GenAI and Data Science Final Project

1/10/2025 - 22/10/2025

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make the code create a folder for all output

0. Requirements

Runtime Versions:

python : 3.12.12

pandas : 2.2.2

numpy : 2.0.2

matplotlib : 3.10.0

seaborn : 0.13.2

statsmodels : 0.14.5

Code provided below at library imports.

Please write your URL of the DataSheet provided below

```
myURL = "/content/drive/MyDrive/University/National Central University/GenAI and DS/Final Project/DataSheet.csv"
```

1. Introduction

1.1 Topic

This project focuses on the monetary and financial conditions of selected European economies, using indicators provided by the Organization for Economic Cooperation and Development (OECD). These monetary and financial indicators are frontline measures of economic stability and policy effectiveness. They are deeply connected to credit activity, bank lending, risk-taking, and asset pricing, which makes their evaluation a central priority for understanding the dynamics of modern financial systems.

I decided to work with these indicators because they play such a major role in shaping economies, they're often the first signs of change, whether positive or negative. They're also entry-level indicators, which made them perfect for my level of experience and for practicing real economic analysis. I chose the OECD as my data source mainly for its reliability, accessibility, and vast historical coverage. Their datasets are well-structured, transparent, and consistent, making them ideal for technical work like this.

The indicators I selected were originally chosen because they were the most available for European analysis within the OECD database. However, as I explored them, I became genuinely interested in seeing how they related to one another. Analyzing their correlations and how they move together over time turned out to be a very rewarding experience. The dataset captures several major economic events, such as the COVID-19 shock, recent inflation surges, and earlier financial downturns, which gave me a clear historical context for understanding how economies react to crises and recoveries. Overall, this analysis provides a general picture of how Europe's financial landscape evolves, helping interpret current trends and policy decisions through the lens of economic history.

1.2 Personal Project Motivation

The intersection between computer engineering and finance fascinates me, so I wanted to choose a topic that combines both fields. My interest in finance actually started before university, when I took an introductory finance course that focused on understanding the basics of the financial system. That experience made me realize how much I enjoy analyzing markets and interpreting data-driven insights. Since then, my goal has been to work in finance, and I see programming and data science as essential tools for modern financial analysis.

Coding and data analysis give me a different perspective compared to traditional economic methods. They make data exploration faster, more accessible, and more transparent, a more democratic way of analyzing economies. Working with European data felt natural because I live here, and understanding the region's financial behavior and policies is something I find both personally and academically relevant.

Throughout the project, I enjoyed seeing how the data reflected real-world dynamics. The dataset was surprisingly complete, but it was also challenging because many indicators are tied to the euro, which most European countries share. That makes comparisons tricky but also very interesting, since you can see how countries with the same currency still differ in policy outcomes. This project helped me develop both technical and analytical skills, and it gave me a clearer sense of how data science can strengthen financial understanding. More importantly, it confirmed that this intersection, using computational tools to study finance, is where I want to continue growing professionally.

1.3 Data Sources

The OECD provided accurate and up-to-date data that is highly accessible to the public. The dataset I chose consists of 26 European countries, each represented through monthly monetary and financial indicators covering several years of observation. The data is well-structured, standardized, and includes detailed metadata such as measurement units, methodologies, and frequency, which made it easier to process and interpret. You can find the exact same data here: [OECD Data]

1.4 Indicator and measurements

In this project, we analyze important economic indicators and their measurements from these 26 European countries. The indicators used include:

- **Long-term interest rates (Percent per annum)**: These rates are derived from the yields on government bonds with longer maturities, like 10-year bonds. They reflect market expectations over a longer horizon.
- **Short-term interest rates (Percent per annum)**: They are based on central bank policy rates or interbank lending rates. They get annualized for easy comparison with other rates. In simple terms they indicate short-term borrowing costs for general bank customers.
- **Nominal exchange rates (National currency per US dollar)**: These represent the straightforward exchange values between national currencies and the US dollar. It is important to note that, While many of these countries use the euro, others like Poland or Hungary have their own currencies, which can lead to higher numerical exchange rates.
- **Real effective exchange rates CPI-based (Index)**: These index values that adjust nominal rates for inflation differences, allowing us to see the currency's value in real terms relative to a base period.
- **Share price (Index)**: Share prices are often presented as an index as well, showing how stock values move compared to a base year.

For ease and confort of understanding, here's a description of each measurment type and how they're calculated:

- **Percent per annum**: Expresses interest rates as a yearly percentage of the principal.
- **National currency per US dollar**: Indicates how much of a country's currency is needed to buy one US dollar. This measurement reflects the direct value of a currency.
- **Index**: Represents relative values compared to a base period, which is usually set to 100. The formula is: (Current Value / Base Value) × 100, where the base value is normally a value that represents a "normal" economic period. This measurement is adjusted for inflation for the real effective exchange rates using the Consumer Price Index (CPI-based).

2. Data Analysis and Modeling

2.1 Configuring Data

2.1.1 Setting Up Libraries and Dependencies

```
!pip install -q pandas matplotlib seaborn openpyxl statsmodels

import platform, importlib
from google.colab import drive
import os

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

from statsmodels.tsa.arima.model import ARIMA
```

- **google.colab.drive**: This is a library that mounts Google Drive so the notebook can read and write files.

- **os**: The standard Python library for working with paths and directories in your local machine.
- **pandas (pd)**: It's the core data toolkit. I mainly use it to read CSV/Excel files, select and rename columns, parse dates, group and pivot data, compute summary statistics, and export results to CSV.
- **seaborn (sns)**: Seaborn is high-level plotting library built on matplotlib that I use for statistical visualizations. It helped me create the completeness heatmap, multi-country time-series lines, cross-country comparisons, boxplots of distributions, and correlation heatmaps.
- **matplotlib.pyplot (plt)**: This is the plotting backend and figure controller. I use it to set figure sizes, add titles and labels, control legends, and save figures, plus any direct plotting done with plt.plot.
- **statsmodels.tsa.arima.model.ARIMA**: This is the classical ARIMA model for time-series forecasting. I use for the Forecasting (ARIMA) to fit models on selected indicator-country series and to generate 12-month-ahead forecasts.
- **openpyxl**: This Library I implicitly use through pandas for the Excel engine to read .xlsx files.

```
pkgs = {
    "python": platform.python_version(),
    "pandas": importlib.import_module("pandas").__version__,
    "numpy": importlib.import_module("numpy").__version__,
    "matplotlib": importlib.import_module("matplotlib").__version__,
    "seaborn": importlib.import_module("seaborn").__version__,
    "statsmodels": importlib.import_module("statsmodels").__version__,
}

print("Runtime Versions")
for name in ["python","pandas","numpy","matplotlib","seaborn","statsmodels"]:
    print(f"{name:12s}: {pkgs[name]}")
```

```
Runtime Versions
python      : 3.12.12
pandas      : 2.2.2
numpy       : 2.0.2
matplotlib  : 3.10.0
seaborn     : 0.13.2
statsmodels : 0.14.5
```

2.1.2 Load Data

```
data_source = myURL

if data_source.endswith(".csv"):
    df = pd.read_csv(data_source)
else:
    df = pd.read_excel(data_source)
```

2.1.3 Clean Data

Before starting any analysis, it’s essential to isolate only the columns that are relevant to the study. The original OECD dataset contains 34 columns, many of which are metadata or identifiers not needed for modeling. Here, we keep only the fields that identify the country, date, indicator type, unit of measurement, and numeric value. We also rename the columns to simpler, more descriptive names for readability in later steps.

```
clean_df = df[[
    "Reference area", "REF_AREA", "TIME_PERIOD",
    "Measure", "Unit of measure", "OBS_VALUE", "UNIT_MULT"
]].copy()

clean_df = clean_df.rename(columns={
    "Reference area": "country",
    "REF_AREA": "iso_code",
    "TIME_PERIOD": "date",
    "Measure": "indicator",
    "Unit of measure": "measurement",
    "OBS_VALUE": "value_original",
    "UNIT_MULT": "unit_multiplier"
})
```

```
clean_df["date"] = pd.to_datetime(clean_df["date"], errors="coerce")
clean_df["value_original"] = pd.to_numeric(clean_df["value_original"], errors="coerce")
```

The dataset contains dozens of economic indicators, but this project focuses on the six most relevant to analyzing financial and monetary stability. We can then filter these, to ensure the analysis stays consistent and focused on the indicators that represent interest rates, exchange rates, and market performance.

```
indicators = [
    "Nominal exchange rates",
    "Real effective exchange rates - CPI based",
    "Long-term interest rates",
    "Short-term interest rates",
    "Immediate interest rates (call money/interbank rate)",
    "Share prices"
]
clean_df = clean_df[clean_df["indicator"].isin(indicators)]
```

