



RESEARCH PAPER

## Modeling Determinants of Renewable Electricity Consumption in Iran

Zahra Fotourehchi<sup>a,\*</sup> , Ahmet Sahinoz<sup>b</sup> 

a. Department of Economics, University of Mohaghegh Ardabili, Ardabil, Iran.

b. Department of Economics and Management, Baskent University, Ankara, Turkey.

\* Corresponding author, E-mail: [z.faturechi@yahoo.com](mailto:z.faturechi@yahoo.com)

**Article History:** Received: 19 October 2022, Revised: 16 December 2022, Accepted: 29 January 2023

**Publisher:** University of Tehran Press.

©Author(s).

### Abstract

Rising concerns about global warming and energy security signal an increasing reliance on renewable energy sources in the future. Recently, renewable energy sources have emerged as a significant component of global energy consumption. However, less information is available addressing the renewable energy consumption determinants. Considering the contribution of renewable energy to future sustainable and reliable energy, its primary factors must be comprehended to derive energy policy consequences. Using Auto Regressive Distributed Lag (ARDL) bounds testing cointegration strategy and the Vector Error Correction Model (VECM) Granger causality test method over the period 2011-2019, the objective of this study is to model the determinants of renewable electricity consumption in Iran empirically. The primary predictors of renewable electricity consumption are combined pollution, per capita Gross Domestic Product (GDP), oil price, and urbanization, according to the investigation results. Long-term and short-term consumption of renewable electricity is positively and negatively affected by combined pollution, oil price, and urbanization, respectively, according to the empirical findings. In the short term, the per capita GDP has a negative and significant effect on renewable electricity consumption, while in the long term, the opposite is true. Finally, the results of Granger causality analysis utilizing the vector error correction model reveal a bidirectional short-term and long-term Granger causality flowing in a positive direction from combined pollution, per capita GDP, and oil price to renewable power usage. Moreover, the positive bilateral short-term Granger causation between the oil price and per capita GDP is verified.

**Keywords:** ARDL, Consumption, Iran, Renewable Electricity, VECM.

**JEL Classification:** Q2, Q4, Q5.

### 1. Introduction

The reduction of climate change is one of the most important Sustainable Development Goals (SDGs) because, from the perspective of authorities and

politicians in both developed and developing nations, climate change is one of the greatest challenges, making its mitigation one of the most essential SDGs (Bisbis et al., 2019). Due to high nonrenewable consumption, the global carbon project predicts a 2.5% increase in emissions in both developing and developed countries. Therefore, countries must alter their energy policies to restrict nonrenewable consumption and eliminate fossil fuels.

Nonrenewable energy sources, such as coal, oil, and natural gas, pose a threat to sustainable economic growth. Due to rapid economic growth, urbanization, and population growth, the demand for such energies exceeds the supply of energy derived from non-depletable resources, resulting in escalating energy prices, rising energy exploitation, and a worsening environment. However, renewable energy sources such as solar energy and wind energy are perpetually replenished by nature and are therefore infinite and sustainable. Renewable energy is a feasible energy source that could put an end to climate change and global warming. The ability to replace renewable energy with nonrenewable energy is contingent upon several variables, including the acceptance and willingness of policymakers to push private and public resources toward renewable technology through stimulating research and development and supporting investment (Olalekan, 2020).

In the first half of 2021, global investments in renewable technology reached \$174 billion, with countries such as the United States and China making significant expenditures in solar, hydro, biofuels, and wind. According to the US Energy Information Administration (EIA), renewables are the fastest-growing source of global energy, with an annual growth rate of 3.0%. Some factors contribute to the increased focus on renewable energy sources. Current concerns over the volatility of crude oil prices, reliance on foreign nonrenewable energy supplies, the increase in global population, and the environmental effects of carbon emissions all contribute to the growing interest in renewable energy sources. Furthermore, to promote renewable energy as an available energy portfolio component for different countries, it is essential to implement government policies such as installation rebates for renewable energy systems, renewable energy portfolio standards, renewable energy production tax credits, and establish markets for renewable energy certificates (Ponce et al., 2020).

Although renewable energy consumption has advantages, it also has disadvantages, such as greater installation costs for wind turbines. This illustrates that the conversion of mechanical energy to electricity is less efficient.

Furthermore, wind energy infrastructure may not be ecologically neutral. Due to the noise level generated by the turbines, for instance, they should not be positioned near homes (the 15 July 2016 act on investments stipulates a 1.5–2 km distance). The local bird population is also affected by wind turbines because birds might become entangled in the blades (Gershon and Emekalam, 2021).

According to the EIA research, renewable energy will be the fastest-growing energy source through 2030. Over the period from 2007 to 2035, it is anticipated that the global consumption of renewable energy for electricity generation will increase by 2.6% year on average (Omri and Nguyen, 2014). The global consumption of renewable energy increased by 3% in 2020. According to the REN21 (2015) report, this increase is insufficient to meet the Sustainable Energy for All (SE4ALL) initiative's 2030 aim.

