Analysis of Global Economic Powers' Rise and Decline

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Abstract

In this paper, we present the research results on the assessment of the economic state of prominent countries, as well as their rise and decline. As of recent years, we have been witness to a great shift in global economic dynamics, the declination of the West juxtaposed by China rising to eminence as potentially the new dominant empire. As proposed by Ray Dalio in The Changing World Order, all great empires experience a broadly similar lifecycle that can be subdivided into stages, and the US has been experiencing patterns of excess and self-reinforcing decline in many sectors. At a time like this, it would be very interesting to analyze these countries' relative position, and what the future might hold for them.

1 Introduction

1.1 Preamble

This project came about after reading the book Principles for Dealing with the Changing World Order by Ray Dalio, which comes highly recommended to any geopolitics/global macroeconomics enthusiasts. After reading the Appendix at the end of the book, wherein Dalio et al. devised a generative model to create composite indices reflecting the strength of a country based on constituents that he decided upon. This was a fascinating concept, one which we attempted to replicate using other methodologies to A. evaluate the countries' economic strengths based on certain indicators, B. verify the integrity of these indicators via unsupervised learning algorithms, and lastly C. attempt to predict the trajectory these countries are headed towards using Recurrent Neural Networks/Regression methods. The main goal is to apply a statistical/deep learning approach to highlighting which countries are rising as dominant global powers and which are waning in power.

This project is by no means an attempt to replicate the research done by Ray Dalio and the folks at Bridgewater Associates; where the process most likely involved millions of time series being analyzed as constituents for each indicator and the data went through significant scrutiny and processing, such that earliest records extended all the way back to the 16th century. For our work here, we are mainly interested in the application of Multi - Criteria Decision Analysis techniques as well as deep learning frameworks into analyzing countries of our own choosing. The data mainly came from reliable open sources (World Bank, dbnomics, ycharts, Macro Trends, etc.) but unfortunately these sources are not always consistent across time and countries. Moreover, certain countries proved rather difficult to gather data on for various reasons, so what we will be able to achieve is a high - level perspective on the overall positions of countries, but not all the data presented here will be absolutely correct on all accounts (something to keep in mind).

1.2 Methodology

Multi Criteria Decision Analysis

MCDA is a field of study that deals with making decisions in the presence of multiple criteria by providing a structured framework for evaluation and comparison of alternatives. Fundamentally, it involves several key components. In MCDA, we consider both the criteria (quantitative or qualitative) as well as the evaluation of different alternatives, based on how well it accommodates the multiple criteria. We can also take into account the benefit factor of each criteria, as a factor like unemployment rate has a strong negative correlation to a country's overall economic health. For this analysis, MCDA is central to our assessment of these countries, and we employ 2 different methods: CODAS and TOPSIS.

CODAS

Combinative Distance-based Assessment (CODAS) is a MCDA technique that evaluates and ranks alternatives utilizing a distance-based approach (as the name suggests). It calculates the distance of each alternative from the negative-ideal, and is adept to a wide range of data including crisp values, fuzzy numbers, and linguistic variables. CODAS has also been shown to be a robust technique with the ability to handle uncertainty and inconsistencies in the input data, and since for some countries a number of data instances had to be imputed due to missing observations or lack of consistency across multiple sources, this will prove to be very helpful.

Algorithm 1 CODAS

1: **Input**: Decision matrix, where the rows represent the alternatives, and the columns are evaluation criteria
2: Determine the weights of the criteria: the relative importance of each individual criterion, often using methods such as Analytic Hierarchy Process (AHP) or entropy-based weighting.
3: Identify the negative-ideal alternatives: These are respectively the worst performing alternatives across all criteria, which can be obtained via examining the lowest or highest values within the criteria depending on their benefit vector.
4: Calculate the Euclidean/Taxicab Distance: For each alternative, the Euclidean and Taxicab (Manhattan) distance from the negative-ideal solution are calculated. The Euclidean distance is the straight-line distance, while the Taxicab distance is the sum of absolute differences between the alternative's values and those of the negative-ideal.

Euclidean Distance:

$$d_i^E = \sqrt{\sum_{j=1}^{n} w_j (x_{ij} - x_j^-)^2}$$

Manhattan Distance:

$$d_i^T = \sum_{j=1}^{n} w_j |x_{ij} - x_j^-|$$

- d_i^E is the Euclidean distance of the i-th alternative
- d_i^T is the Taxicab distance of the i-th alternative
- w_j is the weight of the j-th criterion
- x_{ij} is the value of the i-th alternative for the j-th criterion
- x_j^- is the negative-ideal value for the j-th criterion

5: Calculating the assessment score: The assessment score (H_i) for each alternative is calculated as the difference between the Euclidean distance and the Taxicab distance, weighted by a parameter x_i:

$$H_i = d_i^E - x_i d_i^T$$

The parameter x_i is used to control the relative importance of the Euclidean and Taxicab distances. A higher value of x_i gives more weight to the Taxicab distance, while a lower value gives more weight to the Euclidean distance.