OECD datasets include a unit multiplier to indicate the scale of the data (e.g., thousands, millions). In this case it is a 0 multiplier all around meaning data is in its natural scale. Still, We apply this multiplier for good practice. This ensures that all data points are comparable across countries and indicators.

```
clean_df["value_scaled"] = clean_df["value_original"] * (10 ** clean_df["unit_multiplier"].astype(float))

clean_df = clean_df.sort_values(["indicator", "measurement", "country", "date"]).reset_index(drop=True)

print("Cleaned dataset structure:")
print(clean_df.info())
display(clean_df.head(10))
```

```
Cleaned dataset structure:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61463 entries, 0 to 61462
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          61463 non-null  object
 1   iso_code         61463 non-null  object
 2   date             61463 non-null  datetime64[ns]
 3   indicator        61463 non-null  object
 4   measurement      61463 non-null  object
 5   value_original   61463 non-null  float64
 6   unit_multiplier  61463 non-null  int64
 7   value_scaled     61463 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 3.8+ MB
None
```

	country	iso_code	date	indicator	measurement	value_original	unit_multiplier	value_scaled
0	Austria	AUT	1990-01-01	Long-term interest rates	Percent per annum	8.17	0	8.17
1	Austria	AUT	1990-02-01	Long-term interest rates	Percent per annum	8.60	0	8.60
2	Austria	AUT	1990-03-01	Long-term interest rates	Percent per annum	8.56	0	8.56
3	Austria	AUT	1990-04-01	Long-term interest rates	Percent per annum	8.68	0	8.68
4	Austria	AUT	1990-05-01	Long-term interest rates	Percent per annum	8.83	0	8.83
5	Austria	AUT	1990-06-01	Long-term interest rates	Percent per annum	8.84	0	8.84
6	Austria	AUT	1990-07-01	Long-term interest rates	Percent per annum	8.67	0	8.67
7	Austria	AUT	1990-08-01	Long-term interest rates	Percent per annum	8.83	0	8.83
8	Austria	AUT	1990-09-01	Long-term interest rates	Percent per annum	8.99	0	8.99
9	Austria	AUT	1990-10-01	Long-term interest rates	Percent per annum	9.02	0	9.02

Quick check for the multipliers

```
print("\nUnique unit multipliers per indicator/measurement:")
display(clean_df.groupby(["indicator", "measurement"])["unit_multiplier"].unique())
```

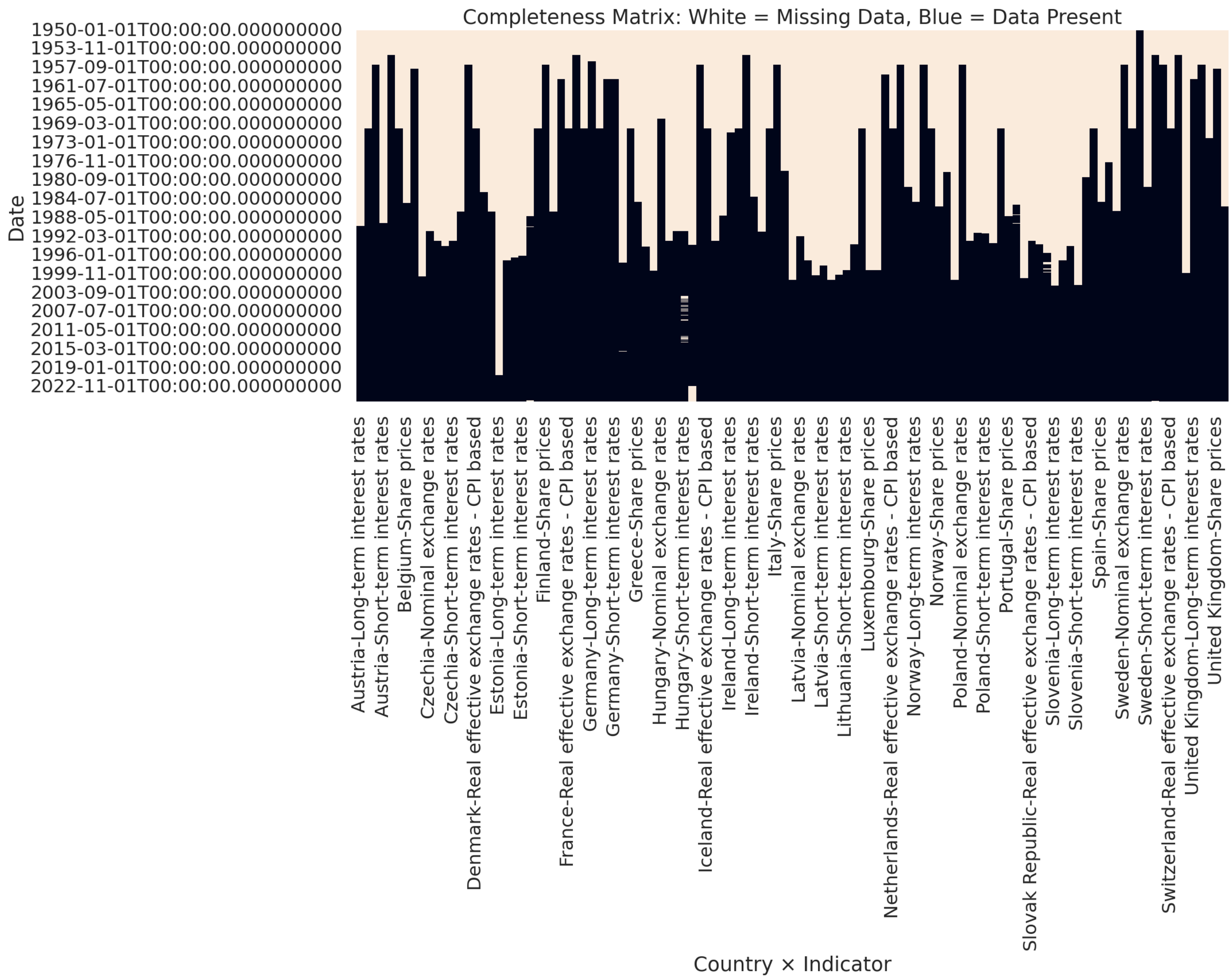
Unique unit multipliers per indicator/measurement:

indicator	measurement	unit_multiplier
Long-term interest rates	Percent per annum	[0]
Nominal exchange rates	National currency per US dollar	[0]
Real effective exchange rates - CPI based	Index	[0]
Share prices	Index	[0]
Short-term interest rates	Percent per annum	[0]

dtype: object

Now we must understand the availability of data across time and countries, so we create a completeness matrix. This heatmap visually displays where data exists (dark blue) and where it's missing (white). It helps identify gaps of some countries, since some have shorter historical records than others.

```
pivot = clean_df.pivot_table(
    index="date",
    columns=["country", "indicator"],
    values="value_scaled"
)

plt.figure(figsize=(14, 6))
sns.heatmap(pivot.isna(), cbar=False)
plt.title("Completeness Matrix: White = Missing Data, Blue = Data Present")
plt.xlabel("Country × Indicator")
plt.ylabel("Date")
plt.show()
```



To complement the visual matrix, I calculate the percentage of available observations per country and indicator. This allows us to quantitatively measure how complete each dataset is, helping later decisions about data reliability and model selection.

```
completeness_summary = (
    clean_df
    .groupby(["country", "indicator"])
    ["value_scaled"]
    .apply(lambda x: 100 * x.notna().sum() / len(x))
    .reset_index(name="percent_non_missing")
    .sort_values("percent_non_missing", ascending=False)
)

print("\n Completeness Summary (percent of non-missing observations):")
display(completeness_summary.head(20))
```

```
Completeness Summary (percent of non-missing observations):
```

	country	indicator	percent_non_missing
0	Austria	Long-term interest rates	100.0
1	Austria	Real effective exchange rates - CPI based	100.0
2	Austria	Share prices	100.0
3	Austria	Short-term interest rates	100.0
4	Belgium	Long-term interest rates	100.0
5	Belgium	Real effective exchange rates - CPI based	100.0
6	Belgium	Share prices	100.0
7	Belgium	Short-term interest rates	100.0
8	Czechia	Long-term interest rates	100.0
9	Czechia	Nominal exchange rates	100.0
10	Czechia	Real effective exchange rates - CPI based	100.0
11	Czechia	Share prices	100.0
12	Czechia	Short-term interest rates	100.0
13	Denmark	Long-term interest rates	100.0
14	Denmark	Nominal exchange rates	100.0
15	Denmark	Real effective exchange rates - CPI based	100.0
16	Denmark	Share prices	100.0
17	Denmark	Short-term interest rates	100.0
18	Estonia	Long-term interest rates	100.0
19	Estonia	Real effective exchange rates - CPI based	100.0

Finally, we save both the cleaned dataset and the completeness summary to the project's output folder. This dedicated folder helps to see output graphs a lot better for analysis.

```
output_dir = "/content/cleaned_outputs"
os.makedirs(output_dir, exist_ok=True)

clean_path = os.path.join(output_dir, "cleaned_data_with_measurement.csv")
summary_path = os.path.join(output_dir, "completeness_summary.csv")

clean_df.to_csv(clean_path, index=False)
completeness_summary.to_csv(summary_path, index=False)

print(f"\n Files saved successfully:")
print(f" - Cleaned dataset with measurement column: {clean_path}")
print(f" - Completeness summary: {summary_path}")
```

```
 Files saved successfully:
 - Cleaned dataset with measurement column: /content/cleaned_outputs/cleaned_data_with_measurement.csv
 - Completeness summary: /content/cleaned_outputs/completeness_summary.csv
```

