How Economic Development and Educational Attainment Impact Female Fertility Rate: A Regression Approach

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Introduction

Female fertility rate is a vital indicator of societal development, reflecting not only population trends but also the economic, educational, and cultural contexts within a country. In today's fast-paced, competitive world, women's willingness and ability to give birth and raise children are profoundly influenced by advancements in economic development and educational attainment. Investigating these factors provides crucial insights into how nations can balance their growth trajectories with population stability, gender equity, and cultural sustainability.

This research explores the relationship between economic development, educational achievement, and female fertility rates, focusing on two key indicators: adolescent fertility (ages 15-19) and total fertility rate (births per woman). These metrics serve as proxies for women's reproductive decisions and societal attitudes towards childbearing. On the other hand, GDP per capita and school enrollment rates at the primary, secondary, and tertiary levels represent key dimensions of economic and educational progress.

Using data from the World Bank, our group aims to construct a multivariable regression model to examine how economic development and educational attainment influence fertility rates across countries in four world regions: Eastern and Southern Africa, North America, East Asia & Pacific, and the European Union. In this model, GDP per capita and school enrollment at all levels will serve as explanatory variables, while adolescent fertility and total fertility rates will be the dependent variables. This approach will allow us to quantify the extent to which economic prosperity and education drive changes in fertility patterns globally.

Insights from this study is critical for policymakers, as fertility rates affect labor markets, public health, and long-term demographic trends. This research contributes to a deeper understanding of how societies can navigate the challenges of development while supporting women's empowerment and well-being.

Data Description

We selected six variables from the World Bank open database: Adolescent fertility rate (births per 1,000 women ages 15-19), Fertility rate, total (births per woman), School enrollment, tertiary (% gross), School enrollment, secondary (% gross), School enrollment, primary (% gross), and GDP per capita (current US$).

Adolescent Fertility Rate

Adolescent fertility rate is the number of births per 1,000 women aged 15-19, providing a critical indicator of reproductive health and societal factors influencing early childbearing. Derived from vital registration systems, censuses, or surveys, it reflects access to education, contraception, and healthcare, with implications for maternal and child well-being in developing and developed regions.

Fertility Rate, Total

Total fertility rate represents the average number of children a woman would bear during her lifetime if age-specific fertility rates remained constant. It is derived from vital registration systems, censuses, or surveys and reflects societal factors influencing reproduction, including economic conditions, healthcare, and women's access to education and family planning.

Tertiary School Enrollment

Female tertiary school enrollment (% gross) measures the gross enrollment ratio of female students in tertiary education as a percentage of the relevant age group population. Tertiary education generally encompasses programs beyond secondary school and may or may not lead to advanced research qualifications. Admission typically requires completing secondary education as a prerequisite. This indicator reflects women's access to higher education and is shaped by educational policies, cultural values, and economic factors. Data is standardized using UNESCO methodologies.

Secondary School Enrollment

School Enrollment, Secondary, Female (% gross) measures the total female enrollment in secondary education as a percentage of the population of the age group officially corresponding to that education level. Secondary education completes the provision of basic education that began at the primary level, and aims at laying the foundations for lifelong learning and human development, by offering more subject- or skill-oriented instruction using more specialized teachers. Data is standardized using UNESCO methodologies.

Primary School Enrollment

School Enrollment, Primary, Female (% gross) measures the gross enrollment ratio of female students in primary education as a percentage of the relevant age group population. Primary education provides children with basic reading, writing, and mathematics skills along with an elementary understanding of such subjects as history, geography, natural science, social science, art, and music. Data is standardized using UNESCO methodologies.

GDP Per Capita

GDP per capita is calculated by dividing the gross domestic product (GDP) by the midyear population. GDP represents the total gross value added by all resident producers in the economy, including product taxes, and excluding subsidies not factored into product values. It does not account for depreciation of manufactured assets or the depletion and degradation of natural resources. The data are expressed in current U.S. dollars.

Data Analysis

Data Cleaning

We used both SQL and Python in our data cleaning process.

```
# This is quoted code and won't run
import pandas as pd
import pandas as pd

csv_file = '/Users/yangziyu/Desktop/QTM 350/final_project/qtm350-final-project/data/WBData.cs
df = pd.read_csv(csv_file)

create_table = "CREATE TABLE wb_data (\n"
for col in df.columns:
    col_name = col.replace(" ", "_").replace("[", "").replace("]", "").replace(".", "_")
    dtype = "REAL" if pd.api.types.is_numeric_dtype(df[col]) else "TEXT"
    create_table += f"    {col_name} {dtype},\n"
create_table = create_table.rstrip(",\n") + "\n);"

insert_statements = []
for _, row in df.iterrows():
    values = ", ".join([f"'{x}'" if pd.notna(x) else "NULL" for x in row])
    insert_statements.append(f"INSERT INTO wb_data VALUES ({values});")
```

~~~python
sql_script = create_table + "\n\n" + "\n".join(insert_statements)

with open("wb_data.sql", "w") as f:
    f.write(sql_script)

print("SQL script saved to wb_data.sql")


```python
# This is quoted code and won't run
import dask.datasets
import dask.dataframe as dd
from dask_sql import Context

c = Context()
df = dd.read_csv("/Users/maxjiang/Desktop/WBData.csv")

c.create_table("wb_data", df)
query = "SELECT * FROM wb_data"
result = c.sql(query)


```python
# This is quoted code and won't run
import dask.dataframe as dd
from dask_sql import Context

c = Context()
df = dd.read_csv("/Users/maxjiang/Desktop/WBData.csv")
c.create_table("wb_data", df)

selected_columns = [
    "Country Name", "Series Name",
    "1975 [YR1975]", "1976 [YR1976]", "2020 [YR2020]", "2021 [YR2021]", "2022 [YR2022]", "20
]
filtered_df = df[selected_columns]

filtered_df = filtered_df.rename(
    columns={
        "1974 [YR1974]": "Year1974",
        "1975 [YR1975]": "Year1975",
        "1976 [YR1976]": "Year1976",
~~~

```
        "1977 [YR1977]": "Year1977",
        "1978 [YR1978]": "Year1978",
        "1979 [YR1979]": "Year1979",
        "1980 [YR1980]": "Year1980",
        "1981 [YR1981]": "Year1981",
        "1982 [YR1982]": "Year1982",
        "1983 [YR1983]": "Year1983",
        "1984 [YR1984]": "Year1984",
        "1985 [YR1985]": "Year1985",
        "1986 [YR1986]": "Year1986",
        "1987 [YR1987]": "Year1987",
        "1988 [YR1988]": "Year1988",
        "1989 [YR1989]": "Year1989",
        "1990 [YR1990]": "Year1990",
        "1991 [YR1991]": "Year1991",
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        "1993 [YR1993]": "Year1993",
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        "1997 [YR1997]": "Year1997",
        "1998 [YR1998]": "Year1998",
        "1999 [YR1999]": "Year1999",
        "2000 [YR2000]": "Year2000",
        "2001 [YR2001]": "Year2001",
        "2002 [YR2002]": "Year2002",
        "2003 [YR2003]": "Year2003",
        "2004 [YR2004]": "Year2004",
        "2005 [YR2005]": "Year2005",
        "2006 [YR2006]": "Year2006",
        "2007 [YR2007]": "Year2007",
        "2008 [YR2008]": "Year2008",
        "2009 [YR2009]": "Year2009",
        "2010 [YR2010]": "Year2010",
        "2011 [YR2011]": "Year2011",
        "2012 [YR2012]": "Year2012",
        "2013 [YR2013]": "Year2013",
        "2014 [YR2014]": "Year2014",
        "2015 [YR2015]": "Year2015",
        "2016 [YR2016]": "Year2016",
        "2017 [YR2017]": "Year2017",
        "2018 [YR2018]": "Year2018",
```

```
        "2019 [YR2019]": "Year2019",
        "2020 [YR2020]": "Year2020",
        "2021 [YR2021]": "Year2021",
        "2022 [YR2022]": "Year2022",
        "2023 [YR2023]": "Year2023",

    }
)


filtered_df = filtered_df.replace("..", None)

year_columns = [
    "Year1974", "Year1975",
    "Year1976", "Year1977", "Year1978", "Year1979", "Year1980", "Year1981",
    "Year1982", "Year1983", "Year1984", "Year1985", "Year1986", "Year1987",
    "Year1988", "Year1989", "Year1990", "Year1991", "Year1992", "Year1993",
    "Year1994", "Year1995", "Year1996", "Year1997", "Year1998", "Year1999",
    "Year2000", "Year2001", "Year2002", "Year2003", "Year2004", "Year2005",
    "Year2006", "Year2007", "Year2008", "Year2009", "Year2010", "Year2011",
    "Year2012", "Year2013", "Year2014", "Year2015", "Year2016", "Year2017",
    "Year2018", "Year2019", "Year2020", "Year2021", "Year2022", "Year2023"
]

numeric_cols = year_columns

for i, col in enumerate(year_columns):
    if i >= 2:
        prev1, prev2 = year_columns[i - 1], year_columns[i - 2]
        query = f"""
            UPDATE wb_data_cleaned
            SET `{col}` = COALESCE(`{col}`, (`{prev1}` + `{prev2}`) / 2)
            WHERE `{col}` IS NULL;
        """
        c.sql(query)

for col in year_columns:
    query = f"""
        UPDATE wb_data_cleaned
        SET `{col}` = COALESCE(`{col}`,
            (SELECT AVG(`{col}`) FROM wb_data_cleaned WHERE `{col}` IS NOT NULL))
        WHERE `{col}` IS NULL;
```

```
    """
    c.sql(query)

categorical_columns = ["Country Name", "Series Name"]
for col in categorical_columns:
    query = f"""
        UPDATE wb_data_cleaned
        SET `{col}` = COALESCE(`{col}`,
            (SELECT `{col}` FROM wb_data_cleaned
             GROUP BY `{col}` ORDER BY COUNT(*) DESC LIMIT 1))
        WHERE `{col}` IS NULL;
    """
    c.sql(query)

for col in numeric_cols:
    filtered_df[col] = filtered_df[col].map_partitions(pd.to_numeric, errors='coerce')

def fill_missing_values(df):
    df["Year2022"] = df["Year2022"].fillna((df["Year2020"] + df["Year2021"]) / 2)
    df["Year2023"] = df["Year2023"].fillna((df["Year2021"] + df["Year2022"]) / 2)
    return df

filled_df = filtered_df.map_partitions(fill_missing_values)
c.create_table("wb_data_Further_cleaned", filled_df)

filled_df.compute().to_csv("/Users/maxjiang/Desktop/WBData_Further_Cleaned.csv", index=False)


