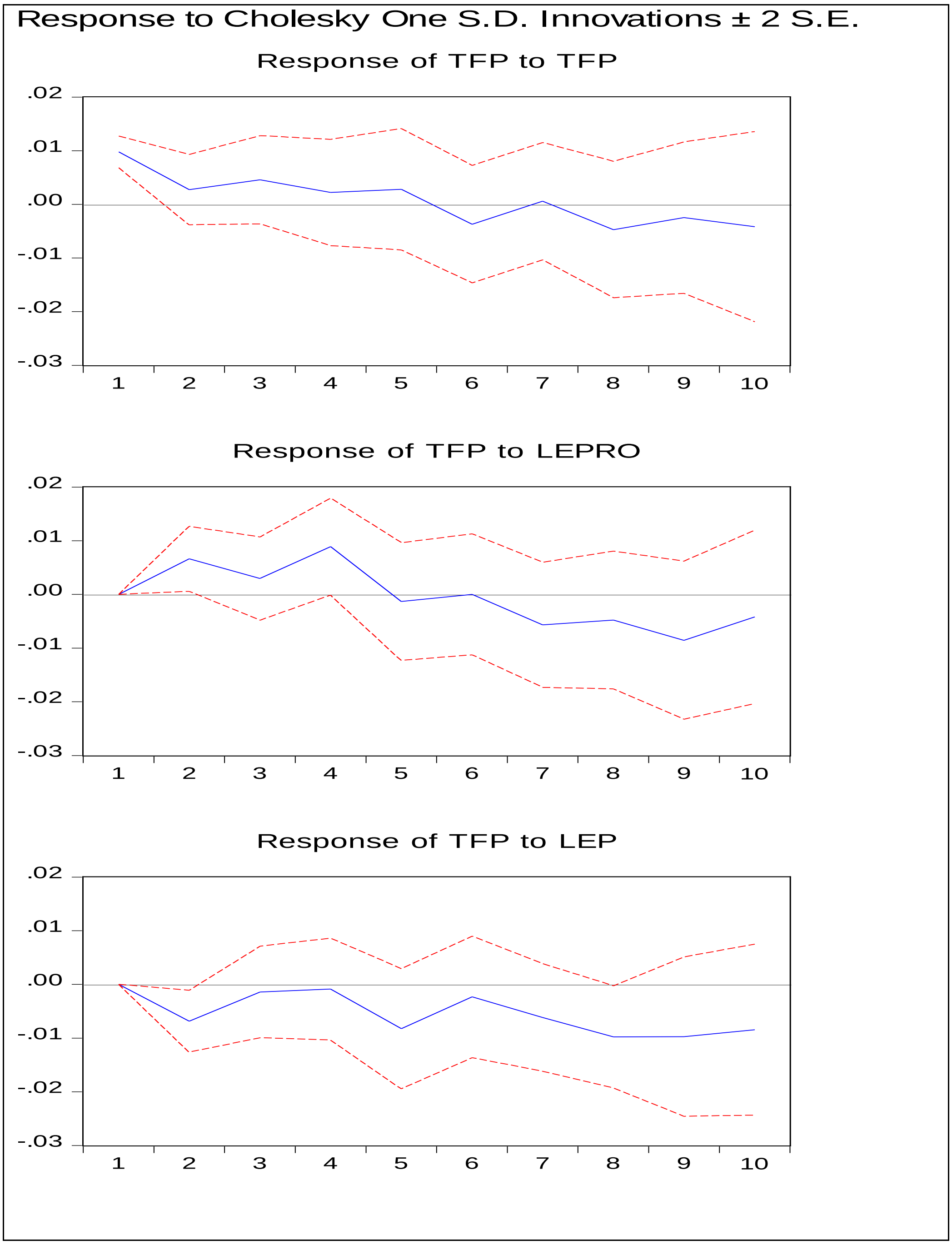

Figure 5.4: Impulse Response Function

Source: Author's computation

In Figure 5.4, the IRF results are presented. It shows the responses of total factor productivity to electricity production and prices because only these two electricity supply shock variables have a shock effect on TFP. The Granger Causality has proven that only electricity production and prices have a causal effect/innovative information on TFP in South Africa. Consequently, the IRF focuses entirely on analysing these two variables. In Figure 5.4, the three lines above (.00) indicate a positive effect, while the lines below (.00) signify a negative impact.

In Figure 5.4, examining the response of TFP to electricity production, a one standard deviation shock to EPRO initially leads to an increase in TFP, persisting up to the second period, indicating a positive short-term effect of electricity production on total factor productivity. However, beyond the fourth period, the impact turns negative, extending to the tenth period, implying a negative long-term response of TFP to EPRO in the economy of South Africa. In contrast, the reaction of TFP to electricity prices demonstrates a different pattern. Throughout the entire 10-year period, electricity prices have consistently hurt TFP in South Africa. This outcome aligns with the study's anticipated expectation, reflecting the acknowledged influence of electricity supply shocks on productivity in the South African context. Consequently, these findings emphasise the significance of energy in the production process, as evidenced by the positive impact of electricity production and the detrimental effect of elevated electricity prices on total factor productivity in South Africa.

5.3. SUMMARY

This chapter presented the study results, following the outlined methodology in Chapter 4. Descriptive statistics and correlation tests assessed variables, and annual time series data stationarity was examined. The ARDL test revealed a long-run relationship between TFP and regressors (electricity production, electricity prices, R&D, patents, and ICT investment), explaining 99% of TFP variance. ARDL's long-run results revealed positive impacts of electricity production and patents, contrasting with negative influences from electricity prices, R&D, and ICT investment on TFP. The Error Correction Term indicated a rapid 86% convergence toward equilibrium. Granger Causality identified only electricity production and prices causally affecting TFP, permitting forecast through VC and IRF tests. The IRF results revealed a positive impact of electricity production and adverse effects of electricity prices on TFP, aligning with expectations. Consequently, these findings emphasise the significance of energy in the production process, as evidenced by the positive impact of electricity production and the detrimental effect of elevated electricity prices on total factor productivity. The next chapter summarises, interprets findings, draws conclusions, discusses contributions, and addresses study limitations.

CHAPTER 6

SUMMARY, RECOMMENDATIONS, CONCLUSION

6.1 INTRODUCTION

Chapter 6 presents the empirical results and conclusions and provides recommendations for policymakers. It summarises the interpretation of the study findings, emphasizing its significance and implications. Following this, the chapter delves into conclusions from the study, highlighting its contributions to the field. Additionally, it critically addresses the study's limitations, acknowledging areas where further exploration or refinement may be necessary. The summary, recommendations, conclusions, and delineation collectively shape the essence of Chapter 6, providing an understanding of the research's findings and their implications for future action and research.

6.2 SUMMARY AND INTERPRETATION OF FINDINGS

The study investigated how electricity production, prices, R&D, patents, and investment in ICT impacted South Africa's TFP from 1999 to 2022. It employed time series data analysis to accomplish the objectives outlined in Chapter 1. By Employing the ARDL technique, the study explored the short and long-run relationship among electricity supply shocks, technological advances, and productivity. The study also employed several econometric techniques to analyse the chosen variables in the model.

Initially, the descriptive statistics analysis evaluated the statistical behaviour of the variables. The results revealed a normal distribution in the study model. Subsequently, correlation analysis revealed positive correlations between electricity production, R&D, patents, and total factor productivity, while investment in ICT demonstrated a negative correlation. The study also employed the unit root technique to analyse variable behaviour and determine the appropriate modelling approach, confirming the suitability of the ARDL method due to differing integration orders. The subsequent steps involved lag length criteria estimation and ARDL cointegration techniques to ascertain the long-run relationship within the model. Descriptive analysis revealed unique characteristics of the variables, while correlation tests indicated low multicollinearity. The unit root tests supported stationarity, enabling the ARDL model with two lags chosen using the Akaike Information Criterion. The Lag Exclusion test further validated the selection of lag order two, meeting the significance criteria.

The ARDL technique established a long-run relationship between TFP and several regressors, indicating the impact of electricity production, prices, R&D, patents, and ICT investment on TFP growth. The ARDL Estimates Summary showed a high goodness of fit, explaining approximately 99% of the variance in the dependent variable. Long-run results highlighted the positive effects of electricity production and patents on TFP, while electricity prices, R&D, and ICT investment negatively influenced TFP. In the short run, patents positively impacted TFP, while other variables did not exhibit statistically significant relationships. The error correction term indicated a rapid convergence towards equilibrium at an 86% rate. This refers to the rate at which TFP returns to equilibrium following a shock in independent variables like electricity supply shocks and technological advances.

The Granger Causality has proven that only electricity production and prices have a causal effect/innovative information on TFP in South Africa. Variance Decomposition revealed electricity production shock initiating at 16.35% in the short-run (period 3), steadily escalating to 18.39% in the long-run (period 10). Similarly, electricity prices exhibited a 15.24% influence in the short run, reaching 18.39% in the long run, reflecting electricity production behaviour. The Impulse Response Function revealed the TFP response to electricity production, where a one standard deviation shock initially boosts TFP, persisting up to the second period, indicating a positive short-term effect. However, beyond the fourth period, the impact becomes negative, extending to the tenth period, suggesting a negative long-term response in the South African economy. Conversely, the TFP response to electricity prices exhibits a consistent negative impact throughout the ten years, aligning with the study's expected outcome. These results emphasise the crucial role of energy, emphasizing the positive impact of electricity production and the adverse effect of elevated electricity prices on total factor productivity in South Africa.

6.3 CONCLUSIONS AND RECOMMENDATIONS

South Africa's declining productivity growth has hindered improvement in living standards over a decade (OECD, 2022). Hence, this study focused on factors impacting South African production, particularly electricity supply shocks and technological advances from 1999 to 2022, using the ARDL model. The ARDL model revealed that electricity production, prices, R&D, patents, and investment in ICT significantly affect South Africa's TFP growth. The long-run results indicate a positive effect of electricity production and patents on TFP, while electricity prices, R&D, and investment in ICT have negative impacts.

The Granger Causality test revealed a two-way causal connection between total factor productivity and electricity production. Additionally, there is a one-way/unidirectional causal link between electricity prices, total factor productivity, and electricity prices and production in South Africa. These findings provide the basis for forecasting these variables. VD and IRF tests uncover short-term and long-term effects of electricity production and prices on South Africa's overall production. The result of the IRF revealed that the TFP response to electricity production had a positive short-term effect. However, beyond the fourth period, the impact becomes negative, extending to the tenth period, suggesting a negative long-term response in the South African economy. Conversely, the TFP response to electricity prices exhibits a consistent negative impact throughout the ten years, aligning with the study's expected outcome.

Based on the study's results, it is crucial to recommend possible action by the South African government to implement policies to foster an improved productivity outlook. One, through low electricity prices to support the long-term enhancement of total factor productivity and electricity production. Businesses will be incentivised to increase production by ensuring affordable electricity rates, contributing to economic growth. To enhance the Eskom Just Energy Transition Project in South Africa, the government should accelerate energy infrastructure development and implement transparent, market-driven pricing mechanisms, fostering increased electricity production and sustained low prices. Additionally, the government should prioritise policies that encourage R&D, leading to an increase in patents and innovation. Increased investment in ICT should also be promoted, as it plays a pivotal role in modernizing industries and boosting productivity. However, given the negative element on productivity in the long run, a revision must be made.

6.4 CONTRIBUTIONS OF THE STUDY

After reviewing the existing literature, it was evident that studies are scarce on the implications of electricity supply shocks and technological advancement on total factor productivity in South Africa. This study addressed this gap by engaging with the empirical literature review outlined in Chapter 3. Apart from augmenting the current empirical evidence, it also advances a grasp of the complex relationship between these factors within the South African economic context. The shock effect from the electricity perspective extends the understanding of how electricity supply influences productivity. The study aimed to help create new directions for future studies in this field to include the variables not included in this study, such as human capital, electricity consumption, and investment in electricity/energy infrastructure, to explore further the implications of electricity supply shocks and technological advancement on total factor productivity.

