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Geopolitical Turmoil and G7 Renewable Electricity Production: Impacts of the Russian-Ukrainian Conflict

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Abstract

This paper scrutinizes the transformation in the electricity production structures of G7 nations in the wake of the Russian invasion of Ukraine. The inquiry centers on discerning shifts in the trajectory of energy production, particularly toward more sustainable and secure sources. With the imposition of economic sanctions against the Russian economy, an anticipatory transition from combustible fuels to renewable energy sources within G7 countries is envisaged. An empirical investigation is conducted utilizing panel data analysis of energy data across the G7. First and second-generation unit root tests have been used. Cointegration tests and the Vector Error Correction Model have been applied to see short-term and long-term relationships between renewable energy-sourced electricity production and combustible energy-sourced electricity production. Additionally, predictive modeling, employing SARIMA and Machine Learning model (Prophet) with Python, is employed to forecast future trends in energy production. This comprehensive analysis sheds light on the profound impact of geopolitical events on the energy landscape of influential global economies. The results of the econometrics and predictive models show that there is a significant effect of Russia-Ukrainian conflicts on electricity production in favor of more secure and clean energy. This trend change in renewable energy-sourced electricity production should fortify more regulatory aspects.

Keywords: Energy, Electricity, Panel Data Analysis, Machine Learning, Python.

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1. Introduction

On the 24th of February 2022, the Russian military launched an invasion of Ukraine, setting off a chain of geopolitical repercussions. In response, G7 nations (comprising Canada, France, Germany, Italy, Japan, the UK, and the USA), along with numerous other countries, swiftly implemented economic sanctions against the Russian economy. A glaring challenge stemming from this embargo lies in the heightened dependence of these nations on fossil fuel-derived energy sources. Russia stands as a pivotal exporter of fuels and natural gas, thereby necessitating a paradigm shift towards alternative energy reservoirs for the importing countries.

The aftermath of the Russian invasion of Ukraine effects profoundly through the global energy market, influencing both current and future energy production methodologies. This impact, akin to a butterfly effect, carries the potential to reshape the energy landscape. An optimistic outlook suggests that this crisis may serve as a catalyst for the acceleration of green and renewable energy sources, spurred by the embargo.

Post-invasion, European countries, encompassing both EU and non-EU members such as the UK and Norway, swiftly enacted stringent regulations favoring renewable energy while seeking to diminish reliance on fossil fuels. This strategic shift in energy policy is anticipated to exert a lasting influence on the transition from conventional, combustible energy sources toward sustainable alternatives.

A cornerstone of the European Union's agenda, the RePowerEU plan, aims to curtail reliance on Russian energy imports by the year 2027. Concurrently, Germany has set forth an ambitious target of achieving 100% clean energy by 2035 (Kuzemko et al., 2022). Furthermore, nations including France, Denmark, the Netherlands, and the UK, among others, have embarked on regulatory reforms designed to bolster renewable energy production. Saktiawan et al. (2022) have conducted a comprehensive study of European countries in the post-war era, emphasizing the EU's commitment to elevating the share of renewable energy to 45% by 2030. In pursuit of this goal, EU governments have allocated an estimated 300 billion euros to finance energy transitions.

This study unfolds in three key stages. Initially, a thorough literature review will be undertaken to establish a robust methodological framework. Subsequently, an in-depth analysis will be conducted to elucidate the relationship between total combustible electricity sources and total renewable electricity sources within G7 countries. The renewable energy sources include wind, solar, hydro, geothermal, combustible renewables, and other renewables. The primary energy sources comprise coal, peat, manufactured gases, oil, petroleum products, natural gas, and nuclear (iea.org). Finally, predictive models will be deployed to forecast future trajectories of electricity production in these nations. This research endeavors to offer critical insights into the evolving dynamics of energy production within the G7 context.

The selection of G7 countries as the cross-sectional sample is motivated by both political and practical considerations. The G7 nations represent a robust economic union of Western countries, particularly in opposition to Russia. Additionally, the availability of comprehensive data for the year 2022, encompassing total electricity production values for 48 countries, including those within the G7, influenced this choice. Notably, the collective electricity production of the G7 countries accounts for approximately 53 percent of the sample total. This strategic selection allows for a focused analysis of a significant portion of global electricity production while considering the geopolitical dynamics inherent to the G7 nations.

The paper centers its attention on electricity, a pivotal element in the energy market with profound implications for modern life. Beyond being a key component of our daily routines, electricity plays a critical role in determining production costs for industries and significantly influences the quality of individual lives. The importance of electricity is underscored by some political regulations that seek to steer future energy consumption patterns. A notable example is the European Union's commitment to ban the sale of petroleum and diesel cars after the year 2035. This policy not only reflects a commitment to environmental sustainability but also serves as a catalyst for the increased adoption of electric vehicles, thus reshaping the demand for electricity in the transportation sector. Recognizing these evolving dynamics is essential for comprehending the broader shifts in energy consumption and production that this study seeks to explore, particularly within the context of G7 countries.