According to the most recent data given by the World Bank for Iran, renewable energy consumption (0.98 in 2019) will be lower than fossil energy consumption (99) in 2015 (World Bank Report, 2022). This demonstrates that Iranian politicians have not given sufficient attention to generating renewable energy sources via investment and providing incentives for private businesses. Iran's primary motivations are its abundant gas and oil resources and their inexpensive pricing relative to their international prices cause the lack of economic justification for investors. Moreover, the lack of technology and infrastructure quality, as well as the refusal of the Iranian government and private investors, contributes to the drop in renewable energy consumption. Because building renewable energy-producing plants is highly expensive.

Electricity is one of the most extensively used energy carriers with a crucial role in sustainable development. According to the most recent estimations, there are between 15,000 and 20,000 MW of economically feasible wind farm installable capacity in Iran at present. According to the most recent available statistics, Iran's renewable energy electricity production reached 8094 million kilowatt hours in June 2022 (Ministry of Energy Information Database 2022). According to the most recent capacity statistics of renewable and clean power plants (governmental and non-governmental) installed in Iran by the end of June 2022, 331.7 MW belongs to wind power plants, 502.1 MW to photovoltaic power plants, 100.3 MW to small hydropower plants, 12.5 MW to biomass power plants, and 9.6 MW to recycled heat loss. According to the records of 2022 published by the Renewable Energy and Electricity Efficiency Organization of the Ministry of Energy, the production

of 8094 million kilowatt hours of electricity from new energies has led to a reduction of 2292 million cubic meters of fossil fuel consumption in Iran, which is one of the primary causes of air pollution in the country, and a reduction of more than 1781 million liters of water consumption (Report of the Renewable Energy and Electricity Efficiency Organization of the Ministry of Energy, 2022). 5343 thousand tons of CO<sub>2</sub> greenhouse gases and 34.3 thousand tons of local pollutants have not been emitted due to the performance of renewable power plants.

The energy industry, which influences Iran's national budget by 70%, is one of the sectors for policy improvement. Iran's geographic location has afforded it access to abundant renewable energy sources like water, solar, geothermal, and wind. However, additional data is required for evaluating their availability or the cause for their utilization. Moreover, due to the higher rate of consumption of energy from non-renewable sources compared to production, non-renewable energy sources are in jeopardy, and as a result, emissions from this type of energy are rising. In addition to the production of mercury, arsenic, nickel, and other waste from fossil fuel power plants, traditional energy consumption and the burning of fossil fuels in electricity power plants result in the emission of numerous pollutants, such as NO<sub>x</sub>, SO<sub>x</sub>, CO, CO<sub>2</sub>, and PM, and effects such as acid rain, ozone depletion, and global warming (Bhattacharyya, 2011).

Therefore, Iran needs to diversify its electricity consumption resources and ensure electrical security. They are crucial to social development and long-term economic prosperity. Iran has the technological challenges of both developing its economy and decarbonizing it.

Therefore, it is essential for Iran to have a thorough understanding of the main factors of renewable electricity consumption and to formulate appropriate energy regulations. Shortly, there will be a higher reliance on renewable energy sources due to the growing worry regarding climate change, water scarcity, energy security, and global warming. However, no research has been conducted on the factors of renewable electricity consumption in Iran, and few studies have addressed the areas of our interest. This study aims to contribute to the existing body of knowledge by: 1. filling the current void in the literature, 2. incorporating the combined pollution index as an environmental subset because of the significance of environmental deterioration in shaping renewable electricity consumption patterns. 3. Choosing the optimal subset of the factors of renewable power consumption in Iran based on the country's economic, social, and

environmental conditions, a factor that has been neglected in earlier research. In addition, we broaden the frontier of study by employing both the Auto Regressive Distributed Lag (ARDL) cointegration strategy and the Vector Error Correction Model (VECM) Granger causality test method using data from 2011-2019. The findings will aid policymakers and authorities in directing energy reforms toward sustainable and reliable electricity consumption.

The remainder of this paper is organized as follows. Section 2 presents a summary of the theoretical and empirical literature about the determinants of renewable energy consumption. The model specifications are reported in Section 3. Section 4 provides the paper's empirical findings, and Section 5 closes the paper with concluding remarks.

## **2. Literature Review**

There are generally three ways to model the procedures for establishing the significance of renewable energy consumption as an alternative energy source, which might be significant in the relevant research. Particular emphasis has been placed on modeling: 1. the proportion of energy from renewable sources in gross final energy consumption; 2. the relationship between economic expansion and renewable energy sources; 3. drivers of renewable energy consumption.

Studies concentrating on renewable energy consumption drivers take different countries. However, they rarely pay exclusive attention to Iran. The methodologies utilized to assess renewables' challenges and the key findings from the reviewed papers are summarized in the next section.

Bekun and Alola (2022) analyzed the factors of renewable energy consumption in the rural economies of Sub-Saharan Africa. The data revealed that a rise in economic activity increases renewable energy consumption in the short term but decreases it in the long term. Furthermore, the energy (electricity from fossil fuels) has a negative impact on renewable energy consumption. In addition, causality analysis employing the heterogeneous panel indicated bidirectional causality from economic growth to renewable energy consumption, as well as a causative association between urbanization and renewable energy, as well as agricultural value added and economic growth.

