CAN ELECTRICITY USAGE SPARK ECONOMIC PROSPERITY? AN EVIDENCE FROM SAUDI ARABIA

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ABSTRACT

This study investigates the causal relationship between electricity consumption and economic growth in Saudi Arabia using annual data from 1970 to 2010. Employing unit root and cointegration tests, followed by the estimation of a Vector Error Correction Model (VECM), we explore both short-run and long-run dynamics among GDP, electricity consumption (EC), and energy prices (EP). Diagnostic tests were applied to ensure the robustness of the VECM equations, and impulse response functions were used to analyze the reaction of variables to shocks over the study period.

Empirical findings indicate that GDP and EC are integrated of order one, while EP is integrated of order zero. The Johansen cointegration test confirms a long-run relationship among the variables with one cointegrating vector. Granger causality tests reveal a negative long-run causality from EC and EP to GDP,

while short-run tests indicate bidirectional causality between EC and GDP, and between EC and EP.

The study highlights that energy conservation policies need to be implemented cautiously, as a reduction in electricity consumption negatively impacts economic growth in the long run. Policy implications suggest that Saudi Arabia should enhance energy efficiency, and shift towards alternative renewable energy sources to sustain economic growth. Overall, the results support the growth hypothesis, underscoring the significant role of electricity consumption in driving economic prosperity in Saudi Arabia.

Keywords: *electricity usage, electricity consumption, economic growth, VECM.*

1. INTRODUCTION

In modern economies, energy has become a crucial factor in determining economic growth. Economists widely acknowledge the significant role of energy in the global economy, influencing the production and consumption of goods and services. Traditional neoclassical growth models assume that technology and energy are neutral in economic growth. However, empirical research challenges this assumption. Ferguson et al. (2000) identified a correlation between electricity usage and economic growth in around 100 countries, suggesting a relationship but not definitively proving a causal link between economic growth and electricity consumption (Payne, 2010).

Empirical studies have further explored this relationship, with numerous papers investigating the causality between electricity consumption and economic growth (Kouakou, 2011). Four testable hypotheses regarding this causal relationship emerge from the literature. The growth hypothesis suggests a unidirectional causality from electricity consumption to economic growth (Ebohon, 1996), implying that economies dependent on energy imports may be negatively affected by electricity-conservation policies (Narayan et al., 2010; Nondo et al., 2010; Squalli, 2007). Conversely, the conservative hypothesis proposes unidirectional causality from economic growth to electricity consumption, indicating that electricity-conservation policies might not hinder economic growth (Payne, 2010). The neutrality hypothesis rejects any causal relationship between economic growth and electricity consumption, implying that conservation policies do not impede growth (Jumbe, 2004). Finally, the feedback hypothesis indicates a bidirectional causality between the two variables (Payne, 2010).

Saudi Arabia, located on the Arabian Peninsula and the 14th largest country in the world, spans approximately two million square kilometers and has a population exceeding 35 million (World Bank, 2011). Understanding the contribution of natural resources to economic output is crucial for analyzing the Saudi energy-electricity and economic growth profile. Saudi Arabia's economy is heavily reliant on crude oil, with oil export revenues accounting for around 90% of total revenues and about 40% of its gross domestic product (GDP). The country has the fourth highest natural resource rents globally, primarily from oil and natural gas (World Bank, 2011). Saudi Aramco, the world's largest oil company in proven reserves and hydrocarbon production, plays a central role in the country's energy policy, with production capacities reaching 12 million barrels per day and spare capacities above 2 million barrels per day.

As a founding member of the Organization of the Petroleum Exporting Countries (OPEC), Saudi Arabia holds 18% of the world's proven petroleum reserves. The petroleum sector contributes about 75% of the country’s budget revenues, 90% of its export earnings, and 45% of its GDP (OPEC, 2011). Despite being the largest net exporter and the second-largest producer of crude oil globally, Saudi Arabia has been diversifying its economic output since the early 1990s by expanding its refining, petrochemicals, and mineral products industries (IEA, 2011).

The development of Saudi Arabia’s electricity sector dates back to the 1960s, initially characterized by a few national companies generating electricity. After 1970, these companies were consolidated into the four regional Saudi Consolidated Electric Companies (SCECO). In the late 1990s, these companies merged into the Saudi Electricity Company, operational since 2000.

Other entities, such as the Saline Water Conversion Corporation (SWCC) and Aramco, also produce electricity for their needs.

Electricity demand and production have grown rapidly in Saudi Arabia since 1970, primarily relying on fossil fuels and natural gas. Electricity production nearly doubled over the last two decades, with total available power capacity reaching 90,000 MWh in 2010 and electrical energy sold totaling 320,000 GWh. In 2010, electricity generation capacity increased by 5.2% compared to the previous year. Saudi Arabia ranks as the largest producer of electricity using fossil fuels (IEA, 2011). Additionally, Saudi Arabia was the sixth-largest oil consumer globally in 2011 and the largest petroleum consumer in the Middle East, with consumption driven by transportation fuels and power generation (EIA, 2011).

Since the 1970s, Saudi Arabia's economy has grown steadily. Several factors have increased pressure on electricity consumption, especially in the household sector, due to population growth, air conditioning use during extremely hot months, and infrastructure improvements across the country. Saudi Arabia's participation in the Gulf Cooperation Council (GCC) efforts to link member states' power grids aims to reduce energy shortages during peak periods (EIA, 2011).

Historically dependent on fossil fuels, Saudi Arabia is now focusing on renewable energy sources, such as solar, wind, nuclear, and other renewable techniques, to diversify its energy mix. Given its status as a net oil exporter and its ongoing search for alternative energy sources, it is pertinent to empirically examine the nexus between electricity consumption and economic growth in Saudi Arabia.

