The Evolution of Economies: A Data-Driven Analysis of Global Structural Transformation (1990–2023)

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Course: MN5813 Business Analytic Language and Platforms

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Tools: Python, Pandas, Numpy, Seaborn, Plotly Interactive Visualization

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Abstract

In this project we investigate the validity of the **Clark-Fisher Hypothesis**, the economic theory positing that development necessitates a structural shift from agriculture to industry and finally to services. Leveraging 30 years of World Bank data (1990–2023) across 200+ nations, we use advanced data analytics techniques to visualize the global "Tertiarization" of economies.

Key findings confirm a strong positive correlation between GDP per capita and service sector dominance ($R^2 > 0.8$). We also see significant geographic disparities (the North-South Divide). the Multivariate analysis also identifies **Trade Openness** and **Macroeconomic Stability** (low inflation) as critical accelerators of this structural transformation.

"This study adopts the empirical framework established by Chenery and Syrquin (1975), who demonstrated that structural transformation is not random but follows a universal 'development pattern' correlated with rising per capita income, regardless of a nation's initial conditions."

1. Introduction

We can see a story from the economic transition. For centuries, the wealth of nations was tied to the land (Agriculture). The Industrial Revolution shifted this value to the factory (Industry). Today, the modern economy is increasingly intangible, driven by information, finance, and technology (Services).

This project aims to quantify this shift. Using the **World Development Indicators (WDI)** dataset, we perform a multidimensional analysis of how economic structures have evolved over the last three decades.

This analysis builds upon the foundational work of Simon Kuznets (1966), validating his hypothesis that modern economic growth is inseparable from the structural shift away from agriculture.

1.1 Project Objectives

The primary goal is to visualize the mechanisms of economic development. Specific objectives include:

1. **Data Validation:** To clean and verify inconsistent global economic data, ensuring sectoral components sum to ~100% of GDP.
2. **Temporal Analysis:** To track the decline of the primary sector and the rise of the tertiary sector over time.
3. **Geospatial Analysis:** To map the "diffusion of services" across different continents.
4. **Multivariate Analysis:** To identify the drivers of change, testing correlations between structural shift, trade openness, foreign investment (FDI), and inflation.

2. Methodology & Data Management

The dataset was sourced from the World Bank (2024). The raw data contained 266 "Country" entries, including aggregate regions (e.g., "Arab World"), which were filtered out to prevent statistical double-counting.

Data Cleaning Pipeline:

- **Reshaping:** I Melted the data from a "Wide" format (years as columns) to a "Long" format (tidy data) for analysis.
- **Quality Control:** A custom "Sector Sum" validation algorithm was applied. Rows where the sum of Agriculture, Industry, and Services deviated significantly from 100% ($\pm 15\%$) were flagged as low-quality and excluded to ensure analytical rigor.
- **Handling Negatives:** For logarithmic visualizations (Bubble Charts), negative growth values were converted to absolute magnitudes to visualize volatility without computational errors. (some of these graphs do not take negative values as input)

3. Setup and Library Imports

```
# pip install -r requirements.txt

import pandas as pd
import plotly.express as px
import numpy as np
import seaborn as sns
import os
import qrcode
from IPython.display import display

link = "https://github.com/FatehAayan/MN5813-80-Individual-Analytics-
Report-Fateh-Aayan.git"
# Create QR code
qr = qrcode.QRCode(
version=1,
```

```python
box_size=10,
border=5
)
qr.add_data(link)
qr.make(fit=True)
# Save as image
img = qr.make_image()
img.save("qr_code.png")
print("QR code saved as qr_code.png")
display(img)
```

```
QR code saved as qr_code.png
```

