```
# Load necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import adfuller
import warnings

# Suppress warnings
#warnings.filterwarnings("ignore")

# Load the data
gdp_data = pd.read_csv('gdp_data.csv')
fdi_data = pd.read_csv('fdi_data.csv')

# Transform the data for visualization
gdp_long = pd.melt(gdp_data, id_vars=['Country'], var_name='Year', value_name='GDP')
fdi_long = pd.melt(fdi_data, id_vars=['Country'], var_name='Year', value_name='FDI')

# Convert Year to numeric
gdp_long['Year'] = gdp_long['Year'].astype(int)
fdi_long['Year'] = fdi_long['Year'].astype(int)

# Merge GDP and FDI data for analysis
merged_data = pd.merge(gdp_long, fdi_long, on=['Country', 'Year'])

# Visualization 1: GDP Growth Trends by Country
plt.figure(figsize=(12, 6))
sns.lineplot(data=gdp_long, x='Year', y='GDP', hue='Country')
plt.title('GDP Trends (2000-2016)')
plt.xlabel('Year')
plt.ylabel('GDP (in Billion $)')
plt.legend(title='Country')
plt.grid(True)
plt.show()

# Visualization 2: FDI Trends by Country
plt.figure(figsize=(12, 6))
sns.lineplot(data=fdi_long, x='Year', y='FDI', hue='Country')
plt.title('FDI Trends (2000-2016)')
plt.xlabel('Year')
plt.ylabel('FDI (in Billion $)')
plt.legend(title='Country')
plt.grid(True)
plt.show()

# Visualization 3: Correlation between GDP and FDI
plt.figure(figsize=(12, 6))
sns.scatterplot(data=merged_data, x='FDI', y='GDP', hue='Country')
sns.regplot(data=merged_data, x='FDI', y='GDP', scatter=False, color='grey')
plt.title('Correlation between FDI and GDP')