TOPSIS

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is another MCDA method that relies on the distance of each alternative from the ideal solution rather than the negative-ideal. The core concept of the method is that an alternative should have the shortest geometric distance from the ideal and longest from the negative-ideal. Like CODAS, TOPSIS is adept at handling a variety of data types, making it a flexible and robust alternative even in cases of missing data and inconsistencies. Therefore, it has been widely applied across many real world domains, due to its intuitive logic and ease of implementation.

Algorithm 2 TOPSIS

1: **Input**: Decision matrix, where the rows represent the alternatives (m), and the columns are evaluation criteria (n)

2: Normalize the decision matrix to make the criteria dimensionless. Normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}}$$

3: Calculate the Weighted Normalized Decision Matrix by assigning weights w_j to each criterion, where the sum of w_j should add up to 1. The weighted normalized v_{ij} is calculated as:

$$v_{ij} = r_{ij} \cdot w_j$$

4: Identify the ideal (A^*) and negative-ideal (A^-) for each criterion:

$$A^* = \{v_1^*, v_2^*, \ldots, v_n^*\}$$

where $v_j^* = \max(\mathrm{v}_{ij})$ if j is a benefit criterion, or $\min(\mathrm{v}_{ij})$ if j is a cost criterion

$$A^- = v_1^-, v_2^-, \ldots, v_n^-$$

where $v_j^- = \min(\mathrm{v}_{ij})$ if j is a benefit criterion, or $\max(\mathrm{v}_{ij})$ if j is a cost criterion

5: Calculate the separation measures, from the Euclidean distance of each alternative from A^* and A^-:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$$

6: Calculate the relative closeness of the alternative to the ideal solution A^*:

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}$$

Clustering Unsupervised Learning

Alongside the implementation of MCDA models, we also employ K-Nearest Neighbors and Hierarchical clustering to assess the relative positions of countries. Though we can't get an absolute ranking of countries via this method, what we can achieve is their relative distance from one another as well as from the centroids, information that can be correlated to their place in the hierarchical structure of economic power.

LSTM Recurrent Neural Network

After obtaining the vectorized data that captures the variance from the original countries, we utilize a Long Short-term Memory RNN to forecast the trajectory of the country over the following years. By converting the vector into a dataframe that presents values in rolling windows year by year, we can train the model to forecast each subsequent year and analyze the trajectory it follows.

2 Data Retrieval + Exploratory Analysis

2.1 Data Retrieval

As previously described, much of the data we are working with was obtained from World Bank Open Data [1]. Our work focused on the time frame from 1991 to 2023, due to the fact that after 1991 the economic data of countries are most consistently recorded. We decided upon using 10 criteria:

- RGDP ($US): Country's total value of goods and services produced in a year, adjusted for inflation and converted to US dollars.
- RGDP % change: Percentage change in a country's RGDP on a year-by-year basis.
- GDP per capita ($US - Adjusted to PPP): Total GDP divided by population. Converted to US dollars, adjusted to purchasing power parity to account for differences in the cost of living and inflation rates between countries.
- Unemployment rate (% tot labor force): Percentage of the total labor force that is unemployed.
- Inflation rate: percentage increase in the general price level of goods and services on a year-to-year basis.
- Government debt-to-GDP ratio: Shows the proportion of a country's government debt to its GDP. Measures a country's ability to pay back its debts.
- Current BoP: The Balance of Payments is a record of a country's transactions with the rest of the world, including trade, services, and financial transactions.
- Labor force participation rate: The percentage of working-age population that is either employed or actively seeking employment.
- Trade: The volume or value of international trade conducted by a country, including both imports and exports.
- % world GDP: Represents the percentage that a country's GDP contributes to the total world GDP.

Unfortunately, while we can get most of the data for the countries being analyzed, some are missing values during certain time periods, which can be due to any number of reasons. To ensure that we arrived at a complete dataset for each country to create a decision matrix for MCDA, a multivariate imputation method was employed to estimate the missing values by modelling each feature with missing values as a function of the other features in a round-robin fashion, employing multiple estimators such as BayesianRidge, ExtraTreesRegressor and KNN. This allows us to make educated guesses on what the missing values could be, so that we could carry on with the analysis.