6.5 LIMITATIONS OF THE STUDY

The study encountered significant limitations regarding data availability, specifically concerning data for TFP, electricity prices, and patents in South Africa. The analysis relied on an annual time series dataset spanning 1999 to 2022, a period chosen due to these constraints. Notably, the data for TFP in South Africa was severely limited. A statistical extrapolation was employed to cover the study's designated period for TFP, a crucial step given the gravity of the data limitation. On the other hand, missing data on energy prices was generated by statistical extrapolation. Furthermore, a statistical extrapolation was employed to account for the absence of patent data. Hence, data availability was a significant limitation for this study, and the methods used to address these limitations were of utmost importance.

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APPENDICES

APPENDIX A: DATA OF THE STUDY

YEAR	TFP	LEPRO	LEP	LR_D	LPAT	LINV_ICT
1999	1,039805	12,167285	3,388054	8,043342	4,927254	8,715224
2000	1,057949	12,207856	3,402132	8,029433	6,796824	8,830982
2001	1,092345	12,209855	3,416209	8,087640	6,873164	8,977273
2002	1,079871	12,252011	3,430287	8,146999	6,890609	9,051931
2003	1,116340	12,313482	3,444365	8,156223	6,826545	9,365719
2004	1,128252	12,359450	3,525419	8,213924	6,862758	9,521128
2005	1,147624	12,359583	3,625726	8,188133	6,910751	9,730978
2006	1,119445	12,403258	3,714459	8,387768	6,763885	9,883591
2007	1,131398	12,440900	3,796579	8,367068	6,818924	10,041988
2008	1,117047	12,420268	4,033921	8,317522	6,756932	10,160530
2009	1,090605	12,392938	4,008998	8,302266	6,711740	10,054748
2010	1,111713	12,434232	4,152108	8,219326	6,710523	9,926471
2011	1,086750	12,436176	4,325601	8,126814	6,486161	10,214715
2012	1,090375	12,419231	4,458833	8,142645	6,410175	10,384895
2013	1,080537	12,408405	4,559674	8,203578	6,458338	9,555560
2014	1,072343	12,390064	4,628893	8,283241	6,687109	9,660396
2015	1,032908	12,361507	4,605170	8,278174	6,790097	10,103403
2016	1,009281	12,363081	4,655952	8,434464	6,556778	10,097285
2017	1,000000	12,364178	4,718788	8,298291	6,590301	10,199547
2018	0,979967	12,359377	4,817241	8,198639	6,487684	10,184145
2019	0,965773	12,339204	4,868055	8,105006	6,340359	10,261232
2020	0,972870	12,279286	4,867137	8,085795	6,295266	10,118559
2021	0,969322	12,290644	5,000886	8,132413	7,497762	10,377826
2022	0,971096	12,248111	5,212739	7,988543	7,078342	10,382977

APPENDIX B: UNIT ROOT TEST RESULTS

Appendix B1: TFP Unit Root Test

ADF Test

Null Hypothesis: TFP has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.703451	0.4010
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TFP)
Method: Least Squares
Date: 12/05/23 Time: 11:14
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.002822	0.004012	-0.703451	0.4892

R-squared	0.000334	Mean dependent var	-0.002987
Adjusted R-squared	0.000334	S.D. dependent var	0.020523
S.E. of regression	0.020519	Akaike info criterion	-4.892405
Sum squared resid	0.009263	Schwarz criterion	-4.843036
Log likelihood	57.26266	Hannan-Quinn criteria.	-4.879989
Durbin-Watson stat	1.914598		

Null Hypothesis: TFP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.115191	0.9365
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TFP)
Method: Least Squares
Date: 12/05/23 Time: 11:15
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.008982	0.077974	-0.115191	0.9094
C	0.006577	0.083149	0.079104	0.9377

R-squared	0.000631	Mean dependent var	-0.002987
Adjusted R-squared	-0.046958	S.D. dependent var	0.020523
S.E. of regression	0.020999	Akaike info criterion	-4.805747
Sum squared resid	0.009260	Schwarz criterion	-4.707008
Log likelihood	57.26609	Hannan-Quinn criter.	-4.780914
F-statistic	0.013269	Durbin-Watson stat	1.903196
Prob(F-statistic)	0.909388		

Null Hypothesis: TFP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.751328	0.2273
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TFP)
Method: Least Squares
Date: 12/05/23 Time: 11:15
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.238725	0.086767	-2.751328	0.0123
C	0.284200	0.098894	2.873801	0.0094
@TREND("1999")	-0.002748	0.000735	-3.740543	0.0013

R-squared	0.411992	Mean dependent var	-0.002987
Adjusted R-squared	0.353191	S.D. dependent var	0.020523
S.E. of regression	0.016505	Akaike info criterion	-5.249173
Sum squared resid	0.005448	Schwarz criterion	-5.101065
Log likelihood	63.36549	Hannan-Quinn criter.	-5.211925
F-statistic	7.006569	Durbin-Watson stat	2.566822
Prob(F-statistic)	0.004941		

Null Hypothesis: D(TFP) has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.444132	0.0173
Test critical values:	1% level	-2.679735	
	5% level	-1.958088	

	10% level	-1.607830	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TFP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:20
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-0.648756	0.265434	-2.444132	0.0244
D(TFP(-1),2)	-0.392398	0.190420	-2.060691	0.0533

R-squared	0.627893	Mean dependent var	-0.001553
Adjusted R-squared	0.608308	S.D. dependent var	0.029556
S.E. of regression	0.018498	Akaike info criterion	-5.051964
Sum squared resid	0.006501	Schwarz criterion	-4.952486
Log likelihood	55.04563	Hannan-Quinn criter.	-5.030375
Durbin-Watson stat	2.014575		

Null Hypothesis: D(TFP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.517440	0.0019
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TFP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:20
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-0.985509	0.218157	-4.517440	0.0002
C	-0.003901	0.004526	-0.862056	0.3989

R-squared	0.505039	Mean dependent var	-0.000744
Adjusted R-squared	0.480291	S.D. dependent var	0.029092
S.E. of regression	0.020973	Akaike info criterion	-4.804673
Sum squared resid	0.008797	Schwarz criterion	-4.705487
Log likelihood	54.85140	Hannan-Quinn criter.	-4.781307
F-statistic	20.40726	Durbin-Watson stat	2.033740
Prob(F-statistic)	0.000210		

Null Hypothesis: D(TFP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.314623	0.0016
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TFP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:21
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-1.222662	0.230056	-5.314623	0.0000
C	0.015084	0.009860	1.529844	0.1425
@TREND("1999")	-0.001580	0.000743	-2.125324	0.0469

R-squared	0.600108	Mean dependent var	-0.000744
Adjusted R-squared	0.558015	S.D. dependent var	0.029092
S.E. of regression	0.019341	Akaike info criterion	-4.927048
Sum squared resid	0.007107	Schwarz criterion	-4.778270
Log likelihood	57.19753	Hannan-Quinn criter.	-4.892001
F-statistic	14.25644	Durbin-Watson stat	1.788769
Prob(F-statistic)	0.000165		

TFP - PP Test

Null Hypothesis: TFP has a unit root
Exogenous: None
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.636384	0.4305
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Residual variance (no correction)	0.000403
HAC corrected variance (Bartlett kernel)	0.000509

Phillips-Perron Test Equation

Dependent Variable: D(TFP)
Method: Least Squares
Date: 12/05/23 Time: 11:24
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.002822	0.004012	-0.703451	0.4892

R-squared	0.000334	Mean dependent var	-0.002987
Adjusted R-squared	0.000334	S.D. dependent var	0.020523
S.E. of regression	0.020519	Akaike info criterion	-4.892405
Sum squared resid	0.009263	Schwarz criterion	-4.843036
Log likelihood	57.26266	Hannan-Quinn criter.	-4.879989
Durbin-Watson stat	1.914598		

Null Hypothesis: TFP has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.310847	0.9089
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Residual variance (no correction)	0.000403
HAC corrected variance (Bartlett kernel)	0.000513

Phillips-Perron Test Equation
Dependent Variable: D(TFP)
Method: Least Squares
Date: 12/05/23 Time: 11:24
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.008982	0.077974	-0.115191	0.9094
C	0.006577	0.083149	0.079104	0.9377

R-squared	0.000631	Mean dependent var	-0.002987
Adjusted R-squared	-0.046958	S.D. dependent var	0.020523
S.E. of regression	0.020999	Akaike info criterion	-4.805747
Sum squared resid	0.009260	Schwarz criterion	-4.707008
Log likelihood	57.26609	Hannan-Quinn criter.	-4.780914
F-statistic	0.013269	Durbin-Watson stat	1.903196
Prob(F-statistic)	0.909388		

Null Hypothesis: TFP has a unit root
Exogenous: Constant, Linear Trend

Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.973152	0.1603
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Residual variance (no correction)	0.000237
HAC corrected variance (Bartlett kernel)	0.000162

Phillips-Perron Test Equation
Dependent Variable: D(TFP)
Method: Least Squares
Date: 12/05/23 Time: 11:25
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.238725	0.086767	-2.751328	0.0123
C	0.284200	0.098894	2.873801	0.0094
@TREND("1999")	-0.002748	0.000735	-3.740543	0.0013

R-squared	0.411992	Mean dependent var	-0.002987
Adjusted R-squared	0.353191	S.D. dependent var	0.020523
S.E. of regression	0.016505	Akaike info criterion	-5.249173
Sum squared resid	0.005448	Schwarz criterion	-5.101065
Log likelihood	63.36549	Hannan-Quinn criter.	-5.211925
F-statistic	7.006569	Durbin-Watson stat	2.566822
Prob(F-statistic)	0.004941		

Null Hypothesis: D(TFP) has a unit root
Exogenous: None
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.540930	0.0001
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Residual variance (no correction)	0.000415
HAC corrected variance (Bartlett kernel)	0.000566

Phillips-Perron Test Equation
Dependent Variable: D(TFP,2)
Method: Least Squares

Date: 12/05/23 Time: 11:25
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-0.956465	0.214217	-4.464936	0.0002

R-squared	0.486648	Mean dependent var	-0.000744
Adjusted R-squared	0.486648	S.D. dependent var	0.029092
S.E. of regression	0.020844	Akaike info criterion	-4.859098
Sum squared resid	0.009124	Schwarz criterion	-4.809506
Log likelihood	54.45008	Hannan-Quinn criter.	-4.847416
Durbin-Watson stat	2.044537		

Null Hypothesis: D(TFP) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.529005	0.0018
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Residual variance (no correction)	0.000400
HAC corrected variance (Bartlett kernel)	0.000451

Phillips-Perron Test Equation
Dependent Variable: D(TFP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:25
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-0.985509	0.218157	-4.517440	0.0002
C	-0.003901	0.004526	-0.862056	0.3989

R-squared	0.505039	Mean dependent var	-0.000744
Adjusted R-squared	0.480291	S.D. dependent var	0.029092
S.E. of regression	0.020973	Akaike info criterion	-4.804673
Sum squared resid	0.008797	Schwarz criterion	-4.705487
Log likelihood	54.85140	Hannan-Quinn criter.	-4.781307
F-statistic	20.40726	Durbin-Watson stat	2.033740
Prob(F-statistic)	0.000210		

Null Hypothesis: D(TFP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.281356	0.0017
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Residual variance (no correction)	0.000323
HAC corrected variance (Bartlett kernel)	0.000385

Phillips-Perron Test Equation
Dependent Variable: D(TFP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:26
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-1.222662	0.230056	-5.314623	0.0000
C	0.015084	0.009860	1.529844	0.1425
@TREND("1999")	-0.001580	0.000743	-2.125324	0.0469

R-squared	0.600108	Mean dependent var	-0.000744
Adjusted R-squared	0.558015	S.D. dependent var	0.029092
S.E. of regression	0.019341	Akaike info criterion	-4.927048
Sum squared resid	0.007107	Schwarz criterion	-4.778270
Log likelihood	57.19753	Hannan-Quinn criter.	-4.892001
F-statistic	14.25644	Durbin-Watson stat	1.788769
Prob(F-statistic)	0.000165		