2. Literature Review

Since the onset of the Russo-Ukrainian War, both the global political agenda and the academic community have shifted their focus towards a multitude of perspectives on the immediate and post-war effects. Scholars from various corners of the world have delved into the economic, financial, political, sociological, environmental, and military dimensions of the invasions. This study aims to scrutinize the potential repercussions of the invasion on the energy market, particularly within the realm of electricity production.

Upon reviewing the literature surrounding the Russo-Ukrainian War, it became evident that not all scholars share the belief that the conflict will act as a catalyst for the transition from combustible to renewable energy sources. This section will provide a comprehensive summary of both perspectives and their respective findings.

Osička and Černoch (2022) assert with conviction that the energy landscape has undergone a paradigm shift since the Russian invasion of Ukraine. Renewable energy sources, previously viewed as unreliable and costly, have supplanted Russian natural gas as an equally precarious and expensive energy source post-invasion. This shift in paradigm paves the way for renewable and green energy to potentially supplant natural gas and fossil-based energy sources.

Joshi et al (2023) examine the effects of conflicts on stock markets in different regions of the world. They identify a negative impact of the conflict on global stock markets. Mohammed et al (2022) direct their focus towards renewable energy stocks, revealing abnormal spikes in returns during both pre- and post-war periods. Employing the CAMP method and VAR modeling, they examined S&P global clean energy index data from August 3, 2021, to March 30, 2022, unveiling a positive and statistically significant reaction in clean energy stocks. Umar et al (2022) corroborate these findings, underlining a notable surge in returns within the renewable energy industry, surpassing gains in the metal market. Baek (2023) emphasizes an interesting aspect of the Russian-Ukrainian War: the connection between the Russian and Eastern European stock markets is weakening after the conflict.

El Khoury et al (2023) meticulously analyzed the financial impact of the Russian-Ukrainian War on the renewable energy sector, drawing data from various sources spanning two years up to May 2022. Through a range of time series analyses, including GARCH and VAR models, they scrutinized the spillover effects of the war on various investment options. Notably, gold and renewable energy stocks emerged as the most positively affected investment options. Karkowska and Urjasz (2023) delved into the spillover effects within the clean and dirty energy market from 2014 to 2022, encompassing the repercussions of the Russian invasion of Ukraine's eastern territory. Their findings suggest that renewable energy carries lower risk in financial markets, albeit with relatively higher hedging costs compared to non-renewable energy. Singh et al (2022) also explored the spillover effects of the war on investment behaviors, emphasizing a notably positive impact on the sustainable and renewable energy sector.

Balsalobre-Lorente and colleagues (2023) employed Cross-Quantilogram and Partial Cross-Quantilogram approaches to dissect oil and gas prices for G7 countries, distinguishing between pre- and post-Russo-Ukrainian War periods. Their findings highlight significant disparities in market returns before and after the war, suggesting that the Russo-Ukrainian War may offer an opening for the renewable energy sector to advance its operations.

Steffen and Patt (2022) delved into public opinion during the early stages of the Russo-Ukrainian war, employing surveys to gauge sentiments towards fossil-based and clean energy sources in Switzerland. Their research uncovered a clear shift in public opinion favoring clean energy sources following the Russian invasion. This suggests a heightened societal readiness for government policies supporting clean energy while penalizing fossil-based alternatives.

Kuzemko et al (2022) conducted a comprehensive survey of post-Russian Invasion of Ukraine regulations, concluding that the most viable long-term solution for securing energy supply in Europe lies in clean and renewable energy sources. In the short term, there is an anticipation of increased reliance on coal and gas-based energy sources. Aitken and Ersoy (2022) focused on both short-term and long-term shifts in European energy structures. In the short term, it appears that subsidizing Russian gas and oil with coal and traditional energy sources may be the only option. Unfortunately, while this may provide short-term stability, it is economically and environmentally costly. In the long run, diversification of energy structures through the development and expansion of renewable energy sources is anticipated.

Liao (2023) adopted a unique approach to the Russo-Ukrainian war, examining the investments made by European companies in renewable energy prior to the invasion. Their findings suggest that companies investing in renewable energy experienced relatively less disruption in the financial market's volatility. Liao proposes a link between geopolitical risk and investments in renewable energy, advocating for diversified energy sources to mitigate political and economic risks.

Ibar-Alonso et al (2022) delved into one of the crucial aspects of the war: sentiment analysis. Analyzing tweets and re-tweets within the period of February 16, 2022, to March 3, 2022, using R programming language and natural language processing (NLP) techniques, their results were intriguing. Prior to the invasion, global sentiment was generally positive, but after the onset of the invasion, sentiment dramatically shifted towards negativity, particularly towards the renewable energy sector, which consistently maintained positive sentiment.