```python

#Improved Version
import dask.dataframe as dd
from dask_sql import Context
import pandas as pd

c = Context()
df = dd.read_csv("/Users/maxjiang/Desktop/WBData.csv")
c.create_table("wb_data", df)

year_columns = [f"Year{year}" for year in range(1970, 2020)]
rename_mapping = {f"{year} [YR{year}]": f"Year{year}" for year in range(1970, 2020)}
rename_mapping.update({"Country Name": "CountryName", "Series Name": "SeriesName"})
```
```

````python
filtered_df = df.rename(columns=rename_mapping)

filtered_df = filtered_df.replace("..", None)

numeric_cols = year_columns
for col in numeric_cols:
    filtered_df[col] = filtered_df[col].map_partitions(pd.to_numeric, errors='coerce')

def fill_missing_values(df):
    for i, col in enumerate(year_columns):
        if i >= 2:
            prev1, prev2 = year_columns[i - 1], year_columns[i - 2]
            df[col] = df[col].fillna((df[prev1] + df[prev2]) / 2)
    return df

filled_df = filtered_df.map_partitions(fill_missing_values)

for col in numeric_cols:
    query = f"""
        UPDATE wb_data_cleaned
        SET `{col}` = COALESCE(`{col}`,
            (SELECT AVG(`{col}`) FROM wb_data_cleaned WHERE `{col}` IS NOT NULL))
        WHERE `{col}` IS NULL;
    """
    c.sql(query)

categorical_columns = ["CountryName", "SeriesName"]
for col in categorical_columns:
    query = f"""
        UPDATE wb_data_cleaned
        SET `{col}` = COALESCE(`{col}`,
            (SELECT `{col}` FROM wb_data_cleaned
             GROUP BY `{col}` ORDER BY COUNT(*) DESC LIMIT 1))
        WHERE `{col}` IS NULL;
    """
    c.sql(query)

filled_df.compute().to_csv("/Users/maxjiang/Desktop/WBData_Further_Cleaned.csv", index=False)


```python
#Final Check using Python
````
````

```
'''
correct_file_path = '/Users/maxjiang/Desktop/WBData.csv'
data = pd.read_csv(correct_file_path)

data.columns = [col.strip().replace(' [', '_').replace(']', '').replace('YR', 'Year') for col

data.replace("..", pd.NA, inplace=True)

for col in data.columns[5:]:  # Assuming first 5 columns are non-numeric metadata
    data[col] = pd.to_numeric(data[col], errors='coerce')

years = [col for col in data.columns if 'Year' in col]
recent_years_average = data[years[-2:]].mean(axis=1, skipna=True)
for col in years:
    data[col] = data[col].fillna(recent_years_average)

output_corrected_path = '/Users/maxjiang/Desktop/WBData_Cleaned.csv'
data.to_csv(output_corrected_path, index=False)

for row_index in [8, 9]:  # 9th and 10th rows (zero-based index)
    row_last_two = data.iloc[row_index][years[-2:]]
    if row_last_two.isnull().all():
        overall_average = data.iloc[row_index][years].mean(skipna=True)
        data.loc[row_index, years[-2:]] = overall_average

data.to_csv(output_corrected_path, index=False)

updated_rows = data.iloc[[8, 9]][years[-2:]]
updated_rows

row_index = 8
row_last_two = data.iloc[row_index][years[-2:]]

if row_last_two.isnull().all():
    overall_average = data.iloc[row_index][years].mean(skipna=True)
    data.loc[row_index, years[-2:]] = overall_average

data.to_csv(output_corrected_path, index=False)

updated_ninth_row_last_two = data.iloc[row_index][years[-2:]]
updated_ninth_row_last_two
```

```
previous_two_years = years[-4:-2]

previous_two_years_average = data.loc[row_index, previous_two_years].mean(skipna=True)

data.loc[row_index, years[-2:]] = previous_two_years_average

data.to_csv(output_corrected_path, index=False)
corrected_ninth_row_last_two = data.loc[row_index, years[-2:]]
corrected_ninth_row_last_two

columns_to_remove = ['Series Code', 'Country Code']
data.drop(columns=columns_to_remove, inplace=True, errors='ignore')

data.columns = [col.split('_')[-1] if 'Year' in col else col for col in data.columns]

output_further_cleaned_path = '/Users/maxjiang/Desktop/WBData_Further_Cleaned.csv'
data.to_csv(output_further_cleaned_path, index=False)
'''

By completing the steps above, we have ensured that the dataset is clean, consistent, and rea

## Summary Statistics

### Summary Statistics By Region

::: {.cell execution_count=1}
``` {.python .cell-code}
import sqlite3
import pandas as pd
# Load the CSV file into a Pandas DataFrame
file_path = "/Users/yangziyu/Desktop/QTM 350/final_project/qtm350-final-project/data/data_fo
data = pd.read_csv(file_path)
# Create an SQLite database (or connect to an existing one)
conn = sqlite3.connect("data1.db")
# Load the DataFrame into an SQL table
data.to_sql("data_table", conn, if_exists="replace", index=False)
# Verify the table content
query = "SELECT * FROM data_table LIMIT 5;"
sample_data = pd.read_sql_query(query, conn)
print(sample_data.head())
```

```
Region  Year  adolescent_fertility  \
```
```

```
0  Africa Eastern and Southern  1974           152.504673
1  Africa Eastern and Southern  1975           151.867914
2  Africa Eastern and Southern  1976           150.533609
3  Africa Eastern and Southern  1977           148.931096
4  Africa Eastern and Southern  1978           146.644103

   Fertility rate, total (births per woman)  gdp_per_capita  \
0                                  6.820429      421.977185
1                                  6.805172      435.977902
2                                  6.785995      430.261244
3                                  6.767943      468.301007
4                                  6.750403      509.479882

   school_enrollment_primary  school_enrollment_secondary  \
0                  65.155342                    17.703409
1                  67.497803                    18.236691
2                  68.989937                    18.696880
3                  70.836258                    19.130159
4                  71.924622                    19.723339

   school_enrollment_tertiary
0                     1.95049
1                     1.99506
2                     2.02551
3                     2.05232
4                     2.12988
```

:::

```
query1 = """
SELECT
    "Region",
    COUNT("adolescent_fertility") AS count_observations,
    AVG("adolescent_fertility") AS avg_adolescent_fertility,
    MIN("adolescent_fertility") AS min_adolescent_fertility,
    MAX("adolescent_fertility") AS max_adolescent_fertility,
    AVG("gdp_per_capita") AS avg_gdp_per_capita,
    AVG("school_enrollment_primary") AS avg_primary_enrollment,
    AVG("school_enrollment_secondary") AS avg_secondary_enrollment,
    AVG("school_enrollment_tertiary") AS avg_tertiary_enrollment
FROM data_table
GROUP BY "Region";
```

```
"""
# Execute the query and fetch results
summary_stats = pd.read_sql_query(query1, conn)
summary_stats
```

	Region	count_observations	avg_adolescent_fertility	min_adolescent_fertility
0	Africa Eastern and Southern	50	123.659179	94.688181
1	East Asia & Pacific	50	27.250583	20.101836
2	European Union	50	18.515741	9.066463
3	North America	50	39.815799	14.375896

Based on the summary statistics above, we can see that Africa Eastern and Southern generally have higher adolescent fertility, lower gdp per capital and education enrollment compared to other regions.

Trend of Female Fertility Rate by Year

```
query2 = """
SELECT
    "Year",
    AVG("adolescent_fertility") AS avg_adolescent_fertility
FROM data_table
GROUP BY "Year"
ORDER BY avg_adolescent_fertility ASC;
"""
# Execute the query and fetch results
summary_stats1 = pd.read_sql_query(query2, conn)
summary_stats1
```

	Year	avg_adolescent_fertility
0	2022	34.558094
1	2023	34.558094
2	2021	35.210953
3	2020	35.593976
4	2019	36.338364
5	2018	36.693597
6	2017	37.727974

	Year	avg_adolescent_fertility
7	2016	38.864585
8	2015	40.097494
9	2014	41.525873
10	2013	42.311942
11	2012	43.514744
12	2011	44.491732
13	2010	45.478098
14	2009	46.511333
15	2006	47.238232
16	2005	47.274225
17	2007	47.274647
18	2008	47.421004
19	2004	47.696507
20	2003	48.225742
21	2002	49.334682
22	2001	50.536227
23	2000	51.100895
24	1999	51.845482
25	1998	51.954309
26	1997	52.734165
27	1996	54.478990
28	1995	55.227043
29	1994	56.726343
30	1993	58.459834
31	1992	59.049802
32	1988	60.434924
33	1987	60.516948
34	1986	60.584687
35	1989	60.730916
36	1991	61.307059
37	1985	61.467961
38	1990	61.952906
39	1984	62.074267
40	1983	62.629157
41	1981	62.792716
42	1980	63.200984
43	1982	63.486551
44	1979	63.783899
45	1978	65.039899
46	1977	67.047197
47	1976	68.273405

	Year	avg_adolescent_fertility
48	1975	69.465068
49	1974	70.672741

The adolescent_fertility generally descrease over time on average.

GDP Growth by Region

```
query3 = """
SELECT
    "Region",
    AVG("gdp_per_capita") AS avg_gdp_per_capita,
    MAX("gdp_per_capita") - MIN("gdp_per_capita") AS gdp_growth
FROM data_table
GROUP BY "Region"
ORDER BY gdp_growth DESC;
"""
# Execute the query and fetch results
summary_stats2 = pd.read_sql_query(query3, conn)
summary_stats2
```

	Region	avg_gdp_per_capita	gdp_growth
0	North America	35286.638374	71466.380836
1	European Union	20890.010973	37143.177577
2	East Asia & Pacific	5103.408136	12529.099105
3	Africa Eastern and Southern	989.952961	1336.021219

The findings highlight significant economic disparities, with North America and the European Union leading in GDP per capita and growth, while Africa Eastern and Southern lags far behind.

