Environmental Economic Module 7QQMM906
Group Four Data report:
Decoupling and policy comparison between countries

Draft Report

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1. Part I: Motivation & Data Context

1a. Dataset Selection and Research Questions

From decoupling and country policy, we see the potential of analyzing the correlation of country emission and their GDP. We gathered emission data from EDGAR - Emissions Database for Global Atmospheric Research , GDP and GNI data from several databases (country economy, database earth, Trading Economics, UNdata). The detailed structure of the dataset is documented in section 2b. Links to the selected databases are included in the reference section.

1a1. Our two research questions

1. To what extent have major Asian countries decoupled CO2 emissions from economic growth?
2. Which economic sectors have been the primary drivers of successful (or failed) decoupling?

The findings in this report can help governments understand their progress and trends in decoupling. Facilitating further decoupling by showing successful decoupling cases with country data.

1b. Data Significance and Relevance

Currently the debate of green growth and degrowth continues, with countries reaching decoupling in GDP and carbon emissions, we decided to analysis the decoupling process of countries. This data of emission and GDP allows us to analysis the decoupling progress of the selected countries, which we will specify in section 2b.

We use GDP and carbon emission to calculate the carbon tensity plot the graph for carbon intensity, i.e. emission per GDP. To achieve this calculation, GDP and emission data are essential. The result can be used to analysis decarbonization progress and policy comparison between countries.

2. Part II: Technical Implementation

In this project, we implemented GitHub for code management, and a Word document on OneDrive for the final report. Both access-controlled by authorising account.

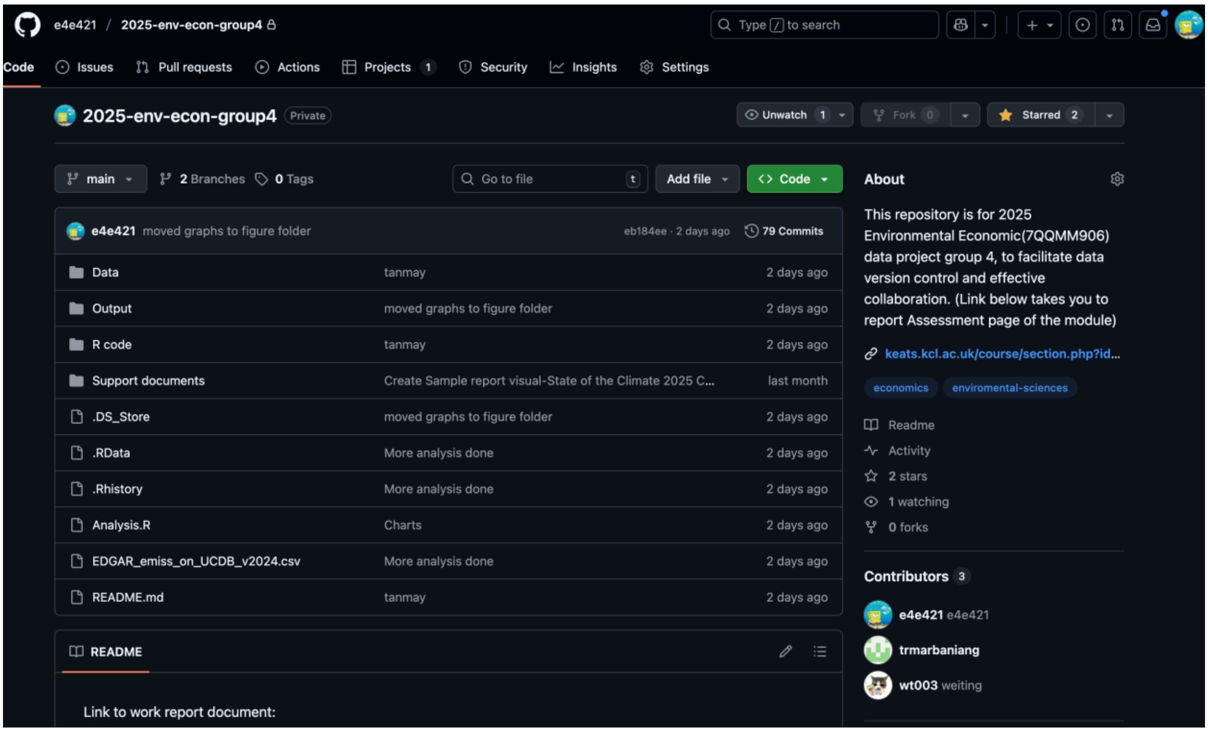
2a. Coding Setup and Documentation

2a1. Data Pipeline and workflow

Based on research questions, databases are downloaded and turned into csv format. Commit the file to GitHub and set the file pathway to the local computer using GitHub desktop. Then we divide into two group functions, one process the csv file in local R studio with commits to GitHub to ensure trackability, another draft the documentation in README.md and final report word docx. We then estimate the analysis outcome and compare them with our research questions. After data analysis and visualisation, we move on to the online word docx file to form our technical reflection and suggestions. We then analysis our visualisation to spot any relevant policy trends.

2a2. GitHub environment

GitHub repository was created on 8 Nov 2025, under Marvin's account (e4e421). With regular commits and updates, documented with naming convention. The following is the repository screenshot on 7 Dec 2025.



2a3. R language and running environment

We chose R as the main data processing tool. Running on Tanmay's local machine, version 2024.12.1+563. Running on MacBook Air M2 2022, model number A2681, MacOS version 26.1.

2b. Data Preparation and Management

We imported two datasets. One is the regional emission data from EDGAR - Emissions Database for Global Atmospheric Research. Another is regional GDP and GNI data from the World Bank, database earth, Country Economy and UN data.

2b1. Data gathering and brief description

2b1.1. EDGAR - Emissions Database for Global Atmospheric Research

The first dataset downloaded from EDGAR - Emissions Database for Global Atmospheric Research (link: https://edgar.jrc.ec.europa.eu/dataset_ucdb), the file is named "EDGAR global emissions in urban areas v2024.xlsx". The Excel file contains three worksheets. The first is named "citation and references", containing links and source names. Second is named "List of variables", containing the variables of the third worksheet. Third is named "EDGAR_emiss_on_UCDB_2024", the main data worksheet.

We extracted the third worksheet in csv format and committed it to GitHub for easy sharing and control.