Appendix B2: Electricity Production Unit Root Test

EPRO ADF Test

Null Hypothesis: LEPRO has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.511894	0.8186
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEPRO)
Method: Least Squares
Date: 12/05/23 Time: 11:29
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO(-1)	0.000278	0.000543	0.511894	0.6138

R-squared	-0.000563	Mean dependent var	0.003514
Adjusted R-squared	-0.000563	S.D. dependent var	0.032164
S.E. of regression	0.032173	Akaike info criterion	-3.992900
Sum squared resid	0.022772	Schwarz criterion	-3.943531
Log likelihood	46.91835	Hannan-Quinn criter.	-3.980484
Durbin-Watson stat	1.262592		

Null Hypothesis: LEPRO has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.057730	0.2621
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEPRO)
Method: Least Squares
Date: 12/05/23 Time: 11:30
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO(-1)	-0.167863	0.081577	-2.057730	0.0522
C	2.076052	1.007216	2.061179	0.0519

R-squared	0.167798	Mean dependent var	0.003514
Adjusted R-squared	0.128169	S.D. dependent var	0.032164
S.E. of regression	0.030032	Akaike info criterion	-4.090186
Sum squared resid	0.018940	Schwarz criterion	-3.991447
Log likelihood	49.03714	Hannan-Quinn criter.	-4.065354
F-statistic	4.234252	Durbin-Watson stat	1.295890
Prob(F-statistic)	0.052243		

Null Hypothesis: LEPRO has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.803824	0.6664
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEPRO)
Method: Least Squares
Date: 12/05/23 Time: 11:30
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO(-1)	-0.136402	0.075618	-1.803824	0.0901
D(LEPRO(-1))	-0.161552	0.190041	-0.850091	0.4078
D(LEPRO(-2))	-0.424004	0.207305	-2.045310	0.0576
C	1.762851	0.931205	1.893085	0.0766
@TREND("1999")	-0.005535	0.001262	-4.385697	0.0005

R-squared	0.676134	Mean dependent var	0.001822
Adjusted R-squared	0.595168	S.D. dependent var	0.032652
S.E. of regression	0.020775	Akaike info criterion	-4.705843
Sum squared resid	0.006906	Schwarz criterion	-4.457147
Log likelihood	54.41135	Hannan-Quinn criter.	-4.651869
F-statistic	8.350806	Durbin-Watson stat	2.228098
Prob(F-statistic)	0.000776		

Null Hypothesis: D(LEPRO) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.249515	0.0024
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEPRO,2)
Method: Least Squares
Date: 12/05/23 Time: 11:30
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEPRO(-1))	-0.672990	0.207105	-3.249515	0.0038

R-squared	0.327240	Mean dependent var	-0.003777
Adjusted R-squared	0.327240	S.D. dependent var	0.036794
S.E. of regression	0.030179	Akaike info criterion	-4.118952
Sum squared resid	0.019126	Schwarz criterion	-4.069360
Log likelihood	46.30848	Hannan-Quinn criter.	-4.107270
Durbin-Watson stat	1.934427		

Null Hypothesis: D(LEPRO) has a unit root

Exogenous: Constant
Lag Length: 2 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.829958	0.7885
Test critical values:	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650413	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEPRO,2)
Method: Least Squares
Date: 12/05/23 Time: 11:31
Sample (adjusted): 2003 2022
Included observations: 20 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEPRO(-1))	-0.243973	0.293958	-0.829958	0.4188
D(LEPRO(-1),2)	-0.408266	0.265878	-1.535538	0.1442
D(LEPRO(-2),2)	-0.565103	0.248693	-2.272294	0.0372
C	-0.005897	0.006684	-0.882266	0.3907

R-squared	0.487702	Mean dependent var	-0.004234
Adjusted R-squared	0.391646	S.D. dependent var	0.036480
S.E. of regression	0.028453	Akaike info criterion	-4.104269
Sum squared resid	0.012953	Schwarz criterion	-3.905122
Log likelihood	45.04269	Hannan-Quinn criter.	-4.065393
F-statistic	5.077270	Durbin-Watson stat	2.287132
Prob(F-statistic)	0.011677		

Null Hypothesis: D(LEPRO) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.402415	0.0015
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEPRO,2)
Method: Least Squares
Date: 12/05/23 Time: 11:31
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEPRO(-1))	-1.690634	0.312940	-5.402415	0.0000
D(LEPRO(-1),2)	0.492854	0.216848	2.272811	0.0363

C	0.083426	0.018892	4.415890	0.0004
@TREND("1999")	-0.006015	0.001313	-4.580889	0.0003

R-squared	0.694040	Mean dependent var	-0.002121
Adjusted R-squared	0.640047	S.D. dependent var	0.036852
S.E. of regression	0.022110	Akaike info criterion	-4.615962
Sum squared resid	0.008310	Schwarz criterion	-4.417006
Log likelihood	52.46760	Hannan-Quinn criter.	-4.572783
F-statistic	12.85429	Durbin-Watson stat	1.986896
Prob(F-statistic)	0.000124		

EPRO PP Test

Null Hypothesis: LEPRO has a unit root
Exogenous: None
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.409981	0.7934
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Residual variance (no correction)	0.000990
HAC corrected variance (Bartlett kernel)	0.001524

Phillips-Perron Test Equation
Dependent Variable: D(LEPRO)
Method: Least Squares
Date: 12/05/23 Time: 11:32
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO(-1)	0.000278	0.000543	0.511894	0.6138

R-squared	-0.000563	Mean dependent var	0.003514
Adjusted R-squared	-0.000563	S.D. dependent var	0.032164
S.E. of regression	0.032173	Akaike info criterion	-3.992900
Sum squared resid	0.022772	Schwarz criterion	-3.943531
Log likelihood	46.91835	Hannan-Quinn criter.	-3.980484
Durbin-Watson stat	1.262592		

Null Hypothesis: LEPRO has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.044687	0.2671

Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Residual variance (no correction)	0.000823
HAC corrected variance (Bartlett kernel)	0.001211

Phillips-Perron Test Equation
Dependent Variable: D(LEPRO)
Method: Least Squares
Date: 12/05/23 Time: 11:32
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO(-1)	-0.167863	0.081577	-2.057730	0.0522
C	2.076052	1.007216	2.061179	0.0519

R-squared	0.167798	Mean dependent var	0.003514
Adjusted R-squared	0.128169	S.D. dependent var	0.032164
S.E. of regression	0.030032	Akaike info criterion	-4.090186
Sum squared resid	0.018940	Schwarz criterion	-3.991447
Log likelihood	49.03714	Hannan-Quinn criter.	-4.065354
F-statistic	4.234252	Durbin-Watson stat	1.295890
Prob(F-statistic)	0.052243		

Null Hypothesis: LEPRO has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 22 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.288681	0.8651
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Residual variance (no correction)	0.000511
HAC corrected variance (Bartlett kernel)	3.92E-05

Phillips-Perron Test Equation
Dependent Variable: D(LEPRO)
Method: Least Squares
Date: 12/05/23 Time: 11:34
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

LEPRO(-1)	-0.075214	0.070981	-1.059632	0.3019
C	0.966620	0.872761	1.107543	0.2812
@TREND("1999")	-0.002872	0.000821	-3.496810	0.0023

R-squared	0.483548	Mean dependent var	0.003514
Adjusted R-squared	0.431903	S.D. dependent var	0.032164
S.E. of regression	0.024242	Akaike info criterion	-4.480323
Sum squared resid	0.011754	Schwarz criterion	-4.332215
Log likelihood	54.52371	Hannan-Quinn criter.	-4.443074
F-statistic	9.362891	Durbin-Watson stat	2.252136
Prob(F-statistic)	0.001350		

Null Hypothesis: D(LEPRO) has a unit root
Exogenous: None
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.233700	0.0025
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Residual variance (no correction)	0.000869
HAC corrected variance (Bartlett kernel)	0.000846

Phillips-Perron Test Equation
Dependent Variable: D(LEPRO,2)
Method: Least Squares
Date: 12/05/23 Time: 11:34
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEPRO(-1))	-0.672990	0.207105	-3.249515	0.0038

R-squared	0.327240	Mean dependent var	-0.003777
Adjusted R-squared	0.327240	S.D. dependent var	0.036794
S.E. of regression	0.030179	Akaike info criterion	-4.118952
Sum squared resid	0.019126	Schwarz criterion	-4.069360
Log likelihood	46.30848	Hannan-Quinn criter.	-4.107270
Durbin-Watson stat	1.934427		

Null Hypothesis: D(LEPRO) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.100437	0.0413
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	

	10% level	-2.642242	

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

Residual variance (no correction)	0.000869
HAC corrected variance (Bartlett kernel)	0.000846

Phillips-Perron Test Equation
Dependent Variable: D(LEPRO,2)
Method: Least Squares
Date: 12/05/23 Time: 11:35
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEPRO(-1))	-0.672967	0.215762	-3.119017	0.0054
C	-3.95E-06	0.006703	-0.000589	0.9995

R-squared	0.327240	Mean dependent var	-0.003777
Adjusted R-squared	0.293602	S.D. dependent var	0.036794
S.E. of regression	0.030924	Akaike info criterion	-4.028043
Sum squared resid	0.019126	Schwarz criterion	-3.928858
Log likelihood	46.30848	Hannan-Quinn criter.	-4.004678
F-statistic	9.728267	Durbin-Watson stat	1.934473
Prob(F-statistic)	0.005406		

Null Hypothesis: D(LEPRO) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 21 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.150172	0.0000
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Residual variance (no correction)	0.000551
HAC corrected variance (Bartlett kernel)	5.79E-05

Phillips-Perron Test Equation
Dependent Variable: D(LEPRO,2)
Method: Least Squares
Date: 12/05/23 Time: 11:35
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEPRO(-1))	-1.152193	0.228036	-5.052682	0.0001
C	0.048156	0.015537	3.099402	0.0059

@TREND("1999")	-0.003638	0.001098	-3.312171	0.0037

R-squared	0.573499	Mean dependent var	-0.003777
Adjusted R-squared	0.528604	S.D. dependent var	0.036794
S.E. of regression	0.025262	Akaike info criterion	-4.392908
Sum squared resid	0.012125	Schwarz criterion	-4.244130
Log likelihood	51.32199	Hannan-Quinn criter.	-4.357860
F-statistic	12.77426	Durbin-Watson stat	2.022841
Prob(F-statistic)	0.000305		

Appendix B3: Electricity Prices Unit Root Test

EP ADF Test

Null Hypothesis: LEP has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		5.520961	1.0000
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEP)
Method: Least Squares
Date: 12/05/23 Time: 11:36
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEP(-1)	0.019142	0.003467	5.520961	0.0000

R-squared	0.027433	Mean dependent var	0.079334
Adjusted R-squared	0.027433	S.D. dependent var	0.070602
S.E. of regression	0.069627	Akaike info criterion	-2.448833
Sum squared resid	0.106653	Schwarz criterion	-2.399464
Log likelihood	29.16158	Hannan-Quinn criter.	-2.436417
Durbin-Watson stat	1.669953		

Null Hypothesis: LEP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.771318	0.9911
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEP)
Method: Least Squares
Date: 12/05/23 Time: 11:36
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEP(-1)	0.020461	0.026527	0.771318	0.4491
C	-0.005574	0.111080	-0.050180	0.9605

R-squared	0.027550	Mean dependent var	0.079334
Adjusted R-squared	-0.018758	S.D. dependent var	0.070602
S.E. of regression	0.071261	Akaike info criterion	-2.361997
Sum squared resid	0.106640	Schwarz criterion	-2.263258
Log likelihood	29.16296	Hannan-Quinn criter.	-2.337164
F-statistic	0.594931	Durbin-Watson stat	1.671874
Prob(F-statistic)	0.449111		

Null Hypothesis: LEP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.267339	0.4336
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEP)
Method: Least Squares
Date: 12/05/23 Time: 11:37
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEP(-1)	-0.325362	0.143499	-2.267339	0.0346
C	1.074133	0.452943	2.371456	0.0279
@TREND("1999")	0.029615	0.012118	2.443925	0.0239