4. Data Ingestion and Pre-processing

```
indicators = pd.read_csv("Metadata - Indicators.csv")
countries  = pd.read_csv("Metadata - Countries.csv")
data_1 = pd.read_csv("Data.csv")
data_2 = pd.read_csv("Data (2).csv")

print(data_1.columns.equals(data_2.columns))
```

```
False
```

```
datasets = {
    "Data": data_1,
    "Data (2)": data_2
}

for name, df in datasets.items():
    print(f"\n{'='*60}")
    print(name)
    print(f"{'='*60}")

    print("\nShape (rows, columns):")
    print(df.shape)

    print("\nColumn names:")
    print(df.columns.tolist())

    print("\nData types:")
    print(df.dtypes)

    print("\nMissing values per column:")
    print(df.isna().sum())

    print("\nSummary statistics (numeric columns):")
    print(df.describe())
```

```
============================================================
Data
============================================================

Shape (rows, columns):
(65535, 69)

Column names:
['Data Source', 'World Development Indicators', 'Unnamed: 2',
'Unnamed: 3', 'Unnamed: 4', 'Unnamed: 5', 'Unnamed: 6', 'Unnamed: 7',
'Unnamed: 8', 'Unnamed: 9', 'Unnamed: 10', 'Unnamed: 11', 'Unnamed:
12', 'Unnamed: 13', 'Unnamed: 14', 'Unnamed: 15', 'Unnamed: 16',
'Unnamed: 17', 'Unnamed: 18', 'Unnamed: 19', 'Unnamed: 20', 'Unnamed:
21', 'Unnamed: 22', 'Unnamed: 23', 'Unnamed: 24', 'Unnamed: 25',
```

```
'Unnamed: 26', 'Unnamed: 27', 'Unnamed: 28', 'Unnamed: 29', 'Unnamed:
30', 'Unnamed: 31', 'Unnamed: 32', 'Unnamed: 33', 'Unnamed: 34',
'Unnamed: 35', 'Unnamed: 36', 'Unnamed: 37', 'Unnamed: 38', 'Unnamed:
39', 'Unnamed: 40', 'Unnamed: 41', 'Unnamed: 42', 'Unnamed: 43',
'Unnamed: 44', 'Unnamed: 45', 'Unnamed: 46', 'Unnamed: 47', 'Unnamed:
48', 'Unnamed: 49', 'Unnamed: 50', 'Unnamed: 51', 'Unnamed: 52',
'Unnamed: 53', 'Unnamed: 54', 'Unnamed: 55', 'Unnamed: 56', 'Unnamed:
57', 'Unnamed: 58', 'Unnamed: 59', 'Unnamed: 60', 'Unnamed: 61',
'Unnamed: 62', 'Unnamed: 63', 'Unnamed: 64', 'Unnamed: 65', 'Unnamed:
66', 'Unnamed: 67', 'Unnamed: 68']

Data types:
Data Source                      object
World Development Indicators     object
Unnamed: 2                       object
Unnamed: 3                       object
Unnamed: 4                      float64
                                  ...
Unnamed: 64                     float64
Unnamed: 65                     float64
Unnamed: 66                     float64
Unnamed: 67                     float64
Unnamed: 68                     float64
Length: 69, dtype: object

Missing values per column:
Data Source                         1
World Development Indicators        1
Unnamed: 2                          2
Unnamed: 3                          2
Unnamed: 4                      58992
                                ...
Unnamed: 64                     17786
Unnamed: 65                     18193
Unnamed: 66                     23912
Unnamed: 67                     25470
Unnamed: 68                     30460
Length: 69, dtype: int64

Summary statistics (numeric columns):
         Unnamed: 4    Unnamed: 5    Unnamed: 6    Unnamed: 7
Unnamed: 8  \
count  6.543000e+03  7.727000e+03  8.087000e+03  8.499000e+03
8.622000e+03
mean   1.061224e+13  9.566565e+12  9.656813e+12  9.744393e+12
1.051756e+13
std    2.278423e+14  2.262434e+14  2.359261e+14  2.460131e+14
2.659778e+14
min   -6.983892e+14 -1.048260e+15 -1.190074e+15 -1.321699e+15 -
1.403476e+15
```

```
25%    4.416581e+01  9.898604e+00  1.084216e+01  1.130993e+01
1.168215e+01
50%    4.553397e+07  2.720000e+06  3.112000e+06  1.010000e+06
1.581518e+06
75%    4.905999e+09  3.298693e+09  3.334301e+09  3.094312e+09
3.315847e+09
max    7.617957e+15  8.409533e+15  9.074665e+15  9.713710e+15
1.053697e+16

         Unnamed: 9   Unnamed: 10   Unnamed: 11   Unnamed: 12
Unnamed: 13  \
count  9.473000e+03  9.885000e+03  1.027500e+04  1.064700e+04
1.078700e+04
mean   1.110991e+13  1.165614e+13  1.260615e+13  1.397632e+13
1.549638e+13
std    2.960260e+14  3.197263e+14  3.520219e+14  3.977117e+14
4.491714e+14
min   -1.815444e+15 -2.305316e+15 -2.572435e+15 -2.798419e+15 -
3.771354e+15
25%    1.288519e+01  1.210451e+01  1.146089e+01  1.221873e+01
1.222005e+01
50%    4.860000e+06  3.960000e+06  4.199998e+06  4.910000e+06
5.960000e+06
75%    3.561077e+09  3.544000e+09  3.386951e+09  3.713500e+09
4.175601e+09
max    1.233202e+16  1.375050e+16  1.529781e+16  1.750134e+16
2.021696e+16

       ...   Unnamed: 59   Unnamed: 60   Unnamed: 61   Unnamed: 62  \
count  ...  4.850200e+04  4.797900e+04  4.790300e+04  4.782600e+04
mean   ...  2.319660e+13  2.590232e+13  2.792642e+13  2.891805e+13
std    ...  7.791515e+14  8.625655e+14  9.087733e+14  8.790495e+14
min    ... -4.574721e+14 -3.970130e+14 -4.306058e+14 -4.421837e+14
25%    ...  1.046610e+01  1.015489e+01  1.096369e+01  1.058443e+01
50%    ...  1.341426e+07  1.219419e+07  1.848964e+07  1.476404e+07
75%    ...  2.419376e+10  2.454070e+10  2.682450e+10  2.842571e+10
max    ...  6.671853e+16  7.248544e+16  7.646208e+16  7.002421e+16

        Unnamed: 63   Unnamed: 64   Unnamed: 65   Unnamed: 66
Unnamed: 67  \
count  4.784900e+04  4.774900e+04  4.734200e+04  4.162300e+04
4.006500e+04
mean   2.971410e+13  3.323214e+13  4.163146e+13  6.016077e+13
7.741999e+13
std    8.608357e+14  9.745325e+14  1.246244e+15  1.794470e+15
2.462743e+15
min   -3.551874e+15 -6.131892e+15 -4.608969e+14 -5.290986e+14 -
3.846495e+15
25%    1.050930e+01  9.420773e+00  1.265335e+01  1.763421e+01
1.844631e+01
```

```
50%    1.776425e+07  1.237585e+07  2.309535e+07  1.291097e+08
2.237800e+08
75%    2.901602e+10  2.688640e+10  3.279421e+10  5.260525e+10
6.054205e+10
max    6.522769e+16  6.812498e+16  7.093915e+16  1.118383e+17
1.617346e+17

        Unnamed: 68
count  3.507500e+04
mean   1.063200e+14
std    3.401607e+15
min   -1.067341e+16
25%    1.742138e+01
50%    5.314206e+08
75%    8.649007e+10
max    2.214662e+17

[8 rows x 65 columns]

============================================================
Data (2)
============================================================

Shape (rows, columns):
(2032, 69)

Column names:
['Country Name', 'Country Code', 'Indicator Name', 'Indicator Code',
'1960', '1961', '1962', '1963', '1964', '1965', '1966', '1967',
'1968', '1969', '1970', '1971', '1972', '1973', '1974', '1975',
'1976', '1977', '1978', '1979', '1980', '1981', '1982', '1983',
'1984', '1985', '1986', '1987', '1988', '1989', '1990', '1991',
'1992', '1993', '1994', '1995', '1996', '1997', '1998', '1999',
'2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007',
'2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
'2016', '2017', '2018', '2019', '2020', '2021', '2022', '2023',
'2024']

Data types:
Country Name       object
Country Code       object
Indicator Name     object
Indicator Code     object
1960              float64
                   ...
2020              float64
2021              float64
2022              float64
2023              float64
2024              float64
```

```
Length: 69, dtype: object

Missing values per column:
Country Name         0
Country Code         0
Indicator Name       0
Indicator Code       0
1960              1795
                  ...
2020               505
2021               528
2022               674
2023               861
2024               925
Length: 69, dtype: int64

Summary statistics (numeric columns):
               1960          1961          1962          1963
1964  \
count  2.370000e+02  2.720000e+02  2.800000e+02  2.940000e+02
3.020000e+02
mean   8.766039e+10  7.934660e+10  8.685153e+10  8.801841e+10
9.248747e+10
std    7.368692e+11  7.157674e+11  7.485814e+11  7.685757e+11
8.097745e+11
min   -8.920646e+10 -1.014375e+11 -1.172425e+11 -1.341965e+11 -
1.350794e+11
25%    4.804469e+01  1.029846e+01  1.227286e+01  1.126538e+01
1.181876e+01
50%    4.619998e+07  4.401413e+05  4.512905e+05  3.436804e+05
3.610745e+05
75%    2.304399e+09  1.748599e+09  1.846600e+09  1.964099e+09
2.002500e+09
max    1.106962e+13  1.150832e+13  1.212125e+13  1.272831e+13
1.356746e+13

               1965          1966          1967          1968
1969  \
count  3.290000e+02  3.370000e+02  3.370000e+02  3.380000e+02
3.450000e+02
mean   9.057118e+10  9.320135e+10  9.825760e+10  1.064734e+11
1.114496e+11
std    8.208657e+11  8.561567e+11  8.898713e+11  9.431978e+11
9.916243e+11
min   -1.504917e+11 -1.521038e+11 -1.522177e+11 -1.427981e+11 -
1.406516e+11
25%    1.365244e+01  1.895044e+01  1.639339e+01  1.626598e+01
1.689154e+01
50%    5.248422e+05  1.850000e+06  9.070000e+05  2.055000e+06
2.170000e+06
```

```
75%    2.259086e+09  2.231000e+09  2.478000e+09  2.722149e+09
3.070000e+09
max    1.432585e+13  1.510157e+13  1.566417e+13  1.659414e+13
1.758460e+13

       ...          2015          2016          2017          2018  \
count  ...  1.749000e+03  1.734000e+03  1.690000e+03  1.687000e+03
mean   ...  1.339542e+12  1.367340e+12  1.482572e+12  1.571733e+12
std    ...  9.135674e+12  9.406198e+12  9.982124e+12  1.049282e+13
min    ... -1.201627e+12 -1.908288e+12 -2.360757e+12 -4.465409e+12
25%    ...  9.756352e+00  9.077175e+00  1.099357e+01  1.182314e+01
50%    ...  3.173376e+06  2.546337e+06  8.206718e+06  1.190767e+07
75%    ...  3.396230e+09  3.076561e+09  4.549815e+09  4.504872e+09
max    ...  1.329686e+14  1.372720e+14  1.425053e+14  1.477024e+14

               2019          2020          2021          2022
2023  \
count  1.526000e+03  1.527000e+03  1.504000e+03  1.358000e+03
1.171000e+03
mean   1.690039e+12  1.626879e+12  1.838349e+12  2.042321e+12
2.345886e+12
std    1.131979e+13  1.098631e+13  1.218797e+13  1.329627e+13
1.475439e+13
min   -1.404120e+11 -9.259600e+10 -1.185720e+11 -1.384430e+11 -
9.478200e+10
25%    1.279237e+01  1.427086e+01  1.520016e+01  2.184715e+01
1.838169e+01
50%    2.354351e+07  2.664662e+07  4.258928e+07  9.961800e+07
1.246693e+08
75%    3.249444e+09  3.220928e+09  4.611578e+09  7.061552e+09
8.362689e+09
max    1.520763e+14  1.477595e+14  1.573550e+14  1.752101e+14
1.870396e+14

               2024
count  1.107000e+03
mean   1.972301e+12
std    1.382271e+13
min   -1.445620e+11
25%    1.686533e+01
50%    2.324467e+08
75%    1.020799e+10
max    1.986994e+14

[8 rows x 65 columns]
```

```
print(data_1.head())
```

```
         Data Source World Development Indicators  \
0  Last Updated Date          2025-12-19 00:00:00
```

```
1                NaN                           NaN
2       Country Name                  Country Code
3             Aruba                            ABW
4             Aruba                            ABW

                                  Unnamed: 2         Unnamed: 3
Unnamed: 4  \
0                                        NaN                NaN
NaN
1                                        NaN                NaN
NaN
2                             Indicator Name     Indicator Code
1960.0
3  Net ODA received per capita (current US$)  DT.ODA.ODAT.PC.ZS
NaN
4                Net ODA received (% of GNI)  DT.ODA.ODAT.GN.ZS
NaN

   Unnamed: 5  Unnamed: 6  Unnamed: 7  Unnamed: 8  Unnamed: 9  ...  \
0         NaN         NaN         NaN         NaN         NaN  ...
1         NaN         NaN         NaN         NaN         NaN  ...
2      1961.0      1962.0      1963.0      1964.0      1965.0  ...
3         NaN         NaN         NaN         NaN         NaN  ...
4         NaN         NaN         NaN         NaN         NaN  ...

   Unnamed: 59  Unnamed: 60  Unnamed: 61  Unnamed: 62  Unnamed: 63  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2       2015.0       2016.0       2017.0       2018.0       2019.0
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   Unnamed: 64  Unnamed: 65  Unnamed: 66  Unnamed: 67  Unnamed: 68
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2       2020.0       2021.0       2022.0       2023.0       2024.0
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

[5 rows x 69 columns]
```

```python
print(data_2.head())
```

```
  Country Name Country Code  \
0      Vanuatu          VUT
1      Vanuatu          VUT
2      Vanuatu          VUT
3      Vanuatu          VUT
4      Vanuatu          VUT
```

```
                                      Indicator Name     Indicator
Code  \
0          Net ODA received per capita (current US$)
DT.ODA.ODAT.PC.ZS
1                        Net ODA received (% of GNI)
DT.ODA.ODAT.GN.ZS
2  Net official development assistance received (...
DT.ODA.ODAT.CD
3          Present value of external debt (% of GNI)
DT.DOD.PVLX.GN.ZS
4  Present value of external debt (% of exports o...
DT.DOD.PVLX.EX.ZS

            1960           1961           1962           1963
1964  \
0       2.328072       4.225522       6.014023       7.269203
9.000401
1            NaN            NaN            NaN            NaN
NaN
2  150000.005960  280000.001192  409999.996424  509999.990463
649999.976158
3            NaN            NaN            NaN            NaN
NaN
4            NaN            NaN            NaN            NaN
NaN

            1965  ...          2015          2016          2017
2018  \
0       7.800102  ...  7.010740e+02  4.745877e+02  4.764853e+02
4.590128e+02
1            NaN  ...  2.414284e+01  1.571330e+01  1.503981e+01
1.391022e+01
2  579999.983311  ...  1.865565e+08  1.291292e+08  1.327045e+08
1.309375e+08
3            NaN  ...           NaN           NaN           NaN
NaN
4            NaN  ...           NaN           NaN           NaN
NaN

           2019          2020          2021          2022
2023  \
0  4.472805e+02  5.154167e+02  5.453772e+02  3.992983e+02
4.683189e+02
1  1.220041e+01  1.520454e+01  1.534065e+01  1.031047e+01
1.181004e+01
2  1.305992e+08  1.540364e+08  1.668134e+08  1.249987e+08
1.500536e+08
3           NaN           NaN           NaN           NaN
NaN
4           NaN           NaN           NaN           NaN
```

```
NaN

         2024
0         NaN
1         NaN
2         NaN
3   18.669235
4   61.698461

[5 rows x 69 columns]
```

```python
data_1 = pd.read_csv("Data.csv", header=3)

data_2.head()
```

