country_CI_comparison

November 18, 2024

0.0.1 Part III: Comparing the carbon intensity across countries/continents

Objectives:

- Calculate the average CI with respect to all countries, or group countries in a logical way if neccesary
- examine if the assumptions for statistical tests hold true (e.g. normal distribution for ANOVA)
- conduct statistical test to find out whether there are significant differences between countries/groups of countries
- formulate hypothesis regarding the reasons for differences if any

Step one: Loading and checking the data set

- **Objective:** Load the first sheet of the dataset and perform basic quality checks.
- **Steps:**
  1. Load the first worksheet into a DataFrame using `pandas`.
  2. Display an overview of the dataset (first few rows, data types, missing values, unique values, summary statistics).
- **Purpose:** Ensure the dataset is ready for analysis and identify any immediate issues like missing data or unexpected values.

[32]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the Excel file
file_path = "PublicTablesForCarbonCatalogueDataDescriptor_v30Oct2021.xlsx"
data = pd.ExcelFile(file_path)

# Load the first sheet into a DataFrame
main_data = data.parse(data.sheet_names[0])  # Load only the first sheet

# Display the first few rows
print("Preview of the first few rows of the dataset:")
display(main_data.head())

# Basic data quality checks
```

```python
# 1. Check data types
print("Data types of each column:")
display(main_data.dtypes)

# 2. Check for missing values
print("Number of missing values per column:")
display(main_data.isnull().sum())

# 3. Get unique value counts for each column
print("Number of unique values per column:")
display(main_data.nunique())

# 4. Get summary statistics
print("Summary statistics of the dataset:")
display(main_data.describe(include='all'))
```

```
Preview of the first few rows of the dataset:

        *PCF-ID  Year of reporting *Stage-level CO2e available  \
0  10056-1-2014               2014                         Yes
1  10056-1-2015               2015                         Yes
2  10222-1-2013               2013                         Yes
3  10261-1-2017               2017                         Yes
4  10261-2-2017               2017                         Yes

                  Product name (and functional unit)  \
0                           Frosted Flakes(R) Cereal
1  Frosted Flakes, 23 oz, produced in Lancaster, …
2                                       Office Chair
3                            Multifunction Printers
4                            Multifunction Printers

                                      Product detail              Company  \
0  Frosted Flakes(R), 23 oz., Produced in Lancast…      Kellogg Company
1                                             Cereal      Kellogg Company
2                   Field not included in 2013 data            KNOLL INC
3                                        bizhub C458  Konica Minolta, Inc.
4                                        bizhub C558  Konica Minolta, Inc.

  Country (where company is incorporated)    Company's GICS Industry Group  \
0                                     USA          Food, Beverage & Tobacco
1                                     USA       Food & Beverage Processing
2                                     USA                    Capital Goods
3                                   Japan  Technology Hardware & Equipment
4                                   Japan  Technology Hardware & Equipment

                          Company's GICS Industry  \
```

```
0                                    Food Products
1                       Not used for 2015 reporting
2                                 Building Products
3  Electronic Equipment, Instruments & Components
4  Electronic Equipment, Instruments & Components

             *Company's sector  …  Relative change in PCF vs previous  \
0              Food & Beverage  …           (not reported by company)
1              Food & Beverage  …           (not reported by company)
2  Comm. equipm. & capital goods  …           (not reported by company)
3         Computer, IT & telecom  …           (not reported by company)
4         Computer, IT & telecom  …           (not reported by company)

  Company-reported reason for change           *Change reason category  \
0                                N/a         N/a (no %change reported)
1                                N/a         N/a (no %change reported)
2                                N/a  N/a (no previous data available)
3                                N/a  N/a (no previous data available)
4                                N/a  N/a (no previous data available)

   *%Upstream estimated from %Operations  \
0                                     No
1                                     No
2                                    Yes
3                                     No
4                                     No

  *Upstream CO2e (fraction of total PCF)  \
0                                  0.575
1                                  0.575
2                                 0.8063
3                                 0.3065
4                                 0.2508

  *Operations CO2e (fraction of total PCF)  \
0                                      0.3
1                                      0.3
2                                   0.1736
3                                   0.0551
4                                   0.0451

  *Downstream CO2e (fraction of total PCF)  \
0                                    0.125
1                                    0.125
2                                   0.0201
3                                   0.6384
4                                   0.7041
```

```
            *Transport CO2e (fraction of total PCF)  \
0                                            0.045
1                                            0.045
2  (included in up/downstream but not reported se…
3                                           0.0101
4                                           0.0083

            *EndOfLife CO2e (fraction of total PCF)  \
0  (included in downstream but not reported separ…
1  (included in downstream but not reported separ…
2                                                0
3                                           0.0276
4                                           0.0226

                  *Adjustments to raw data (if any)
0  Divided stage and total emissions by 1000 (bas…
1  Divided stage and total emissions by 1000 (bas…
2  Changed %change to zero, according to field "c…
3                                              NaN
4                                              NaN

[5 rows x 25 columns]
```

```
Data types of each column:
```

```
*PCF-ID                                        object
Year of reporting                               int64
*Stage-level CO2e available                    object
Product name (and functional unit)             object
Product detail                                 object
Company                                        object
Country (where company is incorporated)        object
Company's GICS Industry Group                  object
Company's GICS Industry                        object
*Company's sector                              object
Product weight (kg)                           float64
*Source for product weight                     object
Product's carbon footprint (PCF, kg CO2e)     float64
*Carbon intensity                             float64
Protocol used for PCF                          object
Relative change in PCF vs previous             object
Company-reported reason for change             object
*Change reason category                        object
*%Upstream estimated from %Operations          object
*Upstream CO2e (fraction of total PCF)         object
*Operations CO2e (fraction of total PCF)       object
*Downstream CO2e (fraction of total PCF)       object
*Transport CO2e (fraction of total PCF)        object
*EndOfLife CO2e (fraction of total PCF)        object
```

```
*Adjustments to raw data (if any)            object
dtype: object

Number of missing values per column:

*PCF-ID                                        0
Year of reporting                              0
*Stage-level CO2e available                    0
Product name (and functional unit)             0
Product detail                                10
Company                                        0
Country (where company is incorporated)        0
Company's GICS Industry Group                  0
Company's GICS Industry                        0
*Company's sector                              0
Product weight (kg)                            0
*Source for product weight                     0
Product's carbon footprint (PCF, kg CO2e)      0
*Carbon intensity                              0
Protocol used for PCF                          0
Relative change in PCF vs previous             0
Company-reported reason for change             0
*Change reason category                        0
*%Upstream estimated from %Operations          0
*Upstream CO2e (fraction of total PCF)         0
*Operations CO2e (fraction of total PCF)       0
*Downstream CO2e (fraction of total PCF)       0
*Transport CO2e (fraction of total PCF)        0
*EndOfLife CO2e (fraction of total PCF)        0
*Adjustments to raw data (if any)            679
dtype: int64

Number of unique values per column:

*PCF-ID                                      866
Year of reporting                              5
*Stage-level CO2e available                    2
Product name (and functional unit)           672
Product detail                               496
Company                                      145
Country (where company is incorporated)       28
Company's GICS Industry Group                 30
Company's GICS Industry                       35
*Company's sector                              8
Product weight (kg)                          340
*Source for product weight                     2
Product's carbon footprint (PCF, kg CO2e)    626
*Carbon intensity                            548
Protocol used for PCF                         26
Relative change in PCF vs previous           145
```

```
Company-reported reason for change          157
*Change reason category                       6
*%Upstream estimated from %Operations         3
*Upstream CO2e (fraction of total PCF)      338
*Operations CO2e (fraction of total PCF)    317
*Downstream CO2e (fraction of total PCF)    276
*Transport CO2e (fraction of total PCF)     208
*EndOfLife CO2e (fraction of total PCF)     122
*Adjustments to raw data (if any)            58
dtype: int64
```

Summary statistics of the dataset:

```
            *PCF-ID  Year of reporting *Stage-level CO2e available  \
count           866         866.000000                         866
unique          866                NaN                           2
top     9792-2-2017                NaN                          No
freq              1                NaN                         445
mean            NaN        2014.762125                         NaN
std             NaN           1.236720                         NaN
min             NaN        2013.000000                         NaN
25%             NaN        2014.000000                         NaN
50%             NaN        2015.000000                         NaN
75%             NaN        2016.000000                         NaN
max             NaN        2017.000000                         NaN

       Product name (and functional unit)                   Product detail  \
count                                 866                              856
unique                                672                              496
top           Residential Air Conditioner  Field not included in 2013 data
freq                                    4                               97
mean                                  NaN                              NaN
std                                   NaN                              NaN
min                                   NaN                              NaN
25%                                   NaN                              NaN
50%                                   NaN                              NaN
75%                                   NaN                              NaN
max                                   NaN                              NaN

           Company Country (where company is incorporated)  \
count          866                                     866
unique         145                                      28
top     Daimler AG                                     USA
freq            37                                     305
mean           NaN                                     NaN
std            NaN                                     NaN
min            NaN                                     NaN
25%            NaN                                     NaN
50%            NaN                                     NaN
```

75%	NaN	NaN
max	NaN	NaN

	Company's GICS Industry Group	Company's GICS Industry \
count	866	866
unique	30	35
top	Technology Hardware & Equipment	Not used for 2015 reporting
freq	195	215
mean	NaN	NaN
std	NaN	NaN
min	NaN	NaN
25%	NaN	NaN
50%	NaN	NaN
75%	NaN	NaN
max	NaN	NaN

	*Company's sector	…	Relative change in PCF vs previous \
count	866	…	866
unique	8	…	145
top	Computer, IT & telecom	…	(not reported by company)
freq	253	…	616
mean	NaN	…	NaN
std	NaN	…	NaN
min	NaN	…	NaN
25%	NaN	…	NaN
50%	NaN	…	NaN
75%	NaN	…	NaN
max	NaN	…	NaN

	Company-reported reason for change	*Change reason category \
count	866	866
unique	157	6
top	N/a	N/a (no %change reported)
freq	654	482
mean	NaN	NaN
std	NaN	NaN
min	NaN	NaN
25%	NaN	NaN
50%	NaN	NaN
75%	NaN	NaN
max	NaN	NaN

	*%Upstream estimated from %Operations \
count	866
unique	3
top	N/a (product with insufficient stage-level data)
freq	445
mean	NaN

```
std                                                      NaN
min                                                      NaN
25%                                                      NaN
50%                                                      NaN
75%                                                      NaN
max                                                      NaN

                  *Upstream CO2e (fraction of total PCF)  \
count                                                    866
unique                                                   338
top     N/a (product with insufficient stage-level data)
freq                                                     445
mean                                                     NaN
std                                                      NaN
min                                                      NaN
25%                                                      NaN
50%                                                      NaN
75%                                                      NaN
max                                                      NaN

                *Operations CO2e (fraction of total PCF)  \
count                                                    866
unique                                                   317
top     N/a (product with insufficient stage-level data)
freq                                                     445
mean                                                     NaN
std                                                      NaN
min                                                      NaN
25%                                                      NaN
50%                                                      NaN
75%                                                      NaN
max                                                      NaN

                *Downstream CO2e (fraction of total PCF)  \
count                                                    866
unique                                                   276
top     N/a (product with insufficient stage-level data)
freq                                                     445
mean                                                     NaN
std                                                      NaN
min                                                      NaN
25%                                                      NaN
50%                                                      NaN
75%                                                      NaN
max                                                      NaN

                 *Transport CO2e (fraction of total PCF)  \
count                                                    866
```

```
unique                                                    208
top     N/a (product with insufficient stage-level data)
freq                                                      445
mean                                                      NaN
std                                                       NaN
min                                                       NaN
25%                                                       NaN
50%                                                       NaN
75%                                                       NaN
max                                                       NaN

               *EndOfLife CO2e (fraction of total PCF)  \
count                                                     866
unique                                                    122
top     N/a (product with insufficient stage-level data)
freq                                                      445
mean                                                      NaN
std                                                       NaN
min                                                       NaN
25%                                                       NaN
50%                                                       NaN
75%                                                       NaN
max                                                       NaN

                        *Adjustments to raw data (if any)
count                                                     187
unique                                                     58
top     Concatenated fields product name and product d…
freq                                                       29
mean                                                      NaN
std                                                       NaN
min                                                       NaN
25%                                                       NaN
50%                                                       NaN
75%                                                       NaN
max                                                       NaN