Data characteristics of EDGAR_emiss_on_UCDB_2024

ID_UC_G0	UC_name (11687 unique entries)	UC_country (192 unique entries)	Data column (See below)
1	Apia	Samoa	...
2	Nuku'alofa	Tonga	...
3	Ewa Beach	United States	...
...	...	...	...

Data points at following years: 1975, 1990, 2000, 2005, 2010, 2015, 2020, 2022

Data columns include 6 sectors in 4 emission categories:

CO2_Agriculture	GWP_100_AR5_GHG_Agriculture	NOx_Agriculture	PM2.5_Agriculture
CO2_Energy	GWP_100_AR5_GHG_Energy	NOx_Energy	PM2.5_Energy
CO2_Industry	GWP_100_AR5_GHG_Industry	NOx_Industry	PM2.5_Industry
CO2_Residential	GWP_100_AR5_GHG_Residential	NOx_Residential	PM2.5_Residential
CO2_Transport	GWP_100_AR5_GHG_Transport	NOx_Transport	PM2.5_Transport
CO2_Waste	GWP_100_AR5_GHG_Waste	NOx_Waste	PM2.5_Waste

2b1.2. GDP and GNI databases

The second dataset contains GDP and GNI for 43 Asian countries, following the data year of the EDGAR dataset. All values are in USD currency.

Data points at following years: 1975, 1990, 2000, 2005, 2010, 2015, 2020, 2022

Country	Region	1975	...	2022
China	East Asia	163,429,530,659.6	...	17,963,171,479,205.3
Japan	East Asia	532,861,438,884.7	...	4,232,173,916,086.7
...	...	...	...	...

2b2. Data scoping and missing data policy

After examining the first dataset and focusing on our research question. We chose the data entry of top 5 emitting Asia countries. All with GDP and emission data. Therefore, we keep the original value without going through missing value cleaning policy.

The missing data policy is as follows.

1. Replace missing value with NA.
2. Analysis NA using interpolation methods.
3. Deciding if a new value is appropriate.

In our case, any missing data will severely deteriorate the quality of our analysis and report. Therefore, we ensure that every chosen country has full data available.

2b3. Data processing code

2b3.1. Data Cleaning and structuring

We filtered through the data and ranked the five highest emission countries. Then turn it into a long format with country, year, GDP, and emission. Organise the sectorial data and save it as a processed csv file. Our analysis code is split into steps as follows.

1. Install package: tidyverse, patchwork, ggplot2.
2. Import data from: EDGAR_emiss_on_UCDB_v2024.csv, GDP.csv.
3. View data and determine the top 5 emitting countries.
4. Filter "China, India, Japan, South Korea, Indonesia" and create new "country, GDP and year" table.
5. Using EMI_CO2 as keyword to extract emissions data.
6. Aggregate city data to calculate country total.
7. Filter emission data by sector.
8. Calculate CO2/GDP in country and year form.
9. Store the processed carbon intensity data (CO2/GDP) and emission by sector data to csv files.

```r
### Data Cleaning

## Install & load data transformation function package
install.packages("tidyverse")
library(tidyverse)

## Install & load data visualisation packages
install.packages("patchwork")
library(patchwork)
install.packages("ggplot2")
library(ggplot2)

## Step 1:Load Data
raw_data <- read_csv("EDGAR_emiss_on_UCDB_v2024.csv")
gdp_data <- read_csv("GDP.csv")

# View the structure to confirm column names
glimpse(raw_data)
head(raw_data)

## Step 2:Filter target countries
target_countries <- c("China", "India", "Japan", "South Korea", "Indonesia")

cleaned_data <- raw_data %>%
  # Filter target countries
  filter(UC_country %in% target_countries) %>%
  # Select all EMI columns for CO2 across all years and sectors
  select(UC_name, UC_country, matches("EMI_CO2_.*_(1975|1990|2000|2005|2010|2015|2020|2022)"))

# Reshape GDP data from wide to long format
gdp_long <- gdp_data %>%
  select(Country, `1975`, `1990`, `2000`, `2005`, `2010`, `2015`, `2020`, `2022`) %>%
  pivot_longer(
    cols = -Country,
    names_to = "Year",
    values_to = "GDP"
  ) %>%
  mutate(Year = as.numeric(Year))


### Step 3: Pivot to long format to extract Year and Sector from column names
long_data <- cleaned_data %>%
  pivot_longer(
    cols = starts_with("EMI_"),
    names_to = "Emission_Variable",
    values_to = "Emission_Value"
  ) %>%
  ## Extract Year, Sector, and Pollutant from the column name
  mutate(
    # Extract year (last 4 digits)
```

```r
### Step 3: Pivot to long format to extract Year and Sector from column names
long_data <- cleaned_data %>%
  pivot_longer(
    cols = starts_with("EMI_"),
    names_to = "Emission_Variable",
    values_to = "Emission_Value"
  ) %>%
  ## Extract Year, Sector, and Pollutant from the column name
  mutate(
    # Extract year (last 4 digits)
    Year = str_extract(Emission_Variable, "\\d{4}$"),
    # Extract sector (between CO2_ and _Year)
    Sector = str_extract(Emission_Variable, "CO2_(.*?)_\\d{4}"),
    Sector = str_remove(Sector, "CO2_"),
    Sector = str_remove(Sector, "_\\d{4}"),
    Pollutant = "CO2"
  ) %>%
  select(-Emission_Variable) %>%
  mutate(Year = as.numeric(Year))

## Step 4: Aggregate from city level to country level
# For total CO2 by country and year (for trend analysis)
country_year_totals <- long_data %>%
  group_by(UC_country, Year) %>%
  summarise(
    Total_CO2 = sum(Emission_Value, na.rm = TRUE),
    .groups = 'drop'
  ) %>%
  rename(Country = UC_country)

# For sector-level data (for sector contribution analysis)
country_sector_year <- long_data %>%
  group_by(UC_country, Sector, Year) %>%
  summarise(
    Sector_CO2 = sum(Emission_Value, na.rm = TRUE),
    .groups = 'drop'
  ) %>%
  rename(Country = UC_country)

## STEP 6: Merge emissions with GDP data
final_trend_data <- country_year_totals %>%
  inner_join(gdp_long, by = c("Country", "Year")) %>%
  mutate(Carbon_Intensity = Total_CO2 / GDP)

## STEP 7: Save cleaned datasets
write_csv(final_trend_data, "country_co2_gdp_trends.csv")
write_csv(country_sector_year, "country_sector_co2.csv")
```

2c. Data Processing structures for research questions

In the decoupling types shown in the paper ***"Decoupling analysis of world economic growth and CO_2 emissions: A study comparing developed and developing countries(2018)".*** It showed four decoupling types, absolute, relative, non-decoupling, and stagnant.