Chen et al (2023) took a multifaceted approach to analyzing the Russo-Ukrainian war, examining its effects across various dimensions from economics to the environment. Notably, they investigated the war's impact on greenhouse gas emissions. Their short-term predictions anticipate a significant reduction in CO2 emissions. However, in the long run, they project a non-sustainable trend, with CO2 emissions ultimately resuming an upward trajectory. This shift is attributed to the substitution of Russian natural gas and fuel oil with less sustainable alternatives such as coal and thermal power plants. Chen and colleagues utilized a multi-region comparative static CGE model to generate different scenarios. Borowski (2022) contends that the EU's aim for zero carbon emissions by 2050 is jeopardized by coal-based energy production following the Russo-Ukrainian War. In this context, Borowski asserts that the war has adversely impacted the trend towards renewable and green energy in EU countries.

Nerlinger and Utz (2022) analyzed investor decisions following the invasion, gathering data from over 1500 companies across 75 countries in the energy sector. Their findings suggest that in the initial days post-invasion, there was no abnormal change in returns for renewable energy companies. Moreover, coal-fired energy firms experienced higher returns compared to their renewable energy counterparts.

To sum up, the literature review reveals that the effects of the Russian-Ukrainian war extend beyond the energy market to encompass all stock markets. The literature also indicates significant impacts on both renewable and combustible energy sources.

The prevailing notion is that, in the long run, the conflict catalyzes the growth of the clean and renewable energy sector in comparison to combustible energy sources.

3. Data and Models

The primary objective of this analytical framework is to ascertain whether the Russian invasion has had discernible effects on the production of renewable electricity within the G7 countries.

The primary energy sources for electricity generation encompass both renewable and combustible energy. A dynamic of substitution exists between these two pivotal sources, wherein an inclination towards renewable electricity can lead to a reduction in the proportion of combustible electricity production in the overall energy mix, and vice versa. The classification by the IEA delineates total renewable electricity production into components such as geothermal, solar, wind, and other sources, while combustible electricity production includes combustible renewables. To elucidate the relationship between these energy sources, combustible renewables have been excluded from both sides of the analysis. Given that the weight of combustible renewables in total electricity production ranges from approximately 1% to 8% across different cross-sections, their exclusion is deemed not to impede the long-term predictive capacity of the model.

3.1. Data

Electricity data for the G7 countries spanning from January 2010 to May 2023 has been sourced from the IEA (iea.org) website. This dataset comprises monthly observations, with the cross-sections pertaining to the G7 member nations, namely Canada, France, Germany, Italy, Japan, the UK, and the USA. A country-specific dataset was entered separately, and the ratios were calculated within each specific country. The ratios of total renewables and total combustible electricity production to overall electricity generation have been computed. The sum of these two ratios nearly approximates 1, indicating their complementary nature. Notably, a distinct negative correlation prevails between these ratios, signifying that as the proportion of $\frac{(\text{Total Combustible Fuels})}{(\text{Total Electricity Production})}$ increases, the proportion of $\frac{(\text{Total Renewable Energy})}{(\text{Total Electricity Production})}$ decreases. The forthcoming econometric models aim to unveil the statistical relationships underpinning these ratios.

3.2. Model Specifications

Panel Data analysis has been employed to examine the relationships between variables. The benefits of using panel data, as opposed to either time series or cross-sectional data, include higher degrees of freedom, lower multicollinearity, and higher data variation, leading to enhanced efficiency of estimators. Furthermore, panel data enables the control of heterogeneity, exploration of dynamics, and testing of more intricate behavioral hypotheses compared to what can be achieved with a sole time series or cross-section (Hsiao, 2006).

Table 1: Variable, acronym, unit of measurement, source

Variables		Acronym	Unit of measurement
$\frac{\text{(Total Renewable Energy)}}{\text{(Total Electricity Production)}}$	Dependant Variable	$Y_{i,t}$	GWh
$\frac{\text{(Total Combustible Fuels)}}{\text{(Total Electricity Production)}}$	Independent Variable	$X_{i,t}$	GWh
Dummy Variable	Independent Variable	$DUM_{i,t}$	0 or 1
Trend Component	Independent Variable	$@trend$	

Source: https://www.iea.org/data-and-statistics/data-product/monthly-electricity-statistics

The basic equation of the study is given below.

