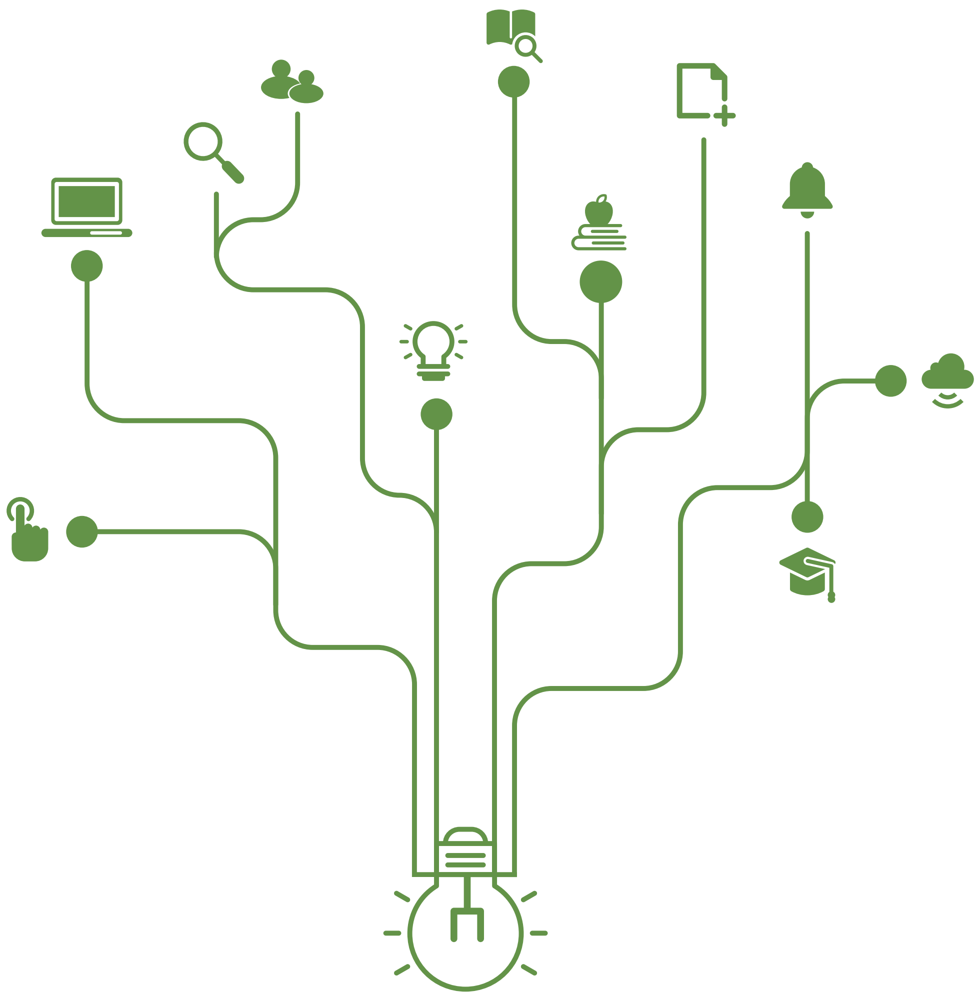
Development Studies Series DS24-01

Energy Transitions Post–Russia–Ukraine War: Challenges and Policy Implications in Germany and Italy

Yeong Jae Kim *(KDI School of Public Policy and Management)*
Kyonggi Min *(KDI School of Public Policy and Management)*
Seong-Hoon Cho *(University of Tennessee)*



KDI SCHOOL
KDI School of Public Policy and Management

Energy Transitions Post–Russia–Ukraine War: Challenges and Policy Implications in Germany and Italy

Yeong Jae Kim[1*]

Kyonggi Min[1]

Seong-Hoon Cho[2]

1 KDI School of Public Policy and Management, 263 Namsejong-ro, Sejong-si, 30149, Republic of Korea

2 Department of Agricultural and Resource Economics, University of Tennessee, 2621 Morgan Circle, 314D Morgan Hall, Knoxville, TN, 37996-4518, USA

*corresponding author:kyj@kdischool.ac.kr

Abstract

In the pursuit of global net-zero emissions by 2050, the Russia–Ukraine War emerges as a potential disruptor, challenging progress toward this critical objective. We explore the repercussions of the conflict on the European Union's (EU) initial energy transition goals, with a keen focus on electricity generation. To analyze projections for coal, natural gas, nuclear, hydro, and renewables in Germany and Italy over the period of 2023 and 2027, we employ the seasonal autoregressive integrated moving average (SARIMA) model. Our findings from Germany presented a contrast with those from Italy, influenced by the impact of the onset of the war. The observed and anticipated shifts in Germany's energy landscape, especially the notable decline in nuclear power generation and the simultaneous increase in coal usage, present considerable obstacles to attaining carbon neutrality. Italy's resilient energy shifts, marked by hydropower fluctuations and increased renewable energy, suggest continued measures for emission reduction. This study not only identifies contrasting energy challenges but also proposes nuanced policy implications tailored to each country's context, providing valuable insights for navigating the complex path toward sustainable and resilient carbon neutrality amidst geopolitical uncertainties.

Keywords: Energy Transition, Geopolitical Impact, Carbon Neutrality, Renewable Energy, Integrated Energy Planning

1. Introduction

The invasion of Ukraine by Russia in February 2022 has intensified the strain on the global supply chain, already affected by the U.S.–China trade conflict and pandemic-related disruptions. This escalation has led to a surge in energy prices worldwide, contributing to the acceleration of global inflation. Europe, in particular, has been severely impacted given its historical reliance on Russia, the largest exporter of pipeline natural gas. The unexpected disruption has prompted some European governments, such as Germany and Italy, to implement measures such as rationing hot water and electricity to mitigate natural gas consumption during the summer of 2022 (Hughes, 2022; Wallace, 2022).

Furthermore, Europe's pursuit of energy transition toward carbon neutrality by 2050, as outlined by the European Commission in 2023, faces additional challenges as Russia curtails its supply of natural gas to the continent in the aftermath of the conflict. Since the onset of the war, the European Union (EU) and its member states have been implementing measures that may pose a significant threat to the ongoing progress toward energy transition.

As the largest economy within the EU, Germany has historically heavily relied on Russian gas for its primary energy consumption (Bella et al., 2022). In 2021, Russian pipeline gas constituted the country's main source of gas supply (Eckert & Abnett, 2022). However, in response to diminished Russian gas supplies following the onset of the conflict, Germany implemented a temporary shift back to coal-fired power plants as part of a transitional strategy (Meredith, 2022). Faced with continued constraints in natural gas supplies right after the onset of the war, the country took the significant step of permanently closing its last three nuclear power plants in early 2023.

Similarly, Italy, as the third-largest economy in the EU, has experienced a heavy dependence on Russian gas, leading to a search for alternatives since the onset of the conflict. Italy's reliance on Russian gas decreased from 40% in 2021 to 25% in 2022 (Reuters, 2022). In an effort to substitute these energy needs, Italy has rapidly transitioned to renewables, such as wind and solar. Consequently, the country witnessed a notable 120% increase in renewable capacity from the first half of 2022 to the corresponding period in 2023. Amidst this transition, hydroelectric power production in Italy faced a substantial decline of approximately 40% during the first half of 2021 compared to the same period in 2022, primarily caused by a drought (AFP, 2022).

The recent challenges faced by Germany and Italy in their energy sectors serve as illustrative examples of the disruptions and cutoffs experienced by EU countries in their energy sources since the onset of the war. Assessing the impact of the onset of the war and its concurrent events on the EU's initial energy transition goals is crucial for determining potential shifts in strategies to achieve climate neutrality by 2050, with a focus on mainstreaming energy transition (Siddi, 2023). Consequently, this research aims to examine the short-term effects of the energy crisis triggered by the Russia–Ukraine War and concurrent events on Europe's ongoing journey toward carbon neutrality.

To achieve our goal, we project electricity supplies from the five main energy sources (coal, natural gas, nuclear, hydro, and renewables) and analyze their respective impacts on greenhouse gas (GHG) emissions in both Germany and Italy over the five-year period following the Russia–Ukraine War (2023–2027). This comparative case study, examining projections with and without the onset of the war's effects, is designed to yield valuable insights. The examination of short-term projections, accounting for the impact of the onset of the war, has the potential to provide meaningful recommendation for strategically adjusting the energy transition roadmap toward the EU's carbon neutrality goals.

Our focus on short-term effects is motivated by their immediacy and visibility, facilitating quicker measurement and analysis compared to long-term effects. This immediacy is vital for policymakers who must swiftly address pressing challenges. A thorough understanding of the immediate impact on energy use and GHG emissions provides valuable insights for shaping policy responses, including measures related to energy security, resource allocation, and diplomatic actions. Moreover, short-term effects hold substantial implications for energy markets. Rapid shifts in energy sources caused by disruptions in energy infrastructure necessitate prompt responses from policymakers. Researching short-term effects aids in comprehending and navigating the dynamic landscape of these changes, contributing to more effective decision-making in the face of evolving energy scenarios.

2. Literature review

Energy transition toward carbon neutrality typically involves the shift from fossil-based energy systems to renewable-based systems. This transition is primarily motivated by concerns related to climate change, energy security, and the long-term sustainability of existing energy practices. Economic research related to energy transition encompasses four key areas:

1. Cost–Benefit Analysis: This involves evaluating the economic costs and benefits associated with transitioning to renewable energy sources compared to maintaining the status quo.

2. Investment and Finance: This area focuses on assessing the economic risks and returns associated with investments in clean energy technologies. It explores the financial aspects of transitioning to cleaner energy sources.

3. Innovation and Technology Adoption: Examining the economic drivers of innovation

in clean energy technologies is crucial. This area explores the economic incentives and factors that accelerate the development and adoption of innovative technologies in the clean energy sector.

4. Economic Modeling and Scenario Analysis: This involves simulating different scenarios of energy transition and assessing their economic impacts. By using economic modeling and scenario analysis, researchers can project and analyze the potential outcomes of various transition pathways.

Each of these areas contributes to our understanding of the economic dimensions of energy transition and aids policymakers and stakeholders in making informed decisions for a sustainable and low-carbon energy future.

The literature on key area (1) is frequently utilized to assist decision-makers in comprehending the potential economic costs and benefits of energy transition (Mathioulakis et al., 2013; Shih & Tseng, 2014). Given that the primary motivation for transitioning to renewable energy often revolves around environmental benefits, including climate change mitigation and improved community health (Yang et al., 2021; Obaideen et al., 2021), the literature in this field offers analyses that encompass the implications of energy transition for environmental, social, and economic sustainability. In key area (2), the literature seeks key risk diversification strategies and actionable insights to mitigate investment risks, ultimately aiming to enhance accessibility to energy. Three primary avenues of investigation within this domain include risk identification (Williams, Jaramillo, and Taneja 2018; Gujba et al. 2012), risk assessment (Zaroni et al. 2019; Wu et al. 2020), and risk mitigation (Bhattacharyya et al., 2019; Schmidt et al., 2013; Kim et al., 2021). For key area (3), the literature has delved into examining the causality between technology innovations and renewable energy (Xie et al., 2020; Khan et al., 2022; Palage et al., 2019; Kim & Brown, 2019). In the context of key area (4), the literature has evaluated the economic implications of energy transitions by considering scenarios of rapid and transformative energy transition (Hainsch et al., 2022; Jacques et al., 2023; Hainsch et al., 2022; Kim & Wilson, 2019).

The existing literature has extensively explored the effects of external shocks—encompassing geopolitical events such as wars, economic fluctuations, and unexpected technological breakthroughs—on the path toward achieving carbon neutrality in energy transitions. Recent studies have specifically focused on discerning both the challenges and opportunities that characterize the landscape of energy transition in the post–COVID-19 era (Hepburn et al., 2021; Chong et al., 2022; Tian et al., 2022).

Moreover, a nascent body of literature is emerging on understanding the impact of the onset of the war on energy transition. Given the war's relatively recent commencement, investigations have predominantly relied on surveys, interviews, and qualitative analyses as the primary methods of inquiry, reflecting the limited timeframe available for comprehensive study. For instance, semi-structured expert interviews were employed to identify the potential catalytic effects of the war on Germany's energy sector, aimed at mitigating climate change and reducing reliance on emission-intensive energy sources (Lomoschitz 2023). Another study utilized a survey to examine how the war altered public support for clean energy policies in Switzerland (Steffen and Patt, 2022). Additionally, limited qualitative analysis has been conducted to comprehend the broader impacts of the war on the environment, including changes in energy policy (Pereira et al. 2022).