This paper aims to investigate the causal relationship between electricity consumption and economic growth in Saudi Arabia. Specifically, it seeks to determine the direction and existence of causality between these variables in a country heavily dependent on energy exports. While many researchers have explored the relationship between economic growth and electricity consumption through various methodologies, few have focused on Saudi Arabia. Additionally, no previous studies have employed panel methods across the main sectors of the country, providing a nuanced understanding of whether specific sectors can stimulate economic growth. Based on the empirical findings, energy policy implications will be considered to evaluate the efficiency of current policies and suggest potential improvements.

Saudi Arabia's notably cheap energy prices, influenced by its status as a net oil exporter, affect the efficiency of electricity use. Fluctuations in oil prices and energy consumption are critical considerations for governmental energy policies impacting the national economy. King Abdullah City for Atomic and Renewable Energy (K.A.CARE), established in 2010, aims to promote cheaper energy sources, such as solar power, to reduce dependence on non-renewable energy for export purposes. This strategic move is expected to enhance the efficient use of natural resources and electricity, potentially leading to sustainable economic growth.

The rest of this study is organized as follows: The next section reviews previous literature, critically examining empirical evidence on the relationship between energy and economic growth. Section three presents the data sources and methodology. Section four reports the main empirical results, followed by a discussion in section five. Finally, section six offers conclusions, policy implications, and suggestions for future research.

2. LITERATURE REVIEW

The interplay between energy and economic growth has long fascinated economists due to its profound implications for the macroeconomic stability of nations. This literature review delves into a wide array of studies that investigate this relationship, starting with the seminal work of Kraft and Kraft (1978), who introduced the causality relationship between energy consumption and economic growth (GNP) in the U.S. economy, finding that causality runs from GNP to energy consumption. As of 2010, over 50 studies have focused on the causality relationship between economic growth and electricity consumption (Narayan et al. 2010).

Al-Iriani (2006), Adjaya and Mahadevan (2007), Squalli (2007), and Narayan et al. (2010) included Saudi Arabia in their studies and used panel causality tests. However, no individual causality study has investigated this subject specifically in Saudi Arabia. Al-Iriani (2006) employed panel cointegration and causality tests in Gulf Cooperation Council countries and found that unidirectional causality runs from GDP to energy consumption, implying that energy conservation policies might not adversely affect economic growth. Despite the generalized results, Al-Iriani's work has been criticized for not providing a country-specific analysis.

Adjaya and Mahadevan (2007) analyzed the relationship between energy consumption, GDP, and energy prices using a panel VECM for 20 developed and developing countries, including Saudi Arabia. They discovered cointegration in Saudi Arabia and other countries, with bidirectional causality between energy consumption and economic growth in energy-exporting countries like Saudi Arabia in the short run, and unidirectional causality from GDP to energy consumption in the long run. Similar results were found for energy-importing developing countries, while developed countries experienced mutual causality.

Squalli (2007) investigated the relationship between electricity consumption and GDP for OPEC members, including Saudi Arabia, using the autoregressive distributed lag (ARDL) model. He found bidirectional causality in Saudi Arabia, with a positive causality running from GDP to electricity and a negative causality from electricity consumption to GDP in the long run, suggesting that energy conservation policies have minimal impact on Saudi Arabia's energy policy.

Narayan et al. (2010) examined the causality relationship between GDP and electricity consumption for 93 countries, including Saudi Arabia, employing panel unit root tests and panel causality tests. They found no long-run causality between electricity consumption and GDP for Middle Eastern countries, supporting the neutrality hypothesis. However, they observed bidirectional causality in Western Europe, G6, Africa, and Latin America, concluding that in 40% of the countries, the relationship between GDP and electricity consumption is either negative or insignificant.

Focusing on specific-country analysis, Yu and Jin (1992) found no cointegration or long-run causality between energy consumption and GNP in the USA, suggesting that energy consumption policies might not effectively boost economic growth. Yang (2000) re-examined this causality in Taiwan, finding bidirectional causality between electricity consumption and GDP. Jumbe (2004) examined Malawi, discovering bidirectional causality between electricity consumption and GDP and unidirectional causality from non-agricultural GDP to electricity consumption.

Lee and Chang (2005) studied Taiwan, allowing for structural breaks in their estimation and finding that energy consumption fosters economic growth in the long run. Narayan and Smyth (2005) analyzed Australia, finding that in the long run, employment and real income Granger causes electricity consumption, while in the short run, income weakly causes both electricity consumption and employment.

Yuan et al. (2007) examined China, finding that electricity consumption Granger causes GDP. Abosedra et al. (2009) investigated Lebanon, finding that electricity consumption causes economic growth without testing for cointegration. Narayan and Singh (2007) tested for causality in Fiji, discovering unidirectional causality from electricity consumption to GDP and labor force.

In multi-country analyses, Masih and Masih (1996) tested for causality between energy consumption and income in six countries, finding varied results, including unidirectional causality from energy to income in India and from income to energy in Indonesia, with mutual causality in Pakistan. Adjaya (2000) found bidirectional causality between energy and income in Thailand and the Philippines, while Fatai et al. (2004)

discovered long-run causality from GDP to energy consumption in Australia and New Zealand, and from energy consumption to GDP in India and Indonesia.

Narayan and Prasad (2008) used a bootstrapped causality test for 30 OECD countries, finding bidirectional causality between economic growth and electricity consumption in the UK, Korea, and Iceland. Ciarreta and Zarraga (2010) investigated 12 European countries, finding cointegration among variables and strong causality from electricity consumption to GDP.

Payne (2010) identified around 40 papers investigating the causality between electricity consumption and economic growth, concluding that 60% of the studies support either the neutrality or conservation hypothesis. Specifically, 31% support the neutrality hypothesis, 28% the conservation hypothesis, 23% the growth hypothesis, and 18% the feedback hypothesis, indicating that electricity consumption policies have varying impacts on economic growth.

