# Determining Economic Growth:
# A Comparative Approach

(Machine Learning, Forecasting and Energy Perspective)

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Abstract

In the world that we live in today, it is obvious that Economic Growth is strongly correlated with Energy Consumption (since there is no advanced economy without a huge amount of energy consumption). Therefore, energy prices and electricity system design have become central to debates about industrial competitiveness, de-industrialisation, and national power, particularly in advanced economies facing high and volatile energy costs. This thesis examines how energy system ownership structures, electricity price levels and composition, and broader energy mixes shape economic growth, manufacturing performance, and trade competitiveness across countries, with a focused comparison of France, Germany, the United Kingdom, the United States, China, South Korea, Japan and other G20 countries. The study also develops a real-time monitoring framework using Kalman filter state-space models to track the evolving impact of energy prices on growth.

The first objective is to quantify how energy prices interact with human capital to influence growth and structural transformation. Standard growth regressions are extended to include both energy price levels and an interaction between energy prices and human capital, testing the hypothesis that high energy costs reduce the growth returns to education and skills, especially in energy-intensive economies. The second objective is to measure how different electricity system ownership and regulatory models from state-dominated to liberalized market structures translate into distinct gaps between underlying production costs and end-user prices, captured through a "price–cost wedge" indicator based on industrial electricity prices, levelized costs of electricity, and grid costs. The third objective is to link energy structures and prices to countries' external performance using trade data from the Observatory of Economic Complexity (OEC), constructing indicators of export specialization and energy-intensive comparative advantage. The fourth objective is to develop a Kalman filter-based dashboard that uses high-frequency energy and commodity prices, together with monthly macro indicators, to provide real-time estimates of the time-varying effect of energy prices on growth.

The empirical strategy combines three layers. First, descriptive and matrix-based analysis of a global country-year panel outlines stylized facts on energy prices, energy intensity, ownership patterns, and growth outcomes, including the six focus countries. Second, static and dynamic panel econometric models – fixed-effects

regressions, System GMM, and panel ARDL/cointegration techniques – are used to estimate long- and short-run effects of energy prices, energy mix, ownership proxies, and their interaction with human capital on GDP growth and manufacturing value added. Third, state-space models with Kalman filtering are specified for a subset of countries, allowing for time-varying energy price coefficients and an "energy-adjusted growth trend" that can be updated at daily and monthly frequencies as new prices and macro data become available.

Data are drawn from multiple sources: Our World in Data (OWID) and the International Energy Agency (IEA) for energy quantities, energy mixes, and emissions; Eurostat and the US Energy Information Administration (EIA) for electricity prices and wholesale markets; the World Bank's World Development Indicators (WDI) for macroeconomic and human capital variables; OEC for bilateral trade and export structures; and several market APIs for daily oil, gas, coal, and metals prices, as well as inflation indicators. The panel covers as many countries as data allow over approximately 2000–2023, with a specific deep-dive into the six key cases.

The expected contribution is threefold. Conceptually, the thesis connects classical ideas of national power – where industrial capacity and control over resources are central – to modern empirical measures of energy costs, human capital, and trade competitiveness. Empirically, it provides new cross-country evidence on how expensive energy can erode the growth benefits of human capital and can be partially offset by particular ownership and pricing models. Methodologically, it demonstrates how panel econometrics and state-space Kalman filtering can be combined to build a real-time "energy competitiveness monitor" for policymakers and analysts.

## 2. Literature Review

### 2.1 Energy Prices and Economic Growth

A first literature strand quantifies how energy prices affect macroeconomic performance in cross-country settings. Huntington and Liddle (2022) study a long panel of OECD economies and find that higher real energy prices are associated with lower long-run growth, with elasticities on the order of −0.015 to −0.02 per 1% increase in energy prices once other determinants are controlled for. Their work highlights heterogeneity across countries: economies with higher energy intensity or more energy-intensive industrial structures exhibit stronger negative growth effects from price increases. Related studies extend the analysis beyond OECD countries or to specific regional groupings; they commonly adopt panel GMM or panel ARDL methods and confirm that energy prices and consumption are jointly linked with GDP in the long run.[1]

A wide literature on the "energy–growth nexus" focuses more broadly on energy consumption and GDP, often finding cointegration between energy use and output and varying directions of Granger causality across income groups. For instance, analyzes of lower-middle and high-income economies conclude that higher energy consumption tends to promote growth in the long run, but short-run causality can run from growth to energy demand, especially during expansion phases. [2]Some work explores asymmetries using nonlinear panel ARDL, showing that positive shocks to energy consumption and negative shocks can have different magnitudes or persistence in their impact on GDP. These findings justify treating energy variables as structural rather than purely cyclical drivers in macroeconomic models.[3]

### 2.2 Energy Intensity, Efficiency, and Industrial Competitiveness

A second strand examines energy intensity and efficiency, particularly in advanced economies. Studies of OECD nations from 2000–2019 derive measures of energy intensity and efficiency using disaggregated data on coal, gas, oil, and zero-emissions energy sources, then assess their association with GDP and structural change. The evidence suggests that although energy intensity has generally declined, substantial cross-country differences remain, and efficiency gains can coexist with sustained or rising output. Work on price and output elasticities of industrial energy demand shows that energy-intensive sectors often display relatively low short-run

[1] Hillard G. Huntington and Brantley Liddle, “How Energy Prices Shape OECD Economic Growth: Panel Evidence from Multiple Decades,” Energy Economics 111 (May 2022): 106076.

[2] Chude Nwokolo and co-authors, “Energy Consumption and Economic Growth Linkage: Global Evidence from Symmetric and Asymmetric Simulations,” *Quaestiones Geographicae* 41, no. 2 (2022): 51–71.