Total Electricity Production = Total Combustible Fuels + Total Renewable Energy

If we divide all parts of the equation by Total Electricity Production, we get the following equation:

$$\frac{\text{(Total Combustible Fuels)}}{\text{(Total Electricity Production)}} + \frac{\text{(Total Renewable Energy)}}{\text{(Total Electricity Production)}} = 1$$

I can represent the basic equation provided above in econometric form as follows:

$$\left(\frac{\text{Total Renewable Energy}}{\text{Total Electricity Production}}\right)_{\boldsymbol{i,t}} = \beta_0 + \beta_1 \left(\frac{\text{Total Combustible Fuels}}{\text{Total Electricity Production}}\right)_{\boldsymbol{i,t}} + u_{i,t}$$

If we incorporate a trend component and a dummy variable, and after some simplification, we arrive at the final form of the econometric model as follows:

$$Y_{i,t} = \beta_0 + \beta_1 X_{i,t} + \beta_2 DUM_{i,t} + @trend + \varepsilon_{i,t}$$

Where:

$Y_{i,t}$ denotes the proportion of Total Renewables (excluding combustible renewables) over Total Electricity Production
$X_{i,t}$ represents the proportion of Total Combustible electricity (excluding combustible renewables) over Total Electricity Production.
$DUM_{i,t}$ is a dummy variable accounting for the period following the Russian invasion of Ukraine.
β_0 signifies the intercept.
β_1 and β_2 denote the coefficients.
@trend: Trend component.
$\varepsilon_{i,t}$: Error term.

Initial scrutiny entailed conducting unit root tests, both cross-sectionally independent and dependent, to assess the stationary properties of the series. In economic terms, a variable exhibiting a unit root (non-stationary) may not naturally revert to a specific long-term level after experiencing a shock. This distinction holds crucial implications for policymakers and decision-makers, influencing the choice between ongoing versus one-time interventions. The results of the Augmented

Dickey-Fuller (ADF) tests confirm that the variables exhibit stationarity at the level, as demonstrated in Table 2 (Dickey and Fuller, 1979).

Table 2: ADF Unit root test

Variable	Method	Statistics	Prob.
Independent	ADF - Fisher Chi-Square	91.91[A]	0.00
	ADF - Choi Z-stat	-6.37[A]	0.00
Dependent	ADF - Fisher Chi-Square	179.03[A]	0.00
	ADF - Choi Z-stat	-8.65[A]	0.00

Notes: A, B and D indicate the 1%, 5%, and 10% of levels of significance, respectively. Unit root test with trend and intercept. Lag Length: Automatic selection: Schwarz info criterion.

For the second-generation unit root test, the Pesaran – CIPS unit root test was employed, accounting for cross-section effects. The results of the Pesaran – CIPS test affirm that the variables exhibit stationarity at the level in both unit root tests (Pesaran, 2007). This reinforces the notion that the examined variables do not exhibit a unit root and are considered stationary, which is crucial for accurate economic interpretations and policy formulation. Please look at Table 3 for Pesaran – CIPS unit root test results and refer to Table 4 for the CADF unit root test results.

Table 3: CIPS Unit Root Test (Model 2)

	Statistics	t-stat	p-value
Independent	CIPS	-3.749	<0.01
	Truncated CIPS	-3.691	<0.01
Dependent	CIPS	-4.828	<0.01
	Truncated CIPS	-4.828	<0.01
	Critical Values		
	Level	CIPS	Trunc. CIPS
	1%	-3.03	-3.03
	5%	-2.83	-2.83
	10%	-2.73	-2.73

Notes: Constant and deterministic trends have been chosen. ADF lag criterion was chosen. Maximum lang is taken as 6.

Table 4: CADF Unit root test (Model 2)

		Independent Variable				**Dependent Variable**			
		CADF		**Truncated CADF**		**CADF**		**Truncated CADF**	
Cross -Sec.	ADF Lags	t-stat	p-val.	t-stat	p-val.	t-stat	p-val.	t-stat	p-val.
1	6	-3.079	>=.10	-3.079	>=.10	-6.381	<0.01	-6.381	<0.01
2	2	-3.758	<0.05	-3.758	<0.05	-3.576	<0.10	-3.576	<0.10
3	1	-4.363	<0.01	-4.363	<0.01	-3.849	<0.05	-3.849	<0.05
4	6	-2.534	>=0.1	-2.534	>=0.1	-3.875	<0.05	-3.875	<0.05
5	6	-2.467	>=0.1	-2.467	>=0.1	-4.818	<0.01	-4.818	<0.01
6	6	-3.219	>=0.1	-3.219	>=0.1	-6.056	<0.01	-6.056	<0.01
7	6	-6.819	<0.01	-6.42	<0.01	-5.241	<0.01	-5.241	<0.01

Notes: Constant and deterministic trend have been chosen. ADF lag criterion was chosen. Maximum lang is taken as 6. Critical values (CADF and Trunc. CADF): -4.31 (%1), -3.70 (5%), -3.40 (10%).

To assess the long-term effects of the Russian Invasion on the production of Total Renewables (Geo, Solar, Wind, Other) electricity production in G7 countries, a regression analysis was conducted. The choice between a Random and Fixed Effect model was determined through a Hausman Test, ultimately leading to the adoption of a one-way random effect panel data analysis.

The Hausman Test is instrumental in gauging whether individual-specific effects bear significant correlation with the independent variables. Should the p-value exceed 0.05, it indicates that these effects are not significantly related to the independent variables. Consequently, in such a scenario, the random effects model is deemed more appropriate. This model posits that individual-specific effects are stochastic and uncorrelated with the independent variables (Hausman, 1978). Please refer to Table 5 for the Hausman Test results.