Bednarczyk et al. (2021) conducted qualitative and quantitative evaluations of energy development determinants about renewable energy sources in Poland from 2005 to 2019. The findings revealed a negative correlation between energy

consumption and the proportion of total energy generation derived from renewable sources. Moreover, the investigation revealed that R&D and overall expenditures on water management and environmental protection investments have no substantial impact on the development of RES.

Gershon and Mekalam (2021) utilized the Toda Yamamoto method to simulate the renewable energy consumption factors for 24 years in Nigeria. The results indicated a long-run relationship between renewable energy consumption as well as its drivers in Nigeria. However, the analysis reveals no causal relationship between renewable energy consumption and its factors.

Akintande et al. (2020) modeled the renewable energy consumption factors in the five most populous African nations using annual data from 1996 to 2016. They classified variables as macroeconomic, socioeconomic, and institutional. The data suggested that urban population, population growth, electric power consumption, energy use, and human capital are the most important predictors of renewable energy consumption in the chosen countries and that increasing any of these factors enhances renewable energy consumption.

Ponce et al. (2020) aimed to research renewable and non-renewable energy consumption determinants in hydroelectric countries for the 53 countries that consumed the most renewable energy from 1990 to 2017 (hydroelectric). The results revealed robustly significant effects of human capital on renewable energy consumption in middle-high-income and low-middle-income countries worldwide, relative to non-renewable energy consumption.

Da Silva et al. (2018) examined the determinants of renewable energy consumption in Sub-Saharan Africa between 1990 and 2014 using a panel ARDL model. The results revealed the existence of long-run relationships between per capita real GDP, renewable energy share in electricity generation, per capita CO<sub>2</sub> emissions, per capita energy use, energy prices (natural gas, crude oil, and coal prices), electricity import, population expansion, and Kyoto protocol ratification. In addition, the per capita energy use and per capita real income raise the renewable energy share. However, the utilization of renewable energy is negatively impacted by changes in per capita CO<sub>2</sub> emissions, population growth, electricity import, and energy prices, as well as Kyoto Protocol ratification.

Akar (2016) examined the renewable energy consumption determinants for the Balkans during 1998-2011 using the dynamic panel data method approach. Results indicated that natural gas rents and trade openness had a positive impact

on renewable energy consumption in the Balkans. However, there is a negative relationship between economic growth and renewable energy consumption.

Omoju (2015) explored the factors influencing the development of renewable energy in China. Although financial development, foreign direct investment, and trade openness have positive effects on renewable energy in China, real GDP growth and fossil fuel have negative effects. That is, unless the adoption of fossil energy is blocked, the adoption of fossil energy will continue to erode the significance of renewable energy. Moreover, the size of renewable energy does not grow at the same rate as overall energy consumption.

Omri and Nguyen (2014) used a dynamic system-GMM panel model to analyze the factors of renewable energy consumption in 64 countries from 1990 to 2011. CO<sub>2</sub> emissions and trade openness are the key drivers of renewable energy consumption, according to the data. The rise in oil prices has a small but negative impact on renewable energy consumption in the global and middle-income panels.

Sadorsky (2012) investigated the G7 countries' renewable energy determinants using panel cointegration methods. They showed positive effects of per capita CO<sub>2</sub> emissions and per capita GDP on the long-run per capita consumption of renewable energy. However, the rise in oil prices has a minor negative impact.

Salim and Rafiq (2012) evaluated the factors of renewable energy consumption for a panel comprising China, Brazil, India, Philippines, Indonesia, and Turkey as the six major emerging nations. Using a variety of econometric techniques, such as the completely modified ordinary least square, the Granger-causality test, and the dynamic ordinary least square, they determined that income and pollutant emissions significantly influence long-term renewable energy consumption in China, Brazil, Indonesia, and India. However, it is only based on income in Turkey and the Philippines.

Considering the significance of renewable energy for a sustainable and dependable energy future, it is necessary to comprehend the primary factors before deriving policy consequences. The majority of studies on developing economies currently utilize panel and other time series approaches. This paper's primary objective is to undertake empirical modeling to choose the optimal subset of the determinants of renewable power consumption in Iran based on economic, social, and environmental situations and a new combined pollution index, as these cases have been disregarded in the literature.

### 3. Materials and Methods

This study is based on a regression function between combined pollution, renewable electricity consumption, oil price, per capita GDP, and urbanization. We adhered to the technique suggested by Omri and Nguyan (2014). In contrast, we reset the model by substituting a combined pollution index for carbon dioxide and adding an urbanization component.

$$REC_t = a_0 + a_1 CP_t + a_2 Y_t + a_3 OP_t + a_4 UR_t + \varepsilon_t \quad (1)$$

where REC represents the renewable electricity consumption. CP is the combined pollution index based on production and consumption; Y is the per capita GDP (constant 2010 US\$); OP is the oil price (measured using the spot price of West Texas Intermediate (WTI) crude oil); and UR is urbanization (urban population). Since Iran is in the early stages of economic development and is one of the world's leading oil exporters, economic growth, urbanization, pollution, and oil prices are among the primary determinants of its power consumption pattern. Therefore, they are chosen as the primary subset of renewable energy consumption.