2.2 A Brief Overview - Exploratory Analysis

2.2.1 Real GDP - US$

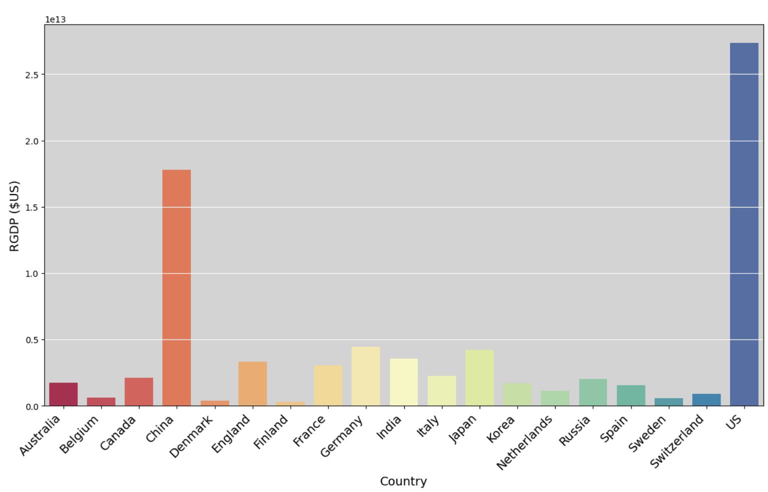

Figure 1: Last Recorded RGDP ($US) for Each Country

The US's dominance and China being the only nation that has any chance of actually competing with it is not unexpected and will be a recurring dynamic for the other categories in our study. Although it is nowhere near enough to conclude about the future trajectories of these two countries, it is worth noting. Among the rest of the nations, it can be seen that Germany, India, and Japan have the highest RGDP behind the two at the top.

2.2.2 RGDP % change

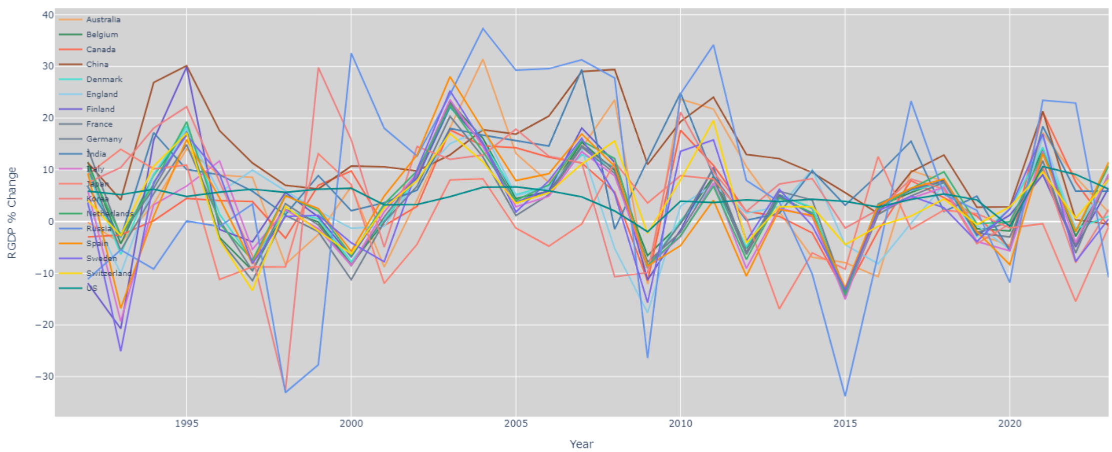

Figure 2: Year-by-Year RGDP % Change for Each Country

Throughout the 90s, it can be said for all countries except the US that their RGDP growth substantially slowed down (early 1990s recession), then saw noticeable recovery before going down from 1996 to 1998 during the Asian financial crisis. One nation which has enjoyed relative stability through this decade is the US. Some Asian countries were able to mitigate the impacts of the crisis including China, India, and Australia which were not as affected as Korea, Japan, and Russia.

In the 2000s, countries experienced similar levels of growth and expansion between the dot-com bubble bursting and the 9/11 attacks at the start of the decade and the global financial crisis at the end of it. In 2005 and 2006, before the global crisis, it can be observed that production growth around the world slowed. Once again, the US, China, and India were able to maintain their growth through the crisis, unlike other countries, especially Sweden, England, and Russia.

From 2010 to 2020, the observed countries followed a quite similar trend in maintaining growth and slowing down mid-decade. There were also country-specific events such as the Japanese earthquakes and tsunami and the 2015 recession in Russia. In 2020, RGDP growth did not see a drop for quite many countries despite the pandemic. Some nations experienced a similar level of growth as of 2019 such as the Netherlands and China while a few experienced a slight increase.