Table 5: Hausman Test

Test Summary	Chi-Sqr Statis.	Chi-Sq. d.f.	Prob
Cross-Section Random	0.00	2	1.00

The outcomes of one-way random effect panel data analysis are given in Table 6.

Table 6: Panel Random Effect Model

Variable	Coefficient	t-statistic
C	0.520[A]	61.04
X	-0.598[A]	-39.67
DUMMY	0.013[A]	3.56
@TREND	0.0004[A]	17.2
R-square	0.969	
A. R-square	0.969	
F statistics	3912[A]	
Akakike	-4.08	
DW stat	0.48	

I have observed a negative and statistically significant coefficient for the dependent variable, in line with my expectations. Additionally, the dummy variable yielded a positive and statistically significant coefficient. This implies that the Russian invasion has led to a shift in production in favor of renewable electricity production sources. In Table 6, C represents the constant of the model.

$$Y_{i,t} = \beta_0 + \beta_1 X_{i,t} + \beta_2 DUM_{i,t} + @trend + \varepsilon_{i,t}$$

Coefficient (β_1) for $X_{i,t}$ (-0.598): Holding all other variables constant, a one-unit increase in $X_{i,t}$ is associated with a decrease in $Y_{i,t}$ by approximately 0.598 units. This indicates a negative relationship between $X_{i,t}$ and $Y_{i,t}$.

Given this negative coefficient, it suggests that there is a form of divergence between $Y_{i,t}$and $X_{i,t}$ in the context of the model. In other words, an increase in $X_{i,t}$ is associated with a decrease in $Y_{i,t}$.

The findings of the model reveal valuable insights into the dynamics of electricity production, particularly the proportion of Total Renewables in the context of combustible electricity and the period following the Russian invasion of Ukraine. The negative coefficient (-0.59) associated with the proportion of combustible electricity suggests that as this component increases, there is a corresponding decrease in the proportion of Total Renewables. This implies that efforts to reduce reliance on combustible electricity could lead to an increase in renewable energy production. Furthermore, the positive coefficient (0.013) for the dummy variable representing the post-Russian invasion period indicates a slight increase in the proportion of Total Renewables during this period. Practically, these findings imply that strategic policy interventions targeting a reduction in combustible electricity and recognizing the impact of geopolitical events, such as the Russian invasion, could be instrumental in promoting a more sustainable and resilient energy mix over time. Additionally, careful consideration of the trend component is essential for anticipating and adapting to long-term shifts in the landscape of electricity production.

3.2.1. Cointegration and Vector Error Correction Model

In order to justify the long-run relationship between Total Renewable Electricity production and Total Combustible Electricity production, it is good to look at cointegration between these two variables.

I have looked at Pedroni (Engel-Granger bases) cointegration test with individual and individual trend. The cointegration test results are given in Table 7 (Pedroni, 1999).

Table 7: Pedroni Cointegration Test

	Statistic	W. Statistic
Panel v- statistic	1.066	0.269
Panel rho-statistic	-16.116^{A}	-17.19^{A}
Panel PP-statistic	-12.366^{A}	-11.94^{A}
Panel ADF-statistic	-10.668^{A}	-10.62^{A}
Group rho-statistic	-25.38^{A}	
Group PP-statistic	-14.24^{A}	
Group ADF-statistic	-11.38^{A}	

A, B and D indicate the 1%, 5%, and 10% of levels of significance, respectively. Cointegration test with trend and intercept. Lag Length: Automatic selection: Schwarz info criterion. Null Hypothesis: No cointegration. Bandwidth selection: Newey-West automatic bandwidth selection and Barnett kernel

Out of the 11 statistics examined, 9 exhibit significant values. Based on the results of the Pedroni Cointegration test, I confidently conclude that a long-term relationship indeed exists between Total Renewable Electricity production and Total Combustible Electricity production, aligning with my initial expectations.

In the short run, various factors can lead to shocks and deviations from the long-term equilibrium. To ascertain whether these short-term discrepancies eventually revert to a long-term equilibrium, the Error Correction model proves invaluable.

Additionally, exploring the Vector Error Correction model, as proposed by Johansen in 1995, holds promise for providing deeper insights into the dynamic interplay between these variables (Johansen, 1995).

Long-Run cointegration regression model: $Y_{i,t} = \beta_0 + \beta_1 X_{i,t} + \varepsilon_{i,t}$

Lagged residuals (cointegrating equation): $\varepsilon_{i,t-1} = ECC_{i,t-1} = Y_{i,t-1} - \beta_0 - \beta_1 X_{i,t-1}$

$$\Delta Y_{i,t} = \alpha_i + \sum_{k=1}^{p} \beta_i \Delta Y_{it-k} + \sum_{k=0}^{q} \delta_i \Delta X_{it-k} + \theta_i ECC_{it-1} + u_{i,t}$$

ECC_{it-1}: Error correction coefficient term

The VEC model outcomes are given Table 8.