[11 rows x 25 columns]
```

Interpretation:

- the data quality seems appropiate
- numeric columns consist of appropiates data types (floats)
- there are no N/a values in columns of interest
- we can already see that we have 28 unique countries to aggregate on

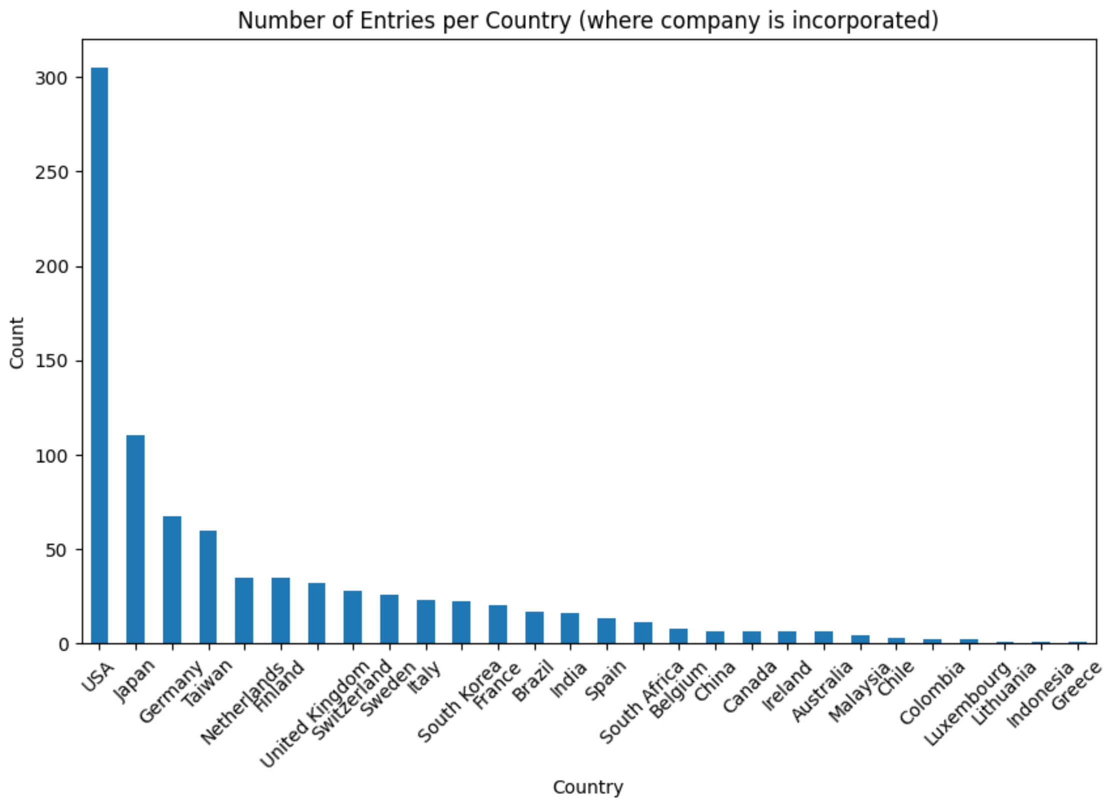
Step two: Understanding the distribution of values across countries

- **Objective:** Determine the unique countries in the dataset and visualize the number of entries per country.
- **Steps:**
  1. Use `value_counts()` to count occurrences of each unique country in the `Country` column.
  2. Display the counts for clarity.
  3. Create a bar plot to visualize the frequency of entries for each country.
- **Purpose:** Understand the geographic distribution of the data, which can help identify any imbalances or regional trends.

[33]:
```
# Identify unique countries and their counts
print("Number of unique countries and their respective counts:")
country_counts = main_data['Country (where company is incorporated)'].
 ↪value_counts()
display(country_counts)

# Plot the counts as a bar plot
plt.figure(figsize=(10, 6))
country_counts.plot(kind='bar')
plt.title('Number of Entries per Country (where company is incorporated)')
plt.xlabel('Country')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```

```
Number of unique countries and their respective counts:

Country (where company is incorporated)
USA               305
Japan             110
Germany            67
Taiwan             60
Netherlands        35
Finland            35
United Kingdom     32
Switzerland        28
Sweden             26
Italy              23
South Korea        22
France             20
Brazil             17
India              16
Spain              13
South Africa       11
Belgium             8
China               6
Canada              6
Ireland             6
```

```
Australia          6
Malaysia           4
Chile              3
Colombia           2
Luxembourg         2
Lithuania          1
Indonesia          1
Greece             1
Name: count, dtype: int64
```



Interpretation:

- One can already see that we will run into issues when using statistical test like ANOVA, since the distribution between is very uneven. While USA, Japan, Germany and Taiwan have a lot of values. However, Greece, Indonesia and others have only few values.
- We could drop all countries with less than 30 values, but that would shrink the information density in the data set. A better alternative would be to group the countries logically.
- Since we do not know where the clients of EcoFuture Analytics are situated, we can not really estimate which countries are most imporant with respect to our clients. One could assume that most clients will be situated in the biggest economies in the dataset (USA, Japan, Germany) and all other countries will be "slightly" less important.
- Therefore we could build groups of countries, if they have less than 30 values by allocating

them to their respective geographic reason.

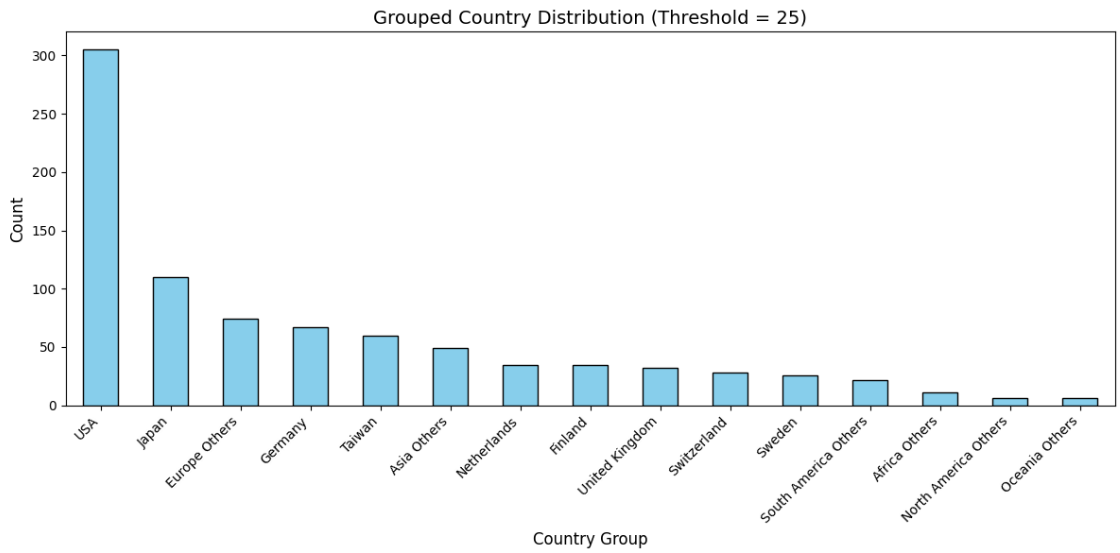
0.0.2 Step three: Building bigger groups

- **Objective:** Group countries with fewer than 30 entries into regional categories (e.g., "Europe Others") while preserving countries with 30 or more entries.
- **Steps:**
  1. Map each country to a continent using a predefined dictionary.
  2. Countries with fewer than 30 entries are assigned to their continent-specific "Others" group.
  3. Display the new distribution and visualize it in a bar plot.
- **Purpose:** Ensure statistically meaningful group sizes for ANOVA, while maintaining logical geographic groupings.

