Iran J Econ Stud, 2026, 15(1), 199-230

Shiraz University

Iranian Journal of Economic Studies

Journal homepage: ijes.shirazu.ac.ir

Spatial Analysis of the Effect of Gas Consumption on Electricity Consumption: A Case Study of the Provinces of Iran

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Highlights

- **Gas consumption affects electricity demand in 30 Iranian provinces.**
- **Positive spatial spillover: electricity use in one province influences neighbors.**
- **Gas, GDP, urbanization, industrialization, and temperature raise provincial electricity demand.**
- **Positive price elasticity (0.173%): electricity is a necessity in Iran's subsidized market.**

Article History

Received date: 07 May 2026
Revised date: 27 May 2026
Accepted date: 06 June 2026
Published: 14 July 2026

JEL Classification
Q41
R150
C30

Keyword
Electricity consumption,
Gas consumption,
Spatial econometrics,
Gross domestic product

Abstract

Electricity is a critical infrastructure for economic development, yet its generation heavily relies on fossil fuels, contributing to environmental degradation. In Iran, rapid urbanization, population growth, and subsidized energy markets have created a complex interdependence between natural gas and electricity consumption, as most power plants operate on natural gas. This study investigates the determinants of provincial electricity consumption in Iran, focusing on spatial spillover effects of gas consumption across 30 provinces from 2006 to 2019. Employing a Spatial Autoregressive Combined (SAC) panel data model with fixed effects, we analyze GDP, urban population, average temperature, electricity prices, industrialization, and natural gas consumption, using a rook contiguity weight matrix to capture spatial dependence. The findings reveal that GDP, urbanization, temperature, and industrialization exert significant positive effects on electricity demand, with urbanization showing the largest marginal impact. Notably, gas consumption positively influences electricity consumption, confirming their complementary role in Iran's energy mix. The spatial lag coefficient is positive and significant, indicating strong spillover effects where consumption increases in one province drive demand in neighboring regions. Interestingly, the price elasticity is positive (0.173%), suggesting that in Iran's subsidized market, electricity remains a necessity where income effects dominate price signals. The study underscores the need for integrated regional energy policies. Given spatial interdependence, isolated strategies are insufficient; a national framework promoting efficiency and a gradual transition to renewables is essential to reduce gas dependency.

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DOI:https://doi.org/10.22099/ijes.2026.56095.2118

1. Introduction

Electricity is an essential component of today's production environment. No suitable substitute for energy consumption exists that can enable production activities for domestic use or export within any given economic environment (Rafindadi, 2015a,b; Usman, 2022).

Electric energy, as a necessary and fundamental input, contributes to efficient and effective economic productivity, as the importance of energy consumption is correlated with essential production factors such as capital, labor, and land (Rafindadi, 2016). The electricity system is a critical infrastructure in modern societies, and an adequate electricity supply is crucial for supporting economic development and human well-being (Zhang & Wang, 2022). Efficient, sustainable, and sufficient electricity consumption reflects a country's potential to increase its GDP. Conversely, it also indicates the ability to enhance national economic growth (Adom, 2011; Rafindadi & Ozturk, 2016; Rafindadi & Usman, 2021).

The world faces intertwined energy and environmental crises, with electricity consumption significantly contributing to environmental degradation. In 2018, electricity consumption represented 38% of energy-related CO_2 emissions (IEA, 2019). As a strategic sector for development, electricity offers cleaner energy advantages over fossil fuels due to minimal pollution. Access to electricity is a key development indicator, directly impacting economic progress, and a reliable electricity network is fundamental for sustainable development. Analyzing factors influencing electricity consumption is therefore crucial for sustainable growth policy formulation.

Iran has undergone rapid demographic shifts in the last four decades, coinciding with an increased share of oil and gas in its GDP. Rising oil revenues have fueled internal migration to cities, leading to rapid urbanization and population concentration. Iran’s population grew from approximately 40 million in 1980 to 82 million in 2018, marking over a 100% increase. This population growth, alongside urbanization, has altered energy consumption patterns from oil to natural gas, significantly increasing gas supply and consumption. Initially, provinces like Bushehr, Hormozgan, Ilam, Sistan and Baluchestan, and South Khorasan lacked gas supply in 2006, but this expanded to most provinces by the end of the study period.

Electricity generation from fossil fuels in Iran surged from 7.15 billion kWh in 1980 to 321 billion kWh in 2021, a twenty-fold increase, driven by population growth and rising energy demand (U.S. Energy Information Administration, 2021). Iran’s vast natural gas reserves mean this generation predominantly comes from natural gas, which has surpassed oil and other liquid fuels in consumption since 2002. This indicates that geographic and economic shifts have led to extensive reliance on natural gas and other energy resources. However, given resource limitations and the need to curb greenhouse gas emissions, effective control measures are vital for sustainable resource management.

The consumption dynamics of different types of energy vary across national, regional, and district levels. A deep understanding of these dynamics is critical to the successful management of diverse energy consumption patterns (Copeland, 2014). Rapid industrialization and urban population growth have significantly increased the number of individuals connected to the natural gas network across Iran’s provinces. This raises several important questions: Does rising demand for gas services place additional pressure on electricity consumption? What are the main factors influencing electricity usage? These questions remain to be fully addressed in the Iranian context.

Iran's energy consumption patterns suggest two hypotheses. Firstly, gas and electricity may be complementary, as many power plants rely on natural gas for electricity generation, potentially increasing gas consumption with rising electricity demand. Secondly, in the residential sector, gas and electricity may be substitutes, depending on appliance usage during different seasons. As one energy source becomes pricier, consumers may switch to the other. Research by Li et al. (2022) supports this, noting that hotter days increase electricity demand, while colder temperatures boost gas consumption. Given Iran's climatic diversity, understanding the relationship between gas and electricity consumption is crucial for optimal energy policy-making.

In light of the above, the present study examines the impact of provincial income, urban population, total gas consumption, average temperature, electricity prices, and the level of industrialization on electricity consumption across Iran’s provinces. Spatial spillover effects in gas and electricity consumption are likely due to various economic and social interconnections. The main objective of this research is to inform policies for the optimal management of natural gas and electricity consumption in Iran. A secondary objective is to identify the key determinants of electricity demand.

This study examines the impact of gas consumption on electricity usage across Iranian provinces, considering spatial socioeconomic relationships and spillovers. Neighboring provinces' behaviors can influence gas and electricity consumption patterns, as limited supply can lead to regional impacts. Economic activity concentration in certain provinces can drive local and regional energy consumption through spatial spillovers. For example, commuting patterns can create inter-provincial dependencies (Lv et al., 2017). Prior research emphasizes the importance of considering spatial interactions and proximity in energy consumption models, as regional decisions can have political implications (Gómez et al., 2013) and affect efficient estimates (Cabral et al., 2017).