Despite significant progress in economic research related to energy transition and the exploration of external shocks, a noticeable dearth of research quantifies the precise impact of these shocks on this transition. This absence is surprising given that neglecting such external shocks has the potential to significantly influence the trajectory and success of the transition. The oversight of these external factors may result in incomplete or overly optimistic assessments, impeding the development of robust strategies and policies for achieving carbon neutrality. Therefore, integrating a comprehensive analysis of potential external shocks is imperative for adopting a more resilient and adaptive approach to address the complex challenges associated with energy transition.

The remainder of the paper is structured as follows. Initially, we provide a detailed elucidation of the data, unveiling unique patterns of electricity generation in both Germany and Italy. Subsequently, we present a comprehensive outline of the time series model employed for forecasting electricity supply from the five energy sources and predicting the resulting GHG emissions. Following the modeling section, we analyze the findings derived from our research and explore their implications on energy transition and associated environmental impacts. In the penultimate section, we draw conclusions based on the insights gained from our study. Finally, we elucidate potential avenues for future research directions, contributing to the ongoing discourse on energy transition and carbon neutrality.

3. Data and method

3.1. Data

We sourced electricity generation data—encompassing coal, natural gas, nuclear, hydro, and renewables—for Germany and Italy from the European Network of Transmission System Operators for Electricity (ENTSO-E) Transparency Platform. Recognized as the largest energy data platform for European power systems (Hirth, Mühlenpfordt, and Bulkeley 2018), ENTSO-E has been extensively utilized in literature for electricity price modeling and forecasting (e.g., Halužan et al., 2020). The platform offers quarterly to hourly electricity generation data categorized by energy source, which we aggregated into monthly values for our time series analysis. At the time of data acquisition for our empirical model, the electricity generation data covers the period from January 2015 to February 2023 for Germany and from January 2016 to February 2023 for Italy, reflecting their reporting period differences.

3.2. Method

The seasonal autoregressive integrated moving average (SARIMA) model is employed as a time analysis because the data exhibits seasonality. For each of the five energy sources between the two countries, we specify two SARIMA models: one using historical data of 2015–2022 by carrying the onset of the war effect in 2022 to forecast electricity supply in 2023–2027 and one using historical data of 2015–2022 without carrying the onset of the war effect in 2022 to forecast electricity supply in 2023–2027 in Germany; and another one using historical data of 2016–2022 by carrying the onset of the war effect in 2022 to forecast electricity supply in 2023–2027 and one using historical data of 2016–2022 without carrying the onset of the war effect in 2022 to forecast electricity supply in 2023–2027 in Italy.

We construct the SARIMA model (i.e., $ARIMA\ (p,d,q)(P,D,Q)_s$) as follows:

$$\phi_p(\mathrm{B})\Phi_P(B^s)(1-B)^d(1-B^s)^D y_t = \alpha + \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{1}$$

$$\phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$$

$$\Phi_P(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{Ps}$$

$$\theta_q(B) = 1 + \theta_1 B + \cdots + \theta_{\mathrm{q}} B^q$$

$$\Theta_Q(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Qs}$$

$$(1 - B)(1 - B^s)y_t = (y_t - y_{t-1}) - (y_{t-s} - y_{t-s-1})$$

$$\varepsilon_t \sim WN(0, \sigma^2)$$

Here, B is the backward shift wherein the operator denotes the monthly electricity generation data with a one-month time lag. p and P are the non-seasonal and seasonal components of autoregressive (AR), which is a combination of the one-month lag of the monthly electricity generation data. q and Q are the non-seasonal and seasonal components of moving average (MA), which is a series of averages calculated from historical monthly electricity generation values. d and D are the numbers of non-seasonal and seasonal differences. s is the duration of the periodic seasonal behavior for data. In our case, we utilize 12 months as a value of s ($s = 12$). y_t is the electricity generation at time t. α is the constant, and ε_t is white noise with the independent and identical distribution that shows no autocorrelation.

The process of choosing the best-fitted SARIMA model involves sequential steps. First, the Hylleberg, Engle, Granger, and Yoo (HEGY) test detects seasonality, which, if present, is eliminated through seasonal differencing (Hyndman and Khandakar 2008). Second, the stationarity of the data is assessed using the Dickey–Fuller generalized least squares (DF-GLS) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, with necessary adjustments made through differencing. Third, the best model fit is determined by incrementally adjusting the parameters p, q, P, and Q to minimize the Akaike information criterion (AIC). Fourth, the Portmanteau test checks whether the time series is more than just white noise by assessing serial correlation. Fifth, if the residuals are white noises, we proceed with forecasting monthly electricity generation using the SARIMA model. Otherwise, we return to step 3 to explore alternative models.

For accurate forecasting of future monthly electricity generation, we aimed to eliminate seasonality and achieve stationarity in the data. In Germany, coal exhibited no seasonality, while natural gas, nuclear, and hydropower required seasonal adjustments to achieve stationarity. Although renewables initially displayed non-stationarity, they were not seasonally adjusted, leading to paradoxical results. In Italy, both coal and renewables exhibited seasonality, with coal requiring an additional first ordinary difference for stationarity. Natural gas was already stationary, while hydropower required further adjustments.

The final model selection for both countries was based on the smallest AIC for each energy source (refer to the appendix for additional details). For Germany, we selected the following models in Appendix Table A.5: coal (Table A.5 Model 1 with AIC 683.2366), natural gas (Table A.5 Model 1 with AIC 463.0139), nuclear (Table A.5 Model 3 with AIC 426.6752), hydropower (Table A.5 Model 2 with AIC 224.6255), and renewables (Table A.5 Model 1 with AIC 727.3991). In Italy, our chosen models were coal (Table A.5 Model 2 with AIC 56.6979), natural gas (Table A.5 Model 2 with AIC 293.9097), hydropower (Table A.5 Model 2 with AIC 153.4951), and renewables (Table A.5 Model 2 with AIC 98.6432).

The projected electricity supply for 2023–2027, considering the impact of the onset of the war, and the projected electricity supply for 2022–2027 without the onset of the war effect for each of the five energy sources in both countries is transformed into GHG emissions based on CO_2 conversion factors specified in Equation (2).

$$CO2 = H \times CF \quad \times MW \tag{2}$$

where *CO2* indicates the quantity of GHG emissions, *H* denotes the heating value, indicating the amount of heat released during the combustion of energy sources, and *CF* stands for CO_2

conversion factors for energy sources used in electricity generation, sourced from the European Commission (2023a). The specific factors for each energy source are as follows: nuclear (1.4 g CO_2 $\frac{eq}{\mathrm{MJ}}$, which stands for grams of carbon dioxide equivalent per megajoule, indicating the amount of GHG emissions measured in grams for each unit of energy produced in megajoules), hard coal (16 g CO_2 $\frac{eq}{\mathrm{MJ}}$), brown coal (1.4 g CO_2 $\frac{eq}{\mathrm{MJ}}$), natural gas (12.8 g CO_2 $\frac{eq}{\mathrm{MJ}}$), hydro (0 g CO_2 $\frac{eq}{\mathrm{MJ}}$), solar (0 g CO_2 $\frac{eq}{\mathrm{MJ}}$), and wind (0 g CO_2 $\frac{eq}{\mathrm{MJ}}$), and MW is a ratio of the molecular weight of carbon dioxide to carbon, which is $\frac{44}{12}$.

4. Results and discussions

4.1. Descriptive analysis

Prior to delving into the analysis of the time series model results, it is advantageous to undertake a comprehensive examination of the historical data related to electricity supplies from primary energy sources. This scrutinty should concentrate on periods marked by significant changes, particularly those occurring just before and immediately after the onset of the war. The preceding descriptive analysis of historical data from 2021 to 2022, conducted around the period just before and immediately after the onset of the war, offers valuable context and insights to enrich the interpretation of subsequent time series model results.

The left panel of Figure 1 depicts the alterations in energy sources between 2021 and 2022 in Germany. The most notable change during this period is the significant decrease in nuclear power generation, which can be attributed to the country’s phaseout of nuclear power plants. Specifically, the Grohnde, Gundremmingen C, and Brokdorf plants were permanently closed at the end of December 2021 (Federal Office for the Safety of Nuclear Waste

Management 2023). Following this, the last three reactors in the country—Isar 2, Emsland, and Neckarwestheim 2—underwent decommissioning in April 2023 (Federal Office for the Safety of Nuclear Waste Management 2023).

Another significant change is the observed increase in both coal and renewable energy supplies. In 2022, Germany has witnessed a resurgence of coal as the country's economy turns to this traditional fuel to address an ongoing energy crisis triggered by the war. Notably, between July and September 2022, over 36% of the electricity supplied to the German power grids originated from coal-fired power plants. This marks a significant increase from the third quarter of the previous year, when coal contributed under 32% to the overall energy mix (Federal Statistical Office of Germany 2023). On the flip side, the crisis has strengthened Germany's resolve to eliminate fossil fuels and expedite the shift to clean energy in the long run. The government has announced its intention to phase out coal entirely by 2030, a decision made in the after the onset of the war, and this marks an advancement of eight years compared to the target set by the previous administration. Germany aspires to source 80% of its electricity from renewable sources by that deadline, exceeding the earlier goal of 65% and almost doubling the 42% share held in 2021.

The right panel of Figure 1 illustrates the shifts in energy sources in Italy over the same period. A prominent pattern in this panel is the significant reduction in hydropower generation, attributed to Italy experiencing its most severe drought in 70 years in 2022 (Reuters 2023a). Furthermore, both coal and renewable energy sources have experienced an increase, mirroring the situation in Germany. The significant rise in the share of renewable energy can be largely attributed to the country's investment of €59 billion as part of the National Resilience and Recovery Plan (NRRP), aimed at incentivizing renewables from 2021 to 2026 (International Trade Administration 2022). Similar to Germany's circumstances, the conflict prompted an increase in the country's short-term coal usage as an alternative to the Russian natural gas it previously imported. Italy raised its electricity production from coal to 7.5% in 2022, up from 4.6% in 2021 (Reuters 2023b).

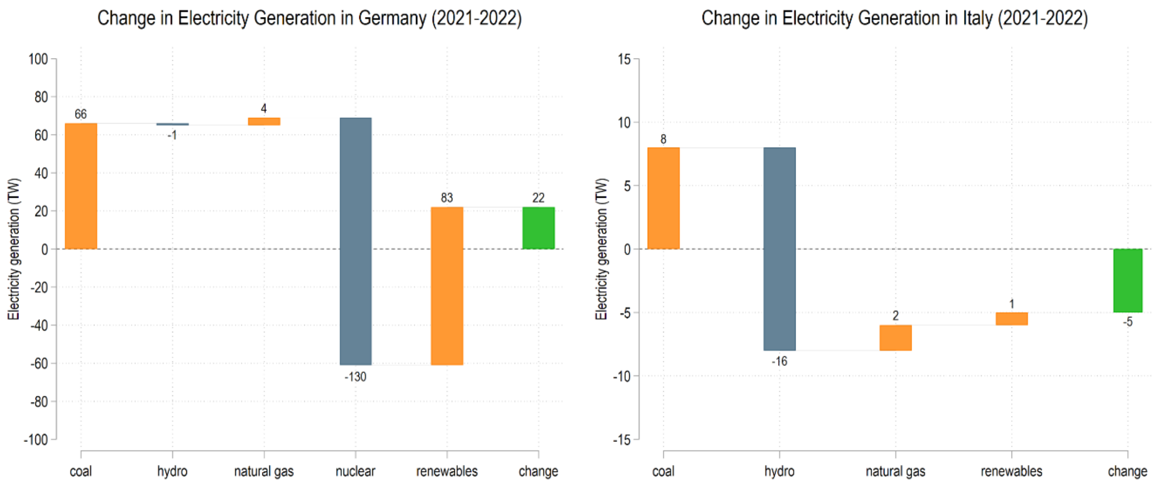


Figure 1. Changes in electricity generation by sources in Germany and Italy in 2021 and 2022.