2c1. Research question 1

Question 1: "To what extent have major Asian countries decoupled CO2 emissions from economic growth?"

We chose the top 5 emitting countries and calculated their carbon Intensity. For each country, calculate CO2 / GDP for each year. Plot these trends on the chart.

We then Identify Decoupling Types. For each country, analyse the trends of Total CO2 and GDP separately. Categories absolute decoupling, relative recoupling, non-decoupling and stagnant.

2c2. Research question 2

Question 2: "Which economic sectors have been the primary drivers of successful (or failed) decoupling?"

We analysis Sectoral Contribution to Change: For the year 1975-2022, calculate the change in Total CO2 from 1975 to 2022, and change in CO2 from each sector (Energy, Industry, Transport, etc.) over the same period.

3. Part III: Descriptive Analysis and Export of Results for Presentation

3a. Summary Statistics Table

3a1. Research question 1

3a1.1. Table 1: Basic Decoupling Status Table

```
# 1. Basic table (countries as columns, years as rows)
decoupling_basic <- tapio_decoupling %>%
  mutate(Decoupling_Type = as.character(Decoupling_Type))
%>%elect(Year, Country, Decoupling_Type) %>%
  pivot_wider(
    names_from = Country,
    values_from = Decoupling_Type
  ) %>%
  arrange(Year)

print("Basic Decoupling Status Table:")
print(decoupling_basic)
```

Year	China	India	Indonesia	Japan	South Korea
1990	Relative Decoupling	Relative Decoupling	Non-Decoupling	Relative Decoupling	Relative Decoupling
2000	Relative Decoupling	Non-Decoupling	Non-Decoupling	Relative Decoupling	Relative Decoupling
2005	Relative Decoupling	Relative Decoupling	Relative Decoupling	Stagnant	Absolute Decoupling
2010	Relative Decoupling	Relative Decoupling	Relative Decoupling	Absolute Decoupling	Relative Decoupling
2015	Relative Decoupling	Relative Decoupling	Absolute Decoupling	Stagnant	Relative Decoupling
2020	Relative Decoupling	Absolute Decoupling	Relative Decoupling	Absolute Decoupling	Relative Decoupling
2022	Relative Decoupling	Relative Decoupling	Relative Decoupling	Stagnant	Non-Decoupling

3a1.2. Table 2: Decoupling performance Summary (1975-2022)

```r
## Table
# Create a summary table
decoupling_performance <- tapio_decoupling %>%
  group_by(Country) %>%
  summarise(
    Years_Absolute_Decoupling = sum(Decoupling_Type == "Absolute Decoupling", na.rm =
TRUE),Years_Relative_Decoupling = sum(Decoupling_Type == "Relative Decoupling", na.rm =
TRUE),Years_Non_Decoupling = sum(Decoupling_Type == "Non-Decoupling", na.rm = TRUE),
    Years_Stagnant = sum(Decoupling_Type == "Stagnant", na.rm = TRUE),
    Percent_Absolute = Years_Absolute_Decoupling / n() * 100,
    Avg_DI = mean(DI, na.rm = TRUE),
    Final_State = last(Decoupling_Type),
    .groups = 'drop'
  ) %>%
  arrange(desc(Percent_Absolute))

# Print formatted table
library(knitr)
kable(decoupling_performance,
      caption = "Decoupling Performance Summary (1975-2022)",
      digits = 2,
      col.names = c("Country", "Abs. Dec.", "Rel. Dec.", "Non-Dec.",
                    "Stagnant", "% Abs.", "Avg DI", "Final State"))
```

Country	Years_Absolute_Decoupling	Years_Relative_Decoupling	Years_Non_Decoupling	Years_Stagnant	Percent_Absolute	Avg_DI	Final_State
Japan	2	2	0	3	28.5714	-0.3354	Stagnant
India	1	5	1	0	14.2857	0.4657	Relative Decoupling
Indonesia	1	4	2	0	14.2857	0.4520	Relative Decoupling
South Korea	1	5	1	0	14.2857	0.5419	Non-Decoupling
China	0	7	0	0	0	0.2794	Relative Decoupling

We are still working on this section. Will add more descriptions to explain what each number means.

3a2. Research question 2

3a2.1. Table 3: Dominant CO_2 Emission Sectors by Country (2022)

```r
##Plot 2: Sectoral analysis 2022
# Analyze sector contributions for 2022
sector_2022 <- country_sector_year %>%
  filter(Year == 2022) %>%
  group_by(Country) %>%
  mutate(
    Total_CO2_2022 = sum(Sector_CO2, na.rm = TRUE),
    Sector_Share_2022 = Sector_CO2 / Total_CO2_2022 * 100,
    Rank = rank(-Sector_CO2, ties.method = "first")  # Rank sectors by emissions
  ) %>%
  ungroup() %>%
  arrange(Country, Rank)

# Identify top contributing sector for each country in 2022
top_sectors_2022_enhanced <- sector_2022 %>%
  filter(Rank == 1) %>%
  select(Country,
         `Dominant Sector` = Sector,
         `Sector Emissions (tons)` = Sector_CO2,
         `Share of Total (%)` = Sector_Share_2022) %>%
  # Format to 2 decimal places
  mutate(
    `Sector Emissions (tons)` = round(`Sector Emissions (tons)`, 2),
    `Share of Total (%)` = round(`Share of Total (%)`, 2)  # Convert to percentage and
ro)n%>%
  arrange(desc(`Share of Total (%)`))
  arrange(desc(`Share of Total (%)`))
print("Table 1: Dominant CO₂ Emission Sectors by Country (2022)")
print(top_sectors_2022_enhanced)
# Save to CSV
write_csv(top_sectors_2022_enhanced, "dominant_sectors_2022.csv")
```