2.2 Summary Statistics

2.2.1 Basic Information

I used available functions to get quick overview of the cleaned dataset and make sure everything looked consistent before moving forward. The code below prints out the structure of the clean_df DataFrame, which includes the number of rows, columns, and the data types for each variable. It also checks for any missing values across columns, since incomplete data could affect later results. Finally, it prints out the number of unique countries, the list of indicators included, and the different types of measurement units used in the dataset.

```
print("Dataset overview:")
print(clean_df.info())

print("\n Missing values by column:")
print(clean_df.isnull().sum())

print("\n Unique countries:", clean_df["country"].nunique())
print("Indicators included:", clean_df["indicator"].unique())
print("Measurement units:", clean_df["measurement"].unique())
```

```
Dataset overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61463 entries, 0 to 61462
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   country         61463 non-null  object
 1   iso_code        61463 non-null  object
 2   date            61463 non-null  datetime64[ns]
 3   indicator       61463 non-null  object
 4   measurement     61463 non-null  object
 5   value_original  61463 non-null  float64
 6   unit_multiplier 61463 non-null  int64
 7   value_scaled    61463 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 3.8+ MB
None

 Missing values by column:
country            0
iso_code           0
date               0
indicator          0
measurement        0
value_original     0
unit_multiplier    0
value_scaled       0
dtype: int64

 Unique countries: 26
Indicators included: ['Long-term interest rates' 'Nominal exchange rates'
 'Real effective exchange rates - CPI based' 'Share prices'
 'Short-term interest rates']
Measurement units: ['Percent per annum' 'National currency per US dollar' 'Index']
```

2.2.2 Summary stats

Summary stats are important for getting a general idea of the data's impact and general direction. I grouped the cleaned data by each indicator and its measurement unit, then used the describe function on the scaled values to get a quick statistical overview. This summarizes key metrics like the mean, standard deviation, and quartiles, rounded to three decimals for readability.

```
summary_stats = (
    clean_df
    .groupby(["indicator", "measurement"])["value_scaled"]
    .describe()
    .round(3)
)

print("Summary statistics by indicator and measurement:")
display(summary_stats)
```

```
Summary statistics by indicator and measurement:
```

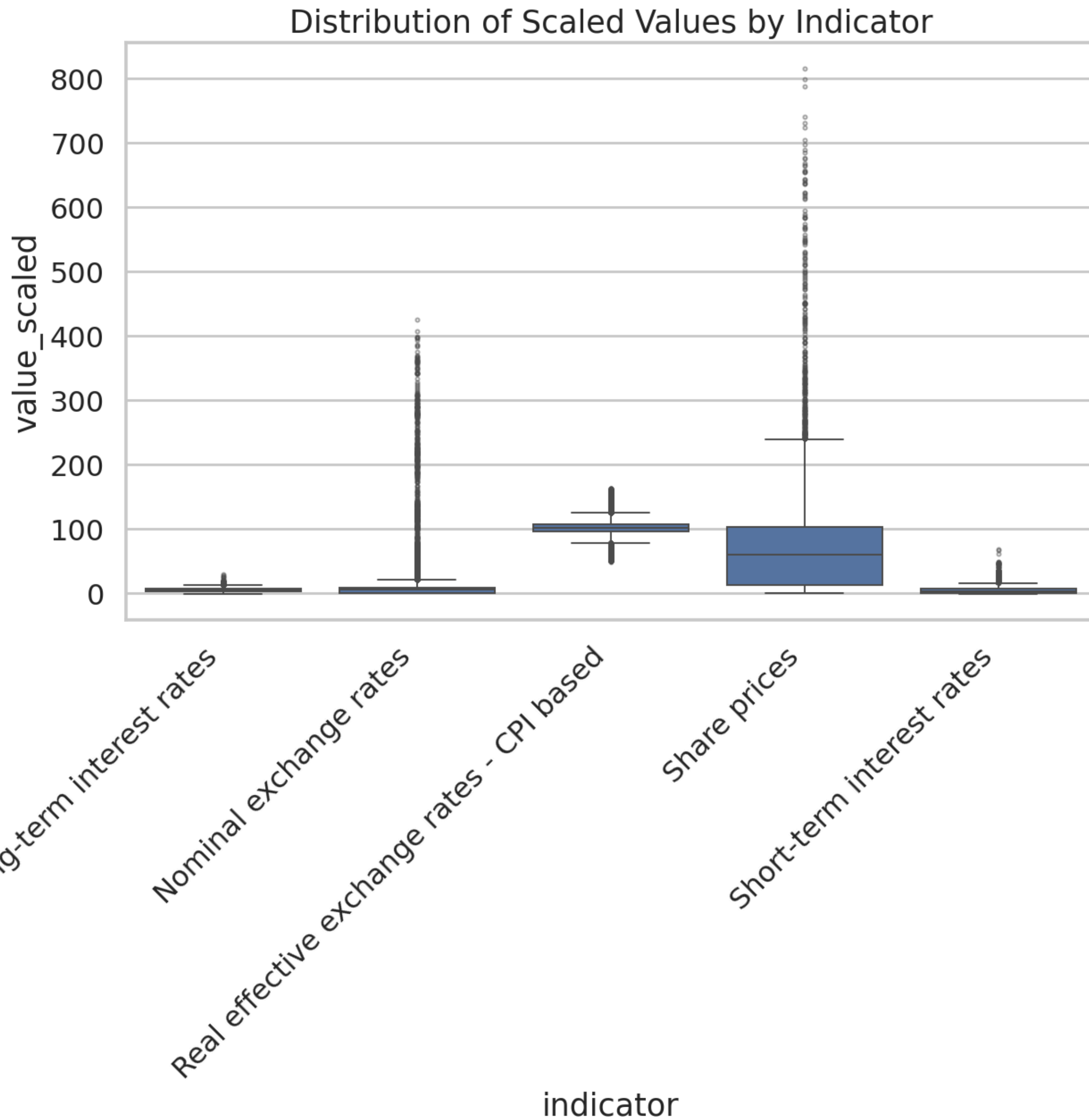
indicator	measurement	count	mean	std	min	25%	50%	75%	max
Long-term interest rates	**Percent per annum**	12451.0	5.245	3.587	-0.975	2.910	4.630	7.175	29.240
Nominal exchange rates	**National currency per US dollar**	7289.0	25.415	58.805	0.000	0.913	5.520	9.063	425.545
Real effective exchange rates - CPI based	**Index**	14625.0	102.187	13.651	49.222	96.424	101.852	108.063	163.648
Share prices	**Index**	14928.0	70.973	72.707	0.000	12.759	60.091	103.637	815.842

Next steps: Generate code with `summary_stats` New interactive sheet

2.2.3 Value Distributions

I used standard boxplots (or as we call them in Spain "mustache graphs") to visualize distributions. They help me to quickly see how the data is spread out, including the median, quartiles, and any outliers (which I had to make smaller to see them). Rotating the labels makes it easier to compare indicators side by side.

```
plt.figure(figsize=(10,6))

sns.boxplot(
    data=clean_df,
    x="indicator",
    y="value_scaled",
    flierprops=dict(marker='o', markersize=2, alpha=0.5)
)

plt.title("Distribution of Scaled Values by Indicator")
plt.xticks(rotation=45, ha='right')
plt.show()
```



2.2.4 Correlations

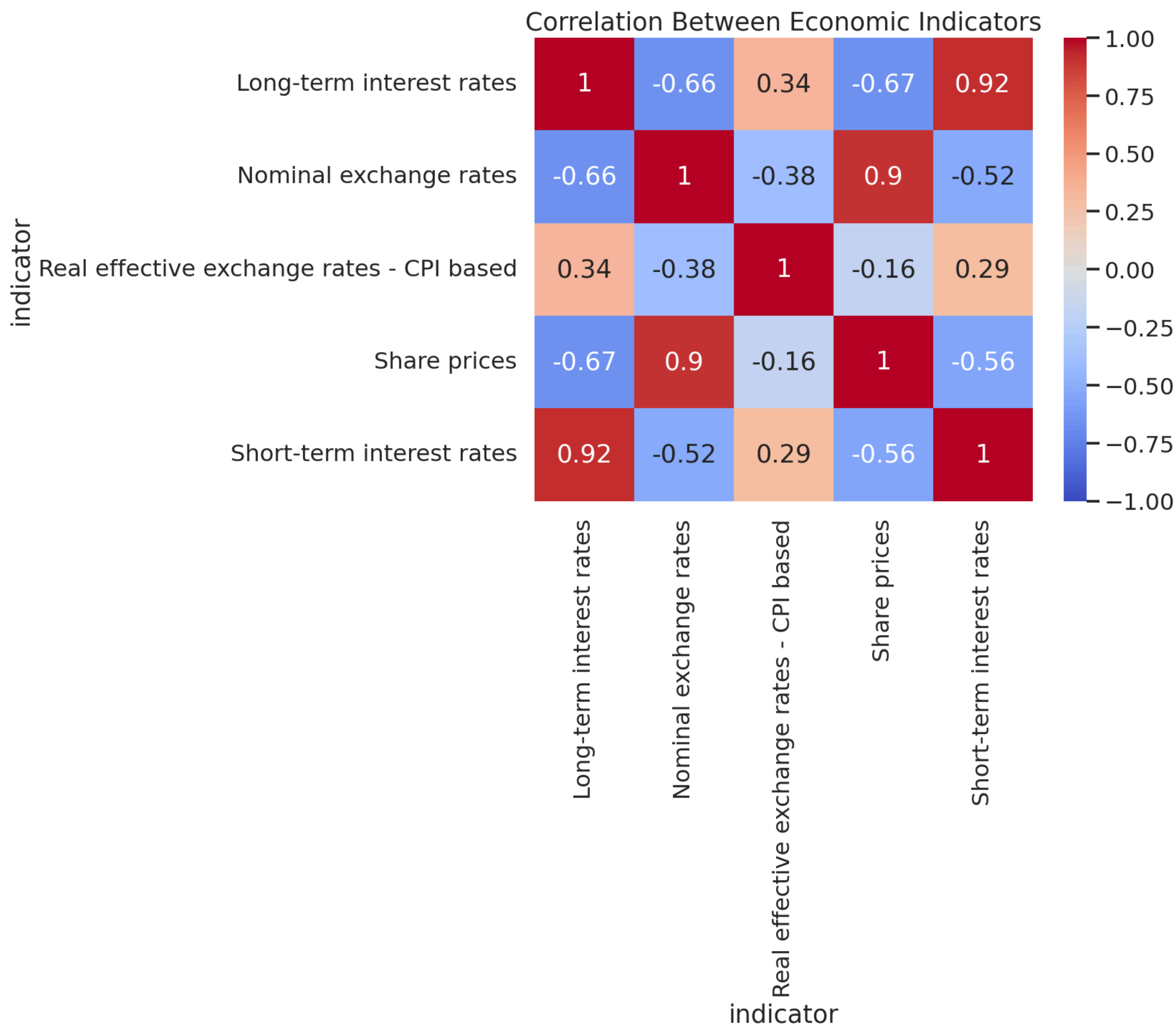
As one of the most important sections, for correlations I calculated and visualized the six main economic indicators to see how they move together over time. I first reshaped the data so that each indicator became a separate column, using the average value across all countries for each month. Then I computed the correlation matrix and rounded it to two decimals. Finally, I plotted a heatmap to clearly show positive and negative relationships between indicators. There were no big surprises in the results.

```
corr_df = (
    clean_df
    .groupby(["date", "indicator"])["value_scaled"]
    .mean()
    .unstack()
)

corr_matrix = corr_df.corr().round(2)

print(" Correlation matrix between indicators:")
```

```
display(corr_matrix)

plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", vmin=-1, vmax=1)
plt.title("Correlation Between Economic Indicators")
plt.show()
```