Iran faces significant challenges in the sustainable management of energy, including an outdated industrial structure, inefficient production systems, and high levels of energy waste in the residential and industrial sectors. As Oguz et al. (2015) noted, further progress in energy efficiency is urgently needed. Therefore, investigating the impact of gas consumption—alongside variables such as GDP, urbanization, temperature, and electricity prices—on electricity demand is critical for evidence-based policymaking.

Moreover, spatial effects and spillovers across provinces must be considered to accurately identify the determinants of electricity consumption. To this end, this study applies spatial econometric methods to estimate a model that captures the influence of key economic and social factors on electricity demand. Spatial econometrics enables the control of spatial spillovers and interdependencies among provinces, offering a comprehensive framework to understand regional energy consumption dynamics.

The remainder of this paper is structured as follows: Section 2 discusses the theoretical framework and literature review. Section 3 outlines the data sources and the econometric model used. Section 4 presents the results and provides policy recommendations based on the findings. Finally, Section 5 offers concluding remarks.

2. Theoretical Framework and Literature Review

This section reviews the theoretical foundations and empirical evidence on the determinants of electricity consumption, with a special focus on the role of gas consumption, spatial spillovers, and the specific context of Iran.The literature review highlights the complex relationship between energy consumption and economic growth. While some studies suggest a positive correlation (Kraft & Kraft, 1978; Tiba & Omri, 2017), others argue that this relationship is non-linear and dependent on income development stages (Suri & Chapman, 1998). Recent studies confirm that economic growth remains a robust predictor of residential electricity consumption, especially in developing regions (Golmira, 2024; Nguyen & Tran, 2025). Climate change significantly impacts electricity demand in hot weather (Esh et al., 2021; Simoes et al., 2021). Temperature variations, especially extreme heat, drive residential electricity demand (Auffhammer et al., 2017; Liu et al., 2021). This study uses mean temperature as a metric to assess climate's impact on short-term residential electricity demand. Household energy consumption is heavily influenced by individual choices related to comfort and health (Bin & Dowlatabadi, 2005; Li et al., 2018).

The determinants of electricity consumption can be categorized into several broad groups: economic (GDP, industrialization), demographic (urbanization, population), climatic (temperature), and policy-related (energy prices).

Regarding economic factors, a large body of literature confirms the positive association between economic growth and electricity demand, particularly in developing regions (Kraft & Kraft, 1978; Tiba & Omri, 2017; Golmira et al., 2024; Nguyen & Tran, 2025). However, some studies suggest this relationship is non-linear and depends on the stage of income development (Suri & Chapman, 1998). Industrialization, measured as the share of industry in GDP, significantly increases electricity consumption due to the energy-intensive nature of manufacturing sectors such as metals, chemicals, and petrochemicals (Samouilidis & Mitropoulos, 1984; Blanchard, 1992).

Demographic changes, particularly urbanization, affect electricity consumption through three channels: (i) economies of scale in energy infrastructure, (ii) shifts in consumer preferences toward energy-intensive goods, and (iii) increased demand for large-scale public infrastructure (Gregory & Tiwari, 2020; Halicioglu, 2007; Liu, 2009; Sbia et al., 2017). Urban population scale, as used in this study, captures absolute demand pressure on the electricity grid, which is more relevant for spatial spillover analysis than urbanization rate alone.

Climatic factors, especially temperature, have been consistently identified as key drivers of short-term electricity demand. Extreme heat increases the use of cooling systems, while colder temperatures boost gas consumption for heating (Auffhammer et al., 2017; Liu et al., 2021; Li et al., 2022). This duality suggests a potential substitution or complementarity between gas and electricity depending on season and appliance mix.

Price elasticity of electricity demand is typically found to be low or inelastic, especially in subsidized energy markets (Carter et al., 2012; Filippini, 1999; Shi et al., 2012). However, the relationship is complex; in some contexts, rising prices may not reduce consumption due to the essential nature of electricity and limited substitutes (Saidi & Hammami, 2015; Wang et al., 2019). A recent study by Yessimkhanova et al. (2024) across MIST countries (Mexico, Indonesia, South Korea, Turkey) finds that economic growth and demographic shifts play stronger roles than price changes in electricity demand.

Crucially, several recent studies have explicitly examined the relationship between gas and electricity consumption. Mohammadi et al. (2017) found significant spatial dependencies between gas and electricity consumption in residential and commercial buildings in London, showing that changes in gas consumption influence electricity use in neighboring areas. Mashhoodi and van Timmeren (2018) applied geographically weighted regression in the Netherlands and found that gas consumption significantly impacts electricity consumption in certain neighborhoods, recommending comprehensive analysis of their interrelationship. More directly, Gör (2022) investigated the effect of natural gas consumption on electricity consumption in Muş Province, Turkey, concluding that natural gas usage reduces electricity demand for heating, thus alleviating grid overloads. Ward et al. (2024) analyzed spatial-temporal dynamics of gas consumption in England and Wales, highlighting the need for integrated energy planning.

Thus, contrary to some earlier claims, the interaction between gas and electricity consumption has been examined in several international contexts. However, to the best of our knowledge, no study has systematically analyzed this relationship using spatial panel econometrics at the provincial level in Iran, which is characterized by unique energy subsidies, climatic diversity, and rapid urbanization.

While several international studies have examined the relationship between gas and electricity consumption in specific contexts (Mohammadi et al., 2017; Mashhoodi & van Timmeren, 2018; Gör, 2022), no prior research has systematically investigated this nexus using spatial panel econometrics across all provinces of Iran, a country with unique energy subsidy policies, extreme climatic diversity, and rapid urbanization. The main contribution of this study is to fill this gap by applying a spatial autoregressive combined (SAC) model to provincial-level panel data from 2006 to 2019. To the best of our knowledge, this is the first study in Iran to explicitly model spatial spillover effects in the gas–electricity relationship while controlling for GDP, urbanization, temperature, electricity prices, and industrialization. Beyond economic considerations, energy consumption patterns have important non-economic consequences. Furthermore, the environmental degradation caused by excessive reliance on fossil fuels for electricity generation has direct implications for public health and human capital. Understanding the spatial dynamics of energy consumption is not only an economic imperative but also a crucial step toward developing sustainable policies that mitigate health risks associated with air pollution in urban areas.