[34]:
```python
# Define the threshold for grouping
threshold = 25

# Define a mapping for countries to continents
continent_mapping = {
    'USA': 'North America',
    'Japan': 'Asia',
    'Germany': 'Europe',
    'Taiwan': 'Asia',
    'Netherlands': 'Europe',
    'Finland': 'Europe',
    'United Kingdom': 'Europe',
    'Switzerland': 'Europe',
    'Sweden': 'Europe',
    'Italy': 'Europe',
    'South Korea': 'Asia',
    'France': 'Europe',
    'Brazil': 'South America',
    'India': 'Asia',
    'Spain': 'Europe',
    'South Africa': 'Africa',
    'Belgium': 'Europe',
    'China': 'Asia',
    'Canada': 'North America',
    'Ireland': 'Europe',
    'Australia': 'Oceania',
    'Malaysia': 'Asia',
    'Chile': 'South America',
    'Colombia': 'South America',
    'Luxembourg': 'Europe',
    'Lithuania': 'Europe',
    'Indonesia': 'Asia',
    'Greece': 'Europe'
}
```

```python
# Create a new column with grouped countries
def group_countries(country):
    count = country_counts.get(country, 0)
    if count >= threshold:
        return country
    else:
        continent = continent_mapping.get(country, 'Other')
        return f"{continent} Others"

main_data['Grouped Country'] = main_data['Country (where company is␣
↪incorporated)'].apply(group_countries)

# Verify the new group distribution
print("New group distribution:")
group_distribution = main_data['Grouped Country'].value_counts()
display(group_distribution)

# Plot the new group distribution with adjusted label alignment
plt.figure(figsize=(12, 6))
group_distribution.plot(kind='bar', color='skyblue', edgecolor='black')
plt.title('Grouped Country Distribution (Threshold = 25)', fontsize=14)
plt.xlabel('Country Group', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)  # Rotate and align labels to␣
↪the right
plt.tight_layout()  # Adjust layout to prevent clipping
plt.show()
```

```
New group distribution:

Grouped Country
USA                      305
Japan                    110
Europe Others             74
Germany                   67
Taiwan                    60
Asia Others               49
Netherlands               35
Finland                   35
United Kingdom            32
Switzerland               28
Sweden                    26
South America Others      22
Africa Others             11
North America Others       6
Oceania Others             6
Name: count, dtype: int64
```



Interpretation

- The grouping helps in creating bigger groups.
- Still some groups are very small. When interpretating the results in the end, we should be aware, that those groups are to small in terms of values. So interpretation with respect to those groups will be limited

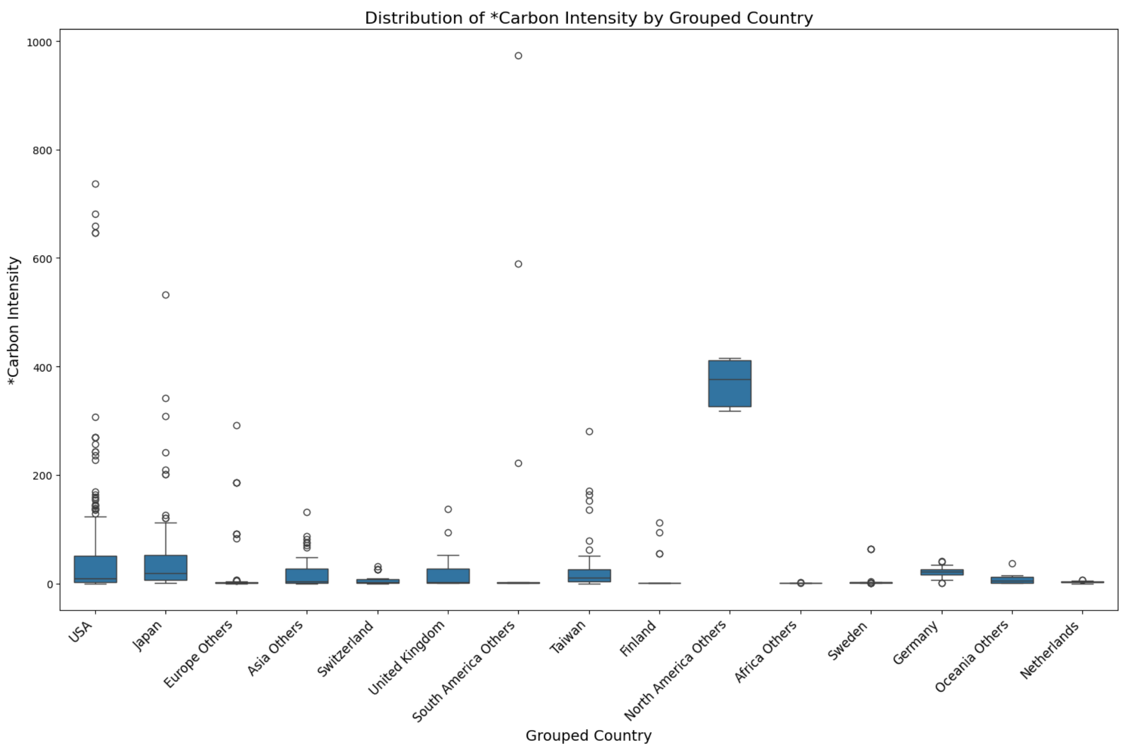
Step four: Checking core assumptions for statistical tests like ANOVA

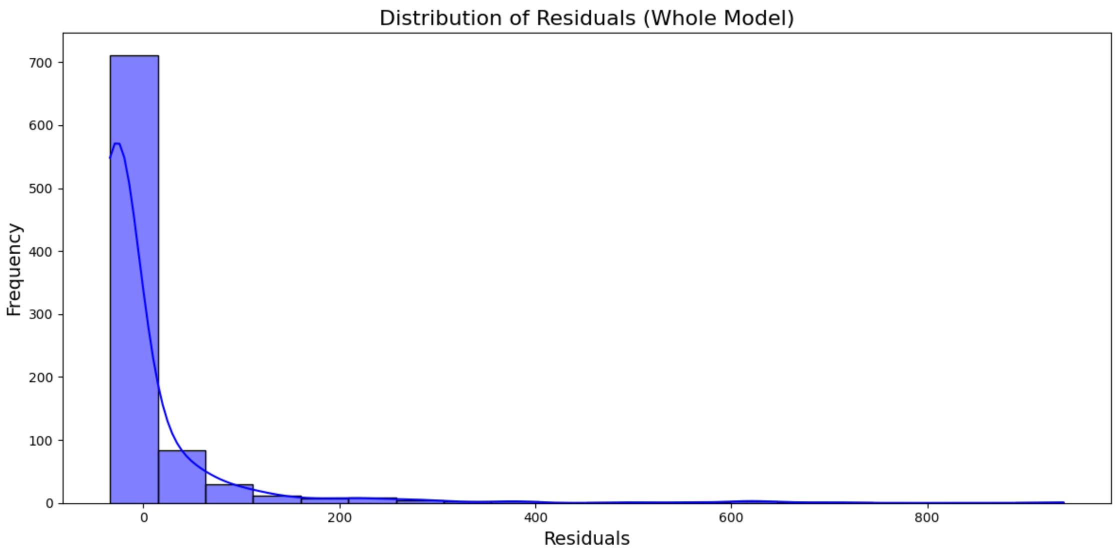
- **Objective:** Assess the data properties for statistical tests related to the `Carbon intensity` column.
- **Steps:**
  1. **Boxplots:** Visualize the distribution of `Carbon intensity` for each group to check for similar variance and normality.
  2. **Residuals:**
     - Calculate residuals by subtracting the overall mean from each observation in `Carbon intensity`.
     - Plot a histogram of these residuals to check for the normality of the entire model.
  3. **Group Residuals:**
     - Group the residuals by country and plot histograms side by side to assess the normality within each group.
- **Purpose:** Ensure the data meets the assumptions for statistical tests such as ANOVA, including similar variances and normality of residuals.