Correlation matrix between indicators:

indicator	Long-term interest rates	Nominal exchange rates	Real effective exchange rates - CPI based	Share prices	Short-term interest rates
indicator					
Long-term interest rates	1.00	-0.66	0.34	-0.67	0.92
Nominal exchange rates	-0.66	1.00	-0.38	0.90	-0.52
Real effective exchange rates - CPI based	0.34	-0.38	1.00	-0.16	0.29
Share prices	-0.67	0.90	-0.16	1.00	-0.56
Short-term interest rates	0.92	-0.52	0.29	-0.56	1.00



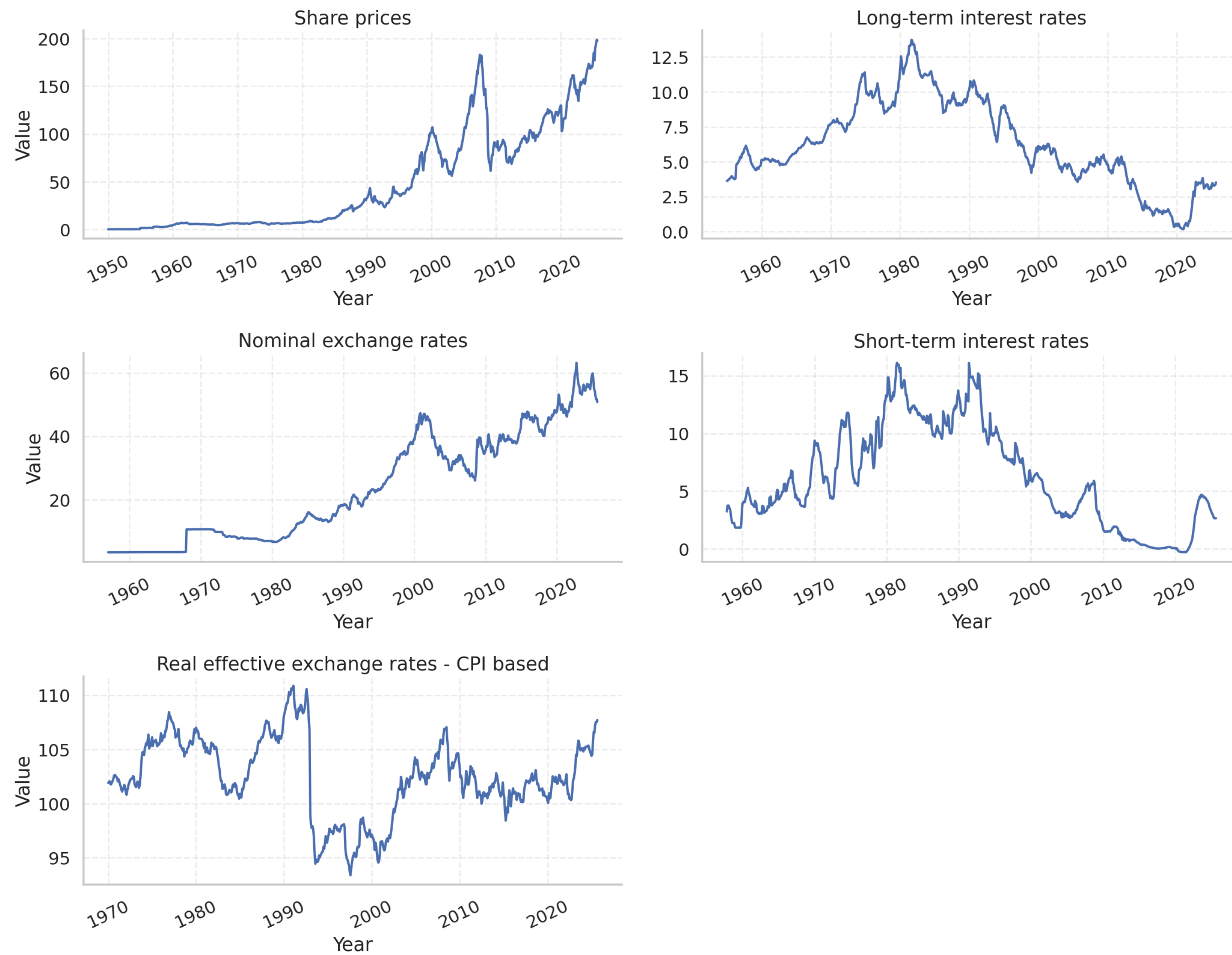
Next steps: Generate code with `corr_matrix` New interactive sheet

3. Visualization

3.1 Time Series Trends

To start off the visualization section, I created seperate charts that show the average value of each indicator across all 26 countries. The goal was to see how the group as a whole evolved over time. I grouped the data by date and indicator, calculating the average scaled value for each month to capture the general economic trend rather than individual country movements. Then, I used line plots to show how the six indicators change throughout the years, which makes it easy to spot long-term patterns, like the a decline in interest rates and the rise in share prices. It's important to note that the value axis's represent all the different measurement units depending on the indicator, as explained earlier in the Introduction section.

```
sns.set_theme(context="talk", style="whitegrid")

avg_over_time["date"] = pd.to_datetime(avg_over_time["date"])

g = sns.FacetGrid(
    avg_over_time,
    col="indicator",
    col_wrap=2,
    sharex=False,
    sharey=False,
    height=5.2,
    aspect=1.6,
    margin_titles=True
)

g.map_dataframe(sns.lineplot, x="date", y="value_scaled")
g.set_titles("{col_name}")
g.set_xlabels("Year")
g.set_ylabels("Value")

for ax in g.axes.ravel():
    ax.tick_params(axis="x", labelrotation=25)
    ax.xaxis.set_major_locator(mdates.AutoDateLocator())
    ax.xaxis.set_major_formatter(mdates.DateFormatter("%Y"))
    ax.set_xlabel("Year")
    ax.grid(True, which='major', axis='both', linestyle='--', alpha=0.3)

g.fig.subplots_adjust(
    top=0.93,
    wspace=0.15,
    hspace=0.55
)

g.fig.set_size_inches(17, 13)
plt.rcParams["figure.dpi"] = 140

plt.show()
```

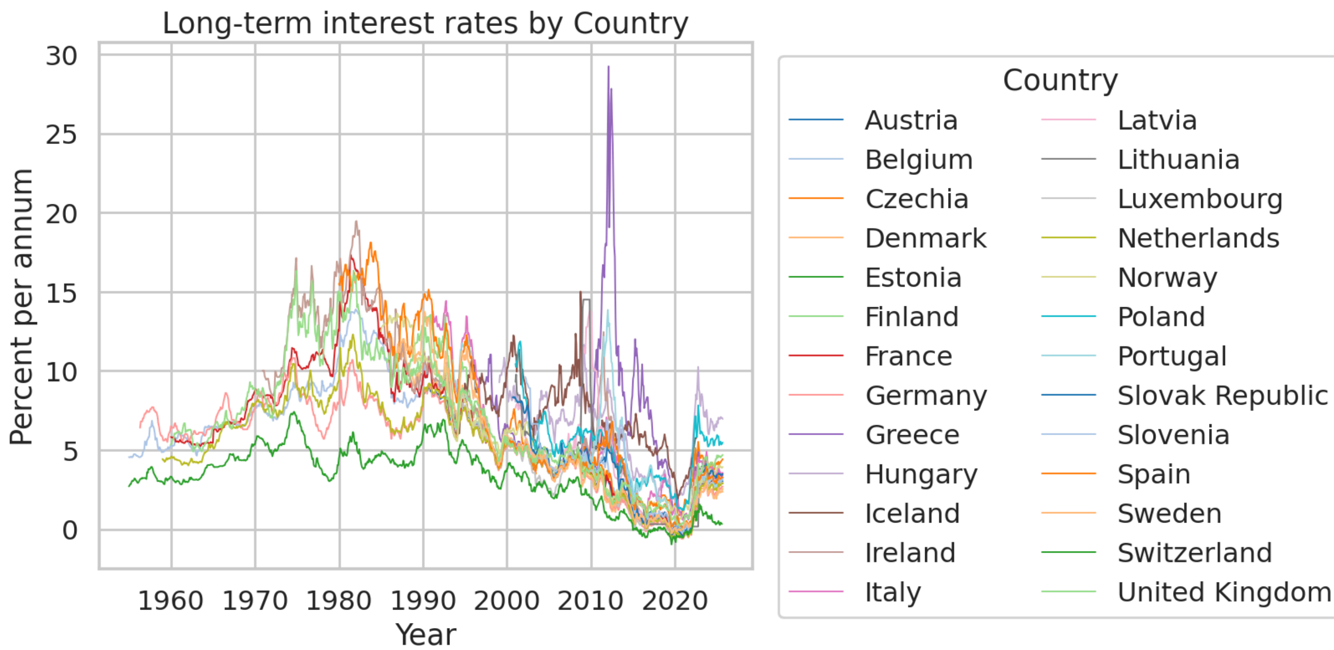


3.2 Cross-Country Comparison

After visualizing the group average for all indicators, this section breaks down each indicator individually across all 26 countries. At first glance, the graphs might look chaotic and intimidating, but taking a closer look reveals valuable information about volatility, convergence, and trend shifts. To compare each indicator across countries, I plotted one chart per indicator, showing how its values change over time for all 26 countries. Each line represents a country, and I applied a custom color palette to make them easier to distinguish.