For the last 3 years, the competitive gap has been narrowed between the US and China although China's growth has slowed down visibly [2][3] [4]after 2021. Many of the other countries have successfully bounced back economically from the pandemic except for Russia, Japan, and Korea. This is not surprising considering how Japan has been dealing with deflationary pressures for the last 25 years [5], Korea relies greatly on exports, especially to the US and EU [6] and Russia has been engaging in military conflict against Ukraine [7].

Throughout the timeline in observation, it can be said that the US holds its position with the most stable growth with little fluctuation as opposed to Russia.

2.2.3 % share world GDP

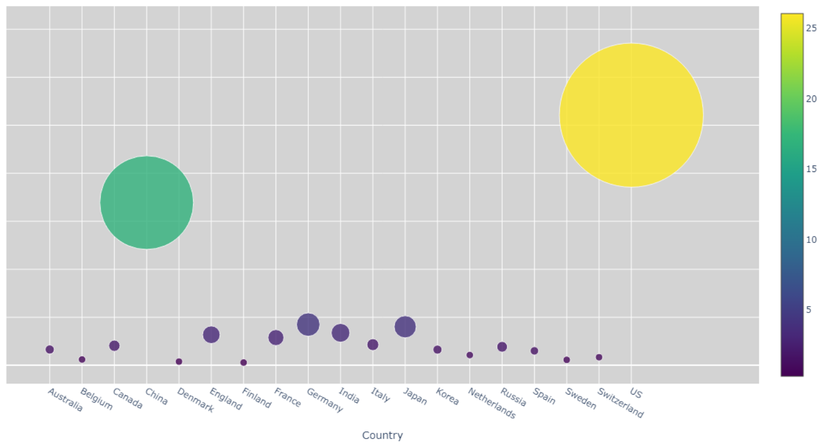

Figure 3: % Share of World GDP by each country

In this regard, it is apparent that the US is still dominating but, more notably is China in second place. These two empires make the 15 other countries look more or less similar. More specifically, Germany, Japan, and India have the biggest world GDP share after the US and China and also have a substantial edge over the rest in the group, although nowhere near the gap between the two top contenders in this category. India, in particular, has shown significant growth with a world GDP share higher than England and in the top 5, 3 of which are Asian countries. This is a good illustration of the rise of Asian countries on the global playing field.

2.2.4 Labor markets

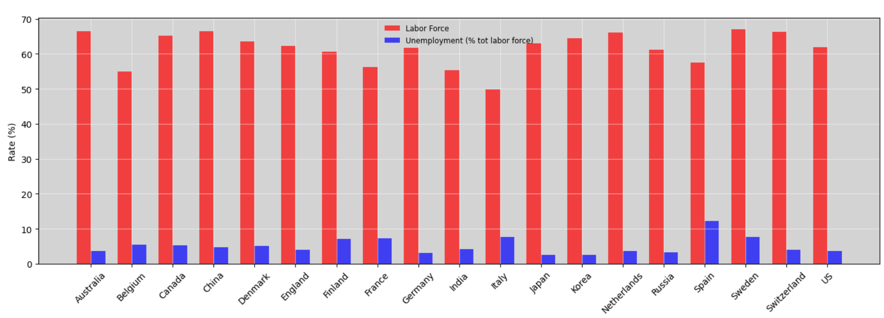

Figure 4: Labor Force Participation and Unemployment Rates

In this category, Sweden, China, and Australia lead in terms of labor participation, followed by Switzerland, the Netherlands, and Canada whereas the lowest unemployment rates belong to Japan and Korea, followed by several countries. Overall, Italy has the worst showing in this area with the highest unemployment rate and second lowest labor participation rate among the group, with the highest unemployment rate belonging to Spain. This is nothing new given Italy's welfare system and the labor market as well as Spain's economic structure [8] with a lack of industry and reliance on services and tourism [9]. On the other hand, Australia, Switzerland [10], and China [11] [12] seem to have the most favorable balance of high labor force participation rate and low unemployment rate.

