

Trends in Renewable Energy Shares

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Abstract

The global challenge of energy security amidst climate change and geopolitical tensions necessitates a transition to renewable energy sources, crucial not only for environmental preservation but also national security in hostile geopolitical contexts. This paper endeavors to forecast trends in countries' renewable energy shares relative to total energy consumption, encompassing a diverse selection based on geographical, economic, and climatic factors. Employing an ARIMA model with Fourier transformation, we elucidate autocorrelation dynamics within the system, effectively addressing structural breaks and seasonality. Our analysis reveals a consistent upward trend in renewable energy adoption post the 2000s, with GDP per capita exerting varied influences across nations. While crude oil prices negatively impact most countries, their effects are insignificant in Germany and the USA. Furthermore, all countries demonstrate substantial reliance on at least one form of renewable energy, notably hydropower in nations like the USA and Brazil. Our model exhibits a strong fit to the data, as indicated by low AIC and BIC values, white noise residuals, and uncorrelated correlograms. These findings underscore the imperative of renewable energy adoption in mitigating energy security risks and advancing sustainable development objectives.

Keywords : Estimation, ARIMA, Renewable energy, Forecasting

1. Introduction

The surge in economic growth experienced by developing nations over recent decades has led to a rapid escalation in energy demand and consumption, a trend expected to persist.

With increasing concerns over the role of economic production in escalating the global climate crisis, nations are pledging to cut down their consumption of fossil fuels and rely upon more sustainable energy sources for their growing consumption of energy.¹ In order to stick to Paris Agreement goals, wind and solar energy needs to make up 57% and 78% of global energy consumption to stay true to net zero emissions goals. Countries across the board from developing to developed have made rapid transitions in shifting to renewables. Added to this concern are geopolitical tensions disrupting energy supply chains and thus creating an urgency among nations to shift to renewable sources of energy. In response to the Ukraine conflict, for example, Europe is intensifying efforts to substitute Russian gas with renewable energy alternatives. Projections suggest a twofold increase in renewable power capacity additions across Europe from 2022 to 2027, driven by concerns over energy security and climate goals.²

Accurately predicting future power consumption becomes imperative for crafting effective environmental and economic policies. Moreover, anticipating future energy usage assists in making informed decisions about investments in renewable energy. International comparisons serve as valuable tools for discerning historical, current, and future power consumption patterns.³ Energy transition trends are important to understand emissions trends in developing and developed countries to have practical standards set in for sustainable economic growth in the future.

In this paper, we aim to estimate and seek patterns in the proportion of renewable energy sources in the total energy consumption of nations, over the past 50-60 years. We study the persistence of past renewable energy shares on future consumption, the nature of transition to renewables, and the impact of specific country profiles. Taking a diverse selection of countries,

¹Dipanita Nath, "Global Renewables and Energy Efficiency Pledge at COP28: What Is the Tripling Renewable Energy Target?," *The Indian Express*, December 10, 2023, <https://indianexpress.com/article/explained/explained-climate/cop28-tripling-renewable-energy-target-9062282/>.

²"Renewable Power's Growth Is Being Turbocharged as Countries Seek to Strengthen Energy Security - News - IEA," IEA, December 6, 2022, <https://www.iea.org/news/renewable-power-s-growth-is-being-turbocharged-as-countries-seek-to-strengthen-energy-security>.

³Kumar. J, Charles Rajesh, and M. A. Majid. "Renewable Energy for Sustainable Development in India: Current Status, Future Prospects, Challenges, Employment, and Investment Opportunities - Energy, Sustainability and Society." *BioMed Central*, January 7, 2020. <https://doi.org/10.1186/s13705-019-0232-1>.

we measure the impact of select variables such as income per capita, share of different kinds of renewable energy sources, prices of renewable energy equipment (proxied by global solar panel prices) and global oil prices on the percentage share of renewable energy sources in the total energy consumption. The aim of the study is firstly, to find a parsimonious estimating strategy for renewable energy shares and secondly, to use data from the estimated models to comment on the trends in renewable energy shares in different countries. The paper is organized as follows: the first section discusses prior literature on estimating renewable energy sources, the succeeding section discusses data and the empirical methods used in our analysis, along with the empirical controls adopted; Finally, the paper discusses the results of our estimation and concludes with our key findings.

2. Literature Review

Energy forecasting plays a crucial role in informing policy decisions and sustainable development strategies by providing insights into the complex nexus enfolding energy consumption, economic growth, and environmental sustainability. This literature review synthesizes recent research in the field, drawing on empirical studies and methodological approaches to shed light on the dynamics of energy consumption and its implications for socio-economic and environmental outcomes.