R-squared	0.251177	Mean dependent var	0.079334
Adjusted R-squared	0.176295	S.D. dependent var	0.070602
S.E. of regression	0.064077	Akaike info criterion	-2.536357
Sum squared resid	0.082117	Schwarz criterion	-2.388249
Log likelihood	32.16810	Hannan-Quinn criter.	-2.499108
F-statistic	3.354289	Durbin-Watson stat	1.603021
Prob(F-statistic)	0.055436		

Null Hypothesis: D(LEP) has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.681683	0.4095
Test critical values:	1% level	-2.679735	
	5% level	-1.958088	
	10% level	-1.607830	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:37
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEP(-1))	-0.145965	0.214124	-0.681683	0.5037
D(LEP(-1),2)	-0.372648	0.238016	-1.565642	0.1339

R-squared	0.209043	Mean dependent var	0.009418
Adjusted R-squared	0.167413	S.D. dependent var	0.093183
S.E. of regression	0.085026	Akaike info criterion	-2.001325
Sum squared resid	0.137359	Schwarz criterion	-1.901847
Log likelihood	23.01392	Hannan-Quinn criter.	-1.979736
Durbin-Watson stat	2.026884		

Null Hypothesis: D(LEP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.671546	0.0124
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:37
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEP(-1))	-0.875331	0.238409	-3.671546	0.0015
C	0.073161	0.023267	3.144367	0.0051

R-squared	0.402633	Mean dependent var	0.008990

Adjusted R-squared	0.372764	S.D. dependent var	0.090960
S.E. of regression	0.072038	Akaike info criterion	-2.336728
Sum squared resid	0.103790	Schwarz criterion	-2.237543
Log likelihood	27.70401	Hannan-Quinn criter.	-2.313363
F-statistic	13.48025	Durbin-Watson stat	1.900992
Prob(F-statistic)	0.001514		

Null Hypothesis: D(LEP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.700286	0.0440
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:38
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEP(-1))	-0.896901	0.242387	-3.700286	0.0015
C	0.050803	0.037120	1.368639	0.1871
@TREND("1999")	0.001915	0.002461	0.778101	0.4461

R-squared	0.421080	Mean dependent var	0.008990
Adjusted R-squared	0.360141	S.D. dependent var	0.090960
S.E. of regression	0.072760	Akaike info criterion	-2.277187
Sum squared resid	0.100585	Schwarz criterion	-2.128409
Log likelihood	28.04906	Hannan-Quinn criter.	-2.242140
F-statistic	6.909875	Durbin-Watson stat	1.914062
Prob(F-statistic)	0.005557		

EP PP Test

Null Hypothesis: LEP has a unit root
Exogenous: None
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		5.520961	1.0000
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Residual variance (no correction)	0.004637
HAC corrected variance (Bartlett kernel)	0.004637

Phillips-Perron Test Equation
Dependent Variable: D(LEP)
Method: Least Squares
Date: 12/05/23 Time: 11:38
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEP(-1)	0.019142	0.003467	5.520961	0.0000

R-squared	0.027433	Mean dependent var	0.079334
Adjusted R-squared	0.027433	S.D. dependent var	0.070602
S.E. of regression	0.069627	Akaike info criterion	-2.448833
Sum squared resid	0.106653	Schwarz criterion	-2.399464
Log likelihood	29.16158	Hannan-Quinn criter.	-2.436417
Durbin-Watson stat	1.669953		

Null Hypothesis: LEP has a unit root
Exogenous: Constant
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.771318	0.9911
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Residual variance (no correction)	0.004637
HAC corrected variance (Bartlett kernel)	0.004637

Phillips-Perron Test Equation
Dependent Variable: D(LEP)
Method: Least Squares
Date: 12/05/23 Time: 11:39
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEP(-1)	0.020461	0.026527	0.771318	0.4491
C	-0.005574	0.111080	-0.050180	0.9605

R-squared	0.027550	Mean dependent var	0.079334
Adjusted R-squared	-0.018758	S.D. dependent var	0.070602
S.E. of regression	0.071261	Akaike info criterion	-2.361997
Sum squared resid	0.106640	Schwarz criterion	-2.263258
Log likelihood	29.16296	Hannan-Quinn criter.	-2.337164

F-statistic	0.594931	Durbin-Watson stat	1.671874
Prob(F-statistic)	0.449111		

Null Hypothesis: LEP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.331612	0.4021
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Residual variance (no correction)	0.003570
HAC corrected variance (Bartlett kernel)	0.004123

Phillips-Perron Test Equation
Dependent Variable: D(LEP)
Method: Least Squares
Date: 12/05/23 Time: 11:39
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEP(-1)	-0.325362	0.143499	-2.267339	0.0346
C	1.074133	0.452943	2.371456	0.0279
@TREND("1999")	0.029615	0.012118	2.443925	0.0239

R-squared	0.251177	Mean dependent var	0.079334
Adjusted R-squared	0.176295	S.D. dependent var	0.070602
S.E. of regression	0.064077	Akaike info criterion	-2.536357
Sum squared resid	0.082117	Schwarz criterion	-2.388249
Log likelihood	32.16810	Hannan-Quinn criter.	-2.499108
F-statistic	3.354289	Durbin-Watson stat	1.603021
Prob(F-statistic)	0.055436		

Null Hypothesis: D(LEP) has a unit root
Exogenous: None
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.662973	0.0901
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Residual variance (no correction)	0.007050

HAC corrected variance (Bartlett kernel)	0.007050

Phillips-Perron Test Equation
Dependent Variable: D(LEP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:40
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEP(-1))	-0.312211	0.187742	-1.662973	0.1112

R-squared	0.107323	Mean dependent var	0.008990
Adjusted R-squared	0.107323	S.D. dependent var	0.090960
S.E. of regression	0.085940	Akaike info criterion	-2.025945
Sum squared resid	0.155100	Schwarz criterion	-1.976352
Log likelihood	23.28539	Hannan-Quinn criter.	-2.014262
Durbin-Watson stat	2.329501		

Null Hypothesis: D(LEP) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.645142	0.0131
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Residual variance (no correction)	0.004718
HAC corrected variance (Bartlett kernel)	0.004529

Phillips-Perron Test Equation
Dependent Variable: D(LEP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:40
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEP(-1))	-0.875331	0.238409	-3.671546	0.0015
C	0.073161	0.023267	3.144367	0.0051

R-squared	0.402633	Mean dependent var	0.008990
Adjusted R-squared	0.372764	S.D. dependent var	0.090960
S.E. of regression	0.072038	Akaike info criterion	-2.336728
Sum squared resid	0.103790	Schwarz criterion	-2.237543
Log likelihood	27.70401	Hannan-Quinn criter.	-2.313363
F-statistic	13.48025	Durbin-Watson stat	1.900992
Prob(F-statistic)	0.001514		

Null Hypothesis: D(LEP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.700286	0.0440
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Residual variance (no correction)	0.004572
HAC corrected variance (Bartlett kernel)	0.004572

Phillips-Perron Test Equation
Dependent Variable: D(LEP,2)
Method: Least Squares
Date: 12/05/23 Time: 11:40
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEP(-1))	-0.896901	0.242387	-3.700286	0.0015
C	0.050803	0.037120	1.368639	0.1871
@TREND("1999")	0.001915	0.002461	0.778101	0.4461

R-squared	0.421080	Mean dependent var	0.008990
Adjusted R-squared	0.360141	S.D. dependent var	0.090960
S.E. of regression	0.072760	Akaike info criterion	-2.277187
Sum squared resid	0.100585	Schwarz criterion	-2.128409
Log likelihood	28.04906	Hannan-Quinn criter.	-2.242140
F-statistic	6.909875	Durbin-Watson stat	1.914062
Prob(F-statistic)	0.005557		

Appendix B4: Research & Development Unit Root Test

R_D ADF Test

Null Hypothesis: LR_D has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.153203	0.6199
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LR_D)
Method: Least Squares
Date: 12/05/23 Time: 11:41
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR_D(-1)	-0.000337	0.002198	-0.153203	0.8796

R-squared	0.000274	Mean dependent var	-0.002383
Adjusted R-squared	0.000274	S.D. dependent var	0.086525
S.E. of regression	0.086513	Akaike info criterion	-2.014536
Sum squared resid	0.164659	Schwarz criterion	-1.965167
Log likelihood	24.16717	Hannan-Quinn criter.	-2.002120
Durbin-Watson stat	1.842500		

Null Hypothesis: LR_D has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.660085	0.4372
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LR_D)
Method: Least Squares
Date: 12/05/23 Time: 11:43
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR_D(-1)	-0.265461	0.159908	-1.660085	0.1118
C	2.176116	1.312396	1.658125	0.1122

R-squared	0.116008	Mean dependent var	-0.002383
Adjusted R-squared	0.073914	S.D. dependent var	0.086525
S.E. of regression	0.083266	Akaike info criterion	-2.050614
Sum squared resid	0.145597	Schwarz criterion	-1.951875
Log likelihood	25.58206	Hannan-Quinn criter.	-2.025781
F-statistic	2.755883	Durbin-Watson stat	1.638206
Prob(F-statistic)	0.111757		

Null Hypothesis: LR_D has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.373936	0.8413
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LR_D)
Method: Least Squares
Date: 12/05/23 Time: 11:43
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR_D(-1)	-0.220297	0.160340	-1.373936	0.1847
C	1.848111	1.309746	1.411045	0.1736
@TREND("1999")	-0.003553	0.002625	-1.353638	0.1910

R-squared	0.190200	Mean dependent var	-0.002383
Adjusted R-squared	0.109220	S.D. dependent var	0.086525
S.E. of regression	0.081663	Akaike info criterion	-2.051317
Sum squared resid	0.133378	Schwarz criterion	-1.903209
Log likelihood	26.59015	Hannan-Quinn criter.	-2.014068
F-statistic	2.348724	Durbin-Watson stat	1.856609
Prob(F-statistic)	0.121277		

Null Hypothesis: D(LR_D) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.209548	0.0002
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LR_D,2)
Method: Least Squares
Date: 12/05/23 Time: 11:43
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LR_D(-1))	-0.981622	0.233189	-4.209548	0.0004

R-squared	0.456273	Mean dependent var	-0.005907
Adjusted R-squared	0.456273	S.D. dependent var	0.120062
S.E. of regression	0.088531	Akaike info criterion	-1.966536
Sum squared resid	0.164593	Schwarz criterion	-1.916943

Log likelihood	22.63189	Hannan-Quinn criter.	-1.954853
Durbin-Watson stat	1.845525		

Null Hypothesis: D(LR_D) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.098977	0.0048
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LR_D,2)
Method: Least Squares
Date: 12/05/23 Time: 11:44
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LR_D(-1))	-0.980424	0.239188	-4.098977	0.0006
C	-0.001938	0.019360	-0.100095	0.9213

R-squared	0.456546	Mean dependent var	-0.005907
Adjusted R-squared	0.429373	S.D. dependent var	0.120062
S.E. of regression	0.090695	Akaike info criterion	-1.876128
Sum squared resid	0.164511	Schwarz criterion	-1.776942
Log likelihood	22.63740	Hannan-Quinn criter.	-1.852762
F-statistic	16.80161	Durbin-Watson stat	1.848658
Prob(F-statistic)	0.000558		

Null Hypothesis: D(LR_D) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.515239	0.0698
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LR_D,2)
Method: Least Squares
Date: 12/05/23 Time: 11:44
Sample (adjusted): 2006 2022

Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LR_D(-1))	-3.749353	1.066600	-3.515239	0.0066
D(LR_D(-1),2)	2.255442	0.877221	2.571121	0.0301
D(LR_D(-2),2)	1.979945	0.737031	2.686380	0.0249
D(LR_D(-3),2)	1.701259	0.666270	2.553406	0.0310
D(LR_D(-4),2)	1.308023	0.562437	2.325635	0.0451
D(LR_D(-5),2)	0.782408	0.353764	2.211669	0.0543
C	0.206898	0.089038	2.323706	0.0452
@TREND("1999")	-0.012930	0.005502	-2.349987	0.0433