[3] Mehmet Mercan et al., "A Panel Dynamic Analysis on Energy Consumption, Energy Prices and Economic Growth in Next 11 Countries," International Journal of Energy Economics and Policy 10, no. 5 (2020): 258–68.

price elasticities but higher output elasticities, implying that high prices may compress margins and competitiveness without inducing proportionate efficiency gains in the short term.[4]

At the policy–sector interface, analyzes for the European Union trace how rising energy prices and energy cost shares have impacted manufacturing activity and competitiveness relative to non-EU regions. European Commission and research institute reports emphasize that energy costs are one important component among several (including labour, capital, and regulatory burdens), but that large and persistent energy price gaps vis-à-vis competitors can contribute to de-industrialisation in energy-intensive activities, especially when firms cannot easily pass through higher costs to export markets. This literature motivates the thesis focus on industrial electricity prices, energy intensity, and sectoral outcomes.[5]

### 2.3 Ownership, Liberalisation, and Electricity Prices

The role of energy system ownership and liberalization has been examined in studies linking public vs private ownership to residential and industrial electricity prices. A prominent panel study of EU15 countries estimates dynamic models of net-of-tax residential electricity prices and finds that public ownership of electricity utilities is associated with significantly lower prices, after controlling for fuel costs, wages, taxes, and liberalization indicators. The effect of market liberalization on prices appears more ambiguous, depending on specific regulatory designs and the degree of competition introduced. These findings suggest that ownership structures and regulatory choices can systematically influence price formation and therefore competitiveness.[6]

Broader policy work on energy prices, energy costs, and industrial competitiveness for the EU also stresses that cross-country differences in taxes, levies, and network charges often contribute substantially to end-user price gaps, beyond differences in underlying generation costs. Such decompositions lend support to constructing a "price-cost wedge" variable that captures the ratio of final industrial

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[4] Toshiyuki Sueyoshi and Mika Goto, "Energy Intensity, Energy Efficiency and Economic Growth among OECD Nations from 2000 to 2019," Energies 16, no. 4 (2023): 1927.

[5] European Commission, Energy Prices, Energy Costs and Competitiveness of European Industries (Brussels: European Commission, various editions; e.g. COM(2014) 21 final).

[6] Carlo V. Fiorio and Massimo Florio, "Electricity Prices and Public Ownership: Evidence from the EU15 over Thirty Years," Energy Economics 39 (July 2013): 222–32.

electricity prices to estimated generation and grid costs, and to relating this wedge to ownership models and industrial performance.

### 2.4 Renewable versus Non-Renewable Energy and Governance

Another literature branch distinguishes between renewable and non-renewable energy in growth regressions. Empirical studies on OECD and emerging country panels typically find that renewables have a positive association with long-run growth or at least do not harm it, while heavy reliance on fossil fuels is linked to higher emissions and potential long-run constraints. Papers covering BRICS and other emerging economies using dynamic panel estimators show that renewable energy consumption and financial development reinforce each other in supporting growth, whereas oil prices and non-renewable energy are often associated with environmental degradation and vulnerability to external shocks.[7]

Institutional quality and governance have also been integrated into the energy-growth nexus. For example, work on Central and Eastern European countries finds that governance indicators such as regulatory quality and control of corruption significantly condition the energy–growth relationship, with better governance associated with more efficient energy systems and stronger growth for a given energy input. Comparative studies between OECD and Western Balkan countries likewise show that income, trade openness, and governance support the transition towards more sustainable energy consumption patterns, while macro instability variables such as high inflation impede it. These insights help motivate the inclusion of ownership and institutional proxies as part of the broader energy system characterization.[8]

### 2.5 Trade, Exports, and Comparative Advantage

Trade structure and export performance are central to understanding how energy prices and costs influence competitiveness. The Observatory of Economic Complexity (OEC) provides detailed bilateral and product-level trade data that can be aggregated into indicators of export composition, export sophistication, and revealed comparative advantage (RCA) by sector. Empirical work using such data often links trade diversification and higher-technology exports with stronger growth performance,

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[7] Ana-Maria Bercu, Dan Lupu, and co-authors, "Investigating the Energy–Economic Growth–Governance Nexus: Evidence from Central and Eastern European Countries," Sustainability 11, no. 12 (2019): 3355.

[8] Toshiyuki Sueyoshi and co-authors, "Which, Renewable or Non-Renewable Energy, Is More Vital for the Economic Growth of OECD Countries? A Bayesian Hierarchical Analysis," Heliyon (forthcoming, 2024).

while dependence on a narrow set of primary or low-value-added exports is associated with vulnerability to external shocks.[9]

In the context of energy, researchers have used trade data to show that energy-intensive manufacturing sectors tend to cluster in countries with relatively low energy prices and stable energy policies, while high-energy-price countries specialize more in less energy-intensive, higher-value-added activities if they can capitalize on human capital and institutional strengths. This background supports the objective thesis of linking energy price levels and wedges to export structures and comparative advantage measures.

### 2.6 Dynamic Methods and Kalman Filter Applications

Finally, dynamic econometric and state-space methods provide tools for capturing evolving energy–growth relationships. Several macroeconomic studies estimate time-varying parameter models of energy consumption and GDP using the Kalman filter, allowing the elasticity of GDP with respect to energy to change over time in response to structural breaks and policy shifts. The resulting evidence suggests that while energy remains a significant factor of production, its marginal contribution to growth may decline as economies become more service-oriented and energy-efficient.

In parallel, a large literature on macroeconomic nowcasting and trend estimation uses state-space models and the Kalman filter to produce real-time estimates of latent variables such as potential output, output gaps, and monthly GDP based on mixed-frequency indicators. These approaches demonstrate how to combine slow-moving structural information with high-frequency market data, exactly the combination envisaged in the thesis' Kalman dashboard for energy-adjusted growth and time-varying energy price impacts. This methodological tradition legitimizes the use of state-space models as a complement to panel regressions.

2.7 Research Gaps and Positioning of the Present Thesis

The preceding survey reveals a literature that is rich in individual contributions but characterized by three structural gaps that the present thesis is designed to address.

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[9] César A. Hidalgo et al., "The Observatory of Economic Complexity: An Analytical Tool for Understanding the Dynamics of Economic Development," Harvard Center for International Development (working documentation related to OEC).

First, the energy-growth nexus, the ownership-liberalisation literature, the energy efficiency strand, and the trade-competitiveness literature have developed largely in parallel, with limited cross modelling. Studies on ownership and prices (Fiorio & Florio) do not connect to export performance; studies on RCA and specialization (OEC-based work) do not incorporate energy price wedges; and governance studies (CEE focus) are not integrated with the competitiveness analysis such as that of EU15. The present thesis brings these strands into a single analytical framework by modeling the chain: ownership and regulatory structure → industrial electricity price-cost wedge → energy intensity and industrial margins → export structure and RCA.