Table 8: Vector Error Correction Model

Cointegrating Eq	CointEq1	t-statistic
Y(-1)	1.00	
X(-1)	-0.211	-0.70
C	-0.169	
Error Correction - D(Y)	Coefficient	t-statistic
CointEq1	*-0.015*[A]	*-2.86*
DY(-1)	-0.138[B]	-2.64
DY(-2)	0.0017	-0.03
DX(-1)	-0.02	-0.41
DX(-2)	0.044	0.93
C	0.002	1.446
R-square	0.026	
A. R-square	0.021	
F statistics	5.88[A]	
Akakike	-3.889	

I have discovered a statistically significant Error Correction Coefficient, which aligns with the theoretical expectations, showing a negative sign. This implies that any short-term disequilibrium in the model will gradually adjust towards the long-run equilibrium at a rate of approximately 1.5% per month. This finding underscores the dynamic nature of the relationship between the variables, with adjustments occurring over a relatively short time frame.

3.2.2. Forecast- SARIMA and Prophet Model

Through the Random Effect Panel Data Analysis, we observe that the Russian invasion of Ukraine has spurred the G7 countries to seek out alternative energy sources. Consequently, they have embarked on a transition in their electricity production, moving away from traditional fuel and natural gas towards renewable energy sources. This section aims to provide future projections for total combustible electricity production and the utilization of renewable electricity production sources within the G7 countries. Unlike the panel data framework, I'll be examining the cumulative electricity production of G7 countries. That is to say, I accumulated all data for the G7 countries, calculated the ratios, and started to forecast using SARIMA and Prophet models.

The results of the panel data analysis show a significant shift in the electricity production structure of G7 countries toward renewable energy sources. For future predictions, a macro-economic perspective is necessary. Therefore, I prefer to utilize the total electricity production dataset of G7 countries instead of employing panel data analysis. To achieve this, I have used a time series dataset to make long-run future predictions with SARIMA and Prophet models.

To forecast the production of electricity from renewable sources within the G7 countries up until 2050, I employed the SARIMAX (1,1,1,12) model. The graph below depicts the trajectory of the proportion of electricity production sourced from renewables relative to the total. The presence of a steadily ascending trend instills optimism about the future prospects for our planet (Box et al., 1994).

$$Y_t = c_0 + \Phi_1 Y_{t-1} + \theta_1 \varepsilon_{t-1} + \Theta_1 Y_{t-12} + \phi_1 \varepsilon_{t-12} + \varepsilon_t$$

Where:

Y_t: Observed time series: Renewable Energy based electricity production and Combustible Energy based electricity production.

c_0: Constant term,

Φ_1: the autoregressive parameter.

Y_{t-1}: Lagged value of observed time series at time t-1.

θ_1: the moving average parameter.

ε_{t-1}: the error term at time t-1.

Θ_1: the seasonal autoregressive parameter.

Y_{t-12}: the values from the same season in the previous year (seasonal lag).

ϕ_1: the seasonal moving average parameter.

ε_{t-12}: the error term from the same season in the previous year (seasonal error term).

ε_t: the error term at time t.

I have also conducted predictions for combustible source electricity production, and an evident negative trend is discernible. This indicates a notable decrease in the reliance on combustible sources for electricity generation in the future.

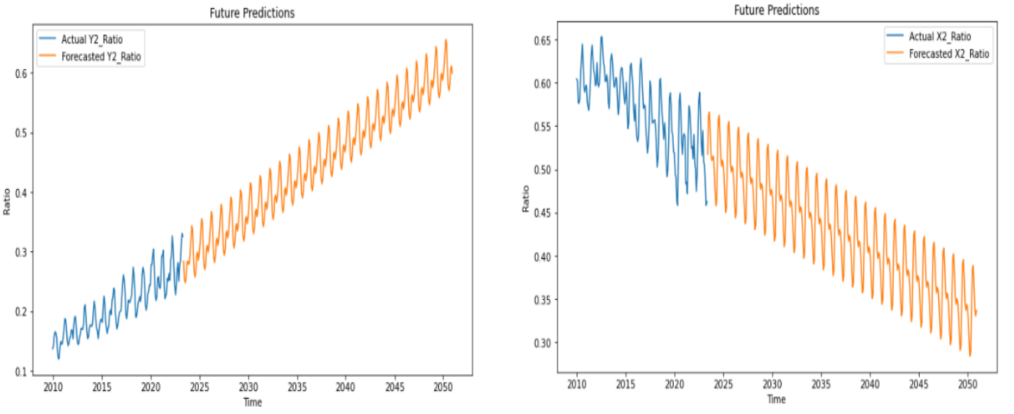

Figure 1: Sarima Model Future Predictions

Additionally, I cross-verified the future predictions using the Prophet Model, as suggested by Taylor and Letham in 2018. Encouragingly, the results from the Prophet Model align closely with the earlier predictions, further reinforcing our outlook.

