Project Milestone 5:

Merging the Data and Storing in a Database/Visualizing Data

Now that you have cleaned and transformed your 3 datasets, you need to load them into a database. You can choose what kind of database (SQLLite or MySQL, Postgre SQL are all free options). You will want to load each dataset into SQL Lite as an individual table and then you must join the datasets together in Python into 1 dataset.

Once all the data is merged together in your database, create 5 visualizations that demonstrate the data you have cleansed. You should have at least 2 visualizations that have data from more than one source (meaning, if you have 3 tables, you must have visualizations that span across 2 of the tables – you are also welcome to use your consolidated dataset that you created in the previous step, if you do that, you have met this requirement).

For the visualization portion of the project, you are welcome to use a python library like Matplotlib, Seaborn, or an R package ggPlot2, Plotly, or Tableau/PowerBI.

Clearly label each visualization. Submit your code for merging and storing in the database, with your code for the visualizations along with a 250-500-word summary of what you learned and had to do to complete the project. In your write-up, make sure to address the ethical implications of cleansing data and your project topic.

In [1]:
```
# Load necessary libraries
import sqlite3
import pandas as pd
import numpy as np
import geopandas as gpd
from shapely.geometry import Polygon
import matplotlib.pyplot as plt
from mpl_toolkits.axes_grid1 import make_axes_locatable
import seaborn as sns
from fuzzywuzzy import process
import warnings

# Ignore all warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Load the three CSV files into DataFrames
flat_file_df = pd.read_csv('C:/Users/aliss/OneDrive - Bellevue University/DSC540/Cleaned_EdStatsData.csv')
website_df = pd.read_csv('C:/Users/aliss/OneDrive - Bellevue University/DSC540/Cleaned_WebsiteData.csv')
api_df = pd.read_csv('C:/Users/aliss/OneDrive - Bellevue University/DSC540/Cleaned_APIData.csv')

# Create a SQLite connection
conn = sqlite3.connect('DSC540Project.db')

# Load each DataFrame into a separate table
flat_file_df.to_sql(name='table_flat_file_df', con=conn, index=False, if_exists='replace')
website_df.to_sql(name='table_website_df', con=conn, index=False, if_exists='replace')
api_df.to_sql(name='table_api_df', con=conn, index=False, if_exists='replace')
```

Out[2]: 66

In [3]:
```
%load_ext sql
%sql sqlite:///DSC540Project.db
```

In [4]:
```
%sql SELECT * FROM table_flat_file_df LIMIT 5;
```

```
 * sqlite:///DSC540Project.db
Done.
```

Out[4]:

Country	Rate	Year
Arab World	77%	2014
East Asia & Pacific	95%	2014
East Asia & Pacific (excluding high income)	95%	2014
Europe & Central Asia	99%	2014
Europe & Central Asia (excluding high income)	99%	2014

In [5]:
```
%sql SELECT * FROM table_website_df LIMIT 5;
```

```
 * sqlite:///DSC540Project.db
Done.
```

Out[5]:

Country	Rate	Year
Afghanistan	32%	2011
Albania	97%	2012
Algeria	75%	2008
American Samoa	97%	1980
Angola	66%	2014

In [6]:
```
%sql SELECT * FROM table_api_df LIMIT 5;
```

```
 * sqlite:///DSC540Project.db
Done.
```

Out[6]:

Country	Rate	Year
Africa Eastern and Southern	73%	2022
Africa Western and Central	60%	2022
Arab World	75%	2022
Azerbaijan	100%	2019
Bangladesh	75%	2020

In [7]:
```
# Append data from table_website_df to table_flat_file_df
insert_query_website = '''
    INSERT INTO table_flat_file_df (Country, Rate, Year)
    SELECT Country, Rate, Year
    FROM table_website_df
    WHERE Country NOT IN (SELECT Country FROM table_flat_file_df);
'''

# Execute the insert query
%sql $insert_query_website

# Append data from table_api_df to table_flat_file_df
insert_query_api = '''
    INSERT INTO table_flat_file_df (Country, Rate, Year)
    SELECT Country, Rate, Year
    FROM table_api_df
    WHERE Country NOT IN (SELECT Country FROM table_flat_file_df);
'''

# Execute the insert query
%sql $insert_query_api

# Select all columns from the updated table_flat_file_df
result_query = '''
    SELECT *
    FROM table_flat_file_df;
'''

# Execute the select query
result = %sql $result_query
```

```python
# Display the result
result.DataFrame()
```

```
 * sqlite:///DSC540Project.db
171 rows affected.
 * sqlite:///DSC540Project.db
22 rows affected.
 * sqlite:///DSC540Project.db
Done.
```

Out[7]:

	Country	Rate	Year
0	Arab World	77%	2014
1	East Asia & Pacific	95%	2014
2	East Asia & Pacific (excluding high income)	95%	2014
3	Europe & Central Asia	99%	2014
4	Europe & Central Asia (excluding high income)	99%	2014
...	...	...	...
262	Latin America & the Caribbean (IDA & IBRD coun...	95%	2022
263	Middle East & North Africa (IDA & IBRD countries)	77%	2022
264	South Asia (IDA & IBRD)	74%	2022
265	Sub-Saharan Africa (IDA & IBRD countries)	68%	2022
266	Turkiye	97%	2019

267 rows × 3 columns

Visualization 1:

In [8]:

```python
# Query to select all columns from the combined table
combined_query = '''
    SELECT *
    FROM table_flat_file_df;
'''

# Execute the select query and load the data into a DataFrame
combined_df = pd.read_sql_query(combined_query, conn)

# Convert 'Year' column to numeric values for visualizations
combined_df['Year'] = pd.to_numeric(combined_df['Year'], errors='coerce')

# Remove '%' from 'Rate' column and convert back to float for visualizations
combined_df['Rate'] = combined_df['Rate'].replace('%', '', regex=True).astype('float')
```

In [9]:

```python
# Load GeoJSON file with country geometries into GeoDataFrame
gdf = gpd.read_file('C:/Users/aliss/OneDrive - Bellevue University/DSC540/countries.geojson')

# Display the GeoDataFrame structure
gdf
```

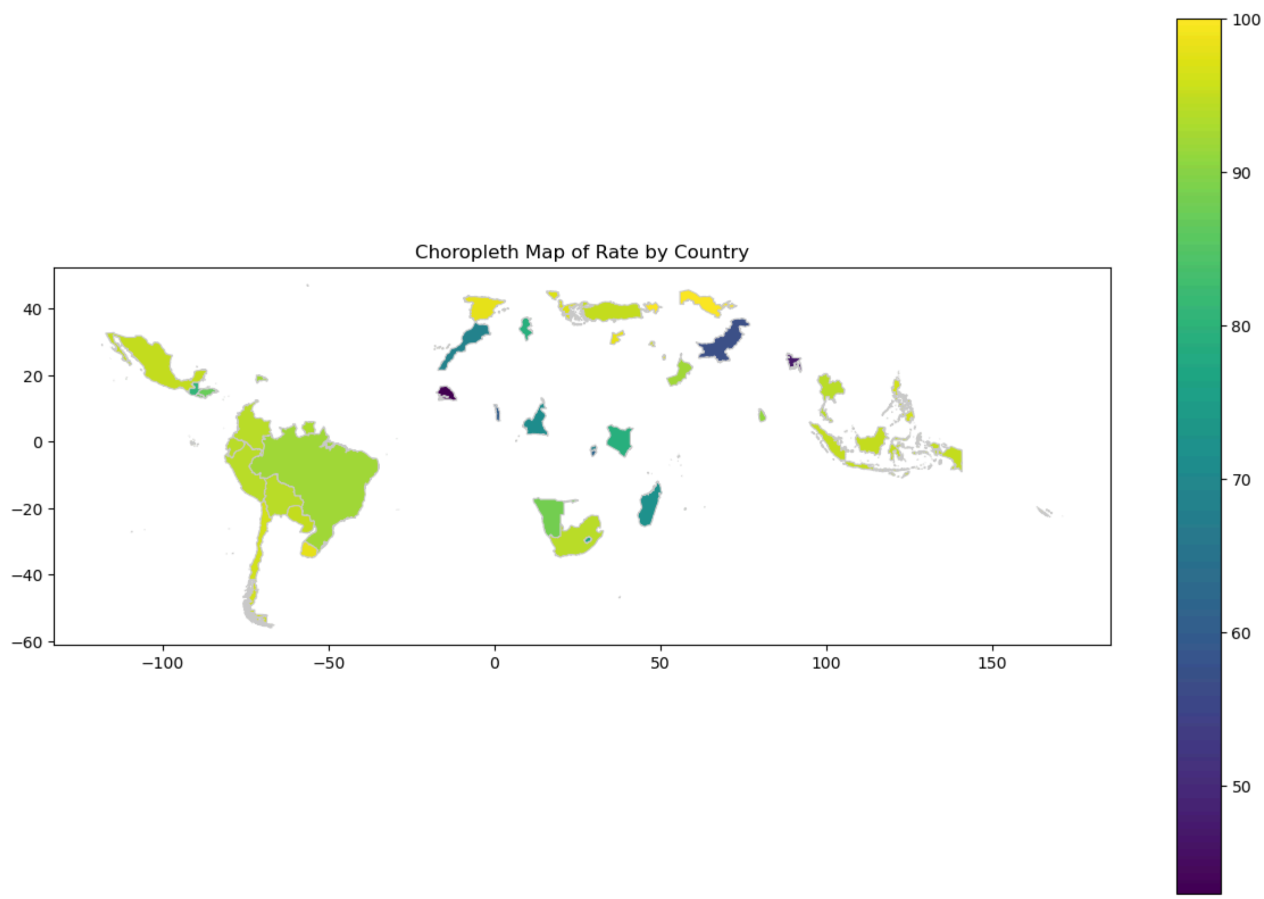
Out[9]:

	ADMIN	ISO_A3	geometry
0	Aruba	ABW	POLYGON ((-69.99694 12.57758, -69.93639 12.531...
1	Afghanistan	AFG	POLYGON ((71.04980 38.40866, 71.05714 38.40903...
2	Angola	AGO	MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...
3	Anguilla	AIA	MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...
4	Albania	ALB	POLYGON ((19.74777 42.57890, 19.74601 42.57993...
...	...	...	...
250	Samoa	WSM	MULTIPOLYGON (((-171.57002 -13.93816, -171.564...
251	Yemen	YEM	MULTIPOLYGON (((53.30824 12.11839, 53.31027 12...
252	South Africa	ZAF	MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...
253	Zambia	ZMB	POLYGON ((31.11984 -8.61663, 31.14102 -8.60619...
254	Zimbabwe	ZWE	POLYGON ((30.01065 -15.64623, 30.05024 -15.640...

255 rows × 3 columns

In [10]:

```python
# Merge the GeoDataFrame with combined_df
merged = gdf.merge(combined_df, left_on='ADMIN', right_on='Country')

# Create a choropleth map using the 'Rate' column
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
merged.plot(column='Rate', cmap='viridis', linewidth=0.8, ax=ax, edgecolor='0.8', legend=True)

# Add a title
plt.title('Choropleth Map of Rate by Country')

# Show the map
plt.show()
```



When merging the map data with my dataframe, there seems to be a lot of missing data, so I'm going to fuzzy match the Country geometries with the Country column in my dataframe and create a new gdf to .GeoDataFrame using the matched data and see if it creates a better map.