4.2. Time series model results

Electricity generation projects, measured in terawatts (TW), based on the time series model for five primary energy sources with and without impact the impact of the onset of the war from March 2017 to February 2027 are presented in three formats for both countries: the pattern of changes in electricity projects depicted by connecting monthly forecasts for each of the five energy sources individually with and without the impact of the onset of the war in Figures 3 and 6; projected GHG emissions from natural gas and coal, presented both with and without the impact of the onset of the war, in Figures 4 and 7; and means and standard deviations of forecasted electricity generation in TW for five major energy sources on a yearly basis in Table 1. For Figures 3, 4, 6, and 7, we consolidate monthly data into annual data.

Table 1 presents the means and standard deviations of forecasted electricity generation in TW for five major energy sources on a yearly basis, utilizing the time series model discussed above. The forecasted values span ten years from March 2017 to February 2027 for Germany and Italy, considering scenarios both with and without the impact of the onset of the war. We emphasize the analysis up to 2027 to provide a focused insight. This selection allows us to highlight specific trends and considerations during this critical period, including scenarios both with and without the impact of the onset of the war.

In the case of Germany, there has been a slight increase in the projected electricity generation from natural gas, rising from 20 TW to 21.53 TW with the war compared to a scenario without the war between March 2023 and February 2024 (Table 1), despite the shutdown of natural gas imports from Russia. The unexpected rise in the share of natural gas is a surprising projection considering the cessation of natural gas imports from Russia following the outbreak of the war. The swift adjustment in the country's import sources, as evident in the 2022 data, can be explained by the increased influx of natural gas imports from third countries such as Norway and Belgium (see Appendix Figure A.1). The percentage of gas imported from Russia significantly declined from 62% before the war to 19% after the conflict. Despite the slight increase in natural gas supply immediately after the onset of the war, its relative share, compared to a scenario without the war, is projected to decrease two years. Precisely, just before the war, its share was 11.4% in February 2023. It is projected to be 13.8% with the war and 14.4% without the war in February 2024 (Figure 3).

Another intriguing observation is the dramatic surge in coal usage, escalating from 38.09 TW to 57.16 TW when compared to counterfactuals covering the period from March 2023 to February 2024 (Table 1). This surge results in a projected 36.5% share of coal with the war, contrasting with a 27.4% share in a scenario without the war by February 2024 (Figure 3). Germany turns to coal as Russia throttles gas supply to Germany. Hydroelectric power generation has experienced minimal change, while renewable energy generation has seen a slight decline, dropping from 83.15 TW to 77.16 TW during the war when compared to a scenario without the conflict over the same period.

The war, with its 3.8% point increase in the share of coal and a corresponding 3.8% point decrease in the share of natural gas in the two years following the conflict (Table 1), is anticipated to pose a substantial challenge to Germany's carbon neutrality goal. The impact on GHG emissions becomes more apparent. Specifically, under a scenario without the war, the combined GHG emissions from both energy sources are projected to be 80 million tons in February 2027. However, this figure surges to 117 million tons (more than 46% higher) with the war in play (Figure 4). The ratio of GHG emissions from coal to those from natural gas was expected to be balanced at 56.3% in March 2023 to 33.2% in February 2027 without the war. However, given the unexpected increase in the share of coal triggered by the war, this ratio shifts to 60.1% to 51.6%. This shift underscores the concerning deviation from the balanced projection and highlights the significant impact of the onset of the war on Germany's GHG emissions landscape.

In contrast to Germany, Italy has witnessed a slight reduction in natural gas usage, dropping from 9.02 TW to 8.70 TW during the war when compared to a scenario without the conflict between March 2023 and February 2024 (Table 1). This anticipated decrease signals a short-term disruption in the supply of natural gas from Russia, underscoring the challenges Italy faces in promptly diversifying its import sources. Despite reducing reliance on Russia from 36% to 13% before and after the onset of the war, the difficulty is underscored by the relatively stagnant influx of natural gas imports from third countries (see Appendix Figure A.2.).

On the contrary, coal utilization in Italy has maintained a relatively stable pattern, showing minimal variation both with and without the war (refer to Figures 6 and 7 and Table 1). Notably, there has been a consistent increase in hydropower generation, rising from 1.55 TW to 2.08 TW during the war compared to a scenario without the conflict between March 2023 and February 2024 (see Table 1). This surge in hydropower electricity during the war is expected to contribute to a higher share (11.9%), as opposed to the scenario without the war (8.9%). Importantly, the projected increase in hydropower share by February 2024 stems from the recovery in hydropower generation following the severe drought experienced in Italy during 2022.

Additionally, renewable energy sources in Italy have experienced a minor decrease, shifting from 4.71 TW to 4.61 TW during the war compared to a scenario without the conflict over the same period. This decline is likely attributed to the impact of the NRRP implementation carried out in 2022 for the model considering the war, an aspect not factored into the model without the conflict.

Despite the substantial impact of the drought on hydropower generation and a slight dip in renewable energy production coinciding with the outbreak of the war, the overall electricity supply from the four energy sources experienced minimal change as a result of the conflict. Consequently, the combined amount of electricity supply between the two scenarios is projected to remain around 200 TW in 2027 (Figure 6). Consequently, there is no significant difference in the anticipated GHG emissions by February 2024 from natural gas and coal, with marginal distributional changes between the two sources, registering 26 tons with the war and 25 tons without the war (Figure 7).

Table 1. Means and standard deviations of forecasted electricity generation for four major energy sources on a yearly basis, utilizing the time series model with and without the impact of the onset of the war

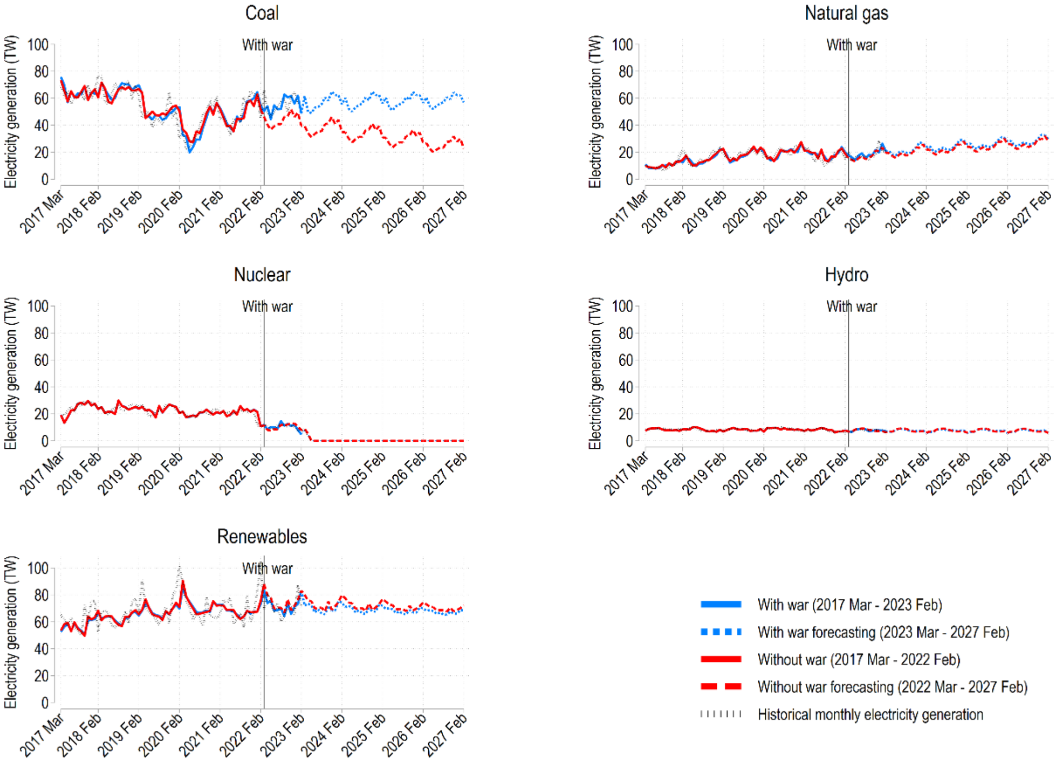
Unit: TW

	Year/Month	Coal		Natural gas		Nuclear		Hydro		Renewables	
		With war	Without war	With war	Without war	With war	Without war	With war	Without war	With war	Without war
Germany	2017/3~2018/2	64.38 (5.03)	63.87 (4.57)	10.27 (1.88)	10.42 (2.08)	23.72 (4.94)	23.77 (4.92)	8.35 (0.77)	8.36 (0.78)	58.29 (4.25)	59.35 (4.98)
	2018/3~2019/2	66.82 (4.24)	65.18 (4.51)	15.16 (3.93)	15.40 (4.15)	23.82 (2.69)	23.81 (2.75)	8.22 (1.22)	8.22 (1.21)	62.77 (3.02)	63.61 (3.50)
	2019/3~2020/2	49.09 (5.35)	50.61 (5.01)	18.09 (3.60)	18.53 (3.51)	23.30 (2.75)	23.27 (2.85)	8.27 (0.83)	8.26 (0.83)	67.85 (3.49)	68.98 (4.29)
	2020/3~2021/2	38.56 (12.57)	41.27 (10.10)	19.43 (3.86)	19.75 (3.83)	20.16 (1.72)	20.16 (1.73)	8.74 (0.74)	8.75 (0.74)	72.17 (5.72)	73.20 (6.59)
	2021/3~2022/2	49.55 (9.34)	48.15 (8.48)	18.48 (2.71)	18.38 (3.15)	20.87 (3.71)	20.83 (3.84)	8.00 (0.96)	8.00 (0.97)	70.86 (2.82)	72.16 (3.42)
	2022/3~2023/2	54.91 (5.84)	43.62 (4.66)	18.66 (3.25)	17.37 (3.21)	10.35 (2.53)	10.32 (2.04)	7.79 (0.78)	7.75 (0.95)	75.48 (5.64)	80.07 (6.05)
	2023/3~2024/2	57.16 (5.21)	38.09 (4.63)	21.53 (3.10)	20.00 (3.06)	6.52 (1.79)	7.54 (2.04)	7.58 (0.92)	7.61 (1.05)	77.16 (3.23)	83.15 (4.06)

	2024/3~2025/2	57.62 (4.57)	33.75 (4.31)	24.07 (2.87)	22.24 (3.01)	0.00 (0.00)	0.00 (0.00)	7.61 (0.86)	7.61 (1.00)	81.05 (2.38)	87.27 (3.16)
	2025/3~2026/2	58.00 (4.19)	29.59 (3.97)	26.07 (2.84)	24.32 (3.00)	0.00 (0.00)	0.00 (0.00)	7.53 (0.88)	7.55 (1.02)	84.50 (1.84)	91.39 (2.51)
	2026/3~2027/2	58.28 (3.85)	25.45 (3.65)	27.98 (2.83)	26.31 (2.97)	0.00 (0.00)	0.00 (0.00)	7.50 (0.86)	7.51 (1.01)	87.90 (1.49)	95.50 (2.05)
Italy	2017/3~2018/2	1.76 (0.83)	1.76 (0.83)	6.26 (1.04)	6.24 (1.07)	N/A	N/A	3.00 (0.94)	3.00 (0.94)	3.71 (0.45)	3.74 (0.45)
	2018/3~2019/2	2.23 (0.26)	2.23 (0.26)	6.89 (1.60)	6.87 (1.64)	N/A	N/A	3.99 (1.39)	3.99 (1.40)	3.91 (0.43)	3.93 (0.42)
	2019/3~2020/2	1.38 (0.36)	1.38 (0.36)	9.44 (1.07)	9.49 (1.10)	N/A	N/A	3.88 (0.72)	3.88 (0.74)	4.04 (0.37)	4.07 (0.39)
	2020/3~2021/2	0.96 (0.29)	0.96 (0.29)	9.39 (1.67)	9.43 (1.74)	N/A	N/A	3.97 (1.15)	3.97 (1.15)	4.16 (0.43)	4.20 (0.44)
	2021/3~2022/2	1.08 (0.28)	1.08 (0.28)	9.80 (1.49)	9.85 (1.53)	N/A	N/A	3.72 (1.00)	3.72 (1.00)	4.36 (0.43)	4.38 (0.42)
	2022/3~2023/2	1.83 (0.25)	1.79 (0.24)	9.78 (1.20)	9.88 (0.77)	N/A	N/A	2.38 (0.79)	2.40 (0.94)	4.52 (0.49)	4.54 (0.50)
	2023/3~2024/2	2.08 (0.27)	2.17 (0.28)	8.70 (0.60)	9.02 (0.41)	N/A	N/A	2.08 (0.87)	1.55 (1.02)	4.61 (0.48)	4.71 (0.50