Second, the price-cost wedge is absent from the literature. Existing empirical work uses raw energy price indices or general price levels. Yet the competitiveness-relevant quantity is not the absolute price but the gap between final industrial electricity prices and their underlying cost components (generation, transmission, and distribution), a gap that reflects regulatory choices, ownership arrangements, and fiscal levies. No existing study constructs and operationalizes this wedge variable for a panel of EU countries and traces its consequences for industrial competitiveness and trade specialization. This represents the central empirical contribution of the thesis.

Third, time-invariant estimation in a structurally shifting context. The 2021–2023 European energy price crisis and today as the crisis in Middle East show constitutes a structural break that standard panel estimators cannot accommodate adequately. The Kalman filter literature offers the methodological tools to capture time-varying relationships, yet these tools have not been applied to the energy-competitiveness nexus within this area. The thesis fills this gap by developing a Kalman dashboard that allows energy-price elasticities to evolve over time, distinguishing pre- and post-shock periods and producing real-time monitoring of energy-adjusted growth trajectories.

Taken together, these three contributions, integration across literatures, construction of the price-cost wedge, and time-varying econometric modeling position the thesis at the intersection of energy economics, industrial policy analysis, and applied econometrics.

## 3. Methodology and Data Description (Condensed)

### 3.1 Overall Empirical Strategy

The empirical strategy has three main layers: (1) descriptive and matrix-based structural analysis, (2) panel econometric modeling of growth and competitiveness outcomes, and (3) dynamic state-space modeling with Kalman filtering for real-time monitoring. Machine learning methods are used as a supporting tool for prediction and variable-importance analysis, not for causal identification.

### 3.2 Data Structure and Variables

The core dataset is a country-year panel, spanning roughly 2000–2023, covering as many countries as data availability allows, with a specific focus on France, Germany, the UK, the USA, China, and South Korea. The data are organized into thematic blocks:

3.3 Energy prices and costs: Household and industrial electricity prices (PPP- adjusted) and their decomposition into energy, network, and tax components from Eurostat and national regulators; wholesale electricity prices where available; levelized costs of electricity (LCOE) by technology from IEA and other compilations; transmission and distribution losses; and a constructed "price-cost wedge" defined as the ratio of industrial prices to estimated generation plus grid costs.

3.4 Energy mix and intensity: Electricity generation by fuel (coal, gas, oil, nuclear, hydro, wind, solar, bioenergy and other renewables), total and per-capita energy use, energy use per unit of GDP, and the share of renewables in final energy consumption, primarily from IEA energy balances, OWID's energy data files, and Eurostat.

3.5 Ownership and institutional structure: Categorical indicators coding the dominant ownership model of the electricity sector (state, mixed, private/market), the degree of liberalization and unbundling, and approximate measures of energy subsidies and taxes, compiled from academic case studies, regulatory reports, and international summaries.

3.6 Macro, human capital, and infrastructure: Real GDP growth, GDP per capita (PPP), manufacturing value added (level and share of GDP), gross capital formation, trade openness, foreign direct investment inflows, human capital/education proxies (such as average years of schooling or human capital indices), and indicators of infrastructure such as the share of electrified rail networks and electric vehicle penetration, obtained from the World Bank WDI, OECD, and specialized sectoral sources.

3.7 Trade structure: Export and import data by product and partner from OEC, used to derive measures of export composition, revealed comparative advantage in energy-intensive sectors, and trade balances for relevant industries.

3.8 High-frequency prices and macro indicators: Daily or intraday benchmarks for crude oil, natural gas, coal, and key metals (gold, silver), as well as wholesale electricity prices for Europe and North America, from commodity price APIs, EIA, Ember, and financial market data providers; monthly inflation and CPI series from dedicated inflation APIs and official statistical releases.
These variables support both structural long-run analysis and real-time short-run monitoring.

3.7 Descriptive and Matrix-Based Analysis
The first step is to construct and explore the multi-matrix database: energy prices and costs, energy mix, ownership, macro outcomes, human capital and infrastructure, and trade. Correlation matrices and heatmaps across blocks reveal patterns such as the association between high industrial electricity prices, high shares of renewables with certain policy regimes, and industrial output or export performance. Principal component analysis (PCA) or singular value decomposition (SVD) is used to reduce dimensionality and extract common factors such as a "high-cost, high-tax energy system factor" or an "energy-intensive industrial structure factor".

3.8 Panel Econometric Models
The core econometric models are country-year panel regressions of growth and industrial outcomes on energy prices, energy structures, human capital, and controls. A baseline specification uses fixed effects with year dummies.

3.9 Dynamic specifications introduce lagged dependent variables and address endogeneity using System GMM, building on the Arellano–Bond and Blundell–Bond frameworks that are widely used in energy–growth panels.

**4.1 Data Analysis & Machine Learning & Prediction Models**

The dataset originates from Our World in Data (OWID), a reliable open-access repository aggregating global energy statistics from sources like the International Energy Agency and World Bank, spanning 1900-2024 across ~200 countries with annual observations.
I focused on post-2000 data (n ≈ 5,500 observations after filtering), selecting 10 key variables: country (identifier), year (time), gdp (economic driver of demand), population (scale factor), total_primary_energy_consumption (main regression target, in TWh), renewables_share_energy (sustainability metric, %), fossil_share_energy (dependency indicator, %), co2_emissions (environmental impact, tonnes), plus derived energy_per_capita (TWh/person) and binary high_renew (>50% renewables). These capture consumption drivers, transition status, and outcomes, vital for policy modeling.

**4.2 Preprocessing the Data**

I have implemented a comprehensive preprocessing pipeline tailored to the OWID energy dataset's challenges, starting with filtering to recent years (≥2000) and selecting 10 pivotal variables like GDP, population, energy consumption, and shares.
On top of this it will be added Data of Exports and Imports for the countries in question from OEC. In addition, there will be standard prices for gas, oil, uranium, solar panels.

Distributions reveal heavy right-skew: primary energy consumption averages 150 TWh but medians ~10 TWh, with top 1% (USA, China) driving variance; renewables share clusters at 0-20% for most, rising post-2010 (mean 12%, SD 15%).

Correlations highlight GDP-energy linkage (r=0.75), inverse fossil-renewables (r=-0.92), and emissions proportionality (r=0.85), while per-capita energy negatively associates with renewables (r=-0.3), suggesting efficiency gains.