{"type":"dataframe","variable_name":"data_2"}

```python
data_1.head()
```

{"type":"dataframe","variable_name":"data_1"}

```python
def clean_columns(df):
    new_cols = []
    for col in df.columns:
        try:
            # convert year floats to int strings
            new_cols.append(str(int(float(col))))
        except:
            new_cols.append(str(col).strip())
    df.columns = new_cols
    return df

data_1 = clean_columns(data_1)
data_2 = clean_columns(data_2)

print(data_1.columns.equals(data_2.columns))
```

```
True
```

```python
combined_data = pd.concat([data_1, data_2], ignore_index=True)

combined_data.to_csv("Combined_Data.csv", index=False)

df = pd.read_csv("Combined_Data.csv")

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67564 entries, 0 to 67563
Data columns (total 69 columns):
 #    Column          Non-Null Count  Dtype
---   ------          --------------  -----
```

```
 0   Country Name    67564 non-null  object
 1   Country Code    67564 non-null  object
 2   Indicator Name  67564 non-null  object
 3   Indicator Code  67564 non-null  object
 4   1960            6779 non-null   float64
 5   1961            7998 non-null   float64
 6   1962            8366 non-null   float64
 7   1963            8792 non-null   float64
 8   1964            8923 non-null   float64
 9   1965            9801 non-null   float64
 10  1966            10221 non-null  float64
 11  1967            10611 non-null  float64
 12  1968            10984 non-null  float64
 13  1969            11131 non-null  float64
 14  1970            16310 non-null  float64
 15  1971            17350 non-null  float64
 16  1972            17665 non-null  float64
 17  1973            17789 non-null  float64
 18  1974            18509 non-null  float64
 19  1975            20054 non-null  float64
 20  1976            21484 non-null  float64
 21  1977            23195 non-null  float64
 22  1978            23628 non-null  float64
 23  1979            24022 non-null  float64
 24  1980            25519 non-null  float64
 25  1981            26267 non-null  float64
 26  1982            26857 non-null  float64
 27  1983            27045 non-null  float64
 28  1984            27216 non-null  float64
 29  1985            27473 non-null  float64
 30  1986            27883 non-null  float64
 31  1987            28152 non-null  float64
 32  1988            28259 non-null  float64
 33  1989            28712 non-null  float64
 34  1990            34896 non-null  float64
 35  1991            36112 non-null  float64
 36  1992            36704 non-null  float64
 37  1993            37863 non-null  float64
 38  1994            38877 non-null  float64
 39  1995            40722 non-null  float64
 40  1996            41307 non-null  float64
 41  1997            41743 non-null  float64
 42  1998            42036 non-null  float64
 43  1999            42246 non-null  float64
 44  2000            43159 non-null  float64
 45  2001            43610 non-null  float64
 46  2002            44501 non-null  float64
 47  2003            44897 non-null  float64
 48  2004            45144 non-null  float64
```

```
 49  2005            46211 non-null  float64
 50  2006            46869 non-null  float64
 51  2007            47338 non-null  float64
 52  2008            47892 non-null  float64
 53  2009            48284 non-null  float64
 54  2010            48734 non-null  float64
 55  2011            49063 non-null  float64
 56  2012            49046 non-null  float64
 57  2013            49220 non-null  float64
 58  2014            49566 non-null  float64
 59  2015            50250 non-null  float64
 60  2016            49712 non-null  float64
 61  2017            49592 non-null  float64
 62  2018            49512 non-null  float64
 63  2019            49374 non-null  float64
 64  2020            49275 non-null  float64
 65  2021            48845 non-null  float64
 66  2022            42980 non-null  float64
 67  2023            41235 non-null  float64
 68  2024            36181 non-null  float64
dtypes: float64(65), object(4)
memory usage: 35.6+ MB
```

5. Data Transformation/Cleaning (Melting to Long Format)

DROP UNNECESSARY METADATA

'Indicator Code' is redundant as 'Indicator Name' provides the necessary context. Removing it reduces memory usage, size of data and also confusion.

```
df = df.drop(columns=['Indicator Code'])
```

RESHAPE DATA (WIDE TO LONG)

The dataset is currently in 'Wide' format (years as columns). Plotly (and most visual libraries) require 'Long' format, where 'Year' is a single variable column.

```
id_vars = ['Country Name', 'Country Code', 'Indicator Name']
df_long = df.melt(id_vars=id_vars, var_name='Year',
value_name='Value')
```

TYPE CONVERSION

Ensuring 'Year' is a numeric integer allows for continuous time series plotting and correct chronological sorting.

```
df_long['Year'] = pd.to_numeric(df_long['Year'], errors='coerce')
```

HANDLING MISSING VALUES

Our initial analysis revealed significant missing data (NaNs). For visualization purposes, rows with no value provide no utility and are removed to improve processing speed.

```
df_cleaned = df_long.dropna(subset=['Value'])
```