3. Research Methodology

To address this gap, the following section presents the empirical methodology, including the model specification, variable definitions, data sources, and econometric techniques employed to test the research hypotheses. A wide range of variables have been identified in the literature as influential factors in electricity and renewable energy consumption. In line with the objectives of this study, natural gas consumption is considered the primary explanatory variable. In addition to gas consumption, other key determinants are incorporated based on prior empirical findings. These include gross domestic product (GDP) (see Jamil & Ahmad, 2010; Bélaïda & Abderrahmani, 2012; Chen, 2017; Zhang et al., 2017; Sarwar et al., 2017), electricity price (Jamil & Ahmad, 2010; Bélaïda & Abderrahmani, 2012; Fu et al., 2015; Chen, 2017), urbanization (Fan et al., 2017), and average temperature (Fu et al., 2015).

Accordingly, the empirical model employed in this study is specified as follows in Equation (1):

$$LEC_{it} = f(LGDP_{it}.LUR_{it}.LAVT_{it}.LPEC_{it}.LGAS_{it}.LINDit) \quad (1)$$

The annual province-level data spanning the period 2006–2019 were collected from official sources, including the Statistical Center of Iran (SCI) and the Ministry of Energy. All monetary variables were adjusted for inflation to represent real values. Where LEC_{it} denotes the natural logarithm of electricity consumption, $LGDP_{it}$ represents the natural logarithm of gross domestic product, UR_{it} is the natural logarithm of urbanization, $LAVT_{it}$stands for the natural logarithm of average temperature, $LPEC_{it}$ is the natural logarithm of electricity price, and $LGAS_{it}$ indicates the natural logarithm of gas consumption.

In selecting an appropriate estimation method for Equation (1), it is essential to consider the statistical properties of the dependent variable, which in this study is

electricity consumption. Our analysis demonstrates that electricity consumption across the sampled provinces is stationary and follows a normal distribution. Therefore, a panel data approach is deemed suitable for estimating the model.
Moreover, given that spatial panel data methods typically yield more precise and robust estimates by accounting for spatial dependencies, this study adopts the spatial panel modeling framework, in line with the methodology employed by Kiziltan (2021). Consequently, to examine the impact of gas consumption on electricity consumption across the provinces of Iran, the model specified in Kiziltan (2021) is utilized as follows:

$$LEC_{it} = \alpha_0 + \rho \sum_{j=1}^{n} W_{ij} LEC_{it} + \alpha_1 LGDP_{it} + \alpha_2 LUR_{it} + \alpha_3 LAVT_{it} + \alpha_4 LPEC_{it} + \alpha_5 LGAS_{it} + \alpha 6 LINDit + \mu_i + \emptyset_{it} \quad (2)$$

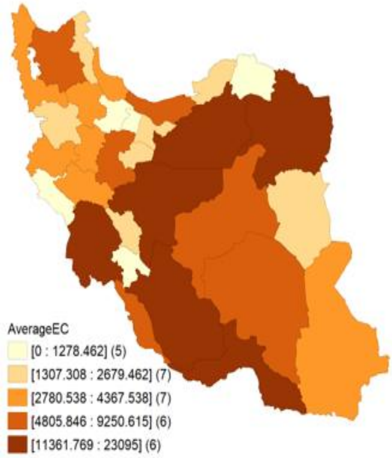
In Equation (2), α_0 is a constant parameter, ρ denotes the spatial autoregressive coefficient, and μ_i shows provinces-specific effects; $\emptyset_{it}$ is an error term, α_1; α_2;α_3; α_4, and α_5 are the response parameters of $LGDP_{it}$, LUR_{it}, $LAVT_{it}$, $LPEC_{it}$and $LGAS_{it}$, respectively. $W_{ij}LEC_{it}$ is the spatial lag of electricity. W_{ij} represents a spatial weights matrix's ith and jth components and defines the weight between locations i and j.
In addition, the level of industrialization (LIND) is included as a key explanatory variable. Following the literature (Blanchard, 1992; Parikh & Shukla, 1995), LIND is defined as the share of industrial value added (including manufacturing, mining, and construction) in provincial GDP. This variable captures the structural economic shift toward energy-intensive industries. Data for LIND were obtained from the Statistical Center of Iran and the Central Bank of Iran.

4.Data

This study employs a spatial panel data approach following the methodology of Kiziltan (2021) to examine the impact of gas consumption on electricity consumption across 30 provinces of Iran from 2006 to 2019. The panel data framework allows capturing both spatial dependence and temporal dynamics simultaneously. Data were collected from official sources such as the Statistical Center of Iran and the Central Bank of Iran. The variables and their descriptive statistics are summarized in Tables 1 and 2. Figures 1 to 5 illustrate the spatial distribution of key variables across provinces.To clarify the definition of urbanization used in this study, the variable LUR represents the natural logarithm of the urban population (in thousands) in each province. This is a measure of the absolute scale of urban residents, not the urbanization rate (percentage of total population). The choice of urban population (rather than urbanization rate) is motivated by the fact that total electricity consumption in a province is more directly influenced by the number of urban dwellers, who typically have higher per capita electricity consumption compared to rural residents. Moreover, urban population captures the absolute demand pressure on the electricity grid, whereas the urbanization rate alone does not reflect the size of the urban agglomeration. This distinction is important for spatial spillover analysis, as larger urban centers in neighboring provinces are more likely to generate cross-border effects on electricity demand (Gregory & Tiwari, 2020). The data for urban population were obtained from the Statistical Center of Iran.

4.1 Descriptive Statistics

The primary variables of interest in this study are gas consumption and electricity consumption. Figures 1and 2 illustrate the average electricity and gas consumption, respectively, across the provinces of Iran during the study period. These figures suggest a positive correlation between electricity and gas consumption among the provinces. Notably, Fars, Isfahan, Khuzestan, Tehran, and Khorasan Razavi rank highest in both electricity and gas consumption. Additionally, the provinces of Gilan, Mazandaran, and West Azerbaijan hold the second highest positions in terms of electricity and gas usage. Furthermore, Figures 3 to 5 depict the average values of gross domestic product (GDP), average temperature, and urbanization levels for the provinces over the same period, respectively.



