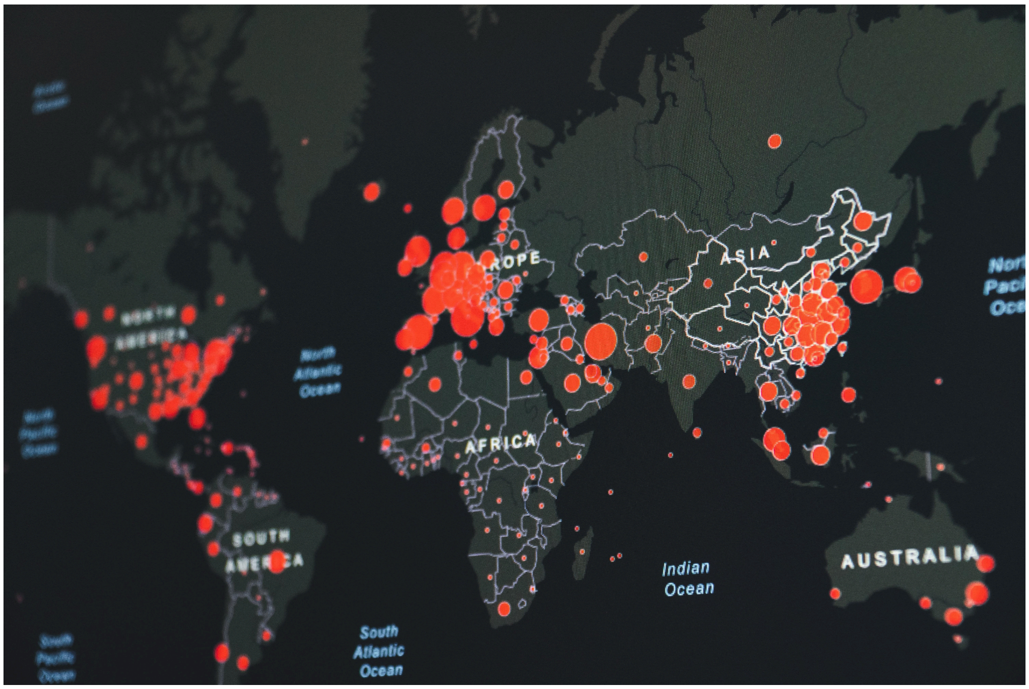
Outcomes of COVID-19 Policy Implementation Across Different Countries as Affected by Economic Disparities



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(Image source: weforum.org)

1. Introduction

At the beginning of 2020, the world was struck with the COVID-19 pandemic, the likes of which were unprecedented in modern history. Originating from Wuhan, China, the virus quickly spread across the world, resulting in over 400,000 cases and 18,000 deaths by March of 2020, causing the World Health Organization (WHO) to declare it a global pandemic on the 12th of that month (Zhou et. al., 2020; Ahn et. al., 2020). Such a worldwide pandemic had a multitude of effects on the general public, including (but not limited to) global declines in mental health, economic recessions, and the loss of over 7 million lives as of April 13, 2024 (Talevi et. al., 2020; Clemente-Suarez et. al., 2021; Worldometer, 2024).

It was not until May of 2023, three years later, that WHO declared the public health emergency of the COVID-19 pandemic to be over (World Health Organization, 2023). During those three years, the world's response to the pandemic varied between countries greatly, highlighting key differences between governments and populations. In particular, the populations of countries in east and southeast Asia were generally more ready to comply with government restrictions, while North American and western European countries generally reacted more slowly (Tang et. al., 2022.) Because of the difference in the reaction of populations between countries, governments had to adjust their national response strategies in kind, resulting in multiple distinct pandemic response strategies (Yan et. al., 2020). In studies conducted on the differences between countries' responses, it is often difficult to compare raw data across countries because of the large variety of responses the government may have to COVID-19. Therefore, more research is needed comparing all of the responses of COVID-19 between countries.