Examining individual countries further highlights the complexities and variances in the energy-economic growth nexus. For instance, Stern (1993) used a multivariate vector autoregression (VAR) approach to analyze the causal relationship between energy consumption and economic growth in the United States from 1948 to 1994. He found a strong relationship between energy use and GDP, suggesting that energy is an important driver of economic growth.

Singh (2008) used a similar VAR approach to examine the relationship in India from 1952 to 1995, finding evidence of bidirectional causality. This finding implies that both energy consumption drives economic growth and economic growth increases energy consumption, indicating a feedback loop that policy-makers must consider when devising energy policies.

In the context of African economies, Odhiambo (2009) explored the causal relationship between energy consumption and economic growth in Tanzania. He employed the ARDL bounds testing approach and found unidirectional causality running from energy consumption to economic growth, suggesting that energy policies that ensure the adequate supply of energy could be crucial for sustaining economic growth in Tanzania.

In a study on South Korea, Yoo (2006) used a cointegration and error-correction model to analyze data from 1970 to 2002. He found evidence of bidirectional causality between electricity consumption and economic growth, highlighting the importance of electricity in driving the economic expansion and vice versa.

For a Middle Eastern context, Mehrara (2007) investigated the causality relationship in Iran using annual data from 1967 to 2002. Employing the Toda-Yamamoto causality approach, Mehrara found unidirectional causality running from economic growth to energy consumption, suggesting that Iran's economic growth drives energy demand rather than the other way around.

Further insights come from studies focusing on specific sectors within economies. For instance, Wolde-Rufael (2005) examined the causal relationship between electricity consumption and economic growth for 17 African countries using a Toda-Yamamoto causality test. The results varied significantly across countries, with some showing unidirectional causality from electricity consumption to economic growth, others showing the reverse, and some exhibiting bidirectional causality. This diversity underscores the need for country-specific policies rather than one-size-fits-all solutions.

Additionally, Huang et al. (2008) explored the relationship between energy consumption and economic growth in 82 countries using panel data techniques. Their findings suggest that the causality between these variables is highly dependent on the level of income. In high-income countries, there was evidence of bidirectional causality, while in low-income countries, unidirectional causality from economic growth to energy consumption was more prevalent. This indicates that the economic development stage significantly influences the energy-growth relationship.

Apergis and Payne (2011) used a panel cointegration and error-correction model to examine the relationship in 88 countries from

1990 to 2006. They found that in both the short and long run, there is bidirectional causality between renewable energy consumption and economic growth. This finding is particularly relevant for countries like Saudi Arabia, which are investing heavily in renewable energy as part of their economic diversification strategies.

From a methodological perspective, various econometric techniques have been employed to investigate this relationship, each with its strengths and limitations. Granger causality tests, vector autoregression (VAR) models, vector error-correction models (VECM), and autoregressive distributed lag (ARDL) models are among the most commonly used methods. Each approach offers unique insights but also requires careful consideration of the underlying assumptions and potential limitations.

For instance, Granger causality tests are widely used to determine the direction of causality but may suffer from issues related to non-stationarity of time series data. VAR models are useful for capturing the dynamic interplay between multiple time series but may be sensitive to the chosen lag length. VECM models are advantageous for examining long-term equilibrium relationships but require the presence of cointegration among variables. ARDL models offer flexibility in handling variables of different integration orders but may be computationally intensive.

In summary, the empirical literature on the relationship between energy consumption and economic growth reveals a complex and multifaceted dynamic that varies across countries, regions, and development stages. The results of these studies are mixed, with some finding evidence of unidirectional causality, others bidirectional causality, and still others supporting the neutrality hypothesis. This diversity of findings underscores the importance of considering country-specific factors, such as economic structure, energy policies, and development levels, when analyzing the energy-growth nexus.

Given the unique economic characteristics of Saudi Arabia, including its heavy reliance on oil exports and ongoing efforts to diversify its energy mix, it is crucial to conduct a detailed and focused investigation into the relationship between electricity consumption and economic growth in the country. This study aims to fill the gap in the literature by providing a comprehensive analysis of this relationship using robust econometric techniques and considering the specific context of Saudi Arabia's economy and energy sector.

The insights gained from this investigation will have significant implications for energy policy, particularly in terms of enhancing the efficiency of electricity use, promoting sustainable economic growth, and achieving the objectives of Saudi Arabia's Vision 2030, which seeks to diversify the economy and reduce its dependence on oil revenues. By understanding the causal dynamics between electricity consumption and economic growth, policymakers can better design and implement strategies that support economic development while ensuring a stable and sustainable energy supply.

3. METHODOLOGY

To investigate the relationship between electricity consumption and economic growth, we employed a time series regression method. Three macroeconomic variables were used, electricity consumption (EC), gross domestic product (GDP), and energy prices (EP). Annual data for the period 1970–2010 were obtained, as this period was selected based on the availability of the data.

Electricity consumption (EC) data were sourced from the World Bank's World Development Indicator (WDI) and IEA Key World Energy Statistics databases for electricity consumption per capita, measured in millions of kilowatt-hours. The GDP and EP data were retrieved from the World Bank WDI database. Real GDP per capita was used for GDP, and the Consumer Price Index (CPI) was used as a proxy for energy prices. All data were converted into natural logarithm form for the analysis.

The choice of these specific indicators was informed by previous literature. For instance, researchers such as Ciarreta and Zarraga (2010) and Fatai et al. (2004) considered energy prices in their estimations. Controlling for energy prices is essential as they significantly influence the relationship between economic growth and energy-electricity consumption (Ciarreta & Zarraga, 2010). This focus is particularly pertinent for Saudi Arabia, a crucial part of the global energy market and a net oil exporter.