Data Visualization

```python
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt

# Load the dataset
file_path = "/Users/yangziyu/Desktop/QTM 350/final_project/qtm350-final-project/data/WBData_I
data = pd.read_csv(file_path)
```

```python
filtered_data = data[data['Series Name'] == 'Adolescent fertility rate (births per 1,000 wome

# Prepare the data for plotting
filtered_data = filtered_data.drop(columns=['Series Name']).set_index('Country Name').T
filtered_data.index = filtered_data.index.str.replace('Year', '')  # Simplify year labels

# Plot the data
plt.figure(figsize=(12, 6))
for country in filtered_data.columns:
    plt.plot(filtered_data.index, filtered_data[country], label=country)

plt.title('Adolescent Fertility Rate (Births per 1,000 Women Ages 15-19)', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Fertility Rate', fontsize=12)
plt.legend(title='Regions', bbox_to_anchor=(1.05, 1), loc='upper left', fontsize=8)

# Customize ticks and grid
plt.xticks(ticks=filtered_data.index[::5], rotation=45)  # Show every 5th year
plt.grid(False)

plt.tight_layout()
plt.show()
```

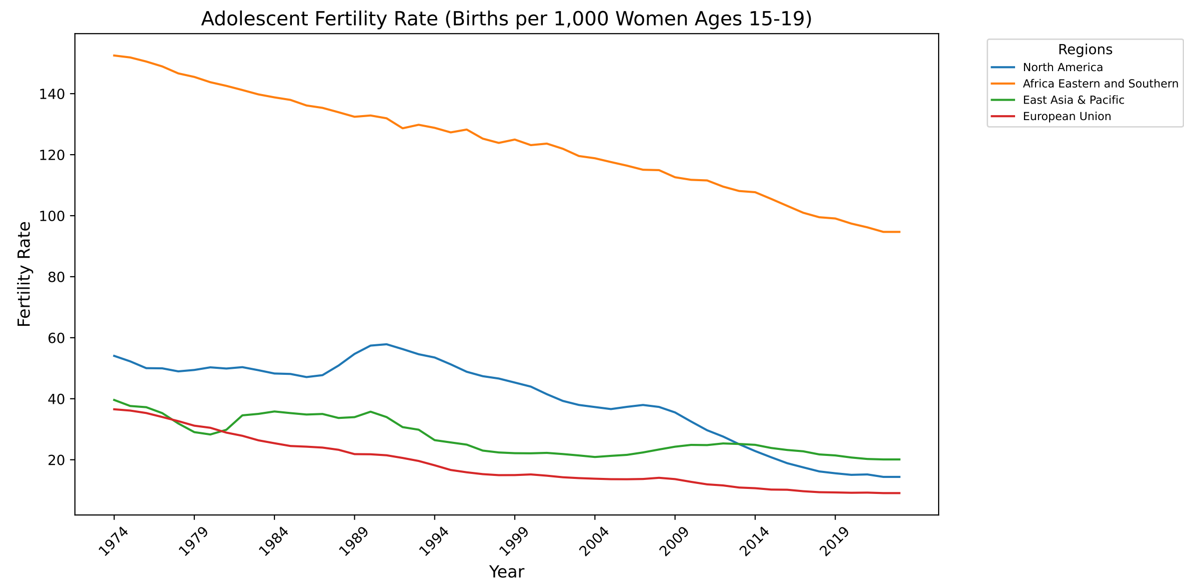


Figure 1: Line Plot showing the adolescent fertility rate from 1974 to 2019

Figure 1 illustrates trends in adolescent fertility rates (births per 1,000 women aged 15-19) across regions from 1974 to 2019: 1. Africa Eastern and Southern consistently shows the highest fertility rates, but there has been a steady decline over time. 2. North America has experienced fluctuations but maintains moderate levels of adolescent fertility compared to other regions. 3. East Asia & Pacific and the European Union have the lowest adolescent fertility rates, showing significant declines and stabilizing at minimal levels over the years.

```
# Reshape the data to include all years
melted_data = data.melt(id_vars=["Country Name", "Series Name"], var_name="Year", value_name=

# Filter relevant data for fertility rate and secondary school enrollment
fertility_data = melted_data[melted_data["Series Name"] == "Adolescent fertility rate (births
secondary_data = melted_data[melted_data["Series Name"] == "School enrollment, secondary (% g

# Merge datasets and clean up
merged_data = (
    pd.merge(fertility_data, secondary_data, on=["Country Name", "Year"], suffixes=("_Fertil
)

# Map regions and assign colors
region_colors = {
    "North America": "blue",
    "Africa Eastern and Southern": "green",
```

```
    "East Asia & Pacific": "orange",
    "European Union": "red"
}
merged_data["Color"] = merged_data["Country Name"].map(region_colors)

# Plot the scatter plot
plt.figure(figsize=(10, 6))
for region, color in region_colors.items():
    group = merged_data[merged_data["Color"] == color]
    plt.scatter(group["Value_Secondary"], group["Value_Fertility"], label=region, color=colo

plt.title("Relationship Between Secondary School Enrollment and Adolescent Fertility Rate")
plt.xlabel("Secondary School Enrollment (% gross)")
plt.ylabel("Adolescent Fertility Rate (births per 1,000 women ages 15-19)")
plt.legend(title="Region")
plt.grid(False)
plt.show()
```

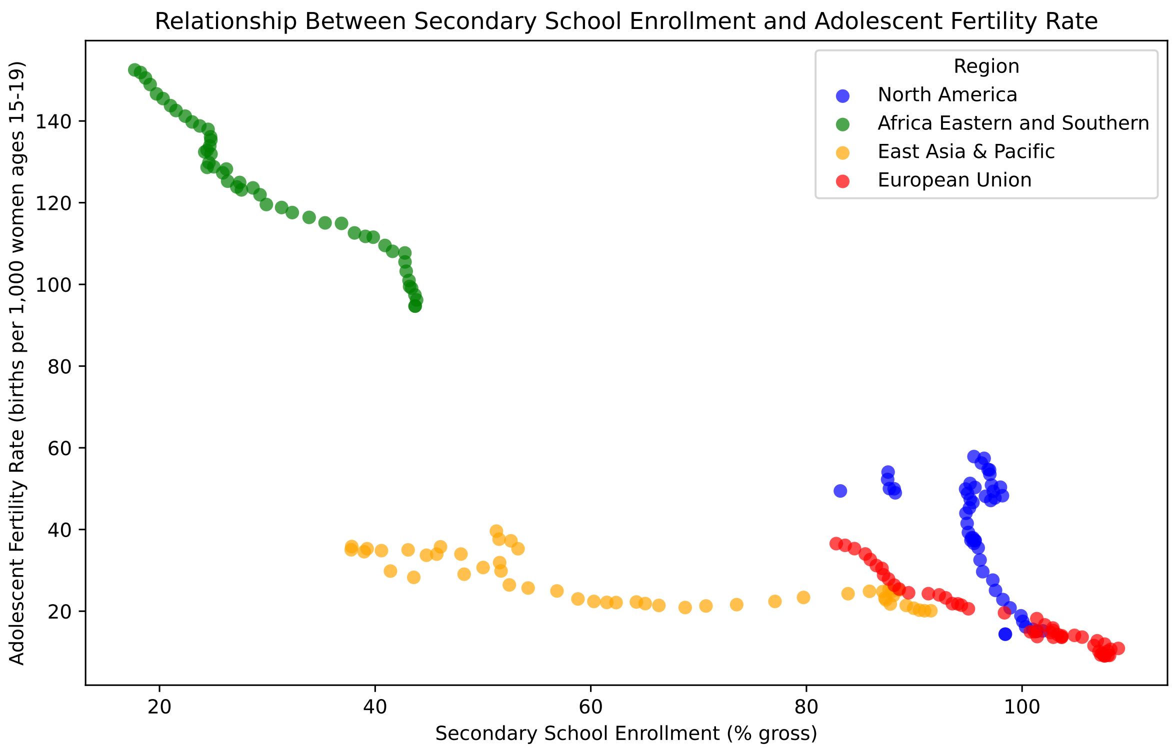


Figure 2: Scatterplot showing the relationship between secondary school enrollment and adolescent fertility rate

Figure 2 shows an obvious negative correlation between secondary school enrollment and adolescent fertility rate.

```
# Filter relevant data for fertility rate and tertiary school enrollment
tertiary_data = melted_data[melted_data["Series Name"] == "School enrollment, tertiary (% gro

# Merge datasets and clean up
merged_data = (
    pd.merge(fertility_data, tertiary_data, on=["Country Name", "Year"], suffixes=("_Fertili
    .dropna(subset=["Value_Fertility", "Value_Tertiary"])
)

# Map regions and assign colors
region_colors = {
    "North America": "blue",
    "Africa Eastern and Southern": "green",
    "East Asia & Pacific": "orange",
    "European Union": "red"
}
merged_data["Color"] = merged_data["Country Name"].map(region_colors)

# Plot the scatter plot
plt.figure(figsize=(10, 6))
for region, color in region_colors.items():
    group = merged_data[merged_data["Color"] == color]
    plt.scatter(group["Value_Tertiary"], group["Value_Fertility"], label=region, color=color

plt.title("Relationship Between Tertiary School Enrollment and Adolescent Fertility Rate")
plt.xlabel("Tertiary School Enrollment (% gross)")
plt.ylabel("Adolescent Fertility Rate (births per 1,000 women ages 15-19)")
plt.legend(title="Region")
plt.grid(False)
plt.show()
```

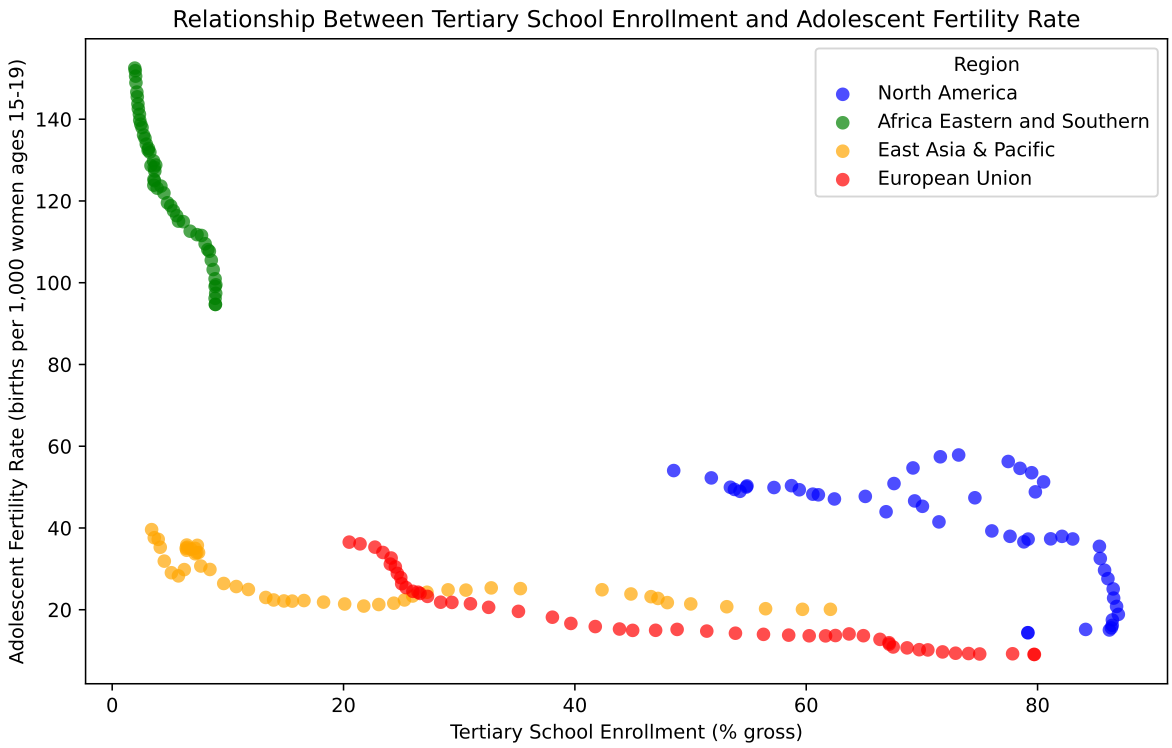


Figure 3: Scatterplot showing the Relationship Between Tertiary School Enrollment and Adolescent Fertility Rate