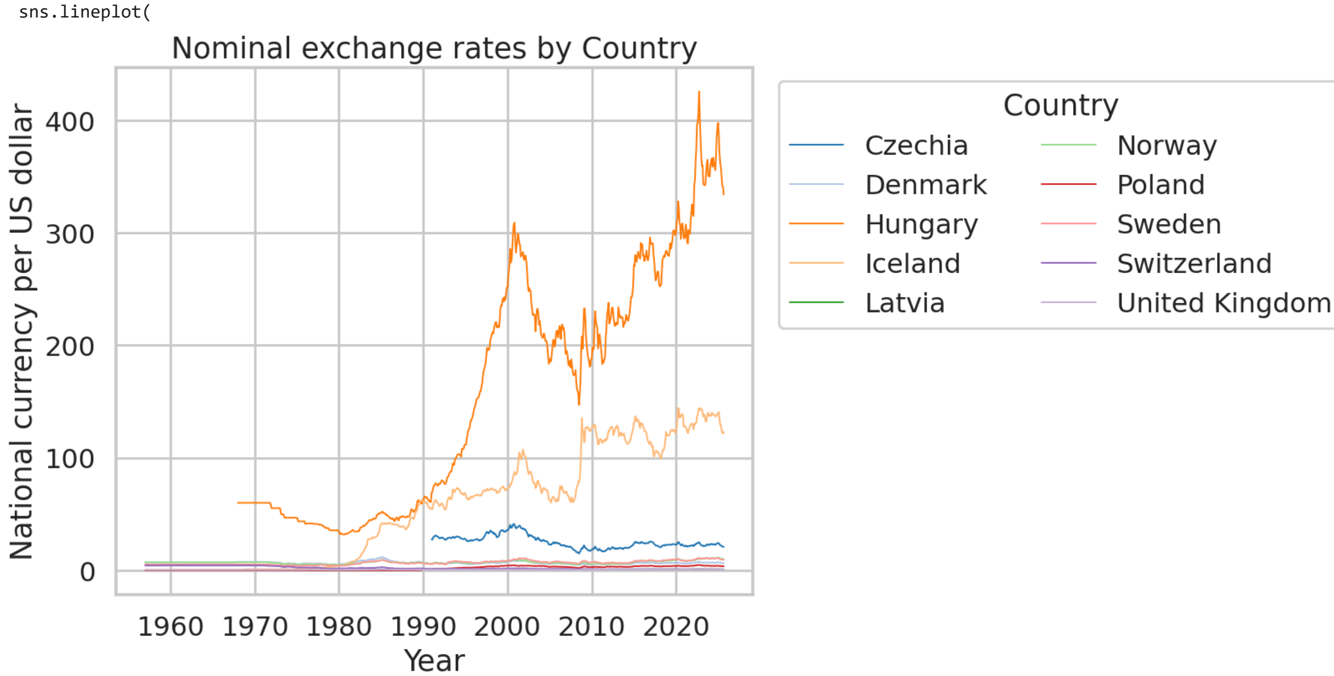
```
import matplotlib.pyplot as plt
import seaborn as sns

palette = sns.color_palette("tab20", n_colors=26)

for indicator_name in clean_df["indicator"].unique():
    subset = clean_df[clean_df["indicator"] == indicator_name]

    plt.figure(figsize=(12, 6))
    sns.lineplot(
        data=subset,
        x="date",
        y="value_scaled",
        hue="country",
        linewidth=1,
        palette=palette
    )
    plt.title(f"{indicator_name} by Country")
    plt.xlabel("Year")
    plt.ylabel(subset["measurement"].iloc[0])  # automatically sets correct unit on Y-axis
```

```
plt.legend(bbox_to_anchor=(1.02, 1), loc="upper left", ncol=2, title="Country")
plt.figtext(0.5, -0.04,
        "Note: Eurozone countries share the same EUR/USD path, so many lines overlap and appear as one.",
        ha="center", fontsize=9)
plt.tight_layout()
plt.show()
```



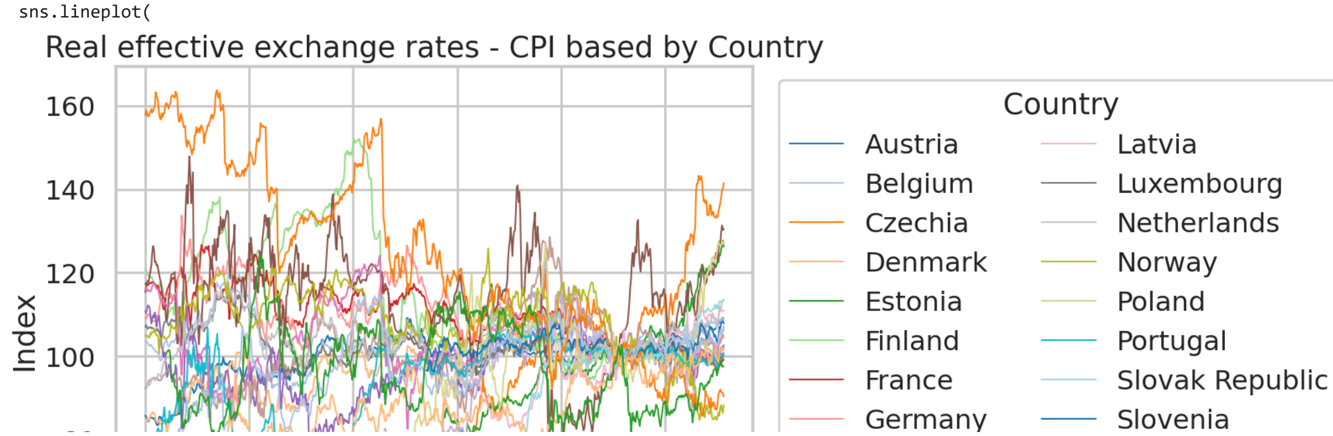
Note: Eurozone countries share the same EUR/USD path, so many lines overlap and appear as one.

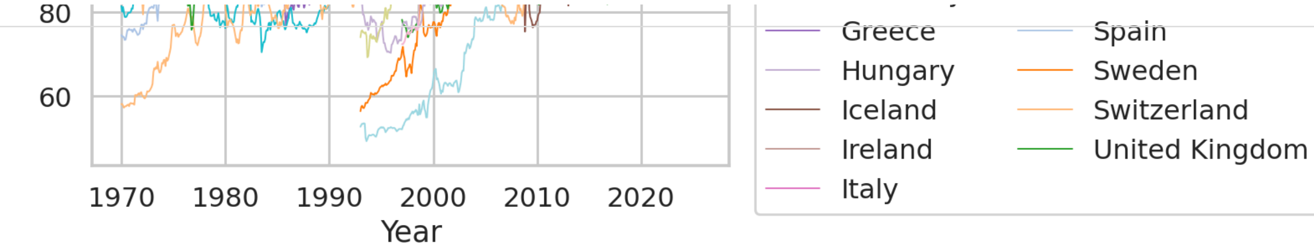
```
/tmp/ipython-input-568135045.py:10: UserWarning: The palette list has more values (26) than needed (10), which may not be intended.
  sns.lineplot(
```