Data associated with REC is collected from the US Energy Information Administration Gs database and the Renewable Energy and Energy Efficiency Organization database (SATBA). International Energy Agency and WDI provide data on consumption-based pollution index components such as CO<sub>2</sub> emissions from transportation, residential, manufacturing, and building, renewable and fossil fuel energy consumption, and improved sanitation facilities. The WDI, Renewable Energy and SATBA, and Ministry of Energy Statistics and Information database are used to compile data about elements of the production-based pollution index, such as the production of electricity from natural gas, coal, oil, renewable hydroelectric sources, and nuclear sources.

The combined pollution index is the total of the pollution indices based on consumption and output. The consumption-based pollution index (PIC) considers the variables responsible for environmental pollution resulting from consumption. This index consists of energy consumption data, CO<sub>2</sub> emissions from various sources, and the availability of enhanced facilities (sanitation). This index is calculated using the following equations (Nazeer et al., 2016):

$$PI_{it}^C = \frac{EC_{it}^X + CO_{it}^Y + IP_{it}^{sanitation}}{W} \quad (2)$$

$$EC_{it}^X = EC_{it}^{fossil\ fuel} + EC_{it}^{renewable} / 2 \quad (3)$$

$$CO_{2it}^Y = CO_{2it}^{transport} + CO_{2it}^{residential} + CO_{2it}^{manufac\&constr} / 3 \quad (4)$$



where  $i$  and  $t$  represent the countries and periods, respectively. Elements of the consumption-based pollution index are as follows:

$EC_{it}^{fossil\ fuel}$  = Consumption of fossil fuel energy (% of total)

$EC_{it}^{renewable}$  = Consumption of renewable energy (% of total final energy consumption)

$CO_{2it}^{transport}$  = Transport CO2 emissions (% of total fuel combustion)

$CO_{2it}^{residential}$  = Residential CO2 emissions

$CO_{2it}^{manufac\&\;constr}$  = Construction and manufacturing industries CO2 emissions (% of total fuel combustion)

$IF_{it}^{sanitation}$  = Facilities of improved sanitation (% of the population that has access)

W = Total number of variables included in Equation 1

The production-based pollution index is computed using the following equation:

$$PI_{it}^P = \frac{w_1 EP_{it}^{coal} + w_2 EP_{it}^{renewable} + w_3 EP_{it}^{nuclear} + w_4 EP_{it}^{oil} + w_5 EP_{it}^{n.gas}}{W} \quad (5)$$

Elements of Equation 5 are as follows (Nazeer et al., 2016):

$EP_{it}^{coal}$  = Production of electricity - coal-based sources (% of total)

$EP_{it}^{renewable}$  = Production of electricity- renewable including hydroelectric sources (% of total)

$EP_{it}^{nuclear}$  = Production of electricity – nuclear-based sources (% of total)

$EP_{it}^{oil}$  = Production of electricity - oil-based sources (% of total)

$EP_{it}^{n.gas}$  = Production of electricity - natural gas-based sources (% of total)

$IF_{it}^{sanitation}$  = Facilities of improved sanitation (% of the population that has access)

w=1.5 Individual weights are given to variables in Equation 4

W=Sum of all individual weights ( $w_i$ )

Combined pollution equals the sum of the different indicators derived from production and consumption.

$$PI_{it} = PI_{it}^P + PI_{it}^C \quad (6)$$

Moreover, the figures for per capita GDP and urbanization come from the World Bank's World Development Indicators. British Petroleum's Statistical Review of World Energy provides information on oil prices.

Using Equation 7, the ARDL model has analyzed the long-run relationship between variables.

$$\ln\text{REC}_t^P = \beta_0 + \sum_{i=1}^P \gamma_i \ln\text{REC}_{t-i}^P + \sum_{j=1}^{q1} \delta_j \text{CP}_{t-j} + \sum_{m=1}^{q2} \varphi_m Y_{t-m} + \sum_{r=1}^{q3} \mu_r \text{OP}_{t-r} + \sum_{f=1}^{q4} \mu_f \text{UR}_{t-f} + \varepsilon_{t0} \tag{7}$$

Furthermore, the short-run dynamics of the variables are evaluated by estimating the VECM described in Equation 8:

$$\Delta(\ln\text{REC}_t^P) = \beta_0 + \sum_{i=1}^P \gamma_i \Delta(\ln\text{REC}_{t-i}^P) + \sum_{j=1}^{q1} \delta_j \Delta(\text{CP}_{t-j}) + \sum_{m=1}^{q2} \varphi_m \Delta(Y_{t-m}) + \sum_{r=1}^{q3} \mu_r \Delta(\text{OP}_{t-r}) + \sum_{f=1}^{q4} \mu_{fr} \Delta(\text{UR}_{t-f}) + \vartheta Z_{t-1} + \varepsilon_{t0} \tag{8}$$

where  $Z_{t-1}$  represents the error correction term (ECT). In the long run, ECT assesses the magnitude of the imbalance that resulted from the cointegration relationship.  $\Delta$  is the first operator of difference.