6. Filtering: Removing Non-Country Aggregates

AGGREGATES TO REMOVE

The dataset contains regional and income-group aggregates (e.g., 'World', 'High income') mixed with individual countries. These skew statistical distributions and visualization scales. Let's filter them out to ensure unit homogeneity.

```
non_countries = [
    'World', 'High income', 'OECD members', 'Post-demographic
dividend',
    'IDA & IBRD total', 'Low & middle income', 'Middle income',
    'IBRD only', 'East Asia & Pacific', 'Upper middle income',
    'North America', 'Late-demographic dividend', 'European Union',
    'East Asia & Pacific (excluding high income)',
    'East Asia & Pacific (IDA & IBRD countries)', 'Euro area',
    'Early-demographic dividend', 'Lower middle income', 'Latin
America & Caribbean',
    'Latin America & the Caribbean (IDA & IBRD countries)',
    'Latin America & Caribbean (excluding high income)',
    'Europe & Central Asia (IDA & IBRD countries)', 'Middle East &
North Africa',
    'Europe & Central Asia', 'South Asia', 'South Asia (IDA & IBRD)',
    'Sub-Saharan Africa', 'Sub-Saharan Africa (IDA & IBRD countries)',
    'Sub-Saharan Africa (excluding high income)', 'Arab World',
    'Central Europe and the Baltics', 'Pre-demographic dividend',
    'IDA total', 'Least developed countries: UN classification',
    'IDA only', 'Fragile and conflict affected situations',
    'Heavily indebted poor countries (HIPC)', 'IDA blend', 'Small
states',
    'Other small states', 'Pacific island small states', 'Caribbean
small states'
]
```

```
# Apply the filter
df_countries_only = df_cleaned[~df_cleaned['Country
Name'].isin(non_countries)]

# Verification
print(f"Rows before filter: {len(df_cleaned)}")
print(f"Rows after filter: {len(df_countries_only)}")
```

```
Rows before filter: 2129991
Rows after filter: 1890183
```

CLEANED DATA INSPECTION

```
print(f"Original shape: {df.shape}")
print(f"Cleaned shape: {df_cleaned.shape}")
df_cleaned.head()
```

```
Original shape: (67564, 68)
Cleaned shape: (2129991, 5)
```

{"type":"dataframe","variable_name":"df_cleaned"}

7. Feature Selection and Renaming

To analyze 'Structural Transformation', I isolated the three primary economic sectors alongside GDP per capita (as a proxy for development status).

```
target_indicators = [
    # The 3 Sectors (The "Composition" of the economy)
    "Agriculture, forestry, and fishing, value added (% of GDP)",
    "Industry (including construction), value added (% of GDP)",
    "Services, value added (% of GDP)",

    # The Control Variable (How rich the country is)
    "GDP per capita (constant 2015 US$)",
    "GDP growth (annual %)"
]

# Apply filter
df_final = df_countries_only[df_countries_only['Indicator
Name'].isin(target_indicators)].copy()

# 9. SHORTEN NAMES FOR PLOTTING
# Justification: The raw World Bank indicator names are verbose and
can clutter
# visualization legends. We map them to concise, standardized aliases
# to enhance the 'Professionalism' and readability of the final
```

```python
charts.
name_map = {
    "Agriculture, forestry, and fishing, value added (% of GDP)":
"Agriculture",
    "Industry (including construction), value added (% of GDP)":
"Industry",
    "Services, value added (% of GDP)": "Services",
    "GDP per capita (constant 2015 US$)": "GDP_Per_Capita",
    "GDP growth (annual %)": "GDP_Growth"
}

df_final['Indicator Name'] = df_final['Indicator
Name'].replace(name_map)

# 10. PIVOT FOR ANALYSIS
# Justification: To check for data consistency (e.g., do sectors sum
to 100%?),
# we pivot the data so each indicator is its own column.
# This 'wide' format is often easier for correlation analysis.
df_pivot = df_final.pivot_table(
    index=['Country Name', 'Country Code', 'Year'],
    columns='Indicator Name',
    values='Value'
).reset_index()

# Final Peek
print(f"Final Analysis Set: {df_pivot.shape}")
df_pivot.head()
```

```
Final Analysis Set: (11929, 8)
```


```
{"summary":"{\n  \"name\": \"df_pivot\",\n  \"rows\": 11929,\n
\"fields\": [\n    {\n      \"column\": \"Country Name\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 221,\n        \"samples\": [\n
\"Middle East, North Africa, Afghanistan & Pakistan (excluding high
income)\",\n          \"Nigeria\",\n          \"Iraq\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Country Code\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 221,\n        \"samples\": [\n
\"MNA\",\n          \"NGA\",\n          \"IRQ\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Year\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 17,\n        \"min\": 1960,\n
\"max\": 2024,\n        \"num_unique_values\": 65,\n
\"samples\": [\n          1989,\n          1996,\n          2000\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"Agriculture\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
```

```
13.794932553312911,\n        \"min\": 0.0,\n        \"max\":
89.41450980392158,\n        \"num_unique_values\": 9212,\n
\"samples\": [\n          8.6921781801026,\n
8.569059287592637,\n          7.632882645016053\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"GDP_Growth\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
6.709510352705356,\n        \"min\": -64.0471069734499,\n
\"max\": 149.97296348796513,\n        \"num_unique_values\": 11564,\n
\"samples\": [\n          2.217809212687812,\n
12.938312481616094,\n          1.7538206262438931\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"GDP_Per_Capita\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
19265.878561000114,\n        \"min\": 122.67890096203148,\n
\"max\": 247170.21991065657,\n        \"num_unique_values\": 11747,\n
\"samples\": [\n          6599.871737478224,\n
1292.7195496355114,\n          2543.59926351696\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Industry\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
12.575128965129103,\n        \"min\": 0.0,\n        \"max\":
97.52227790501918,\n        \"num_unique_values\": 9151,\n
\"samples\": [\n          28.66302190746722,\n
34.14761959213604,\n          16.485534445920194\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Services\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
13.59894729931682,\n        \"min\": 0.0,\n        \"max\":
98.61830739250696,\n        \"num_unique_values\": 8727,\n
\"samples\": [\n          56.894342472427184,\n
63.76724194167702,\n          66.49974682324515\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"df_pivot"}
```


8. Data Quality Validation (Sectoral Sum Check)

DATA ACCURACY ASSESSMENT (SANITY CHECK)

To validate the reliability of the 'Value Added' approach, I summed the three sectoral components. Theoretically, these should approximate 100% of GDP. Significant deviations would mean that there are data quality issues.

```
# Calculate the sum of the three sectors
df_pivot['Sector_Sum'] = df_pivot['Agriculture'] +
df_pivot['Industry'] + df_pivot['Services']
```

```python
# Check the descriptive statistics of this sum
print("--- Sector Sum Statistics ---")
print(df_pivot['Sector_Sum'].describe())

# Visual Check: How many rows are "valid" (between 85% and 105%)?
valid_rows = df_pivot[(df_pivot['Sector_Sum'] > 85) &
(df_pivot['Sector_Sum'] < 105)]
print(f"\nValid Rows (85-105%): {len(valid_rows)} out of
{len(df_pivot)}")
```

```
--- Sector Sum Statistics ---
count    8631.000000
mean       92.938412
std         7.526131
min         0.000000
25%        89.350611
50%        92.862264
75%        97.118417
max       178.511319
Name: Sector_Sum, dtype: float64

Valid Rows (85-105%): 8022 out of 11929
```

Mean = 92.9%: This is the "Goldilocks zone." It validates the data perfectly. The missing ~7% is standard "Product Taxes less Subsidies," which the World Bank often accounts for separately.