R-squared	0.738501	Mean dependent var	-0.006946
Adjusted R-squared	0.535113	S.D. dependent var	0.133610
S.E. of regression	0.091098	Akaike info criterion	-1.648564
Sum squared resid	0.074690	Schwarz criterion	-1.256464
Log likelihood	22.01280	Hannan-Quinn criter.	-1.609589
F-statistic	3.631000	Durbin-Watson stat	1.578863
Prob(F-statistic)	0.038134		

R_D PP Test

Null Hypothesis: LR_D has a unit root
Exogenous: None
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.152290	0.6202
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Residual variance (no correction)	0.007159
HAC corrected variance (Bartlett kernel)	0.007287

Phillips-Perron Test Equation
Dependent Variable: D(LR_D)
Method: Least Squares
Date: 12/05/23 Time: 11:44
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR_D(-1)	-0.000337	0.002198	-0.153203	0.8796

R-squared	0.000274	Mean dependent var	-0.002383
Adjusted R-squared	0.000274	S.D. dependent var	0.086525
S.E. of regression	0.086513	Akaike info criterion	-2.014536
Sum squared resid	0.164659	Schwarz criterion	-1.965167
Log likelihood	24.16717	Hannan-Quinn criter.	-2.002120
Durbin-Watson stat	1.842500		

Null Hypothesis: LR_D has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.833233	0.3560
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Residual variance (no correction)	0.006330
HAC corrected variance (Bartlett kernel)	0.007574

Phillips-Perron Test Equation
Dependent Variable: D(LR_D)
Method: Least Squares
Date: 12/05/23 Time: 11:45
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR_D(-1)	-0.265461	0.159908	-1.660085	0.1118
C	2.176116	1.312396	1.658125	0.1122

R-squared	0.116008	Mean dependent var	-0.002383
Adjusted R-squared	0.073914	S.D. dependent var	0.086525
S.E. of regression	0.083266	Akaike info criterion	-2.050614
Sum squared resid	0.145597	Schwarz criterion	-1.951875
Log likelihood	25.58206	Hannan-Quinn criter.	-2.025781
F-statistic	2.755883	Durbin-Watson stat	1.638206
Prob(F-statistic)	0.111757		

Null Hypothesis: LR_D has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.373936	0.8413
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Residual variance (no correction)	0.005799
HAC corrected variance (Bartlett kernel)	0.005799

Phillips-Perron Test Equation
Dependent Variable: D(LR_D)
Method: Least Squares
Date: 12/05/23 Time: 11:45
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LR_D(-1)	-0.220297	0.160340	-1.373936	0.1847
C	1.848111	1.309746	1.411045	0.1736
@TREND("1999")	-0.003553	0.002625	-1.353638	0.1910

R-squared	0.190200	Mean dependent var	-0.002383
Adjusted R-squared	0.109220	S.D. dependent var	0.086525
S.E. of regression	0.081663	Akaike info criterion	-2.051317
Sum squared resid	0.133378	Schwarz criterion	-1.903209
Log likelihood	26.59015	Hannan-Quinn criter.	-2.014068
F-statistic	2.348724	Durbin-Watson stat	1.856609
Prob(F-statistic)	0.121277		

Null Hypothesis: D(LR_D) has a unit root
Exogenous: None
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.210846	0.0002
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Residual variance (no correction)	0.007482
HAC corrected variance (Bartlett kernel)	0.007506

Phillips-Perron Test Equation
Dependent Variable: D(LR_D,2)
Method: Least Squares
Date: 12/05/23 Time: 11:45
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LR_D(-1))	-0.981622	0.233189	-4.209548	0.0004

R-squared	0.456273	Mean dependent var	-0.005907
Adjusted R-squared	0.456273	S.D. dependent var	0.120062
S.E. of regression	0.088531	Akaike info criterion	-1.966536
Sum squared resid	0.164593	Schwarz criterion	-1.916943
Log likelihood	22.63189	Hannan-Quinn criter.	-1.954853
Durbin-Watson stat	1.845525		

Null Hypothesis: D(LR_D) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.100154	0.0048
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Residual variance (no correction)	0.007478
HAC corrected variance (Bartlett kernel)	0.007497

Phillips-Perron Test Equation
Dependent Variable: D(LR_D,2)
Method: Least Squares
Date: 12/05/23 Time: 11:46
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LR_D(-1))	-0.980424	0.239188	-4.098977	0.0006
C	-0.001938	0.019360	-0.100095	0.9213

R-squared	0.456546	Mean dependent var	-0.005907
Adjusted R-squared	0.429373	S.D. dependent var	0.120062
S.E. of regression	0.090695	Akaike info criterion	-1.876128
Sum squared resid	0.164511	Schwarz criterion	-1.776942
Log likelihood	22.63740	Hannan-Quinn criter.	-1.852762
F-statistic	16.80161	Durbin-Watson stat	1.848658
Prob(F-statistic)	0.000558		

Null Hypothesis: D(LR_D) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.619439	0.0069
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Residual variance (no correction)	0.006406
HAC corrected variance (Bartlett kernel)	0.006406

Phillips-Perron Test Equation
Dependent Variable: D(LR_D,2)
Method: Least Squares
Date: 12/05/23 Time: 11:46
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LR_D(-1))	-1.081307	0.234078	-4.619439	0.0002
C	0.064944	0.041776	1.554576	0.1365
@TREND("1999")	-0.005318	0.002983	-1.782898	0.0906

R-squared	0.534435	Mean dependent var	-0.005907
Adjusted R-squared	0.485428	S.D. dependent var	0.120062
S.E. of regression	0.086125	Akaike info criterion	-1.939913
Sum squared resid	0.140932	Schwarz criterion	-1.791134
Log likelihood	24.33904	Hannan-Quinn criter.	-1.904865
F-statistic	10.90532	Durbin-Watson stat	1.949121
Prob(F-statistic)	0.000701		

Appendix B5: Patents Unit Root Test

PAT ADF Test

Null Hypothesis: LPAT has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.655877	0.8506
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LPAT)
Method: Least Squares
Date: 12/05/23 Time: 11:46
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPAT(-1)	0.010076	0.015363	0.655877	0.5187

R-squared	-0.018977	Mean dependent var	0.093526
Adjusted R-squared	-0.018977	S.D. dependent var	0.484841
S.E. of regression	0.489420	Akaike info criterion	1.451313
Sum squared resid	5.269702	Schwarz criterion	1.500682
Log likelihood	-15.69010	Hannan-Quinn criter.	1.463729
Durbin-Watson stat	1.514684		

Null Hypothesis: LPAT has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.212264	0.0000
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LPAT)
Method: Least Squares
Date: 12/05/23 Time: 11:48
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPAT(-1)	-0.913785	0.126699	-7.212264	0.0000
C	6.150332	0.841624	7.307695	0.0000

R-squared	0.712395	Mean dependent var	0.093526
Adjusted R-squared	0.698699	S.D. dependent var	0.484841
S.E. of regression	0.266133	Akaike info criterion	0.273304
Sum squared resid	1.487368	Schwarz criterion	0.372042
Log likelihood	-1.142994	Hannan-Quinn criter.	0.298136
F-statistic	52.01676	Durbin-Watson stat	1.334281
Prob(F-statistic)	0.000000		

Null Hypothesis: LPAT has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.769761	0.2216
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LPAT)
Method: Least Squares
Date: 12/05/23 Time: 11:48
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPAT(-1)	-0.756157	0.273004	-2.769761	0.0126
D(LPAT(-1))	0.113158	0.139830	0.809257	0.4289
C	5.099142	1.859019	2.742920	0.0134

@TREND("1999")	-0.002328	0.009390	-0.247911	0.8070

R-squared	0.320311	Mean dependent var	0.012796
Adjusted R-squared	0.207029	S.D. dependent var	0.298715
S.E. of regression	0.266003	Akaike info criterion	0.352345
Sum squared resid	1.273634	Schwarz criterion	0.550717
Log likelihood	0.124203	Hannan-Quinn criter.	0.399076
F-statistic	2.827565	Durbin-Watson stat	1.943971
Prob(F-statistic)	0.067787		

PAT PP Test

Null Hypothesis: LPAT has a unit root
Exogenous: None
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.706610	0.8609
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Residual variance (no correction)	0.229117
HAC corrected variance (Bartlett kernel)	0.207386

Phillips-Perron Test Equation
Dependent Variable: D(LPAT)
Method: Least Squares
Date: 12/05/23 Time: 11:49
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPAT(-1)	0.010076	0.015363	0.655877	0.5187

R-squared	-0.018977	Mean dependent var	0.093526
Adjusted R-squared	-0.018977	S.D. dependent var	0.484841
S.E. of regression	0.489420	Akaike info criterion	1.451313
Sum squared resid	5.269702	Schwarz criterion	1.500682
Log likelihood	-15.69010	Hannan-Quinn criter.	1.463729
Durbin-Watson stat	1.514684		

Null Hypothesis: LPAT has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.705965	0.0000
Test critical values:	1% level	-3.752946	

5% level	-2.998064	
10% level	-2.638752	

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

Residual variance (no correction)	0.064668
HAC corrected variance (Bartlett kernel)	0.083401

Phillips-Perron Test Equation
Dependent Variable: D(LPAT)
Method: Least Squares
Date: 12/05/23 Time: 11:50
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPAT(-1)	-0.913785	0.126699	-7.212264	0.0000
C	6.150332	0.841624	7.307695	0.0000

R-squared	0.712395	Mean dependent var	0.093526
Adjusted R-squared	0.698699	S.D. dependent var	0.484841
S.E. of regression	0.266133	Akaike info criterion	0.273304
Sum squared resid	1.487368	Schwarz criterion	0.372042
Log likelihood	-1.142994	Hannan-Quinn criter.	0.298136
F-statistic	52.01676	Durbin-Watson stat	1.334281
Prob(F-statistic)	0.000000		

Null Hypothesis: LPAT has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.993069	0.0000
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Residual variance (no correction)	0.062285
HAC corrected variance (Bartlett kernel)	0.062285

Phillips-Perron Test Equation
Dependent Variable: D(LPAT)
Method: Least Squares
Date: 12/05/23 Time: 11:50
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPAT(-1)	-0.898908	0.128543	-6.993069	0.0000

C	6.140821	0.846436	7.254914	0.0000
@TREND("1999")	-0.007425	0.008488	-0.874830	0.3921

R-squared	0.722995	Mean dependent var	0.093526
Adjusted R-squared	0.695294	S.D. dependent var	0.484841
S.E. of regression	0.267633	Akaike info criterion	0.322708
Sum squared resid	1.432549	Schwarz criterion	0.470816
Log likelihood	-0.711142	Hannan-Quinn criter.	0.359957
F-statistic	26.10040	Durbin-Watson stat	1.404769
Prob(F-statistic)	0.000003		

Appendix B6: Investment in ICT Unit Root Test

INV_ICT ADF Test

Null Hypothesis: LINV_ICT has a unit root
Exogenous: None
Lag Length: 2 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.695288	0.9739
Test critical values:	1% level	-2.679735	
	5% level	-1.958088	
	10% level	-1.607830	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LINV_ICT)
Method: Least Squares
Date: 12/05/23 Time: 11:52
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINV_ICT(-1)	0.009977	0.005885	1.695288	0.1072
D(LINV_ICT(-1))	-0.137417	0.218199	-0.629779	0.5368
D(LINV_ICT(-2))	-0.396806	0.220787	-1.797231	0.0891

R-squared	0.151977	Mean dependent var	0.066938
Adjusted R-squared	0.057753	S.D. dependent var	0.252940
S.E. of regression	0.245527	Akaike info criterion	0.160746
Sum squared resid	1.085105	Schwarz criterion	0.309964
Log likelihood	1.312167	Hannan-Quinn criter.	0.193130
Durbin-Watson stat	1.874523		

Null Hypothesis: LINV_ICT has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on AIC, maxlag=5)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.505076	0.1284

Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LINV_ICT)
Method: Least Squares
Date: 12/05/23 Time: 11:52
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINV_ICT(-1)	-0.296638	0.118415	-2.505076	0.0227
D(LINV_ICT(-1))	-0.085746	0.191131	-0.448623	0.6594
D(LINV_ICT(-2))	-0.402353	0.192356	-2.091714	0.0518
C	3.036466	1.171584	2.591760	0.0190

R-squared	0.392155	Mean dependent var	0.066938
Adjusted R-squared	0.284889	S.D. dependent var	0.252940
S.E. of regression	0.213897	Akaike info criterion	-0.077004
Sum squared resid	0.777781	Schwarz criterion	0.121953
Log likelihood	4.808541	Hannan-Quinn criter.	-0.033825
F-statistic	3.655891	Durbin-Watson stat	2.011227
Prob(F-statistic)	0.033619		

Null Hypothesis: LINV_ICT has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.401720	0.3685
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LINV_ICT)
Method: Least Squares
Date: 12/05/23 Time: 11:53
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINV_ICT(-1)	-0.444283	0.184985	-2.401720	0.0273
D(LINV_ICT(-1))	0.048333	0.217359	0.222366	0.8265
C	4.220148	1.686377	2.502494	0.0222
@TREND("1999")	0.017839	0.013189	1.352581	0.1929

R-squared	0.281555	Mean dependent var	0.070545
Adjusted R-squared	0.161814	S.D. dependent var	0.247423
S.E. of regression	0.226522	Akaike info criterion	0.031016

Sum squared resid	0.923620	Schwarz criterion	0.229388
Log likelihood	3.658821	Hannan-Quinn criter.	0.077747
F-statistic	2.351371	Durbin-Watson stat	2.028119
Prob(F-statistic)	0.106423		

Null Hypothesis: D(LINV_ICT) has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.209944	0.0002
Test critical values:	1% level	-2.679735	
	5% level	-1.958088	
	10% level	-1.607830	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LINV_ICT,2)
Method: Least Squares
Date: 12/05/23 Time: 11:53
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LINV_ICT(-1))	-1.317431	0.312933	-4.209944	0.0005
D(LINV_ICT(-1),2)	0.292372	0.222229	1.315632	0.2040

R-squared	0.555179	Mean dependent var	-0.006721
Adjusted R-squared	0.531768	S.D. dependent var	0.376093
S.E. of regression	0.257351	Akaike info criterion	0.213641
Sum squared resid	1.258361	Schwarz criterion	0.313119
Log likelihood	-0.243226	Hannan-Quinn criter.	0.235230
Durbin-Watson stat	1.852889		

Null Hypothesis: D(LINV_ICT) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.806820	0.0011
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LINV_ICT,2)
Method: Least Squares
Date: 12/05/23 Time: 11:53
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LINV_ICT(-1))	-1.544721	0.321360	-4.806820	0.0001
D(LINV_ICT(-1),2)	0.402817	0.218735	1.841579	0.0821
C	0.104309	0.057681	1.808378	0.0873

R-squared	0.623569	Mean dependent var	-0.006721
Adjusted R-squared	0.581743	S.D. dependent var	0.376093
S.E. of regression	0.243230	Akaike info criterion	0.141942
Sum squared resid	1.064892	Schwarz criterion	0.291160
Log likelihood	1.509609	Hannan-Quinn criter.	0.174326
F-statistic	14.90876	Durbin-Watson stat	1.878684
Prob(F-statistic)	0.000152		

Null Hypothesis: D(LINV_ICT) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on AIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.184749	0.0023
Test critical values:	1% level	-4.467895	
	5% level	-3.644963	
	10% level	-3.261452	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LINV_ICT,2)
Method: Least Squares
Date: 12/05/23 Time: 11:54
Sample (adjusted): 2002 2022
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LINV_ICT(-1))	-1.699916	0.327869	-5.184749	0.0001
D(LINV_ICT(-1),2)	0.493261	0.220148	2.240593	0.0387
C	0.288861	0.135680	2.128988	0.0482
@TREND("1999")	-0.013364	0.008956	-1.492292	0.1539

R-squared	0.667169	Mean dependent var	-0.006721
Adjusted R-squared	0.608434	S.D. dependent var	0.376093
S.E. of regression	0.235341	Akaike info criterion	0.114081
Sum squared resid	0.941552	Schwarz criterion	0.313038
Log likelihood	2.802147	Hannan-Quinn criter.	0.157260
F-statistic	11.35897	Durbin-Watson stat	1.966193
Prob(F-statistic)	0.000250		

INV_ICT PP Test

Null Hypothesis: LINV_ICT has a unit root
Exogenous: None
Bandwidth: 22 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		2.567536	0.9961
Test critical values:	1% level	-2.669359	
	5% level	-1.956406	
	10% level	-1.608495	

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

Residual variance (no correction)	0.056690
HAC corrected variance (Bartlett kernel)	0.016144

Phillips-Perron Test Equation
Dependent Variable: D(LINV_ICT)
Method: Least Squares
Date: 12/05/23 Time: 11:54
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINV_ICT(-1)	0.006872	0.005173	1.328525	0.1976

R-squared	-0.012680	Mean dependent var	0.072511
Adjusted R-squared	-0.012680	S.D. dependent var	0.241918
S.E. of regression	0.243447	Akaike info criterion	0.054671
Sum squared resid	1.303863	Schwarz criterion	0.104040
Log likelihood	0.371282	Hannan-Quinn criter.	0.067087
Durbin-Watson stat	2.186125		

Null Hypothesis: LINV_ICT has a unit root
Exogenous: Constant
Bandwidth: 22 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.963982	0.0535
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

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

Residual variance (no correction)	0.046222
HAC corrected variance (Bartlett kernel)	0.008199

Phillips-Perron Test Equation
Dependent Variable: D(LINV_ICT)
Method: Least Squares
Date: 12/05/23 Time: 11:55
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

LINV_ICT(-1)	-0.199684	0.094835	-2.105599	0.0474
C	2.029571	0.930639	2.180837	0.0407

R-squared	0.174319	Mean dependent var	0.072511
Adjusted R-squared	0.135001	S.D. dependent var	0.241918
S.E. of regression	0.224997	Akaike info criterion	-0.062519
Sum squared resid	1.063095	Schwarz criterion	0.036219
Log likelihood	2.718974	Hannan-Quinn criter.	-0.037687
F-statistic	4.433547	Durbin-Watson stat	2.181386
Prob(F-statistic)	0.047449		

Null Hypothesis: LINV_ICT has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.120381	0.5083
Test critical values:	1% level	-4.416345	
	5% level	-3.622033	
	10% level	-3.248592	

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

Residual variance (no correction)	0.042296
HAC corrected variance (Bartlett kernel)	0.017548

Phillips-Perron Test Equation
Dependent Variable: D(LINV_ICT)
Method: Least Squares
Date: 12/05/23 Time: 11:55
Sample (adjusted): 2000 2022
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LINV_ICT(-1)	-0.375093	0.158794	-2.362146	0.0284
C	3.555094	1.444216	2.461607	0.0230
@TREND("1999")	0.016136	0.011843	1.362503	0.1882

R-squared	0.244450	Mean dependent var	0.072511
Adjusted R-squared	0.168895	S.D. dependent var	0.241918
S.E. of regression	0.220545	Akaike info criterion	-0.064325
Sum squared resid	0.972799	Schwarz criterion	0.083783
Log likelihood	3.739739	Hannan-Quinn criter.	-0.027076
F-statistic	3.235384	Durbin-Watson stat	2.005860
Prob(F-statistic)	0.060623		

Null Hypothesis: D(LINV_ICT) has a unit root
Exogenous: None
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*

Phillips-Perron test statistic		-4.649467	0.0001
Test critical values:	1% level	-2.674290	
	5% level	-1.957204	
	10% level	-1.608175	

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

Residual variance (no correction)	0.063406
HAC corrected variance (Bartlett kernel)	0.061769

Phillips-Perron Test Equation
Dependent Variable: D(LINV_ICT,2)
Method: Least Squares
Date: 12/05/23 Time: 11:56
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LINV_ICT(-1))	-1.009687	0.217169	-4.649312	0.0001

R-squared	0.507132	Mean dependent var	-0.005028
Adjusted R-squared	0.507132	S.D. dependent var	0.367115
S.E. of regression	0.257731	Akaike info criterion	0.170592
Sum squared resid	1.394936	Schwarz criterion	0.220185
Log likelihood	-0.876512	Hannan-Quinn criter.	0.182275
Durbin-Watson stat	2.014289		

Null Hypothesis: D(LINV_ICT) has a unit root
Exogenous: Constant
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.480996	0.0002
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

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

Residual variance (no correction)	0.057828
HAC corrected variance (Bartlett kernel)	0.025621

Phillips-Perron Test Equation
Dependent Variable: D(LINV_ICT,2)
Method: Least Squares
Date: 12/05/23 Time: 11:56
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LINV_ICT(-1))	-1.102068	0.222683	-4.949041	0.0001

C	0.078259	0.056344	1.388954	0.1801

R-squared	0.550491	Mean dependent var	-0.005028
Adjusted R-squared	0.528016	S.D. dependent var	0.367115
S.E. of regression	0.252212	Akaike info criterion	0.169415
Sum squared resid	1.272218	Schwarz criterion	0.268600
Log likelihood	0.136440	Hannan-Quinn criter.	0.192780
F-statistic	24.49301	Durbin-Watson stat	2.078713
Prob(F-statistic)	0.000077		

Null Hypothesis: D(LINV_ICT) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 21 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.360063	0.0000
Test critical values:	1% level	-4.440739	
	5% level	-3.632896	
	10% level	-3.254671	

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

Residual variance (no correction)	0.055436
HAC corrected variance (Bartlett kernel)	0.007056

Phillips-Perron Test Equation
Dependent Variable: D(LINV_ICT,2)
Method: Least Squares
Date: 12/05/23 Time: 11:57
Sample (adjusted): 2001 2022
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LINV_ICT(-1))	-1.137751	0.227139	-5.009046	0.0001
C	0.178795	0.124636	1.434531	0.1677
@TREND("1999")	-0.007827	0.008645	-0.905371	0.3766

R-squared	0.569082	Mean dependent var	-0.005028
Adjusted R-squared	0.523722	S.D. dependent var	0.367115
S.E. of regression	0.253357	Akaike info criterion	0.218086
Sum squared resid	1.219602	Schwarz criterion	0.366865
Log likelihood	0.601049	Hannan-Quinn criter.	0.253134
F-statistic	12.54595	Durbin-Watson stat	2.125926
Prob(F-statistic)	0.000336		

APPENDIX C: LAG LENGTH SELECTION

C1: Lag length selection Criteria

VAR Lag Order Selection Criteria

Endogenous variables: TFP LEPRO LEP LR_D LPAT LINV_ICT
Exogenous variables: C
Date: 12/05/23 Time: 11:02
Sample: 1999 2022
Included observations: 22

Lag	LogL	LR	FPE	AIC	SC	HQ
0	98.29784	NA	9.15e-12	-8.390713	-8.093155	-8.320617
1	215.2717	159.5097	6.66e-15	-15.75197	-13.66907	-15.26130
2	277.8703	51.21705*	1.49e-15*	-18.17002*	-14.30178*	-17.25878*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

C2: Lag Exclusion Test

VAR Lag Exclusion Wald Tests

Date: 12/05/23 Time: 10:59

Sample: 1999 2022

Included observations: 22

Chi-squared test statistics for lag exclusion:

Numbers in [ ] are p-values

	TFP	LEPRO	LEP	LR_D	LPAT	LINV_ICT	Joint
Lag 1	19.43280	29.89323	35.47578	10.79753	7.013339	4.056336	249.3589
	[0.003492]	[4.12e-05]	[3.48e-06]	[0.094839]	[0.319615]	[0.669053]	[0.000000]
Lag 2	28.82065	27.24214	15.51143	5.641801	2.950401	1.218952	200.6647
	[6.58e-05]	[0.000130]	[0.016631]	[0.464486]	[0.815046]	[0.975938]	[0.000000]
df	6	6	6	6	6	6	36

APPENDIX D: ARDL TEST RESULTS

Appendix D1: Summary of ARDL Estimates

Dependent Variable: TFP
Method: ARDL
Date: 12/05/23 Time: 10:52
Sample (adjusted): 2001 2022