[35]:
```
# Check if the required column exists
if '*Carbon intensity' not in main_data.columns:
    print("The column '*Carbon intensity' is missing from the dataset.")
else:
    # Boxplot: Distribution of Carbon Intensity for each group
```

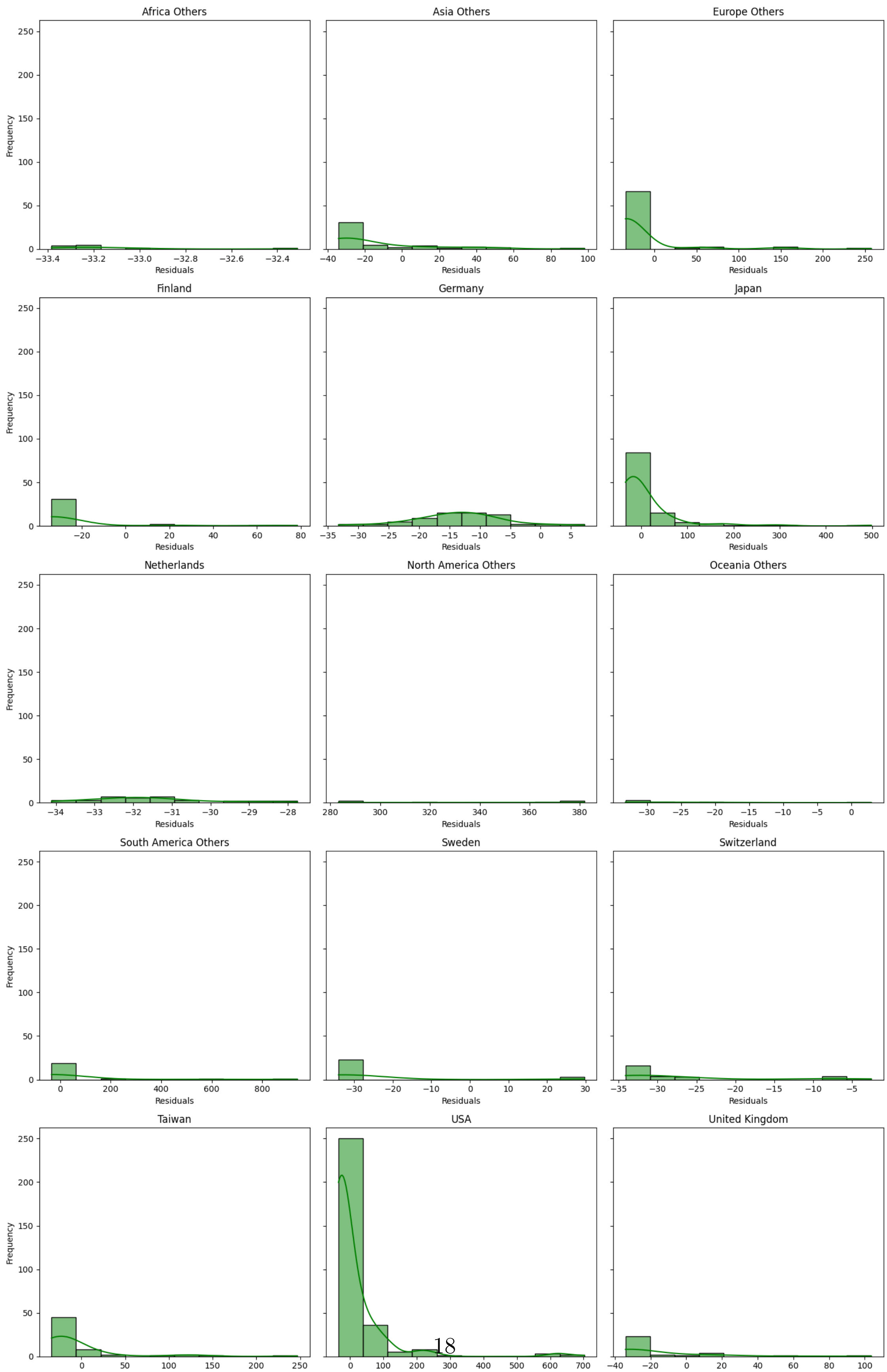
```
plt.figure(figsize=(15, 10))  # Increased figure size
sns.boxplot(data=main_data, x='Grouped Country', y='*Carbon intensity',␣
↪width=0.6)
plt.title('Distribution of *Carbon Intensity by Grouped Country',␣
↪fontsize=16)
plt.xlabel('Grouped Country', fontsize=14)
plt.ylabel('*Carbon Intensity', fontsize=14)
plt.xticks(rotation=45, ha='right', fontsize=12)
plt.tight_layout()
plt.show()

# Calculate residuals for the whole model
overall_mean = main_data['*Carbon intensity'].mean()
main_data['Residuals'] = main_data['*Carbon intensity'] - overall_mean

# Histogram: Residuals of the whole model
plt.figure(figsize=(12, 6))  # Increased figure size
sns.histplot(main_data['Residuals'], kde=True, bins=20, color='blue',␣
↪edgecolor='black')
plt.title('Distribution of Residuals (Whole Model)', fontsize=16)
plt.xlabel('Residuals', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.tight_layout()
plt.show()

# Histogram: Residuals for each group
grouped_residuals = main_data.groupby('Grouped Country')['Residuals']

# Adjusted layout for individual group histograms
n_groups = len(grouped_residuals)
n_cols = 3  # Number of columns for the grid
n_rows = (n_groups + n_cols - 1) // n_cols  # Calculate required rows

fig, axes = plt.subplots(n_rows, n_cols, figsize=(5 * n_cols, 5 * n_rows),␣
↪sharey=True)
fig.suptitle('Distribution of Residuals by Grouped Country', fontsize=18)

# Flatten axes array for easier iteration
axes = axes.flatten()

for i, (group, residuals) in enumerate(grouped_residuals):
    sns.histplot(residuals, kde=True, bins=10, color='green',␣
↪edgecolor='black', ax=axes[i])
    axes[i].set_title(group, fontsize=12)
    axes[i].set_xlabel('Residuals', fontsize=10)
    axes[i].set_ylabel('Frequency', fontsize=10)
```

```
    # Hide unused subplots
    for j in range(i + 1, len(axes)):
        fig.delaxes(axes[j])

    plt.tight_layout(rect=[0, 0, 1, 0.95])  # Adjust layout for title space
    plt.show()

    # Summary table: mean, variance, and standard deviation for each group
    summary_table = main_data.groupby('Grouped Country')['*Carbon intensity'].
↪agg(
        mean='mean',
        variance='var',
        std_dev='std'
    ).reset_index()

    print("Summary table of each group's statistics:")
    display(summary_table)
```