Country	Dominant Sector	Sector Emissions (tons)	Share of Total (%)
Indonesia	Industry	92221427.8	55.96
India	Industry	214642720.74	53.7
China	Industry	1067784607.08	49.15
Japan	Energy	143146767.42	40.91
South Korea	Energy	53334116.91	37.58

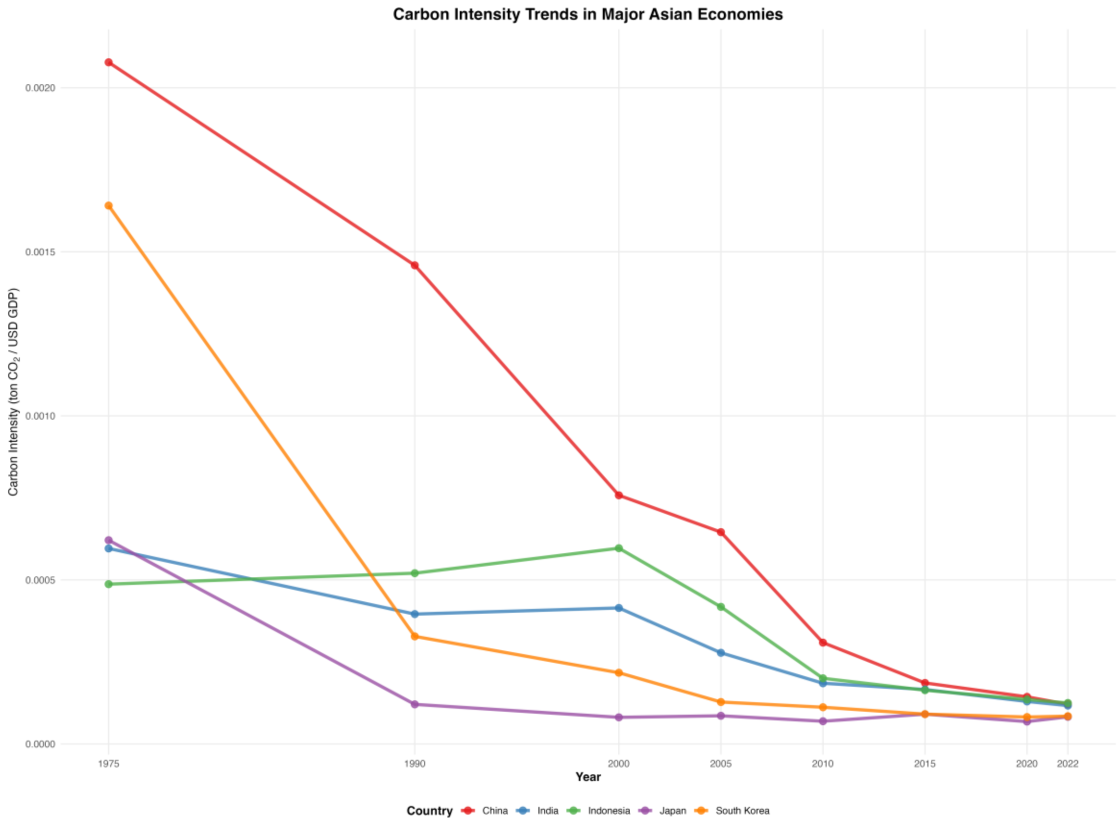
3b. Data Visualization and Exploration

3b1. Research question 1

Question 1: "To what extent have major Asian countries decoupled CO2 emissions from economic growth?"

3b1.1. Figure 1: Carbon Intensity Trends in Major Asian Economies

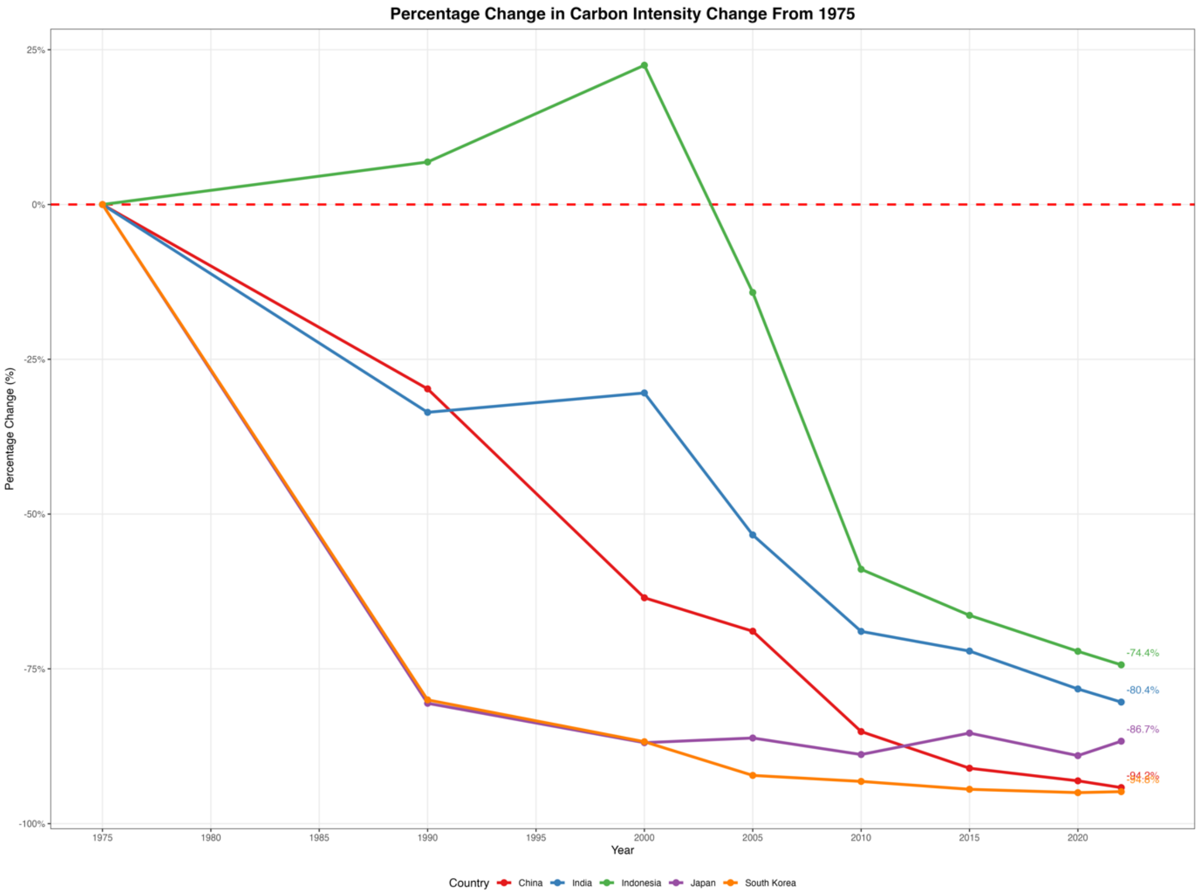
```r
## Plot 1: Carbon Intensity Trends
carbon_intensity_plot <- ggplot(final_trend_data,
                                aes(x = Year, y = Carbon_Intensity, color = Country))
+
  # Thicker, more prominent lines
  geom_line(linewidth = 1.5, alpha = 0.8) +
  geom_point(size = 3, alpha = 0.8) +

  # Labels and title
  labs(
    title = "Carbon Intensity Trends in Major Asian Economies",
    x = "Year",
    y = expression("Carbon Intensity (ton CO"[2]~"/ USD GDP)"),
    color = "Country",
  ) +

  # Theme
  theme_minimal(base_size = 12) +
  theme(
    plot.title = element_text(face = "bold", size = 16, hjust = 0.5),
    plot.subtitle = element_text(size = 12, hjust = 0.5, lineheight = 1.2),
    plot.caption = element_text(face = "italic", color = "gray50"),
    legend.position = "bottom",
    legend.title = element_text(face = "bold"),
    axis.title = element_text(face = "bold"),
    panel.grid.minor = element_blank(),
    plot.margin = margin(1, 1, 1, 1, "cm")
  ) +

  # Color scheme (colorblind friendly)
  scale_color_brewer(palette = "Set1") +

  # Axis formatting
  scale_x_continuous(breaks = unique(final_trend_data$Year)) +
  scale_y_continuous(labels = comma_format())

# Display the plot
print(carbon_intensity_plot)
ggsave("Carbon Intensity over time.png", carbon_intensity_plot,
       width = 16, height = 12, dpi = 400, bg = "white")
```