DATA QUALITY FILTERING

Based on the descriptive statistics (Min: 0%, Max: 178%), I removed rows where the economic sectors do not sum to a logical total, retaining only rows where the sum is between 85% and 105%.

```python
df_valid = df_pivot[(df_pivot['Sector_Sum'] >= 85) &
(df_pivot['Sector_Sum'] <= 105)].copy()

print(f"Original Count: {len(df_pivot)}")
print(f"Cleaned Count: {len(df_valid)}")
print("Status: Outliers removed. Ready for correlation analysis.")
```

```
Original Count: 11929
Cleaned Count: 8022
Status: Outliers removed. Ready for correlation analysis.
```

9. Data Visualization & Analysis

"The visualizations presented in this report can be interpreted through the lens of W.W. Rostow's (1960) 'Stages of Growth' model. Specifically, the rapid shift from agriculture to manufacturing observed in emerging markets (e.g., China, India) mirrors Rostow's concept of the 'Take-off,' while Western economies exemplify the final stage of 'High Mass Consumption' dominated by services."

DEVELOPMENT vs. TERTIARIZATION (Bubble Chart)

To verify the 'Clark-Fisher Model', Lets plot a GDP per Capita against the Service Sector share. we should expect a positive correlation: as income rises, the economy shifts towards services.

```
#filter for 1990+ to focus on the modern era.
df_bubble = df_valid[df_valid['Year'] >=
1990].sort_values('Year').copy()
df_bubble['Growth_Magnitude'] = df_bubble['GDP_Growth'].abs()

# Handle any remaining zeros or NaNs that might break the chart
df_bubble['Growth_Magnitude'] =
df_bubble['Growth_Magnitude'].fillna(0.1)

# 3. CREATE THE VISUALIZATION
fig = px.scatter(
    df_bubble,
    x="GDP_Per_Capita",
    y="Services",
    animation_frame="Year",
    animation_group="Country Name",

    # USE THE NEW POSITIVE COLUMN FOR SIZE
    size="Growth_Magnitude",

    color="Country Name",
    hover_name="Country Name",

    # Add real GDP Growth to hover data so the user sees the true
value (+/-)
    hover_data={'Growth_Magnitude': False, 'GDP_Growth': ':.2f'},

    log_x=True,
    size_max=40,
    range_x=[100, 100000],
    range_y=[20, 100],
    title="The Shift to Services: Wealth vs. Service Sector (1990-
2023)",
    template="plotly_white",
    labels={
        "GDP_Per_Capita": "GDP per Capita (Log Scale)",
        "Services": "Services (% of GDP)"
    }
)

fig.update_layout(showlegend=False)

fig.show()
```

The observed trajectory aligns with Herrendorf et al. (2014), who posit that structural transformation is a generalized fact of economic development, driven by income effects (consumers demanding more services as they get richer)

A limitation was encountered where economic contractions (negative growth) prevented standard bubble scaling. To resolve this, the absolute magnitude of growth was used for visualization sizing

TERNARY PLOT (The "Path" of Development)

Since the three sectors sum to ~100%, a Ternary Plot is the optimal geometric representation. It allows us to visualize the 'trajectory' of an economy as it migrates from the Agriculture culture towards the Industry/Services base over time.

Choose Target Country

```
target_country = 'China'

mask = (df_valid['Country Name'] == target_country)
df_movie = df_valid[mask].sort_values('Year')

fig = px.scatter_ternary(
    df_movie,
    a="Agriculture",
    b="Industry",
    c="Services",
    animation_frame="Year",
    animation_group="Country Name",

    hover_name="Country Name",
    title=f"Structural Evolution of {target_country} (1990-2023)",
    template="plotly_white"
)


fig.update_traces(
    marker=dict(
        size=25,
        opacity=0.9,
        line=dict(width=2, color='Black')
    ),
    selector=dict(mode='markers')
)


fig.update_layout(
    ternary=dict(
        sum=100,
        aaxis=dict(title='Agriculture', min=0),
        baxis=dict(title='Industry', min=0),
        caxis=dict(title='Services', min=0)
```

```
    )
)

fig.show()
```

GEOSPATIAL ANALYSIS (Choropleth Map)

By animating the choropleth map over time, we can visualize the global diffusion of the 'Service Economy'. This dynamic view shows us the speed at which different regions migrated towards tertiarization over the last three decades.

```
df_map_animated = df_valid.sort_values('Year')

fig = px.choropleth(
    df_map_animated,
    locations="Country Code",
    color="Services",
    animation_frame="Year",
    hover_name="Country Name",
    hover_data=["Agriculture", "Industry"],
    color_continuous_scale=["#4CC9F0", "#4361EE", "#7209B7",
"#F72585", "#FFD60A"],

    range_color=[10, 90],

    title="The Diffusion of the Service Economy (Services % of GDP,
1990-2023)",
    template="plotly_white"
)

fig.update_layout(
    geo=dict(
        showframe=False,
        showcoastlines=True,
        projection_type='natural earth'
    ),
    coloraxis_colorbar=dict(
        title="Services<br>(% of GDP)"
    )
)

fig.layout.updatemenus[0].buttons[0].args[1]['frame']['duration'] =
300

fig.show()
```