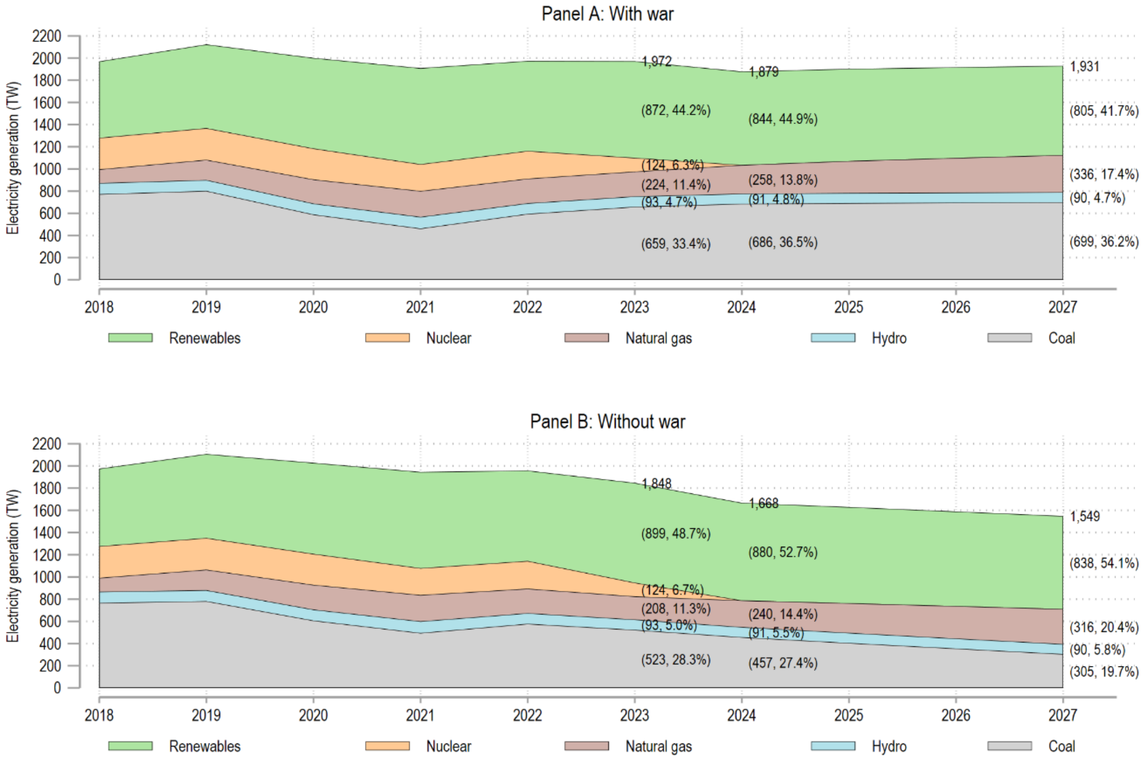
	2024/3~2025/2	2.52 (0.27)	2.67 (0.26)	8.31 (0.30)	8.53 (0.22)	N/A	N/A	1.41 (0.78)	0.69 (0.87)	4.69 (0.55)	4.85 (0.50)
	2025/3~2026/2	2.87 (0.27)	3.11 (0.27)	8.12 (0.15)	8.27 (0.12)	N/A	N/A	0.90 (0.79)	0.31 (0.50)	4.85 (0.50)	5.01 (0.50)
	2026/3~2027/2	3.27 (0.27)	3.58 (0.27)	8.03 (0.07)	8.13 (0.06)	N/A	N/A	0.45 (0.66)	0.05 (0.14)	4.96 (0.53)	5.16 (0.50)

Notes: Means and standard deviations are calculated for the ten-year period from March 2017 to February 2027. For Germany, “With war” represents forecasted results using the entire sample from January 2015 to February 2023, while “Without war” is based on data from January 2015 to February 2022. For Italy, “With war” reflects forecasted results using the entire sample from January 2016 to February 2023, while “Without war” is based on data from January 2016 to February 2022. The category “Renewables” encompasses the sum of biomass, solar, geothermal, wind offshore, and wind onshore. The unit of electricity is terawatt (TW), and standard deviations are presented in parentheses. The data source is ENTSO-E. In the case of hydro in Italy, if the value is negative, it is adjusted to 0 when calculating the average and standard deviation for the years 2025–2027.



Notes: A vertical line is included to delineate the impact of the onset of the war. Germany completely shut down its nuclear power plants in mid-April, so we present the historical electricity generation from nuclear by May 2023.

Figure 2. Pattern of changes in electricity projects depicted by connecting monthly forecasts for each of the five energy sources individually with and without the impact of the onset of the war in Germany.



Notes: We aggregate monthly data to yearly data (i.e., we consolidate monthly data from March 2017 to February 2018 into annual data for the year 2018).

Figure 3. Forecasts for the electricity generation projects from five energy sources, presented both with and without the impact of the onset of the war in Germany.

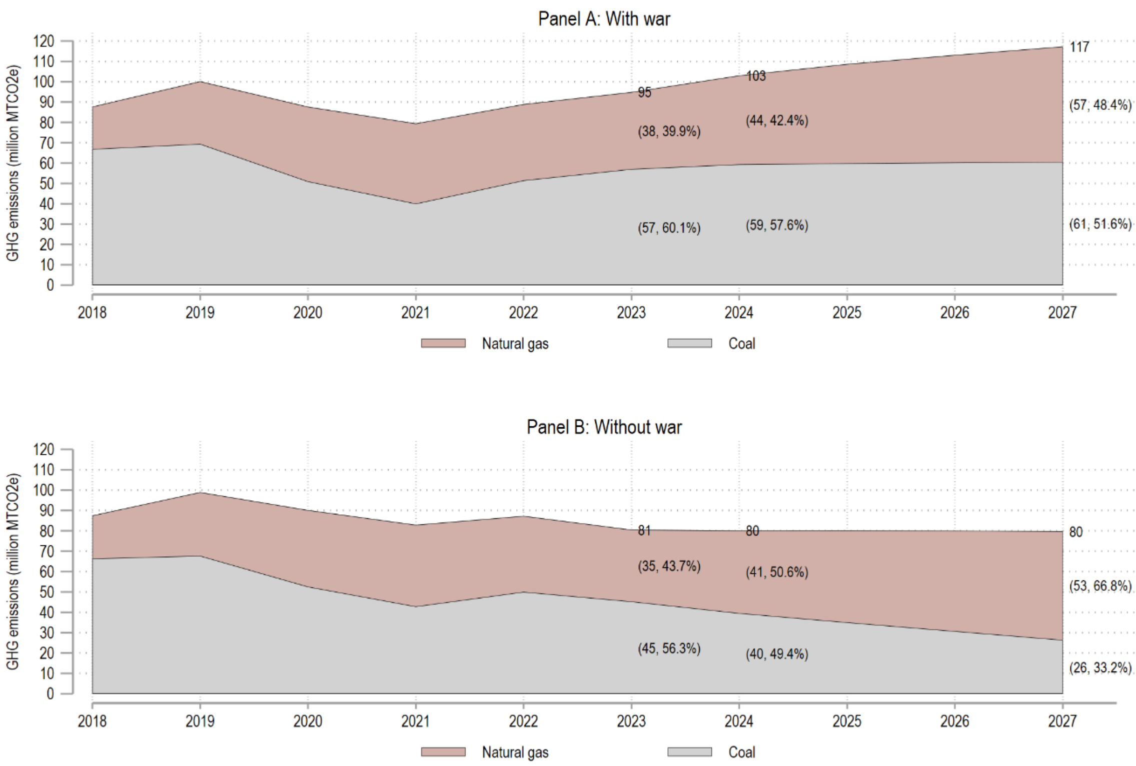
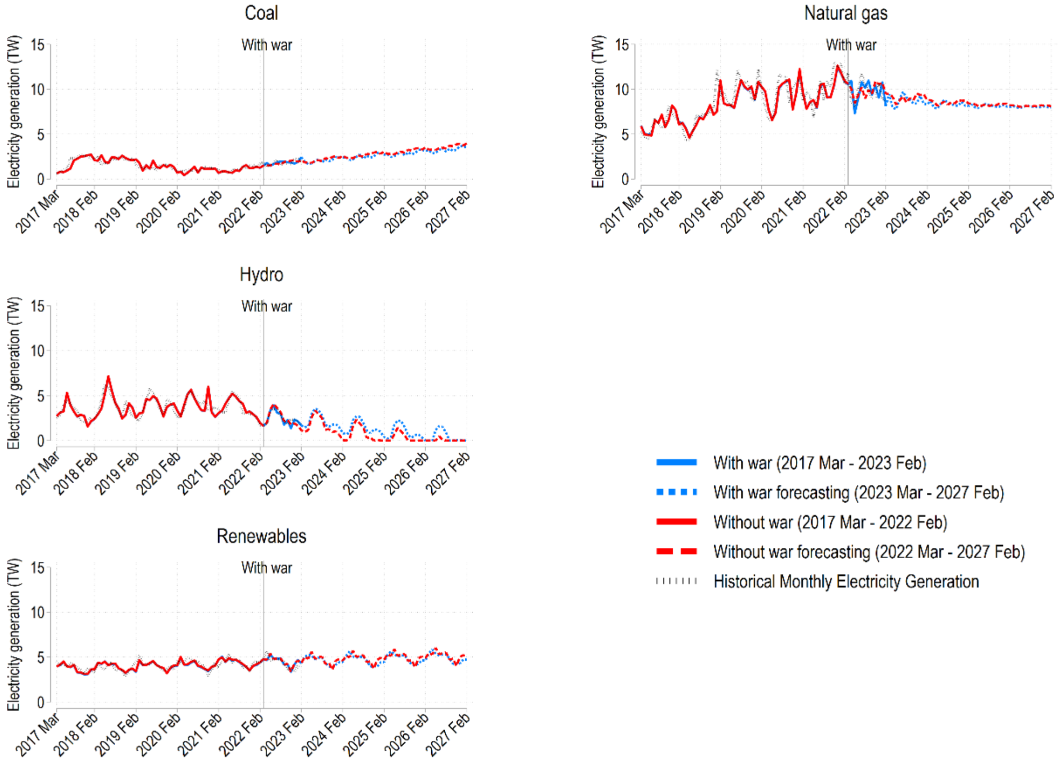


Figure 4. Projected greenhouse gas emissions between natural gas and coal, presented both with and without the impact of the onset of the war in Germany.



Notes: A vertical line is included to demarcate the impact of the onset of the war.

Figure 5. Pattern of changes in electricity projects depicted by connecting monthly forecasts for each of the five energy sources individually with and without the impact of the onset of the war in Italy.

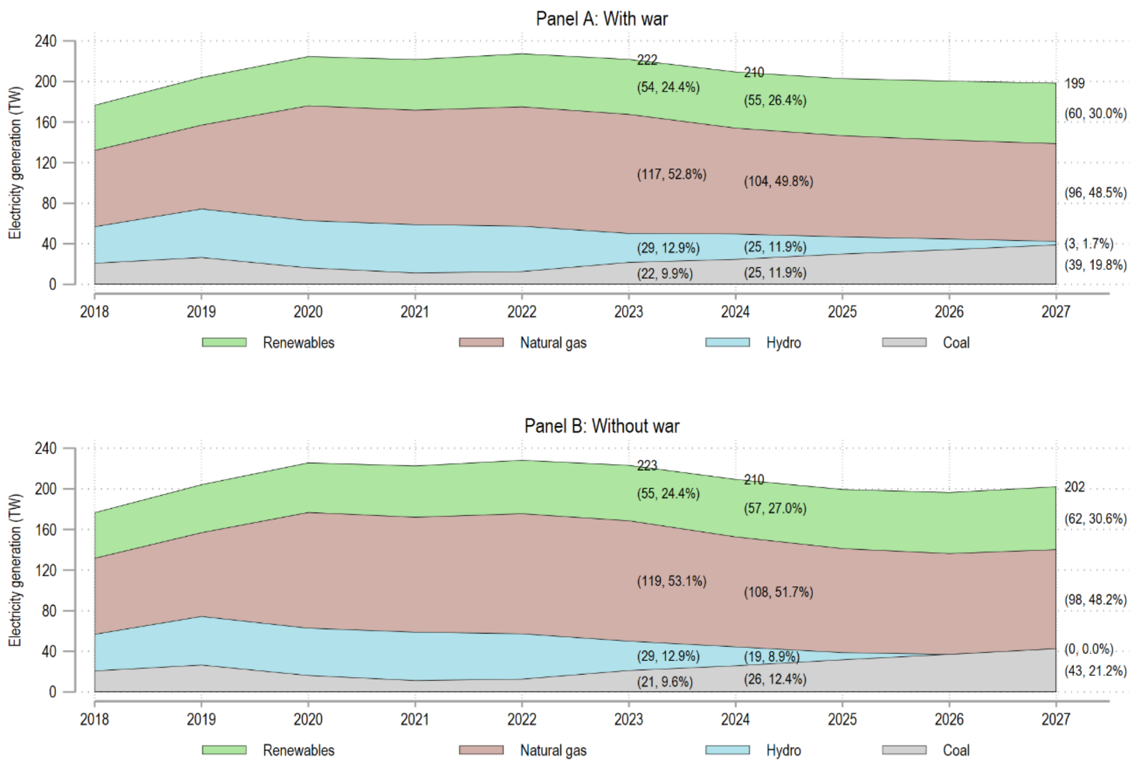


Figure 6. Forecasts for the electricity generation projects from five energy sources, presented both with and without the impact of the onset of the war in Italy.