To measure the response from governments to the effects of the pandemic, we used the COVID-19 Stringency Index from the Oxford Coronavirus Government Response Tracker (OxCGRT). This metric is calculated from nine response metrics: school closures, workplace closures, cancellations of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls. In addition, three indices are calculated for each country, one for those who are vaccinated, one for those who are unvaccinated, and a national average. For this index, a score of 100 indicates a stricter response, while a score of 0 indicates a more lenient response (Our World in Data, 2021). **This metric, with World GDP data, provides an important insight into which we can analyze the economic impacts of COVID-19 policies, by reflecting the financial output of various countries. Countries with higher GDP often have more resources to provide effective healthcare responses, which may influence the effectiveness of government policies. Furthermore, GDP allows global comparisons, giving insights into how economic strength affects a country's ability to sustain policies without severe financial repercussions.** These metrics, in combination with COVID testing rates, and general population data (cases and deaths), will aid in the comparison of government responses across hundreds of different countries.

In this report, we aim to answer the following questions:

1. **How does the COVID-19 Stringency Index correlate with the total number of COVID-19 cases across countries?**
2. **What is the relationship between GDP and the effectiveness of COVID-19 policies in reducing mortality rates?**
3. **How do economic disparities influence the duration and intensity of COVID-19 policy implementation across countries?**

By answering these questions, we hope to paint a more comprehensive picture of the entire pandemic and each government's response.

2. Data Collection and Data Processing

2.1 World GDP Data Acquisition Using the World Bank API

The World Bank API gives access to various economic indicators, such as GDP, healthcare spending, and population metrics, for countries worldwide. For this project, the API's two primary endpoints were utilized. This includes the country endpoint ("https://api.worldbank.org/v2/country"), which provides metadata about country names, ISO codes, and regions, and the indicator endpoint ("https://api.worldbank.org/v2/country/{country_code}/indicator/{indicator_code}"), which collects time-series data for economic indicators such as the country's GDP (NY.GDP.MKTP.CD).

The users can access data filtered by country, region, or period using specific parameters such as 'country' (ISO 3-letter country codes), 'indicator' (using specific indicator codes such as 'NY.GDP.MKTP.CD' for GDP in current US$), 'date' (by year), and 'format' (specifying the response format).

For the initial attempt to use the API, a search endpoint ("https://search.worldbank.org/api/v3/wds") with a generic keyword ("health") was used. This attempt intended to explore the API's capabilities. While this query was successful in retrieving the data, the retrieved results were overly broad and did not consist of relevant socioeconomic indicator data such as GDP required for this project. Overall, this result highlighted the need to use more specific endpoints using relevant indicators to retrieve more structured indicator data.

The second attempt targeted a single country and utilized the indicator endpoint ("https://api.worldbank.org/v2/country/usa/indicator/NY.GDP.MKTP.CD") to access GDP data for a single country using the three-letter ISO code for the United States ("usa") and the indicator code for (NY.GDP.MKTP.CD). While this attempt was successful and returned precise data for the precise period, it was not scalable, as retrieving data for all countries would require using separate endpoints for each country, which was concluded to be inefficient for global datasets.

To scale the process, the "all" parameter was used with the indicator endpoint ("https://api.worldbank.org/v2/country/all/indicator/NY.GDP.MKTP.CD") to request data for all countries at once. However, the query returned incomplete data, where the data was limited to GDP data of "Africa Eastern and Southern," and did not include the data of other countries. This indicated that the "all" parameter was not functioning as intended.

To address the limitations of the first three attempts, a more precise strategy was implemented. First, using the country endpoint ("https://api.worldbank.org/v2/country"), a list of ISO country codes was fetched. This endpoint successfully provided data for over 200 countries, allowing users to precisely target specific countries. With this list of country codes, the indicator endpoint ("https://api.worldbank.org/v2/country/{country_code}/indicator/NY.GDP.MKTP.CD") was used to retrieve GDP data in batches. To avoid the URLs from becoming excessively long, the country codes were grouped into batches of 50. Separate requests were made for each batch, allowing for more efficient data retrieval. Additionally, a delay was introduced between requests for potential blockings due to API's rate limits.

To process the retrieved data, irrelevant fields were removed, and the remaining data was reorganized. The remaining dataset was pivoted with years (2020 to 2022) as columns and each country was represented by its full name. The final dataset, in a pandas data frame, includes GDP data for nearly all countries worldwide. Each entry specifies the country name and the corresponding GDP values for each year (2020-2022) in current US dollars. The resulting dataset provides a comprehensive view of the global financial trends during the years 2020-2022.