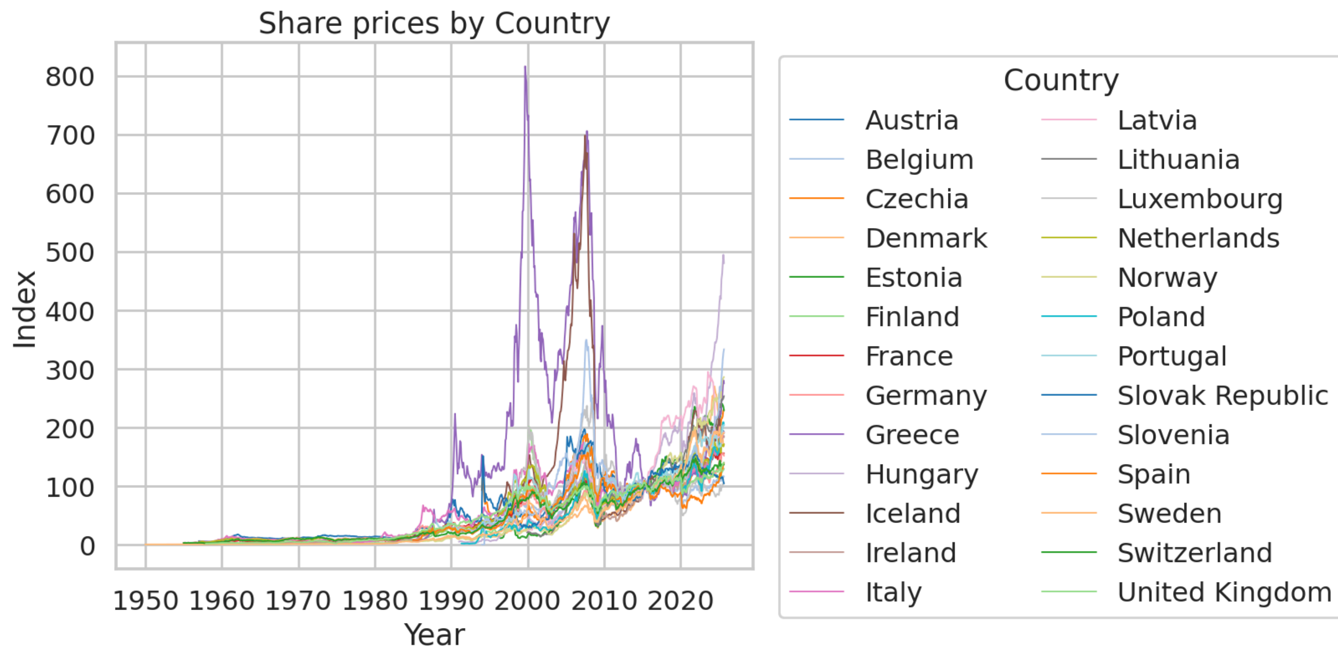
Note: Eurozone countries share the same EUR/USD path, so many lines overlap and appear as one.

```
/tmp/ipython-input-568135045.py:10: UserWarning: The palette list has more values (26) than needed (25), which may not be intended.
  sns.lineplot(
```

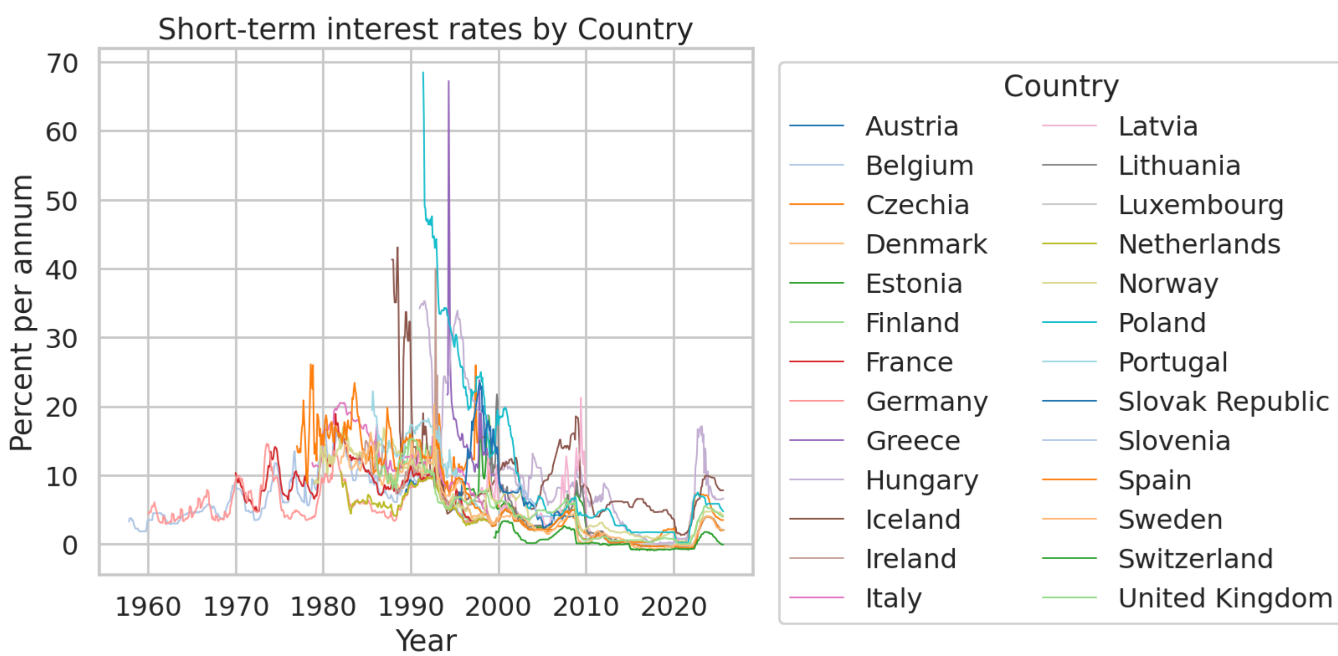




Note: Eurozone countries share the same EUR/USD path, so many lines overlap and appear as one.



Note: Eurozone countries share the same EUR/USD path, so many lines overlap and appear as one.

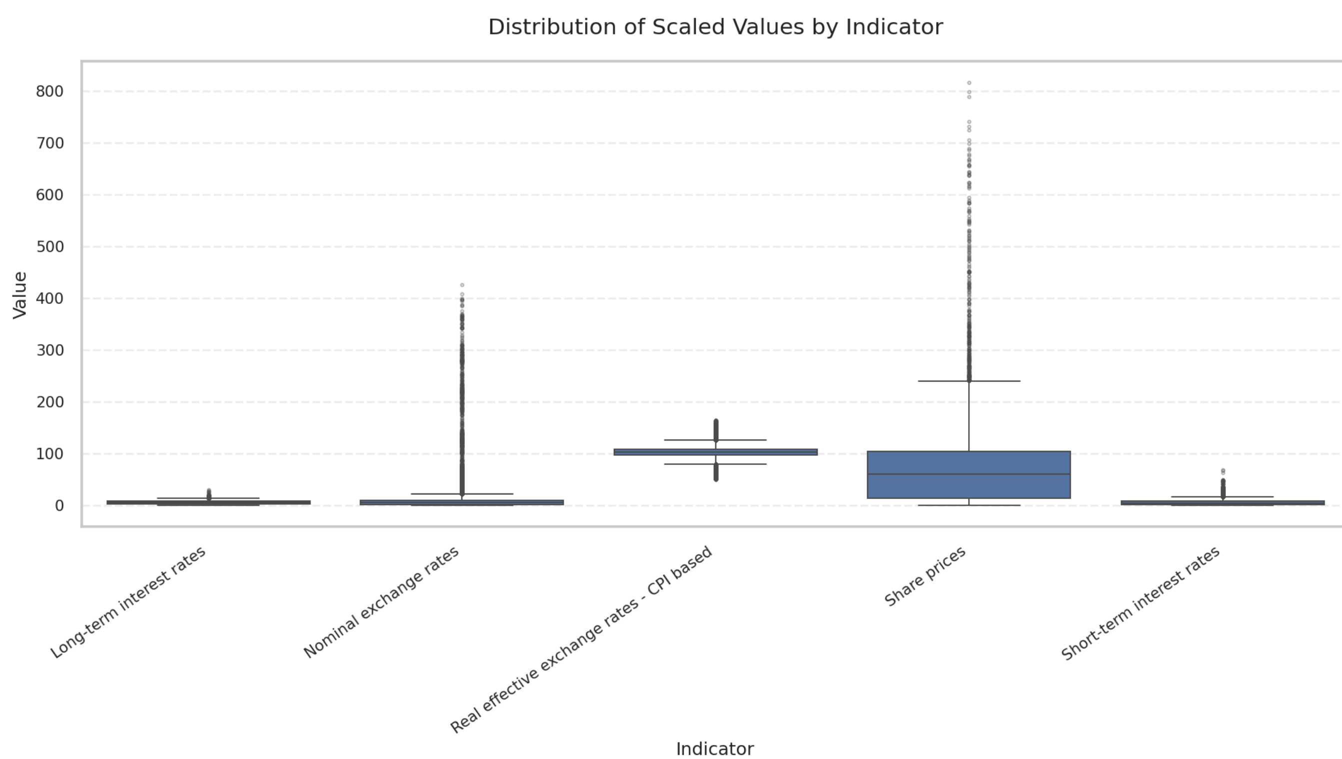


Note: Eurozone countries share the same EUR/USD path, so many lines overlap and appear as one.