Included observations: 22 after adjustments
Maximum dependent lags: 2 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (2 lags, automatic): LEPRO LEP LR_D LPAT LINV_ICT

Fixed regressors: C
Number of models evalulated: 486
Selected Model: ARDL(2, 1, 2, 2, 1, 0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TFP(-1)	-0.318465	0.198817	-1.601801	0.1479
TFP(-2)	0.362658	0.165315	2.193741	0.0596
LEPRO	0.097827	0.111999	0.873466	0.4079
LEPRO(-1)	0.608555	0.170972	3.559394	0.0074
LEP	-0.003329	0.049909	-0.066701	0.9485
LEP(-1)	-0.145654	0.049863	-2.921109	0.0193
LEP(-2)	0.055717	0.045388	1.227560	0.2545
LR_D	-0.052844	0.033108	-1.596090	0.1491
LR_D(-1)	-0.058964	0.039708	-1.484959	0.1759
LR_D(-2)	-0.082656	0.032336	-2.556125	0.0339
LPAT	0.037020	0.013235	2.797096	0.0233
LPAT(-1)	0.018384	0.014100	1.303834	0.2286
LINV_ICT	-0.028631	0.011666	-2.454232	0.0397
C	-5.810013	2.189597	-2.653462	0.0291

R-squared	0.994190	Mean dependent var	1.062085
Adjusted R-squared	0.984749	S.D. dependent var	0.061904
S.E. of regression	0.007645	Akaike info criterion	-6.648474
Sum squared resid	0.000468	Schwarz criterion	-5.954174
Log likelihood	87.13321	Hannan-Quinn criter.	-6.484918
F-statistic	105.3059	Durbin-Watson stat	2.566059
Prob(F-statistic)	0.000000		

Appendix D2: ARDL BOUNDS TEST

ARDL Bounds Test
Date: 12/05/23 Time: 09:33
Sample: 2001 2022
Included observations: 22
Null Hypothesis: No long-run relationships exist

Test Statistic	Value	k
F-statistic	8.362001	5

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	2.08	3
5%	2.39	3.38
2.5%	2.7	3.73
1%	3.06	4.15

Appendix D3: ARDL Long-Run Coefficients

Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEPRO	0.739043	0.077417	9.546237	0.0000
LEP	-0.097579	0.012192	-8.003418	0.0000
LR_D	-0.203455	0.055665	-3.655017	0.0064
LPAT	0.057966	0.016305	3.555037	0.0075
LINV_ICT	-0.029955	0.010649	-2.812949	0.0227
C	-6.078646	0.967689	-6.281611	0.0002

Appendix D4: ARDL Short-Run and ECM Results

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TFP(-1))	-0.374760	0.125549	-2.984960	0.0175
D(LEPRO)	0.069884	0.090238	0.774441	0.4609
D(LEP)	0.008290	0.034639	0.239317	0.8169
D(LEP(-1))	-0.048836	0.040397	-1.208900	0.2612
D(LR_D)	-0.037950	0.029091	-1.304520	0.2283
D(LR_D(-1))	0.070548	0.029880	2.361029	0.0459
D(LPAT)	0.031437	0.008902	3.531608	0.0077
LINV_ICT	-0.000342	0.000478	-0.715295	0.4948
CointEq(-1)	-0.867607	0.117697	-7.371560	0.0001

Cointeq = TFP - (0.7390*LEPRO -0.0976*LEP -0.2035*LR_D + 0.0580 *LPAT -0.0300*LINV_ICT -6.0786)

APPENDIX E: GRANGER CAUSALITY TEST RESULTS

Pairwise Granger Causality Tests
Date: 12/05/23 Time: 10:32
Sample: 1999 2022
Lags: 2

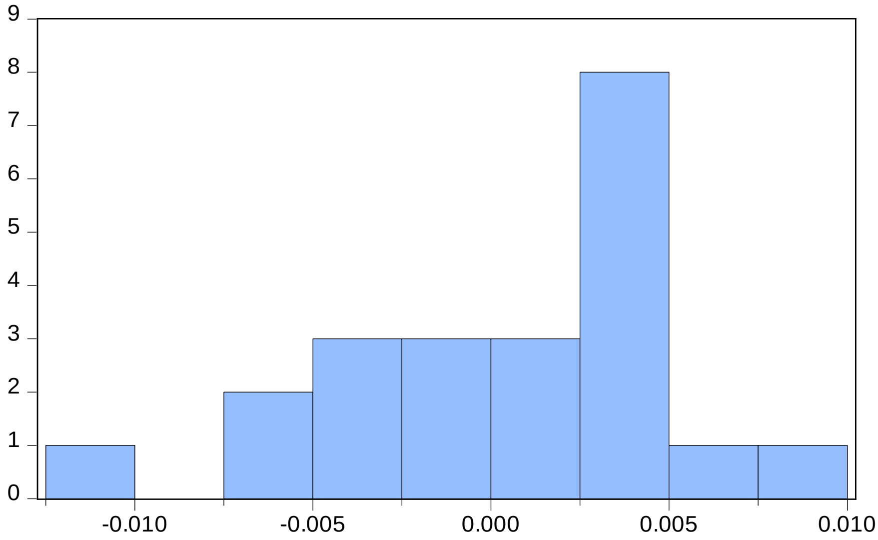
Null Hypothesis:	Obs	F-Statistic	Prob.
LEPRO does not Granger Cause TFP	22	8.16965	0.0033
TFP does not Granger Cause LEPRO		6.21728	0.0094
LEP does not Granger Cause TFP	22	9.92260	0.0014
TFP does not Granger Cause LEP		1.09319	0.3576
LR_D does not Granger Cause TFP	22	3.44713	0.0554
TFP does not Granger Cause LR_D		3.02893	0.0750
LPAT does not Granger Cause TFP	22	1.01713	0.3826
TFP does not Granger Cause LPAT		1.03707	0.3759
LINV_ICT does not Granger Cause TFP	22	2.82247	0.0874
TFP does not Granger Cause LINV_ICT		0.21251	0.8107

LEP does not Granger Cause LEPRO	22	10.1098	0.0013
LEPRO does not Granger Cause LEP		2.05438	0.1588
LR_D does not Granger Cause LEPRO	22	0.77731	0.4753
LEPRO does not Granger Cause LR_D		0.52471	0.6010
LPAT does not Granger Cause LEPRO	22	3.42961	0.0561
LEPRO does not Granger Cause LPAT		2.17666	0.1440
LINV_ICT does not Granger Cause LEPRO	22	1.73535	0.2062
LEPRO does not Granger Cause LINV_ICT		0.19380	0.8256
LR_D does not Granger Cause LEP	22	0.24088	0.7886
LEP does not Granger Cause LR_D		0.96676	0.4003
LPAT does not Granger Cause LEP	22	0.99182	0.3914
LEP does not Granger Cause LPAT		0.94781	0.4071
LINV_ICT does not Granger Cause LEP	22	3.48564	0.0539
LEP does not Granger Cause LINV_ICT		0.37344	0.6939
LPAT does not Granger Cause LR_D	22	0.43300	0.6555
LR_D does not Granger Cause LPAT		2.41495	0.1194
LINV_ICT does not Granger Cause LR_D	22	0.66436	0.5275
LR_D does not Granger Cause LINV_ICT		0.70702	0.5070
LINV_ICT does not Granger Cause LPAT	22	0.70204	0.5094
LPAT does not Granger Cause LINV_ICT		0.49182	0.6199

[1]

APPENDIX F: DIAGNOSTIC AND STABILITY TESTS RESULTS

Appendix F1: Diagnostic Tests



Series: Residuals
Sample 2001 2022
Observations 22

Mean	7.67e-16
Median	0.000904
Maximum	0.008556
Minimum	-0.010883
Std. Dev.	0.004718
Skewness	-0.502151
Kurtosis	2.734698
Jarque-Bera	0.989090
Probability	0.609848

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.247678	Prob. F(2,6)	0.3523
Obs*R-squared	6.462100	Prob. Chi-Square(2)	0.0395

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 12/05/23 Time: 09:53
Sample: 2001 2022
Included observations: 22
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TFP(-1)	-0.015465	0.194722	-0.079420	0.9393
TFP(-2)	-0.019459	0.178897	-0.108771	0.9169
LEPRO	0.000817	0.146474	0.005576	0.9957
LEPRO(-1)	0.015822	0.168116	0.094116	0.9281
LEP	0.013024	0.056338	0.231179	0.8249
LEP(-1)	-0.015891	0.060555	-0.262429	0.8018
LEP(-2)	-7.00E-06	0.044414	-0.000158	0.9999
LR_D	0.011283	0.033920	0.332650	0.7507
LR_D(-1)	-0.002231	0.039074	-0.057108	0.9563
LR_D(-2)	-0.016501	0.036251	-0.455198	0.6650
LPAT	-0.007831	0.017682	-0.442882	0.6734
LPAT(-1)	0.005008	0.014114	0.354787	0.7349
LINV_ICT	0.001939	0.012414	0.156209	0.8810
C	-0.096403	2.303310	-0.041854	0.9680
RESID(-1)	-0.391490	0.458542	-0.853772	0.4260
RESID(-2)	-0.678434	0.592868	-1.144325	0.2961

R-squared	0.293732	Mean dependent var	7.67E-16
Adjusted R-squared	-1.471939	S.D. dependent var	0.004718
S.E. of regression	0.007419	Akaike info criterion	-6.814416
Sum squared resid	0.000330	Schwarz criterion	-6.020930
Log likelihood	90.95857	Hannan-Quinn criter.	-6.627494
F-statistic	0.166357	Durbin-Watson stat	2.301702
Prob(F-statistic)	0.997731		

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.879816	Prob. F(13,8)	0.5982
Obs*R-squared	12.94539	Prob. Chi-Square(13)	0.4520
Scaled explained SS	1.484717	Prob. Chi-Square(13)	1.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/05/23 Time: 09:55
Sample: 2001 2022
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	0.002776	0.008529	0.325525	0.7531
TFP(-1)	1.39E-05	0.000774	0.017887	0.9862
TFP(-2)	-0.000440	0.000644	-0.683259	0.5137
LEPRO	0.000319	0.000436	0.732317	0.4849
LEPRO(-1)	-0.000533	0.000666	-0.800018	0.4468
LEP	3.55E-05	0.000194	0.182542	0.8597
LEP(-1)	0.000108	0.000194	0.556673	0.5930
LEP(-2)	-0.000174	0.000177	-0.986233	0.3529
LR_D	6.63E-05	0.000129	0.513786	0.6213
LR_D(-1)	0.000226	0.000155	1.462141	0.1818
LR_D(-2)	-0.000190	0.000126	-1.510734	0.1693
LPAT	-8.68E-05	5.16E-05	-1.683367	0.1308
LPAT(-1)	-3.29E-05	5.49E-05	-0.599679	0.5653
LINV_ICT	4.16E-05	4.54E-05	0.915596	0.3866

R-squared	0.588427	Mean dependent var	2.13E-05
Adjusted R-squared	-0.080380	S.D. dependent var	2.86E-05
S.E. of regression	2.98E-05	Akaike info criterion	-17.74449
Sum squared resid	7.09E-09	Schwarz criterion	-17.05019
Log likelihood	209.1894	Hannan-Quinn criter.	-17.58093
F-statistic	0.879816	Durbin-Watson stat	2.848130
Prob(F-statistic)	0.598184		

Heteroskedasticity Test: Harvey

F-statistic	1.028542	Prob. F(13,8)	0.5032
Obs*R-squared	13.76456	Prob. Chi-Square(13)	0.3906
Scaled explained SS	22.70117	Prob. Chi-Square(13)	0.0454