Figure 3 shows the relationship between tertiary school enrollment and adolescent fertility rate. The graph shows an obvious negative correlation between tertiary school enrollment and adolescent fertility rate; and compared to the previous graph of secondary education, the slope is steeper.

```
# Filter relevant data for adolescent fertility and GDP per capita
gdp_data = melted_data[melted_data["Series Name"] == "GDP per capita (current US$)"]

# Merge datasets and clean up
merged_data = (
    pd.merge(fertility_data, gdp_data, on=["Country Name", "Year"], suffixes=("_Fertility", "
    .dropna(subset=["Value_Fertility", "Value_GDP"])
)

# Map regions and assign colors
region_colors = {
    "North America": "blue",
```

```
    "Africa Eastern and Southern": "green",
    "East Asia & Pacific": "orange",
    "European Union": "red"
}
merged_data["Color"] = merged_data["Country Name"].map(region_colors)

# Plot the scatter plot
plt.figure(figsize=(10, 6))
for region, color in region_colors.items():
    group = merged_data[merged_data["Color"] == color]
    plt.scatter(group["Value_GDP"], group["Value_Fertility"], label=region, color=color, alph

plt.title("Relationship Between GDP per Capita and Adolescent Fertility Rate")
plt.xlabel("GDP per Capita (US$)")
plt.ylabel("Adolescent Fertility Rate (births per 1,000 women ages 15-19)")
plt.legend(title="Region")
plt.grid(False)
plt.show()
```

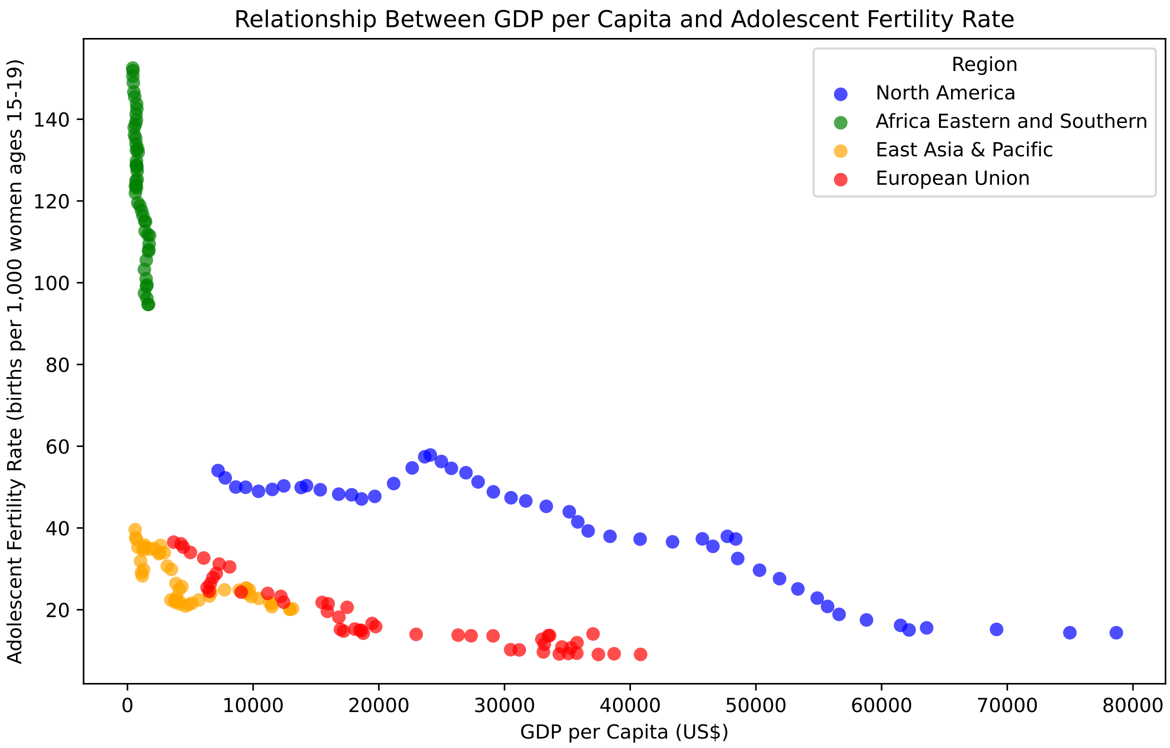


Figure 4: Scatterplot showing the Relationship Between GDP per Capita and Adolescent Fertility Rate

Figure 4 shows an obvious negative correlation between GDP per capita and adolescent fertility rate; and compared to the previous graphs, the slope is the steepest.

```
# Filter relevant data for GDP per capita, secondary, and tertiary school enrollment
gdp_data = melted_data[melted_data["Series Name"] == "GDP per capita (current US$)"]
secondary_data = melted_data[melted_data["Series Name"] == "School enrollment, secondary (% g
tertiary_data = melted_data[melted_data["Series Name"] == "School enrollment, tertiary (% gro

# Merge GDP with secondary school enrollment
merged_secondary = pd.merge(gdp_data, secondary_data,
                            on=["Country Name", "Year"],
                            suffixes=("_GDP", "_Secondary"))

# Merge GDP with tertiary school enrollment
merged_tertiary = pd.merge(gdp_data, tertiary_data,
                           on=["Country Name", "Year"],
                           suffixes=("_GDP", "_Tertiary"))
```

```
# Define regions and assign colors (example mapping, adjust as necessary)
region_colors = {
    "North America": "blue",
    "Africa Eastern and Southern": "green",
    "East Asia & Pacific": "orange",
    "European Union": "red"
}

# Map colors to regions
merged_secondary["Color"] = merged_secondary["Country Name"].map(region_colors)
merged_tertiary["Color"] = merged_tertiary["Country Name"].map(region_colors)

# Plot for secondary school enrollment
plt.figure(figsize=(10, 6))
for region, color in region_colors.items():
    group = merged_secondary[merged_secondary["Color"] == color]
    plt.scatter(group["Value_Secondary"], group["Value_GDP"], label=region, color=color, alpl
plt.title("Relationship Between Secondary School Enrollment and GDP per Capita")
plt.xlabel("Secondary School Enrollment (% gross)")
plt.ylabel("GDP per Capita (current US$)")
plt.legend(title="Region")
plt.grid(False)
plt.show()
```

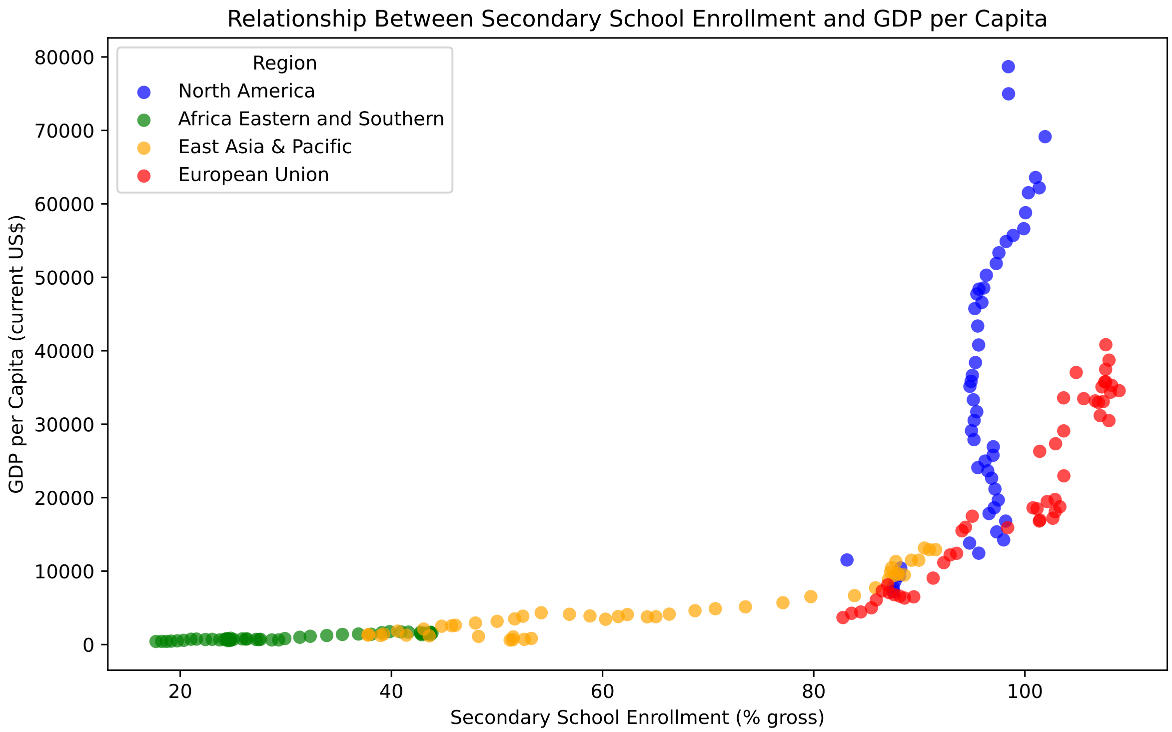


Figure 5: Scatterplot showing the Relationship Between Secondary School Enrollment and GDP per Capita

Figure 5 demonstrates a positive relationship between secondary school enrollment (% gross) and GDP per capita across regions. Countries with higher secondary school enrollment tend to have higher GDP per capita, with distinct clustering patterns by region. North America and the European Union show the highest GDP per capita with high enrollment rates, while Africa exhibits lower GDP levels despite varying enrollment percentages.

```
# Plot for tertiary school enrollment
plt.figure(figsize=(10, 6))
for region, color in region_colors.items():
    group = merged_tertiary[merged_tertiary["Color"] == color]
    plt.scatter(group["Value_Tertiary"], group["Value_GDP"], label=region, color=color, alpha
plt.title("Relationship Between Tertiary School Enrollment and GDP per Capita")
plt.xlabel("Tertiary School Enrollment (% gross)")
plt.ylabel("GDP per Capita (current US$)")
plt.legend(title="Region")
plt.grid(False)
plt.show()
```