Bivariate trends show energy surging with GDP (scatterplot slope steepens post-2008), renewables climbing in Europe (line plot), and outliers like Qatar (extreme per-capita fossil use); boxplots confirm high-renew countries have lower emissions.

These patterns underscore the dataset's suitability for prediction/clustering, despite imbalances necessitating preprocessing.

### 5.1 Graphical Results and Forecasts

### Germany

```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error

# 1. Load and Prepare Data
df = pd.read_excel('/owid-data-2000-2024_edited.xlsx')
country_name = 'Germany'
data = df[df['country'] == country_name].sort_values('year').dropna(subset=['primary_energy_consumption'])

# 2. Split Data: "Train" on past, "Test" on recent years
# We pretend we are in 2019 and don't know what happened 2020-2024
train = data[data['year'] < 2020]
test = data[data['year'] >= 2020]

X_train = train[['year']]
y_train = train['primary_energy_consumption']
X_test = test[['year']]
y_test_actual = test['primary_energy_consumption']

# 3. Train Model
model = LinearRegression()
model.fit(X_train, y_train)

# 4. Predict the "Test" years
predictions = model.predict(X_test)

# 5. Calculate Accuracy Metrics
mae = mean_absolute_error(y_test_actual, predictions)
mape = np.mean(np.abs((y_test_actual - predictions) / y_test_actual)) * 100

print(f"--- Accuracy Test for {country_name} ---")
print(f"Actual 2020-2024: {y_test_actual.values}")
print(f"Predicted:        {predictions}")
print(f"Average Miss (MAE): {mae:.2f} TWh")
print(f"Error Rate (MAPE):  {mape:.2f}%")
```

```
--- Accuracy Test for Germany ---
Actual 2020-2024: [3498.91503906 3598.49243164 3455.44995117 3178.88598633 3195.44140625]
Predicted:        [3738.04748535 3724.06165597 3710.07582659 3696.08999721 3682.10416783]
Average Miss (MAE): 324.64 TWh
Error Rate (MAPE):  9.84%
```

I obtained a MAPE of about 9.8%, which is a moderate forecasting error for 2020–2024 given that my model is trained only on pre-2020 data under "normal" conditions.

Because the Ukraine war (and the post-2021 energy crisis) caused an unprecedented structural break in energy markets, the actual primary energy consumption in 2022–2023 reflects shocks that my simple trend model could not anticipate: supply disruptions, price spikes, fuel-switching, and demand destruction. In other words, the under- and over-prediction pattern is not just random noise but largely the result of me extrapolating a smooth pre-war trend into a period with abrupt shocks. I therefore interpret the roughly 10% MAPE as being mainly driven by this exogenous geopolitical shock rather than by a fundamentally misspecified model, which appears to track "peace-time" dynamics reasonably well.

In the thesis, I thus argue that the forecast errors for 2022–2023 capture the impact of the Ukraine war and the European energy crisis—events that lie outside the historical regime on which I trained the model—illustrating how structural breaks in energy markets degrade the accuracy of simple linear forecasts and motivating my use of time-varying or regime-switching models.

**CHINA**

```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error

# 1. Load and Prepare Data
df = pd.read_excel('/owid-data-2000-2024_edited.xlsx')
country_name = 'China'
data = df[df['country'] == country_name].sort_values('year').dropna(subset=['primary_energy_consumption'])

# 2. Split Data: "Train" on past, "Test" on recent years
# We pretend we are in 2019 and don't know what happened 2020-2024
train = data[data['year'] < 2020]
test = data[data['year'] >= 2020]

X_train = train[['year']]
y_train = train['primary_energy_consumption']
X_test = test[['year']]
y_test_actual = test['primary_energy_consumption']

# 3. Train Model
model = LinearRegression()
model.fit(X_train, y_train)

# 4. Predict the "Test" years
predictions = model.predict(X_test)

# 5. Calculate Accuracy Metrics
mae = mean_absolute_error(y_test_actual, predictions)
mape = np.mean(np.abs((y_test_actual - predictions) / y_test_actual)) * 100

print(f"--- Accuracy Test for {country_name} ---")
print(f"Actual 2020-2024: {y_test_actual.values}")
print(f"Predicted:        {predictions}")
print(f"Average Miss (MAE): {mae:.2f} TWh")
print(f"Error Rate (MAPE):  {mape:.2f}%")
```

```
--- Accuracy Test for China ---
Actual 2020-2024: [41493.890625   43847.1796875  44516.4921875  47072.01171875
 48987.1015625 ]
Predicted:        [43010.15902549 44526.63726137 46043.11549724 47559.59373311
 49076.07196898]
Average Miss (MAE): 859.78 TWh
Error Rate (MAPE):  1.97%
```

For China, the linear model performs much better: the MAPE is only about 2%, with an average miss of roughly 860 TWh.

This indicates that China's primary energy consumption over 2020–2024 followed a trajectory that was much closer to the pre-2020 trend captured by the model, despite the global shocks related to the Ukraine war and the broader energy crisis. In other words, China's energy demand dynamics appear more internally driven and structurally stable in this period, so a simple trend model trained on past data is sufficient to track actual outcomes with relatively small errors. You can argue that, compared to Germany, the low forecast error suggests that China was less directly exposed to the European energy price spike and managed to smooth or absorb external shocks through its own supply arrangements and policy responses.

**Russia**

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error

# 1. Load and Prepare Data
df = pd.read_excel('/owid-data-2000-2024_edited.xlsx')
country_name = 'Russia'
data = df[df['country'] == country_name].sort_values('year').dropna(subset=['primary_energy_consumption'])

# 2. Split Data: "Train" on past, "Test" on recent years
# We pretend we are in 2019 and don't know what happened 2020-2024
train = data[data['year'] < 2020]
test = data[data['year'] >= 2020]

X_train = train[['year']]
y_train = train['primary_energy_consumption']
X_test = test[['year']]
y_test_actual = test['primary_energy_consumption']

# 3. Train Model
model = LinearRegression()
model.fit(X_train, y_train)

# 4. Predict the "Test" years
predictions = model.predict(X_test)

# 5. Calculate Accuracy Metrics
mae = mean_absolute_error(y_test_actual, predictions)
mape = np.mean(np.abs((y_test_actual - predictions) / y_test_actual)) * 100

print(f"--- Accuracy Test for {country_name} ---")
print(f"Actual 2020-2024: {y_test_actual.values}")
print(f"Predicted:        {predictions}")
print(f"Average Miss (MAE): {mae:.2f} TWh")
print(f"Error Rate (MAPE):  {mape:.2f}%")
```