Distribution of Residuals (Whole Model)
Frequency
Residuals
0
100
200
300
400
500
600
700
0
200
400
600
800

Distribution of Residuals by Grouped Country



```
Summary table of each group's statistics:
         Grouped Country        mean      variance     std_dev
0          Africa Others    1.106364      0.084665    0.290973
1            Asia Others   20.764490    919.639421   30.325557
2          Europe Others   17.612838   2699.850903   51.960090
3                Finland    9.669714    716.462068   26.766809
4                Germany   20.763582     58.250648    7.632211
5                  Japan   44.831364   5813.141783   76.243962
6            Netherlands    2.706571      2.529206    1.590348
7    North America Others  370.148333   2193.847657   46.838527
8         Oceania Others   10.500000    198.753560   14.097998
9    South America Others   82.125455  56941.583626  238.624357
10                Sweden    8.676923    414.432374   20.357612
11           Switzerland    6.869286    101.064362   10.053077
12                Taiwan   29.098000   2609.065826   51.079016
13                   USA   45.086623   9687.224246   98.423698
14        United Kingdom   17.763125   1004.746816   31.697741
```

Interpretation

- Test for homogenity of variances: variances differ a lot, so this assumption is violated
- Test for normality of residuals: nearly all distributions in the groups are highly skewed. This assumption is also violated.
- additionally the sample size between groups still differs significantly
- We will have to proceed with a different statistical test than the "normal" ANOVA
- One could now decide to group differently for example by continent. But then the information density will be shrinked a lot.
- Furthermore we can also see that the mean between groups is highly different, with North America (excluding the USA) in first position.

Step five: Checking for significant differences

- **Objective:** Perform Welch's ANOVA to test for significant differences in the means of `*Carbon intensity` across groups, accounting for unequal variances and group sizes.
- **Steps:**
  1. **Data Preparation:** Filter the dataset to include only `Grouped Country` (independent variable) and `*Carbon intensity` (dependent variable). Remove rows with missing values to ensure valid calculations.
  2. **Model Fitting:** Use the ordinary least squares (OLS) model to estimate group means and variances.
     - Apply the `robust='hc3'` option to correct for heteroscedasticity (unequal variances).
  3. **Welch's ANOVA Test:** Conduct the ANOVA test using the fitted model and extract the p-value to determine statistical significance.

- **Purpose:** Welch's ANOVA is a robust alternative to traditional ANOVA, suitable for datasets with unequal variances and/or group sizes.

[36]:
```
import pandas as pd
import statsmodels.api as sm
from statsmodels.formula.api import ols

# Ensure the required column exists
if '*Carbon intensity' not in main_data.columns:
    print("The column '*Carbon intensity' is missing from the dataset.")
else:
    # Step 1: Prepare the data and rename columns
    clean_data = main_data[['Grouped Country', '*Carbon intensity']].dropna()
    clean_data = clean_data.rename(columns={
        '*Carbon intensity': 'Carbon_intensity',
        'Grouped Country': 'Grouped_Country'
    })

    # Step 2: Perform Welch's ANOVA
    formula = 'Carbon_intensity ~ C(Grouped_Country)'  # Match renamed columns
    model = ols(formula, data=clean_data).fit()
    welch_anova = sm.stats.anova_lm(model, typ=2, robust='hc3')  # Use robust␣
↪HC3 for heteroscedasticity
    print("Welch's ANOVA Results:")
    display(welch_anova)

    # Step 3: Interpret the Results
    # Use .iloc[0] to access the first p-value by position
    p_value = welch_anova['PR(>F)'].iloc[0]
    if p_value < 0.05:
        print(f"Significant differences found between groups (p = {p_value:.
↪4f}).")
    else:
        print(f"No significant differences found between groups (p = {p_value:.
↪4f}).")
```

```
Welch's ANOVA Results:

                          sum_sq     df          F         PR(>F)
C(Grouped_Country)  5.760656e+06   14.0  66.647689  2.907430e-126
Residual            5.253979e+06  851.0        NaN            NaN

Significant differences found between groups (p = 0.0000).
```

Intrepration:

- Welch's ANOVA shows that the differences between groups are significant. This is not surprising because we could already see that in the boxplot.

Step six: Examining differences between groups

- **Objective:** Compare how groups differ from each other after Welch's ANOVA by performing a pairwise comparison.
- **Method:** Use the **Games-Howell post-hoc test**, which is robust to unequal variances and group sizes.
- **Steps:**
  1. **Data Preparation:**
     - Filter the dataset to include only the dependent variable (`*Carbon intensity`) and the grouping variable (`Grouped Country`).
     - Rename columns to avoid issues with special characters or spaces.
  2. **Perform Games-Howell Test:**
     - Use the `pairwise_gameshowell()` function from the `pingouin` library to compare all possible pairs of groups.
     - Compute p-values for each pairwise comparison, adjusted for Type I error.
  3. **Display Results:**
     - The results table shows mean differences, standard errors, test statistics, and adjusted p-values.

[37]:
```python
import pingouin as pg

# Ensure the required column exists
if '*Carbon intensity' not in main_data.columns:
    print("The column '*Carbon intensity' is missing from the dataset.")
else:
    # Step 1: Prepare the data and rename columns
    clean_data = main_data[['Grouped Country', '*Carbon intensity']].dropna()
    clean_data = clean_data.rename(columns={
        '*Carbon intensity': 'Carbon_intensity',
        'Grouped Country': 'Grouped_Country'
    })

    # Step 2: Perform the Games-Howell test
    posthoc_results = pg.pairwise_gameshowell(
        data=clean_data,
        dv='Carbon_intensity',    # Dependent variable
        between='Grouped_Country'  # Independent variable (grouping)
    )

    # Step 3: Display the results
    print("Games-Howell Post-Hoc Test Results:")
    display(posthoc_results)
```

```
Games-Howell Post-Hoc Test Results:

               A              B   mean(A)    mean(B)       diff        se  \
0  Africa Others    Asia Others  1.106364  20.764490 -19.658126  4.333111
1  Africa Others  Europe Others  1.106364  17.612838 -16.506474  6.040875
2  Africa Others        Finland  1.106364   9.669714  -8.563351  4.525267
```

```
3    Africa Others         Germany   1.106364  20.763582 -19.657218  0.936541
4    Africa Others           Japan   1.106364  44.831364 -43.725000  7.270106
..             …               …         …          …          …        …
100    Switzerland             USA   6.869286  45.086623 -38.217337  5.947338
101    Switzerland  United Kingdom   6.869286  17.763125 -10.893839  5.916737
102         Taiwan             USA  29.098000  45.086623 -15.988623  8.674435
103         Taiwan  United Kingdom  29.098000  17.763125  11.334875  8.653483
104            USA  United Kingdom  45.086623  17.763125  27.323498  7.947310

             T          df          pval    hedges
0    -4.536724   48.039339  3.098933e-03 -0.703308
1    -2.732464   73.030780  3.071073e-01 -0.335666
2    -1.892342   34.025556  8.409098e-01 -0.357698
3   -20.989165   67.139032  0.000000e+00 -2.736134
4    -6.014355  109.031728  2.501564e-06 -0.595433
..         …           …           …        …
100  -6.425957  329.158131  4.799881e-08 -0.404065
101  -1.841190   37.960991  8.661228e-01 -0.444910
102  -1.843189  160.088809  8.765225e-01 -0.172689
103   1.309863   87.820709  9.920746e-01  0.247863
104   3.438082  113.585767  5.441158e-02  0.289243

[105 rows x 10 columns]
```