Applying the ARDL approach to analyze the statistical correlations between variables entails the three phases outlined in Table 1:

**Table 1.** ARDL Approach Steps

Step 1	Unit root test	1. The traditional augmented Dicky–Fuller (ADF) 2. Philips-Perron (PP) analysis
Step 2	ARDL method	1. The ARDL bounds testing strategy 2. Long-term coefficient estimation 3. Short-term coefficients estimation
Step 3	Granger causality analysis	1. VECM

**Source:** Research finding.

## 4. Empirical Results

### 4.1 Unit Root Test

First, the conventional augmented Dicky–Fuller (ADF) and Philips–Perron (PP) analyses are carried out to establish the order of integration of each variable. Since the F statistics presented by Pesaran et al. (2001) have adequate credit in the presence of I(1), I(0), it is crucial to ensure that none of the variables are I(2). Table 2 reports the findings of the ADF and PP tests:

**Table 2.** Unit Root Tests

Variables	ADF (test statistics)	ADF (critical values)	PP (test statistics)	PP (critical values)
Ln REC	-5.303	-7.934***	7.373	8.412**
Ln CP	-8.382	-9.104**	6.534	7.997**
Ln Y	-8.201	-9.395**	6.912	8.409***
Ln OP	-8.166	-8.978*	6.921	8.512**
Ln UR	-7.342	-6.832	5.834	8.001*

**Source:** Research finding.

**Note:** \*, \*\* and \*\*\* indicate a 10%, 5%, and 1% significance level, respectively.

According to the results of the ADF analysis, REC, Y, CP, and OP are non-stationary at both the level and trend levels, and their order of integration is one. UR is stationary I(0). The findings of the PP test reveal that all variables are non-stationary and I(1) at both level and trend. Generally, none of the variables are I(2) or beyond.

#### 4.2 ARDL Method

In this stage, we employ the Autoregressive Distributed Lag approach proposed by Pesaran et al. (2001) to determine the long-run relationships between variables (cointegration). This method applies to both the explanatory variables of I(0) and I(1). ARDL can provide the error correction model (ECM). There are both long-term and short-term dynamics involved. The ARDL bound testing is appropriate for small data sets, but the Johansen cointegration technique is suitable for large data sets. Even if the independent variables are endogenous, the ARDL can be estimated; without residual correlation, endogeneity in the ARDL is less debatable (Pesaran & Shin 1999). Instead of assuming the existence of a unique cointegration vector, the ARDL gives explicit tests for its existence.

Generally, the ARDL technique requires the following primary steps: 1- the Bounds test for integration; 2- Estimating coefficients of long-term and short-term.

##### 4.2.1 The ARDL Bounds Testing Strategy

The results of testing for cointegration using ARDL bounds confirm the presence of cointegration in the first model (Table 3). When the dependent variable is REC, the F-statistic of 5.39 exceeds the upper border of the critical value at a significance level of 1%. Therefore, the null hypothesis of no cointegration is rejected. When CP, Y, OP, and UR are dependent variables, the respective F-statistics of 1.44, 1.76, 1.14, and 1.12 are less than the appropriate limit of the critical value at a

significance level of 1%. Table 3 confirms the existence of a long-run relationship between model 1's variables.

**Table 3.** ARDL Cointegration Test Results

Bounds testing to cointegration		
Estimated models	Optimal lag length	F-statistic
F(REC   CP, Y, OP, UR)	2	5.39*
F(CP   REC, Y, OP, UR)	2	1.44
F(Y   REC, CP, OP, UR)	2	1.76
F(OP   REC, CP, OP, UR)	1	1.14
F(UR   REC, CP, Y, OP)	2	1.12
Significance level		Critical values
Lower bounds I(0)		Upper bounds I(1)
1% level	4.43	5.36
5% level	2.62	2.32
10% level	2.21	2.17

**Source:** Research finding.

**Note:** \*Significant at 1% level.

#### 4.2.2 Long-Term Coefficient Estimation Results

Examining the long-term impact of pollution, oil price, per capita GDP, and urbanization on renewable electricity consumption is the next stage. The long-term results in Table 4 imply that the effects of combined pollution, oil price, and per capita GDP on renewable electricity consumption are significantly positive, while urbanization negatively affects renewable electricity consumption. Moreover, the effect of oil price (0.021) on renewable electricity consumption is insignificant in comparison to pollution and per capita GDP (0.43, 0.32). Hence, combined pollution and per capita GDP are more influential than oil price and urbanization in determining renewable electricity consumption in Iran.

**Table 4.** Long-run Analysis

Dependent variable: REC				
Variables	Coefficient	Std. Error	T-Statistic	Prob.
CP	0.43	0.023	3.34	0.001
Y	0.32	0.031	4.82	0.005
OP	0.021	0.087	2.63	0.001
UR	-0.02	0.92	2.11	0.008
	R <sup>2</sup>		0.673	
	Adjusted R <sup>2</sup>		0.512	

**Source:** Research finding.

#### **4.2.3 Results of Short-Term Coefficients Estimation**

Table 5 displays the short-term results. As can be seen, in the short term combined pollution and oil prices have significantly positive effects on renewable electricity consumption but their effects are smaller than in the long term (0.26, 0.0012). A high level of combined pollution increases the demand for environmental protection and encourages the adoption and development of carbon-free renewable energy alternatives. This result is consistent with Omoju (2005), Omri and Nguyen (2014), and Sadorsky (2012), and contradicts da Silva et al. (2018), who claimed that CO<sub>2</sub> emissions have a negative effect on renewable energy consumption.