The motivation for energy forecasting research is underscored best by Aslan (2022) et al.'s study, which examines the association between proportion of renewable energy to total energy consumed and economic growth, particularly in the context of oil reserve ownership.⁴ Their utilization of a Panel VAR approach highlights the intricate connections among economic growth, foreign direct investments, trade, fossil fuels consumption, renewable energy consumption and CO₂ emissions, stratified by countries with and without oil reserves. This approach offers valuable insights into the multi-dimensional impacts of energy policies on economic and environmental variables. They find that there is a negative relationship between emission and foreign direct investments for oil importing countries and a positive relationship

⁴ Alper Aslan et al., "Renewable Energy and Economic Growth Relationship Under the Oil Reserve Ownership: Evidence From Panel VAR Approach," *Renewable Energy* 188 (April 1, 2022): 402–10, <https://doi.org/10.1016/j.renene.2022.02.039>.

between CO₂ and trade in the oil-exporting group. In addition, they find that across groups, countries have forced into a trade-off: they must reduce national income to reduce carbon emissions, which makes it difficult to reduce emissions in the world.

Further exploration into the dynamics of energy consumption and environmental impacts has been facilitated by studies on the persistence of shocks in energy markets. Baygin and Çil's (2023) investigation into the persistence of shocks on both non-renewable energy and renewable energy consumption in 15 countries, employing the Fourier unit root test, enhances our understanding of the resilience and adaptability of energy systems. Such research underscores the importance of understanding how sudden disturbances in energy markets affect consumption patterns, considering factors like geopolitical events, technological advancements, and policy changes. They discover that, with the exception of Sweden and the US, shocks to per capita non-renewable energy consumption are persistent in 13 countries, while shocks to per capita renewable energy consumption are persistent in 12 nations, with the exception of Canada, Sweden, and the UK. Their paper concludes that sustained policy measures have a greater impact on non-renewable energy consumption in 13 countries, with the exception of Sweden and the United States. Policies have modest impact on non-renewable energy consumption in Sweden and the US, and on renewable energy consumption in Canada, Sweden, and the UK, because energy consumption quickly returns to its trend path.⁵

The transition towards renewable energy sources represents a strategic approach to addressing environmental concerns while promoting economic development. The causality of variables in the investigation of these results often run through multiple channels. For example, studies have demonstrated that renewable energy adoption not only mitigates CO₂ emissions but also fosters economic growth through job creation, innovation, and enhanced energy security like Guliyev et al's paper on "The relationship between renewable energy and economic growth in European countries".⁶ According to their research, modelling notable

⁵ Burcu Kiran and Nilgün Çil, "Persistence of Shocks on Non-renewable and Renewable Energy Consumption: Evidence From 15 Leading Countries With Fourier Unit Root Test," *Environment, Development and Sustainability*, January 19, 2023, <https://doi.org/10.1007/s10668-023-02944-4>.

⁶ Hasraddin Guliyev and Ferda Yerdelen Tatoğlu, "The Relationship Between Renewable Energy and Economic Growth in European Countries: Evidence From Panel Data Model With Sharp and Smooth Changes," *Renewable Energy Focus* 46 (September 1, 2023): 185–96, <https://doi.org/10.1016/j.ref.2023.06.005>.

structural breaks aids in defining time dynamics in relationships, taking nonlinearity in the model structure into account, and gaining fresh perspectives.

Further, the implementation of renewable energy sources improves the quality of life and adds to GDP growth and this further enables an economy to increase investments in renewable energy. Multiple methodological approaches such as Vector Autoregressive (VAR), ARIMA and ARCH-GARCH models offer a robust framework for analyzing the dynamic relationships among energy consumption, economic growth, and environmental variables. By disentangling the short- and long-term causal effects of exogenous shocks, VAR models provide valuable insights for policymakers seeking to design effective energy and environmental policies.

The Autoregressive Integrated Moving Average (ARIMA) method, extensively researched and employed in prior studies, has demonstrated effectiveness in the field of forecasting⁷. The ARIMA model, known for its simplicity, requires transforming non-stationary time series data into stationary ones for application. The quality of these models depend on the quality of the data.

ARIMA models, blending autoregressive and moving average components, are widely employed for energy consumption forecasting across various studies. Examples include predicting energy usage, analyzing building consumption, and addressing system load forecasting in developed cities. They are also used for electricity demand, tourism demand forecasting, and examining energy trends in China and India. However, ARIMA's reliance on extensive data series, often requiring a minimum of 50 observations, is a notable limitation.⁸

Autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models are often used to control for predictions of wind power generation at hourly or daily levels. Tastu et al. (2014) utilize an ARCH model to generate variances in probabilistic forecasts of wind power production for an offshore wind farm in

⁷ Ahzam Shadab, Shamshad Ahmad, and Salim Said, "Spatial Forecasting of Solar Radiation Using ARIMA Model," *Remote Sensing Applications* 20 (November 1, 2020): 100427, <https://doi.org/10.1016/j.rsase.2020.100427>.

⁸ Anca Mehedințu, Mihaela Sterpu, and Georgeta Șoavă, "Estimation and Forecasts for the Share of Renewable Energy Consumption in Final Energy Consumption by 2020 in the European Union," *Sustainability* 10, no. 5 (May 10, 2018): 1515, <https://doi.org/10.3390/su10051515>.