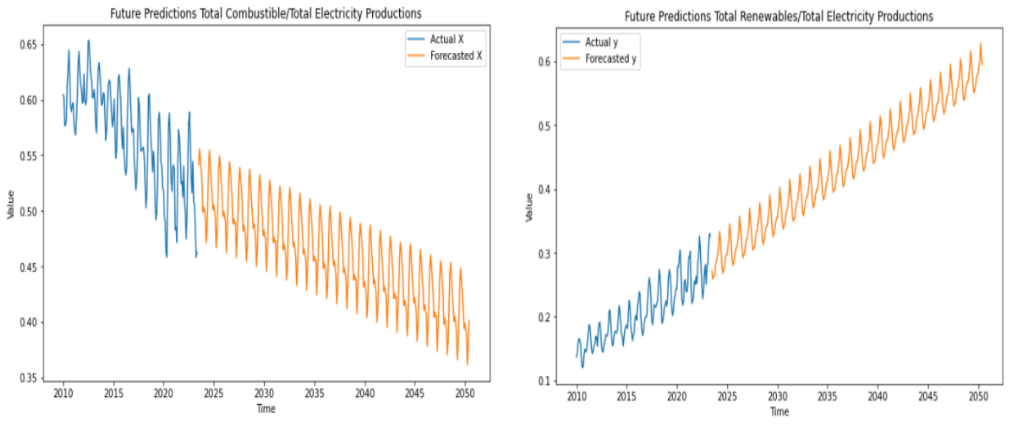

Figure 2: Prophet Model Predictions

4. Results and Discussion

The analysis presented in this study underscores the significant impact of the Russian invasion of Ukraine on the electricity production of G7 countries. Through Random Effect Panel Data Analysis, we observed a decisive shift towards alternative energy sources, marking a departure from traditional reliance on fossil fuels and natural gas. This transition is poised to shape the future of electricity production in these nations.

Forecasts for both renewable and combustible electricity production were conducted, revealing distinct trends. The proportion of electricity sourced from renewables exhibited a promising upward trajectory, affirming the potential for a more sustainable energy future. Conversely, combustible source electricity production exhibited a discernible negative trend, indicating a declining reliance on these traditional energy sources.

These projections, derived from SARIMA and Prophet models, provide valuable insights for policymakers, industry leaders, and stakeholders alike. The findings suggest a clear imperative for further investments in renewable electricity infrastructure and policies to facilitate this transition.

5. Conclusion and Policy Recommendations

The analysis conducted highlights the effectiveness of employing advanced modeling techniques in predicting future trends in electricity production. Looking forward, it becomes abundantly clear that a unified effort towards the adoption of renewable energy is not only justified but also entirely feasible.

In summary, the aftermath of the Russian invasion of Ukraine has served as a catalyst for a transformative shift in the electricity production landscape of G7 countries. By embracing alternative energy sources, these nations stand to not only alleviate environmental impacts but also develop a more resilient and sustainable energy future.

It is crucial to recognize that G7 countries play a considerable role in the global electricity production, holding a significant share of the overall pie. Consequently, from both political and economic perspectives, the trajectory of electricity production in these nations will undoubtedly reflect globally, influencing a more secure and environmentally friendly trend in the realm of energy generation.

To further solidify the commitment to renewable energy, implementing additional regulations favoring these sources will widen the gap between renewable and combustible energy sources. These regulations, when effectively enforced, serve as a pivotal step in making renewable energy sources a permanent fixture in the landscape of electricity production. By creating a regulatory environment that incentivizes the use of clean energy, G7 countries can set a precedent for sustainable practices, encouraging other nations to follow suit.

In conclusion, the comprehensive adoption of renewable energy within the G7 countries is not only a strategic environmental choice but also a powerful driver for fostering global energy security and sustainability. Through sustained commitment and the implementation of supportive policies, these nations can lead the way towards a cleaner, more resilient energy landscape for the benefit of both current and future generations.