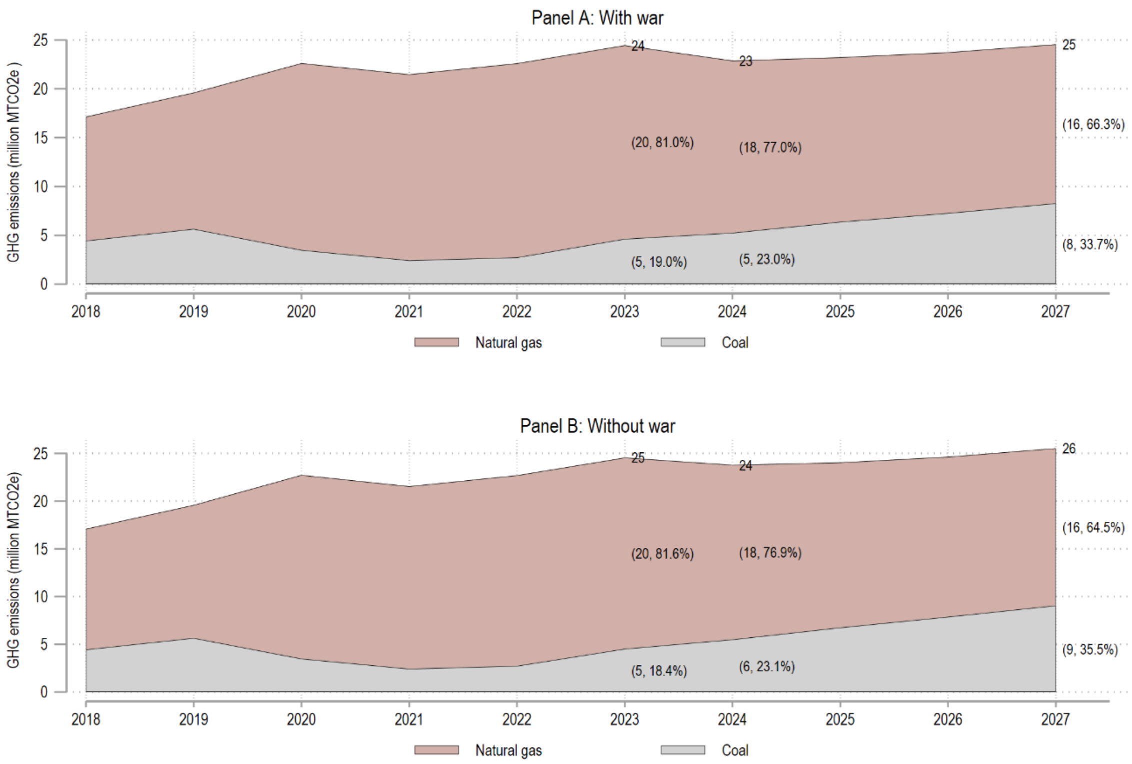


Figure 7. Projected greenhouse gas emissions from natural gas and coal, presented both with

and without the impact of the onset of the war in Italy.

5. Discussion and conclusions

Moving toward achieving net-zero emissions by 2050 stands as a critical global objective for numerous countries. However, conflicts such as the Russia–Ukraine War might pose challenges to progress in attaining this goal. Our assessment delves into the impact of the Russia–Ukraine War and its concurrent events on the EU's initial energy transition goals, with a specific focus on mainstreaming electricity generation. This involves projecting electricity supplies from the five primary energy sources (coal, natural gas, nuclear, hydro, and renewables) and analyzing their corresponding effects on GHG emissions in both Germany and Italy over the five-year period following the war (2023–2027).

Our findings from Germany presented a contrast with those from Italy, influenced by the impact of the onset of the war. The observed and anticipated shifts in Germany's energy landscape, both pre- and post-the onset of the war, especially the notable decline in nuclear power generation and the simultaneous increase in coal usage, present considerable obstacles to attaining carbon neutrality. Based on these findings, several energy policy implications are evident.

First, given the surge in coal usage during crises, there is a critical need to accelerate the deployment of renewable energy sources. Policies should focus on incentivizing and promoting the rapid expansion of renewable infrastructure to counterbalance the increased reliance on coal. Second, the unexpected rise in natural gas supply, despite the cessation of imports from Russia, underscores the importance of diversifying energy sources to enhance resilience. Policies should prioritize strengthening energy security by fostering diverse and resilient supply chains. Third, the surge in coal usage and the corresponding impact on GHG emissions as a response to gas supply disruptions emphasizes the necessity to reevaluate dependency on fossil fuels, especially in times of geopolitical instability. Fourth, Germany's commitment to phasing out coal entirely by 2030 is commendable, but policies should be robustly implemented to ensure this target is met. Continued support for the development of clean energy technologies and a just transition for affected communities is crucial.

The findings from the energy shifts in Italy—particularly the fluctuation in hydropower generation, the rise in coal and renewable energy, and the overall stability of electricity supply before and after the onset of the war—suggest several energy policy implications for achieving carbon neutrality. Despite minimal changes in electricity supply and GHG emissions, policymakers should continue implementing measures to reduce GHG emissions further. Continued support for energy efficiency, carbon capture technologies, and stricter emission standards can contribute to achieving carbon neutrality goals.

Italy can navigate the complexities introduced by the observed energy shifts, ensuring a more resilient and sustainable path toward carbon neutrality by incorporating the following policy implications based on our findings. First, the substantial reduction in hydropower generation caused by severe drought underscores the vulnerability of water-dependent energy sources. The consistent increase in hydropower generation, especially following the severe drought, indicates the importance of resilient hydropower infrastructure. Policies should encourage investments in modernizing and expanding hydropower facilities to harness the potential of this renewable energy source. Second, Italy's significant rise in renewable energy share, driven by the NRRP, demonstrates the effectiveness of targeted investments. Continued support for renewable energy initiatives and financial incentives can further enhance the transition to cleaner and sustainable energy sources. Third, the challenges faced by Italy in diversifying natural gas imports highlight the need for a strategic approach to ensure a stable energy supply. Policymakers should develop comprehensive plans to diversify import sources, minimizing dependence on a single country and mitigating supply disruptions during geopolitical events. Collaborative efforts with neighboring countries and international partners can facilitate the sharing of resources, enhancing energy security and sustainability. Fourth, the overall stability in electricity supply, despite the challenges faced, suggests the importance of integrated energy planning. Policymakers should develop comprehensive strategies that consider the interplay of various energy sources, ensuring a reliable and balanced energy supply.

Considering the tangible implications presented for each of the two countries, we acknowledge the following limitations that could be addressed and improved in future research efforts. Our study focuses on the impact of the Russia–Ukraine War on energy sources in Germany and Italy. However, geopolitical dynamics are highly complex and subject to rapid changes. Future research should consider a broader geopolitical context and potential geopolitical shifts that may influence energy policies. Our analysis primarily explores energy shifts in the context of geopolitical events. Future research could delve deeper into the economic variables, considering the impact of economic conditions, trade relationships, and market forces on energy transitions in the aftermath of conflicts. Our study also primarily examines quantitative data related to energy sources. Incorporating qualitative aspects such as public opinion, the social acceptance of energy transitions, and the role of civil society can provide a more comprehensive understanding of the challenges and opportunities in achieving carbon neutrality. Finally, our study analyzes a specific five-year period following the war. Future research could extend the temporal scope to assess the longer-term impacts of energy policies on GHG emissions and neutrality goals, considering the potential evolution of energy landscapes over an extended period. Our study also consider the war as a singular disruption in the data-generating process. However, in reality, the war is ongoing and continues to exert a dynamic impact on the energy policies of EU countries, suggesting a direction for future studies.

References

Bhattacharyya, Subhes C, Debajit Palit, Gopal K Sarangi, Vivek Srivastava, and Prerna Sharma. 2019. “Solar PV Mini-Grids versus Large-Scale Embedded PV Generation: A Case Study of Uttar Pradesh (India).” *Energy Policy* 128: 36–44. https://doi.org/https://doi.org/10.1016/j.enpol.2018.12.040.

Bolotov, Ilya. 2022. “ARIMAAUTO: Stata Module to Find the Best ARIMA Model with the Help of a Stata-Adjusted Hyndman-Khandakar (2008) Algorithm.” https://ideas.repec.org/c/boc/bocode/s459043.html.

Chong, Cheng Tung, Yee Van Fan, Chew Tin Lee, and Jiří Jaromír Klemeš. 2022. “Post COVID-19 ENERGY Sustainability and Carbon Emissions Neutrality.” *Energy* 241: 122801. https://doi.org/https://doi.org/10.1016/j.energy.2021.122801.

European Commission. 2023. “Annex to the Commission Delegated Regulation (EU).” https://energy.ec.europa.eu/system/files/2023-02/C_2023_1086_1_EN_annexe_acte_autonome_part1_v4.pdf.

Federal Office for the Safety of Nuclear Waste Management. 2023. “The Nuclear Phase-out in Germany.” 2023. https://www.base.bund.de/EN/ns/nuclear-phase-out/nuclear-phase-out_node.html#:~:text=The Grohnde%2C Gundremmingen C and,planned for 31 December 2022.

Federal Statistical Office of Germany. 2023. “Federal Statistical Office of Germany.” 2023. https://www.destatis.de/EN/Home/_node.html.

Gujba, Haruna, Steve Thorne, Yacob Mulugetta, Kavita Rai, and Youba Sokona. 2012.

“Financing Low Carbon Energy Access in Africa.” *Energy Policy* 47: 71–78. https://doi.org/https://doi.org/10.1016/j.enpol.2012.03.071.

Hainsch, Karlo, Konstantin Löffler, Thorsten Burandt, Hans Auer, Pedro Crespo del Granado, Paolo Pisciella, and Sebastian Zwickl-Bernhard. 2022. “Energy Transition Scenarios: What Policies, Societal Attitudes, and Technology Developments Will Realize the EU Green Deal?” *Energy* 239: 122067. https://doi.org/https://doi.org/10.1016/j.energy.2021.122067.

Halužan, Marko, Miroslav Verbič, and Jelena Zorić. 2020. “Performance of Alternative Electricity Price Forecasting Methods: Findings from the Greek and Hungarian Power Exchanges.” *Applied Energy* 277: 115599. https://doi.org/https://doi.org/10.1016/j.apenergy.2020.115599.

Hepburn, Cameron, Ye Qi, Nicholas Stern, Bob Ward, Chunping Xie, and Dimitri Zenghelis. 2021. “Towards Carbon Neutrality and China’s 14th Five-Year Plan: Clean Energy Transition, Sustainable Urban Development, and Investment Priorities.” *Environmental Science and Ecotechnology* 8: 100130. https://doi.org/https://doi.org/10.1016/j.ese.2021.100130.

Hirth, Lion, Jonathan Mühlenpfordt, and Marisa Bulkeley. 2018. “The ENTSO-E Transparency Platform – A Review of Europe’s Most Ambitious Electricity Data Platform.” *Applied Energy* 225: 1054–67. https://doi.org/https://doi.org/10.1016/j.apenergy.2018.04.048.

Hyndman, Rob J, and Yeasmin Khandakar. 2008. “Automatic Time Series Forecasting: The Forecast Package for R.” *Journal of Statistical Software* 27: 1–22.