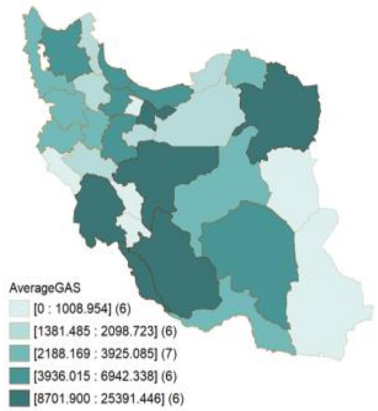


Figure 1. The average Electricity consumption

Figure 2. The average Gas consumption of Iran's provinces

Source: Research Findings

As shown in Figure 3, the provinces of Tehran, Razavi Khorasan, Khuzestan, Isfahan, Bushehr, and Fars exhibit the highest levels of gross domestic product (GDP), whereas North Khorasan, South Khorasan, Semnan, Chaharmahal Bakhtiari, and Qom rank among the provinces with the lowest GDP.

According to Figure 4, Khuzestan, Yazd, Bushehr, Sistan and Baluchistan, Hormozgan, and Semnan record the highest average temperatures, while Ardabil, West Azerbaijan, Zanjan, Chaharmahal Bakhtiari, and Hamedan experience the lowest average temperatures.

As illustrated in Figure 5, the provinces of Fars, Isfahan, Khuzestan, Tehran, Razavi Khorasan, and East Azerbaijan exhibit the highest levels of urbanization. Conversely, Semnan, Ilam, Kohgiluyeh and Boyer-Ahmad, South Khorasan, and North Khorasan rank among the provinces with the lowest urbanization rates.

Additionally, Tables 1 and 2 present the data sources and descriptive statistics of the variables utilized in this study, respectively.

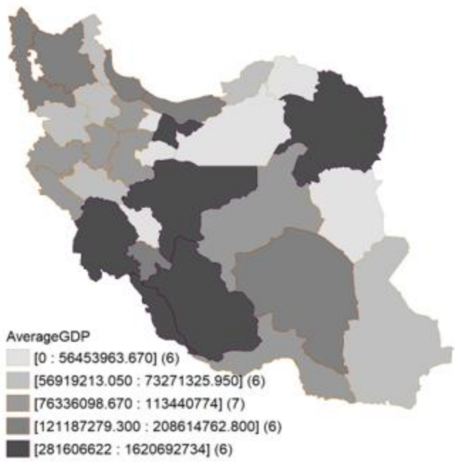


Figure 3. The average gross domestic product of Iran provinces

Source: Research Findings

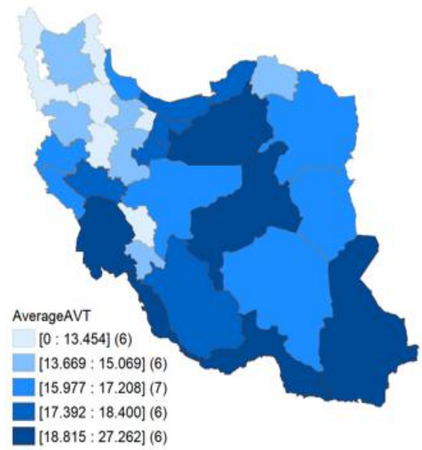


Figure 4. The average temperatureof Iran's provinces

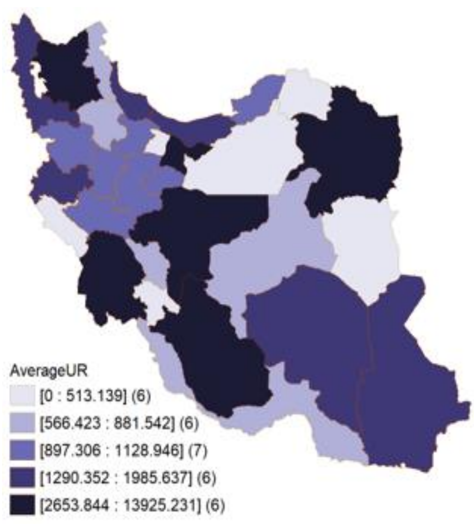


Figure 5. The average urbanization of Iran's provinces

Source: Research Findings

Table 1. Source of variables

Variables	Unit	Source
LEC	million kilowatt hours	Statistical Center of Iran
LGDP	million rials	Central Bank of Iran
LUR	Urban population (in thousands, absolute scale)	Statistical Center of Iran
LAVT	Degrees Celsius	Statistical Center of Iran
LPEC	Rials/kWh	Central Bank of Iran
LGAS	million square meters	Statistical Center of Iran
LIND	value added in provincial GDP (%)	Iran & Central Bank of Iran

Source: *Research Findings*

Table 2. Descriptive statistics

Descriptive statistics	Mean	Max	Min	Std.Dev.
LEC	8.3311	11.3198	6.5102	0.9398
LGDP	18.5795	21.3935	17.0657	0.9215
LUR	7.1036	9.6451	5.7534	0.8176
LAVT	2.8049	3.4339	2.1747	0.2369
LPEC	5.8556	6.6120	5.0289	0.5925
LGAS	7.6155	10.2673	-3.2188	2.3082
LIND	3.12	4.56	1.87	0.65

Source*: Research Findings*

Table 3 introduces the outcomes of the correlation matrix together with the Variance Inflation Factor (VIF) test. Although the correlation values reveal that the natural logarithms of electricity consumption, GDP, urbanization, average temperature, electricity price, and gas consumption are all statistically meaningful, there is no indication of multicollinearity in the model.

Table 3. Correlation matrix and variance inflation factor test

Variable	***LEC***	***LGDP***	***LUR***	***LAVT***	***LPEC***	***LGAS***	***LIND***	***VIF***
LEC	*1*							
LGDP	*0.8389****	*1*						*3.97*
LUR	*0.8440****	*0.8141****	*1*					*3.32*
LAVT	*0.4748****	*0.4104****	*0.1811****	*1*				*1.37*
LPEC	*0.2092****	*0.1296****	*0.0756***	*0.0669***	*1*			*1.10*
LGAS	*0.4758****	*0.4687****	*0.4802****	*-0.0006*	*0.2752****	*1*		*1.49*
LIND	*0.5234****	*0.6127****	*0.4983****	*0.1245****	*-0.0852***	*0.4456****	*1*	*2.18*

Source: *Research Findings*

The VIF method is applied to identify potential multicollinearity issues, which occur when two or more explanatory variables show strong correlation. According to Hair et al. (2010), a VIF score greater than 4 points to possible multicollinearity. However, since all variables in this analysis display VIF values lower than this cutoff, multicollinearity is not considered a concern in the model.