3.3 Distribution of Indicators

To dive deeper into the data, I used a boxplot to visualize the distribution of values for each indicator. This is pretty similar to the 2.2.3 Value Distributions step, since both show how the values are spread out. The main difference here is the idea of getting a quick sense of how each indicator's data is distributed, whether it's tightly clustered or more spread out, and where the medians and outliers fall. THis is a way to see the "shape" of the data for a visual understanding.

```
plt.figure(figsize=(14, 8))

sns.boxplot(
    data=clean_df,
    x="indicator",
    y="value_scaled",
    flierprops=dict(marker='o', markersize=2, alpha=0.4)
)

plt.title("Distribution of Scaled Values by Indicator", fontsize=16, pad=20)
plt.xlabel("Indicator", fontsize=13)
plt.ylabel("Value", fontsize=13)

plt.xticks(rotation=35, ha='right', fontsize=11)
plt.yticks(fontsize=11)

plt.subplots_adjust(bottom=0.25, top=0.9)

plt.grid(axis='y', linestyle='--', alpha=0.3)
plt.tight_layout()
plt.show()
```



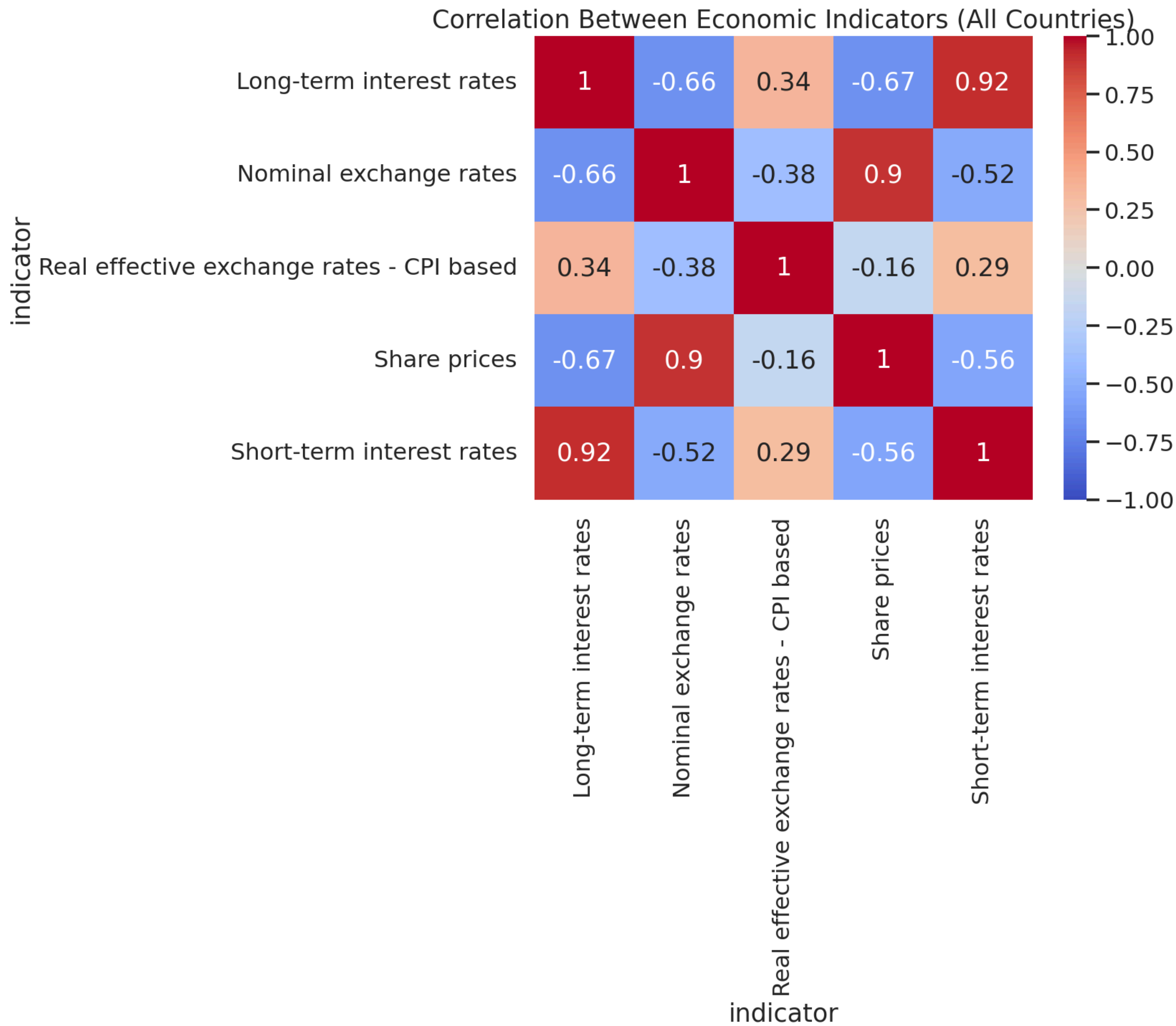
3.4 Correlation Heatmap

For this part, I created a correlation heatmap that combines all 26 countries by averaging their indicator values for each date. This gives a single, clear view of how the six indicators relate to each other overall. The heatmap makes it easy to identify which variables tend to move together and which move in opposite directions across Europe as a whole.

```
corr_all = (
    clean_df
```

```
    .groupby(["date", "indicator"])["value_scaled"]
    .mean()
    .unstack()
    .corr()
)

plt.figure(figsize=(8,6))
sns.heatmap(corr_all, annot=True, cmap="coolwarm", vmin=-1, vmax=1)
plt.title("Correlation Between Economic Indicators (All Countries)")
plt.tight_layout()
plt.show()
```

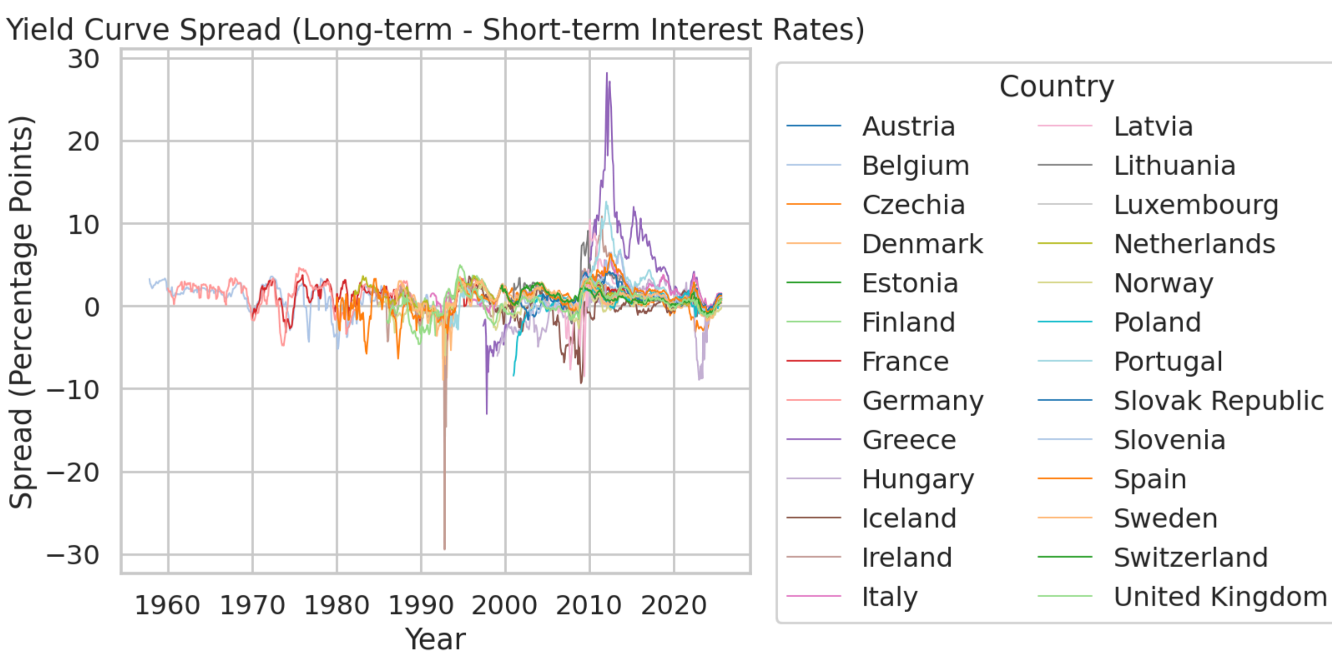
```
/tmp/ipython-input-4234705816.py:12: UserWarning: Tight layout not applied. The bottom and top margins cannot be made large enough to
  plt.tight_layout()
```



3.5 Yield Curve Long vs Short-term Interest Rate Spread

To better understand the relationship between long-term and short-term interest rates (one of my personal interests), I calculated the yield curve spread for each country by subtracting short-term rates from long-term rates. This measure helps show whether borrowing costs are higher in the long run or the short run, which often signals market expectations about future growth or recessions. I used the same color palette as in the cross-country comparison to keep country colors consistent across graphs. The resulting plot highlights periods when spreads narrow or turn negative.

```
countries_all = sorted(clean_df["country"].unique())
base_palette = sns.color_palette("tab20", n_colors=len(countries_all))
color_map = dict(zip(countries_all, base_palette))

spread_df = (
    clean_df[clean_df["indicator"].isin(["Long-term interest rates", "Short-term interest rates"])]
    .pivot_table(index=["date", "country"], columns="indicator", values="value_scaled")
    .dropna()
)
spread_df["Spread (Long - Short)"] = spread_df["Long-term interest rates"] - spread_df["Short-term interest rates"]

plt.figure(figsize=(12,6))
sns.lineplot(
    data=spread_df.reset_index(),
    x="date",
    y="Spread (Long - Short)",
    hue="country",
    linewidth=1,
    palette=color_map,
    hue_order=countries_all
)

plt.title("Yield Curve Spread (Long-term - Short-term Interest Rates)")
plt.xlabel("Year")
plt.ylabel("Spread (Percentage Points)")
plt.legend(bbox_to_anchor=(1.02, 1), loc="upper left", ncol=2, title="Country")
plt.tight_layout()
plt.show()
```