2.2 COVID-19 Stringency Index Data Acquisition and Processing

The Stringency Index dataset is originally from the Oxford COVID-19 Response Tracker, and the "Our World in Data" (OWID) hosts this data, allowing access to the public. The data provides detailed information about the policy responses. The data source used for this project to acquire the COVID-19 Stringency index data is the publicly accessible GitHub repository maintained by OWID. The data is available in the URL https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/internal/megafile--stringency.json and is stored in a JSON format.

This dataset tracks daily COVID-19 policy stringency measures across countries worldwide, allowing users to have access to the numerical representation of the strictness of various government policies related to the pandemic (e.g. lockdowns, school closures, and travel restrictions). The dataset contains several key fields which include, the 'location' (specifies country name), 'date' (date of the policy measure), and 'stringency_index' (overall strictness of government policies). It also includes additional fields such as 'stringency_index_vac', 'stringency_index_nonvac', and 'stringency_index_weighted_avg', representing vaccination policies, non-vaccination-specific policies, and weighted averages of all measures, respectively. Each entry represents a specific country and the date.

Unlike traditional APIs, the dataset is static and does not support query capabilities. It is provided as a JSON file hosted on OWID's GitHub, requiring users to download the entire dataset rather than request specific subsets. The JSON structure necessitates additional processing to convert it into a format suitable for analysis. Furthermore, the considerable size of the dataset, with over 200,000 rows of daily data, requires efficient processing and memory management. This large size is due to redundancy, as the data includes daily entries for multiple years and countries. Further processing is therefore necessary to make the dataset more manageable and useful.

Using Python's 'request' library and sending a 'GET' request to the specified URL (https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/internal/megafile--stringency.json), the JSON file was programmatically retrieved. Upon receiving an HTTP status code of 200, indicating a successful response, the JSON content was converted into a Python dictionary for further data processing. This dataset was then loaded into the pandas data frame. The resulting data frame contained 200,490 rows, each representing a unique combination of 'location' and 'date' with stringency index measures ('stringency_index', 'stringency_index_vac', 'stringency_index_nonvac', and 'stringency_index_weighted_avg').

To make the dataset more manageable and usable, the daily stringent index values were aggregated into yearly averages for each country. First, the 'date' was converted into datetime format, and the year was extracted to group the data at the yearly level. Data from the years 2020, 2021, and 2022 were retained for the data analysis. Then, the data was grouped by 'location' (country name), and 'year.' The average of the 'stringency_index' values was calculated for each group. Additional stringency index measures such as 'stringency_index_vac', 'stringency_index_nonvac', and 'stringency_index_weighted_avg' were excluded for simplicity of the data analysis. The resulting dataset contained rows each representing a unique combination of country and year, with a single stringency index value summarizing the average policy strictness of the year. Such aggregation of the data reduced the redundancy of the data and resulted in more interpretable data, easier to use to identify overall trends in government responses to the pandemic.

2.3 Worldometer Data Acquisition Using Web Scraping

The Worldometer Coronavirus dataset is from the Worldometer website (https://www.worldometers.info/), which aims to provide global statistics to a global audience in interactive and easy-to-use formats. In addition to providing population data for countries around the world, the website provides comprehensive daily data for 229 countries' COVID-19 outcomes. The Coronavirus data is collected from official reports from each country's government communication channels, gained through local news outlets. As the data on Worldometer is global, there is a large list of over 5000 sources, each of which is vetted by a team of researchers that validate this data, as well as users of the website who are able to report inconsistencies in data. More information about the data sources for Worldometer can be found at https://www.worldometers.info/coronavirus/about/.

The home page for Coronavirus data can be found at https://www.worldometers.info/coronavirus/. This page contains the global totals for COVID-19 statistics, which contains a summary of total cases, deaths, and recovered cases, as of April 13, 2024. The page also contains a table of the totals for each country (229 countries total) as of April 13, 2024, as well as a link to each country's web page. The data for each country's daily statistics is contained in its own web page (e.g. Italy's data can be found at https://www.worldometers.info/coronavirus/country/italy/). Among the daily statistics for Coronavirus is data for the number of currently infected (currently active cases), total number of cases, total number of deaths, number of new cases, and number of new deaths. The daily statistics are displayed on the website as graphs. The Coronavirus dataset does not have a publicly available API for use. Therefore, for this data source, we used a web scraping technique, utilizing Python libraries requests, BeautifulSoup4, pandas, and statistics, to attain this dataset.