2.2.5 Inflation rate

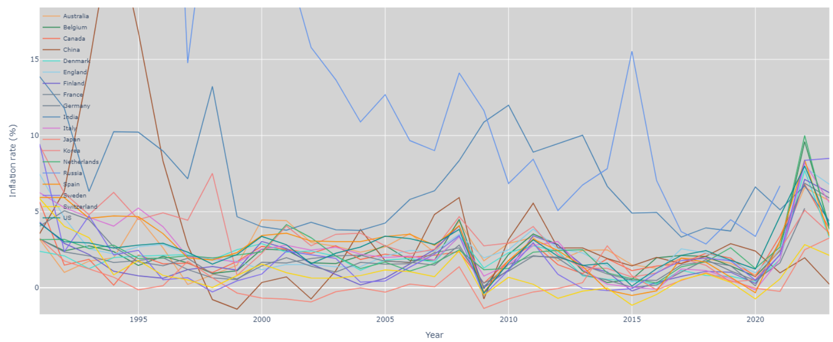

Figure 5: Historical Inflation rate for each country

Throughout the 90s, it can be observed that inflation rates differed between countries more than later on. Firstly, in the early 1990s, the collapse of the USSR in 1991 showed up in this category as hyperinflation in Russia (2600% in 1992)[13], and also with inflation in China. Other countries, however, experienced the effects of the early 1990s recession[14] leading to a decrease in inflation. A similar dynamic is seen with the 1997 - 1998 Asian financial crisis[15], during which, India and Korea[16] [17] experienced a significant rise in inflation. Australia, on the other hand, was much less affected. In both of these events, Japan experienced low inflation and struggled against deflationary pressures which would continue to the present day[18].

In the 2000s, there was less volatility with inflation, especially in developed countries. Russia and China, on the other hand, experienced significantly higher inflation with Russia, both reforming and recovering after the collapse of the USSR as well as China's spike in 2004. The only country that experienced an inflation spike during the global financial crisis was India due to various factors including but not limited to, the reversal of inflows from foreign institutional investors (FIIs), depreciation against major foreign currencies, a steep decline in foreign trade, and policy responses[19][20]. This pattern of an inflation spike opposite to other countries would go on to repeat in 2013 and 2019.

The 2010s saw much of the same similarity with countries with some exceptions. Other than India in 2013 and 2019 as mentioned above, 2 countries whose inflation spiked and divulged from the shared trajectory were Japan in 2014 and Russia in 2015, with Japan's case generally stemming from the effect of policies[21] while Russia was hit by external influences (falling oil prices and economic sanctions).

After the pandemic, inflation in all of the countries followed a similar trajectory, hitting a spike in 2022 and then dropping down in 2023, except for Japan with the highest inflation rate it has seen since 1982[**?**].

3 Multi-Criteria Decision Analysis

For both MCDA methods, there are multiple options for assigning weight to each features (Cilos, Critic, Entropy, idocriw, etc.) Here, we've decided upon using Entropy criteria weight for our analysis, which follows a linear calculation process. Entropy in this context is a measure of uncertainty or disorder within a system, and can be used to measure the amount of information associated with each criterion. Criteria with higher entropy values are considered more uncertain or less informative, and therefore will be assigned a lower weight value. After calculation, the weight vector will be normalized to ensure that they sum up to 1, making them suitable for our models.

Following this, we begin normalising our data using vector normalisation technique. For each criterion, the data is normalized differently depending on whether it is a cost or benefit criterion. If the criterion x is classified as **cost criterion**, the normalized value N is calculated as:

$$N = 1 - \frac{x}{\sqrt{\sum x^2}}$$

This transformation decreases the normalized value for higher (undesirable) values of x. On the contrary, if criterion x is considered to be a **beneficial criterion**, then the normalized value for higher (desirable) values of x is increased.

$$N = \frac{x}{\sqrt{\sum x^2}}$$

In the case of our project, we can filter out three cost features: 'Unemployment rate (% tot labor force)', 'inflation rate' and 'government debt-to-GDP ratio'. Then with normalised data and criterion weights in hand, we can apply CODAS and TOPSIS to measure relative scores of each alternative (nation).

Country	Score
Australia	-1.157093
Italy	-1.831214
Belgium	-1.669379
Japan	-0.921982
Canada	-1.231541
Korea	-0.838746
China	7.366324
Netherlands	-0.980239
Denmark	-1.229176
Russia	-0.530604
England	-1.308261
Spain	-2.199139
Finland	-1.828069
Sweden	-1.561467
France	-1.475592
Switzerland	-0.768636
Germany	0.276680
US	12.505262
India	-0.617129

Table 1: Codas Score 2023

Country	Score
Australia	0.176298
Italy	0.140458
Belgium	0.146120
Japan	0.202231
Canada	0.175703
Korea	0.190448
China	0.649808
Netherlands	0.180775
Denmark	0.169673
Russia	0.203665
England	0.173776
Spain	0.128042
Finland	0.140976
Sweden	0.150065
France	0.159559
Switzerland	0.189035
Germany	0.238358
US	0.896838
India	0.207114

Table 2: Topsis Score 2023

4 K-Neighbors and Hierarchical clustering

4.1 Data Preprocessing

To perform clustering on the datasets of these countries' economic data, we must first vectorise them so that we can arrange the data by year for each of these countries. The method we used to accomplish this was Singular Vector Decomposition, reducing them to 1 extracted feature while capturing more than 90% of the cumulative explained variance from the original data, so that when we perform clustering the crucial discriminative information and underlying structures are still retained. This is where other dimensionality reduction methods like PCA and t-SNE fall short, as they either rely on the assumption of linearity or can lead to the loss of global structure in the data.