The electricity consumption data are expressed in GWh by sector. However, data before 2000 were available in MWh, so for consistency, we converted these values to GWh by dividing the MWh values by 1000. All data were then transformed into natural logarithm form.

3.2 Empirical framework

3.2.1 Time Series Regression Estimation Procedure

From the literature, we found no individual study focused on Saudi Arabia concerning the GDP–electricity consumption nexus. The mixed results for this relationship in Saudi Arabia encouraged us to apply the time series regression method. We estimate the following model:

$$lnEC_t = \propto + \beta_1 ln\, EP_t + \beta_2 ln\, GDP_t + u_t \ (eq.1)$$

where EC denotes the natural logarithm of electricity consumption per capita, GDP is the natural logarithm of the real GDP per capita used as a proxy for economic growth, EP is the natural logarithm of energy prices, α is the intercept, β_1 and β_2 are the parameters to be estimated, and u_t is the error term. Additionally, since we investigated the causality relationship between the variables, each variable in Equation (1) is presented as a dependent variable.

The estimation procedure required four steps. First, we tested the stationarity of the variables by employing ADF and PP unit root tests. Second, we investigated the long-run relationship among variables by employing the Johansen multivariate cointegration procedure. Third, we tested for causality in both the short and long run by estimating the VECM and using Granger causality and Wald statistics for joint causality. We further proceeded to apply a battery of diagnostic tests on our VECM equations. Lastly, since our data sample included some economic and political events, especially in the early 1980s (e.g., the Gulf War), we employed the impulse response functions (IRFs) procedure to investigate the reaction of each variable to shocks that occurred to other variables in the system. We considered that applying structural breaks might lead to complications in the estimation and forecasting errors, particularly due to the shifts in some series.

3.2.2 Stationarity Test

In order to employ the Granger causality test, the time series should be stationary (Granger & Newbold, 1974). For this reason, we undertook the unit root test to test for stationarity in the time series and identify the integration order of the variables.

Generally, stationarity or unit root tests consider the mean of the variable's variation. A series is said to be stationary when the mean, variance, and covariance are constant over time. If any one of these conditions is not satisfied, the series is considered non-stationary. Non-stationarity indicates that the regression is spurious and there is the possibility of a deterministic or stochastic trend. A deterministic trend is predictable, while a stochastic trend is not.

The most commonly used unit root tests for time series analysis are the simple Dickey Fuller (DF), the augmented Dickey Fuller (ADF) (1979), and the Phillips-Perron (PP) (1988) tests.

For the ADF test, Dickey and Fuller extended the DF test by including extra lagged terms of the dependent variable to reduce the possibility of autocorrelation. The critical values are the same as the DF test (based on t-statistics of the lagged dependent variables coefficients). The general model of the ADF test is as follows:

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 t + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t \; (eq.2)$$

The null hypothesis, H_0:ρ=1, suggests that the series has a unit root (non-stationary), while the alternative, H_1:ρ<1, implies that the series does not have a unit root. This test can be performed in three types of models: random walk, random walk with drift, and random walk with drift and time trend.

Phillips and Perron (1988) developed a generalized version of the ADF test that allows for some assumptions concerning the errors' distribution by considering the AR(1) process for the PP test regression as follows:

$$\Delta y_{t-1} = \alpha_0 + \gamma y_{t-1} + e_t \quad (eq.3)$$

The null hypothesis indicates non-stationarity in the series, while the alternative indicates stationarity. The t-statistics are modified ADF t-statistics, as this test corrects for the t-statistics of the coefficient γ to account for the error term's serial correlation from the AR(1) regression. The PP test is frequently used as an alternative to the ADF test. However, this test relies on asymptotic theory and performs well in large samples. Despite this, we employed both ADF and PP tests, as it is common practice to use both tests to verify unit roots.

3.2.3 Cointegration Test

Granger (1988) introduced the concept of cointegration, which refers to the existence of a long-run relationship among variables even if the individual series are non-stationary. Evidence of a cointegration relationship implies interdependence between the variables in the long run.

Engle and Granger (1987) provided a simple method to test for cointegration by examining the stationarity of the residuals. According to the Engle-Granger (EG) approach, if two series are individually non-stationary but their linear combination is stationary, they are considered cointegrated. This indicates a stable long-term relationship between the series, despite short-term deviations.

However, the EG approach has limitations, especially when dealing with more than two variables, as it assumes only one cointegrating vector. To address this, we employed the Johansen-Juselius multivariate cointegration procedure (1990), which allows for multiple cointegrating vectors and treats all variables as endogenous, avoiding the normalization problem. This method requires that all variables be integrated to the same order.

The Johansen-Juselius procedure uses a vector autoregressive (VAR) model that includes all variables in levels and captures both short-run and long-run dynamics. The general form of the matrix system is as follows:

$$\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \cdots + \Gamma_{k-1} \Delta Z_{t-k-1} + \Pi Z_{t-1} + u_t \quad \textit{(eq.4)}$$

To investigate the cointegration relationship, we first estimated the VAR model to choose the optimal lag length using criteria such as AIC, FPE, LR, and HQ. We then determined the number of cointegration vectors using the critical values for Johansen and Juselius (1990) and applied the Pantula principle to test for the rank order and deterministic components. The estimated cointegration equation for our model is of the following form:

$$EC_t = \alpha_0 + \delta_1 t + \beta_2 GDP_t + \gamma_3 EP_t + \varepsilon_t \quad \textit{(eq.5)}$$

Rewriting:

$$\varepsilon_t - EC_t - \alpha_0 - \delta_1 t - \beta_2 GDP_t - \gamma_3 EP_t \; (eq.6)$$

Where the cointegrating vector is

$$(1 - \alpha_0 - \delta_1 - \beta_2 - \gamma_3) \; (eq.7)$$

Here, EC, GDP, and EP are as defined earlier, αα and δδ are country and time fixed effects, and ϵtϵt is the error term. The cointegration vector is treated as homogeneous across series. While cointegration tests indicate the presence or absence of Granger causality, they do not determine the direction of causality. This direction is found using the VECM derived from the cointegrating vector in the long run (Masih & Masih, 1996).