International Trade Administration, U.S. Department of Commerce. 2022. “Italy - Country Commercial Guide: Natural Gas & Renewable Energy.” International Trade Administration. 2022. https://www.trade.gov/country-commercial-guides/italy-natural-gas-renewable-energy.

Jacques, Pierre, Louis Delannoy, Baptiste Andrieu, Devrim Yilmaz, Hervé Jeanmart, and Antoine Godin. 2023. “Assessing the Economic Consequences of an Energy Transition through a Biophysical Stock-Flow Consistent Model.” *Ecological Economics* 209: 107832. https://doi.org/https://doi.org/10.1016/j.ecolecon.2023.107832.

Khan, Khalid, Chi Wei Su, Ashfaq U Rehman, and Rahman Ullah. 2022. “Is Technological Innovation a Driver of Renewable Energy?” *Technology in Society* 70: 102044. https://doi.org/https://doi.org/10.1016/j.techsoc.2022.102044.

Kim, Y.J., and M. Brown. 2019. “Impact of Domestic Energy-Efficiency Policies on Foreign Innovation: The Case of Lighting Technologies.” *Energy Policy*. https://doi.org/10.1016/j.enpol.2019.01.032.

Kim, Y.J., and C. Wilson. 2019. “Analysing Future Change in the EU’s Energy Innovation System.” *Energy Strategy Reviews* 24. https://doi.org/10.1016/j.esr.2019.04.012.

Kim, Yeong Jae, Seong-Hoon Cho, and Bijay P Sharma. 2021. “Constructing Efficient Portfolios of Low-Carbon Technologies.” *Renewable and Sustainable Energy Reviews* 150: 111515. https://doi.org/https://doi.org/10.1016/j.rser.2021.111515.

Lomoschitz, Paul. 2023. “Towards Net Zero: The RussiaUkraine Conflict as a Catalyst for Green Technologies in the German Energy Sector.”

Mathioulakis, Emmanouil, George Panaras, and Vassilis Belessiotis. 2013. “Cost-Benefit

Analysis of Renewable Energy Systems under Uncertainties” 09002: 09002. https://doi.org/10.1051/metrology/201309002.

Obaideen, Khaled, Maryam Nooman AlMallahi, Abdul Hai Alami, Mohamad Ramadan, Mohammad Ali Abdelkareem, Nabila Shehata, and A G Olabi. 2021. “On the Contribution of Solar Energy to Sustainable Developments Goals: Case Study on Mohammed Bin Rashid Al Maktoum Solar Park.” *International Journal of Thermofluids* 12: 100123. https://doi.org/https://doi.org/10.1016/j.ijft.2021.100123.

Palage, Kristoffer, Robert Lundmark, and Patrik Söderholm. 2019. “The Innovation Effects of Renewable Energy Policies and Their Interaction: The Case of Solar Photovoltaics.” *Environmental Economics and Policy Studies* 21 (2): 217–54. https://doi.org/10.1007/s10018-018-0228-7.

Pereira, Paulo, Ferdo Bašić, Igor Bogunovic, and Damia Barcelo. 2022. “Russian-Ukrainian War Impacts the Total Environment.” *Science of The Total Environment* 837: 155865. https://doi.org/https://doi.org/10.1016/j.scitotenv.2022.155865.

Reuters. 2023a. “Italy’s Water Resources Hit Rock Bottom in 2022.” 2023. https://www.reuters.com/world/europe/italys-water-resources-hit-rock-bottom-2022-2023-07-07/.

———. 2023b. “Italy to Cut Coal-Fired Power to Minimum.”

Sabine Kinkartz. 2022. “Germany’s Energy U-Turn: Coal Instead of Gas.” Deutsche Welle. 2022.

Schmidt, Tobias S, Nicola U Blum, and Ratri Sryantoro Wakeling. 2013. “Attracting Private Investments into Rural Electrification — A Case Study on Renewable Energy Based

Village Grids in Indonesia." *Energy for Sustainable Development* 17 (6): 581–95. https://doi.org/https://doi.org/10.1016/j.esd.2013.10.001.

Schreurs, Miranda A. 2016. "Is Germany Really an Environmental Leader?" *Current History* 115 (779): 114–16.

Shih, Yi-Hsuan, and Chao-Heng Tseng. 2014. "Cost-Benefit Analysis of Sustainable Energy Development Using Life-Cycle Co-Benefits Assessment and the System Dynamics Approach." *Applied Energy* 119: 57–66. https://doi.org/https://doi.org/10.1016/j.apenergy.2013.12.031.

Steffen, Bjarne, and Anthony Patt. 2022. "A Historical Turning Point? Early Evidence on How the Russia-Ukraine War Changes Public Support for Clean Energy Policies." *Energy Research & Social Science* 91: 102758. https://doi.org/https://doi.org/10.1016/j.erss.2022.102758.

Tian, Jinfang, Longguang Yu, Rui Xue, Shan Zhuang, and Yuli Shan. 2022. "Global Low-Carbon Energy Transition in the Post-COVID-19 Era." *Applied Energy* 307: 118205. https://doi.org/https://doi.org/10.1016/j.apenergy.2021.118205.

Williams, Nathaniel J, Paulina Jaramillo, and Jay Taneja. 2018. "An Investment Risk Assessment of Microgrid Utilities for Rural Electrification Using the Stochastic Techno-Economic Microgrid Model: A Case Study in Rwanda." *Energy for Sustainable Development* 42: 87–96. https://doi.org/https://doi.org/10.1016/j.esd.2017.09.012.

Wu, Yunna, Jing Wang, Shaoyu Ji, and Zixin Song. 2020. "Renewable Energy Investment Risk Assessment for Nations along China's Belt & Road Initiative: An ANP-Cloud Model Method." *Energy* 190: 116381.

https://doi.org/https://doi.org/10.1016/j.energy.2019.116381.

Xie, Fangming, Yali Liu, Fangyuan Guan, and Ning Wang. 2020. “How to Coordinate the Relationship between Renewable Energy Consumption and Green Economic Development: From the Perspective of Technological Advancement.” *Environmental Sciences Europe* 32 (1): 71. https://doi.org/10.1186/s12302-020-00350-5.

Yang, Lan, Xue-Chao Wang, Min Dai, Bin Chen, Yuanbo Qiao, Huijing Deng, Dingfan Zhang, et al. 2021. “Shifting from Fossil-Based Economy to Bio-Based Economy: Status Quo, Challenges, and Prospects.” *Energy* 228: 120533. https://doi.org/https://doi.org/10.1016/j.energy.2021.120533.

Zaroni, Hebert, Letícia B Maciel, Diego B Carvalho, and Edson de O Pamplona. 2019. “Monte Carlo Simulation Approach for Economic Risk Analysis of an Emergency Energy Generation System.” *Energy* 172: 498–508. https://doi.org/https://doi.org/10.1016/j.energy.2019.01.145.

Acknowledgment

We are grateful to the KDI School of Public Policy and Management Research Grant Program. This work was also supported by the Korea Environment Industry & Technology Institute (KEITI) through the Climate Change R&D Project for New Climate Regime, funded by Korea Ministry of Environment (MOE: RS-2023-00218794). We acknowledge the constructive comments from the 17th International Conference on Energy Economics and Technology (ENERDAY 2023) and the 2024 Korea Environmental Economics Association Conference.

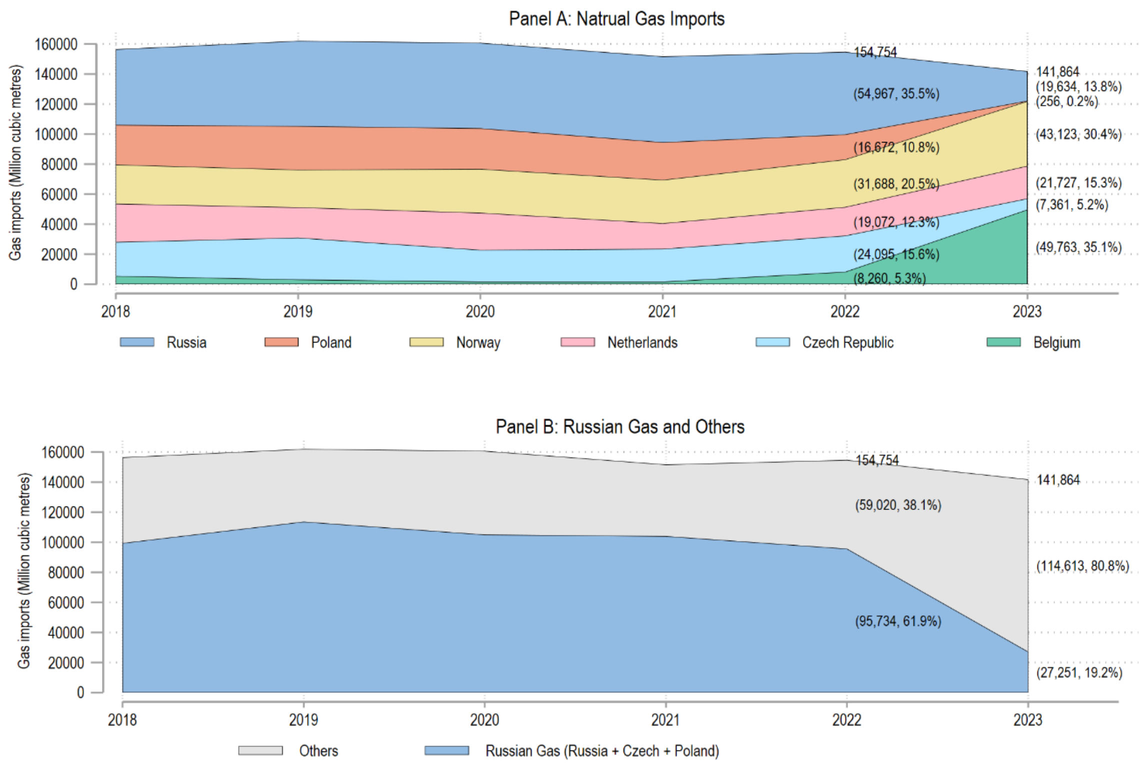
Appendix

Table A.1 reports the components of each energy source in Germany and Italy, respectively. Germany is abundant with hard coal and brown coal (Schreurs 2016). Hence, brown and hard coal account for 20% and 10% of the electricity mix in 2021, respectively (Sabine Kinkartz 2022). Conversely, Italy relies on hard coal in electricity generation. Figures A.1 and A.2 describe gas flows in Germany and Italy, while Figures A.3 and A.4 describe historical electricity generation data in the two countries.

Table A.1. Construction of raw data

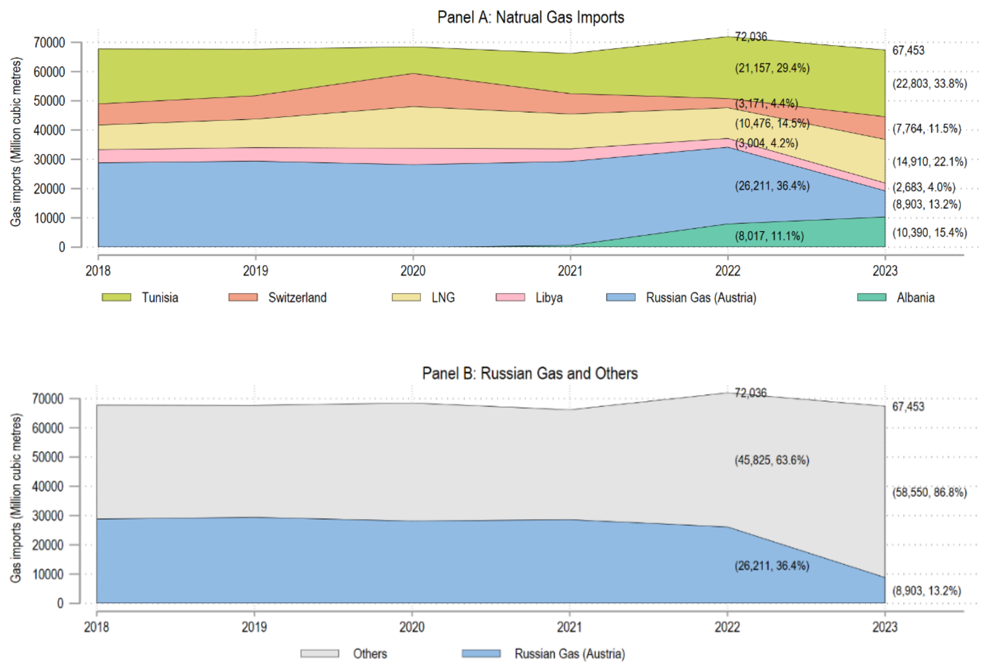
Germany		**Italy**	
Coal	Fossil: Brown coal/Lignite	Coal	Fossil: Hard coal
	Fossil: Hard coal		
Natural gas	Fossil: Coal-derived gas	Natural gas	Fossil: Coal-derived gas
	Fossil: Gas		Fossil: Gas
Nuclear	Nuclear	Nuclear	
Hydro	Hydro: Pumped storage	Hydro	Hydro: Pumped storage
	Hydro: Run-of-river and poundage		Hydro: Run-of-river and poundage
	Hydro: Water reservoir		Hydro: Water reservoir
Renewables	Solar	Renewables	Solar
	Wind: Onshore		Wind: Onshore
	Wind: Offshore		Wind: Offshore
	Biomass		Biomass
	Geothermal		Geothermal

Notes: Germany's data spans from January 2015 to February 2023, and Italy's data spans from January 2016 to February 2023. Since all nuclear power plants in Italy were closed by 1990, no nuclear for Italy exists. The data is obtained from the ENTSO-E Transparency Platform.