[38]:

```python
# Filter results where p-value is significant
significant_results = posthoc_results[posthoc_results['pval'] < 0.05]
print("Significant Pairwise Comparisons:")
display(significant_results)
```

```
Significant Pairwise Comparisons:

                        A                     B     mean(A)     mean(B)  \
0           Africa Others           Asia Others    1.106364   20.764490
3           Africa Others               Germany    1.106364   20.763582
4           Africa Others                 Japan    1.106364   44.831364
5           Africa Others           Netherlands    1.106364    2.706571
6           Africa Others  North America Others    1.106364  370.148333
11          Africa Others                Taiwan    1.106364   29.098000
12          Africa Others                   USA    1.106364   45.086623
18            Asia Others           Netherlands   20.764490    2.706571
19            Asia Others  North America Others   20.764490  370.148333
31          Europe Others  North America Others   17.612838  370.148333
40                Finland                 Japan    9.669714   44.831364
42                Finland  North America Others    9.669714  370.148333
48                Finland                   USA    9.669714   45.086623
51                Germany           Netherlands   20.763582    2.706571
52                Germany  North America Others   20.763582  370.148333
56                Germany           Switzerland   20.763582    6.869286
58                Germany                   USA   20.763582   45.086623
```

60	Japan	Netherlands	44.831364	2.706571
61	Japan	North America Others	44.831364	370.148333
62	Japan	Oceania Others	44.831364	10.500000
64	Japan	Sweden	44.831364	8.676923
65	Japan	Switzerland	44.831364	6.869286
69	Netherlands	North America Others	2.706571	370.148333
74	Netherlands	Taiwan	2.706571	29.098000
75	Netherlands	USA	2.706571	45.086623
77	North America Others	Oceania Others	370.148333	10.500000
78	North America Others	South America Others	370.148333	82.125455
79	North America Others	Sweden	370.148333	8.676923
80	North America Others	Switzerland	370.148333	6.869286
81	North America Others	Taiwan	370.148333	29.098000
82	North America Others	USA	370.148333	45.086623
83	North America Others	United Kingdom	370.148333	17.763125
88	Oceania Others	USA	10.500000	45.086623
97	Sweden	USA	8.676923	45.086623
100	Switzerland	USA	6.869286	45.086623

	diff	se	T	df	pval	hedges
0	-19.658126	4.333111	-4.536724	48.039339	3.098933e-03	-0.703308
3	-19.657218	0.936541	-20.989165	67.139032	0.000000e+00	-2.736134
4	-43.725000	7.270106	-6.014355	109.031728	2.501564e-06	-0.595433
5	-1.600208	0.282772	-5.659008	40.082453	1.270075e-04	-1.119526
6	-369.041970	19.121950	-19.299390	5.000211	1.470025e-04	-12.952464
11	-27.991636	6.594856	-4.244465	59.020877	6.244861e-03	-0.586164
12	-43.980259	5.636407	-7.802889	304.146814	1.040190e-11	-0.453051
18	18.057918	4.340555	4.160279	48.369328	9.690883e-03	0.770406
19	-349.383844	19.606362	-17.819922	5.524951	1.048967e-04	-10.680678
31	-352.535495	20.053073	-17.580123	6.043483	5.605603e-05	-6.760019
40	-35.161649	8.562540	-4.106451	141.657666	5.762694e-03	-0.515631
42	-360.478619	19.649723	-18.345226	5.572951	8.382133e-05	-11.745144
48	-35.416909	7.227153	-4.900534	174.401694	2.120159e-04	-0.377032
51	18.057011	0.970400	18.607806	76.402807	1.920686e-14	2.858527
52	-349.384751	19.144469	-18.249906	5.023804	1.869973e-04	-23.931601
56	13.894296	2.116330	6.565278	40.609719	6.749049e-06	1.639309
58	-24.323041	5.712338	-4.257984	319.767113	2.479362e-03	-0.271905
60	42.124792	7.274545	5.790712	109.297643	6.900172e-06	0.629462
61	-325.316970	20.456980	-15.902493	6.543494	5.464530e-05	-4.297743
62	34.331364	9.272127	3.702642	30.158145	4.782352e-02	0.457100
64	36.154441	8.293760	4.359234	132.223099	2.325987e-03	0.518598
65	37.962078	7.513733	5.052359	122.098501	1.506784e-04	0.551901
69	-367.441762	19.123638	-19.214009	5.001977	1.498468e-04	-21.401726
74	-26.391429	6.599749	-3.998853	59.195973	1.336572e-02	-0.643263
75	-42.380052	5.642132	-7.511354	305.370752	6.833012e-11	-0.453014
77	359.648333	19.969148	18.010199	5.898584	5.922884e-05	9.598332
78	288.022879	54.349748	5.299434	25.237055	1.243414e-03	1.297983
79	361.471410	19.534098	18.504638	5.443372	9.601332e-05	13.214468

80	363.279048	19.215898	18.905130	5.099111	1.408529e-04	17.143721
81	341.050333	20.226856	16.861263	6.252488	5.471107e-05	6.639771
82	325.061710	19.934961	16.306112	5.905644	1.039427e-04	3.315469
83	352.385208	19.925853	17.684824	5.888586	6.668134e-05	10.086381
88	-34.586623	8.055246	-4.293677	18.899061	2.122818e-02	-0.353363
97	-36.409700	6.906598	-5.271727	168.780989	4.098835e-05	-0.383287
100	-38.217337	5.947338	-6.425957	329.158131	4.799881e-08	-0.404065