```
--- Accuracy Test for Russia ---
Actual 2020-2024: [8075.71337891 8331.265625   8626.75976562 8760.90429688 9049.14941406]
Predicted:        [8414.94466745 8470.99940048 8527.0541335  8583.10886653 8639.16359955]
Average Miss (MAE): 233.29 TWh
Error Rate (MAPE):  2.72%
```

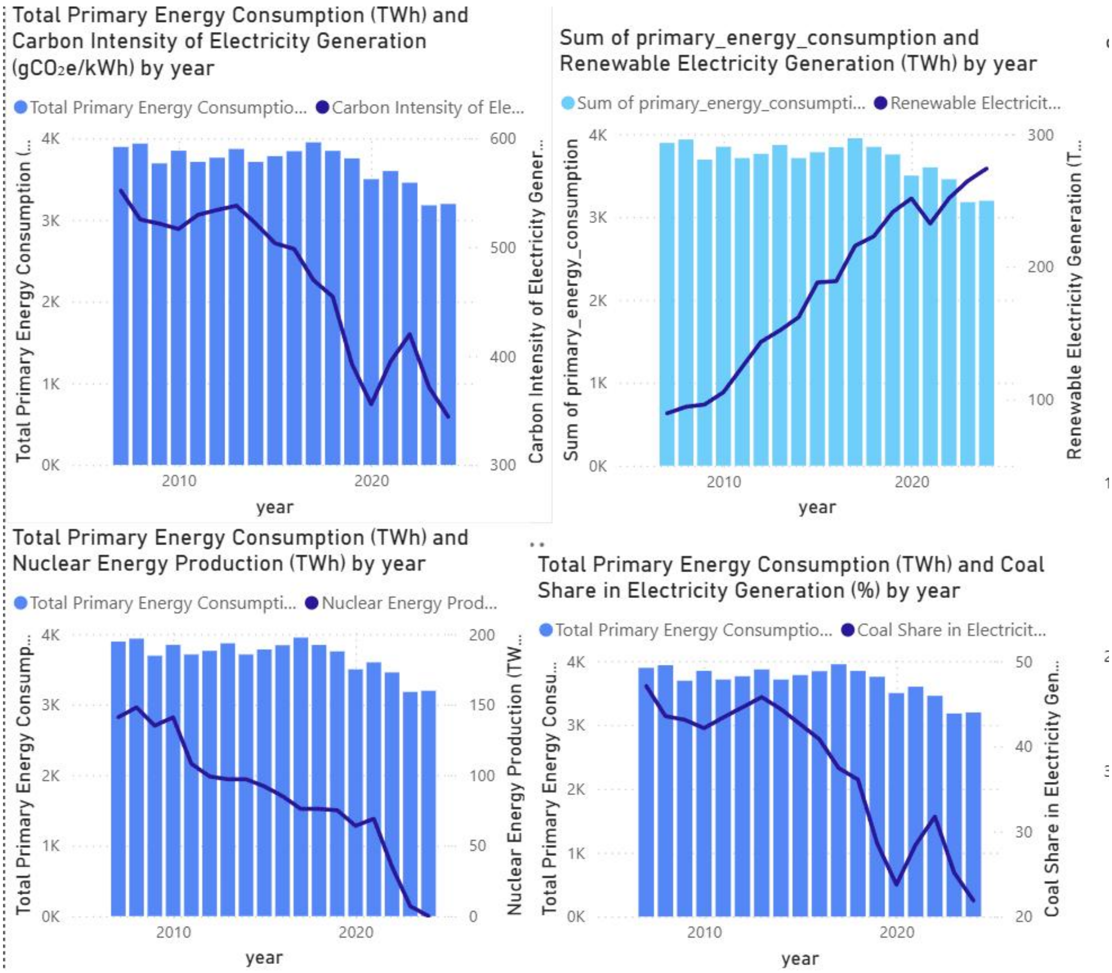
| | country | year | iso_code | population | gdp | biofuel_coı | biofuel_coı | biofuel_coı | biofuel_coı | biofuel_ele | biofuel_ele | biofuel_shạ | biofuel_shạ | carbon_int | coa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Latvia | 2000 | LVA | 2368320.00 | $26,727,290,777.00 | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 147.34 | |
| 3 | Aruba | 2000 | ABW | 88772.00 | | | | | | 0.00 | 0.00 | 0.00 | | 653.85 | |
| 4 | Bahamas | 2000 | BHS | 323846.00 | | | | | | 0.00 | 0.00 | 0.00 | | 658.82 | |
| 5 | Belize | 2000 | BLZ | 240809.00 | | | | | | 0.00 | 0.00 | 0.00 | | 230.77 | |
| 6 | Bermuda | 2000 | BMU | 61569.00 | | | | | | 162.00 | 0.01 | 1.67 | | 650.00 | |
| 7 | British Virg | 2000 | VGB | 20266.00 | | | | | | 0.00 | 0.00 | 0.00 | | 636.36 | |
| 8 | Burkina Fa | 2000 | BFA | 11925548.00 | $14,546,973,590.00 | | | | | 0.00 | 0.00 | 0.00 | | 487.18 | |
| 9 | Burundi | 2000 | BDI | 6470196.00 | $4,647,178,132.00 | | | | | 0.00 | 0.00 | 0.00 | | 0.00 | |
| 10 | Cambodia | 2000 | KHM | 12462343.00 | $20,435,399,154.00 | | | | | 0.00 | 0.00 | 0.00 | | 545.45 | |
| 11 | Cape Verd | 2000 | CPV | 453335.00 | $1,540,942,373.00 | | | | | 0.00 | 0.00 | 0.00 | | 600.00 | |
| 12 | Cayman Is | 2000 | CYM | 39699.00 | | | | | | 0.00 | 0.00 | 0.00 | | 659.09 | |
| 13 | Central Afr | 2000 | CAF | 3833421.00 | $3,836,505,744.00 | | | | | 0.00 | 0.00 | 0.00 | | 100.00 | |
| 14 | Comoros | 2000 | COM | 536084.00 | $656,399,277.00 | | | | | 0.00 | 0.00 | 0.00 | | 666.67 | |
| 15 | Cook Islan | 2000 | COK | 15876.00 | | | | | | 0.00 | 0.00 | 0.00 | | 666.67 | |