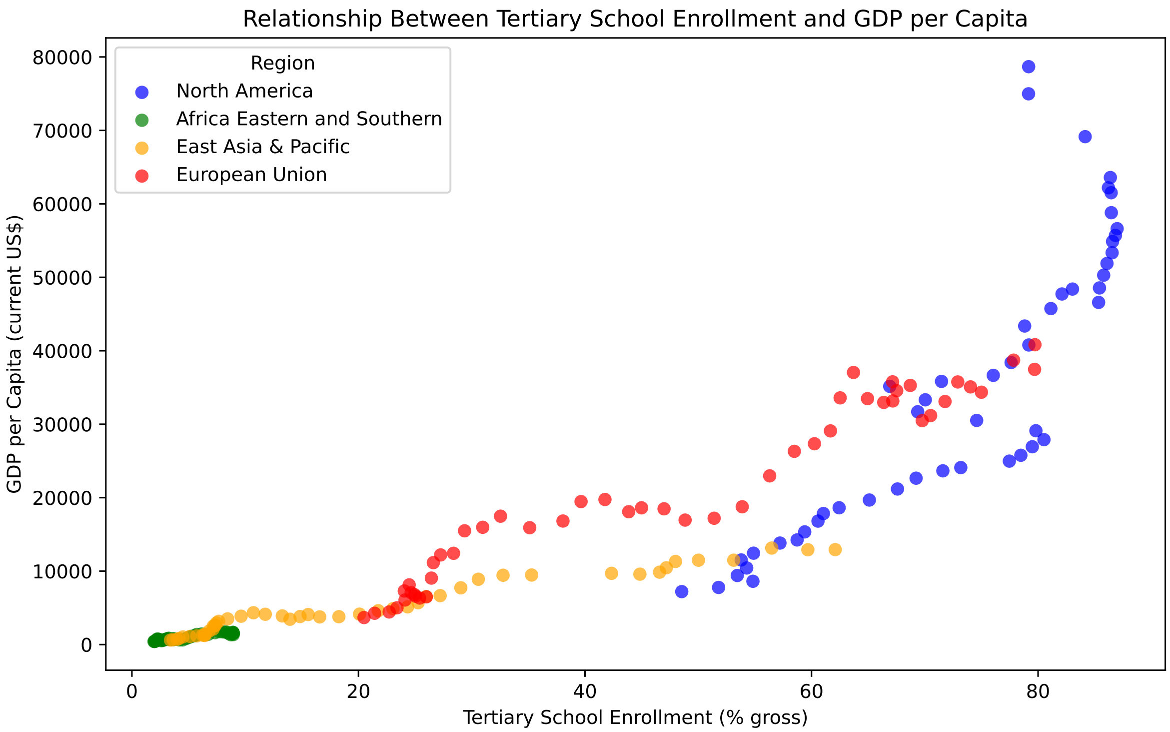


Figure 6: Scatterplot showing the Relationship Between Tertiary School Enrollment and GDP per Capita

Figure 6 highlights a positive correlation between tertiary school enrollment (% gross) and GDP per capita. Regions such as North America and the European Union exhibit high GDP per capita alongside higher tertiary enrollment rates, indicating the potential influence of advanced education on economic prosperity. Conversely, regions like Africa show lower GDP per capita and tertiary enrollment, suggesting gaps in higher education access and economic outcomes.

Regression Analysis

Rename and Reshape dataset

```
# import necessary packages and dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
import scipy.stats as stats

from stargazer.stargazer import Stargazer
from IPython.core.display import HTML
```

```
# use relative paths to increase reproducibility
data = pd.read_csv("/Users/yangziyu/Desktop/QTM 350/final_project/qtm350-final-project/data/W
```

```
# Rename "Country Name" to "Region"
data.rename(columns={"Country Name": "Region"}, inplace=True)
# Reshape the dataset to a long format
data_long = data.melt(id_vars=["Region", "Series Name"],
                      var_name="Year",
                      value_name="Value")
```

```
# Inspect the dataset
data_long.head(5)
```

	Region	Series Name	Year	Value
0	North America	Adolescent fertility rate (births per 1,000 wo...	Year1974	54.047027
1	North America	Fertility rate, total (births per woman)	Year1974	1.835234
2	North America	School enrollment, tertiary (% gross)	Year1974	48.543449
3	North America	School enrollment, secondary (% gross)	Year1974	87.572639
4	North America	School enrollment, primary (% gross)	Year1974	95.018700

```
# Clean the Year column
data_long['Year'] = data_long['Year'].str.extract('(\d+)').astype(int)
# Pivot to create a clean dataset for analysis
analysis_data = data_long.pivot_table(index=["Region", "Year"],
                                      columns="Series Name",
                                      values="Value").reset_index()

analysis_data.rename(columns={
    "Adolescent fertility rate (births per 1,000 women ages 15-19)": "adolescent_fertility",
    "GDP per capita (current US$)": "gdp_per_capita",
    "School enrollment, primary (% gross)": "school_enrollment_primary",
    "School enrollment, secondary (% gross)": "school_enrollment_secondary",
```

```
    "School enrollment, tertiary (% gross)": "school_enrollment_tertiary"
}, inplace=True)
```

Correlation Analysis

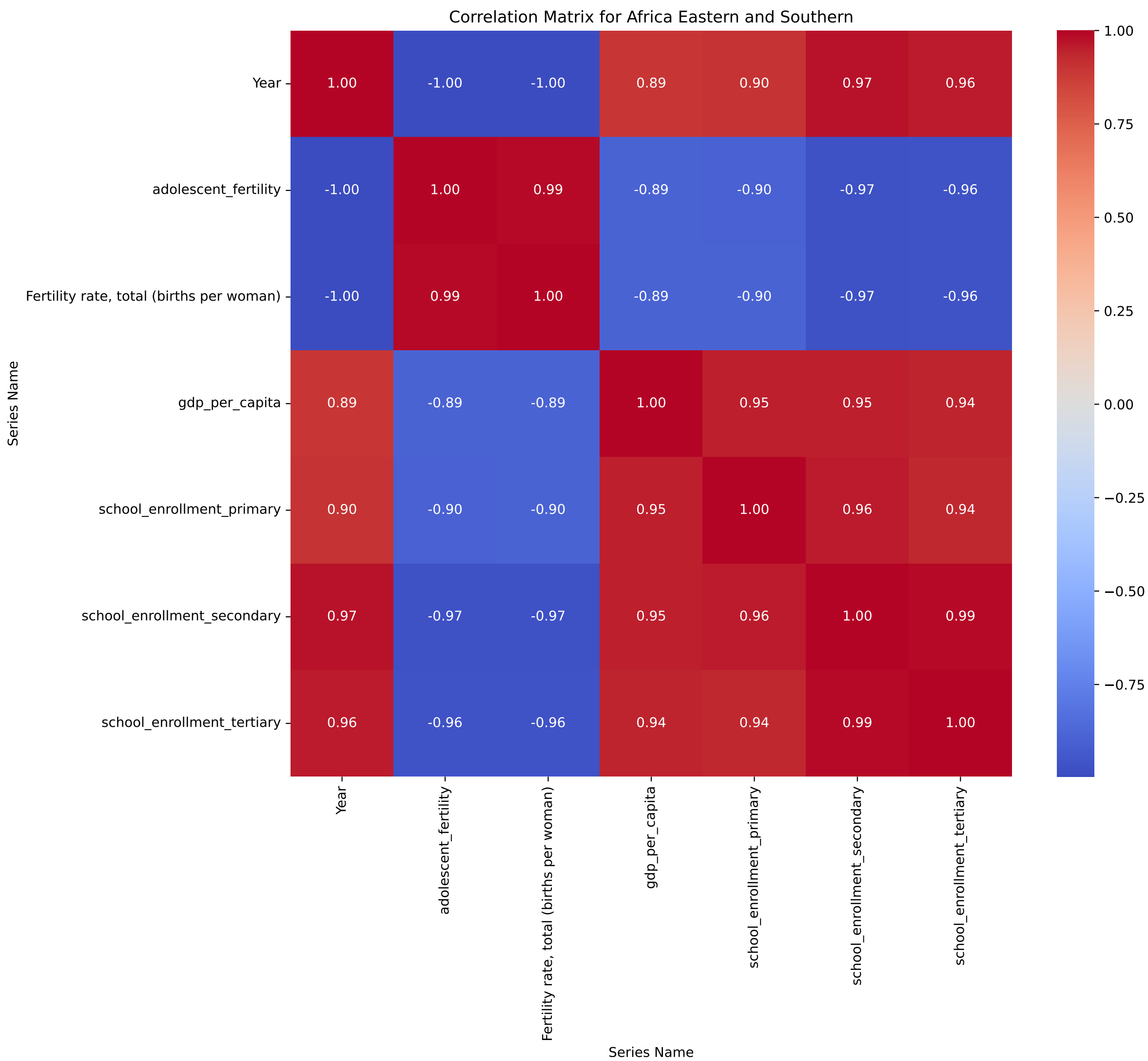
In this part, we generate the correlation matrices for all variables in four regions.