Denmark.⁹ Liu et al. (2011) assess the efficacy of ARMA-GARCH methods in modeling the mean and volatility of wind speed, incorporating various GARCH models like EGARCH and TGARCH.¹⁰ Lau and McSharry (2010) pinpoint an ARIMA-GARCH model for aggregated wind power data in Ireland, providing forecasts of wind power density up to 24 hours ahead.¹¹ Nonetheless, wind speed and wind power data often manifest random breaks and nonlinear behaviors. Traditional ARMA and ARMA-GARCH models might prove overly restrictive in capturing such nonlinear dynamic processes. However, these concerns are eliminated from our paper since we have used yearly data without such seriously volatile fluctuations.

Energy forecasting research offers valuable insights into the complex nexus of energy consumption, economic growth, and environmental sustainability. By integrating economic, energy, and environmental perspectives, studies contribute to our understanding of the challenges and opportunities associated with sustainable development. Future research endeavors should further explore the heterogeneity of energy consumption patterns across different sectors and regions, as well as the potential impacts of policy interventions aimed at promoting renewable energy adoption.

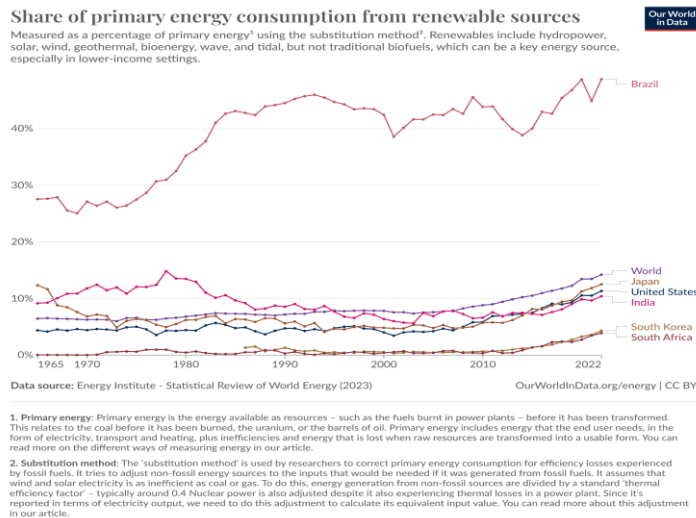
3. Data and Methods

⁹ Benedikt Sommer et al., "Online Distributed Learning in Wind Power Forecasting," *International Journal of Forecasting* 37, no. 1 (January 1, 2021): 205–23, <https://doi.org/10.1016/j.ijforecast.2020.04.004>.

¹⁰ Jinyuan Liu et al., "Natural Gas Consumption Forecasting: A Discussion on Forecasting History and Future Challenges," *Journal of Natural Gas Science and Engineering* 90 (June 1, 2021): 103930, <https://doi.org/10.1016/j.jngse.2021.103930>.

¹¹ Ada Lau and Patrick E. McSharry, "Approaches for Multi-step Density Forecasts With Application to Aggregated Wind Power," *Annals of Applied Statistics/the Annals of Applied Statistics* 4, no. 3 (September 1, 2010), <https://doi.org/10.1214/09-aos320>.

The data has been sourced from the Statistical Review of World Energy (2023) by the



Energy Institute, the International Renewable Energy Agency (2023) and the Maddison Project database (2020), curated by Our World in Data. The years range from 1965 to 2022 for most variables. The "substitution method," sometimes referred to as the "input-equivalent" methodology, is used in the data to measure primary energy for non-fossil electricity sources, like nuclear and renewable energy. It calculates how much fossil fuel thermal power plants must use in order to generate the same amount of energy that is not generated by fossil fuels. For example, if a nation produces 100 TWh of electricity using nuclear power and assumes an efficiency of 38% for standard thermal power plants, the input-equivalent primary energy would be 263 TWh, or 0.95 exajoules (EJ). This computation provides a more precise estimate of the consumption share of each energy source by accounting for the inefficiencies in the production of energy from fossil fuels. The graph below shows historical trends about the share of renewable energy in energy consumption for the entities in our sample.

Our dataset has variables for year, entity (India, Brazil, Japan, South Korea, South Africa, USA), renewable share of energy consumption, crude oil prices, electricity generated from hydroelectric power, wind energy, prices for solar PV panels and GDP per capita. The countries we have chosen help us get a good mix of developing and developed countries. We have captured renewable energy share as an aggregate as well as disaggregated into its most common constituents hydroelectric power and wind energy, also considering prices of renewable energy technology proxied by prices of solar PV modules. We use GDP per capita following the

findings of Aslan et.al (2022) where they find that countries sacrifice their national income to shift greater shares of their energy consumption towards renewable energy.¹² This implies that countries with lower GDP per capita might have lower renewable share, ceteris paribus.

We have used an ARIMA (Autoregressive Integrated Moving Average) model with Fourier series and exogenous variables to forecast renewable share of energy consumption based on lagged values of renewable energy share. The ARIMA model is a popular time series forecasting model that combines autoregressive (AR), differencing (I), and moving average (MA) components to capture the underlying patterns and dynamics in the data. They are simple models used for univariate time series data, where a single variable is being forecasted helping us understand the autocorrelation structure in the data.