The first dataframes attained were a summary of all continents (continents_df) and a summary of all countries (countries_df), both from the table at the main page of the Coronavirus Worldometer page (https://www.worldometers.info/coronavirus/). First, the source HTML code for the webpage was attained using the requests package, and parsed using BeautifulSoup. The table was contained in a '<table>' element, so each row was tagged with '<tr>', and each cell tagged with '<td>'. The data was then extracted using HTML parsing methods and put into a pandas dataframe. The first 6 rows of the table made up continents_df, which had columns 'continent', 'total_cases', 'total_deaths', 'total_recovered', 'tot_cases_per_1m' (Total number of cases per 1 million people in that continent), 'tot_deaths_per_1m' (Total number of deaths per 1 million people in that continent), and 'population'. There was data for North America, Asia, Europe, South America, Oceania, and Africa (6 rows total). The rest of the rows made up the pandas dataframe countries_df, which had columns 'country', 'total_cases', 'total_deaths', 'total_recovered', 'tot_cases_per_1m' (Total number of cases per 1 million people in that country), 'tot_deaths_per_1m' (Total number of deaths per 1 million people in that country), 'population', and the additional column 'link', which contained a link to the country's individual page for further use in the daily statistics extraction. The resulting DataFrame had 229 rows total.

The next dataframes obtained were extracted from the graphs on each country's individual page, as well as the graphs from the global population on the main page. Each graph plotted data on the y axis with the time (in days) on the x axis. Using the links saved in countries_df, we were able to use the requests package to obtain the HTML source code for each country. Each source was then parsed with BeautifulSoup for ease of extraction. Each graph was contained in a '<script>' element, meaning the source code for it was in Javascript, not in HTML, which presented a problem as the Javascript code was harder to understand and parse than the HTML code, and BeautifulSoup did not extract Javascript elements as easily as HTML elements. To get around this issue, we split each script element by the call to the charts function ('Highcharts.chart'), which resulted in each chart in its own chunk. After this, the logic for each chart was understood, and we used string methods to extract the title of the chart (the first value after the 'Highcharts.chart' call), the dates (values contained in brackets after 'xAxis'), and the data (values contained in brackets after 'data:'). Each chart was then made into a pandas dataframe, with columns 'dates' and 'data1', and titled with the title of the chart.

Finally, to standardize the data from the individual countries' dataframes, a master dataframe was calculated from each country's dataframes. The daily statistics were each aggregated into averages or totals (depending on the statistic) by year and by country, for the years 2020, 2021, and 2022. The resulting dataframe had 687 rows and 7 columns, consisting of

3 rows for each country (one for 2020, 2021, and 2022), and a column for the average currently infected, total cases at the end of that year, total deaths at the end of that year, average daily new cases, and average daily deaths. The aggregation of the data made it easier to merge the dataset with the other datasets from other sources.

3. Combining Data

3.1 Merging GDP and Stringency Index Datasets

To conduct a comparative analysis between economic mercies and governmental responses to the pandemic across countries, the two datasets, one containing GDP data and the other capturing the COVID-19 Stringency Index, were merged into a unified dataset.

The initial step involved assessing the compatibility of the two datasets by identifying common and unique country names. Using the ‘set’ function, unique country names were extracted from the GDP data frame and the Stringency Index data frame. The ‘intersection’ and ‘difference’ operations were used to identify countries common and unique to the datasets. The results showed: 161 common countries were present in both datasets, 56 countries were unique to the GDP dataset, and 24 countries were unique to the Stringency Index dataset.

The next step of this analysis involved filtering the datasets not present in both datasets to ensure consistency and meaningful comparisons. Both datasets were filtered to include only rows with common countries. The filtered datasets were then merged using the pd.merge() function on the shared columns ‘location’ (country names) and ‘year’. The resulting dataset contained the following columns: ‘location,’ ‘year,’ ‘gdp,’ and ‘stringency_index.’ By aligning and merging the two datasets, a clean and comprehensive dataset was created that captures both economic and policy response data for 161 countries over three years (2020-2022).