3.2.4 Causality Test

Granger causality can be defined as follows: A time series X is said to Granger cause time series Y if the prediction error of current Y decreases by using past values of X and Y, and vice versa. Granger (1969) developed a simple causal test based on estimating the VAR model for two stationary variables. Sims (1980) provided an alternative causality test also based on VAR estimation. However, both tests do not predict the direction of causality when variables are cointegrated.

Engle and Granger (1987) extended standard Granger causality tests by allowing the possibility for two time series to share a long-run common stochastic trend. When two time series are cointegrated, Granger causality can originate from short-run causality (tested by partial F-test of the lagged coefficients of the first-differences) and long-run causality (tested by t-statistics of the error correction terms (ECTs)). If the variables are not cointegrated but each is integrated of order one, standard Granger causality tests of the variables in first difference are implemented. Researchers like Jumbe (2004) have tested for causality within VECM after finding cointegration among variables.

Engle and Granger (1987) and Granger (1988) stated that the causal relationship should hold within a dynamic error correction model when there is a cointegration relationship among variables. Thus, short-run elasticities can be computed using the VECM approach suggested by Engle and Granger (1987). Changes in dependent variables are built at the level of the disequilibrium in the cointegration relationship, captured by the error correction term (ECT), while changes in other explanatory variables capture short-term relationships.

We chose VECM because the VAR model might indicate a short-run relationship while omitting long-run adjustments after taking the first difference. VECM allows for distinguishing between long and short-run relationships (Johansen-Juselius, 1990).

When variables are cointegrated, short-run deviations from the long-run equilibrium feedback to force movements towards equilibrium. If this is not the case, the variables respond only to short-term shocks. For differenced explanatory variables, the F-test tests short-run causality, while the significance of the t-statistics of the lagged ECT coefficient implies long-run causality. Non-significance in ECTs affects long-run relationships and may indicate a theory violation, while non-significance in differenced variables affects short-run relationships without theoretical violations (Masih & Masih, 1996). To test for Granger causality, VECM is specified as follows:

$$\vartriangle EC_t = \alpha_1 + \sum_{i=1}^{I} \beta_{1i} \vartriangle GDP_{t-i} + \sum_{i=1}^{m} \gamma_{1i} \vartriangle EP_{t-i} + \sum_{i=1}^{m} \delta_{1i} \vartriangle EC_{t-i} + \lambda_1 ECT_{t-1} + u_{1t} (eq.8)$$

$$\vartriangle GDP_t = \alpha_2 + \sum_{i=1}^{I} \beta_{2i} \vartriangle GDP_{t-i} + \sum_{i=1}^{m} \gamma_{2i} \vartriangle EP_{t-i} + \sum_{i=1}^{m} \delta_{2i} \vartriangle EC_{t-i} + \lambda_2 ECT_{t-1} + u_{2t} (eq.9)$$

$$\vartriangle EP_t = \alpha_3 + \sum_{i=1}^{I} \beta_{3i} \vartriangle GDP_{t-i} + \sum_{i=1}^{m} \gamma_{3i} \vartriangle EP_{t-i} + \sum_{i=1}^{m} \delta_{3i} \vartriangle EC_{t-i} + \lambda_3 ECT_{t-1} + u_{3t} (eq.10)$$

Where Δ is the difference operator, ECT denotes the error correction term derived from the long-run cointegrating relationship through the Johansen procedure, the coefficient of ECT shows how fast the variables return to long-run equilibrium levels obtained by estimating residuals, u_1, u_2, and u_3 are serially uncorrelated random error terms with zero mean, and i to I is the optimal lag length. The estimation of long-run and short-run relationships is done by OLS method and normality tests.

3.2.5 Impulse Response Functions

Impulse response functions (IRFs) analyze the behavior of each variable in response to shocks to other variables in the model. This process is based on a one-period standard deviation shock to another variable. According to Lutkepohl and Reimers (1992), IRFs are useful for observing the behavior between variables in a VAR model, and the results are obtained using Cholesky factorization, which is invariant with regard to the order of variables.

Considering the main structural information related to our estimation period helps specify meaningful shocks, we employed IRFs rather than standard variance decompositions (VDCs), as the latter cannot be generalized for exogenous variables. This procedure was extended to investigate the interaction of variables towards shocks to the cointegrated variables and to non-linear models. However, this method cannot explain which shocks are relevant for studying specific economic problems.

The responses were projected to estimate the economic-political shocks on the Saudi economy during the study period, including both direct and indirect impacts from endogenous responses of other variables in the system. To employ IRFs, we estimated the following VAR model:

$$EC_t = \alpha_0 + \beta_1 GDP_{t-i} + \gamma_1 EC_{t-i} + \theta_1 EP_{t-i} + u_{1t} \quad (eq.11)$$

$$GDP_t = \alpha_0 + \beta_2 GDP_{t-i} + \gamma_2 EC_{t-i} + \theta_2 EP_{t-i} + u_{2t} \quad (eq.12)$$

$$EP_t = \alpha_0 + \beta_3 GDP_{t-i} + \gamma_3 EC_{t-i} + \theta_3 EP_{t-i} + u_{3t} \quad (eq.13)$$

All variables are assumed to be endogenous, and the error terms are the innovations (impulses). If there is a shock, the IRFs investigate whether in u_1 or u_2 its effect on the variables. It is important to determine the order of variables; hence, we chose the Cholesky adjusted model to account for degrees of freedom.