We first conducted a Dickey-Fuller test to check for stationarity and found that the time series was non-stationary. This ruled out the use of VAR as the VAR model necessitates a stationary time series. We also ruled out the ARCH GARCH model as our time series is yearly, implying we didn't have to control volatility.

In order to deal with non-stationarity, we took the first differences and obtained a stationary series. However, despite being stationary the fit achieved was not appropriate. To get a better fit, we decided to use Fourier transformation akin to what is described by Enders (2012).¹³ Traditional unit root tests often have low power and provide results favoring the acceptance of the null hypothesis of nonstationarity. To address this limitation, Christopoulos and Leon-Ledesma propose Fourier unit root tests, which account for both structural breaks and non-linear adjustments, leading to more reliable results.¹⁴ The Fourier approximation is frequently useful in capturing a slow changing process in a time-varying intercept. Furthermore, researchers discovered that the test frequently captures various kinds of nonlinear trends and

¹² Alper Aslan et al., "Renewable Energy and Economic Growth Relationship Under the Oil Reserve Ownership: Evidence From Panel VAR Approach," *Renewable Energy* 188 (April 1, 2022): 402–10, <https://doi.org/10.1016/j.renene.2022.02.039>.

¹³ Walter Enders and Junsoo Lee, "A Unit Root Test Using a Fourier Series to Approximate Smooth Breaks*," *Oxford Bulletin of Economics and Statistics* 74, no. 4 (August 25, 2011): 574–99, <https://doi.org/10.1111/j.1468-0084.2011.00662.x>.

¹⁴ Burak Gürış, "A New Nonlinear Unit Root Test With Fourier Function," *Communications in Statistics. Simulation and Computation* 48, no. 10 (August 30, 2018): 3056–62, <https://doi.org/10.1080/03610918.2018.1473591>.

abrupt breaks. The fact that a Fourier approximation is a global approximation as opposed to a local one is an additional benefit.

We use a similar Fourier transformation to improve the fit of our model. Thus, any gradual changes in the data, which are not explained by the changes on GDP per capita, fluctuations in global oil prices (particularly during the oil wars of 1970s) and prices of solar PV modules, have also been accounted for in the model.

4. Results

From the graphs we can see that all the countries have shown a positive growth rate in terms of renewable energy implementation and consumption. We can see that most countries have majorly shown growth post the 2000's especially in the last 10-15 years. Countries like Brazil and India can be exceptions to this case. Brazil has always been above the world right from the beginning but had immense growth in the 1980's and in recent years has seen variable renewable energy consumption. India on the other hand has seen a decline in renewable energy compared to its peak in the 1970s and 1980s. This however does not mean there has not been an increase in renewable energy consumption, it could just be that renewable energy as a share of total energy has gone down. This applies to every country, the share of renewable energy in total energy has mostly increased.

From the tables we can see that for GDP per capita, it is negative and significant for India, USA and Brazil while it is positive and significant for Germany and South Africa. It is not significant at all for Japan and South Korea. For Crude oil prices, we can see negative and significant values for all countries except Germany and USA, whereas, in these two countries we can see insignificant values.

When it comes to the three types of renewable energy, all countries show significant and positive values for at least one of wind, hydropower or solar energy. For countries like the USA and Brazil hydropower plays a huge role in the renewable energy sector and contributes for the large part of it. The lag values are also mostly significant for every country except the USA and South Africa. This just means that the other variables are doing a good job in explaining the renewable energy shares in the current time periods. What we also observe is Brazil and Japan are showing divergence as the coefficient is greater than 1, even after controlling with fourier series.

From the table (in appendix) we can also see that the AIC and BIC values are low and the residuals are showing white noise in the portmanteau test, at significant p values. We have chosen the best model for estimating the data based on minimum AIC, BIC (best in-sample fit, least sum of squared residuals). In the end, we have conducted a portmanteau white noise test for the residual and found that we failed to reject the model we have approximated. The correlograms show there is no correlation in the residuals.

5. Conclusion

Energy security in the face of climate change and geopolitical tension is one of the biggest challenges the world faces in this century. A shift to renewable energy is vital not only for environmental concerns but also to ensure national security in the face of hostile geopolitical conditions.

This paper aims to predict trends in renewable energy shares of countries as a percentage of their total energy consumption. We have chosen countries in order to get a diverse mix in terms of factors like geography, per capita GDP, climatic conditions, growth trajectory etc. We use an ARIMA model with Fourier transformation in order to understand autocorrelation trends in the system. Fourier transformation helps us deal with structural breaks, seasonality and get a good fit for our dataset.

Our findings reveal a general upward trajectory in renewable energy implementation and consumption post the 2000s. GDP per capita significantly influences renewable energy trends, with varied impacts across countries. Crude oil prices exert negative effects on most countries except Germany and the USA, where the effects are insignificant. Additionally, all countries demonstrate significant reliance on at least one type of renewable energy, with hydropower playing a pivotal role for nations like the USA and Brazil.

Moreover, lag values indicate robust explanatory power of other variables in explaining renewable energy shares, while Brazil and Japan exhibit notable divergence in coefficients. Our model exhibits good fit and captures data patterns effectively, as evidenced by low AIC and BIC values, white noise characteristics in residuals, and lack of correlation in correlograms. These

insights underscore the importance of renewable energy adoption in mitigating energy security risks and advancing sustainable development goals.