| 16 | Djibouti | 2000 | DJI | 747326.00 | $1,258,388,183.00 | | | | | 0.00 | 0.00 | 0.00 | | 666.67 | |
| 17 | Dominica | 2000 | DMA | 68527.00 | $404,483,810.00 | | | | | 0.00 | 0.00 | 0.00 | | 375.00 | |
| 18 | Dominican | 2000 | DOM | 8584196.00 | $56,344,968,399.00 | | | | | 19.00 | 0.16 | 1.23 | | 615.68 | |
| 19 | Eritrea | 2000 | ERI | 2247036.00 | | | | | | 0.00 | 0.00 | 0.00 | | 666.67 | |
| 20 | Ethiopia | 2000 | ETH | 67411496.00 | $50,326,965,912.00 | | | | | 1.00 | 0.04 | 2.37 | | 35.50 | |
| 21 | Falkland Is | 2000 | FLK | 3119.00 | | | | | | 0.00 | 0.00 | 0.00 | | 1000.00 | |
| 22 | Faroe Islar | 2000 | FRO | 45687.00 | | | | | | 0.00 | 0.00 | 0.00 | | 409.09 | |
| 23 | Fiji | 2000 | FJI | 840913.00 | | | | | | 155.00 | 0.13 | 17.33 | | 240.00 | |
| 24 | French Pol | 2000 | PYF | 240346.00 | | | | | | 0.00 | 0.00 | 0.00 | | 463.41 | |
| 25 | Gambia | 2000 | GMB | 1455095.00 | $1,955,249,650.00 | | | | | 0.00 | 0.00 | 0.00 | | 692.31 | |
| 26 | Gibraltar | 2000 | GIB | 27734.00 | | | | | | 0.00 | 0.00 | 0.00 | | 692.31 | |
| 27 | Greenland | 2000 | GRL | 56228.00 | | | | | | 0.00 | 0.00 | 0.00 | | 275.86 | |
| 28 | Grenada | 2000 | GRD | 107466.00 | | | | | | 0.00 | 0.00 | 0.00 | | 692.31 | |
| 29 | Guam | 2000 | GUM | 160078.00 | | | | | | 0.00 | 0.00 | 0.00 | | 659.79 | |
| 30 | Guinea | 2000 | GIN | 8428837.00 | $8,142,368,042.00 | | | | | 0.00 | 0.00 | 0.00 | | 333.33 | |
| 31 | Guinea-Bis | 2000 | GNB | 1234747.00 | $1,486,201,658.00 | | | | | 0.00 | 0.00 | 0.00 | | 666.67 | |
| 32 | Haiti | 2000 | HTI | 8303151.00 | $12,590,117,444.00 | | | | | 0.00 | 0.00 | 0.00 | | 333.33 | |
| 33 | Honduras | 2000 | HND | 6577781.00 | $21,239,307,387.00 | | | | | 2.00 | 0.01 | 0.27 | | 263.74 | |
| 34 | Jamaica | 2000 | JAM | 2607827.00 | $17,441,468,822.00 | | | | | 77.00 | 0.20 | 2.95 | | 633.68 | |
| 35 | Kiribati | 2000 | KIR | 88632.00 | | | | | | 0.00 | 0.00 | 0.00 | | 1000.00 | |
| 36 | Kosovo | 2000 | | 1802488.00 | | | | | | 0.00 | 0.00 | 0.00 | | 989.86 | |