Moreover, our findings contradict those of Omri and Nguyen (2014) and Sadorsky (2012), who found a negligible negative impact of oil prices on renewable energy consumption. Therefore, rising oil prices should encourage businesses and households in Iran to reduce their oil consumption, purchase more energy-efficient products, and even move to renewable electricity consumption, as renewable energy is an alternative to crude oil in Iran.

However, the per capita GDP has a negative and significant short-term effect on renewable electricity consumption. The per capita GDP decreases renewable power consumption in the short term while increasing it in the long term. Hence, the per capita GDP has a persistent impact on Iran's electricity consumption pattern. In other words, economic expansion under the strain of increasing environmental degradation and climate change should lead to a high level of renewable energy consumption; however, in the short run, the size of renewable energy in Iran does not increase as much as total energy consumption. Our results are consistent with those of Akar (2016) and Omoju (2015) in the short term and with those of da Silva et al. (2018) in the long term.

Statistically, urbanization influences the consumption of renewable-based electricity with preceding signs and smaller coefficients compared to the long term. This result contradicts Bekun and Alola (2022) and Akintande et al. (2020), who discovered that the urban population has a positive impact on renewable energy consumption. Our findings are similarly congruent with those of da Silva et al. (2018), who demonstrated that urbanization limits the development of renewable energy sources. Iran's urban populace is ignorant of environmental issues and the consequences of a polluted economy.

In addition, when comparing the long-term and short-term results, it is evident that the coefficients of all variables in the long-term are greater than in the short-

term. The coefficient of error correction ECM-1 indicates how many percentage points of the short-term imbalance in the consumption of renewable electricity are adjusted in each period to achieve long-term equilibrium. As anticipated, the coefficient of ECM-1 falls between 0 and -1 and is statistically significant with a 99% degree of confidence; its value is 0.574. This demonstrates that around 0.574% of the renewable electricity consumption imbalances produced by last year’s shock have been brought to long-term equilibrium for this year. R2 also implies a relatively good fit.

**Table 5.** Results of the Short-Run Test

Dependent variable = ΔREC				
Variables	Coefficient	Std. Error	T-Statistic	Prob.
Δ(CP)	0.26	0.23	3.67	0.0004
Δ(Y)	-0.17	0.65	-3.78	0.000
Δ(OP)	0.0012	0.45	2.02	0.032
Δ(UR)	-0.013	0.76	-2.69	0.0087
(ECT <sub>t-1</sub> )	0.574	0.11	4.102	0.000
	R <sup>2</sup>		0.691	
	Adjusted R <sup>2</sup>		0.589	

**Source:** Research finding.

**4.3 Test of Granger Causality**

In this stage, the direction and sources of causality are determined by the VECM with an error term derived from the second-level developed long-run cointegration vector. If there is cointegration between the variables, the VECM model specifies the long- and short-run relationships between the variables. This study employs the Granger causality analysis according to the error correction model as follows:

$$\Delta \ln REC_t = \alpha_{01} + \sum_{i=1}^1 \alpha_{11} \Delta \ln REC_{t-i} + \sum_{j=1}^m \alpha_{22} \Delta \ln CP_{t-j} + \sum_{j=1}^m \alpha_{33} \Delta \ln Y_{t-r} + \sum_{j=1}^m \alpha_{44} \Delta \ln OP_{t-s} + \sum_{j=1}^m \alpha_{55} \Delta \ln UR_{t-f} + \eta_1 ECT_{t-1} + u_{1i} \tag{9}$$

$$\ln CP_t = \beta_{01} + \sum_{i=1}^1 \beta_{11} \Delta \ln CP_{t-i} + \sum_{j=1}^m \beta_{22} \Delta \ln REC_{t-j} + \sum_{j=1}^m \beta_{33} \Delta \ln Y_{t-r} + \sum_{j=1}^m \beta_{44} \Delta \ln OP_{t-s} + \sum_{j=1}^m \beta_{55} \Delta \ln UR_{t-f} + \eta_2 ECT_{t-1} + u_{2i} \tag{10}$$

$$\ln Y_t = \phi_{01} + \sum_{i=1}^1 \phi_{11} \Delta \ln Y_{t-i} + \sum_{j=1}^m \phi_{22} \Delta \ln REC_{t-j} + \sum_{j=1}^m \phi_{33} \Delta \ln CP_{t-r} + \sum_{j=1}^m \phi_{44} \Delta \ln OP_{t-s} + \sum_{j=1}^m \phi_{55} \Delta \ln UR_{t-f} + \eta_3 ECT_{t-1} + u_{3i} \tag{11}$$

$$\begin{aligned} \text{Ln OP}_t = & \delta_{01} + \sum_{i=1}^1 \delta_{11} \Delta \text{Ln OP}_{t-i} + \sum_{j=1}^m \delta_{22} \Delta \text{Ln REC}_{t-j} + \sum_{j=1}^m \delta_{33} \Delta \text{Ln CP}_{t-r} + \\ & \sum_{j=1}^m \delta_{44} \Delta \text{Ln Y}_{t-s} + \sum_{j=1}^m \delta_{55} \Delta \text{Ln UR}_{t-f} + \eta_4 \text{ECT}_{t-1} + u_{4i} \end{aligned} \quad (12)$$

$$\begin{aligned} \text{Ln UR}_t = & f_{01} + \sum_{i=1}^1 f_{11} \Delta \text{Ln UR}_{t-i} + \sum_{j=1}^m f_{22} \Delta \text{Ln REC}_{t-j} + \sum_{j=1}^m f_{33} \Delta \text{Ln CP}_{t-r} + \\ & \sum_{j=1}^m f_{44} \Delta \text{Ln Y}_{t-s} + \sum_{j=1}^m f_{55} \Delta \text{Ln OP}_{t-f} + \eta_5 \text{ECT}_{t-1} + u_{5i} \end{aligned} \quad (13)$$