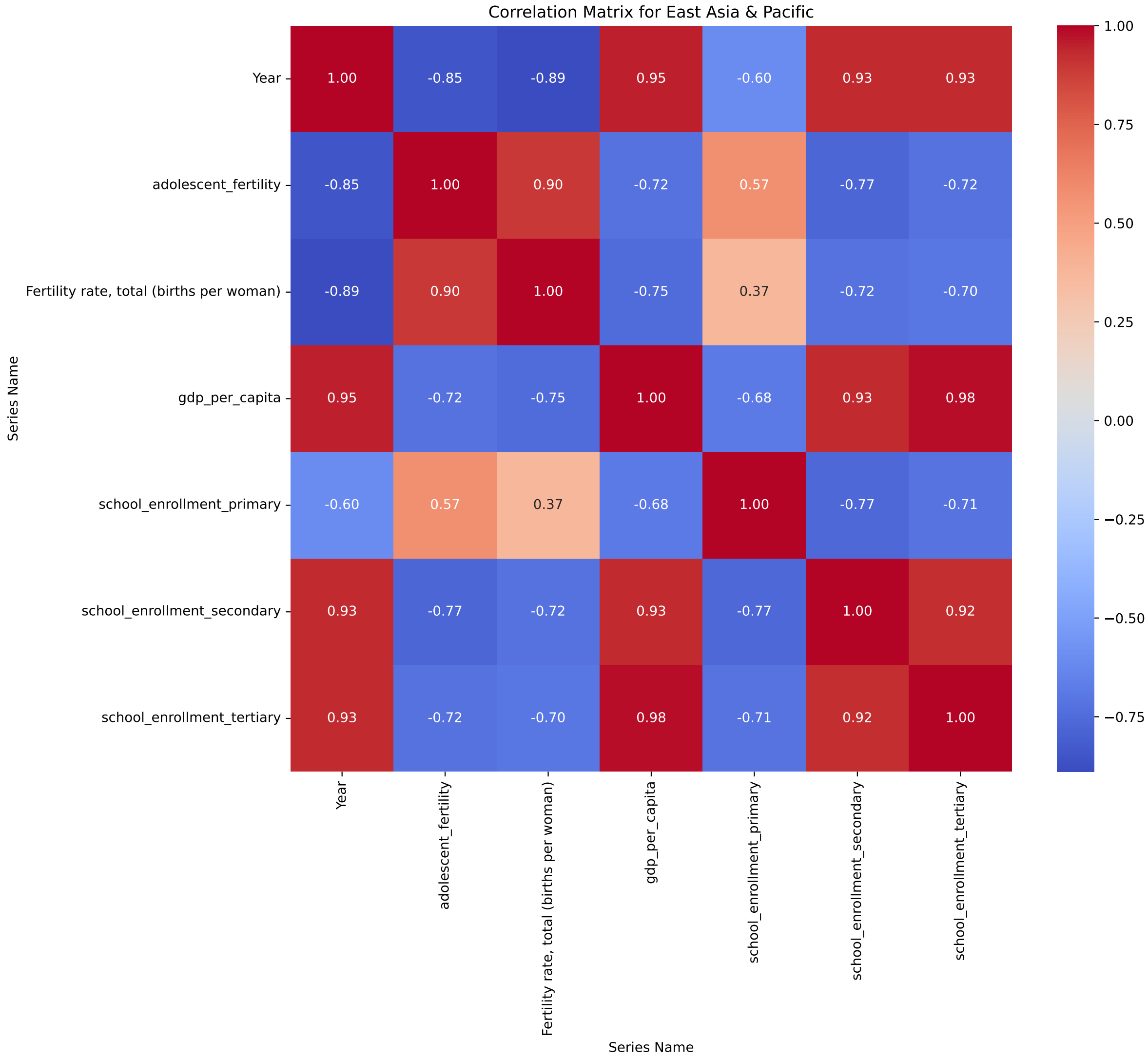
```
import seaborn as sns
import matplotlib.pyplot as plt

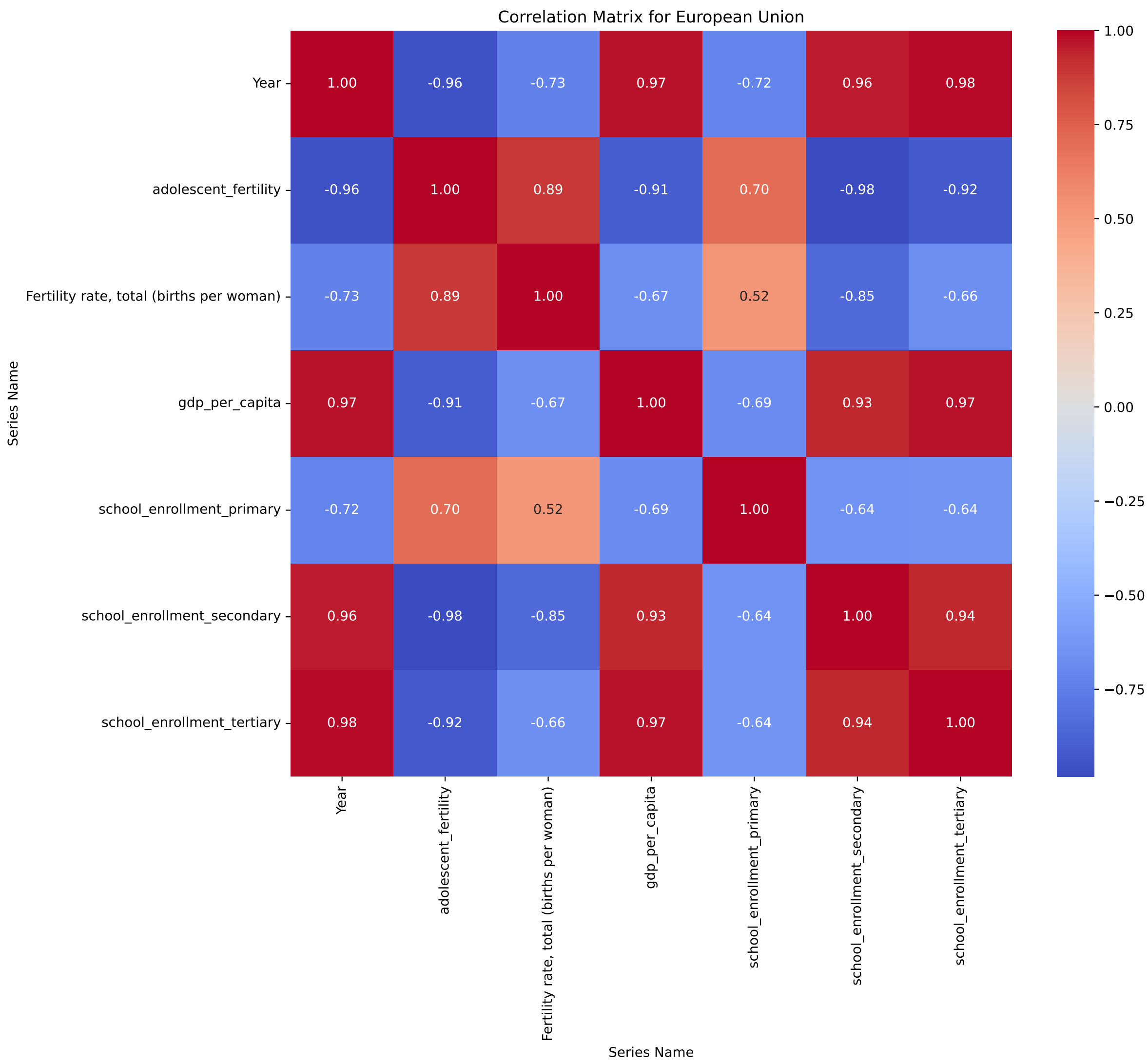
# Get the unique regions
regions = analysis_data['Region'].unique()

# Loop through each region and calculate the correlation matrix
for region in regions:
    region_data = analysis_data[analysis_data['Region'] == region]
    numeric_data = region_data.select_dtypes(include=[float, int])
    correlation_matrix = numeric_data.corr()

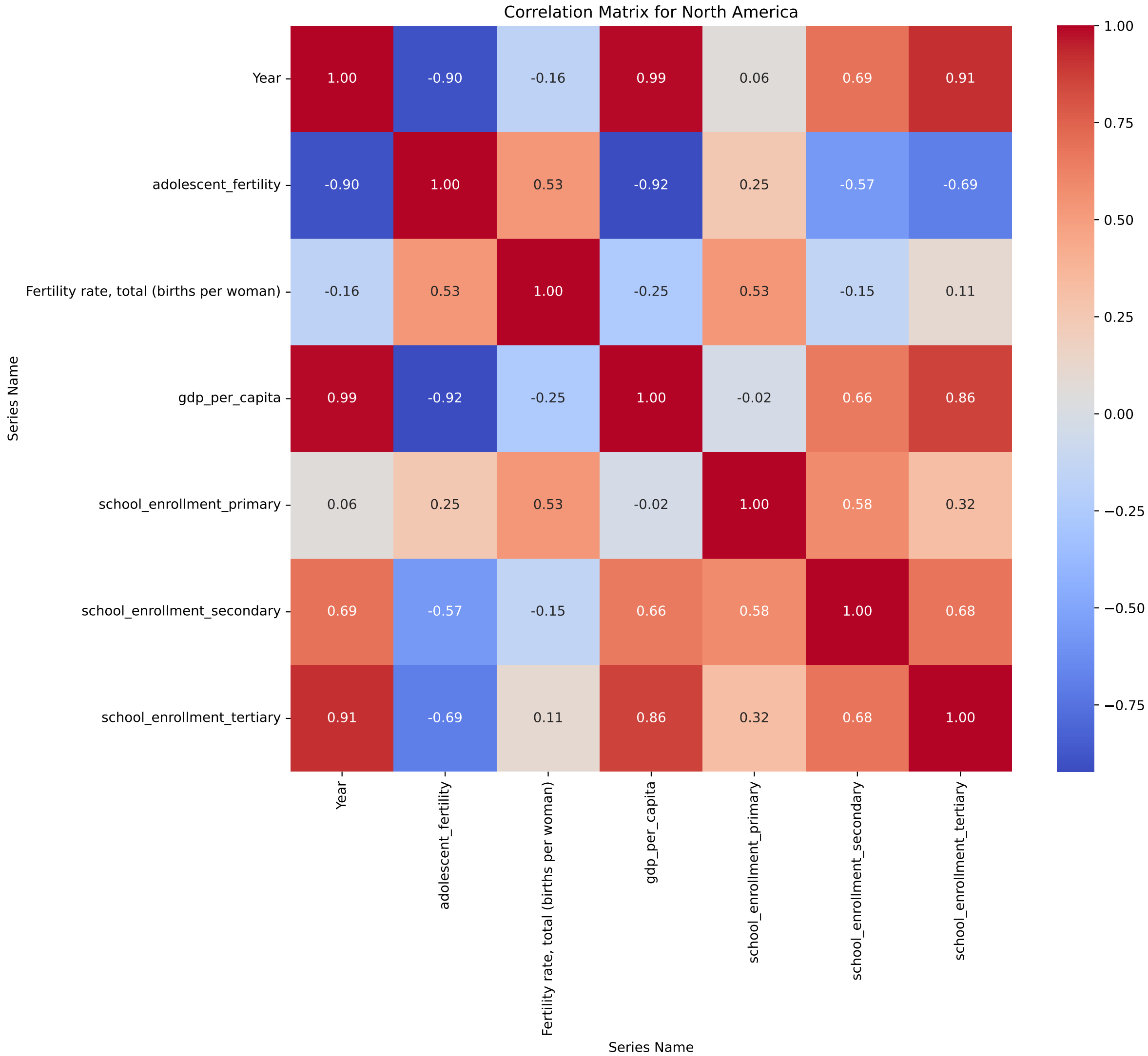
    # Plot the heatmap
    plt.figure(figsize=(12, 10))
    sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
    plt.title(f"Correlation Matrix for {region}")
    plt.savefig(f"{region}_correlation_matrix.png")
    plt.show()  # Close the plot to avoid overlapping
```


Correlation Matrix for Africa Eastern and Southern
Year
adolescent_fertility
Fertility rate, total (births per woman)
gdp_per_capita
school_enrollment_primary
school_enrollment_secondary
school_enrollment_tertiary
Series Name
1.00 -1.00 -1.00 0.89 0.90 0.97 0.96
-1.00 1.00 0.99 -0.89 -0.90 -0.97 -0.96
-1.00 0.99 1.00 -0.89 -0.90 -0.97 -0.96
0.89 -0.89 -0.89 1.00 0.95 0.95 0.94
0.90 -0.90 -0.90 0.95 1.00 0.96 0.94
0.97 -0.97 -0.97 0.95 0.96 1.00 0.99
0.96 -0.96 -0.96 0.94 0.94 0.99 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75