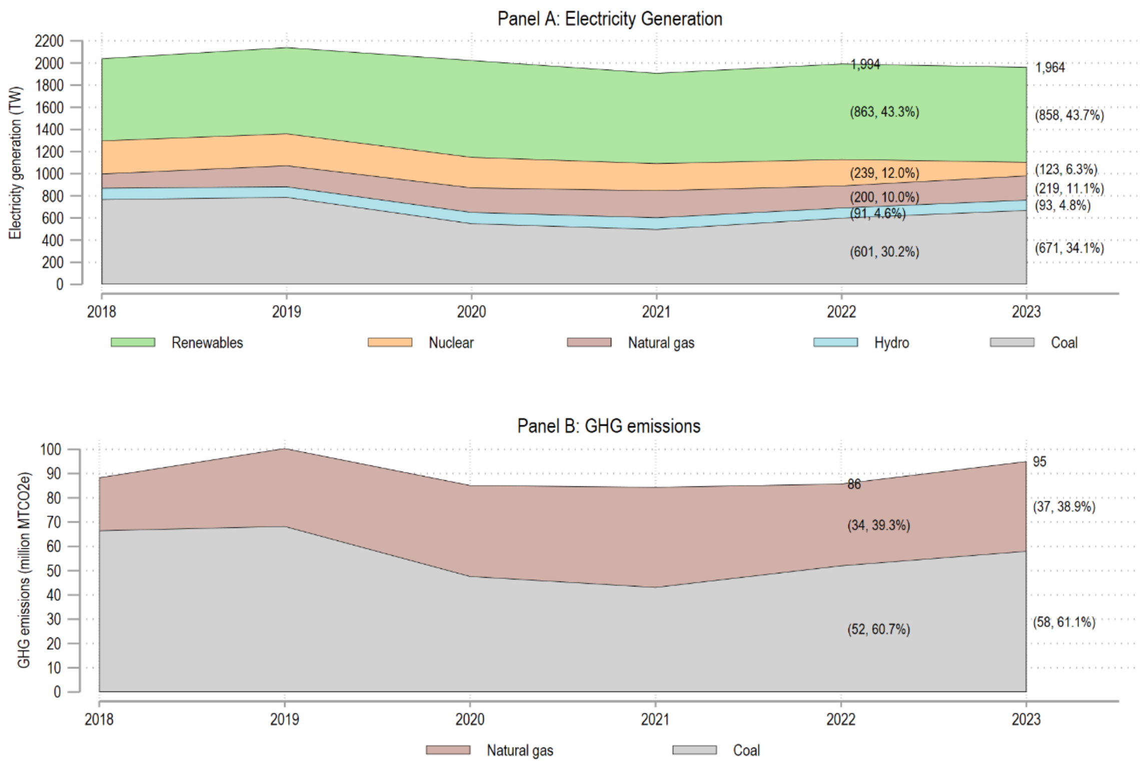
Notes: We aggregate monthly data to yearly data. Denmark and Austria were excluded. Source: https://www.iea.org/data-and-statistics/data-product/gas-trade-flows#gas-trade-flows

Figure A.1. Gas trade flows in Germany.



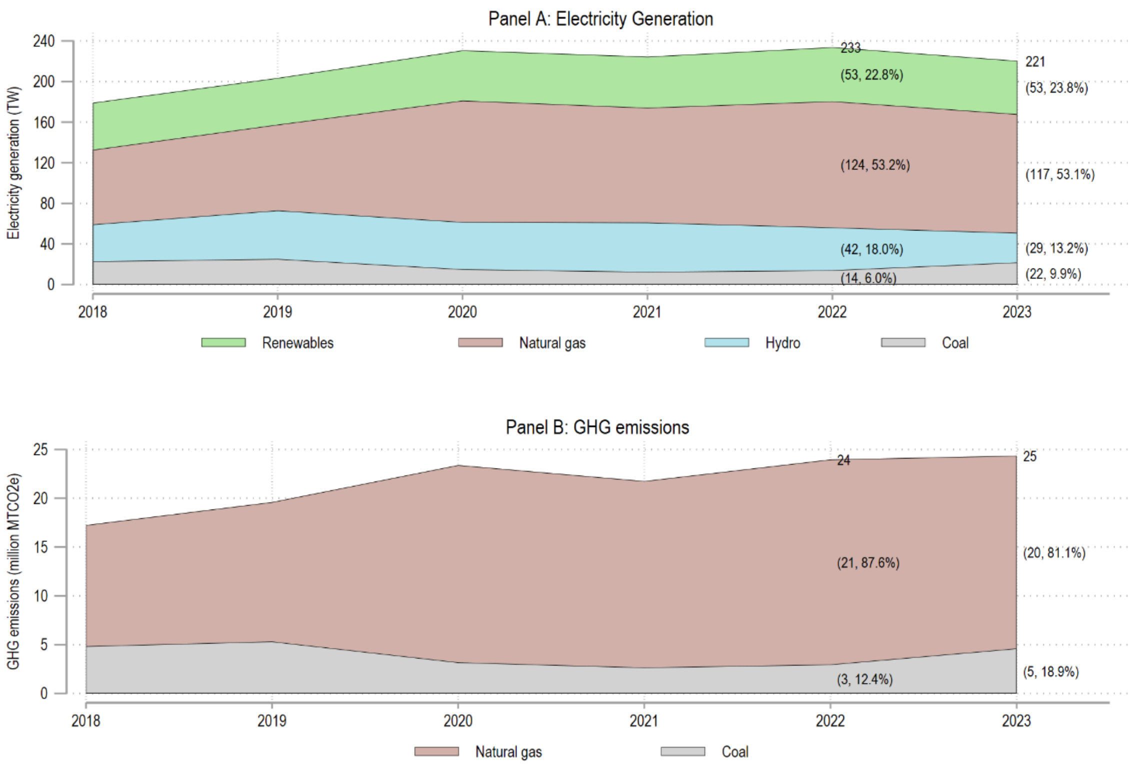
Notes: We aggregate monthly data to yearly data. Croatia and Slovenia were excluded.

Figure A.2. Gas trade flows in Italy.



Notes: We aggregate monthly data to yearly data. In Panel B, we use the fuel emission factor (g $CO_{2\ eq}/MJ_{fuel}$): hard coal = 16, brown coal = 1.7, and natural gas = 12.8. We aggregate hard coal and brown coal into one coal by employing a weighted average based on historical monthly electricity generation, in which the calculation is 0.66 × 1.7 (hard coal) + 0.34 × 16 (brown coal).

Figure A.3. Historical electricity generation trend in Germany.



Notes: We aggregate monthly data to yearly data. In Panel B, we use the fuel emission factor (g $CO_{2\,eq}/MJ_{fuel}$): hard coal = 16 and natural gas = 12.8.

Figure A.4. Historical electricity generation trend in Italy.

The process of choosing the best-fitted SARIMA model involves sequential steps, which are shown in Figure 1. The detail steps are described as follows.

1.1. Steps of construction of SARIMA model

First, since monthly electricity generation data shows seasonal fluctuations, we need to test seasonality. To detect seasonality, we use the HEGY test, which comprises seasonal unit root tests for the monthly data. If the data has seasonality, we take the seasonal difference to eliminate seasonality.

Second, the data needs to be tested for its stationarity. We use the DF-GLS unit root test to test the stationarity of time-series data. The DF-GLS test, more powerful than the augmented Dickey–Fuller (ADF) test, controls for trends in unstable time series via generalized least squares before applying ADF methodology. To prevent overdifferencing, the KPSS unit root test is also conducted to determine *d* and *D*. Using both tests enhances reliability by testing mutually exclusive hypotheses. If the data remains non-stationary after seasonal differences, additional differences will be conducted to make the data stationary. Then the DF-GLS and KPSS tests are performed again. When the data has no seasonality at step 1, we test stationarity using these two tests. If the data remains non-stationary after the tests, the first difference will be considered to make the data stationary. In this case, seasonal difference is not required. After that, the DF-GLS and KPSS tests are performed once more.

Third, we initialize $p, q, P,$ and Q to 1, increment each by 1, and iterate this process until we find the best-fitted model based on the smallest AIC (Bolotov 2022).

Fourth, while stationarity is a time series where the statistical properties remain constant over time, stationarity does not guarantee that the time series is a series of random values, which is white noise. We conduct the Portmanteau white noise test to test whether the given time series is serially correlated. If the p-value of the test is less than 0.05, it is not white noise.

Fifth, we forecast the montly electricity generation based on the determined $p, q, P, Q,$ and s.

1.2. Seasonality test results

Table A.2 showcases the outcomes of seasonality tests conducted in both Germany and Italy. In the case of Germany, seasonal adjustments were applied to natural gas, nuclear, and hydro data to achieve stationarity. For coal in Germany, no seasonality is apparent, indicated by a test statistic of −3.268, compared to the 5% critical value of −2.670 (with a p-value less than 0.05). Conversely, seasonality is observed for natural gas in Germany, with a test statistic of −0.994, exceeding the 5% critical value of −2.776 (with a p-value greater than 0.05). Similarly, seasonal patterns exist for nuclear energy in Germany, supported by a test statistic of −1.929 compared to the 5% critical value of −2.710 (with a p-value greater than 0.05). Hydropower in Germany also exhibits seasonality, with a test statistic of −2.126 compared to the 5% critical value of −2.710 (with a p-value greater than 0.05). Conversely, no discernible seasonality is found in renewables, indicated by a test statistic of −3.110, which is below the 5% critical value of −2.670 (with a p-value less than 0.05).

Table A.2 also incorporates results from the examination of Italy's seasonality. In this context, seasonal adjustments were applied to coal, hydro, and renewables data to achieve stationarity. Regarding coal in Italy, seasonality is apparent, as indicated by a test statistic of −2.140, surpassing the 5% critical value of −2.849 (with a p-value greater than 0.05). Conversely, no seasonality is observed for natural gas, supported by a test statistic of −3.143, below the 5% critical value of −2.829 (with a p-value less than 0.05). Hydropower in Italy exhibits seasonal patterns, evidenced by a test statistic of −2.465 compared to the 5% critical value of −2.829 (with a p-value greater than 0.05). Similarly, renewables in Italy display seasonality, with a test statistic of −1.514, exceeding the 5% critical value of −3.121 (with a p-value greater than 0.05).

Table A.2. Seasonal unit roots test results

	Germany					Italy			
	Coal	Natural gas	Nuclear	Hydro	Renewables	Coal	Natural gas	Hydro	Renewables
Unit root	0	1	1	1	0	1	0	1	1
Lags	.	9	4	4	.	1	.	.	10
Test statistics	−3.268	−0.994	−1.929	−2.126	−3.110	−2.140	−3.143	−2.465	−1.514
1% critical values	−3.210	−3.297	−3.243	−3.243	−3.210	−3.355	−3.339	−3.339	−3.568

5% critical values	−2.670	−2.776	−2.710	−2.710	−2.670	−2.849	−2.829	−2.829	−3.121
10% critical values	−2.410	−2.530	−2.455	−2.455	−2.410	−2.614	−2.590	−2.590	−2.927

Notes: If "Unit root" equals 1, it indicates the presence of a seasonal unit root in the data; otherwise, there is no seasonal unit root. If "Lags" is equal to ".," it signifies that lags were not utilized for the HEGY test.