In the equations,  $\Delta$  refers to the first difference operator and  $ui$  stands for the serially uncorrelated residual terms.  $k$  is the lag length regarding the test of likelihood ratio.  $\eta_i$  is an adjustment coefficient.  $ECT_{t-1}$  is the cointegration vector. Table 6 displays the findings of both short- and long-term Granger causality analyses using the vector error correction model. According to Table 6, a positive one-way Granger short-term causality exists between combined pollution, per capita GDP, and oil price and renewable electricity consumption. Moreover, the short-term Granger causality between oil price and per capita GDP is confirmed to be positive and bidirectional.

Table 6 displays the estimated coefficient on the lagged error correction term in Equation 9. According to Table 6, this coefficient is significant at the 1% level. Equation 9 confirms the existence of long-term unidirectional causality between the variables combined pollution, oil price, per capita GDP, and renewable electricity consumption.

The ECT coefficient is 0.565, which indicates that the model's pace towards long-term equilibrium has been modified. 56% of long-term link deviations are currently corrected by REC to return the system to equilibrium.

**Table 6.** The VECM Granger Causality Test Results

Dependent variable	Short-run		Long-run				SR	LR
	$\Delta(\text{REC})$	$\Delta(\text{CP})$	$\Delta(\text{Y})$	$\Delta(\text{OP})$	$\Delta(\text{UR})$	$ECT_{t-1}$		
$\Delta(\text{REC})$	-	0.43 *** (3.626)	0.28* (2.981)	0.033* (2.354)	-0.001 (-1.56)	-0.565 * (-7.812)		
$\Delta(\text{CP})$	0.021 (1.39)	-	0.45 (1.96)	0.45 (1.88)	0.88 (1.96)	0.654 (1.56)	CP, Y, OP → REC	
$\Delta(\text{Y})$	0.011 (1.37)	0.087 (1.67)	-	0.96** (2.67)	0.37 (1.12)	0.06 (1.58)		CP, Y, OP → REC
$\Delta(\text{OP})$	0.264 (1.23)	0.024 (1.76)	0.006* (3.32)	-	0.12 (1.23)	-0.045 (-1.121)	Y ↔ OP	
$\Delta(\text{UR})$	0.001 (1.43)	0.67 (1.30)	0.006 (1.67)	0.07 (1.56)	-	0.038 (1.292)		

**Source:** Research finding.

**Note:** \*, \*\* and \*\*\* demonstrate a 10%, 5%, and 1% significance level, respectively.



## 5. Conclusion

This article examines the dynamic relationship between renewable electricity consumption, combined pollution, oil price, per capita GDP, and urbanization in Iran from 2011 to 2019. Generally, our results suggest that the main factors of renewable electricity consumption in Iran are combined pollution, oil price, per capita GDP, and urbanization. Based on the ARDL bounds testing cointegration approach, combined pollution and oil prices boost renewable electricity consumption over the short- and long-term. However, per capita GDP decreases renewable electricity consumption in the short term but raises it in the long term. The per capita GDP can contribute to long-term energy security and sustainable energy development. Consequently, pollution, oil price, and per capita GDP can be viewed as the primary tools for Iran's long-term sustainable electricity consumption goal. However, urbanization has statistically negative effects on renewable electricity consumption in both the short- and long-term, but with smaller coefficients in the long run.

Several policy recommendations are made for Iran based on our findings, including the modification of electricity consumption patterns and the rapid transition of energy policies from polluting energy consumption and production to clean, carbon-free energy, energy diversification in Iran to more renewable energy sources, and the development of electricity generation capacities from renewable energy sources to reduce air pollution and protect the environment.

Using the VECM Granger causality analysis, the second phase of the current study provides a broader overview of the causal relationship between renewable electricity consumption, combined pollution, oil price, per capita GDP, and urbanization. The results indicate a bilateral short-term and long-term Granger causality running positively from combined pollution, per capita GDP, and oil price to renewable electricity consumption. Increasing pollution, oil prices, and per capita GDP all result in an increase in RE consumption. Hence, based on the VECM Granger causality analysis, it is essential to conclude that oil price, per capita GDP, and combined pollution are the primary determinants of RE consumption in Iran.

Moreover, the positive bilateral short-term Granger causality between oil price and per capita GDP is verified, indicating that an increase in oil price results in a rise in per capita GDP and that the reverse is also true. In Iran, an increase in oil

prices leads to an increase in GDP per capita through an increase in oil revenues and the net value of oil exports.