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Appendix: ARIMA Models and Fit

Country	AR, MA	Sin, Cos	Endogenous Variable	Exogenous Variables
India	1,2	1,1	Renewable share	Crude Oil Prices, GDP percapita, Solar PV prices, Hydropower
Germany	4,0	1,1	Renewable share	Crude oil price, GDP per capita,Hydropower,Wind electricity, Solar PV
USA	1,2	1,1	Renewable share	Crude oil price, GDP per capita,Hydropower,Wind electricity, Solar PV
Japan	2,2	1,1	Renewable share	Crude oil price, GDP per capita,Hydropower,Wind electricity, Solar PV
Brazil	2,2	1,1	Renewable share	Crude oil price, GDP per capita,Hydropower,Wind electricity, Solar PV

South Korea	1,0	1,1	Renewable share	Crude oil price, GDP per capita,Hydropower,Wind electricity, Solar PV
South Africa	1,0	1,1	Renewable share	Crude oil price, GDP per capita,Hydropower,Wind electricity, Solar PV

of Fit **1 India** Goodness

	(1) renewable_share	(2) renewable_share
<hr/>		
main		
L.renewable_share	0.178 (2.00)	
sin1	1.084** (2.97)	2.962*** (4.41)
cos1	2.825*** (6.08)	1.895* (2.17)
crude_oil_prices	-0.00352*** (-4.72)	-0.00190 (-1.48)
gdppercapita	-0.00441*** (-6.45)	-0.00213*** (-5.39)
elec_from_hydro	0.0869*** (9.13)	0.0801*** (6.26)
solar_prices	-0.0173* (-2.41)	-0.00819 (-0.14)
wind_elec	0.158*** (3.77)	
_cons	13.46*** (6.48)	9.715*** (5.01)
<hr/>		
ARMA		
L.ar		0.564* (2.43)
L2.ma		0.181 (0.75)
<hr/>		
sigma		
_cons		0.395*** (7.37)
<hr/>		
N	44	44
<hr/>		

t statistics in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

2 Germany

	(1) renewable_share	(2) renewable_share
main		
L.renewable_share	0.152 (1.30)	
sin1	0.260 (1.49)	0.211 (1.44)
cos1	1.412*** (5.19)	1.757*** (25.27)
crude_oil_prices	0.000500 (0.73)	
gdppercapita	0.000221* (2.52)	0.000246*** (3.52)
elec_from_hydro	0.00496 (0.18)	
solar_prices	-0.289** (-3.22)	-0.355*** (-4.31)
wind_elec	0.0502*** (5.30)	0.0594*** (10.20)
_cons	-2.596 (-0.88)	-2.248 (-0.81)
ARMA		
L.ar		-0.0701 (-0.32)
L2.ar		-0.261 (-1.15)
L3.ar		-0.405 (-1.89)
L4.ar		-0.400 (-1.72)
sigma		
_cons		0.217*** (5.47)
N	32	33

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3 United States

	(1) renewable_share	(2) renewable_share
main		
L.renewable_share	-0.0353 (-0.57)	
sin1	-0.276* (-2.62)	-0.698* (-2.18)
cos1	0.00654 (0.05)	-0.851* (-2.22)
crude_oil_prices	-0.0000102 (-0.04)	
gdppercapita	-0.0000686** (-3.17)	-0.000194** (-2.64)
elec_from_hydro	0.0114*** (13.14)	
solar_prices	-0.00859 (-0.41)	0.0257 (0.37)
wind_elec	0.0210*** (9.10)	0.0318*** (5.64)
_cons	4.269*** (4.07)	11.97*** (3.74)
ARMA		
L.ar		0.604 (1.90)
L.ma		-0.453 (-0.00)
L2.ma		-0.547 (-0.00)
sigma		
_cons		0.250 (0.00)
<i>N</i>	35	36

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



4 Japan

	(1) renewable_share	(2) renewable_share
main		
L.renewable_share	0.336** (3.29)	
L2.renewable_share	0.0614 (0.61)	
sin1	0.895* (2.27)	1.368 (1.01)
cos1	0.119 (0.33)	3.991 (0.90)
crude_oil_prices	-0.00188** (-3.06)	-0.00106 (-0.57)
gdppercapita	0.0000216 (0.35)	
elec_from_hydro	0.0567*** (8.08)	0.0619*** (11.27)
solar_prices	-0.00488 (-1.14)	
wind_elec	0.403* (2.06)	
_cons	-1.647 (-1.04)	2.163* (1.97)
ARMA		
L.ar		1.959*** (51.92)
L2.ar		-0.993*** (-84.89)
L.ma		-1.007 (.)
L2.ma		0.00721 (0.05)
sigma		
_cons		0.328*** (7.77)
N	44	54