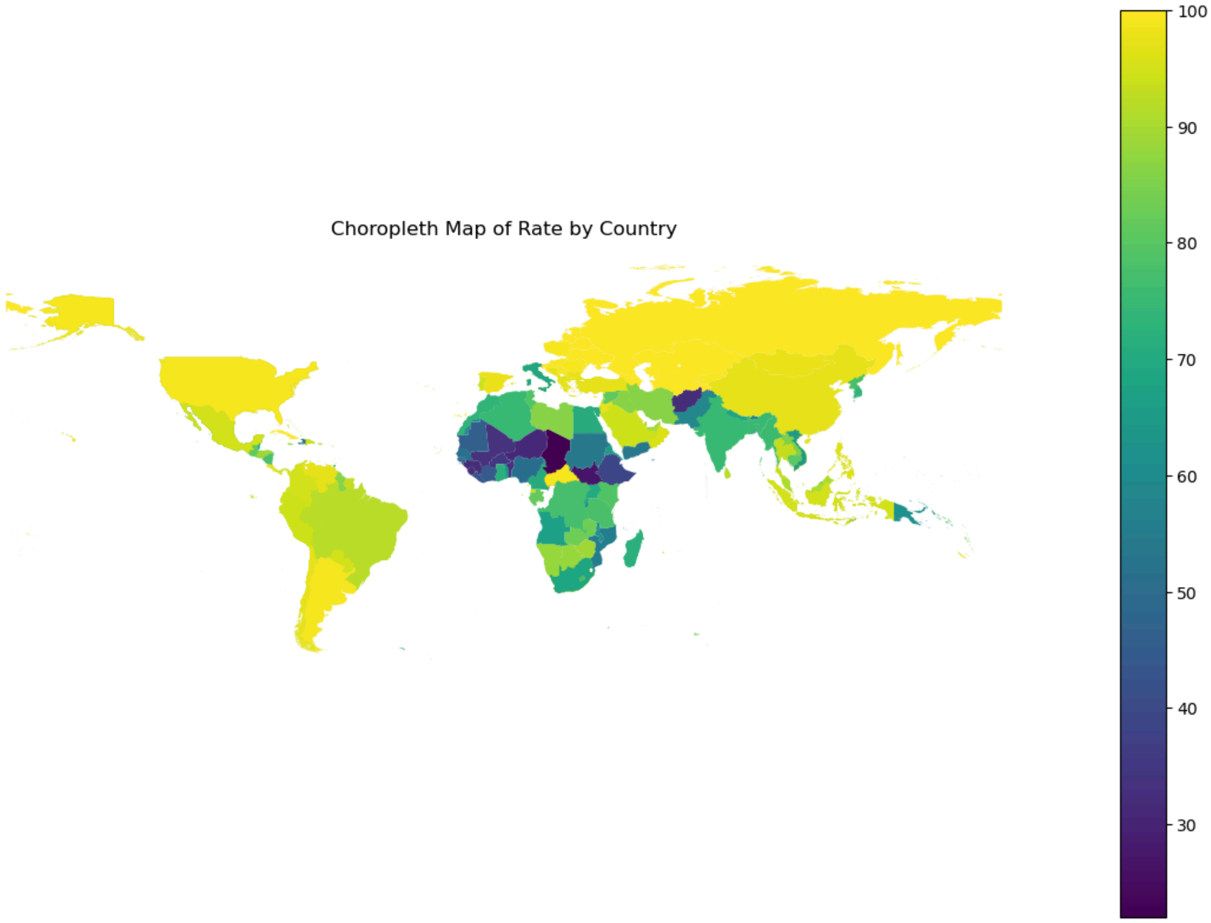
In [11]:
```
gdf_names = gdf['ADMIN'].tolist()
combined_df_names = combined_df['Country'].tolist()

# Use fuzzy matching to find the best match for each country
matches = [(country, process.extractOne(country, gdf_names)[0]) for country in combined_df_names]

# Create a dictionary mapping combined_df country names to gdf country names
mapping_dict = {combined_country: gdf_country for combined_country, gdf_country in matches}

# Add the 'geometry' column from gdf to combined_df based on the mapping
combined_df['geometry'] = combined_df['Country'].map(mapping_dict).map(gdf.set_index('ADMIN')['geometry'])

# Now combined_df contains the 'geometry' column
combined_df
```

Out[11]:

	Country	Rate	Year	geometry
0	Arab World	77.0	2014	MULTIPOLYGON (((53.86305 24.23469, 53.88860 24...
1	East Asia & Pacific	95.0	2014	MULTIPOLYGON (((124.35456 -9.36418, 124.34789 ...
2	East Asia & Pacific (excluding high income)	95.0	2014	MULTIPOLYGON (((124.35456 -9.36418, 124.34789 ...
3	Europe & Central Asia	99.0	2014	MULTIPOLYGON (((111.41245 2.38736, 111.41334 2...
4	Europe & Central Asia (excluding high income)	99.0	2014	POLYGON ((22.55576 10.97897, 22.57705 10.98512...
...	...	...	...	...
262	Latin America & the Caribbean (IDA & IBRD coun...	95.0	2022	MULTIPOLYGON (((-73.03393 21.15673, -73.09759 ...
263	Middle East & North Africa (IDA & IBRD countries)	77.0	2022	MULTIPOLYGON (((125.31275 37.74140, 125.29575 ...
264	South Asia (IDA & IBRD)	74.0	2022	MULTIPOLYGON (((126.82337 33.55944, 126.83522 ...
265	Sub-Saharan Africa (IDA & IBRD countries)	68.0	2022	MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...
266	Turkiye	97.0	2019	MULTIPOLYGON (((26.04005 39.84504, 26.04623 39...

267 rows × 4 columns

In [12]:
```
# Create new GeoDataFrame using combined_df and gdf geometries
gdf2 = gpd.GeoDataFrame(combined_df, geometry='geometry')

# Plotting
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
gdf2.plot(column='Rate', cmap='viridis', linewidth=0.8, ax=ax, legend=True)

# Customize the plot as needed
ax.set_title('Choropleth Map of Rate by Country')
ax.set_axis_off()

plt.show()
```



SO MUCH BETTER! :D

In [13]:
```
# Create new GeoDataFrame using combined_df and gdf geometries
gdf2 = gpd.GeoDataFrame(combined_df, geometry='geometry')

# Plotting
fig, ax = plt.subplots(1, 1, figsize=(15, 10))
gdf2.plot(column='Year', cmap='viridis', linewidth=0.8, ax=ax, legend=True)

# Customize the plot as needed
ax.set_title('Choropleth Map of Year by Country')
ax.set_axis_off()

plt.show()
```

Because the gdp geometries also contain Continent and Population data, I'm going to merge the full data frame with my combined_df to get some better visuals to graph.

In [14]:

```
# Prepare data to merge and fuzzymatch
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Add column for GDP per capita
world = world[(world.pop_est>0) & (world.name!="Antarctica")]
world['gdp_per_cap'] = world.gdp_md_est / world.pop_est
#world.plot(column='gdp_per_cap')

# Create copy of df
combined_df_2 = combined_df.copy()

# Use fuzzy matching to find the best match for each country
matches = [(country, process.extractOne(country, world['name'])[0]) for country in combined_df_2['Country']]

# Create a dictionary mapping combined_df country names to gdf country names
mapping_dict = {combined_country: gdf_country for combined_country, gdf_country in matches}

# Add the 'geometry' column from gdf to combined_df based on the mapping
combined_df_2['gdf_name'] = combined_df_2['Country'].map(mapping_dict)
merged_df = pd.merge(combined_df_2, world, left_on='gdf_name', right_on='name', how='left')

# Now combined_df contains the 'continent', 'pop_est', and 'gdp_per_capita' columns
combined_df_2 = pd.concat([combined_df_2, merged_df[['continent', 'pop_est', 'gdp_per_cap']]], axis=1)

# Drop the intermediate column 'gdf_name' if needed
combined_df_2 = combined_df_2.drop('gdf_name', axis=1)

# Display the resulting DataFrame
combined_df_2
```

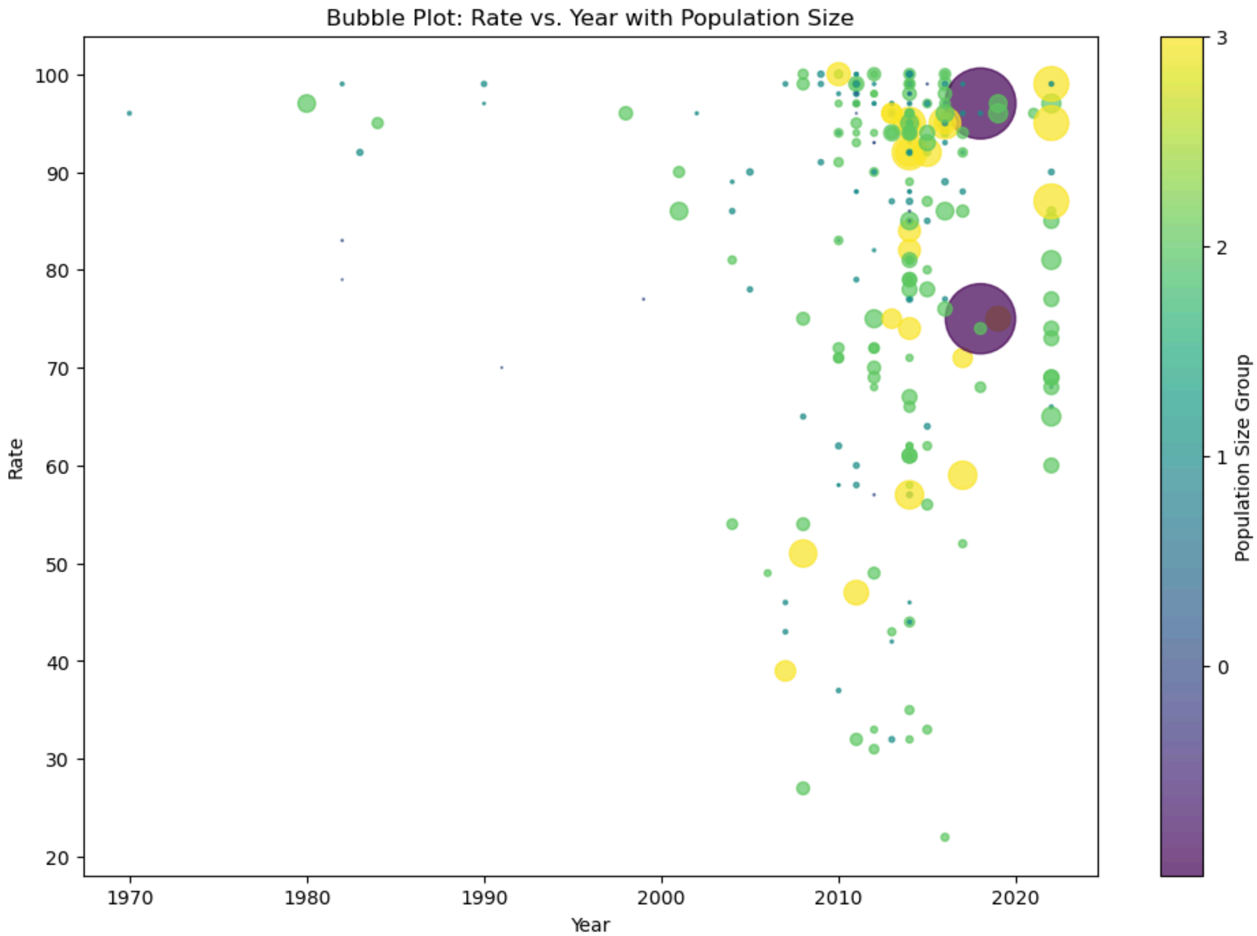
Out[14]:

	Country	Rate	Year	geometry	continent	pop_est	gdp_per_cap
0	Arab World	77.0	2014	MULTIPOLYGON (((53.86305 24.23469, 53.88860 24...	Asia	9770529.0	0.043103
1	East Asia & Pacific	95.0	2014	MULTIPOLYGON (((124.35456 -9.36418, 124.34789 ...	Oceania	25364307.0	0.055060
2	East Asia & Pacific (excluding high income)	95.0	2014	MULTIPOLYGON (((124.35456 -9.36418, 124.34789 ...	Oceania	25364307.0	0.055060
3	Europe & Central Asia	99.0	2014	MULTIPOLYGON (((111.41245 2.38736, 111.41334 2...	Asia	31949777.0	0.011414
4	Europe & Central Asia (excluding high income)	99.0	2014	POLYGON ((22.55576 10.97897, 22.57705 10.98512...	Africa	4745185.0	0.000468
...	...	...	...	...	...	...	...
262	Latin America & the Caribbean (IDA & IBRD coun...	95.0	2022	MULTIPOLYGON (((-73.03393 21.15673, -73.09759 ...	North America	328239523.0	0.065298
263	Middle East & North Africa (IDA & IBRD countries)	77.0	2022	MULTIPOLYGON (((125.31275 37.74140, 125.29575 ...	Africa	58558270.0	0.006001
264	South Asia (IDA & IBRD)	74.0	2022	MULTIPOLYGON (((126.82337 33.55944, 126.83522 ...	Africa	58558270.0	0.006001
265	Sub-Saharan Africa (IDA & IBRD countries)	68.0	2022	MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...	Africa	58558270.0	0.006001
266	Turkiye	97.0	2019	MULTIPOLYGON (((26.04005 39.84504, 26.04623 39...	Asia	83429615.0	0.009127

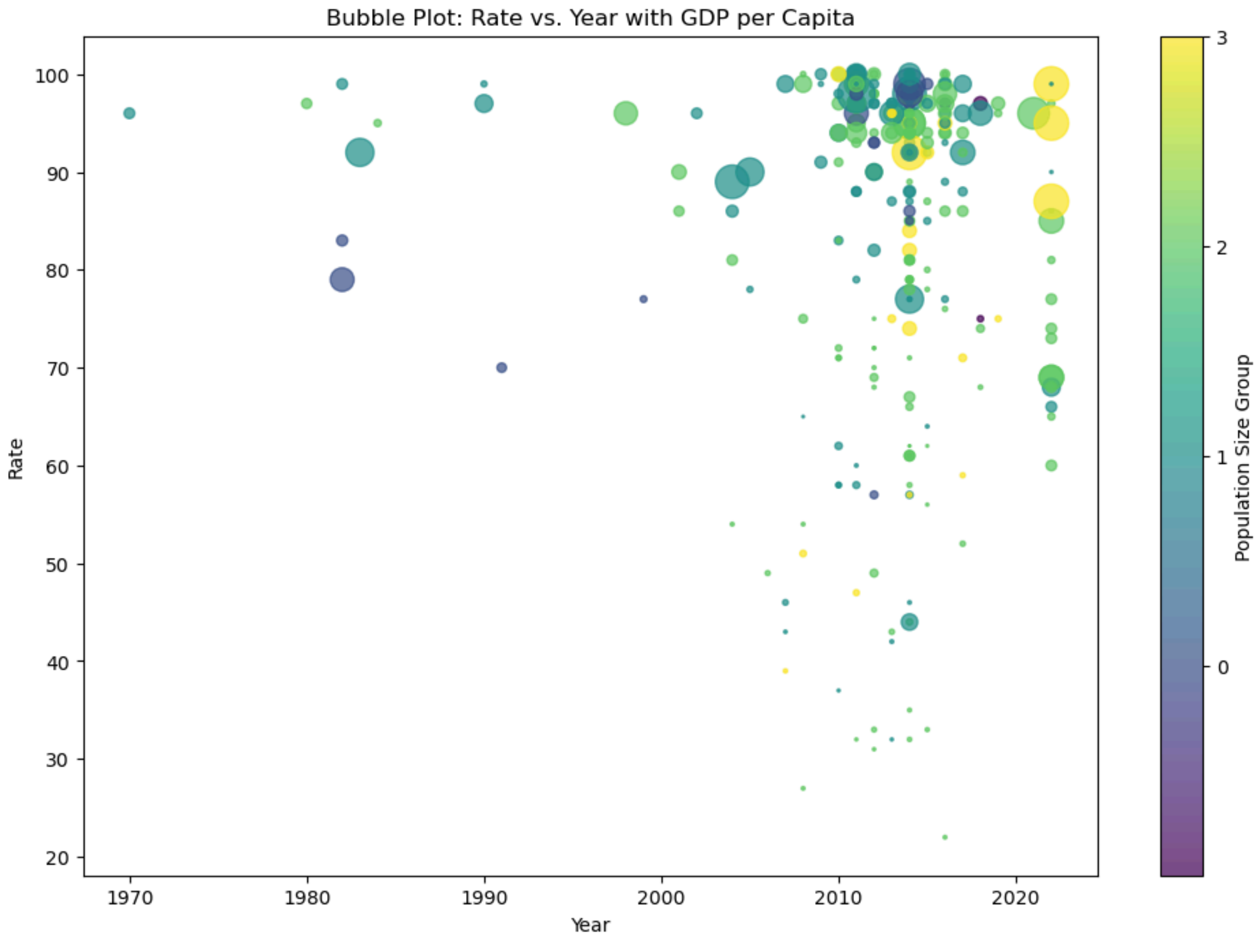
267 rows × 7 columns

In [15]:

```
# Create a 'pop_est_group' column based on population size
bins = [0, 10**6, 10**7, 10**8, 10**9]  # Define your population size bins
labels = ['<1M', '1M-10M', '10M-100M', '>100M']
combined_df_2['pop_est_group'] = pd.cut(combined_df_2['pop_est'], bins=bins, labels=labels, right=False)

# Bubble plot
plt.figure(figsize=(12, 8))
scatter = plt.scatter(
    combined_df_2['Year'],
    combined_df_2['Rate'],
    s=combined_df_2['pop_est'] / 1000000,  # Adjust the scaling factor as needed
    c=combined_df_2['pop_est_group'].cat.codes,  # Color by population size group
    cmap='viridis',
    alpha=0.7
)

# Add colorbar
cbar = plt.colorbar(scatter, ticks=range(len(labels)))
cbar.set_label('Population Size Group')

# Set labels and title
plt.xlabel('Year')
plt.ylabel('Rate')
plt.title('Bubble Plot: Rate vs. Year with Population Size')

# Show the plot
plt.show()
```

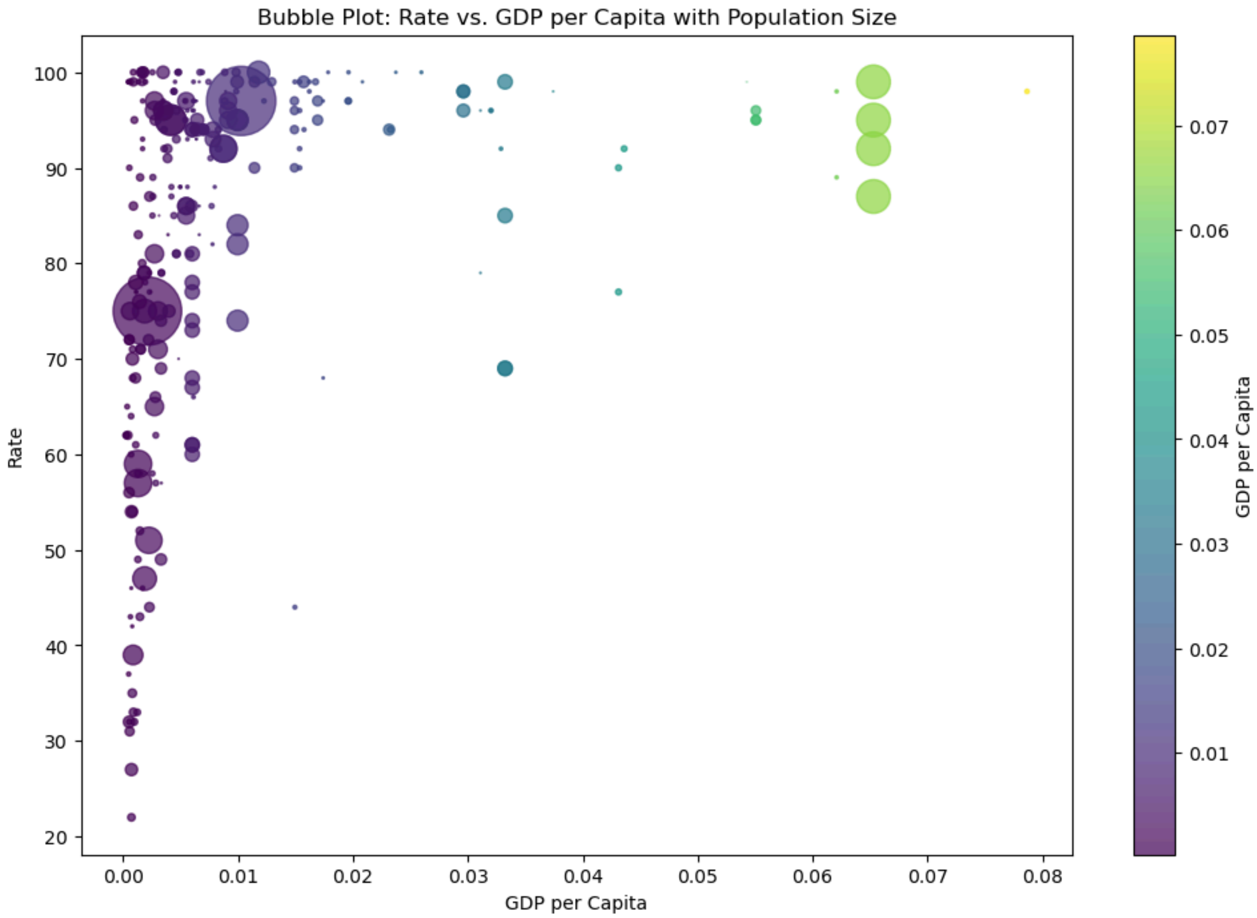


In [16]:
```
# Convert 'pop_est_group' to numerical codes
combined_df_2['pop_est_group_code'] = combined_df_2['pop_est_group'].cat.codes

# Bubble plot with size based on 'gdp_per_cap'
plt.figure(figsize=(12, 8))
scatter = plt.scatter(
    combined_df_2['Year'],
    combined_df_2['Rate'],
    s=combined_df_2['gdp_per_cap'] * 5000,  # Adjust the scaling factor as needed
    c=combined_df_2['pop_est_group_code'],  # Color by numerical code of population size group
    cmap='viridis',
    alpha=0.7
)

# Add colorbar
cbar = plt.colorbar(scatter, ticks=range(len(combined_df_2['pop_est_group'].unique())))
cbar.set_label('Population Size Group')

# Set labels and title
plt.xlabel('Year')
plt.ylabel('Rate')
plt.title('Bubble Plot: Rate vs. Year with GDP per Capita')

# Show the plot
plt.show()
```