4. EMPIRICAL ANALYSIS

4.1Unit root test

In alignment with the methodology, assessing the stationarity of variables through the unit root test is crucial for the validity of subsequent analyses. This study employed Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for unit roots to investigate the stationarity of the series. We estimated the GDP series with intercept only, while both EC and EP series were estimated with intercept and deterministic time trend.

The results of the ADF and PP tests for stationarity of the variables are reported in Table (1). Notably, the optimal lag structure for the ADF test was determined based on the Akaike Information Criterion (AIC). The results for the PP and ADF tests show that the t-statistics in absolute value for both GDP and EC series are less than the critical value at the 5% significance level in their level forms. Therefore, the null hypothesis of unit roots cannot be rejected, suggesting that GDP and EC are non-stationary at their level forms.

However, both PP and ADF test results for the EP series indicate that the t-statistics in absolute value are greater than the critical value at the 5% significance level. Consequently, the null hypothesis of unit roots is rejected, indicating that the EP series is stationary at its level form.

After taking the first difference, the results for both GDP and EC series show that the ADF and PP test statistics in absolute value are greater than the critical value at the 5% significance level. Therefore, we can reject the null hypothesis of non-stationarity, indicating that the GDP and EC series are stationary in their first difference forms.

In conclusion, the GDP and EC series are integrated of order one, denoted as I(1), while the EP series is integrated of order zero, denoted as I(0). Thus, we conclude that all variables are integrated of order one.

Table 1. Unit root test results for time series regression

Variables	ADF test				PP test		
	t statistics	t critical values 5%	The model	Lag length	t statistics	t critical values 5%	The model
EC	-2.36 (0.39)	-3.5	Intercept+ trend	(1)	-1.73 (0.71)	-3.52	Intercept + trend
∆ EC	-4.81* (0.00)	-3.5		(1)	-4.99* (0.00)	-3.53	
GDP	-2.47 (0.12)	-2.94	Intercept	(2)	-1.73 (0.40)	-2.93	Intercept
∆ GDP	-4.05* (0.00)	-3.96		(8)	-3.65* (0.00)	-2.94	
EP	-4.8* (0.00)	-3.5	Intercept + trend	(2)	-3.92 (0.02)**	-3.52	Intercept + trend

Notes: Numbers in parentheses are p values.
(*), (**) Denote rejection of null hypothesis of non-stationarity at 1% and 5%, respectively.

4.2Cointegration Test

The Johansen procedure suggests that all variables should be integrated to order one, I(1). To test for cointegration relationships among our variables, we first estimated the VAR model using E-Views to determine the optimal lag length, as this step is crucial for employing the Johansen procedure.

The optimal lag length was found to be 5, as suggested by various information criteria, including the Akaike Information Criterion (AIC), Final Prediction Error (FPE), Likelihood Ratio (LR), and Hannan-Quinn (HQ), all of which were at their minimum. We then proceeded to test for cointegration among variables by estimating the unrestricted VAR model and conducting the cointegration vectors.

The results of the Johansen cointegration test are shown in Table (2). We rejected the null hypothesis of no cointegrating vector, as both the trace statistics and maximum eigenvalue statistics were above the critical value at the 5% significance level. For the hypothesis $H_0{:}r=1$, $H_1{:}r\geq1$, we accepted the null hypothesis since the trace statistics and maximum eigenvalue were below the critical value at the 5% significance level, implying that there is no more than one cointegrating vector. Further, by looking at p-values, the same results apply.

We can conclude that, as the results indicate a reduced rank, variables are cointegrated, and one cointegration equation exists among our variables. The equation in the last row in Table 6 expresses the normalized cointegration coefficients, with the numbers in parentheses being the standard errors. The signs of the coefficients suggest that a negative relationship exists between EC and EP, and between EC and GDP, respectively.

By calculating the t-statistics of the variables using the coefficients and standard errors, the t-statistics for EP and GDP are -12.88747 and -2.23647, respectively, implying that these variables are significant. The adjustment coefficient (α) for EC (0.350832025) is positive and insignificant (less than 2), for EP (2.67585407) is positive and significant, and for GDP (3.594973042) is positive and significant. Hence, EC is weakly exogenous, meaning that there are no short-run adjustments from either GDP or EP to determine EC, while both GDP and EP are endogenous and determined by the system of the equation.

Table 2. Johansen Cointegration Estimation Results.

Null+Alternative hypothesis		**Test statistics**	**Critical values**	**Test statistics**	**Critical values**
H_0	H_1	Trace	5%	Max-eigenvalue	5%
None* H_0: r=0	 H_0:r ≥0	43.73 (0.00)	35.19	25.02 (0.02)	22.29
At most 1 H_0: r=1	 H_0:r ≥1	18.71 (0.08)	20.26	13.68 (0.11)	15.89
At most 2 H_0: r=2	 H_0:r ≥2	5.03 (0.28)	9.16	5.03 (0.28)	9.16
Normalized Cointegration Equation: EC = 15.83057 + (-3.001363)EP + (-1.182717)GDP (4.620) (0.232) (0.528)					

Notes: Numbers between parentheses are the p values.
* Denotes rejection of the null hypothesis at the 0.05 level

4.3Causality test

To investigate the existence, direction, and sign of the causality relationship between the series, we estimated the unrestricted VAR model, specifically the Vector Error Correction Model (VECM), for Eqs. (8), (9), and (10). This was followed by estimating the residuals using OLS to obtain the ECT coefficients. Additionally, we employed Wald statistics to test for joint causality in the short run. The results of these tests are reported in Table (3).