Country	Explained Variance	Country	Explained Variance
Australia	0.9352	Italy	0.9170
Belgium	0.9662	Japan	0.9676
Canada	0.9847	Korea	0.8512
China	0.9934	Netherlands	0.9969
Denmark	0.9011	Russia	0.9099
England	0.9650	Spain	0.9503
Finland	0.9308	Sweden	0.9101
France	0.9555	Switzerland	0.9185
Germany	0.9022	US	0.9952
India	0.9824		

Table 3: Cumulative Explained Variance Ratio by country following SVD

For most countries, after feature extraction we achieved over 90% CEVR, suggesting that this data sufficiently captures most of the essential information in the data while reducing to only 1 feature. The only complication is with Korea, as post SVD the data only retains 85% of the explained variance. We will have to keep this in mind when later performing clustering and analysis.

4.2 Clustering

The process of finding the best number of clusters (k) after feature extraction often involves using techniques like the Elbow method, Silhouette analysis, Gap statistic, or any number of other measures. Here we've elected to use both the Elbow method and the Dunn Index analysis to determine the number of clusters appropriate for this task.

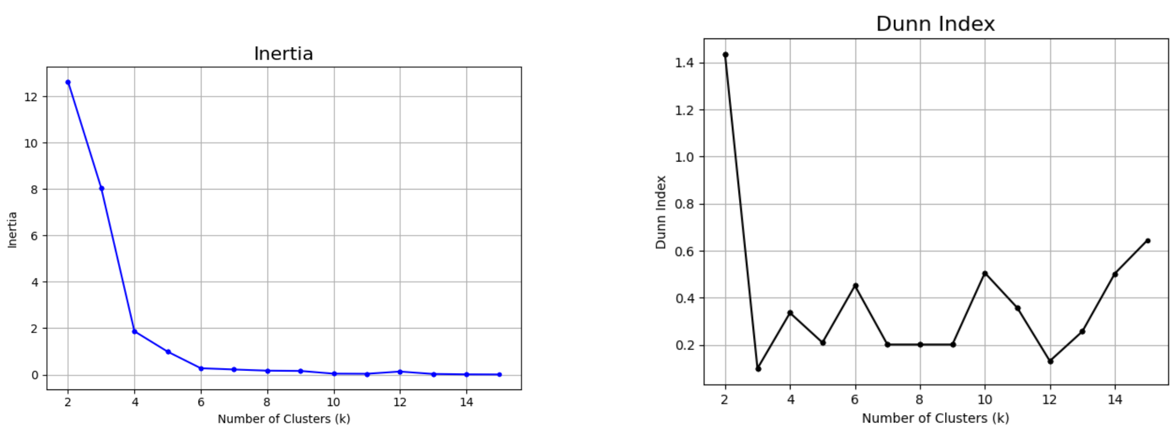

Figure 6: Cluster evaluation

The 2 measures being analyzed, Inertia and Dunn Index, correspond to the within-cluster sum of squared distances and the ratio between min/max inter-cluster distances respectively. Following the plots, we can clearly see that applying the Elbow method the ideal number of clusters sit at around 4-5. This figure is reflected also by the Dunn Index.