1.3. Stationary test results

Table A.3 presents the results of the DF-GLS and KPSS tests. In the case of Germany, natural gas achieves stationarity after a seasonal difference (d = 0, D = 1). Initially, it demonstrates stationarity in the first step, indicated by a test statistic of −3.405, exceeding the 5% critical value of −3.071 (with a p-value less than 0.05). In the second step, it maintains stationarity, supported by a test statistic of 0.135 compared to the 5% critical value of 0.146 (with a p-value greater than 0.05).

Nuclear attains stationarity after an additional first ordinary difference and seasonal difference (d = 1, D = 1). Initially non-stationary, it records a test statistic of −2.735, surpassing the 5% critical value of −3.023 (with a p-value greater than 0.05) in the first step. In the second step, it remains non-stationary, with a test statistic of 0.172 compared to the 5% critical value of 0.146 (with a p-value less than 0.05). The third step, after an additional ordinary difference, finally achieves stationarity, with a test statistic of −6.965 compared to the 5% critical value of −3.074 (with a p-value less than 0.05). The fourth step also confirms stationarity, with a test statistic of 0.021 and the 5% critical value of 0.146 (with a p-value greater than 0.05).

Hydropower becomes stationary after a seasonal difference (d = 0, D = 1). In the first step, it demonstrates stationarity, with a test statistic of −3.144 compared to the 5% critical value of −3.049 (with a p-value less than 0.05). In the second step, it continues to remain stationary, supported by a test statistic of 0.101 in comparison to the 5% critical value of

0.146 (with a p-value greater than 0.05).

In Italy’s case, coal achieves stationarity after an additional first ordinary difference and seasonal difference (d = 1, D = 1). Initially non-stationary, it records a test statistic of −2.412, surpassing the 5% critical value of −3.083 (with a p-value greater than 0.05) in the first step. In the second step, it remains non-stationary, with a test statistic of 0.400 compared to the 5% critical value of 0.146 (with a p-value less than 0.05). Although remaining non-stationary in the third step after an additional ordinary difference, it achieves stationarity in the fourth step, with a test statistic of 0.086 compared to the 5% critical value of 0.146 (with a p-value greater than 0.05).

Hydropower becomes stationary after an additional first ordinary difference and seasonal difference (d = 1, D = 1). Initially non-stationary, it records a test statistic of −2.748, surpassing the 5% critical value of −3.050 (with a p-value greater than 0.05) in the first step. In the second step, it remains non-stationary, with a test statistic of 0.161 compared to the 5% critical value of 0.146 (with a p-value less than 0.05). Despite remaining non-stationary in the third step after an additional ordinary difference, it achieves stationarity in the fourth step, with a test statistic of 0.069 compared to the 5% critical value of 0.146 (with a p-value greater than 0.05).

Renewables become stationary after a seasonal difference (d = 0, D = 1). In the first step, they demonstrate stationarity, with a test statistic of −3.734, surpassing the 5% critical value of −3.083 (with a p-value less than 0.05). In the second step, they also remain stationary, supported by a test statistic of 0.068 compared to the 5% critical value of 0.146 (with a p-value more than 0.05).

Table A.3. DF-GLS and KPSS test results (if the data has seasonality)

	Germany			Italy		
	Natural gas	Nuclear	Hydro	Coal	Hydro	Renewables
	1. DF-GLS (*after seasonal difference*)					
Unit root	0	1	0	1	1	0
Lags	1	3	2	2	3	2
Test statistics	−3.405	−2.735	−3.144	−2.412	−2.748	−3.734
1% critical values	−3.633	−3.633	−3.633	−3.679	−3.679	−3.679
5% critical values	−3.071	−3.023	−3.049	−3.083	−3.050	−3.083
10% critical values	−2.777	−2.733	−2.757	−2.789	−2.759	−2.789
	2. KPSS (*after seasonal difference*)					
Unit root	0	1	0	1	1	0
Lags	1	3	2	2	3	2
Test statistics	0.135	0.172	0.101	0.400	0.161	0.068
1% critical values	0.216	0.216	0.216	0.216	0.216	0.216
5% critical values	0.146	0.146	0.146	0.146	0.146	0.146
10% critical values	0.119	0.119	0.119	0.119	0.119	0.119
	3. DF-GLS (*additional first ordinary difference*)					
Unit root		0		1	1	
Lags		1		7	9	
Test statistics		−6.965		−1.029	−1.651	
1% critical values		−3.637		−3.683	−3.683	
5% critical values		−3.074		−2.891	−2.801	
10% critical values		−2.780		−2.610	−2.523	
	4. KPSS (*additional first ordinary difference)*					
Unit root		0		0	0	
Lags		1		7	9	
Test statistics		0.021		0.086	0.069	
1% critical values		0.216		0.216	0.216	
5% critical values		0.146		0.146	0.146	
10% critical values		0.119		0.119	0.119	

Notes: The "ARIMAAUTO algorithm" utilizes the minimum of mean absolute information Criterion (Min MAIC) as a criterion for selecting the optimal lags to determine whether the data exhibits stationarity. Since our data is in monthly format, we employ 12 lags for conducting the DF-GLS and KPSS tests. In this context, "Unit root" indicates the presence of a unit root in the data. Specifically, when "Unit root" equals 1, it signifies the existence of a unit root.

Table A.4 comprises coal and renewables in Germany as well as natural gas in Italy, variables identified as lacking seasonality based on seasonal unit root test results (Table 2). The table encompasses four steps outlined below. In the first step, the DF-GLS test is conducted without any difference to assess whether the data is stationary. The second step involves the KPSS test to prevent overdifferencing. If the data remains non-stationary after steps 1 and 2, the process continues to the third step. In this step, the DF-GLS test is performed after the first ordinary difference to ascertain whether the data is stationary. The fourth step entails the KPSS test to prevent overdifferencing.

In the case of Germany, coal achieves stationarity after an additional first ordinary difference ($d = 1$, $D = 0$). Initially non-stationary, it records a test statistic of −1.117, exceeding the 5% critical value of −2.838 (with a p-value greater than 0.05). Despite remaining non-stationary in the second step (test statistic of 0.150 compared to the 5% critical value of 0.146), the third step, following an additional ordinary difference, finally achieves stationarity (test statistic of −4.099, surpassing the 5% critical value of −3.003). The fourth step confirms stationarity (test statistic of 0.028 compared to the 5% critical value of 0.146).

Renewables become stationary after the first ordinary difference ($d = 1$, $D = 0$). Initially non-stationary, they record a test statistic of −1.685, exceeding the 5% critical value of −2.775. Despite remaining non-stationary in the second step (test statistic of 0.171 compared to the 5% critical value of 0.146), the third step, following an additional ordinary difference, remains non-stationary (test statistic of −1.793, surpassing the 5% critical value of −2.773). However, in the fourth step, stationarity is achieved (test statistic of 0.089 compared to the 5% critical value of 0.146).

Interestingly, for renewables in Germany, no first ordinary difference was applied despite the initial non-stationarity. Paradoxically, forecasting results from the non-stationary state appear to perform better than those from the stationary state, with a smaller gap between observed and predicted values.

In Italy's case, natural gas is stationary without any difference (d = 0, D = 0). Initially non-stationary, it records a test statistic of −1.201, exceeding the 5% critical value of −2.750. The second step confirms stationarity (test statistic of 0.140 compared to the 5% critical value of 0.146).

Table A.4. DF-GLS and KPSS test results (if the data has no seasonality)

	Germany		Italy
	Coal	Renewables	Natural gas
	1. DF-GLS (*non-difference*)		
Unit root	1	1	1
Lags	9	11	11
Test statistics	−1.117	−1.685	−1.201
1% critical values	−3.588	−3.588	−3.633
5% critical values	−2.838	−2.775	−2.750
10% critical values	−2.561	−2.501	−2.476
	2. KPSS (*non-difference*)		
Unit root	1	1	0
Lags	9	11	11
Test statistics	0.150	0.171	0.140
1% critical values	0.216	0.216	0.216
5% critical values	0.146	0.146	0.146
10% critical values	0.119	0.119	0.119
	3. DF-GLS (*after first ordinary difference*)		
Unit root	0	1	
Lags	3	11	
Test statistics	−4.099	−1.793	
1% critical values	−3.591	−3.591	
5% critical values	−3.003	−2.773	
10% critical values	−2.714	−2.499	

	4. KPSS (***after first ordinary difference***)		
Unit root	0	0	
Lags	3	11	
Test statistics	0.028	0.089	
1% critical values	0.216	0.216	
5% critical values	0.146	0.146	
10% critical values	0.119	0.119	

Notes: The "ARIMAAUTO algorithm" utilizes the minimum of mean absolute information criterion (Min MAIC) as a criterion to select optimal lags and assess the stationarity of the data. Given that our data is in monthly format, we employ a total of 12 lags when conducting the DF-GLS and KPSS tests. In this context, "Unit root" refers to the presence of a unit root in the data, with "Unit root" being equal to 1 indicating its presence.

1.4. Final model selection

In Table A.5, we present the model and AIC values for five energy sources in both Germany and Italy. The selection of the best-fitted model for each of the five sources is based on the smallest AIC.

Table A.5. Candidates of best-fitted model

		Germany					Italy			
Model		Coal	Natural gas	Nuclear	Hydro	Renewables	Coal	Natural gas	Hydro	Renewables
1	p	2	2	0	0	2	0	0	0	0
	q	2	2	0	0	2	0	0	0	0
	P	1	1	0	0	1	0	0	0	0
	Q	1	1	0	0	1	0	0	0	0
	$const$	1	1	0	1	1	0	1	0	1
AIC		683.2366	463.0139	460.2482	290.2372	727.3991	74.7320	401.3156	165.8530	114.8239
2	p	0	0	1	1	0	1	1	1	1
	q	0	0	0	0	0	0	0	0	0
	P	0	0	1	1	0	1	1	1	1
	Q	0	0	0	0	0	0	0	0	0
	$const$	1	1	0	1	1	0	1	0	1
AIC		705.4674	508.3125	434.7499	224.6255	776.7684	56.6979	293.9097	153.4951	98.6432
3	p	1	1	0		1		0		
	q	0	0	1		0		1		
	P	1	1	0		1		0		
	Q	0	0	1		0		1		

	const	1	1	0		1		1		
AIC		688.0587	465.8801	426.6752		733.1767		335.7711		
4	p	0	0			0				
	q	1	1			1				
	P	0	0			0				
	Q	1	1			1				
	const	1	1			1				
AIC		687.4156	478.4234			746.4934				

Table A.6 displays the outcomes of the Portmanteau white noise test. In the German context, data labeled “With war” and “Without war” for coal exhibit characteristics of white noise, as evidenced by p-values surpassing 0.05. Similarly, for natural gas, both “With war” and “Without war” datasets are classified as white noise, with p-values exceeding 0.05. Additionally, data labeled “With war” and “Without war” for nuclear, hydro, and renewables are all identified as white noise, with their respective p-values greater than 0.05.

In Italy, data labeled “With war” and “Without war” for coal are categorized as white noise, supported by p-values greater than 0.05. For natural gas in Italy, both “With war” and “Without war” datasets are considered white noise, with p-values exceeding 0.05. Moreover, data labeled “With war” and “Without war” for hydro and renewables in Italy are recognized as white noise, with p-values greater than 0.05.

Table A.6. Portmanteau white noise test

	Germany									
	Coal		Natural gas		Nuclear		Hydro		Renewables	
	W	C	W	C	W	C	W	C	W	C
Test statistics	6.1404	11.2287	9.0606	15.6700	17.1073	16.2324	5.6871	6.1631	6.4300	6.3328
p-value	0.9088	0.5094	0.6977	0.2068	0.1456	0.1808	0.9310	0.9076	0.8929	0.8984
	Italy									
	Coal		Natural gas		Nuclear		Hydro		Renewables	

	W	C	W	C	W	C	W	C	W	C
Test statistics	9.8155	10.0536	10.1044	11.5565	-	-	13.4570	12.5896	15.3327	14.8814
p-value	0.6321	0.6113	0.6068	0.4819	-	-	0.3367	0.3996	0.2237	0.2480

Notes: We use 12 lags for the test since our data is monthly data. Each source has "W" and "C," each of which means "With war" and "Without war," respectively.