Empirical evidence found that the ECT is only significant for Eqs. (9) and (10), as indicated by the t-statistics value and the p-value. This implies that long-run causality runs from EC and GDP to EP, and from EC and EP to GDP. Specifically, for Eq. (9), a decrease in electricity consumption leads to an increase in GDP, while for Eq. (10), a decrease in electricity consumption leads to an increase in energy prices. However, no long-run causality exists for Eq. (8), implying that economic growth and energy prices do not cause electricity consumption in the long run.

For short-run causality, when the F-statistics are significant and the p-value is less than 0.05, we reject the null hypothesis of no causality, indicating that the independent variable causes the dependent variable in the short run. The results of the F-test indicated bidirectional Granger causality between energy prices and electricity consumption, and bidirectional causality between economic growth and electricity consumption. However, the results also indicated unidirectional Granger causality running from energy prices to economic growth. For Eq. (8), by looking at the χ^2 statistics and p-values, we reject the null hypothesis that EP and GDP cannot jointly cause EC in the short run. The same conclusion is reached for Eqs. (9) and (10).

The causality results indicate long-run causality from EC and EP to GDP, and from EC and GDP to EP. This means that a decrease in electricity consumption stimulates economic growth. This result supports the growth hypothesis, suggesting that efficient use of electricity might be translated into an increase in GDP.

Table 3. Granger causality and VECM estimation results

Dependent variable	Source of Causation (independent)						
	Short-run [F statistics]		Long-run [t statistics]		Shot-run-joint Wald test (χ^{2}-statistics)		
	ΔEC	ΔGDP	ΔEP	ECT	ΔEC, ΔEP	ΔGDP, ΔEP	ΔGDP, ΔEC
ΔEC	----	[5.52]* (0.00)	[10.46]* (0.00)	**[0.35]** 0.02 (0.729)	----	56.57* (0.00)	----
ΔGDP	[6.46]* (0.00)	----	[6.03]* (0.00)	**[-3.59]*** -0.26 (0.00)	48.39* (0.00)	----	----
ΔEP	[6.41]* (0.00)	[1.17] (0.32)	----	**[-2.67]**** -0.38 (0.01)	----	----	19.77** (0.01)

Notes: Numbers in the parentheses are the p values.

(*), (**) Denotes rejection of the null hypothesis of no causality at 1% and 5%, respectively.

4.4Diagnostic tests

After estimating the VECM by OLS, we applied several diagnostic tests to each equation from (8) to (10) to check for serial correlation, heteroscedasticity, and normality of the residuals. The results of these tests are reported in Table(4).

For Eqs. (8) and (9), we cannot reject the null hypothesis for any of the diagnostic tests mentioned above. This implies that the two models show no evidence of serial correlation, no evidence of autocorrelation in the error term residuals' conditional variance (indicating no ARCH effect), and no evidence of non-normally distributed residuals.

However, for Eq. (10), the results of the LM test indicated evidence of first and second-order serial correlation, suggesting potential issues with this equation due to the presence of serial correlation. This finding casts doubt on the reliability of Eq. (10), given the existence of serial correlation.

Table 4. Summary of diagnostic tests for equations used in vector error correction models estimation.

Equation	Serial correlation LM(1)	LM(2)	Heteroscedasticity ARCH-effect	Normality JB-test
Δ **EC**	0.000 (1.000)	0.000	0.0349 (0.851)	(0.704)
Δ **GDP**	0.805 (0.379)	0.408 (0.67)	0.06 (0.798)	(0.575)
Δ **EP**	6.866 (0.008)	7.431 (0.024)	0.0026 (0.959)	(0.247)

Numbers in parentheses are the p values.

From the causality results, we found that some of the estimated coefficients were not statistically significant; therefore, we employ the impulse response functions in the next section.

4.5Impulse Response Functions

Impulse response functions (IRFs) explain how each variable reacts to shocks from other variables in the system. In other words, IRFs show the response of an endogenous variable over time to a specific shock based on dynamic models (Lutkepohl & Reimers, 1992). The results of the IRF estimation from one standard deviation shock of other variables in the system are presented in Figure 8 below.

Electricity consumption (EC) responded positively to its own shock (first fissure), while it responded less positively to shocks in GDP and energy prices (EP).

The response of GDP to its own shock was positive for the first eight years, then it started to react negatively in the ninth and tenth years. Unlike EC, GDP responded positively to shocks from EC for the first six years, then negatively for the remaining four years. The GDP response to shocks from EP was mostly negative over the ten-year period.

Energy prices responded positively to their own shock for the first six years, then negatively, with no response in the tenth year. The response of energy prices to both GDP and EC was similar, showing a positive reaction that started to decrease after six years to less positive.

From the IRF results, it can be seen that EC increased significantly when a shock occurred in GDP and when its own shocks occurred, while GDP decreased significantly when shocks occurred in EC or when its own shocks occurred.

The results align with the expected relationship between energy-electricity consumption and economic growth, as the IRF analysis results were consistent with the literature. Changes in electricity consumption affect economic growth, which supports the growth hypothesis, while changes in GDP positively affect electricity consumption.

These findings are in agreement with some previous literature, such as Squalli (2005), who found a negative causality from EC to GDP. However, our results do not fully support his findings regarding the effect of GDP on EC.