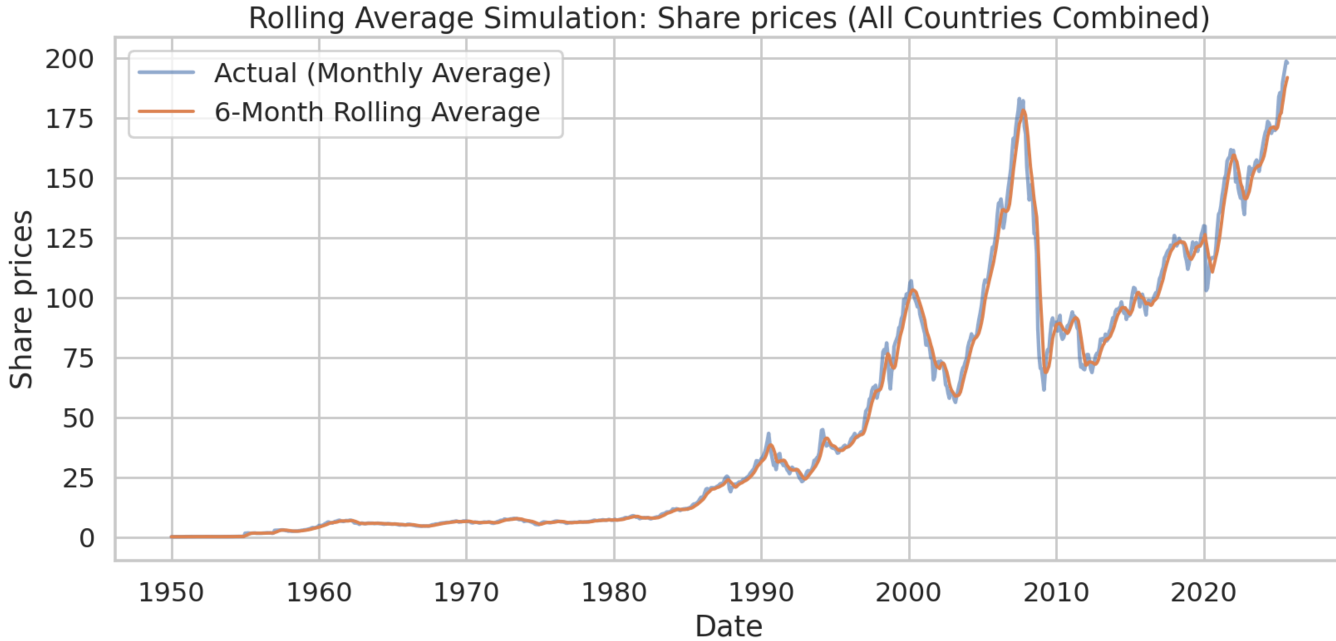
4. Simulation or Other Techniques

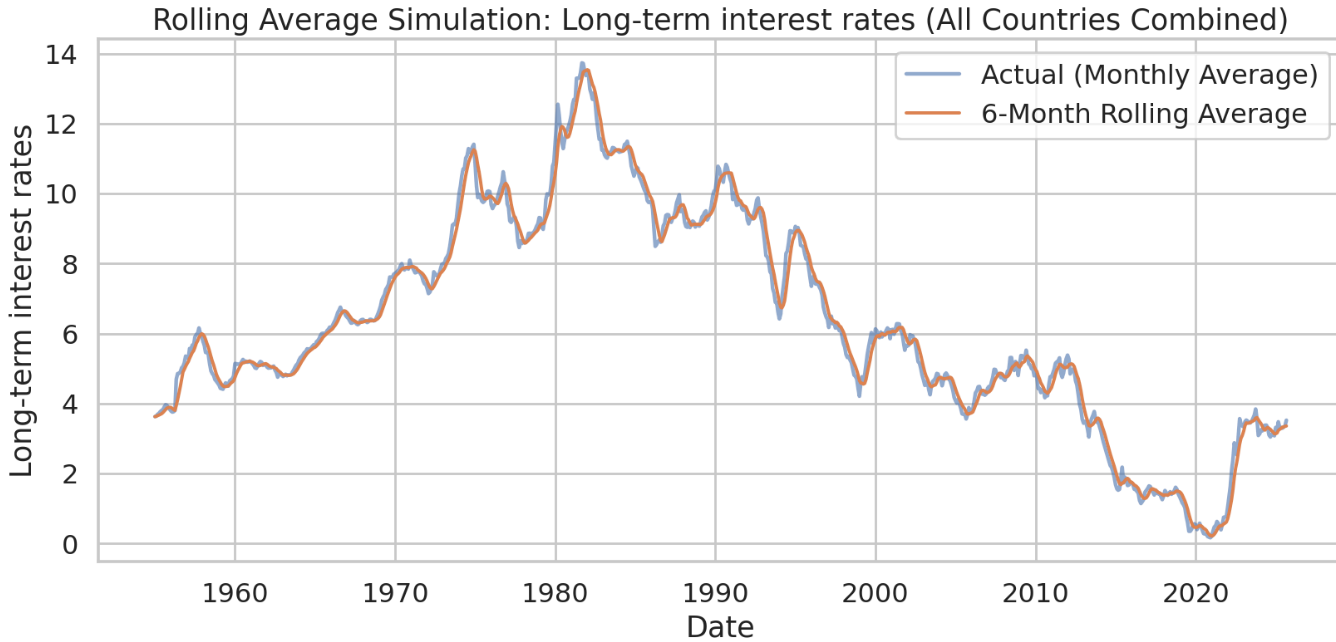
4.1 Rolling Average Trend Simulation

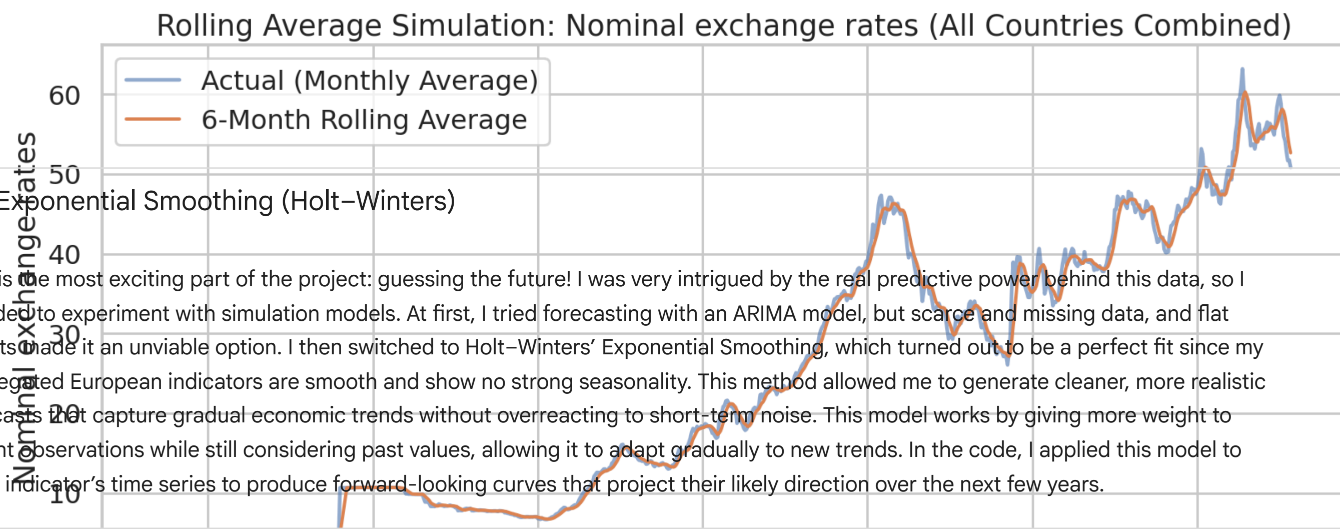
To smooth out short-term fluctuations and highlight longer trends, I used applied a rolling average on the combined dataset of all 26 countries with a 6 month window. This method helps us see the overall direction of each indicator by averaging their, reducing noise. It makes the line less jumpy, allowing the main economic trend to stand out more clearly. The code first groups all countries together by date and indicator, calculates the monthly average, and then applies a six-month rolling mean for each indicator separately. This gives a clearer, more stable view of how each economic measure evolves over time across Europe.

```
avg_df = (
    clean_df.groupby(["date", "indicator"])["value_scaled"]
    .mean()
```

```
    .reset_index()
)

avg_df["rolling_mean"] = (
    avg_df.groupby("indicator")["value_scaled"]
    .transform(lambda x: x.rolling(window=6, min_periods=1).mean())
)

for indicator_name in avg_df["indicator"].unique():
    subset = avg_df[avg_df["indicator"] == indicator_name]

    plt.figure(figsize=(12,6))
    plt.plot(subset["date"], subset["value_scaled"], label="Actual (Monthly Average)", alpha=0.6)
    plt.plot(subset["date"], subset["rolling_mean"], label="6-Month Rolling Average", linewidth=2)
    plt.title(f"Rolling Average Simulation: {indicator_name} (All Countries Combined)")
    plt.xlabel("Date")
    plt.ylabel(subset["indicator"].iloc[0])
    plt.legend()
    plt.tight_layout()
    plt.show()
```







4.2 Exponential Smoothing (Holt–Winters)

This is the most exciting part of the project: guessing the future! I was very intrigued by the real predictive power behind this data, so I decided to experiment with simulation models. At first, I tried forecasting with an ARIMA model, but scarce and missing data, and flat results made it an unviable option. I then switched to Holt–Winters' Exponential Smoothing, which turned out to be a perfect fit since my aggregated European indicators are smooth and show no strong seasonality. This method allowed me to generate cleaner, more realistic forecasts that capture gradual economic trends without overreacting to short-term noise. This model works by giving more weight to recent observations while still considering past values, allowing it to adapt gradually to new trends. In the code, I applied this model to each indicator's time series to produce forward-looking curves that project their likely direction over the next few years.

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import matplotlib.pyplot as plt
```