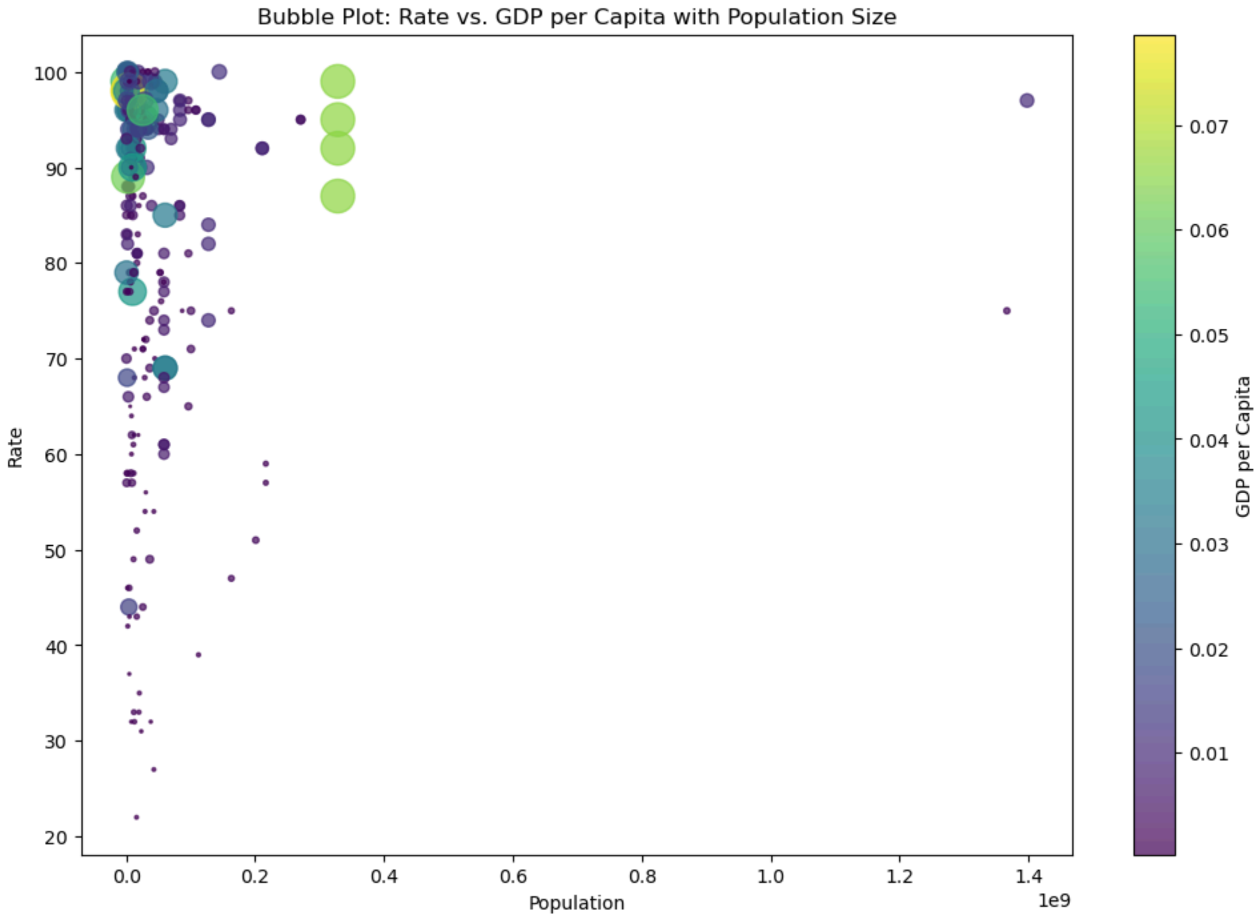


In [17]:

```
# Bubble plot with size based on 'pop_est' and color based on 'gdp_per_cap'
plt.figure(figsize=(12, 8))
scatter = plt.scatter(
    combined_df_2['gdp_per_cap'],
    combined_df_2['Rate'],
    s=combined_df_2['pop_est'] / 1000000,  # Adjust the scaling factor as needed
    c=combined_df_2['gdp_per_cap'],  # Color by GDP per Capita
    cmap='viridis',
    alpha=0.7
)

# Add colorbar
cbar = plt.colorbar(scatter)
cbar.set_label('GDP per Capita')

# Set labels and title
plt.xlabel('GDP per Capita')
plt.ylabel('Rate')
plt.title('Bubble Plot: Rate vs. GDP per Capita with Population Size')

# Show the plot
plt.show()
```

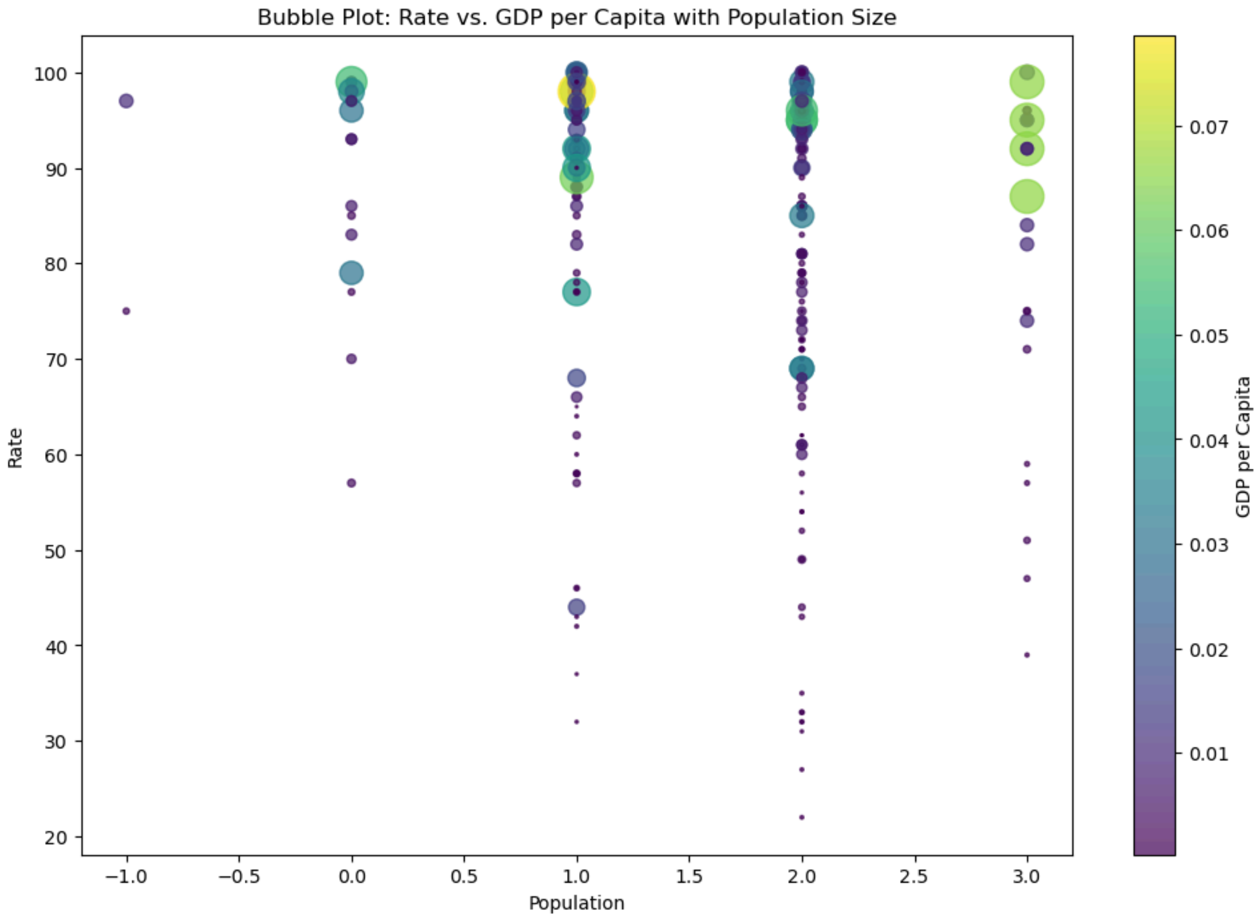


In [18]:
```
# Bubble plot with size based on 'pop_est' and color based on 'gdp_per_cap'
plt.figure(figsize=(12, 8))
scatter = plt.scatter(
    combined_df_2['pop_est'],
    combined_df_2['Rate'],
    s=combined_df_2['gdp_per_cap'] * 5000,  # Adjust the scaling factor as needed
    c=combined_df_2['gdp_per_cap'],  # Color by GDP per Capita
    cmap='viridis',
    alpha=0.7
)

# Add colorbar
cbar = plt.colorbar(scatter)
cbar.set_label('GDP per Capita')

# Set labels and title
plt.xlabel('Population')
plt.ylabel('Rate')
plt.title('Bubble Plot: Rate vs. GDP per Capita with Population Size')

# Show the plot
plt.show()
```



In [19]:

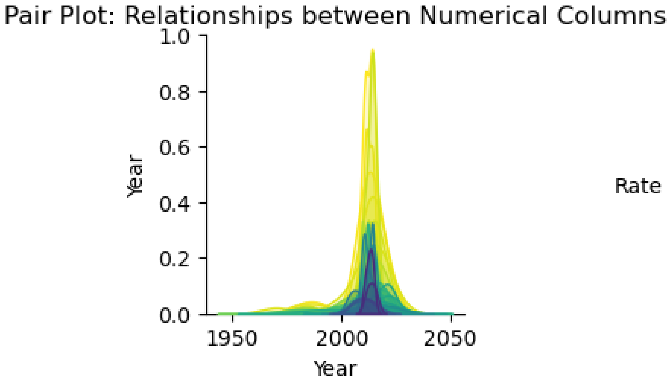
```python
# Convert 'pop_est_group' to numerical codes
combined_df_2['pop_est_group_code'] = combined_df_2['pop_est_group'].cat.codes

# Bubble plot with size based on 'pop_est' and color based on 'gdp_per_cap'
plt.figure(figsize=(12, 8))
scatter = plt.scatter(
    combined_df_2['pop_est_group_code'],
    combined_df_2['Rate'],
    s=combined_df_2['gdp_per_cap'] * 5000,  # Adjust the scaling factor as needed
    c=combined_df_2['gdp_per_cap'],  # Color by GDP per Capita
    cmap='viridis',
    alpha=0.7
)

# Add colorbar
cbar = plt.colorbar(scatter)
cbar.set_label('GDP per Capita')

# Set labels and title
plt.xlabel('Population')
plt.ylabel('Rate')
plt.title('Bubble Plot: Rate vs. GDP per Capita with Population Size')

# Show the plot
plt.show()
```



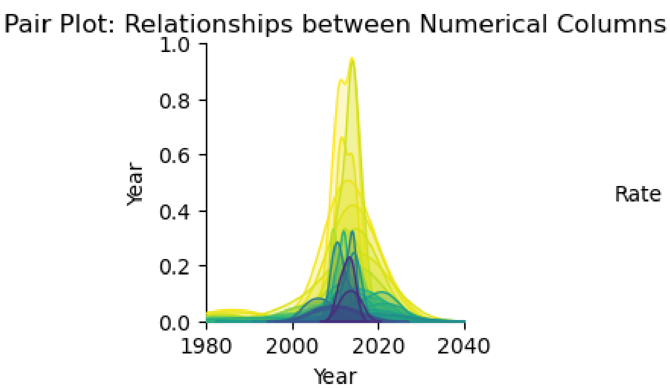
In [20]:
```
print(combined_df_2.dtypes)
```

```
Country                  object
Rate                    float64
Year                      int64
geometry               geometry
continent                object
pop_est                 float64
gdp_per_cap             float64
pop_est_group          category
pop_est_group_code         int8
dtype: object
```

In [21]:
```
# Visualization 4: Pair Plot (Relationships between numerical columns)

# Replace infinity values with NaN to avoid FutureWarnings #still occurs
combined_df.replace([np.inf, -np.inf], np.nan, inplace=True)

combined_df_pair_plot = combined_df[['Rate', 'Year']].dropna()

sns.pairplot(combined_df_pair_plot, hue='Rate', palette='viridis')
plt.suptitle('Pair Plot: Relationships between Numerical Columns', y=1.02)
plt.show()
```



In [22]:
```python
# Visualization 4: Pair Plot (Relationships between numerical columns)

# Replace infinity values with NaN to avoid FutureWarnings
combined_df.replace([np.inf, -np.inf], np.nan, inplace=True)

combined_df_pair_plot = combined_df[['Rate', 'Year']].dropna()

# Set the desired x-axis range
x_range = (1980, 2040)

# Pair plot with limited x-axis range
sns.pairplot(combined_df_pair_plot, hue='Rate', palette='viridis')
plt.suptitle('Pair Plot: Relationships between Numerical Columns', y=1.02)
plt.xlim(x_range)  # Set x-axis range
plt.show()
```