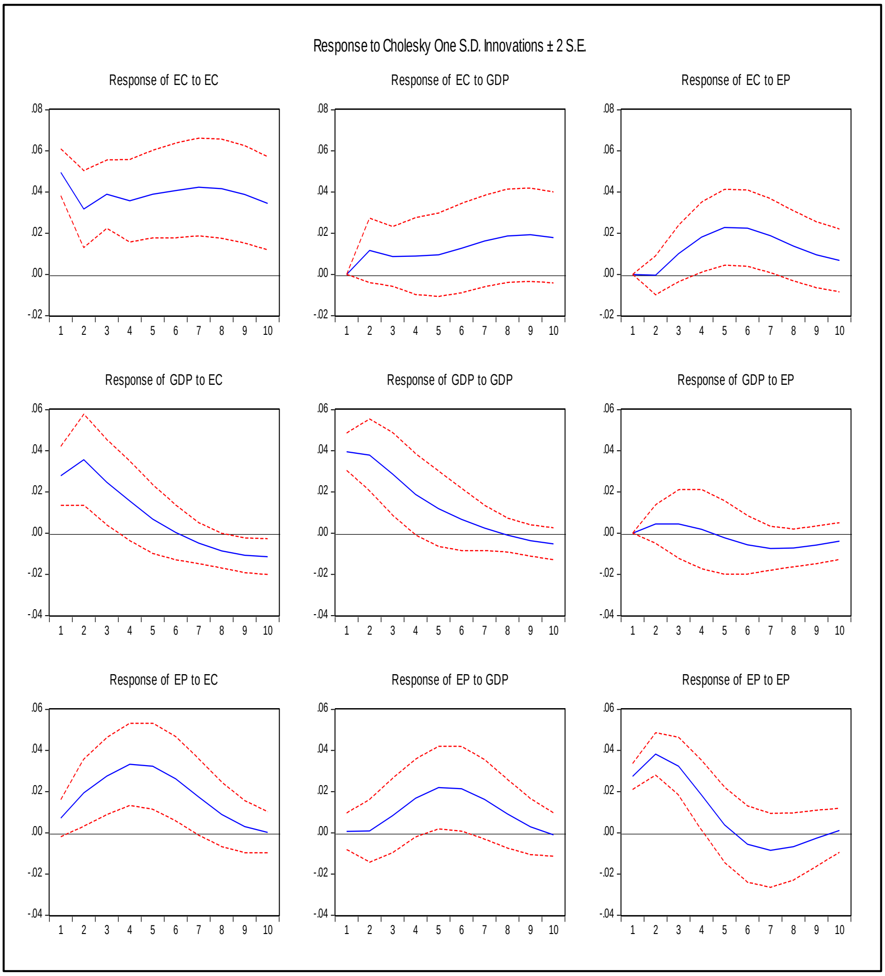

Figure 1. Impulse Response Function Estimation Results.

6. CONCLUSION & POLICY IMPLICATIONS

This study investigated the causal relationship between electricity consumption and economic growth in Saudi Arabia using annual data for the period 1970–2010 for GDP, EC, and EP. We applied unit root and cointegration tests, followed by the estimation of the VECM to obtain the short-run and long-run relationships between the variables. Diagnostic tests were then applied to the VECM equations to test for autocorrelation, serial correlation, and non-normality of residuals. Finally, impulse response functions were estimated to measure the reaction of variables to any shocks during the study period.

Empirical findings were as follows: ADF and PP unit root tests confirmed integration of order one, I(1). The Johansen procedure revealed evidence of cointegration among electricity consumption, economic growth, and energy prices, with one cointegrating vector. Granger causality tests through VECM and Wald statistics indicated a negative long-run causality from EC and EP to GDP. Diagnostic tests validated only the first two equations, where EC and GDP are the dependent variables. The impulse response functions yielded results consistent with the causality tests, further confirming the relationship dynamics.

The study found that when causality runs from energy-electricity to GDP, there is more caution needed in implementing conservative energy policies, as these policies might adversely affect GDP. Specifically, a negative causality from electricity consumption to economic growth in the long run was identified.

According to Henriques & Kander (2010), countries tend to move their production to less energy-demanding service sectors. This is applicable to Saudi Arabia, which has a developing economy. The negative causality was expected due to fluctuations in oil production in the early 1980s, influenced by political and economic events such as the Gulf War and the Iranian Revolution. These events negatively affected oil production, although electricity consumption was increasing. Our findings differ from the historical work of Kraft and Kraft (1978) except in the short run, where evidence of short-run causality from GDP to electricity consumption was found.

Policy Implications

Several policy implications arise from this study. First, Saudi Arabia should aim to decrease its electricity usage as it exhibits the characteristics of a growing economy. Interestingly, Saudi Arabia is moving towards reducing its dependence on oil revenues by increasing government spending to expand private sectors and attract foreign investments. As an oil-exporting country, Saudi Arabia benefits from cheap energy sources, leading to higher electricity consumption that contributes to GDP growth. However, this has led to a lack of focus on reducing energy usage.

The empirical evidence supports the growth hypothesis that electricity consumption stimulates economic growth. Energy policies cannot be generalized without considering other country-specific factors such as the balance of payments and national fuel industries, which complicate energy policy decisions. For Saudi Arabia, implementing energy-saving technologies or improving energy efficiency in production can help manage excessive energy demand. There is also a crucial need to overcome the lack of knowledge and technical skills affecting behavior related to the purchase and use of energy consumption equipment.

In Saudi Arabia, the artificially low domestic energy prices result from low government tariffs and high consumer subsidies. According to Alyousef & Abu-Ebid (2012) of the Conservation of Electricity and Cogeneration Regulatory Authority, government spending to support the increase in energy demand is expected to reach 15 billion SR in the next five years.

Energy policymakers in Saudi Arabia are advised to focus on increasing efficiency in electricity consumption. A general decrease in electricity consumption is required in efficient ways. Attention should also be focused on alternative renewable energy sources for electricity rather than oil and natural gas.

While this study provides valuable insights, it is not exhaustive. More work is needed to further improve the understanding of the relationship between economic growth and energy-electricity consumption. Overall, we conclude that electricity consumption is a significant factor in Saudi Arabia's growing economy. The estimated causality relationship shows that electricity consumption stimulates economic growth, and this relationship should be considered when formulating energy policies for Saudi Arabia. The inclusion of energy prices and employment in the analysis was essential for improving the estimation and providing consistent results, as expected.

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