1. Figure one: Line Charts with carbon intensity changes
   x-axis: years
   y-axis: CO2 emission over GDP USD
   a. Carbon intensity for India and Indonesia increases between 1990 and 2000.
   b. We then use percentage change to see in detail

3b1.2. Figure 2: Percentage Change in Carbon Intensity Change From 1975

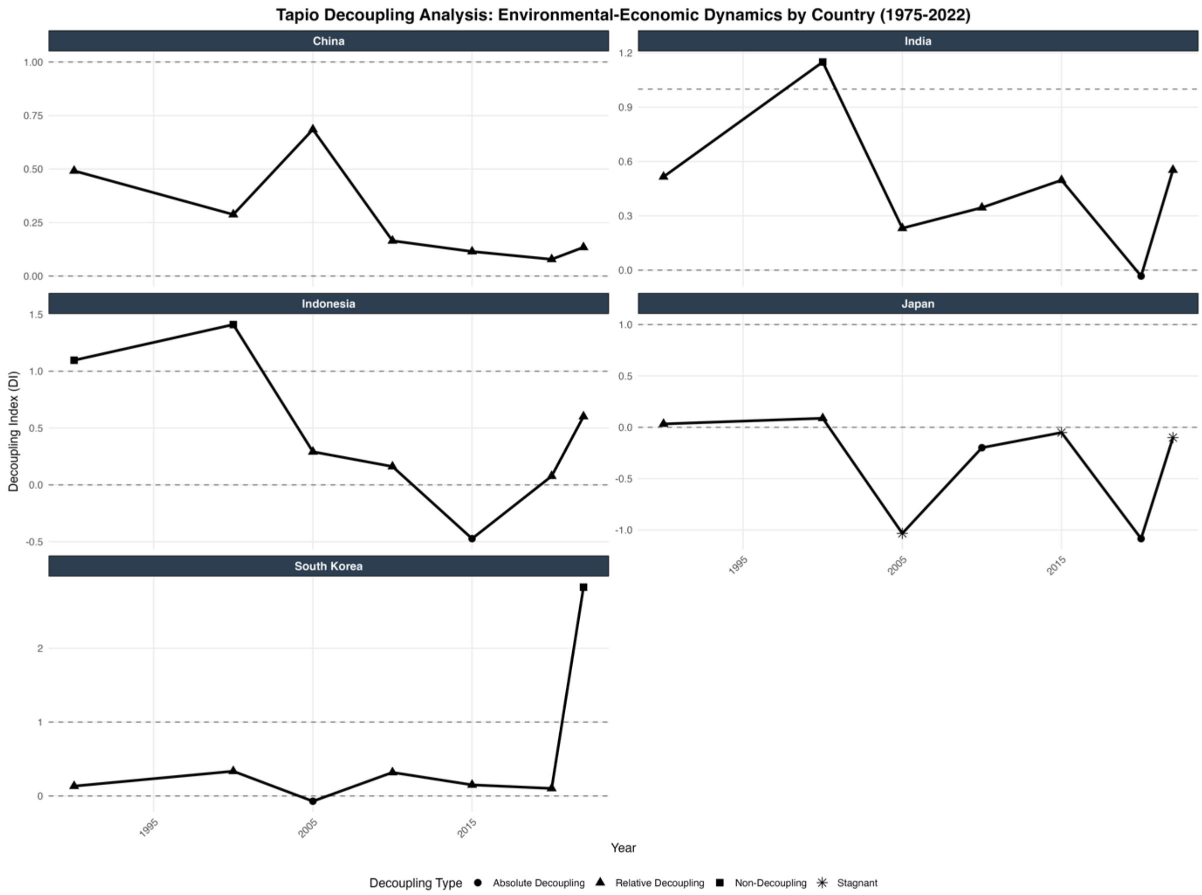
```r
# plot
pct_change_plot <- ggplot(carbon_intensity_change,
                          aes(x = Year, y = pct_change, color = Country)) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "red", linewidth = 1)
+ geom_line(linewidth = 1.3) +
  geom_point(size = 2.5) +
  labs(
    title = "Percentage Change in Carbon Intensity Change From 1975",
    x = "Year",
    y = "Percentage Change (%)",
    color = "Country",
    fill = "Country"
  ) +
  theme_bw() +
  theme(
    plot.title = element_text(face = "bold", size = 16, hjust = 0.5),
    plot.subtitle = element_text(size = 12, hjust = 0.5),
    legend.position = "bottom",
    panel.grid.minor = element_blank()
  ) +
  scale_x_continuous(breaks = seq(1975, 2022, by = 5)) +
  scale_y_continuous(labels = function(x) paste0(x, "%")) +
  scale_color_brewer(palette = "Set1") +
  scale_fill_brewer(palette = "Set1") +

  geom_text(data = carbon_intensity_change %>%
              group_by(Country) %>%
              filter(Year == max(Year)),
            aes(label = paste0(round(pct_change, 1), "%")),
            nudge_x = 1, nudge_y = 2, size = 3.5, show.legend = FALSE)

# Display the plot
print(pct_change_plot)
ggsave("Carbon Intensity Percentage change.png", pct_change_plot,
       width = 16, height = 12, dpi = 400, bg = "white")
```