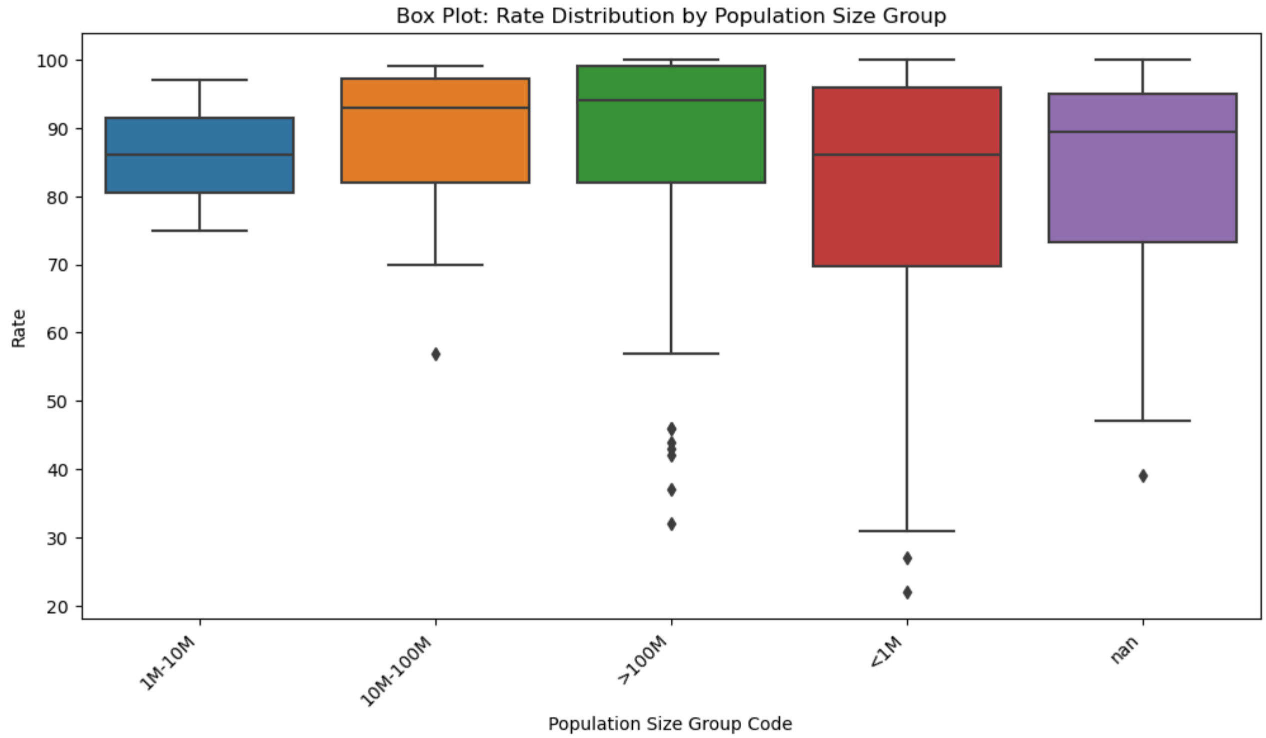


In [23]:
```python
# Visualization 1: Box Plot (Rate Distribution by Country)
# Convert 'Country' to categorical data and assign numerical codes
combined_df_2['Country'] = combined_df['Country'].astype('category')
combined_df_2['Country_Code'] = combined_df['Country'].cat.codes

plt.figure(figsize=(12, 6))
sns.boxplot(x='Country_Code', y='Rate', data=combined_df)
plt.title('Box Plot: Rate Distribution by Country')
plt.xticks(ticks=range(len(combined_df['Country'].unique())), labels=combined_df['Country'].unique(), rotation=45,
plt.show()
```

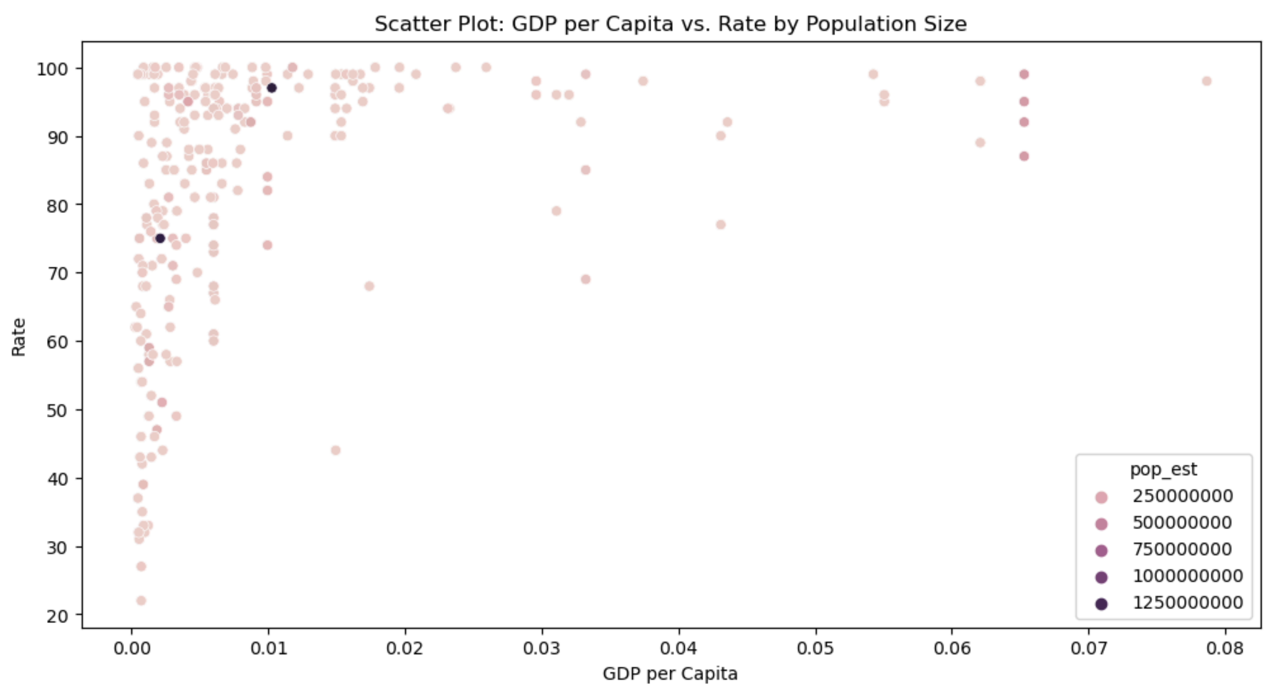
```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[23], line 4
      1 # Visualization 1: Box Plot (Rate Distribution by Country)
      2 # Convert 'Country' to categorical data and assign numerical codes
      3 combined_df_2['Country'] = combined_df['Country'].astype('category')
----> 4 combined_df_2['Country_Code'] = combined_df['Country'].cat.codes
      6 # Visualization 1: Box Plot (Rate Distribution by Country)
      7 plt.figure(figsize=(12, 6))

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:6296, in NDFrame.__getattr__(self, name)
   6289 if (
   6290     name not in self._internal_names_set
   6291     and name not in self._metadata
   6292     and name not in self._accessors
   6293     and self._info_axis._can_hold_identifiers_and_holds_name(name)
   6294 ):
   6295     return self[name]
-> 6296 return object.__getattribute__(self, name)

File ~\anaconda3\Lib\site-packages\pandas\core\accessor.py:224, in CachedAccessor.__get__(self, obj, cls)
    221 if obj is None:
    222     # we're accessing the attribute of the class, i.e., Dataset.geo
    223     return self._accessor
--> 224 accessor_obj = self._accessor(obj)
    225 # Replace the property with the accessor object. Inspired by:
    226 # https://www.pydanny.com/cached-property.html
    227 # We need to use object.__setattr__ because we overwrite __setattr__ on
    228 # NDFrame
    229 object.__setattr__(obj, self._name, accessor_obj)

File ~\anaconda3\Lib\site-packages\pandas\core\arrays\categorical.py:2896, in CategoricalAccessor.__init__(self, dat
a)
   2895 def __init__(self, data) -> None:
-> 2896     self._validate(data)
   2897     self._parent = data.values
   2898     self._index = data.index

File ~\anaconda3\Lib\site-packages\pandas\core\arrays\categorical.py:2905, in CategoricalAccessor._validate(data)
   2902 @staticmethod
   2903 def _validate(data):
   2904     if not isinstance(data.dtype, CategoricalDtype):
-> 2905         raise AttributeError("Can only use .cat accessor with a 'category' dtype")

AttributeError: Can only use .cat accessor with a 'category' dtype
```

In [24]:

```
# Visualization 1: Box Plot (Rate Distribution by Population Size Group)
plt.figure(figsize=(12, 6))
sns.boxplot(x='pop_est_group_code', y='Rate', data=combined_df_2)
plt.title('Box Plot: Rate Distribution by Population Size Group')
plt.xticks(ticks=range(len(combined_df_2['pop_est_group'].unique())),
           labels=combined_df_2['pop_est_group'].unique(), rotation=45, ha='right')
plt.xlabel('Population Size Group Code')
plt.ylabel('Rate')
plt.show()
```

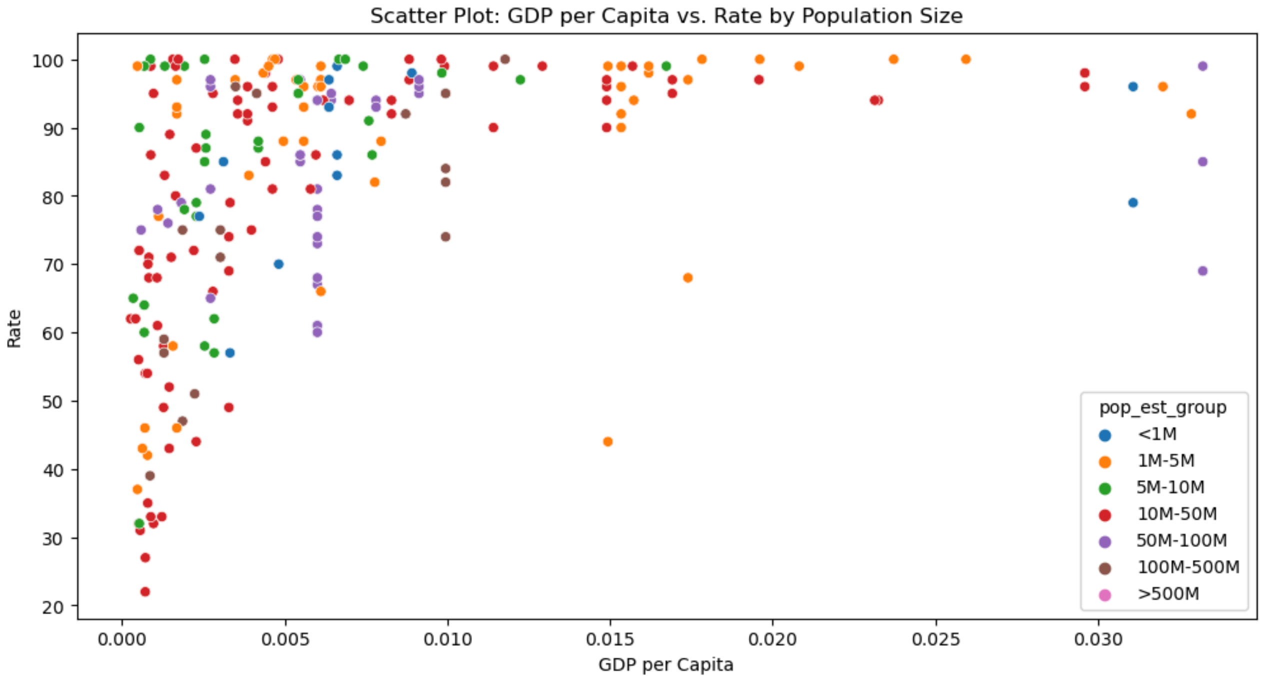


In [25]:
```
# Visualization 3: Scatter Plot (GDP per Capita vs. Rate)
plt.figure(figsize=(12, 6))
sns.scatterplot(x='gdp_per_cap', y='Rate', hue='pop_est', data=combined_df_2)
plt.title('Scatter Plot: GDP per Capita vs. Rate by Population Size')
plt.xlabel('GDP per Capita')
plt.ylabel('Rate')
plt.show()
```