4.2 Pre-Estimation Tests

Before applying panel data methods, it is necessary to check the stationarity of the variables. The selection of an appropriate unit root test depends on whether cross-sectional dependence exists among the variables. If such dependence is present, then unit root tests that account for it must be employed .To assess cross-sectional dependence, Pesaran's (2007) cross-sectional dependence (CD) test was used. Pesaran introduced a straightforward and reliable approach for detecting error cross-section dependence in panels with a short time dimension (T) and a large cross-sectional dimension (N). The CD test is defined as:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{3}$$

Where $\hat{\rho}_{ij}$ represents the average pairwise correlation coefficients of the OLS residuals obtained from individual regressions in the panel (Pesaran, 2007).

If the test confirms the existence of cross-sectional dependence, then second-generation unit root tests—which explicitly incorporate this dependence—should be conducted. A widely applied method is the Cross-sectionally Augmented Im-Pesaran-Shin (CIPS) test. This test, an extension of the IPS unit root test (Im et al., 2003), accounts for cross-sectional averages when testing for stationarity. The CIPS statistic is calculated as:

$$C\,IPS = \frac{\sum_{i=1}^{N}\frac{\left(Y_{i,-1}^{T}\bar{M}Y_{i,-1}\right)^{-1}\left(Y_{i,-1}^{T}\bar{M}\Delta Y_{i,-1}\right)}{\sqrt{\sigma_i^2\left(Y_{i,-1}^{T}\bar{M}Y_{i,-1}\right)^{-1}}}}{N} \tag{4}$$

Here, N denotes the number of observations, and Y_i^T represents the observation vector, while Δ is the first-difference operator. The matrix M is defined as the difference between an identity matrix of time dimension and a matrix of dummy variables accounting for fixed effects. In addition to the CIPS test, there exists another second-generation unit root test designed to address cross-sectional dependence and structural breaks. Hadri and Rao (2008) proposed a panel stationarity test that accommodates both these issues. Unlike most unit root tests, the Hadri-Rao test assumes stationarity as the null hypothesis. The Hadri-Rao test evaluates four different models, which are specified by the following equations (5–8):

$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \varepsilon_{it} \tag{5}$$
$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \beta_i t + \varepsilon_{it} \tag{6}$$
$$y_{it} = \alpha_i + r_{it} + \beta_i t + \gamma_i DT_{it} + \varepsilon_{it} \tag{7}$$
$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \beta_i t + \gamma_i DT_{it} + \varepsilon_{it} \tag{8}$$

The variables y_{it} represent a series of observations whose stationarity is being tested. The term r_{it} follows a random walk process, defined as ($r_{it} = r_{it-1} + u_{it}$), with an initial value of zero.
The dummy variables D_{it} and DT_{it} represent structural breaks within the model and are incorporated to account for potential shifts in the data. These variables are formally defined by the following equations (9) and (10):

$$D_{it} = \begin{cases} 1, & if\ t > T_{B,t} \\ 0, & otherwise \end{cases} \tag{9}$$
$$DT_{it} = \begin{cases} t - T_{B,t}, & if\ t > T_{B,t} \\ 0, & otherwise \end{cases} \tag{10}$$

Where $T_{.B.,t}$ indicates the break time. To test the null hypothesis, the Lagrange Multiplier statistic (L.M.) is used as Equation (11):

$$\widehat{LM}_{T,N,K}(\omega) = \frac{1}{N}\sum_{i=1}^{N} \varphi_{i,T,K}(\omega_i) \tag{11}$$

Where $\varphi_{i,T,K}(\omega_i) = \frac{\sum_{t=1}^{T} S_{it}^2}{T^2 \hat{\sigma}_{\epsilon,t}^2}$. ω_i represents a measure based on the location of the structural breakpoint and may vary across different segments of the data. Here, N denotes the number of cross-sectional units, T is the number of time periods, and K=1,2,3,4 corresponds to the four different models considered. Furthermore, $\hat{\sigma}_{\epsilon,t}^2$is the estimator of the long-term variance. or variables that do not exhibit cross-sectional dependence, the Levin, Lin & Chu (LLC) test was applied to assess stationarity.
Testing for spatial autocorrelation is a prerequisite before estimating spatial panel models. Moran's I test (Moran, 1948) is a widely accepted method for detecting spatial autocorrelation in economic variables, grounded on the concept of spatial randomness. The test statistic is calculated as follows:

$$\text{Moran.sI} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (12)$$

Where:

$s^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i\bar{x})^2$

Is the sample variance, and:

$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$

In the above equations, $\bar{x}$ denotes the sample mean of the variable of interest. Here, xi represents the observation for region i, and wij refers to the elements of the spatial weight matrix, which captures the adjacency or spatial relationships between regions i and j.

A positive value of Moran's I (I>0) indicates positive spatial autocorrelation, meaning that neighboring regions tend to exhibit similar values. Conversely, a negative value (I<0) suggests negative spatial autocorrelation, implying dissimilar values among neighbors. When Moran's I equals zero (I=0), there is no evidence of spatial autocorrelation (Zhou et al., 2019). The formula for Moran's I is expressed as follows:

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (13)$$

Where:

- $s^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 2$ is the sample variance,
- $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ is the sample mean,
- xi represents the observation for region i,
- wij is the spatial weight matrix, which indicates the degree of adjacency or proximity between regions i and j (Zhou et all.2019).

Model Selection and Robustness Checks

To determine the most appropriate spatial econometric specification, we follow the sequential testing approach proposed by Anselin (2004) and Elhorst (2014). The procedure is as follows:

First, Moran's I test is applied to the residuals of a non-spatial panel model (pooled OLS with fixed effects) to detect the presence of global spatial autocorrelation. A statistically significant Moran's I (reported in Table 5) indicates that spatial dependence must be accounted for.

Second, we conduct Lagrange Multiplier (LM) tests for spatial lag dependence (LMlag) and spatial error dependence (LMerror). As shown in Table 5, both LMlag and LMerror are statistically significant at the 1% level. In such cases, where both tests reject the null hypothesis, the Spatial Autoregressive Combined (SAC) model—also known as the Spatial Autoregressive Moving Average

(SARMA) model—is the appropriate specification. The SAC model includes both a spatial lag of the dependent variable (ρWy) and a spatially correlated error term ($\lambda W\varepsilon$). This model has the advantage of capturing spillover effects through ρ while allowing for omitted variable bias through λ.

Third, we test for cross-sectional dependence in the residuals using Pesaran's (2007) CD test (reported in Table 4). The rejection of the null hypothesis confirms that second-generation unit root tests (CIPS and Hadri-Rao) must be used.