2. Figure 2: Percentage Change in Carbon Intensity Change
   x-axis: years
   y-axis: Carbon Intensity change in percentage (carbon emission per GDP)
   a. Finding: We can see Indonesia have positive change from 1975 to 2000.

3b1.3. Figure 3: Tapio Decoupling Analysis: Environmental-Economic Dynamics by Country (1975-2022)

```
# Plot 1: Decoupling Trajectories Over Time
decoupling_trajectory_faceted <- ggplot(tapio_decoupling,
                                     aes(x = Year, y = DI)) +
  # Reference lines
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray50") +
  geom_hline(yintercept = 1, linetype = "dashed", color = "gray50") +


  # Data points and lines
  geom_line(linewidth = 1.2) +
  geom_point(aes(shape = Decoupling_Type), size = 3) +

  # Facet by country
  facet_wrap(~ Country, ncol = 2, scales = "free_y") +

  # Labels and titles
  labs(
    title = "Tapio Decoupling Analysis: Environmental-Economic Dynamics by Country (1975-
2022)", "Year",
    y = "Decoupling Index (DI)",
    shape = "Decoupling Type"
  ) +

  # Theme and formatting
  theme_minimal(base_size = 12) +
  theme(
    plot.title = element_text(face = "bold", size = 16, hjust = 0.5),
    plot.subtitle = element_text(size = 12, hjust = 0.5, margin = margin(b = 15)),
    legend.position = "bottom",
    legend.box = "vertical",
    panel.grid.minor = element_blank(),
    strip.background = element_rect(fill = "#2c3e50"),
    strip.text = element_text(face = "bold", color = "white", size = 11),
    axis.text.x = element_text(angle = 45, hjust = 1)
  ) +

  # Scales
  scale_x_continuous(breaks = seq(1975, 2022, by = 10)) +
  scale_color_brewer(palette = "Set1") +
  scale_shape_manual(values = c(16, 17, 15, 8, 4))

print(decoupling_trajectory_faceted)
ggsave("decoupling_trajectory_faceted.png", decoupling_trajectory_faceted,
       width = 16, height = 12, dpi = 400, bg = "white")
```



3. Figure 3: Line Charts decoupling panels
   x-axis: years
   y-axis: Carbon Intensity (with decoupling type notation)
   Each country has their panel
   a. Finding: China showed Absolute decoupling throughout

We are still working on this section. Will add more descriptions to the graph.

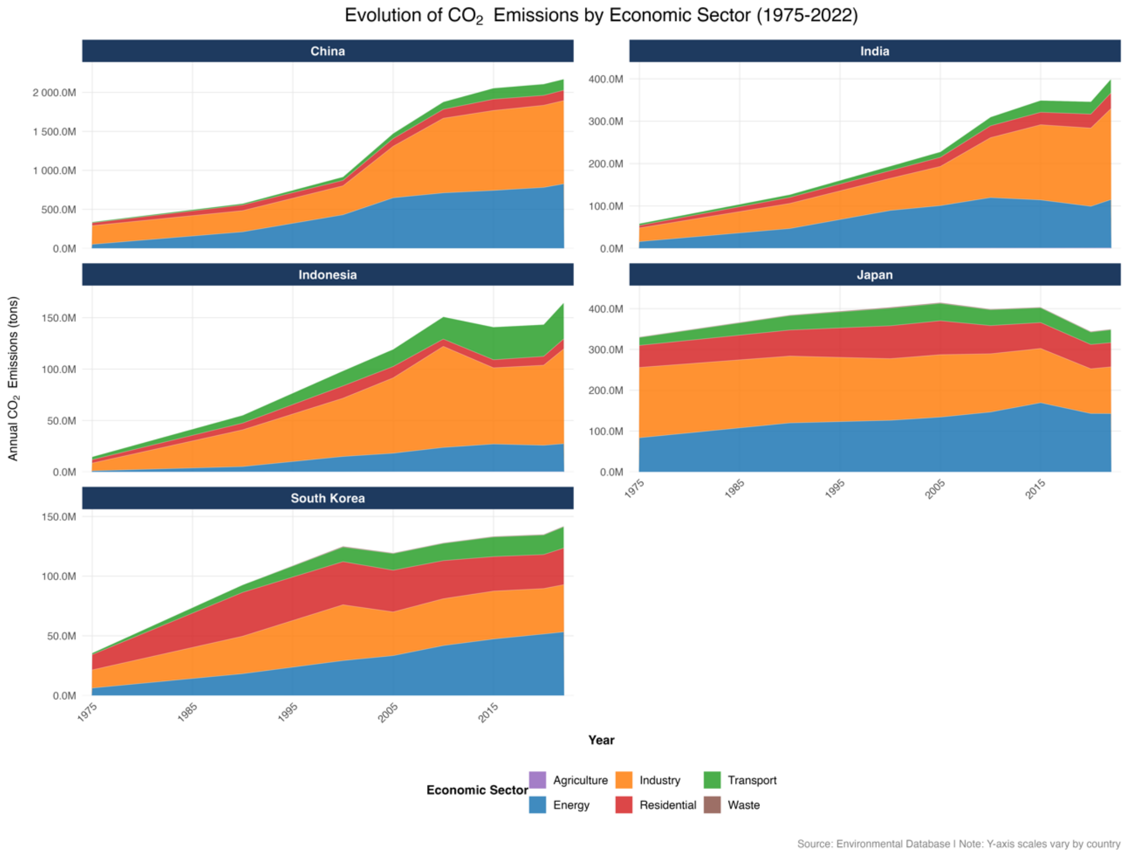
3b2. Research question 2

Question 2: "Which economic sectors have been the primary drivers of successful (or failed) decoupling?"