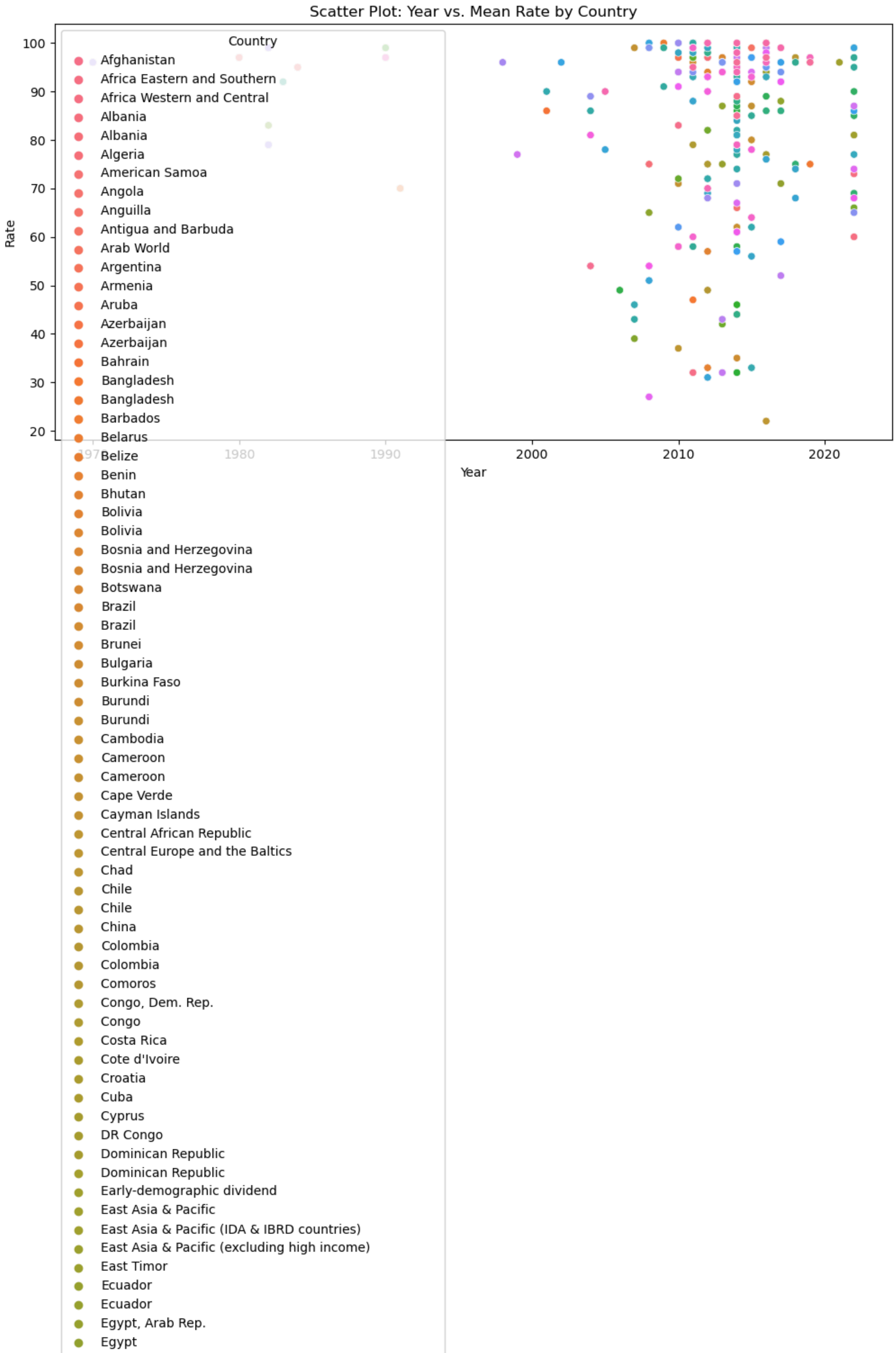


In [26]:
```
# Create more population size groups
bins = [0, 10**6, 5 * 10**6, 10**7, 5 * 10**7, 10**8, 5 * 10**8, 10**9]
labels = ['<1M', '1M-5M', '5M-10M', '10M-50M', '50M-100M', '100M-500M', '>500M']
combined_df_2['pop_est_group'] = pd.cut(combined_df_2['pop_est'], bins=bins, labels=labels, right=False)

# Visualization 3: Scatter Plot (GDP per Capita vs. Rate)
plt.figure(figsize=(12, 6))
```

```python
# Filter data to exclude outliers (gdp_per_cap > 0.05)
filtered_df = combined_df_2[combined_df_2['gdp_per_cap'] <= 0.035]

sns.scatterplot(x='gdp_per_cap', y='Rate', hue='pop_est_group', data=filtered_df)
plt.title('Scatter Plot: GDP per Capita vs. Rate by Population Size')
plt.xlabel('GDP per Capita')
plt.ylabel('Rate')
plt.show()
```

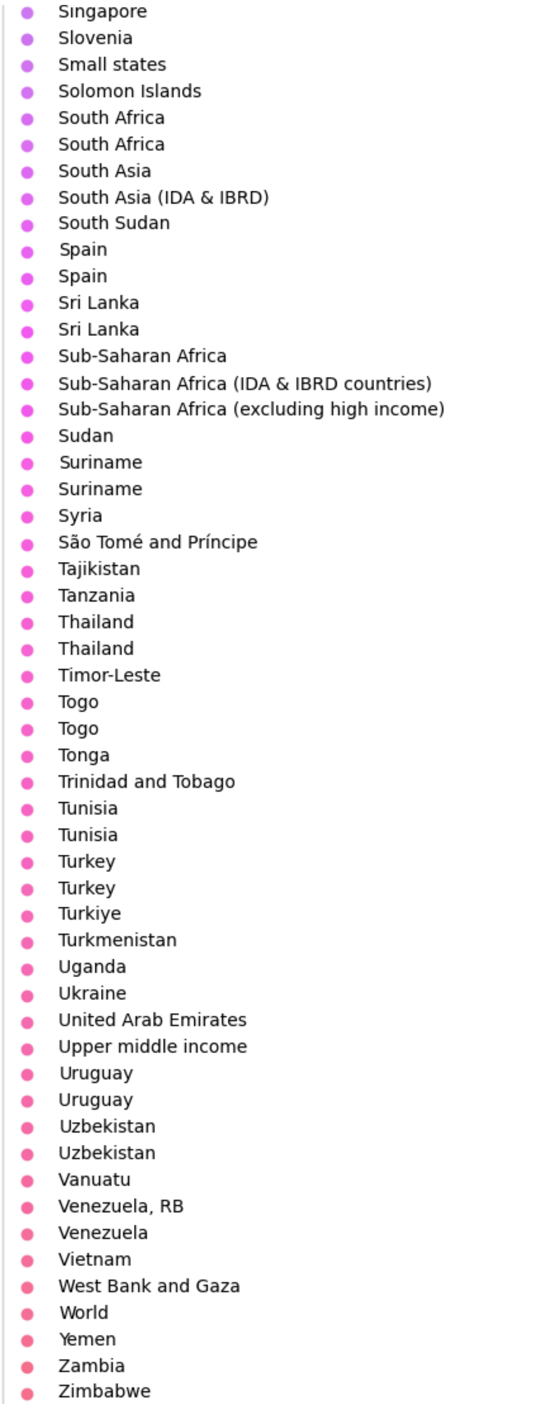


In [27]:
```python
# Aggregate data by country and year
agg_data = combined_df_2.groupby(['Country', 'Year']).agg({'Rate': 'mean'}).reset_index()

# Plotting aggregated data
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Year', y='Rate', hue='Country', data=agg_data)
plt.title('Scatter Plot: Year vs. Mean Rate by Country')
plt.show()
```


Scatter Plot: Year vs. Mean Rate by Country
Rate
Year
100
90
80
70
60
50
40
30
20
1980
1990
2000
2010
2020
Country
Afghanistan
Africa Eastern and Southern
Africa Western and Central
Albania
Albania
Algeria
American Samoa
Angola
Anguilla
Antigua and Barbuda
Arab World
Argentina
Armenia
Aruba
Azerbaijan
Azerbaijan
Bahrain
Bangladesh
Bangladesh
Barbados
Belarus
Belize
Benin
Bhutan
Bolivia
Bolivia
Bosnia and Herzegovina
Bosnia and Herzegovina
Botswana
Brazil
Brazil
Brunei
Bulgaria
Burkina Faso
Burundi
Burundi
Cambodia
Cameroon
Cameroon
Cape Verde
Cayman Islands
Central African Republic
Central Europe and the Baltics
Chad
Chile
Chile
China
Colombia
Colombia
Comoros
Congo, Dem. Rep.
Congo
Costa Rica
Cote d'Ivoire
Croatia
Cuba
Cyprus
DR Congo
Dominican Republic
Dominican Republic
Early-demographic dividend
East Asia & Pacific
East Asia & Pacific (IDA & IBRD countries)
East Asia & Pacific (excluding high income)
East Timor
Ecuador
Ecuador
Egypt, Arab Rep.
Egypt

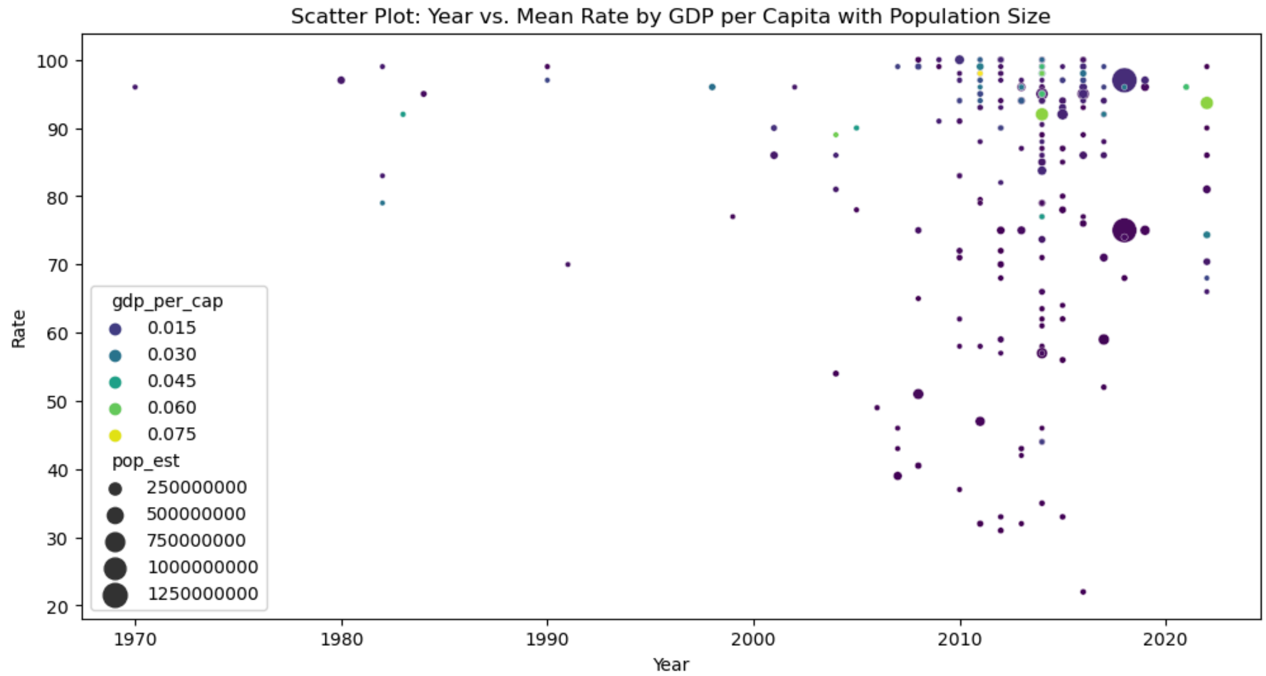
- El Salvador
- El Salvador
- Equatorial Guinea
- Eritrea
- Estonia
- Eswatini
- Ethiopia
- Europe & Central Asia
- Europe & Central Asia (IDA & IBRD countries)
- Europe & Central Asia (excluding high income)
- Fragile and conflict affected situations
- French Guiana
- Gabon
- Gambia
- Georgia
- Ghana
- Greece
- Greece
- Grenada
- Guadeloupe
- Guam
- Guatemala
- Guatemala
- Guinea-Bissau
- Guinea
- Guyana
- Haiti
- Heavily indebted poor countries (HIPC)
- Honduras
- Honduras
- Hungary
- IBRD only
- IDA & IBRD total
- IDA blend
- IDA only
- IDA total
- India
- Indonesia
- Indonesia
- Iran, Islamic Rep.
- Iran
- Iraq
- Israel
- Italy
- Ivory Coast
- Jamaica
- Jordan
- Jordan
- Kazakhstan
- Kenya
- Kenya
- Kuwait
- Kuwait
- Kyrgyzstan
- Lao PDR
- Laos
- Late-demographic dividend
- Latin America & Caribbean
- Latin America & Caribbean (excluding high income)
- Latin America & the Caribbean (IDA & IBRD countries)
- Latvia
- Least developed countries: UN classification
- Lebanon
- Lesotho
- Lesotho
- Liberia
- Libya
- Lithuania
- Low & middle income
- Low income
- Lower middle income
- Macau
- Madagascar