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Brazil

	(1) renewable_share	(2) renewable_share
<hr/>		
main		
L.renewable_share	0.181 (1.14)	
L2.renewable_share	0.121 (0.70)	
sin1	0.154 (0.15)	1.527** (2.86)
cos1	1.963** (2.97)	1.813*** (7.33)
crude_oil_prices	-0.00658* (-2.49)	-0.00621*** (-3.51)
gdppercapita	-0.00112* (-2.35)	-0.000867** (-3.23)
elec_from_hydro	0.0817*** (5.76)	0.0687*** (7.63)
solar_prices	0.724* (2.19)	0.389* (2.29)
wind_elec	0.0199 (0.56)	
_cons	15.26 (1.74)	31.33*** (5.95)
<hr/>		
ARMA		
L.ar		1.812*** (33.43)
L2.ar		-0.989*** (-20.54)
L.ma		-1.983*** (-14.75)
L2.ma		1.000 (.)
<hr/>		
sigma		
_cons		0.376*** (4.04)
<hr/>		
<i>N</i>	32	34
<hr/>		

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 South Africa

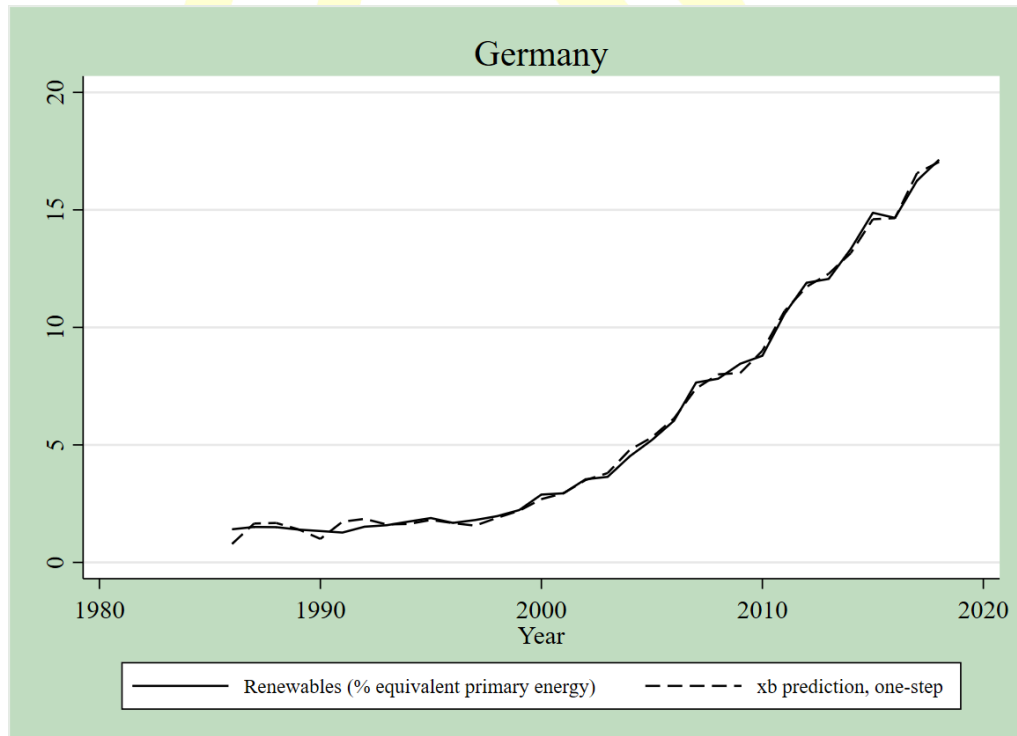
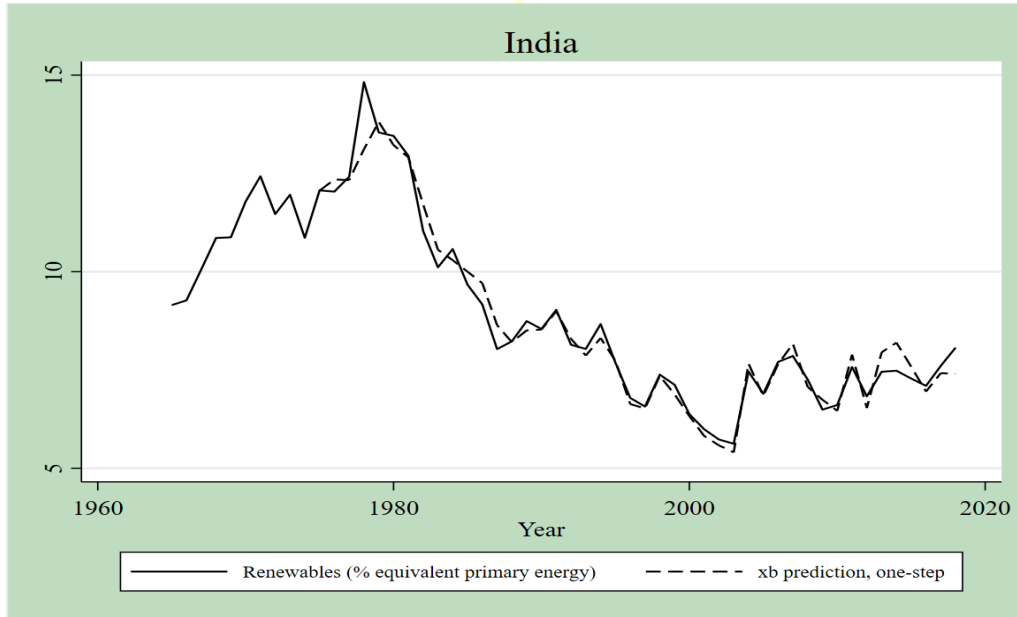
	(1)	(2)
	renewable_share	renewable_share
main		
L.renewable_share	0.00551 (0.04)	
L2.renewable_share	-0.0812 (-0.62)	
sin1	-0.388* (-2.66)	-0.651*** (-7.06)
cos1	0.577* (2.63)	0.701*** (5.30)
crude_oil_prices	-0.000698** (-3.03)	-0.000927*** (-4.08)
gdppercapita	0.0000627* (2.13)	0.0000809*** (5.07)
elec_from_hydro	0.167*** (5.39)	0.203*** (5.76)
solar_prices	0.0708* (2.09)	0.0714* (1.99)
wind_elec	0.334 (1.62)	
_cons	-1.342 (-1.72)	-1.631** (-2.66)
ARMA		
L.ar		-0.0314 (-0.11)
sigma		
_cons		0.110*** (4.89)
N	31	33