3b2.1. Figure 4: Evolution of CO2 Emissions by Economic Sector (1975-2022)

```r
## Plot 1: Emissions Stacked Line Chart
sector_stacked_enhanced <- ggplot(country_sector_year,
                                  aes(x = Year, y = Sector_CO2, fill = Sector)) +

  # Stacked area with outline
  geom_area(alpha = 0.85, linewidth = 0.2, color = "white",
            position = position_stack(reverse = TRUE)) +

  # Facet by country with clean layout
  facet_wrap(~ Country, scales = "free_y", ncol = 2) +

  # Labels and titles
  labs(
    title = expression("Evolution of CO"[2]~" Emissions by Economic Sector (1975-2022)"),
    x = "Year",
    y = expression("Annual CO"[2]~" Emissions (tons)"),
    fill = "Economic Sector",
    caption = "Source: Environmental Database | Note: Y-axis scales vary by country"
  ) +

  # Professional theme
  theme_minimal(base_size = 13) +
  theme(
    # Title styling
    plot.title = element_text(
      face = "bold",
      size = 18,
      hjust = 0.5,
      margin = margin(b = 10)
    ),
    plot.subtitle = element_text(
      size = 14,
      hjust = 0.5,
      color = "gray40",
      margin = margin(b = 20)
    ),
    plot.caption = element_text(
      size = 10,
      color = "gray50",
      margin = margin(t = 15)
    ),

    # Facet styling
    strip.background = element_rect(
      fill = "#1e3a5f",
      color = "#1e3a5f",
      linewidth = 0.5
    ),
    strip.text = element_text(
      face = "bold",
      color = "white",
      size = 12,
      margin = margin(5, 0, 5, 0)
    ),

    # Axis styling
    axis.title = element_text(
      face = "bold",
      size = 12
    ),
    axis.title.x = element_text(margin = margin(t = 10)),
    axis.title.y = element_text(margin = margin(r = 10)),
    axis.text.x = element_text(
      angle = 45,
      hjust = 1,
      size = 10
    ),
    axis.text.y = element_text(size = 10),

    # Legend styling
```

```
    # Legend styling
    legend.position = "bottom",
    legend.title = element_text(
      face = "bold",
      size = 12,
      margin = margin(b = 5)
    ),
    legend.text = element_text(size = 11),
    legend.box = "horizontal",
    legend.box.just = "left",
    legend.margin = margin(t = 10, b = 10),

    # Grid and panel styling
    panel.grid.minor = element_blank(),
    panel.grid.major = element_line(
      color = "gray90",
      linewidth = 0.3
    ),
    panel.spacing = unit(1, "lines"),

    # Plot margins
    plot.margin = margin(1, 1.5, 1, 1.5, "cm"),

    # Background
    plot.background = element_rect(fill = "white", color = NA),
    panel.background = element_rect(fill = "white", color = NA)
  ) +

  # Color palette
  scale_fill_manual(
    values = c(
      "Energy" = "#1f77b4",       # Blue
      "Industry" = "#ff7f0e",     # Orange
      "Transport" = "#2ca02c",    # Green
      "Residential" = "#d62728", # Red
      "Agriculture" = "#9467bd", # Purple
      "Waste" = "#8c564b"         # Brown
    )
  ) +

  # Axis scaling
  scale_x_continuous(
    breaks = seq(1975, 2022, by = 10),
    expand = expansion(mult = c(0.02, 0.02))
  ) +
  scale_y_continuous(
    labels = scales::label_number(
      scale = 1e-6,  # Convert to millions
      suffix = "M",
      accuracy = 0.1
    ),
    expand = expansion(mult = c(0, 0.1))
  )

# Display the plot
print(sector_stacked_enhanced)

# Save high-resolution version
ggsave("sector_co2_stacked_area_enhanced.png", sector_stacked_enhanced,
       width = 16, height = 12, dpi = 400, bg = "white")
```



4. Figure 4: CO2 emissions sector, for each country Includes China, Indonesia, India, Japan, South Korea
    a. Finding: Energy and Industry account for most emission

We are still working on this section. Will add more descriptions to the graph.

4. Part IV: Discussion and Conclusions

4a. Key Findings Summary

4a1. Research question 1: To what extent have major Asian countries decoupled CO2 emissions from economic growth?

Based on: *3a1.2. Table 2: Decoupling performance Summary (1975-2022)* and *3b1.3. Figure 3: Tapio Decoupling Analysis: Environmental-Economic Dynamics by Country (1975-2022)*. We see China have most relative decoupling performance.

4a2. Research question 2: Which economic sectors have been the primary drivers of successful (or failed) decoupling?

Based on: 3b2.1. Figure 4: Evolution of CO2 Emissions by Economic Sector (1975-2022). The change in Industry sector accounts for the decoupling.

4b. Policy and Research Implications

4b1. Research question 1: To what extent have major Asian countries decoupled CO2 emissions from economic growth?

We are still working on this section. Will write about the observation of China and Japan and how Japan experience Stagnant in the decoupling process.

4b2. Research question 2: Which economic sectors have been the primary drivers of successful (or failed) decoupling?

We are still working on this section. Will write about how this sectional change is reflecting the total emission change. We also review how emission and GDP are both determining factors, and if it's hard to tell which is the primary driver.

4c. Technical Reflection

4c1. Strength and weakness of our approach

For the strength, we have clear documentation of our data and workflow. This enabled clear task division and process control. For weaknesses,

4c2. Challenges

We are still discussing and reviewing our challenges. Will write about our task arrangement and workflow. Also, about how we improved it.

4c3. Future extensions of our work

There are many ways in which we extend our work, whether it’s in width or depth. In depth, we can incorporate databases and manage manufacturing emissions and plotting in real-time. In width, we can include more countries and limit it to 2020-2025.

1. Extend our emission data to include water and land pollution.

5. Reference

Countryeconomy. (2018). Bangladesh GDP - Gross Domestic Product 2017. Available at: https://countryeconomy.com/gdp/bangladesh. [Accessed: 19 November 2025].