- Madagascar
- Malawi
- Malaysia
- Maldives
- Mali
- Malta
- Marshall Islands
- Martinique
- Mauritania
- Mauritius
- Mauritius
- Mexico
- Mexico
- Middle East & North Africa
- Middle East & North Africa (IDA & IBRD countries)
- Middle East & North Africa (excluding high income)
- Middle income
- Moldova
- Mongolia
- Montenegro
- Morocco
- Morocco
- Mozambique
- Myanmar
- Namibia
- Namibia
- Nepal
- New Caledonia
- Nicaragua
- Nigeria
- Niger
- North America
- North Korea
- North Macedonia
- Oman
- Oman
- Other small states
- Pakistan
- Pakistan
- Palau
- Palestine
- Panama
- Papua New Guinea
- Paraguay
- Paraguay
- Peru
- Peru
- Philippines
- Philippines
- Poland
- Portugal
- Pre-demographic dividend
- Puerto Rico
- Qatar
- Qatar
- Romania
- Russia
- Rwanda
- Rwanda
- Réunion
- Saint Helena
- Saint Pierre and Miquelon
- Saint Vincent and the Grenadines
- Samoa
- Sao Tome and Principe
- Saudi Arabia
- Senegal
- Senegal
- Serbia
- Seychelles
- Sierra Leone
- Singapore

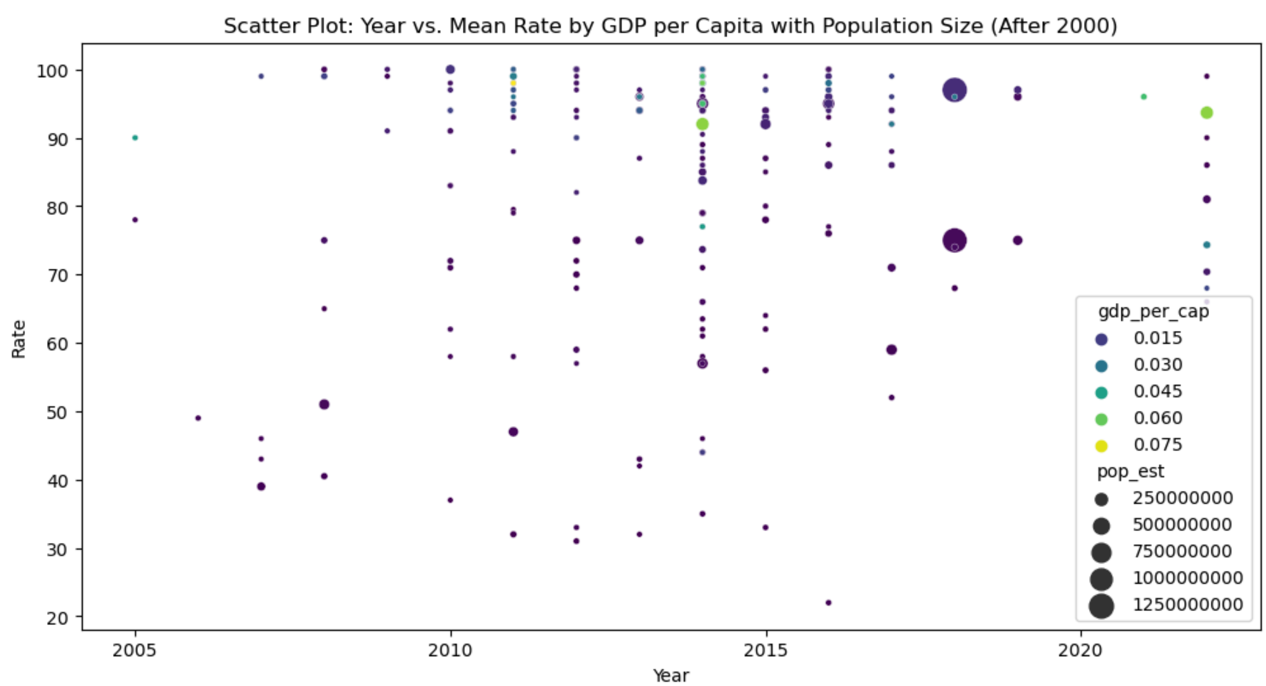


In [28]:

```
# Aggregate data by gdp_per_cap and year, including population size for size of dots
agg_data_gdp_pop = combined_df_2.groupby(['gdp_per_cap', 'Year']).agg({'Rate': 'mean', 'pop_est': 'mean'}).reset_in

# Plotting aggregated data
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Year', y='Rate', hue='gdp_per_cap', size='pop_est', sizes=(10, 200), data=agg_data_gdp_pop, pale
plt.title('Scatter Plot: Year vs. Mean Rate by GDP per Capita with Population Size')
plt.show()
```

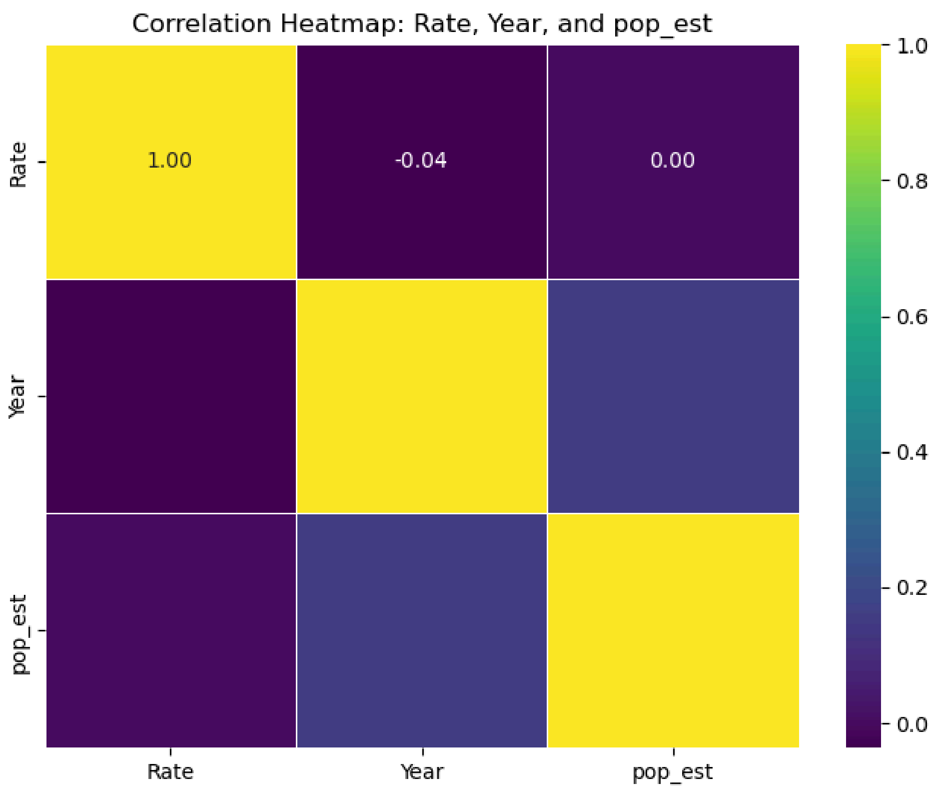


In [29]:
```
# Filter data for years after 2000
filtered_data = combined_df_2[combined_df_2['Year'] > 2004]

# Aggregate data by gdp_per_cap and year, including population size for the size of dots
agg_data_gdp_pop = filtered_data.groupby(['gdp_per_cap', 'Year']).agg({'Rate': 'mean', 'pop_est': 'mean'}).reset_in

# Set the x-axis ticks to show every five years
x_ticks = range(filtered_data['Year'].min(), filtered_data['Year'].max() + 1, 5)

# Plotting aggregated data
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Year', y='Rate', hue='gdp_per_cap', size='pop_est', sizes=(10, 200), data=agg_data_gdp_pop, pale
plt.title('Scatter Plot: Year vs. Mean Rate by GDP per Capita with Population Size (After 2000)')
plt.xticks(ticks=x_ticks)
plt.show()
```