3.2 Merging GDP, Stringency Index, and Worldometer COVID Dataset

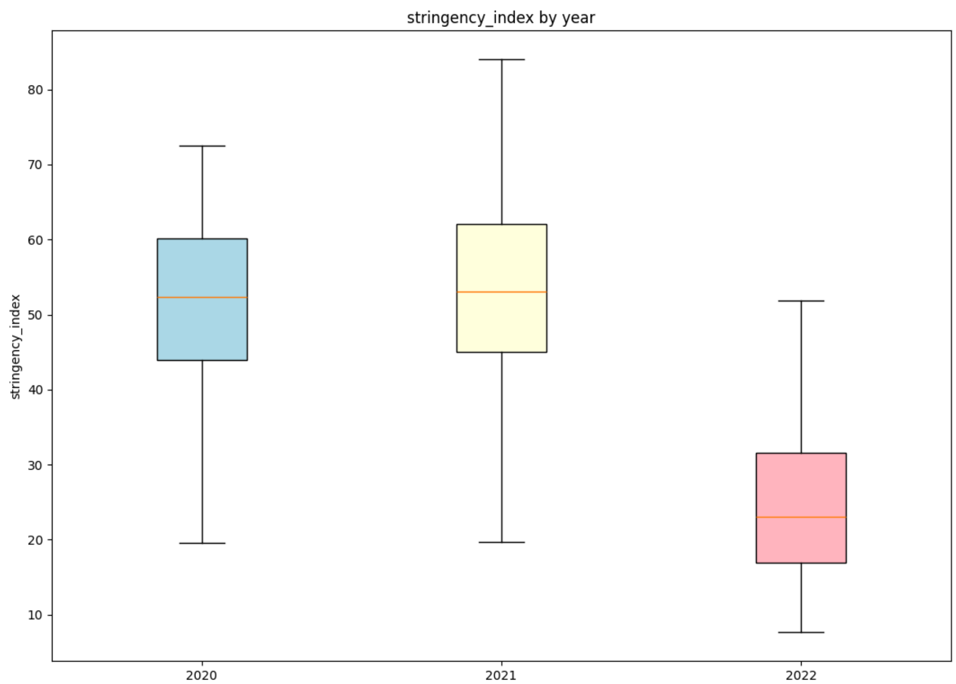
The final merging process involved combining the three datasets, GDP, COVID-19 Stringency Index, and Worldometer statistics into a united dataset. Initially, the country names of each dataset were compared. It was identified that a total of 151 countries were common for all datasets, while 10 countries were unique to the GDP/Stringency index, and 78 countries were unique to the Worldometer dataset. The final dataset retained only the common countries and was aligned by year to ensure consistency.

The final dataset provides a combination of GDP, Stringency Index, and Worldometer COVID-19 statistics for 151 countries over three years (2020-2022). Each row represents a unique combination of country and year and provides variables such as GDP (current US$), average Stringency Index, total COVID-19 cases, total deaths, average daily new cases, average daily deaths, and average currently infected individuals for the year. The structure of this data frame allows for efficient cross-country and temporal analysis that will capture each country’s economic impact, policy responses, and pandemic outcomes in an organized format. The dataset includes economic and health-related variables, enabling an in-depth analysis of how government responses to the pandemic influenced health and economic outcomes.