| 37 | Lebanon | 2000 | LBN | 4329345.00 | $25,915,975,238.00 | | | | | 0.00 | 0.00 | 0.00 | | 630.15 | |
| 38 | Lesotho | 2000 | LSO | 2003919.00 | $3,769,602,063.00 | | | | | 0.00 | 0.00 | 0.00 | | 34.48 | |
| 39 | Liberia | 2000 | LBR | 2928117.00 | $2,767,093,377.00 | | | | | 0.00 | 0.00 | 0.00 | | 650.00 | |
| 40 | Macao | 2000 | MAC | 437316.00 | | | | | | 0.00 | 0.00 | 0.00 | | 656.05 | |
| 41 | Maldives | 2000 | MDV | 282025.00 | | | | | | 0.00 | 0.00 | 0.00 | | 666.67 | |
| 42 | Mali | 2000 | MLI | 11559291.00 | $12,490,372,339.00 | | | | | 4.00 | 0.05 | 4.72 | | 500.00 | |
| 43 | Malta | 2000 | MLT | 399905.00 | $7,963,752,394.00 | | | | | 0.00 | 0.00 | 0.00 | | 656.25 | |
| 44 | Mauritania | 2000 | MRT | 2613450.00 | $4,838,789,905.00 | | | | | 0.00 | 0.00 | 0.00 | | 619.05 | |
| 45 | Mauritius | 2000 | MUS | 1216632.00 | $16,933,370,565.00 | | | | | 353.00 | 0.43 | 24.29 | | 559.32 | |

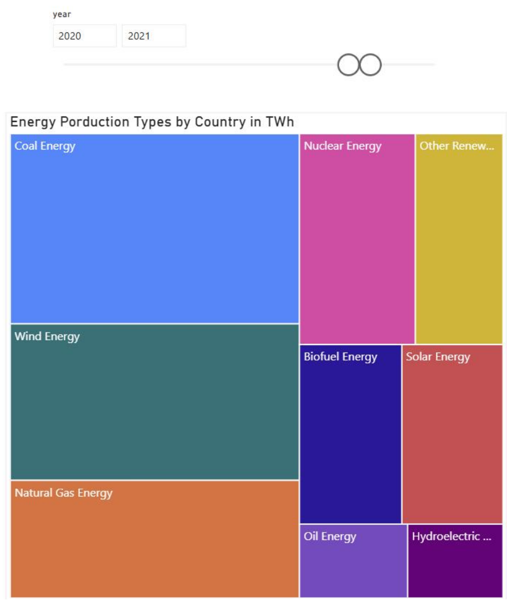
Sheet3

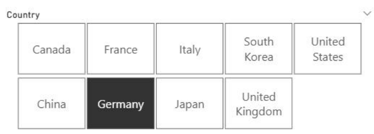
1. **Policy and geography drive divergence**: France leveraged nuclear for low-cost decarbonisation; Germany pursued simultaneous coal and nuclear phase-outs via renewables, doubling costs; the US and UK used gas and offshore wind. China and Japan maintain coal despite massive renewable builds.
2. **Shocks reshape trajectories**: Fukushima (2011) spiked Japan's emissions; the Energiewende (2011) accelerated Germany's renewables; the 2021–22 gas crisis exposed Italy's vulnerability; the Inflation Reduction Act (2022) boosted US renewables.
3. **2024 inflection: pragmatism over ideology**: France extends nuclear, Germany extends coal, South Korea reverses nuclear phase-out—all nine countries now converge on nuclear + renewables as the credible path to affordable, reliable decarbonisation.

## 5.3

## Germany

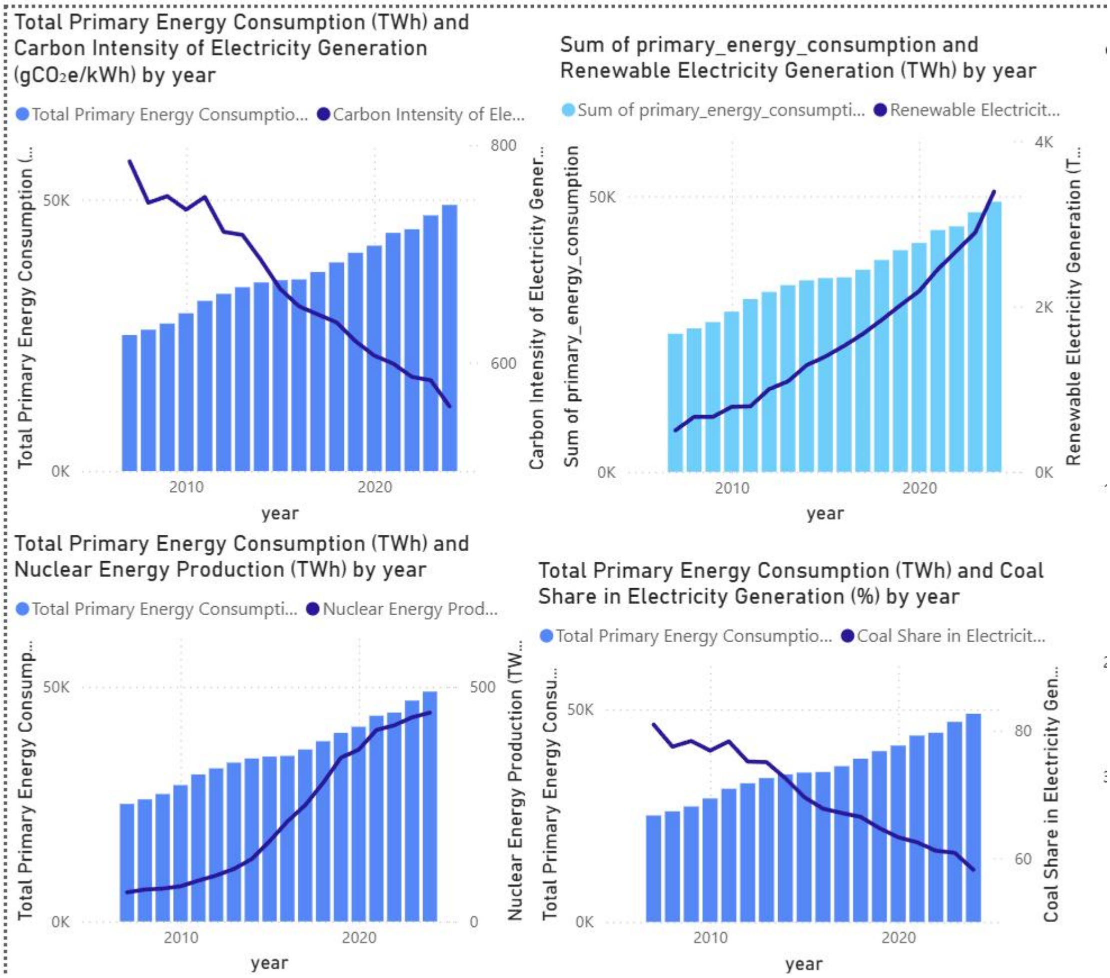