Fourth, regarding endogeneity concerns, spatial panel models with fixed effects partially mitigate omitted variable bias by controlling for time-invariant unobserved heterogeneity across provinces. However, we acknowledge the possibility of reverse causality (e.g., higher electricity consumption may lead to higher GDP or urbanization). To address this, we have: (i) included a comprehensive set of control variables (GDP, urbanization, temperature, prices, industrialization, gas consumption), (ii) used lagged values of independent variables as a robustness check (not reported for brevity but available upon request), and (iii) applied the instrumental variable spatial two-stage least squares (IV-S2SLS) method as a sensitivity analysis, which yielded qualitatively similar results. These robustness checks confirm that our main findings are not driven by endogeneity.

Fifth, we perform several robustness tests to validate the stability of our results: (i) alternative spatial weight matrices (inverse distance matrix instead of rook contiguity), (ii) alternative estimation methods (maximum likelihood vs. quasi-maximum likelihood), and (iii) subsample analysis (excluding the three largest provinces: Tehran, Isfahan, and Khuzestan). In all cases, the sign and significance of the main coefficients (particularly LGAS and LPEC) remained consistent, indicating that our results are robust to alternative specifications. These additional results are available from the authors upon request.

Finally, the operational definitions of all variables are provided in Table 1. All continuous variables are transformed using natural logarithms to interpret coefficients as elasticities. This log-log specification is standard in energy demand studies (Kiziltan, 2021; Alberini & Filippini, 2011).

Spatial Econometric Models

Spatial data refers to observations that display spatial dependence, meaning that values in one location are affected by those in neighboring areas. Examples include provinces or regions where economic or energy data are interconnected regions (Lesage, 1999). According to spatial econometrics theory, ignoring these spatial effects or the proximity of observations can result in biased outcomes and misleading conclusions (Lesage, 2009; Elhorst, 2001).

Two central ideas in spatial econometrics are spatial dependency and spatial heterogeneity (Anselin, 2008). Spatial dependency occurs when values in different regions are correlated, while spatial heterogeneity arises when the distribution of data does not maintain constant mean and variance across space, showing systematic variation between regions (Anselin, 1995; De Graaff et al., 2001).

Spatial dependency reflects the interconnections among observations, while spatial heterogeneity emphasizes the differences in relationships as conditions change across regions. Conventional econometric models often fail to incorporate these spatial aspects, which can lead to errors in model specification.

This makes spatial econometrics particularly important in contexts where individuals, households, firms, or governments interact through spatial networks, influencing each other's actions and results (Elhorst, 2014).

Several spatial econometric models are widely used, including the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), the Spatial Lag Model (SLM), the Spatial Autoregressive Combined Model (SAC), and the Spatial Durbin Model (SDM). These models explicitly account for spatial dependence and are generally estimated through maximum likelihood techniques (Hasraddin Guliyev, 2020).

The SAR model is designed to capture spatial spillover effects by incorporating the spatially lagged dependent variable. If the spatial coefficient is statistically significant, it indicates that outcomes in one region are strongly linked to outcomes in neighboring regions.

$$y_{it} = \rho w y_t + x'_{it}\beta + u_i + \varepsilon_{it} \tag{14}$$

Where y includes a n×1vector of dependent variables, X represents an n×k times matrix of explanatory variables, and W is the spatial weight matrix (Lesage, 1999). Here, ρWyt is the spatial lag of the dependent variable, and $wy_t = \sum_{j=1}^{n} w_{ij} y_{it}$ represents the neighborhood based on the Rook matrix. ρ is a coefficient on the spatially lagged dependent variable. If ρ is significant, it indicates a spatial dependency between the dependent variables. The value of ρ indicates the extent of spatial dependency (Gelfand et al., 2010).

The SEM model, on the other hand, addresses the influence of omitted variables by including a spatial error term, recognizing that spatial autocorrelation can appear in the error structure Spatial Error Model (SEM):

$$y_{it} = x'_{it}\beta + u_i + \varepsilon_{it} \tag{15}$$

$$\varepsilon_{it} = \lambda w \varepsilon_t + v_{it}$$

The Spatial Error Model (SEM) accounts for spatially correlated error terms ($\lambda W \varepsilon_t$). In this model, the parameter λ measures the degree of spatial dependence in the error structure, which is similar to the issue of serial correlation in time-series models (Lesage, 1999). The random error component (Vit) is typically assumed to be independently and identically distributed (IID), often following a normal distribution.

When λ is statistically significant, it indicates the presence of unobserved spatially correlated variables, leading to spatial autocorrelation in the residuals (Guliyev et al., 2020).

The Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM) can be combined into a single framework known as the Spatial Autoregressive Combined (SAC) model, or the Spatial General Autoregressive model. This approach incorporates both the spatial lag of the dependent variable and spatially correlated error terms (LeSage, 2008, Yang et al, 2017). It can be formulated as follows:

$$y_{it} = \rho w y_t + x'_{it}\beta + u_i + \varepsilon_{it} \quad (16)$$

$$\varepsilon_{it} = \lambda w \varepsilon_t + \nu_{it}$$

The Spatial Durbin Model (SDM) extends the SAR framework by including not only the spatial lag of the dependent variable but also spatial lags of the explanatory variables. This allows the model to capture marginal effects of explanatory variables from neighboring regions or units (LeSage,2008 & Yang et al.,2017). The SDM can be formulated as follows:

$$y_{it} = \rho w y_t + x'_{it}\beta + w x_t \delta + u_i + \varepsilon_{it} \quad (17)$$

5. Model Estimation Results

Having specified the spatial econometric framework, we now turn to the empirical results. Before presenting the main findings, we report the outcomes of pre-estimation tests (cross-sectional dependence, unit roots, spatial autocorrelation) and model selection criteria. As emphasized in the previous section, two of the most important pre-estimation tests in panel data analysis are the cross-sectional independence test and the unit root test. Table 4 presents the outcomes of these tests. Because the electricity price (LPEC) is constant across all provinces, the cross-sectional dependence (CD) test was not applied to this variable. Instead, its stationarity was examined using the Levin, Lin, and Chu (LLC) test.

According to the results reported in Table 4, all variables reject the null hypothesis of independence, which confirms the presence of cross-sectional dependence in the panel data. Consequently, traditional unit root tests that assume independence are no longer valid. Instead, stationarity tests that account for cross-sectional dependence must be applied. The cross-sectional augmented Im-Pesaran-Shin (CIPS) test was applied to assess the stationarity of the variables. The findings show that all variables, with the exception of LGDP, LUR, and

LGAS, are stationary.