plt.xlabel('FDI (in Billion $)')
plt.ylabel('GDP (in Billion $)')
plt.grid(True)
plt.show()

# Forecasting GDP for India using time series analysis
india_gdp = gdp_long[gdp_long['Country'] == 'India']
india_gdp_ts = india_gdp.set_index('Year')['GDP']

# Fit an ARIMA model
gdp_model = ARIMA(india_gdp_ts, order=(1, 1, 1)).fit()

gdp_forecast = gdp_model.get_forecast(steps=5)
gdp_forecast_df = gdp_forecast.conf_int()
gdp_forecast_df['Forecast'] = gdp_forecast.predicted_mean

# Plot forecast
gdp_forecast_df['Forecast'].plot(label='Forecast', color='blue')
plt.fill_between(gdp_forecast_df.index, gdp_forecast_df.iloc[:, 0], gdp_forecast_df.iloc[:, 1], color='lightblue', alpha
plt.title('GDP Forecast for India (Next 5 Years)')
plt.xlabel('Year')
plt.ylabel('GDP (in Billion $)')
```

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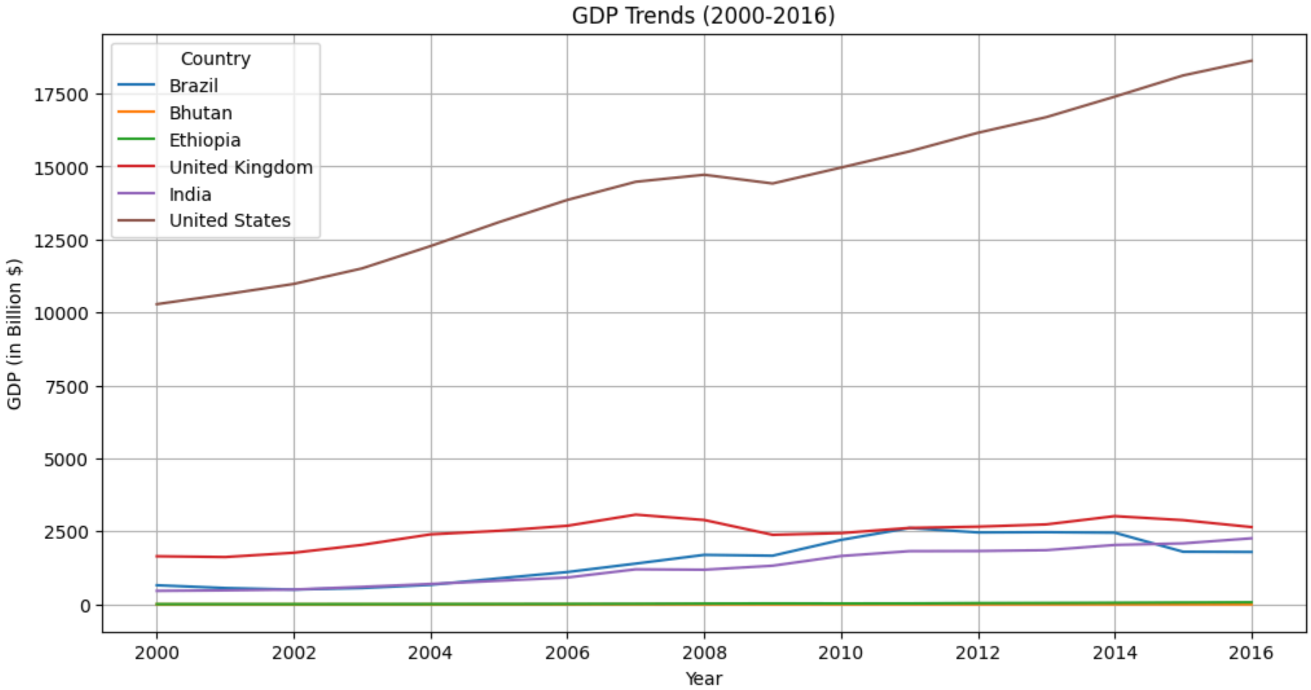
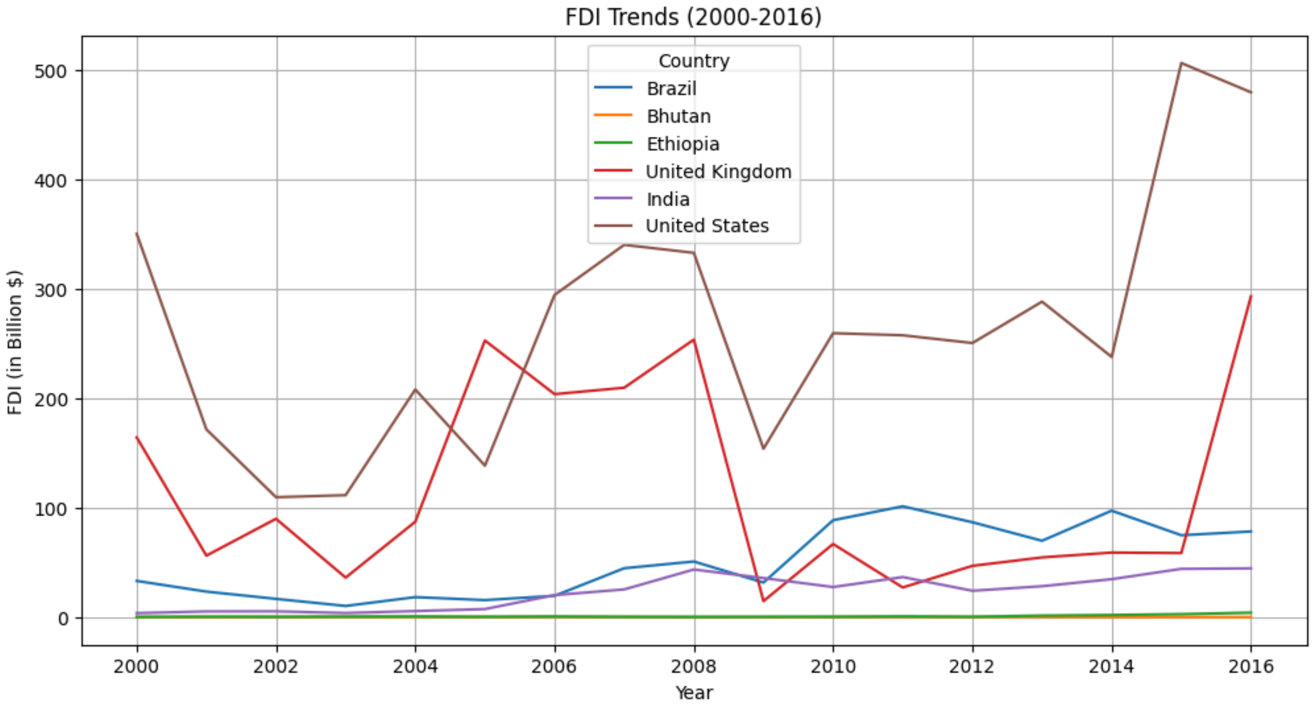
plt.ylabel('GDP (in Billion $)')
plt.legend(['Forecast', 'Confidence Interval'])
plt.grid(True)
plt.show()

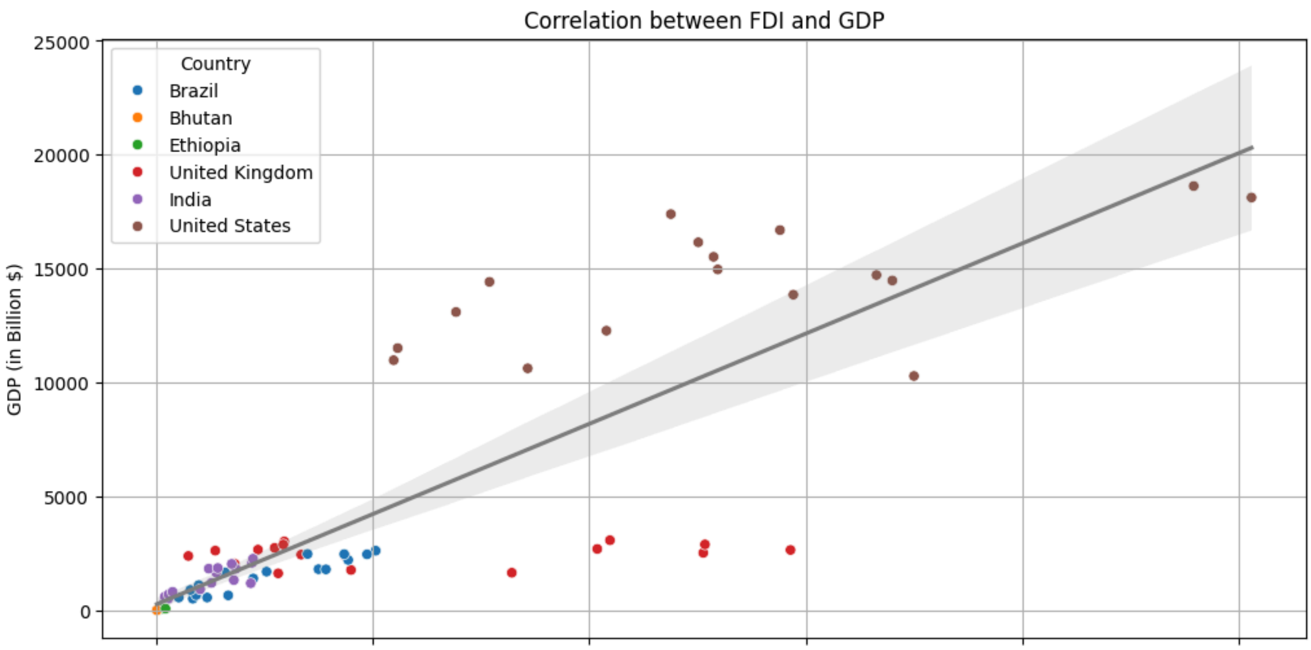
# Print model summary
print(gdp_model.summary())
```



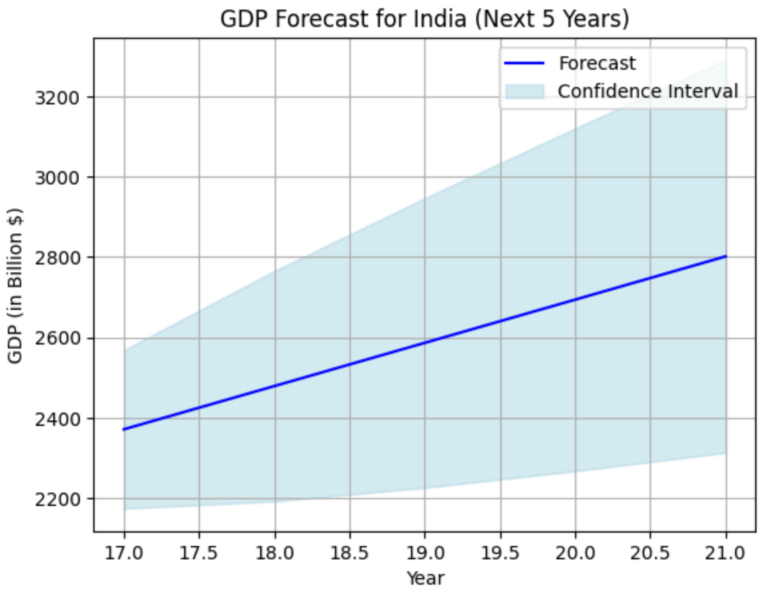
GDP Trends (2000-2016)
Country
Brazil
Bhutan
Ethiopia
United Kingdom
India
United States
GDP (in Billion $)
0
2500
5000
7500
10000
12500
15000
17500
Year
2000
2002
2004
2006
2008
2010
2012
2014
2016



FDI Trends (2000-2016)
Country
Brazil
Bhutan
Ethiopia
United Kingdom
India
United States
FDI (in Billion $)
0
100
200
300
400
500
Year
2000
2002
2004
2006
2008
2010
2012
2014
2016



Correlation between FDI and GDP
Country
Brazil
Bhutan
Ethiopia
United Kingdom
India
United States
GDP (in Billion $)
0
5000
10000
15000
20000
25000




```
                               SARIMAX Results
==============================================================================
Dep. Variable:                    GDP   No. Observations:                   17
Model:                 ARIMA(1, 1, 1)   Log Likelihood                 -97.495
Date:                Tue, 12 Nov 2024   AIC                            200.989
Time:                        15:00:29   BIC                            203.307
Sample:                             0   HQIC                           201.108
                                 - 17
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.0000      0.003    333.663      0.000       0.994       1.006
ma.L1         -0.9912      0.438     -2.264      0.024      -1.849      -0.133
sigma2      9626.6431   4.74e-05   2.03e+08      0.000    9626.643    9626.643
===================================================================================
Ljung-Box (L1) (Q):                   0.18   Jarque-Bera (JB):                 0.34
Prob(Q):                              0.67   Prob(JB):                         0.85
Heteroskedasticity (H):               2.93   Skew:                             0.36
Prob(H) (two-sided):                  0.26   Kurtosis:                         2.99
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 8.43e+23. Standard errors may be unstable.
```