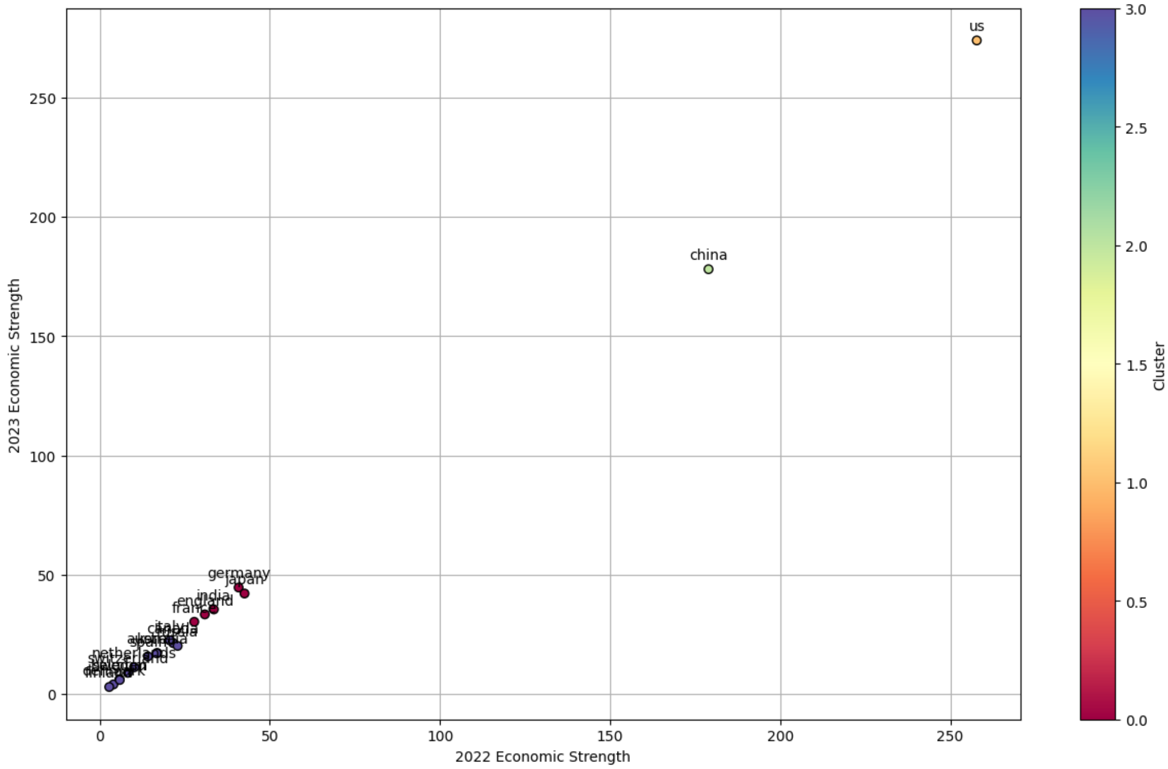

Figure 7: K-Means clustering of countries based on recent economic strength

To break down the plot above, we have the following:

- The US and China are placed in their own cluster apart from other countries.
- Germany, India, France, Japan, and England are grouped in one cluster. These countries have relatively strong economic power.
- The rest of the countries are classified in the remaining cluster. Strictly speaking, these countries have weaker economies, though the distinction is very minimal.

This structure is also reflected in the hierarchical clustering we performed:

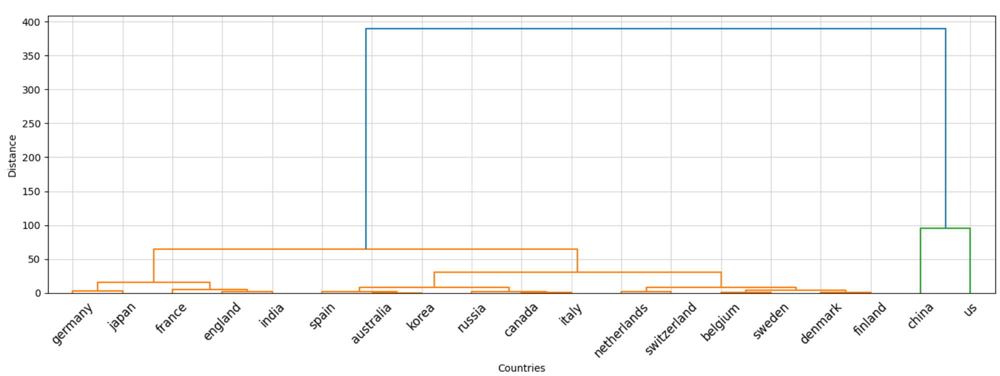

Figure 8: Hierarchical Clustering Dendrogram

Here, we can clearly visualize the distance between these countries represented by their respective clusters. This is achieved through Ward's linkage, an agglomerative clustering technique based on data points' similarity. After convergence, the US and China are placed in their own group as being the 2 most prominent economies in our analysis, while all the other countries are placed into a singular cluster that subdivides into smaller pairings. Based on this particular representation alone we can broadly draw the ranking of each country, with Germany and Japan grouped into 1 cluster having the second greatest distance value from the average distribution, followed by France/England/India, etc. This structure validates our findings from earlier when measuring their relative positions based on MCDA methods, though these 2 findings do not corroborate one another perfectly. As described before, though after performing SVD we were able to capture most of the local variance while maintaining the global structure of the data, some countries are represented as accurately as others, which lead to some minor discrepancies in the clusters (Spain and Australia/Korea, Netherlands and Sweden). Fortunately, on a larger scale, the results are reliably correct, so now we can draw from these findings to map out the positions these countries are in.

5 Relative position and trajectory of countries

5.1 Relative position

From the extracted feature of these countries' data, we follow by attempting to forecast the trajectory they're headed towards, and from this make an educated assessment of how these countries are going to change with respect to their position on the global scale.