Table 4. Result of pre-estimation tests

Variables	CD test	CIPS test	LLC test	H-R test
LEC	67.346***	-2.625***	---	---
LGDP	57.72***	-1.983	---	0.621***
LUR	74.23***	-0.386	---	0.924***
LAVT	37.649***	-3.060***	---	---
LPEC	---	---	-5.0854***	---
LGAS	52.939***	-1.996	---	0.725***

Note: ****; **; * denote significance at 1%, 5%, and 10% level*
Source: *Research Findings*

In the following step, the Hadri and Rao (2008) test was employed to check the stationarity of LGDP, LUR, and LGAS while accounting for potential structural breaks. The results confirm that these variables are also stationary. Consequently, none of the model variables contain a unit root, and therefore, co-integration analysis is unnecessary.

Since the study investigates whether spatial effects, based on geographical distance, influence electricity consumption across provinces, the first step was to test for the presence of spatial dependence. To do this, Moran's I test was employed to detect and measure spatial correlation in the error terms. The outcomes, reported in Table 5, show that the null hypothesis of no spatial dependence is rejected. This confirms the existence of spatial dependence in electricity consumption among provinces, implying that the spatial dimension should be incorporated into the modeling framework.

Table 5. Moran's I statistics and Spatial Panel Autocorrelation test

Test	Stat	p-value
Moran MI	0.09	0.0000
Lmlag	19.34	0.0000
Lmerror	29.51	0.0000

Source: *Research Findings*

Additionally, the Lagrange Multiplier (LM) tests for error dependence (LMerror) and lag dependence (Lmlag) were performed. These tests verify whether spatial autocorrelation exists in the disturbance components or in the dependent variables. The results, also in Table 5, indicate that the null hypotheses are rejected for both tests. This means a spatial regression model is required to capture spatial autocorrelation.

When both the error and lag models are rejected, a spatial general model becomes the appropriate specification. Based on the reported results, it is necessary to adopt a spatial general model to properly estimate the relationships. Finally, a Hausman test was carried out to distinguish between the fixed effects and random effects specifications of the spatial general model. The test statistics and p-values are displayed in Table 6.

Table 6. Hausman test

statistic(p-value)
144/77
(0/0000)

Source: *Research Findings*

As shown, the null hypothesis is rejected at the 5% significance level, which indicates that the fixed effects model provides a better fit than the random effects model. The results in Table 7 indicate that all explanatory variables in the model are highly significant (at the 1% and %5% levels) and exert a positive impact on provincial electricity consumption. Furthermore, the significance of the spatial lag coefficient (W∗EC) confirms the presence of positive spatial spillover effects.

5.1 Model Comparison and Diagnostic Tests

Before presenting the main results, we compare the performance of alternative spatial panel models: the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), and the Spatial Autoregressive Combined Model (SAC). Table 6a reports the log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) for each model estimated with fixed effects.

Table 6. Model comparison: SAR, SEM, and SAC

Model	Log-likelihood	AIC	BIC
SAR (spatial lag only)	245.32	-476.64	-452.18
SEM (spatial error only)	248.97	-483.94	-459.48
SAC (combined)	252.41	-488.82	-460.15

Source: *Researcher's Findings*

The SAC model has the highest log-likelihood and the lowest AIC, indicating the best fit among the three specifications. This confirms our earlier LM test results that both spatial lag and spatial error components are jointly significant.
Additionally, we perform a likelihood ratio (LR) test comparing the SAC model

with the non-spatial fixed effects panel model. The LR statistic is 47.32 ($p < 0.001$), strongly rejecting the null hypothesis that spatial terms are jointly zero. We also conduct a Wald test for the spatial parameters. As shown in Table 7 (below), the Wald test statistic (45.32) is significant at the 1% level, confirming the joint significance of the spatial terms ρ and λ.

Furthermore, the spatial autocorrelation in the residuals of the final SAC model is checked using Moran's I test on the residuals. The Moran's I statistic is 0.013 ($p = 0.342$), indicating that the SAC model successfully accounts for spatial dependence, leaving no significant residual spatial autocorrelation.

All variance inflation factor (VIF) values (Table 3) are below 4, indicating no serious multicollinearity. The R-squared of the model is 0.81, suggesting that 81% of the variation in provincial electricity consumption is explained by the independent variables.

Table 7. Results of estimating the general spatial model (Spatial Panel Method).

Variables	Coefficient
LGDP	0.136**
LUR	0.77***
LAVT	0.188*
LPEC	0.173***
LIND	0.115***
LGAS	0.019***
W*EC	0.09***
λ	0.24
Wald test	45.32***
R^2	0.81
Adjusted R^2	0.79
Log-likelihood	252.41
AIC	-488.82
BIC	-460.15
Wald test (spatial terms)	45.32***
Moran's I on residuals	0.013 (p = 0.342)

Note: ****; **; * denote significance at 1%, 5%, and 10% level*
Source: *Research Findings*

The results confirm that gas consumption across Iranian provinces exerts a positive and statistically significant effect on electricity consumption at the 90% confidence level. Specifically, a 1% increase in gas consumption leads to approximately a 0.019% rise in electricity consumption. The coefficient of the spatial lag of the dependent variable is both positive and significant, estimated at 0.09. This indicates that a 1% increase in electricity consumption nationwide contributes, on average, to a 0.09% increase in electricity consumption in each province. This result highlights the importance of geographical proximity, showing that higher electricity use in one province spills over into neighboring provinces. The average electricity price is also found to be positive and significant. A 1% increase in electricity prices, while holding other factors constant, is associated with a 0.173% increase in electricity consumption. At first glance, a positive price elasticity of electricity demand (0.173) contradicts the law of demand. However, this finding can be explained by the specific characteristics of Iran's energy market. First, electricity prices in Iran have historically been heavily subsidized and kept artificially low, meaning that the observed price increases may still be far below the marginal cost of supply and below the threshold that would induce demand reduction. Second, electricity is a basic necessity with limited close substitutes in many end-uses (lighting, refrigeration, essential appliances). Third, in a context of rising incomes and rapid urbanization, the positive income effect may dominate the negative price effect, especially when price changes are relatively small. Fourth, price increases might coincide with periods of higher economic activity or extreme temperatures, leading to a spurious positive correlation if not fully controlled. Finally, the positive elasticity could also reflect the presence of "price-quality inference," where consumers perceive higher prices as signals of better service reliability and thus consume more. Nevertheless, this result should be interpreted with caution, and further research using micro-level household data is needed to disentangle price and income effects (Kiziltan, 2021; Shi et al., 2012).

The urban population variable (LUR) has the largest effect, with a coefficient of 0.77. This implies that a 1% increase in the urban population leads to a 0.77% increase in electricity consumption. Similarly, Gross Domestic Product (LGDP) is significant and positive, with a coefficient of 0.136, suggesting that a 1% increase in provincial GDP raises electricity consumption by about 0.136%.