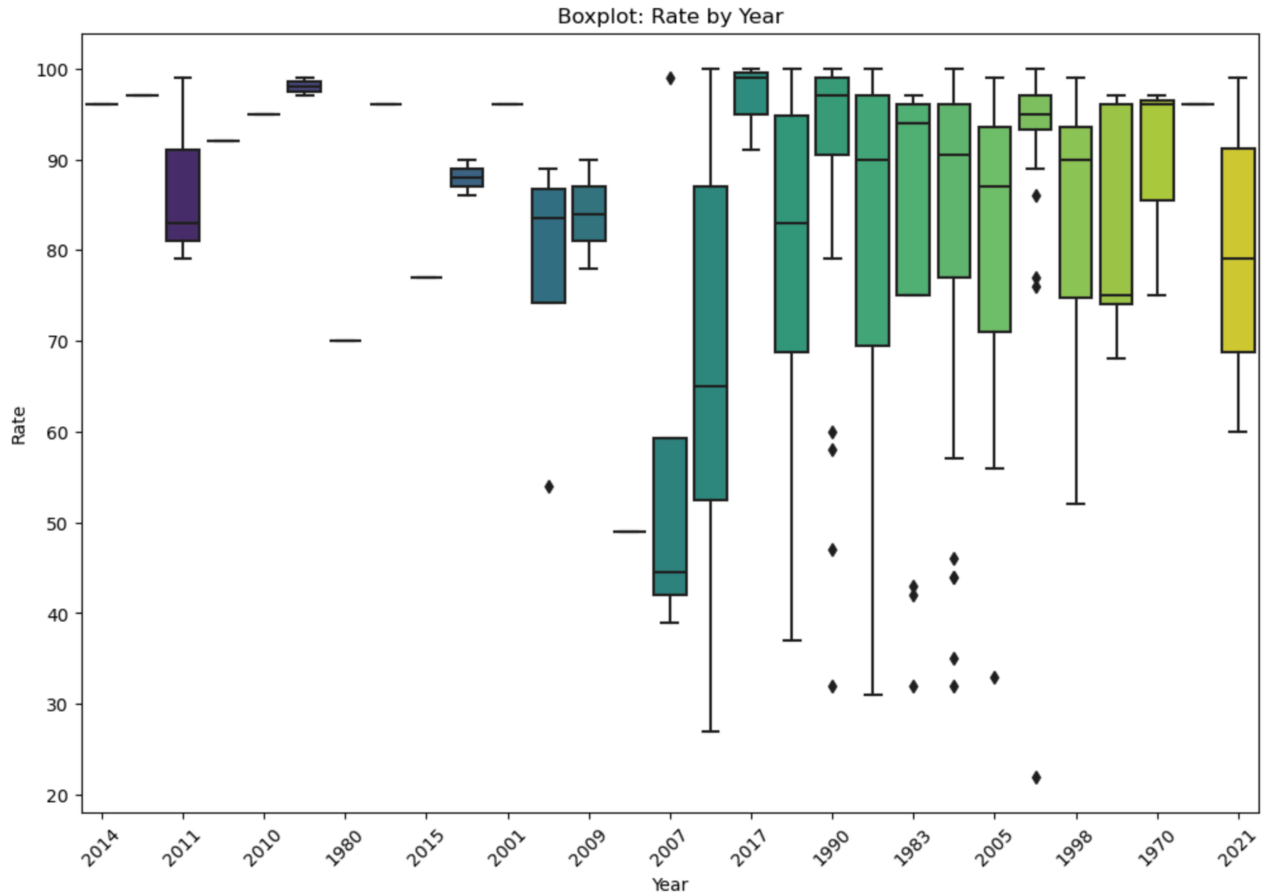


In [30]:
```
# Visualization 5: Correlation Heatmap
import seaborn as sns
```

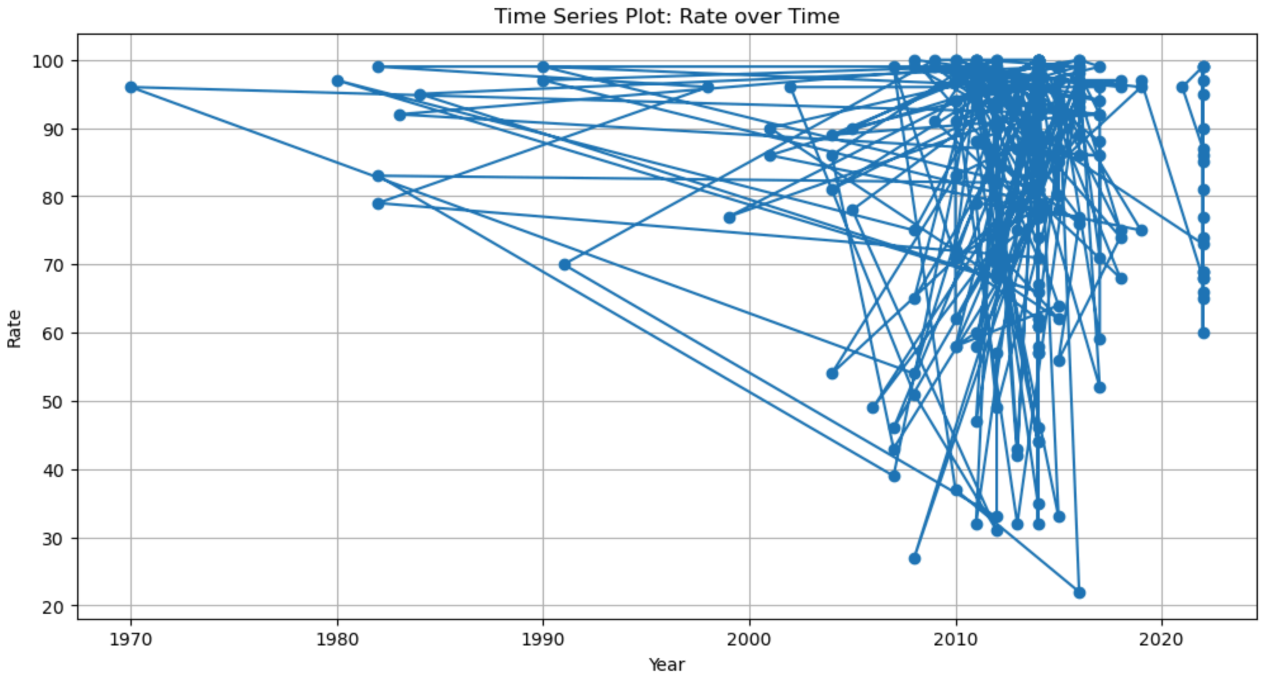
```
import matplotlib.pyplot as plt

# Select relevant columns for correlation
correlation_columns = ['Rate', 'Year', 'pop_est']

# Create a subset of the DataFrame with the selected columns
correlation_subset = combined_df_2[correlation_columns]

# Calculate the correlation matrix
correlation_matrix = correlation_subset.corr()

# Set up the matplotlib figure
plt.figure(figsize=(8, 6))

# Create a heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='viridis', fmt=".2f", linewidths=.5)

# Set the title
plt.title('Correlation Heatmap: Rate, Year, and pop_est')

# Show the plot
plt.show()
```



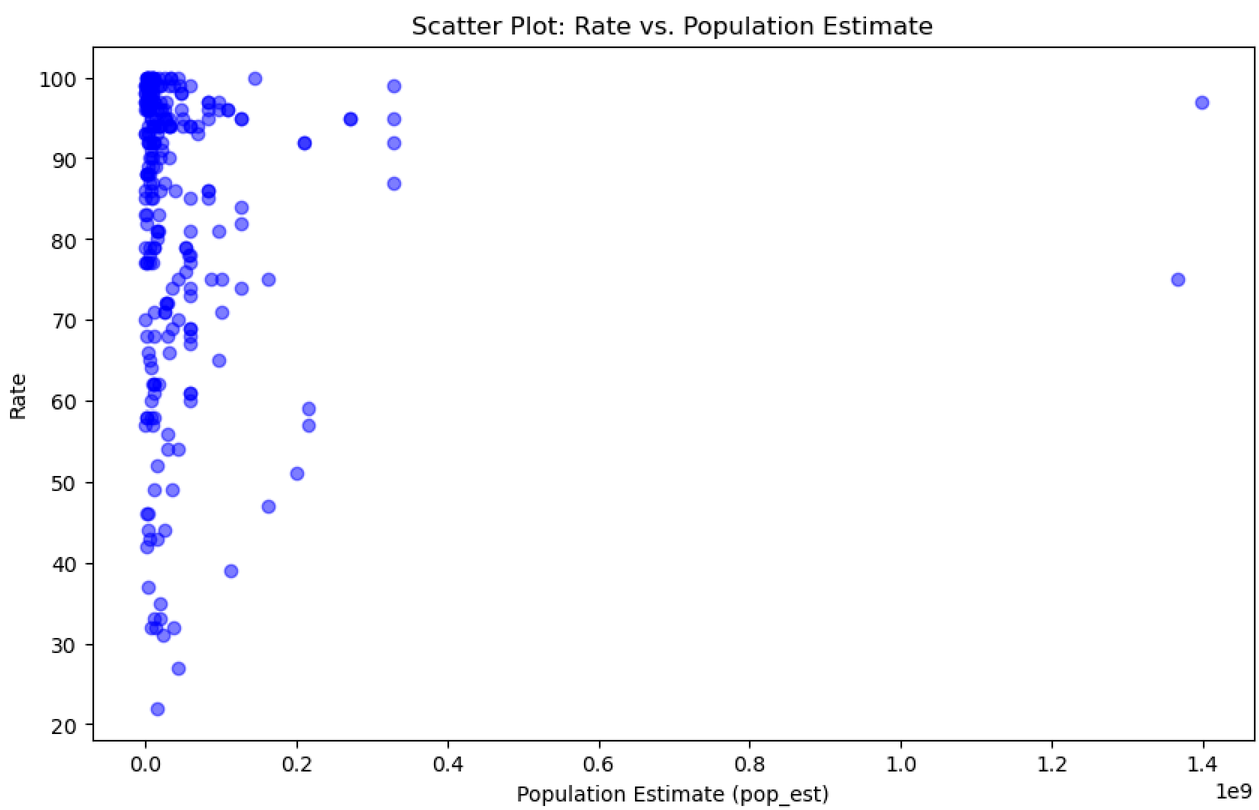
In [31]:
```
# Boxplot
plt.figure(figsize=(12, 8))
sns.boxplot(x='Year', y='Rate', data=combined_df, palette='viridis')
plt.title('Boxplot: Rate by Year')
plt.xlabel('Year')
plt.ylabel('Rate')

# Set ticks for every 10 years
unique_years = combined_df['Year'].unique()
tick_positions = range(0, len(unique_years), len(unique_years)//10)
tick_labels = unique_years[tick_positions]
plt.xticks(tick_positions, tick_labels, rotation=45)

plt.show()
```



In [32]:
```
import matplotlib.pyplot as plt

# Assuming 'Year' is the column containing the time information
# and 'Rate' is the numerical variable you want to visualize
plt.figure(figsize=(12, 6))
plt.plot(combined_df['Year'], combined_df['Rate'], marker='o', linestyle='-')

plt.title('Time Series Plot: Rate over Time')
plt.xlabel('Year')
plt.ylabel('Rate')
plt.grid(True)
plt.show()
```



In [33]:
```
import matplotlib.pyplot as plt

# Scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(combined_df_2['pop_est'], combined_df_2['Rate'], alpha=0.5, color='blue')

# Set labels and title
plt.xlabel('Population Estimate (pop_est)')
plt.ylabel('Rate')
plt.title('Scatter Plot: Rate vs. Population Estimate')

# Show the plot
plt.show()
```



Summary:

This project involved merging and storing three datasets related to adult literacy rates from csv files, website data, and API data into a SQLite database, followed by creating visualizations to demonstrate the cleansed data. The project also involved fuzzy matching to address missing data when merging geographical information for creating a choropleth map.

In terms of merging the geographical data with the main DataFrame, fuzzy matching was employed to find the best match for each country between the two datasets, significantly improving the resulting choropleth map. I got a little overzealous with my visualizations, trying to cover a wide range, but was unable to push some of them to their full potential. They include some (really really cool) choropleth maps, bubble plots, pair plots, box plots, scatter plots, and time series plots. These visualizations aimed to reveal insights into the relationships between adult literacy rates rates, geographical data, GDP per capita, and population size. The unfinished visuals also included a correlation heatmap and a boxplot illustrating the distribution of literacy rates over the years.

Throughout the project, I learned many, many things. The significance of data cleaning and preprocessing was evident, especially when dealing with multiple datasets that required merging. Fuzzy matching proved to be an insanely valuable technique for handling missing or mismatched data, greatly enhancing the accuracy of the geographical representations. Additionally, the power of visualizations in uncovering patterns and trends in complex datasets became apparent. Various libraries like Matplotlib, Seaborn, and GeoPandas were employed to create meaningful and insightful visual representations.

From an ethical standpoint, the project highlights the importance of transparency in data cleaning processes. Fuzzy matching, while a useful technique, involves subjective decisions that may introduce biases. It is crucial to document and communicate the steps taken during data cleansing to ensure the reproducibility of results and allow for scrutiny. Furthermore, the project's focus on literacy rates and its correlation with GDP per capita raises ethical considerations related to global inequalities. Analyzing and visualizing such data should be done with a sensitivity to potential biases and a commitment to promoting fairness and inclusivity.

In conclusion, the project demonstrated the intricacies of merging, cleaning, and visualizing diverse datasets. The use of fuzzy matching and various visualization techniques contributed to a more comprehensive understanding of the data. Ethical considerations underscored the need for transparency and fairness in data cleansing processes, especially when dealing with topics that have societal implications.