To assess the relative position of the countries in observation, we will divide them into three groups, as mentioned above:

- The US and China
- Japan, Germany, England, France and India
- The rest of the countries

The US and China: At first glance, it is easy to see that the US, at the point of our analysis (2023) is still the top-performing economy, by a substantial margin. However, China's placement also reflects the fact that both of the nations have a more than comfortable lead over others in terms of economic strength. This is even more notable for China considering the time frame through which it rose to its current place. Of course, this does not guarantee whether China can or will catch up to the US in the near future, or how their relationship will turn out.

Japan, Germany, England, France, and India: This group includes relatively strong economies, noticeably above the rest of the countries despite lagging far behind America and China. Unlike the first group, their positions are much closer to each other. At the top of the group would be Japan and Germany, both being industrial giants highly developed and reliant on advanced technology and exports. Right behind them are India, the UK, and France with India having a slightly higher position than the other two. This is notable seeing as India is a younger, emerging world power, unlike England and France who have been dominant powers for much of the world's recent history. This comes with certain advantages that will come into play once we look at the trajectories of the countries.

The rest of the countries: among these, what can be seen is that they can be divided into two smaller groups:

- Spain, Australia, Korea, Russia, Canada, and Italy
- The Netherlands, Switzerland, Finland, Sweden, Denmark, and Belgium

The first of these two groups is ahead according to our clustering.

5.2 Future Trajectory

By creating a rolling window of the countries' respective vector, we can learn from historical data to make a prediction of their relative trajectory, and from there compare how their positions in the near future may change. Predicting something as complex and multivariate as a country's economic position is something economists have been trying to figure out for centuries, and this will only be a very oversimplified approximation of that process. For the following output, we used ridge regression to project countries' movement over the next 5 years:

Country	Trajectory	Country	Trajectory
Australia	Neutral - Positive	Italy	Negative
Belgium	Neutral	Japan	Positive
Canada	Neutral	Korea	Positive
China	Highly Positive	Netherlands	Negative
Denmark	Neutral - Negative	Russia	Negative
England	Negative	Spain	Negative
Finland	Neutral	Sweden	Neutral
France	Neutral - Negative	Switzerland	Positive
Germany	Neutral - Negative	US	Positive
India	Highly Positive		

Table 4: Trajectories of countries' economic power

The US and China:

According to our findings, The US' trajectory would be classified as "positive" whereas that of China would be classified as "highly positive". This can be supported by many factors in comparing these two nations such as how the US has many problems involving heavy indebtedness, social-political division, thinly spread geopolitical influence, and so on yet can still extend its lead over the rest thanks to its reserve currency status and position as the most dominant political, economic and military force in the world. China, while still lagging behind in areas such as currency strength and financial centers, is striving to catch up and compete in geopolitical influence and, more notably, technology. This led to what we currently know as the technology decoupling, alongside tension in other areas.

Another factor in this dynamic is the fact that China currently owns the second most amount of US debt (right behind Japan). It is likely that, the gap between the two will narrow in various areas and more direct and drastic measures will be taken by both parties. The results of the 2024 US election and the following policy changes made by the succeeding administration can and will affect this. The strengths that the US already has may not be enough to support it if the issues with other areas (social-political division, education, outdated infrastructure,...) are not sufficiently remedied. Of course, China also has its own set of internal challenges, both short-term and long-term, that it will have to address to ensure stability in its growth and rise to global dominance.

Japan, Germany, England, France, and India:

For Japan and Germany, our projection suggests a "neutral-negative" direction for Germany and a "positive" trend for Japan. Between these two tech-behemoths, Japan is heading to another potential "end of deflation"[23] while Germany is hindered by an aging workforce[24] and challenges in infrastructure and energy[25]. It is without question that Japan also has its obstacles to overcome aside from stimulating the economy such as maintaining the Yen, an aging and mentally burnt-out workforce[26], record low birth rates[27], and high government debt.

As for The UK and France, we found both of their trajectories on the negative side with the UK's being "negative" and France's being "neutral-negative". For England, this could be reflected by factors such as the cost of living crisis, high inflation levels combined with tightening monetary policy in response, contributing to a post-pandemic rise in economic inactivity, trade barriers between it in the EU, and policy uncertainty[28]. France is also reportedly facing a slowdown in 2024[29]. Unlike England, a big of France's debts are foreign-owned and denominated in euros[30], which constitutes a risk. India's trajectory resulted in "highly positive". This is no surprise given its rapid growth, young workforce, robust exports in both services and manufacturing[31].

The rest of the countries:

Among these countries, Australia, Korea, and Switzerland are the only countries whose trajectories resulted in "positive" or "neutral-positive". The others all saw a "negative" trajectory except for Sweden with a "neutral" prediction. Even though the first group of the two previously divided performed better in the relative position assessment, only two of them (Australia and Korea) had a "positive" prediction, and the second group also had one country with this result, Switzerland.

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