Test Equation:
Dependent Variable: LRESID2
Method: Least Squares
Date: 12/05/23 Time: 09:56
Sample: 2001 2022
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	154.9407	829.0452	0.186891	0.8564
TFP(-1)	82.69968	75.27791	1.098592	0.3039
TFP(-2)	-52.36269	62.59301	-0.836558	0.4271
LEPRO	50.41847	42.40596	1.188948	0.2686
LEPRO(-1)	-66.86693	64.73483	-1.032936	0.3318
LEP	-1.252254	18.89707	-0.066267	0.9488
LEP(-1)	-1.801512	18.87946	-0.095422	0.9263
LEP(-2)	6.565740	17.18525	0.382057	0.7124
LR_D	0.051753	12.53583	0.004128	0.9968
LR_D(-1)	15.97162	15.03447	1.062333	0.3191
LR_D(-2)	-17.83261	12.24349	-1.456497	0.1834
LPAT	-8.310203	5.011236	-1.658314	0.1358
LPAT(-1)	-0.821703	5.338625	-0.153917	0.8815
LINV_ICT	6.658509	4.417121	1.507432	0.1701

R-squared	0.625662	Mean dependent var	-11.97332
Adjusted R-squared	0.017362	S.D. dependent var	2.919978
S.E. of regression	2.894518	Akaike info criterion	5.224640
Sum squared resid	67.02586	Schwarz criterion	5.918940

Log likelihood	-43.47105	Hannan-Quinn criter.	5.388197
F-statistic	1.028542	Durbin-Watson stat	1.914463
Prob(F-statistic)	0.503157		

Heteroskedasticity Test: Glejser

F-statistic	1.387719	Prob. F(13,8)	0.3283
Obs*R-squared	15.24126	Prob. Chi-Square(13)	0.2925
Scaled explained SS	4.687461	Prob. Chi-Square(13)	0.9814

Test Equation:
Dependent Variable: ARESID
Method: Least Squares
Date: 12/05/23 Time: 09:57
Sample: 2001 2022
Included observations: 22

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.410202	0.672808	0.609687	0.5590
TFP(-1)	0.032127	0.061091	0.525882	0.6132
TFP(-2)	-0.045109	0.050797	-0.888015	0.4004
LEPRO	0.026695	0.034414	0.775688	0.4602
LEPRO(-1)	-0.060742	0.052535	-1.156209	0.2810
LEP	0.006776	0.015336	0.441836	0.6703
LEP(-1)	0.000782	0.015322	0.051023	0.9606
LEP(-2)	-0.008974	0.013947	-0.643480	0.5379
LR_D	0.007703	0.010173	0.757219	0.4706
LR_D(-1)	0.022655	0.012201	1.856784	0.1004
LR_D(-2)	-0.021522	0.009936	-2.166068	0.0622
LPAT	-0.010523	0.004067	-2.587410	0.0322
LPAT(-1)	-0.003599	0.004333	-0.830798	0.4302
LINV_ICT	0.005554	0.003585	1.549493	0.1599

R-squared	0.692784	Mean dependent var	0.003837
Adjusted R-squared	0.193559	S.D. dependent var	0.002616
S.E. of regression	0.002349	Akaike info criterion	-9.008499
Sum squared resid	4.41E-05	Schwarz criterion	-8.314199
Log likelihood	113.0935	Hannan-Quinn criter.	-8.844943
F-statistic	1.387719	Durbin-Watson stat	2.622828
Prob(F-statistic)	0.328251		

Heteroskedasticity Test: ARCH

F-statistic	0.184147	Prob. F(2,17)	0.8335
Obs*R-squared	0.424099	Prob. Chi-Square(2)	0.8089

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/05/23 Time: 09:59
Sample (adjusted): 2003 2022
Included observations: 20 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.85E-05	1.07E-05	1.719922	0.1036
RESID^2(-1)	-0.023269	0.240775	-0.096641	0.9241
RESID^2(-2)	0.141035	0.240088	0.587429	0.5646

R-squared	0.021205	Mean dependent var	2.12E-05
Adjusted R-squared	-0.093947	S.D. dependent var	2.93E-05
S.E. of regression	3.06E-05	Akaike info criterion	-17.81270
Sum squared resid	1.59E-08	Schwarz criterion	-17.66334
Log likelihood	181.1270	Hannan-Quinn criter.	-17.78354
F-statistic	0.184147	Durbin-Watson stat	1.906207
Prob(F-statistic)	0.833451		

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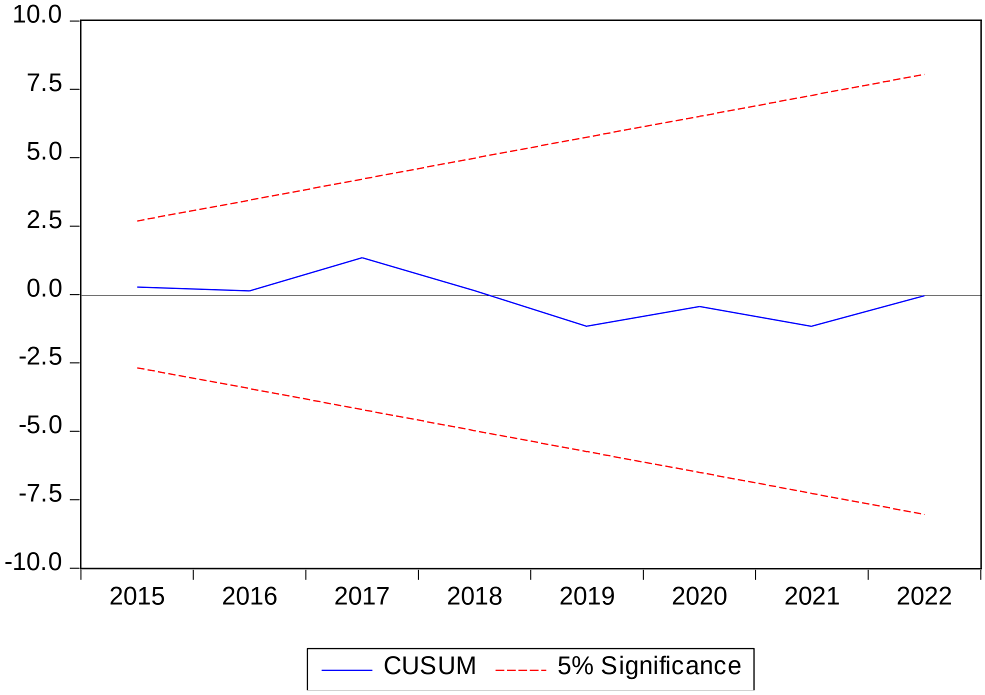
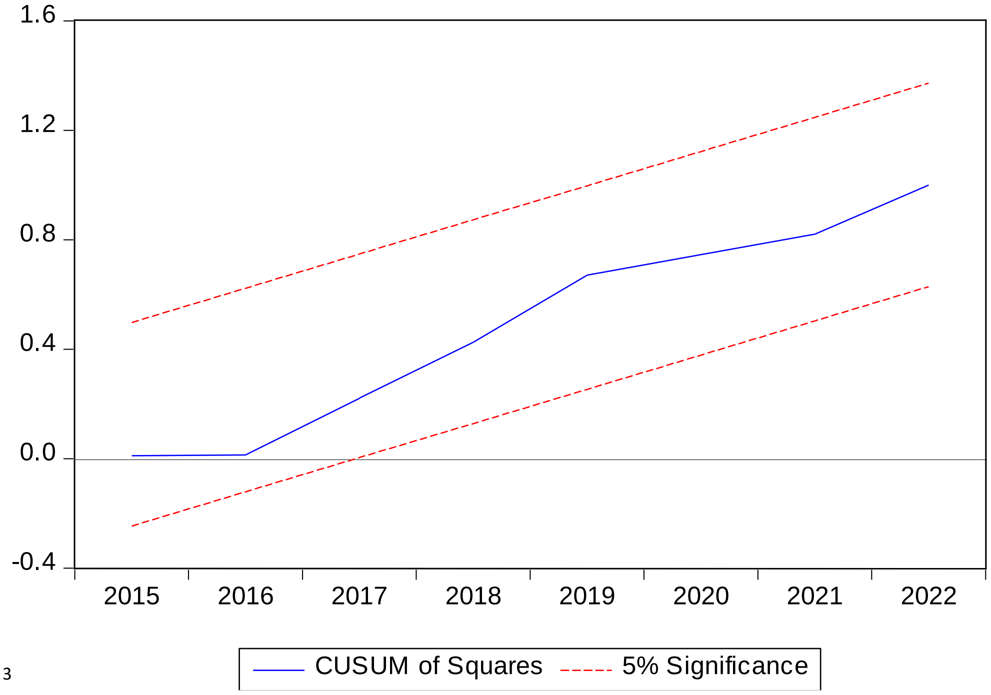
Appendix F2: Stability Tests

CUSUM Test



CUSUM of Squares Test

2



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Ramsey RESET Test

Equation: UNTITLED
Specification: TFP TFP(-1) TFP(-2) LEPRO LEPRO(-1) LEP LEP(-1) LEP(
        -2) LR_D LR_D(-1) LR_D(-2) LPAT LPAT(-1) LINV_ICT C
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.247750	7	0.8114
F-statistic	0.061380	(1, 7)	0.8114

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	4.06E-06	1	4.06E-06
Restricted SSR	0.000468	8	5.84E-05
Unrestricted SSR	0.000463	7	6.62E-05

Unrestricted Test Equation:
Dependent Variable: TFP
Method: ARDL
Date: 12/05/23   Time: 10:14
Sample: 2001 2022
Included observations: 22
Maximum dependent lags: 2 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (2 lags, automatic):
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TFP(-1)	-0.039703	1.144901	-0.034679	0.9733

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TFP(-2)	0.129280	0.958284	0.134908	0.8965
LEPRO	0.014439	0.357068	0.040438	0.9689
LEPRO(-1)	0.121194	1.975551	0.061347	0.9528
LEP	0.004826	0.062494	0.077222	0.9406
LEP(-1)	-0.037408	0.440130	-0.084992	0.9346
LEP(-2)	0.013956	0.175345	0.079594	0.9388
LR_D	-0.017039	0.148757	-0.114539	0.9120
LR_D(-1)	-0.013001	0.190278	-0.068324	0.9474
LR_D(-2)	-0.016767	0.268168	-0.062523	0.9519
LPAT	0.007701	0.119176	0.064620	0.9503
LPAT(-1)	0.002537	0.065699	0.038622	0.9703
LINV_ICT	-0.008029	0.084081	-0.095487	0.9266
C	-0.631718	21.03083	-0.030038	0.9769
FITTED^2	0.349903	1.412323	0.247750	0.8114

R-squared	0.994241	Mean dependent var	1.062085
Adjusted R-squared	0.982722	S.D. dependent var	0.061904
S.E. of regression	0.008137	Akaike info criterion	-6.566295
Sum squared resid	0.000463	Schwarz criterion	-5.822402
Log likelihood	87.22924	Hannan-Quinn criter.	-6.391056
F-statistic	86.31565	Durbin-Watson stat	2.577668
Prob(F-statistic)	0.000002		

*Note: p-values and any subsequent tests do not account for model selection.

APPENDIX G: VARIANCE DECOMPOSITION TEST RESULTS

Variance Decomposition of TFP: Period	S.E.	TFP	LEPRO	LEP	LR_D	LPAT	LINV_ICT
1	0.009791	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.014273	50.72826	21.52078	23.05623	2.145977	2.544585	0.004164
3	0.017924	38.66765	16.34570	15.23767	16.57221	9.187875	3.988896
4	0.021763	27.25241	27.80016	10.49386	13.09057	16.53505	4.827948
5	0.025162	21.62935	21.08140	18.60189	14.42749	20.53965	3.720228
6	0.025764	22.69299	20.10761	18.56030	14.13057	20.94231	3.566225
7	0.027814	19.51559	21.41877	20.82852	12.99099	21.38517	3.860959
8	0.031002	18.02078	19.61751	26.72467	10.70134	19.49846	5.437249
9	0.036437	13.50971	19.69634	26.48014	9.919560	26.10089	4.293369
10	0.038954	12.96627	18.38758	27.85746	9.577907	25.19835	6.012437

APPENDIX H: IMPULSE RESPONSE FUNCTION TEST RESULTS

Response to Cholesky One S.D. Innovations ± 2 S.E.