Correlation Matrix for East Asia & Pacific
Series Name
Year
adolescent_fertility
Fertility rate, total (births per woman)
gdp_per_capita
school_enrollment_primary
school_enrollment_secondary
school_enrollment_tertiary
1.00 -0.85 -0.89 0.95 -0.60 0.93 0.93
-0.85 1.00 0.90 -0.72 0.57 -0.77 -0.72
-0.89 0.90 1.00 -0.75 0.37 -0.72 -0.70
0.95 -0.72 -0.75 1.00 -0.68 0.93 0.98
-0.60 0.57 0.37 -0.68 1.00 -0.77 -0.71
0.93 -0.77 -0.72 0.93 -0.77 1.00 0.92
0.93 -0.72 -0.70 0.98 -0.71 0.92 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75



Correlation Matrix for European Union
Year
adolescent_fertility
Fertility rate, total (births per woman)
gdp_per_capita
school_enrollment_primary
school_enrollment_secondary
school_enrollment_tertiary
Series Name
1.00 -0.96 -0.73 0.97 -0.72 0.96 0.98
-0.96 1.00 0.89 -0.91 0.70 -0.98 -0.92
-0.73 0.89 1.00 -0.67 0.52 -0.85 -0.66
0.97 -0.91 -0.67 1.00 -0.69 0.93 0.97
-0.72 0.70 0.52 -0.69 1.00 -0.64 -0.64
0.96 -0.98 -0.85 0.93 -0.64 1.00 0.94
0.98 -0.92 -0.66 0.97 -0.64 0.94 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75



Findings:

1. The Role of Education: In all regions, higher secondary and tertiary school enrollments are strongly negatively correlated with adolescent fertility, which highlights the importance of advanced education in reducing teenage fertility rates.

2. Economic Influence: GDP per capita consistently shows a strong negative correlation with adolescent fertility rates, with wealthier regions tending to have lower adolescent fertility.

3. Regional Differences: Africa shows the strongest link between education and reduced fertility, while North America and East Asia show weaker correlations, indicating other factors may be at play.

Regression Analysis

OLS Regression before standardizing variables

We only include school__enrollment__secondary and tertiary since there is perfect multicollinearity within the school__enrollment category.

```
m1 = smf.ols(formula='adolescent_fertility ~ gdp_per_capita+ school_enrollment_secondary+scho
             data=analysis_data).fit()
# add dummies region and year
m2 = smf.ols(formula='adolescent_fertility ~ gdp_per_capita + school_enrollment_secondary+scl
             data=analysis_data).fit()
m2.summary()
```

Table 5: OLS Regression Results

Dep. Variable:	adolescent_fertility	R-squared:	0.995
Model:	OLS	Adj. R-squared:	0.993
Method:	Least Squares	F-statistic:	502.7
Date:	Mon, 09 Dec 2024	Prob (F-statistic):	1.76e-141
Time:	18:33:16	Log-Likelihood:	-512.12
No. Observations:	200	AIC:	1136.
Df Residuals:	144	BIC:	1321.
Df Model:	55		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	147.1038	2.190	67.184	0.000	142.776	151.432
C(Region)[T.East Asia & Pacific]	-108.1089	1.984	-54.502	0.000	-112.030	-104.188
C(Region)[T.European Union]	-133.3580	4.085	-32.647	0.000	-141.432	-125.284
C(Region)[T.North America]	-125.4724	4.295	-29.214	0.000	-133.962	-116.983
C(Year)[T.1975]	-1.8602	2.610	-0.713	0.477	-7.020	3.299
C(Year)[T.1976]	-3.7630	2.611	-1.441	0.152	-8.924	1.398
C(Year)[T.1977]	-4.9278	2.612	-1.886	0.061	-10.091	0.236
C(Year)[T.1978]	-7.1518	2.613	-2.737	0.007	-12.317	-1.987
C(Year)[T.1979]	-8.2173	2.612	-3.146	0.002	-13.380	-3.054
C(Year)[T.1980]	-9.2459	2.617	-3.533	0.001	-14.418	-4.074
C(Year)[T.1981]	-10.0428	2.616	-3.839	0.000	-15.213	-4.873
C(Year)[T.1982]	-9.6984	2.617	-3.705	0.000	-14.872	-4.525
C(Year)[T.1983]	-10.6243	2.618	-4.059	0.000	-15.798	-5.450
C(Year)[T.1984]	-11.4365	2.620	-4.365	0.000	-16.616	-6.257

C(Year)[T.1985]	-12.2202	2.623	-4.660	0.000	-17.404	-7.037
C(Year)[T.1986]	-13.4189	2.631	-5.101	0.000	-18.619	-8.219
C(Year)[T.1987]	-13.9575	2.641	-5.285	0.000	-19.178	-8.737
C(Year)[T.1988]	-14.4751	2.649	-5.464	0.000	-19.711	-9.239
C(Year)[T.1989]	-14.5984	2.654	-5.501	0.000	-19.843	-9.353
C(Year)[T.1990]	-13.7811	2.663	-5.176	0.000	-19.044	-8.518
C(Year)[T.1991]	-14.9258	2.669	-5.592	0.000	-20.201	-9.650
C(Year)[T.1992]	-18.0794	2.682	-6.742	0.000	-23.380	-12.779
C(Year)[T.1993]	-19.4731	2.696	-7.222	0.000	-24.802	-14.144
C(Year)[T.1994]	-22.0077	2.715	-8.107	0.000	-27.373	-16.642
C(Year)[T.1995]	-23.9605	2.730	-8.776	0.000	-29.357	-18.564
C(Year)[T.1996]	-25.0960	2.745	-9.142	0.000	-30.522	-19.670
C(Year)[T.1997]	-26.6556	2.752	-9.687	0.000	-32.094	-21.217
C(Year)[T.1998]	-26.9160	2.757	-9.764	0.000	-32.365	-21.467
C(Year)[T.1999]	-27.5346	2.768	-9.948	0.000	-33.005	-22.064
C(Year)[T.2000]	-28.2337	2.773	-10.180	0.000	-33.716	-22.752
C(Year)[T.2001]	-30.1111	2.792	-10.786	0.000	-35.629	-24.593
C(Year)[T.2002]	-32.6140	2.810	-11.606	0.000	-38.168	-27.060
C(Year)[T.2003]	-34.5024	2.844	-12.133	0.000	-40.123	-28.882
C(Year)[T.2004]	-35.7343	2.876	-12.424	0.000	-41.419	-30.049
C(Year)[T.2005]	-36.5688	2.912	-12.557	0.000	-42.325	-30.812
C(Year)[T.2006]	-37.3614	2.956	-12.640	0.000	-43.204	-31.519
C(Year)[T.2007]	-37.6682	3.016	-12.490	0.000	-43.629	-31.707
C(Year)[T.2008]	-37.9738	3.072	-12.361	0.000	-44.046	-31.902
C(Year)[T.2009]	-39.9337	3.083	-12.951	0.000	-46.028	-33.839
C(Year)[T.2010]	-41.5612	3.125	-13.300	0.000	-47.738	-35.385
C(Year)[T.2011]	-42.9045	3.173	-13.521	0.000	-49.177	-36.633
C(Year)[T.2012]	-44.3375	3.181	-13.940	0.000	-50.624	-38.051
C(Year)[T.2013]	-46.0675	3.223	-14.294	0.000	-52.438	-39.697
C(Year)[T.2014]	-48.0340	3.239	-14.830	0.000	-54.436	-41.632
C(Year)[T.2015]	-50.1660	3.221	-15.575	0.000	-56.532	-43.800
C(Year)[T.2016]	-51.7542	3.227	-16.036	0.000	-58.133	-45.375
C(Year)[T.2017]	-53.0040	3.258	-16.268	0.000	-59.444	-46.564
C(Year)[T.2018]	-54.1821	3.298	-16.426	0.000	-60.702	-47.662
C(Year)[T.2019]	-54.9807	3.321	-16.553	0.000	-61.546	-48.416
C(Year)[T.2020]	-56.4061	3.325	-16.966	0.000	-62.977	-49.835
C(Year)[T.2021]	-57.0683	3.408	-16.747	0.000	-63.804	-50.333
C(Year)[T.2022]	-57.5480	3.410	-16.876	0.000	-64.288	-50.808
C(Year)[T.2023]	-57.7344	3.457	-16.699	0.000	-64.568	-50.900
gdp_per_capita	-0.0001	5.04e-05	-2.067	0.041	-0.000	-4.54e-06
school_enrollment_secondary	0.0788	0.058	1.347	0.180	-0.037	0.194

school_enrollment_tertiary	0.5862	0.042	13.949	0.000	0.503	0.669

Omnibus:	4.037	Durbin-Watson:	0.172
Prob(Omnibus):	0.133	Jarque-Bera (JB):	2.651
Skew:	-0.079	Prob(JB):	0.266
Kurtosis:	2.458	Cond. No.	1.41e+06

```
ms = Stargazer([m1,m2])

HTML(ms.render_html())

ms.title('Regression on Fertility')
ms.custom_columns(['All','With Dummies'], [1, 1])
HTML(ms.render_html())
```

Through runing the OLS regression, we find that due to the inconsistent scale of different variables, it is difficult to make comparison between regressors. Also, there is strong multi-collinearity in our model. To address these problems, we standardize variables and use Ridge regression to compare with OLS regression. There might be too many dummy variables as well. So we create a different variable called year_grouped that classify them into decades.