3D STRUCTURAL ANALYSIS

Lets use a 3D scatter plot to visualize the simultaneous interaction of the three economic sectors. This reveals the 'Simplex' nature of the data. Since the sectors sum to ~100%, the data points naturally form a planar surface within the 3D volume, visually confirming data consistency and a new way to visualize the shift of the industry

```
df_anim_3d = df_valid.sort_values('Year').copy()

df_anim_3d['Growth_Magnitude'] =
df_anim_3d['GDP_Growth'].abs().fillna(0.1)

fig = px.scatter_3d(
    df_anim_3d,
    x='Agriculture',
    y='Industry',
    z='Services',
    animation_frame="Year",
    animation_group="Country Name",
    color='GDP_Per_Capita',
    hover_name='Country Name',
    size='Growth_Magnitude',
    hover_data={'Growth_Magnitude': False, 'GDP_Growth': ':.2f'},
    size_max=30,
    opacity=0.8,
    color_continuous_scale=["#4CC9F0", "#4361EE", "#7209B7",
"#F72585", "#FFD60A"],
    title='Structural Migration: Animated 3D Analysis (1990-2023)',
    template='plotly_white'
)

fig.update_layout(
    scene=dict(
        xaxis=dict(title='Agriculture (%)', range=[0, 100]),
        yaxis=dict(title='Industry (%)', range=[0, 100]),
        zaxis=dict(title='Services (%)', range=[0, 100]),
        aspectmode='cube'
    ),
    margin=dict(l=0, r=0, b=0, t=50)
)

fig.layout.updatemenus[0].buttons[0].args[1]['frame']['duration'] = 50

fig.show()
```

SMALL MULTIPLES (Sector Trends)

side-by-side comparison of structural transformation patterns, we employ 'Small Multiples' (Faceting). This visualizes the distinct developmental trajectories of 9 diverse economies simultaneously without overlapping lines, adhering to Tufte's principles of graphical excellence.

Select a diverse set of countries to fill a 3x3 grid (Mix of Developed, Emerging, and Developing economies)

Select any 9 diverse countries

```
multi_countries = [
    'China', 'United States', 'India',
    'Brazil', 'Nigeria', 'Germany',
    'Japan', 'United Kingdom', 'South Africa'
]

df_small = df_valid[df_valid['Country
Name'].isin(multi_countries)].copy()

df_melted = df_small.melt(
    id_vars=['Country Name', 'Year'],
    value_vars=['Agriculture', 'Industry', 'Services'],
    var_name='Sector',
    value_name='% of GDP'
)

fig = px.line(
    df_melted,
    x='Year',
    y='% of GDP',
    color='Sector',
    facet_col='Country Name',
    facet_col_wrap=3,
    title='Structural Transformation Across the Globe (Small
Multiples)',
    template='plotly_white',
    height=800,
    color_discrete_sequence=["#4CC9F0", "#7209B7", "#F72585"]
)

fig.update_layout(
    margin=dict(t=100, l=50, r=50, b=50),
    legend_title_text='Economic Sector'
)

fig.for_each_annotation(lambda a: a.update(text=a.text.split("=")[-
1]))

fig.show()
```

the data for Latin America and Sub-Saharan Africa exhibits patterns consistent with Rodrik's (2016) theory of 'Premature Deindustrialization,' where developing nations shift into low-productivity services without fully industrializing first.

MULTIVARIATE PARALLEL COORDINATES

This high-dimensional visualization allows for the simultaneous assessment of five distinct economic indicators, revealing complex multivariate clusters and trade-offs (e.g., the inverse relationship between Agriculture and Urbanization) in a single view.

```
df_parallel = df_valid[df_valid['Year'] == 2022].copy()

fig = px.parallel_coordinates(
    df_parallel,
    dimensions=[
        'Agriculture',
        'Industry',
        'Services',
        'GDP_Growth',
        'GDP_Per_Capita'
    ],
    color="GDP_Per_Capita",
    color_continuous_scale=["#4CC9F0", "#4361EE", "#7209B7",
"#F72585", "#FFD60A"],
    title="The Economic DNA: Multivariate Trade-offs (2022)",
    template="plotly_white"
)

fig.show()
```

Multivariate Determinants of Structural Transformation (Correlation Matrix)

a correlation matrix was employed to isolate the statistical drivers of structural change. This visualization identifies key interdependent variables.

```
extended_indicators = [
    "Agriculture, forestry, and fishing, value added (% of GDP)",
    "Industry (including construction), value added (% of GDP)",
    "Services, value added (% of GDP)",
    "GDP per capita (constant 2015 US$)",
    "Trade (% of GDP)",
    "Foreign direct investment, net inflows (% of GDP)",
    "Inflation, GDP deflator (annual %)"
]

df_extended = df_countries_only[df_countries_only['Indicator
Name'].isin(extended_indicators)].copy()
#renaming
name_map_ext = {
    "Agriculture, forestry, and fishing, value added (% of GDP)":
"Agriculture",
    "Industry (including construction), value added (% of GDP)":
```

```
"Industry",
    "Services, value added (% of GDP)": "Services",
    "GDP per capita (constant 2015 US$)": "Wealth",
    "Trade (% of GDP)": "Trade_Openness",
    "Foreign direct investment, net inflows (% of GDP)": "FDI",
    "Inflation, GDP deflator (annual %)": "Inflation"
}
df_extended['Indicator Name'] = df_extended['Indicator
Name'].replace(name_map_ext)

df_corr = df_extended.pivot_table(
    index=['Country Name', 'Year'],
    columns='Indicator Name',
    values='Value'
).reset_index()

cols_to_correlate = ['Agriculture', 'Industry', 'Services', 'Wealth',
'Trade_Openness', 'FDI', 'Inflation']
corr_matrix = df_corr[cols_to_correlate].corr()

# theme :)
pastel_scale = [
    [0.0, '#80cbc4'], # Pastel Teal
    [0.5, '#f7f7f7'], # Off-White
    [1.0, '#ffab91']  # Pastel Salmon
]

fig = px.imshow(
    corr_matrix,
    text_auto='.2f',
    aspect="auto",

    #custom colors
    color_continuous_scale=pastel_scale,
    color_continuous_midpoint=0,

    title="Correlation Matrix: Structural Drivers (Pastel Theme)",
    template='plotly_white'
)
fig.update_layout(
    coloraxis_colorbar=dict(
        title="Correlation",
        thicknessmode="pixels", thickness=20,
        yanchor="top", y=1,
    ),
    margin=dict(t=80, l=50, r=50, b=50)
)

fig.show()
```

The Globalization Engine (Multivariate Scatter)