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Appendices

A.1. Python Codes: For Sarimax Model

```
import pandas as pd
import numpy as np
from statsmodels.tsa.statespace.sarimax import
SARIMAX
import matplotlib.pyplot as plt
df =
pd.read_csv('C:\\Users\\...\\model1_two_variabl
e.csv')
df['Time'] = pd.to_datetime(df['Time'],
format='%b/%y')
df.set_index('Time', inplace=True)
df.head()
df.tail()
# Assuming you have prepared your dataframe
df as described
# Train SARIMA model for Y2_Ratio
model = SARIMAX(df['Y2_Ratio'], order=(1, 1, 1),
seasonal_order=(1, 1, 1, 12))
results = model.fit()
# Generate future dates up to 2050
future_dates = pd.date_range(start='2023-06-
01', end='2050-12-31', freq='M')
# Make predictions
future_Y2_Ratio_predictions =
results.get_forecast(steps=len(future_dates))
# Get the predicted values
predicted_values =
future_Y2_Ratio_predictions.predicted_mean
# Combine predictions with original data
df_combined = pd.concat([df,
predicted_values.rename('Y2_Ratio_Forecast')],
axis=1)
# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(df_combined.index,
df_combined['Y2_Ratio'], label='Actual
Y2_Ratio')
plt.plot(df_combined.index,
df_combined['Y2_Ratio_Forecast'],
label='Forecasted Y2_Ratio')
plt.xlabel('Time')
plt.ylabel('Ratio')
plt.title('Future Predictions')
plt.legend()
plt.show()
```

```
### SARIMAX Model for X2_Ratio
independent variable no exog variables.
# Train SARIMA model for Y2_Ratio
model = SARIMAX(df['X2_Ratio'], order=(1,
1, 1), seasonal_order=(1, 1, 1, 12))
results = model.fit()
# Generate future dates up to 2050
future_dates = pd.date_range(start='2023-
06-01', end='2050-12-31', freq='M')
# Make predictions
future_X2_Ratio_predictions =
results.get_forecast(steps=len(future_dat
es))
# Get the predicted values
predicted_values =
future_X2_Ratio_predictions.predicted_m
ean
# Combine predictions with original data
df_combined = pd.concat([df,
predicted_values.rename('X2_Ratio_Forec
ast')], axis=1)
# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(df_combined.index,
df_combined['X2_Ratio'], label='Actual
X2_Ratio')
plt.plot(df_combined.index,
df_combined['X2_Ratio_Forecast'],
label='Forecasted X2_Ratio')
plt.xlabel('Time')
plt.ylabel('Ratio')
plt.title('Future Predictions')
plt.legend()
plt.show()
```

A2. Python codes for Prophet Model

```
#For Prophet Model for Total Combustible
pip install fbprophet # makes error.
pip install prophet
from prophet import Prophet
df =
pd.read_csv('C:\\Users\\...\\model1_two_variable.csv')
df['Time'] = pd.to_datetime(df['Time'], format='%b/%y')
df.set_index('Time', inplace=True)
df.head()
df3 = df[['X2_Ratio']].copy()
df3.head()
df3 = df3.rename(columns={'X2_Ratio': 'y'})
df3.head()
df3.index = pd.to_datetime(df3.index)
# Initialize the Prophet model
model = Prophet(yearly_seasonality=True,
weekly_seasonality=False, daily_seasonality=False)
# Prepare the data for Prophet
df_prophet = df3.reset_index()
df_prophet.columns = ['ds', 'y']  # Prophet requires
column names to be 'ds' and 'y'
df_prophet.head()
# Fit the model
model.fit(df_prophet)
# Generate future dates up to 2050
future_dates = pd.date_range(start='2023-06-01',
periods=324, freq='M')  # Generate 324 months (27
years)
future_df = pd.DataFrame({'ds': future_dates})
# Make predictions
future_predictions = model.predict(future_df)
predicted_values = future_predictions['yhat']
# Combine predictions with original data
df_combined = pd.concat([df_prophet.set_index('ds'),
predicted_values.rename('yhat')], axis=1)
# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(df_combined.index, df_combined['y'],
label='Actual X')
plt.plot(future_dates, predicted_values,
label='Forecasted X')
plt.xlabel('Time')
plt.ylabel('Value')
plt.title('Future Predictions Total Combustible/Total
Electricity Productions')
plt.legend()
plt.show()
```

```
#For Prophet Model for Total Renewable
Energy
df2 = df[['Y2_Ratio']].copy()
df2 = df2.rename(columns={'Y2_Ratio':
'y'})
df2.index = pd.to_datetime(df2.index)
# Initialize the Prophet model
model =
Prophet(yearly_seasonality=True,
weekly_seasonality=False,
daily_seasonality=False)
# Prepare the data for Prophet
df_prophet = df2.reset_index()
df_prophet.columns = ['ds', 'y']  # Prophet
requires column names to be 'ds' and 'y'
df_prophet.head()
# Fit the model
model.fit(df_prophet)
# Generate future dates up to 2050
future_dates =
pd.date_range(start='2023-06-01',
periods=324, freq='M')  # Generate 324
months (27 years)
future_df = pd.DataFrame({'ds':
future_dates})
# Make predictions
future_predictions =
model.predict(future_df)
predicted_values =
future_predictions['yhat']
# Combine predictions with original data
df_combined =
pd.concat([df_prophet.set_index('ds'),
predicted_values.rename('yhat')], axis=1)
# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(df_combined.index,
df_combined['y'], label='Actual y')
plt.plot(future_dates, predicted_values,
label='Forecasted y')
plt.xlabel('Time')
plt.ylabel('Value')
plt.title('Future Predictions Total
Renewables/Total Electricity Productions')
plt.legend()
plt.show()
```