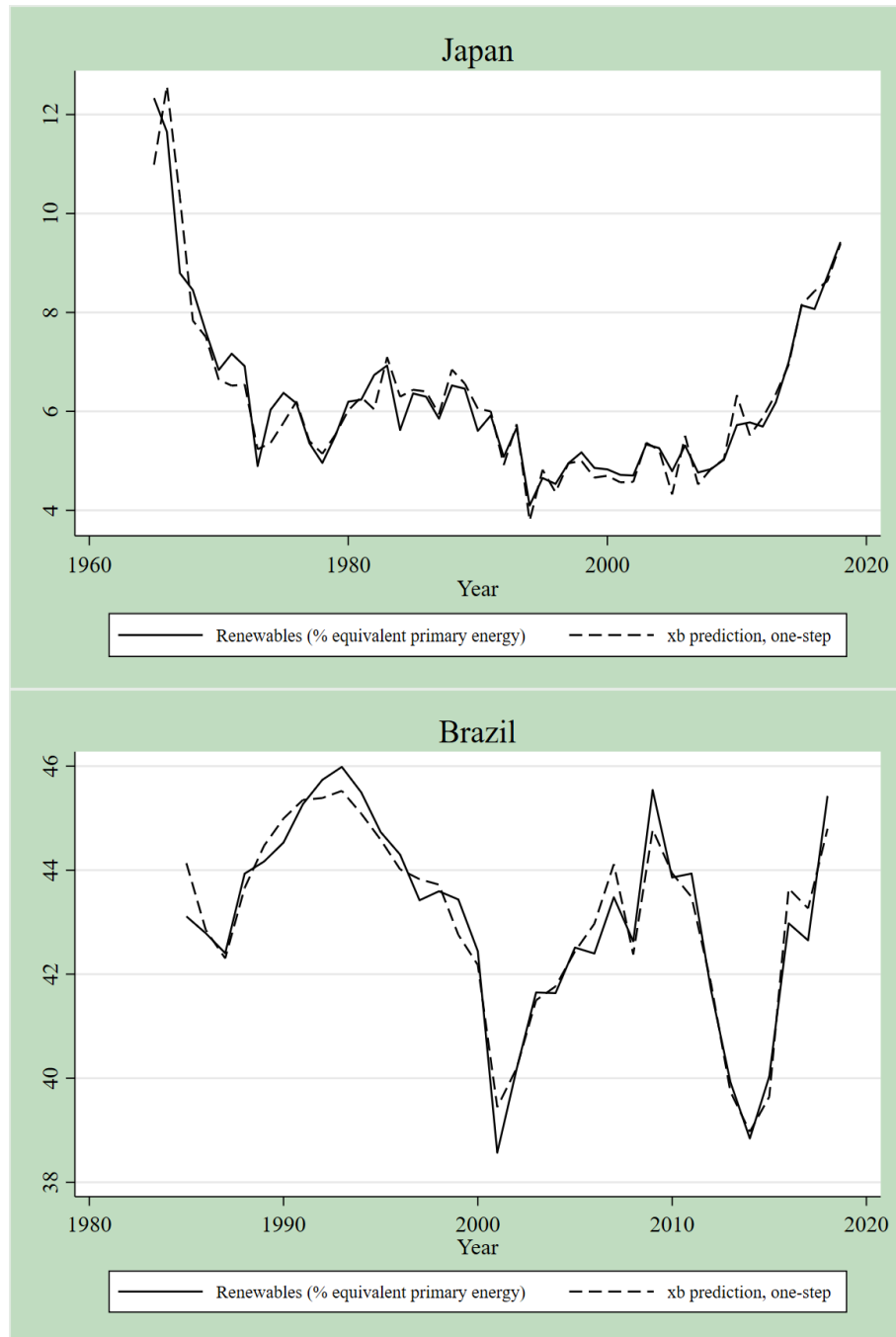
t statistics in parentheses

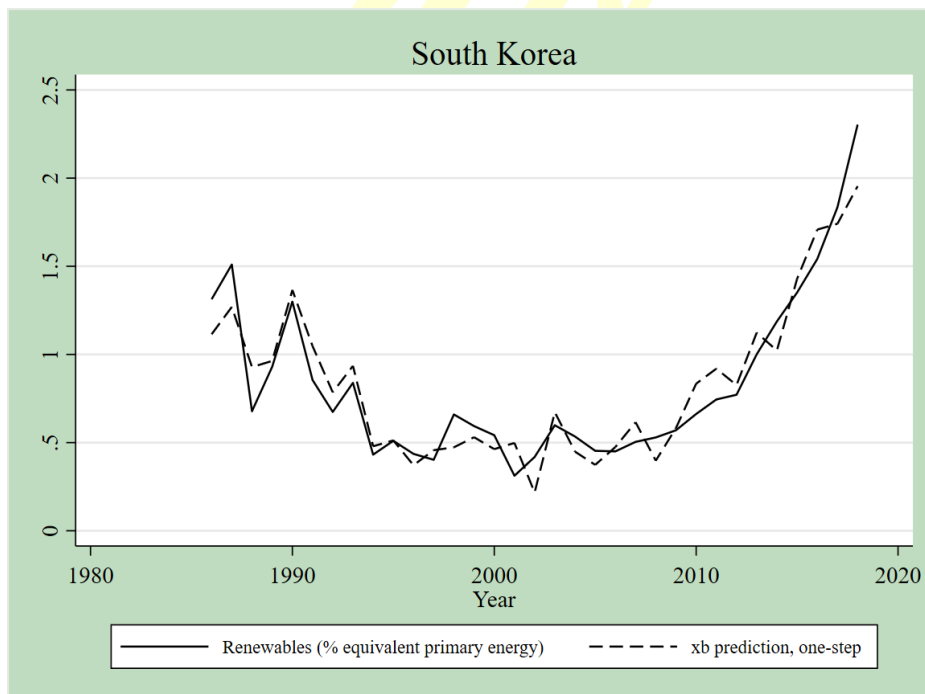
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

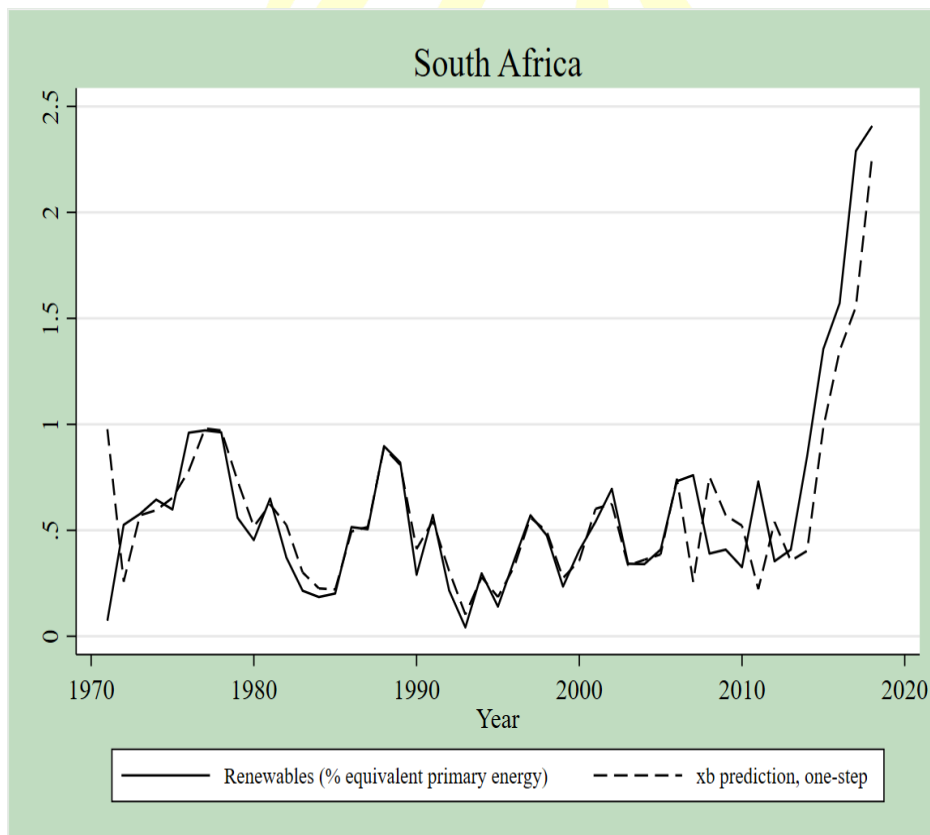
6 South Korea

	(1)	(2)
	renewable_share	renewable_share
main		
L.renewable_share	0.101 (0.77)	
L2.renewable_share	0.00243 (0.02)	
sin1	0.0924 (1.99)	0.178 (1.49)









Summary Statistics of Variables