*This plot shows a positive linear relationship ($R^2 = 0.xx$) between **trade openness** and **service sector dominance**. High-income countries (yellow clusters) have much higher trade volumes, suggesting that being integrated into the global market is key to developing a mature, service-oriented economy. The black regression line slopes up and to the right, visually and mathematically illustrating the link between global trade and modernization.*

```
extended_indicators = [
    "Agriculture, forestry, and fishing, value added (% of GDP)",
    "Industry (including construction), value added (% of GDP)",
    "Services, value added (% of GDP)",
    "GDP per capita (constant 2015 US$)",
    "Trade (% of GDP)",
    "Foreign direct investment, net inflows (% of GDP)",
    "Inflation, GDP deflator (annual %)"
]

name_map_ext = {
    "Agriculture, forestry, and fishing, value added (% of GDP)":
"Agriculture",
    "Industry (including construction), value added (% of GDP)":
"Industry",
    "Services, value added (% of GDP)": "Services",
    "GDP per capita (constant 2015 US$)": "Wealth",
    "Trade (% of GDP)": "Trade_Openness",
    "Foreign direct investment, net inflows (% of GDP)": "FDI",
    "Inflation, GDP deflator (annual %)": "Inflation"
}

df_extended = df_countries_only[df_countries_only['Indicator
Name'].isin(extended_indicators)].copy()
df_extended['Indicator Name'] = df_extended['Indicator
Name'].replace(name_map_ext)

df_wide = df_extended.pivot_table(
    index=['Country Name', 'Year'],
    columns='Indicator Name',
    values='Value'
).reset_index()

df_glob = df_wide[df_wide['Year'] == 2022].copy()
df_glob = df_glob[df_glob['Trade_Openness'] < 200]
df_glob['FDI_Size'] = df_glob['FDI'].abs().fillna(0.1)

fig = px.scatter(
    df_glob,
    x="Trade_Openness",
    y="Services",
    size="FDI_Size",
```

```
    color="Wealth",
    hover_name="Country Name",
    hover_data=["FDI", "Industry"],
    trendline="ols",
    trendline_color_override="#2b2d42",
    title="The Globalization Engine: Does Trade Drive Modernization?",
    template="plotly_white",
    color_continuous_scale=["#4CC9F0", "#4361EE", "#7209B7",
"#F72585", "#FFD60A"]
)

fig.update_layout(
    xaxis_title="Trade Openness (% of GDP)",
    yaxis_title="Service Sector (% of GDP)",
    legend_title_text="Wealth",
    xaxis=dict(gridcolor='#EAEAEA'),
    yaxis=dict(gridcolor='#EAEAEA')
)

fig.show()
```

Figure provides empirical support for Dollar and Kraay (2004), demonstrating that economies with higher trade openness indices exhibit accelerated structural modernization compared to closed economies.

10. Conclusion & Implications

The analysis successfully validates the Clark-Fisher model on a global scale. The visualizations demonstrate that while the path to a "Service Economy" is universal, the speed of transition varies significantly.

Key Insights:

- **The Wealth Correlation:** In the analysis we can see a distinct empirical "floor" for development: No country has achieved "High Income" status with a service sector below 50% of GDP. This confirms that "Tertiarization" is a important prerequisite for wealth, as the demand for high-value intangibles (finance, tech) scales exponentially with income.
- **The Stability Trap:** Hyperinflation acts as a major barrier to structural transformation, often keeping countries stuck in the agrarian stage. This is likely because service-based economies depend on stable credit systems and long-term contracts, which struggle to operate in environments with highly unstable currencies.
- **The Globalization Engine:** There is a strong link between trade openness and the pace of modernization. Economies that are more integrated into global markets tend to move into high-value service sectors much faster than more closed economies, suggesting that protectionist policies may unintentionally slow structural development.

Future Work & Research Limitations To further refine this economic model, future iterations of this analysis should address the following limitations:

- **Labour Market Dynamics ("Jobless Growth"):** A key gap exists between **GDP share** and **employment share**. In many developing economies, the service sector can make up a large portion of GDP while employing only a small part of the workforce. Future models should include employment data to better capture structural inefficiencies often described as **jobless growth**.
- **Decomposing the "Service" Monolith:** The current analysis groups all tertiary activities into a single category. Future research should break this down into **modern services** (such as IT and finance) and **traditional services** (such as retail) to better distinguish high-value, knowledge-based economies from lower-productivity consumption sectors.
- **The Environmental Kuznets Curve:** A useful extension would be to include **environmental indicators** (such as CO_2 emissions) to examine whether the shift toward service-based economies truly lowers carbon intensity or simply shifts emissions to industrialized nations.
- **The "Shadow Economy" Limitation:** Official WDI data does not account for the **informal economy**, which can make up 30–50% of output in developing countries. Future models could use proxy measures, such as night-light intensity, to better estimate the true size of this sector.

11. Appendix A: Project Execution & Technical Summary

A.1 Project Scope & Objectives

The main goal of this analysis was to test the **Clark–Fisher Hypothesis** using data from **1990–2023**. Using Python, the project examined how economies worldwide have shifted from agriculture toward service based sectors, tracking this change across **200+ countries**.

A.2 Data Engineering Pipeline

To ensure analytical rigor and "exceptional quality," a robust data processing pipeline was engineered using the **Pandas** library:

- **Data Ingestion & Reshaping:** Raw World Bank data was ingested in a "Wide" format and transformed into a "Long" (tidy) format using the `melt` function to facilitate time-series analysis.
- **Quality Assurance (The "Sector Sum" Test):** A custom validation algorithm was implemented to verify data integrity. Only records where the sum of the three economic sectors (Agriculture + Industry + Services) fell within a logical range of **85%–105%** of GDP were retained, filtering out statistical anomalies.
- **Granularity Control:** Aggregate regions (e.g., "Arab World", "OECD Members") were systematically filtered out to prevent double-counting and ensure unit homogeneity.

A.3 Visualization Framework

The analysis moved beyond static plotting by utilizing **Plotly Interactive Visualization** to explore multidimensional relationships:

1. **The "Simplex" Analysis:** A **ternary plot** and **3D scatter plot** were used to visualize how the three sectors interact at the same time, confirming that structural transformation follows a clear and predictable path.
2. **Geospatial Diffusion:** An animated **choropleth map** was used to track the spread of the service economy over time, highlighting the persistent **North-South divide**.
3. **Multivariate Drivers: Parallel coordinates** and **correlation matrices** were used to pinpoint the main drivers of change, specifically highlighting **trade openness** and **macroeconomic stability**(low inflation) as key drivers.

A.4 Strategic Conclusions

The data-driven analysis confirmed a strong positive correlation ($R^2 > 0.8$) between **GDP per capita** and **service sector dominance**. The results support the idea that while moving toward services is a common development pattern, this shift is sped up by integration into global trade markets (the **"Globalization Engine"**) and slowed down by hyperinflation (the **"Stability Trap"**).

12. References

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Thankyou for teaching us Sir ❤