Interpretation

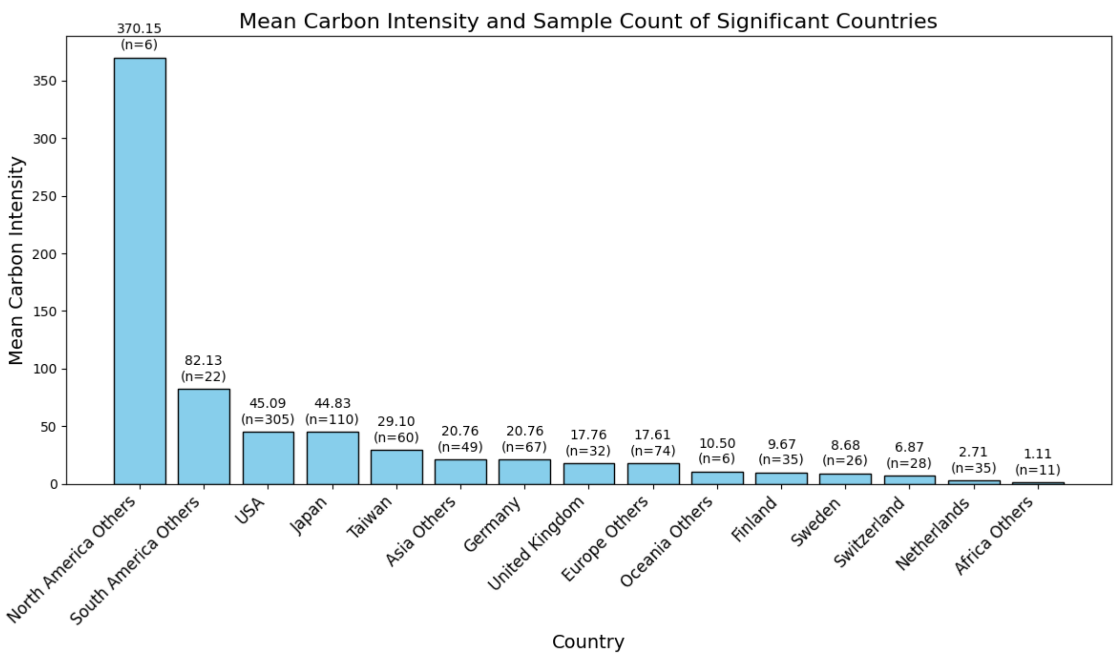
- this table is only helpful if there are specific case where a client wants to know if there is a significant difference between pairwise groups.
- We can see that a lot of pairs differ significantly between each other. We can also see the respective means, which makes it really clear.

0.0.3 Overall Interpretation for policy makers and limitations

[39]:

```
import matplotlib.pyplot as plt

# Step 1: Filter significant results
significant_results = posthoc_results[posthoc_results['pval'] < 0.05]

# Step 2: Extract unique countries from significant comparisons
unique_countries = set(significant_results['A']).
 ↪union(set(significant_results['B']))

# Step 3: Calculate means and counts for these countries
country_means = clean_data.groupby('Grouped_Country')['Carbon_intensity'].mean()
country_counts = clean_data.groupby('Grouped_Country')['Carbon_intensity'].
 ↪count()

# Step 4: Filter and sort the means and counts for only the significant␣
 ↪countries
significant_means = country_means[country_means.index.isin(unique_countries)].
 ↪sort_values(ascending=False)
significant_counts = country_counts[significant_means.index]

# Step 5: Plot the means as a bar chart
plt.figure(figsize=(12, 7))
bars = plt.bar(significant_means.index, significant_means.values,␣
 ↪color='skyblue', edgecolor='black')

# Add value labels to each bar
for bar, count in zip(bars, significant_counts):
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width() / 2,  # Center the text on the bar
```

```
        height + 5,  # Slightly above the bar
        f'{height:.2f}\n(n={count})',  # Format to include mean and count
        ha='center', va='bottom', fontsize=10
    )

# Add chart details
plt.title('Mean Carbon Intensity and Sample Count of Significant Countries',␣
 ↪fontsize=16)
plt.xlabel('Country', fontsize=14)
plt.ylabel('Mean Carbon Intensity', fontsize=14)
plt.xticks(rotation=45, ha='right', fontsize=12)
plt.tight_layout()
plt.show()
```



0.0.4 Key Findings and Limitations

Significant Differences Across Groups:

- **Welch's ANOVA** confirmed that there are significant differences in *Carbon Intensity* between groups (p-value from ANOVA = (2.91 ×10^{-126})).
- The post-hoc analysis revealed specific pairwise differences, with **37 significant comparisons** ($p < 0.05$).

Groups with High Differences:

- **North America Others** stands out as a major outlier, consistently showing significantly higher *Carbon Intensity* compared to almost all other groups (e.g., Netherlands, Japan, Oceania Others).

- **USA, Japan, and Germany** also display relatively high *Carbon Intensity*, with significant differences compared to lower-intensity groups like **Netherlands, Switzerland, and Sweden**.
- Groups like **Africa Others, Oceania Others, and Switzerland** generally show low *Carbon Intensity* and are often significantly different from high-intensity groups.

0.0.5 2. Possible Reasons for the Differences

a. Industrialization Level and Energy Mix

- **North America Others and USA:**
  - Likely reflects high-carbon industries and reliance on fossil fuels for energy.
  - Large-scale industrial activities, including resource extraction and manufacturing, drive high emissions.
- **Europe Others, Netherlands, and Switzerland:**
  - Lower *Carbon Intensity* may result from cleaner energy sources (e.g., renewables, nuclear) and stringent environmental regulations.

b. Nature of Products

- High-intensity regions may focus on producing energy-intensive goods, such as heavy machinery, automobiles, or chemicals.
- Low-intensity regions may produce less energy-demanding goods, such as textiles or services.

c. Regulations and Sustainability Initiatives

- **Europe (e.g., Germany, Netherlands):**
  - Stringent regulations on emissions and higher adoption of energy-efficient technologies may lower *Carbon Intensity*.
- **Developing regions (e.g., Africa Others):**
  - Limited industrial activities and cleaner supply chains contribute to lower intensity but may also reflect lower economic output.

d. Economic Development Stage

- **Developed regions (e.g., USA, Japan):**
  - Higher industrial activity and energy demand, leading to higher emissions.
- **Developing regions (e.g., Africa Others):**
  - Fewer emissions due to limited industrialization.

0.0.6 3. Strategic Insights

Regions Requiring Attention:

- **North America Others, USA, and Japan** should be targeted for carbon reduction strategies, as they consistently show high *Carbon Intensity*.

- These regions may benefit from:
  - Transitioning to renewable energy.
  - Implementing stricter emissions standards.
  - Encouraging carbon offset programs.

Benchmarks for Low Emissions:

- Groups like **Netherlands, Switzerland, and Sweden** demonstrate significantly lower *Carbon Intensity* and could serve as benchmarks for sustainability practices.

0.0.7 4. Challenges in Interpretation

Aggregate Data:

- The analysis uses aggregate data per region, which may mask intra-regional variations (e.g., emissions vary across states or industries).
- The decision for one approach of grouping the countries may have an significant influence on the output.

Underlying Factors Not Captured:

- Factors such as trade, raw material sourcing, and supply chain complexity are not directly analyzed but may influence *Carbon Intensity*.

0.0.8 Overall Interpretation

Big Picture:

- The results confirm that *Carbon Intensity* varies significantly between regions, driven by differences in industrial activity, energy sources, and regulations.

Actionable Insights:

- High-emission groups like **North America Others** and **USA** require immediate intervention, while low-emission regions like **Switzerland** and **Netherlands** offer valuable models for sustainable practices. “‘