The primary way to encourage renewable electricity consumption and particularly to increase energy efficiency is by implementing appropriate measures and investments, such as: 1. Realizing the price of non-renewable electricity so that all environmental and social costs are included; and 2. Concurrently investing in economic activities and renewable electricity to grow sustainable per capita GDP along with sustainable electricity. These will result in an immediate shift in the pattern of electricity consumption in Iran.

In conclusion, this work lays the groundwork for future research into the modeling of the determinants of renewable electricity consumption in Iran. Future research could compare the results of additional economic, social, and environmental indicators for renewable electricity consumption. In addition, the application of additional models and technical methods to validate our theory is a further way to enhance this paper. However, accessing and collecting data on the components of the combined pollution index was challenging and the main limitation of the research.

### **Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could be perceived as having influenced the work described in this paper.

### **Acknowledgment**

We appreciate the reviewers' insightful comments and recommendations. Any errors that remain are, of course, our fault.

### **References**

- Akar, B. G. (2016). The Determinants of Renewable Energy Consumption: An Empirical Analysis for the Balkans. *European Scientific Journal*, 12(11), 594-607.
- Akintande, O. J., Olubusoye, O. E., Adenikinju, A. F., & Olanrewaju, B. T. (2020). Modeling the Determinants of Renewable Energy Consumption: Evidence from the Five Most Populous Nations in Africa. *Energy*, 206, 117992.

- Bednarczyk, J. L., Brzozowska-Rup, K., & Luściński, S. (2021). Determinants of the Energy Development Based on Renewable Energy Sources in Poland. *Energies*, *14*(20), 1-21.
- Bekun, F. V., & Alola, A. A. (2022). Determinants of Renewable Energy Consumption in Agrarian Sub-Sahara African Economies. *Energy, Ecology and Environment*, *7*, 227-235.
- Bisbis, M. B., Gruda, N. S., & Blanke, M. M. (2019). Securing Horticulture in a Changing Climate-A Mini-Review. *Horticulturae*, *5*(3), 1-10.
- Da Silva, P. P., Cerqueira, P. A., & Ogbe, W. (2018). Determinants of Renewable Energy Growth in Sub-Saharan Africa: Evidence from Panel ARDL. *Energy*, *156*, 45-54.
- Fotourehchi, F. (2020). Are UN and US Economic Sanctions A Cause or Cure for The Environment: Empirical Evidence from Iran. *Environment, Development and Sustainability*, *22*, 5483-5501.
- International Energy Agency Report. (2022). Retrieved from <https://www.iea.org/reports/world-energy-outlook-2022>
- Gershon, O., & Emekalam, P. (2021). Determinants of Renewable Energy Consumption in Nigeria: a Toda Yamamoto Approach. *IOP Conference Series: Earth and Environmental Science*, *665*(1), 1-11.
- Ministry of Energy Statistics and Information Database. (2022). Retrieved from <https://moe.gov.ir>
- Nazeer, M., Tabassum, U., & Alam, S. (2016). Environmental Pollution and Sustainable Development in Developing Countries. *The Pakistan Development Review*, *55*(4), 589-604.
- Omoju, O. E. (2015). Determinants of Renewable Energy Development in China. *China Center for Energy Economics Research (CCEER)*. Retrieved 6 February 2019 from <https://www.iaee.org/proceedings/article/12709>
- Omri, A., & Nguyen, D. K. (2014). On the Determinants of Renewable Energy Consumption: International Evidence. *Energy*, *72*, 554-560.
- Pesaran, M. N., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, *16*, 289-326.

Pesaran, M. H., & Shin, Y. (1999). An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis. In S. Strom (Ed.), *Econometrics and Economic Theory in 20<sup>th</sup> Century: The Ragnar Frisch Centennial Symposium*, 11. Cambridge: Cambridge University Press.

Ponce, P., López-Sánchez, M., Guerrero-Riofrío, P., & Flores-Chamba, J. (2020). Determinants of Renewable and Non-Renewable Energy Consumption in Hydroelectric Countries. *Environmental Science and Pollution Research*, 27(23), 29554-29566.

Renewable Energy and Energy Efficiency Organization (SATBA). (2022). Retrieved from <http://www.satba.gov.ir/fa/satba/information>

Sadorsky, P. (2012). Energy Consumption, Output, and Trade in South America. *Energy Economy*, 34, 476-88.

Salim, R.A., & Rafiq, S. (2012). Why do Some Emerging Economies Proactively Accelerate the Adoption of Renewable Energy? *Energy Economy*, 34, 1051-1057.

The British Petroleum Statistical Review of World Energy. (2022). Retrieved from <https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>

US Energy Information Administration Gs Database. (2022). Retrieved from <https://www.eia.gov/odata>

World Bank Report. (2022). Retrieved from <https://documents.worldbank.org/en/publication/documents-reports/documentdetail/630671538158537244/the-world-bank-annual-report-2022>

World Bank, World Development Indicator. (2022). Retrieved from <https://datatopics.worldbank.org/world-development-indicators>

This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license.



**Cite this article:** Fotourehchi, Z., & Sahinoz, A. (2024). Modeling Determinants of Renewable Electricity Consumption in Iran. *Iranian Economic Review*, 28(4), 1228-1247.