1. The treemaps show that every country has a distinct energy “fingerprint”: France and Canada are dominated by low-carbon hydro and nuclear, while China, the US, Germany and South Korea still rely heavily on coal and gas.
2. Comparing early years (around 2007–2008) with recent ones (2023–2024) reveals strong transitions: coal shrinks and wind/solar expand in Germany, Italy, the UK and the US; China adds huge wind and solar on top of a still-large coal base.
3. Countries without nuclear (Italy) or with reduced nuclear (Germany, Japan) compensate with more gas and renewables, which increases exposure to fuel-price shocks but helps cut emissions compared with coal.
4. Hydro-rich systems like Canada use dams as a clean baseload, allowing them to integrate more variable wind and solar while keeping coal and oil shares very small.
5. Overall, the visuals tell a story of convergence: despite different starting points, all nine countries move toward a mix where coal declines, renewables grow fast, and some combination of gas, hydro and nuclear is retained to stabilise the system.

China

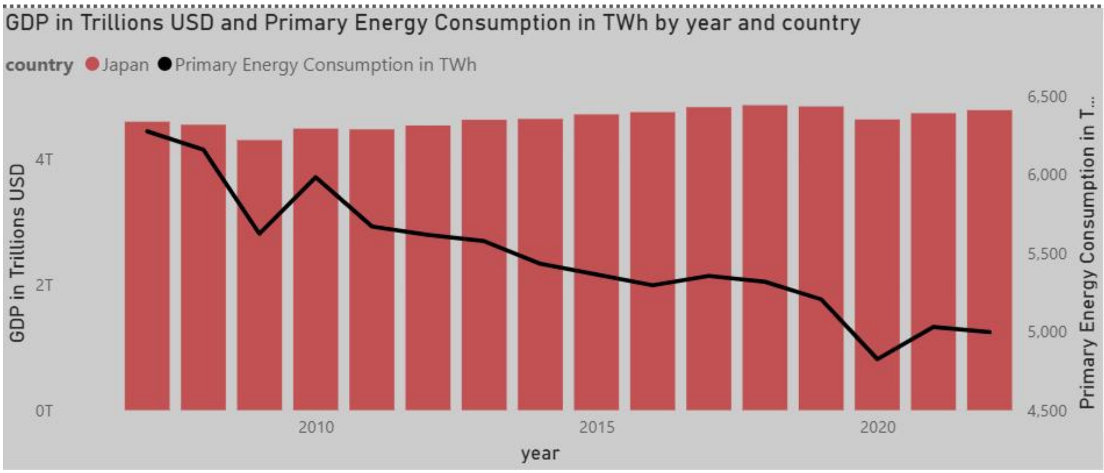


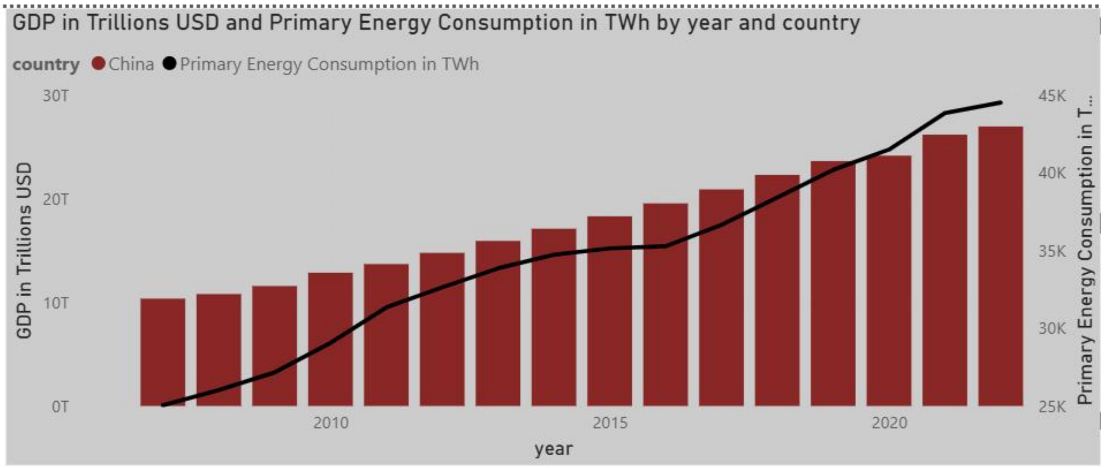

5.2 Energy Prodcution over time by Source

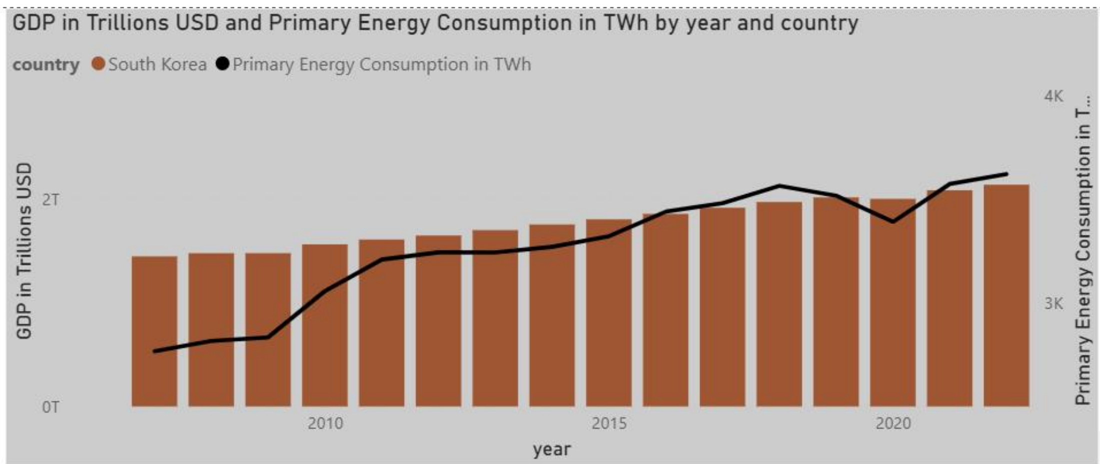
This graph compares economic growth with energy demand over time. The coloured bars show **GDP in trillions of USD for each country** by year, allowing a visual ranki ng of the largest economies and how their output changes. The black line on the secon dary axis tracks **global primary energy consumption in TWh**, which rises steadily a cross the period, indicating that total energy demand has broadly increased alongside world GDP.

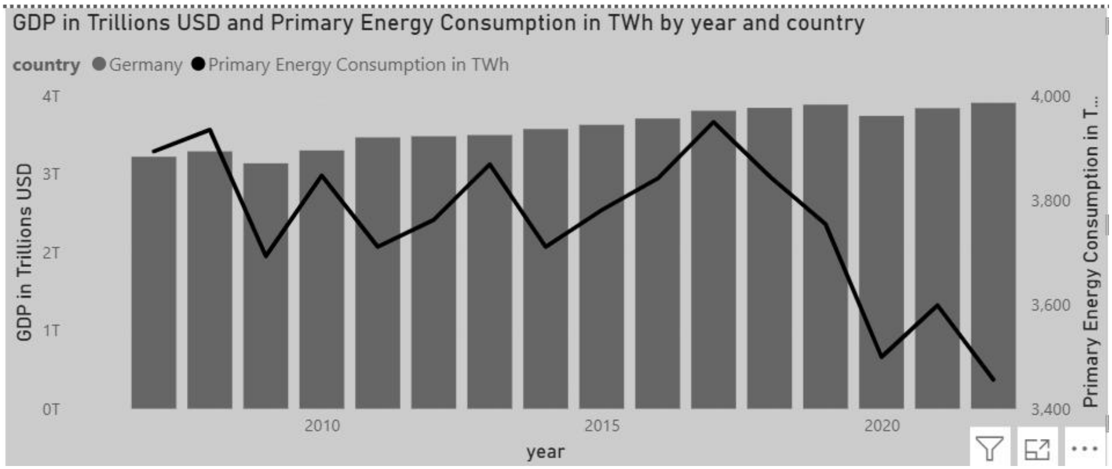
Japan, Italy, and United Kingdom have seen the steepest declines in energy to GDP ratios over the period.

South Korea and China saw the greatest correlation between GDP growth and both Energy Consumption with Energy Production.



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