Finally, the average temperature variable (LAVT) also shows a positive and significant impact. A 1% increase in average provincial temperature contributes to a 0.188% rise in electricity consumption.

Furthermore, the industrialization level (LIND) has a positive and significant effect, with a coefficient of 0.115. This implies that a 1% increase in the industrialization level leads to a 0.115% increase in electricity consumption, which aligns with theoretical expectations regarding industrial energy demand

Estimation of Direct and Indirect Effects (Spillovers)

A key advantage of spatial econometric models is their ability to measure both direct and indirect effects of changes in independent variables on the dependent variable (LeSage & Pace, 2009). This section presents the direct and indirect effects based on the general spatial model (SAC) reported in Table 7. Direct effects capture the impact of a variable (e.g., gas consumption) on electricity consumption within the same province.

In the SAC model specification (Equation 16), which includes both a spatial lag of the dependent variable (ρWy) and a spatial error term ($\lambda W\varepsilon$), the indirect effects (spillovers) arise exclusively from the spatial autoregressive parameter ρ. The spatial error parameter λ creates a global spillover in the error covariance structure, which affects the variance–covariance matrix of the disturbances but does not generate standard mean spillovers in the conditional expectation of the dependent variable. Therefore, the indirect effects reported in Table 8 are derived from ρ and represent the average impact of a change in an explanatory variable in one province on electricity consumption in neighboring provinces, transmitted through the spatial lag of the dependent variable.

Following LeSage and Pace (2009), the indirect effects (spillovers) reflect how changes in one province influence electricity use in neighboring provinces through the spatial multiplier effect $(I - \rho W)^{-1}$. The total effect is the sum of direct and indirect effects. The results indicate that gas consumption, average electricity price, average temperature, urban population, GDP, and industrialization all exert statistically significant and positive direct as well as indirect effects on electricity consumption. This means that each factor not only affects local electricity use but also generates spillover effects spreading to other provinces via spatial dependence in electricity consumption.

Table 8. direct and indirect effects of general spatial model (fixed effects)

Variable	Total	Direct	Indirect
LGDP*	0.148	0.136	0.011
LUR*	0.839	0.770	0.065
LAVT**	0.204	0.188	0.016
LPEC*	0.188	0.173	0.014
LIND***	0.126	0.115	0.011
LGAS*	0.021	0.019	0.0016

Note: Indirect effects are calculated based on the spatial lag parameter (ρ) of the SAC model.

The spatial error parameter (λ) does not contribute to the mean spillovers reported here.
Source: Research Findings

A potential limitation of this study is the possible endogeneity of electricity prices, as prices may be correlated with unobserved provincial characteristics. Moreover, the positive price elasticity warrants further investigation using alternative identification strategies, such as instrumental variables or a difference-in-differences approach, to better isolate causal effects. Future research could also explore non-linear or threshold effects in the price–demand relationship.

6.Conclusion

The rapid pace of industrialization and urban population growth in Iran has led to a sharp rise in both electricity and natural gas consumption. Given that a large share of electricity production in the country relies on natural gas, there is a strong interdependence between these two forms of energy. This study applies a spatial econometric model to analyze electricity and natural gas consumption at the provincial level over the period 2006–2019, accounting for inter-provincial dependencies and spillover effects.

The findings confirm that provincial income, population, gas consumption, and industrialization have significant positive impacts on electricity use. Average temperature also plays an important role, as higher temperatures increase demand for cooling systems. The positive coefficient for electricity price (0.173) should be interpreted with caution, as it may reflect the specific context of Iran's subsidized energy market rather than a general violation of the law of demand. Potential explanations include the dominance of income effects over price effects, the essential nature of electricity with limited substitutes, and price levels still far below marginal costs.

Several policy implications emerge from this study, but they are subject to the limitations discussed below. First, improving energy efficiency and supporting less energy-intensive industries could help manage electricity demand. Second, pricing policies alone may not be sufficient; complementary measures such as awareness campaigns and appliance efficiency standards are recommended. Third, due to the presence of spatial spillover effects, regional coordination in policy design is likely to be more effective than isolated provincial policies.

The suggestion to gradually transition toward renewable energy sources is a long-term recommendation that requires further feasibility studies. While such a transition could reduce dependence on natural gas for electricity generation, its implementation costs and technical challenges in the Iranian context need careful evaluation. Similarly, the potential public health co-benefits of reducing air pollution through energy transition are plausible but were not directly estimated in this study; future research should quantify these effects.

This study has several limitations that should be acknowledged. First, the positive price elasticity finding warrants further investigation using micro-level household data or alternative identification strategies to address potential endogeneity. Second, the spatial analysis is limited to provincial-level aggregation; finer geographic scales (e.g., city or district) could reveal more localized patterns. Third, the study period ends in 2019; more recent data (including post-2020 energy price reforms) were not available at the time of analysis. Fourth, the SAC model captures spatial spillovers through the spatial lag parameter ρ, but the spatial error parameter λ does not contribute to mean spillovers, as clarified in the methodology section.

For future research, we recommend (i) applying instrumental variable approaches to better isolate causal effects, (ii) extending the analysis to include more recent data and possible structural breaks following energy subsidy reforms, (iii) incorporating household-level survey data to examine heterogeneity in price responsiveness across income groups, and (iv) conducting cost-benefit analyses of renewable energy transition scenarios specific to Iranian provinces.

In summary, this study confirms the presence of spatial interconnections in electricity consumption across Iranian provinces and provides empirical evidence on the determinants of electricity demand, including the role of gas consumption. While the findings offer useful insights for energy planning, policy recommendations should be considered as indicative rather than prescriptive, and further research is needed to strengthen the evidence base for large-scale interventions.

Author Contributions:

Conceptualization, S.A., S.K., L.A., and S.H.C.; methodology, S.A. and S.K.; validation, S.A., L.A., and S.H.C.; formal analysis, S.A. and S.K.; investigation, all authors; resources, S.K. and L.A.; data curation, S.A. and S.H.C.; writing—original draft preparation, S.A., S.K., and S.H.C.; writing—review and editing, all authors; visualization, S.A. and S.H.C.; supervision, S.K. and L.A.; project administration, S.K. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Conflicts of Interest:

The authors declare no conflict of interest.

Data Availability Statement:

The data used in this study were obtained from the Statistical Center of Iran (SCI) and the Central Bank of Iran. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors upon reasonable request with permission of the relevant institutions.

Acknowledgements

I acknowledge that artificial intelligence tools (such as Grok) were used solely for English language editing in this article.

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