Standardizing and refining dataset

```
# Step 1: Group years into decades
analysis_data["Year_grouped"] = (analysis_data["Year"] // 10) * 10
from sklearn.preprocessing import StandardScaler

# Create a copy of the dataset
scaled_data = analysis_data.copy()

# Initialize the scaler
scaler = StandardScaler()

# Select numeric columns to scale, excluding 'Year' and 'Year_grouped'
numeric_columns_to_scale = [
    col for col in scaled_data.select_dtypes(include=['float64', 'int64']).columns
    if col not in ['Year', 'Year_grouped']
]
```

```python
# Scale the selected numeric columns
scaled_data[numeric_columns_to_scale] = scaler.fit_transform(scaled_data[numeric_columns_to_s

# Ensure 'Year' and 'Year_grouped' remain unscaled
scaled_data['Year'] = analysis_data['Year']
scaled_data['Year_grouped'] = analysis_data['Year_grouped']
scaled_data['Region'] = analysis_data['Region']
```

```python
# Step 2: Add dummy variables for 'Region' and the new 'Year_grouped' column
df = pd.get_dummies(scaled_data, columns=["Region", "Year_grouped"], drop_first=True)

# Step 3: Replace boolean values (False -> 0, True -> 1) in the entire dataset
df = df.replace({False: 0, True: 1})

# Step 4: Confirm the changes
df.head()
```

```
/var/folders/ht/cp5bzsp52l15g4wdvrjntjmh0000gn/T/ipykernel_20207/1281065974.py:5: FutureWarn

Downcasting behavior in `replace` is deprecated and will be removed in a future version. To 
```

	Year	adolescent_fertility	Fertility rate, total (births per woman)	gdp_per_capita	school_enrollmen
0	1974	2.302721	2.313122	-0.853996	-3.083716
1	1975	2.288087	2.304245	-0.853207	-2.873967
2	1976	2.257421	2.293087	-0.853529	-2.740359
3	1977	2.220591	2.282584	-0.851384	-2.575036
4	1978	2.168030	2.272379	-0.849062	-2.477582

Comparison between Ridge and OLS Regression after revising dataset

```python
from sklearn.linear_model import RidgeCV, Ridge
from sklearn.metrics import r2_score, mean_squared_error
import statsmodels.api as sm

# Define predictors (X) and dependent variable (y)
X = df.drop(columns=["adolescent_fertility",'Fertility rate, total (births per woman)','Year
y = df['adolescent_fertility']
```

```python
# Fine-tune Ridge regression with cross-validation to select the best alpha
alphas = [0.1, 1.0, 10.0, 100.0]
ridge_cv = RidgeCV(alphas=alphas, cv=5).fit(X, y)

# Best alpha selected by cross-validation
best_alpha = ridge_cv.alpha_

# Fit Ridge regression with the best alpha
ridge_model = Ridge(alpha=best_alpha).fit(X, y)

# Extract coefficients from Ridge regression
ridge_coefficients = pd.DataFrame({
    'Variable': X.columns,
    'Coefficient': ridge_model.coef_
})

# Predictions and performance for Ridge regression
y_pred_ridge = ridge_model.predict(X)
ridge_r2 = r2_score(y, y_pred_ridge)
ridge_mse = mean_squared_error(y, y_pred_ridge)

# Fit OLS regression for comparison
ols_model = sm.OLS(y, sm.add_constant(X)).fit()
ols_r2 = ols_model.rsquared
ols_mse = mean_squared_error(y, ols_model.predict(sm.add_constant(X)))

# Extract coefficients from OLS regression
ols_coefficients = pd.DataFrame({
    'Variable': ['const'] + list(X.columns),
    'Coefficient': ols_model.params
})

# Display Results
print("Ridge Regression Coefficients:")
print(ridge_coefficients)
print(f"\nRidge Regression: R^2 = {ridge_r2:.3f}, MSE = {ridge_mse:.3f}, Best Alpha = {best_a

print("\nOLS Regression Coefficients:")
print(ols_coefficients)
print(f"\nOLS Regression: R^2 = {ols_r2:.3f}, MSE = {ols_mse:.3f}")
```

```
Ridge Regression Coefficients:
```

```
                      Variable  Coefficient
0               gdp_per_capita    -0.217385
1     school_enrollment_primary    -0.322671
2   school_enrollment_secondary    -0.516964
3    Region_East Asia & Pacific    -0.648517
4         Region_European Union    -0.294195
5          Region_North America     0.171980
6             Year_grouped_1980     0.000768
7             Year_grouped_1990    -0.009741
8             Year_grouped_2000     0.076593
9             Year_grouped_2010     0.137006
10            Year_grouped_2020     0.067865

Ridge Regression: R^2 = 0.958, MSE = 0.042, Best Alpha = 10.0

OLS Regression Coefficients:
                                                Variable  Coefficient
const                                              const     1.712919
gdp_per_capita                            gdp_per_capita    -0.078603
school_enrollment_primary      school_enrollment_primary    -0.125334
school_enrollment_secondary  school_enrollment_secondary     0.031347
Region_East Asia & Pacific    Region_East Asia & Pacific    -1.981365
Region_European Union              Region_European Union    -2.212790
Region_North America                Region_North America    -1.677342
Year_grouped_1980                      Year_grouped_1980    -0.053124
Year_grouped_1990                      Year_grouped_1990    -0.181312
Year_grouped_2000                      Year_grouped_2000    -0.308774
Year_grouped_2010                      Year_grouped_2010    -0.453222
Year_grouped_2020                      Year_grouped_2020    -0.571979

OLS Regression: R^2 = 0.987, MSE = 0.013
```

As shown in the table, ridge is better since it address multicollinearity and remain in a high r squared.

Run Ridge Model to Check Rubustness

```python
from sklearn.linear_model import RidgeCV, Ridge
from sklearn.metrics import r2_score, mean_squared_error
import pandas as pd
```

```
# Define a function to run Ridge regression with specified variable inclusions
def run_ridge_with_inclusion(X, y, variables_to_include):
    # Include only specified variables
    X_subset = X[variables_to_include]

    # Fine-tune Ridge regression with cross-validation to select the best alpha
    alphas = [0.1, 1.0, 10.0, 100.0]
    ridge_cv = RidgeCV(alphas=alphas, cv=5).fit(X_subset, y)

    # Best alpha selected by cross-validation
    best_alpha = ridge_cv.alpha_

    # Fit Ridge regression with the best alpha
    ridge_model = Ridge(alpha=best_alpha).fit(X_subset, y)

    # Predictions and performance metrics
    y_pred_ridge = ridge_model.predict(X_subset)
    ridge_r2 = r2_score(y, y_pred_ridge)
    ridge_mse = mean_squared_error(y, y_pred_ridge)

    # Return coefficients, R^2, MSE, and selected alpha
    coefficients = pd.DataFrame({
        'Variable': X_subset.columns,
        'Coefficient': ridge_model.coef_
    })
    return coefficients, ridge_r2, ridge_mse, best_alpha

# Example dataset (assume scaled_data is preprocessed and available)
X = df.drop(columns=["adolescent_fertility",'Fertility rate, total (births per woman)','Year
y = df['adolescent_fertility']

# Define variable inclusion sets
variable_sets = [
    ['gdp_per_capita'],  # Step 1: GDP per capita only
    ['gdp_per_capita', 'school_enrollment_primary', 'school_enrollment_secondary'],  # Step 2
    ['gdp_per_capita', 'school_enrollment_primary', 'school_enrollment_secondary', 'Region_Ea
    ['gdp_per_capita', 'school_enrollment_primary', 'school_enrollment_secondary', 'Region_Ea
]

# Loop through variable sets and run Ridge regression
results = []
for variables in variable_sets:
```

```python
    coefficients, ridge_r2, ridge_mse, best_alpha = run_ridge_with_inclusion(X, y, variables_
    results.append({
        'Included Variables': variables,
        'R^2': ridge_r2,
        'MSE': ridge_mse,
        'Best Alpha': best_alpha,
        'Coefficients': coefficients
    })

# Display the results
for result in results:
    print(f"Included Variables: {result['Included Variables']}")
    print(f"R^2: {result['R^2']:.3f}, MSE: {result['MSE']:.3f}, Best Alpha: {result['Best Al
    print("Coefficients:")
    print(result['Coefficients'])
    print("\n" + "="*80 + "\n")
```

```
Included Variables: ['gdp_per_capita']
R^2: 0.225, MSE: 0.775, Best Alpha: 100.0
Coefficients:
         Variable  Coefficient
0  gdp_per_capita    -0.335722

================================================================================

Included Variables: ['gdp_per_capita', 'school_enrollment_primary', 'school_enrollment_secon
R^2: 0.851, MSE: 0.149, Best Alpha: 1.0
Coefficients:
                    Variable  Coefficient
0             gdp_per_capita    -0.010159
1    school_enrollment_primary    -0.471573
2  school_enrollment_secondary    -0.587996

================================================================================

Included Variables: ['gdp_per_capita', 'school_enrollment_primary', 'school_enrollment_secon
R^2: 0.952, MSE: 0.048, Best Alpha: 10.0
Coefficients:
                    Variable  Coefficient
0             gdp_per_capita    -0.186083
1    school_enrollment_primary    -0.316172
2  school_enrollment_secondary    -0.509877
```

```
3   Region_East Asia & Pacific    -0.656009
4        Region_European Union    -0.328958
5         Region_North America     0.117550

================================================================================

Included Variables: ['gdp_per_capita', 'school_enrollment_primary', 'school_enrollment_secon
R^2: 0.958, MSE: 0.042, Best Alpha: 10.0
Coefficients:
                      Variable  Coefficient
0               gdp_per_capita    -0.217385
1    school_enrollment_primary    -0.322671
2  school_enrollment_secondary    -0.516964
3   Region_East Asia & Pacific    -0.648517
4        Region_European Union    -0.294195
5         Region_North America     0.171980
6            Year_grouped_1980     0.000768
7            Year_grouped_1990    -0.009741
8            Year_grouped_2000     0.076593
9            Year_grouped_2010     0.137006
10           Year_grouped_2020     0.067865

================================================================================
```

After trying different ridge models, the coefficients for regressors do not change significantly.

1. Economic and Educational Factors:

- gdp_per_capita (-0.217): A 1-standard-deviation increase in GDP per capita is associated with a 0.217 standard deviation decrease in adolescent fertility. This aligns with the expectation that economic development reduces fertility rates, particularly among adolescents.
- school_enrollment_primary (-0.323) and school_enrollment_secondary (-0.517): Higher enrollment rates in primary and secondary education are strongly associated with lower adolescent fertility rates. Secondary education has a more effect, indicating its critical role in delaying childbearing.

2. Regional Effects:

- Region_East Asia & Pacific (-0.649) and Region_European Union (-0.294): Adolescent fertility is significantly lower in these regions compared to Africa Eastern and Southern.
- Region_North America (0.172): This positive coefficient indicates slightly higher fertility in North America compared to Africa Eastern and Southern.

3. Temporal Trends

- Year Dummies (Year_grouped_1980 to Year_grouped_2020): The coefficients for year groups are relatively small, indicating gradual changes in fertility over decades. Later years (e.g., 2010, 2020) show positive coefficients compared to earlier years, suggesting slight increases in adolescent fertility over time, though the effects are minimal.

Discussion

The findings underscore the critical importance of economic and educational interventions in addressing adolescent fertility, particularly in high-fertility regions. However, several limitations should be noted.

First, the use of grouped year variables may oversimplify temporal changes and miss finer trends within shorter time intervals. Second, multicollinearity among predictors, especially between education and regional variables, could influence the stability of coefficients despite the use of Ridge regression. Third, the exclusion of potentially relevant variables, such as cultural factors or healthcare access, limits the scope of the analysis.

Future studies could address these limitations by incorporating additional predictors, testing interaction effects, and using alternative modeling techniques to further disentangle the complex relationships influencing adolescent fertility. Despite these limitations, the results provide valuable insights for policymakers aiming to reduce adolescent fertility rates through targeted investments in education and economic development.

References