Countryeconomy. (2019). Taiwan GDP - Gross Domestic Product 2018. countryeconomy.com. Available at: https://countryeconomy.com/gdp/taiwan. [Accessed: 19 November 2025].

Countryeconomy. (2021). Afghanistan GDP - Gross Domestic Product 2020. Available at: https://countryeconomy.com/gdp/afghanistan. [Accessed: 19 November 2025].

database.earth. (n.d.a). Annual GDP (Gross Domestic Product) by Country in 1975 (World Map). Available at: https://database.earth/economy/gdp/1975. [Accessed: 18 November 2025].

database.earth. (n.d.b). Annual GDP (Gross Domestic Product) by Country in 1980 (World Map). Available at: https://database.earth/economy/gdp/1980. [Accessed: 18 November 2025].

database.earth. (n.d.c). Annual GDP (Gross Domestic Product) by Country in 1985 (World Map). Available at: https://database.earth/economy/gdp/1985. [Accessed: 18 November 2025].

database.earth. (n.d.d). Annual GDP (Gross Domestic Product) by Country in 1990 (World Map). Available at: https://database.earth/economy/gdp/1990. [Accessed: 18 November 2025].

database.earth. (n.d.e). Annual GDP (Gross Domestic Product) by Country in 1995 (World Map). Available at: https://database.earth/economy/gdp/1995. [Accessed: 18 November 2025].

database.earth. (n.d.f). Annual GDP (Gross Domestic Product) by Country in 2000 (World Map). Available at: https://database.earth/economy/gdp/2000. [Accessed: 18 November 2025].

database.earth. (n.d.g). Annual GDP (Gross Domestic Product) by Country in 2005 (World Map). Available at: https://database.earth/economy/gdp/2005. [Accessed: 18 November 2025].

database.earth. (n.d.h). Annual GDP (Gross Domestic Product) by Country in 2010 (World Map). Available at: https://database.earth/economy/gdp/2010. [Accessed: 18 November 2025].

database.earth. (n.d.i). Annual GDP (Gross Domestic Product) by Country in 2015 (World Map). Available at: https://database.earth/economy/gdp/2015. [Accessed: 18 November 2025].

database.earth. (n.d.j). Annual GDP (Gross Domestic Product) by Country in 2020 (World Map). Available at: https://database.earth/economy/gdp/2020. [Accessed: 18 November 2025].

database.earth. (n.d.k). Annual GDP (Gross Domestic Product) by Country in 2022 (World Map). Available at: https://database.earth/economy/gdp/2022. [Accessed: 18 November 2025].

database.earth. (n.d.l). Annual GNI (Gross National Income) by Country in 1975 (World Map). Available at: https://database.earth/economy/gni/1975 [Accessed 19 November 2025].

database.earth. (n.d.m). Annual GNI (Gross National Income) by Country in 1980 (World Map). Available at: https://database.earth/economy/gni/1980 [Accessed 19 November 2025].

database.earth. (n.d.n). Annual GNI (Gross National Income) by Country in 1985 (World Map). Available at: https://database.earth/economy/gni/1985 [Accessed 19 November 2025].

database.earth. (n.d.o). Annual GNI (Gross National Income) by Country in 1990 (World Map). Available at: https://database.earth/economy/gni/1990 [Accessed 19 November 2025].

database.earth. (n.d.p). Annual GNI (Gross National Income) by Country in 1995 (World Map). Available at: https://database.earth/economy/gni/1995 [Accessed 19 November 2025].

database.earth. (n.d.q). Annual GNI (Gross National Income) by Country in 2000 (World Map). Available at: https://database.earth/economy/gni/2000 [Accessed 19 November 2025].

database.earth. (n.d.r). Annual GNI (Gross National Income) by Country in 2005 (World Map). Available at: https://database.earth/economy/gni/2005 [Accessed 19 November 2025].

database.earth. (n.d.s). Annual GNI (Gross National Income) by Country in 2010 (World Map). Available at: https://database.earth/economy/gni/2010 [Accessed 19 November 2025].

database.earth. (n.d.t). Annual GNI (Gross National Income) by Country in 2015 (World Map). Available at: https://database.earth/economy/gni/2015 [Accessed 19 November 2025].

database.earth. (n.d.u). Annual GNI (Gross National Income) by Country in 2020 (World Map). Available at: https://database.earth/economy/gni/2020 [Accessed 19 November 2025].

database.earth. (n.d.v). Annual GNI (Gross National Income) by Country in 2022 (World Map). Available at: https://database.earth/economy/gni/2022 [Accessed 19 November 2025].

Trading Economics. (2019). North Korea GDP. Tradingeconomics.com. Available at: https://tradingeconomics.com/north-korea/gdp. [Accessed: 19 November 2025].

Trading Economics. (2019). Yemen GDP. Available at: https://tradingeconomics.com/yemen/gdp. [Accessed: 19 November 2025].

Trading Economics. (n.d.). Lebanon GDP | 1988-2019 Data | 2020-2021 Forecast | Historical | Chart | News. Available at: https://tradingeconomics.com/lebanon/gdp. [Accessed: 19 November 2025].

UNdata. (n.d.a). UNdata | record view. Available at: https://data.un.org/Data.aspx?q=North+korea&d=SNAAMA&f=grID%3A103%3BcurrID%3AUSD%3BpcFlag%3A0%3BcrID%3A408%2C410%2C807. [Accessed: 19 November 2025].

UNdata. (n.d.b). UNdata | record view | GNI at current prices - US dollars. Available at: https://data.un.org/Data.aspx?q=afghanistan&d=SNAAMA&f=grID%3a103%3bcurrID%3aUSD%3bpcFlag%3a0%3bcrID%3a4 [Accessed: 19 November 2025].

UNdata. (n.d.c). UNdata | record view | GNI at current prices - US dollars. Available at: https://data.un.org/Data.aspx?q=yemen&d=SNAAMA&f=grID%3a103%3bcurrID%3aUSD%3bpcFlag%3a0%3bcrID%3a720%2c886%2c887 [Accessed: 19 November 2025].

World Bank. (n.d.). GDP (current US$) - Syrian Arab Republic | Data. Available at: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=SY. [Accessed: 19 November 2025].