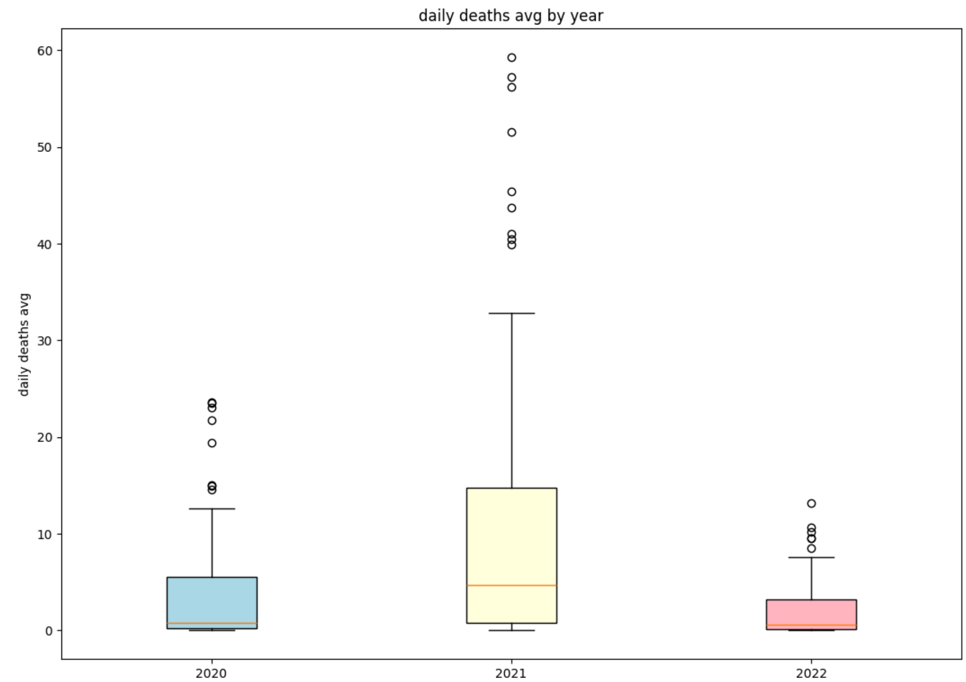
4. Data Analysis and Visualizations

4.1 Global Trends

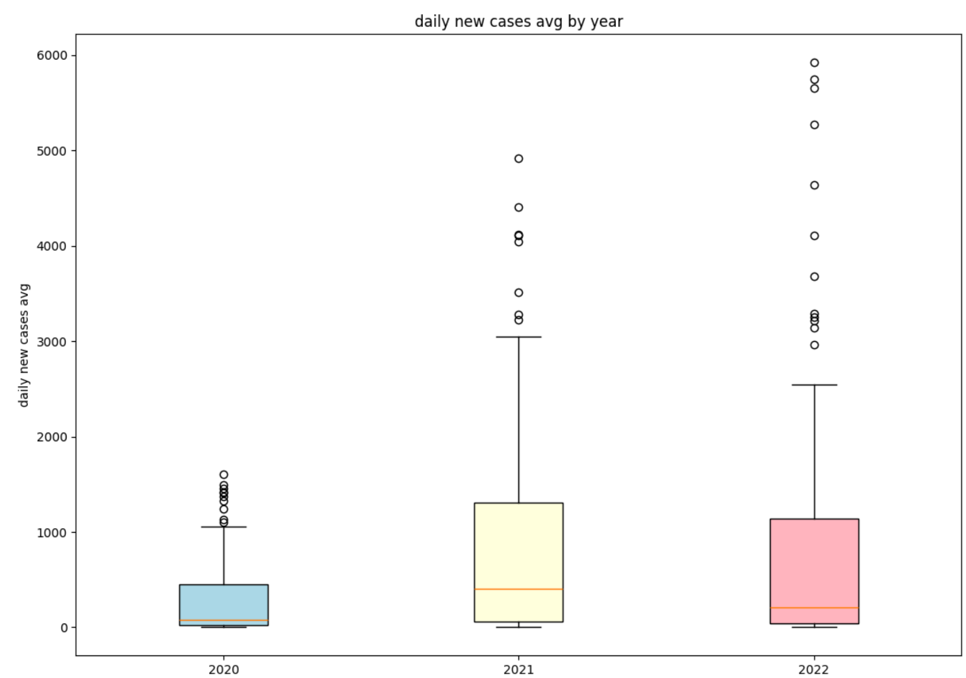
To see a general overview of the data contained in the final merged dataset, several boxplots were generated highlighting global trends in each of the metrics: GDP, Stringency Index, average currently infected individuals, total cases, total deaths, average daily deaths, and average daily new cases. Each boxplot was separated by year (2020, 2021, and 2022) to investigate how each metric changed as the pandemic progressed. Below are the boxplots with the most significant data.



The most dramatic change over time was highlighted in the Stringency Index boxplot (seen above), which showed a sharp decrease between 2021 and 2022. 2020 and 2021 had a global median of 52.38 and 53.05, respectively, while 2022 had a global median of 23.04.



Another evident change over time was the average daily deaths, seen above. This data showed a large increase in daily deaths from 2020 to 2021, with medians 0.77 deaths and 4.67 deaths respectively. However, there was a large decrease in daily deaths between 2021 and 2022, with 2022 having a median of 0.62 deaths.

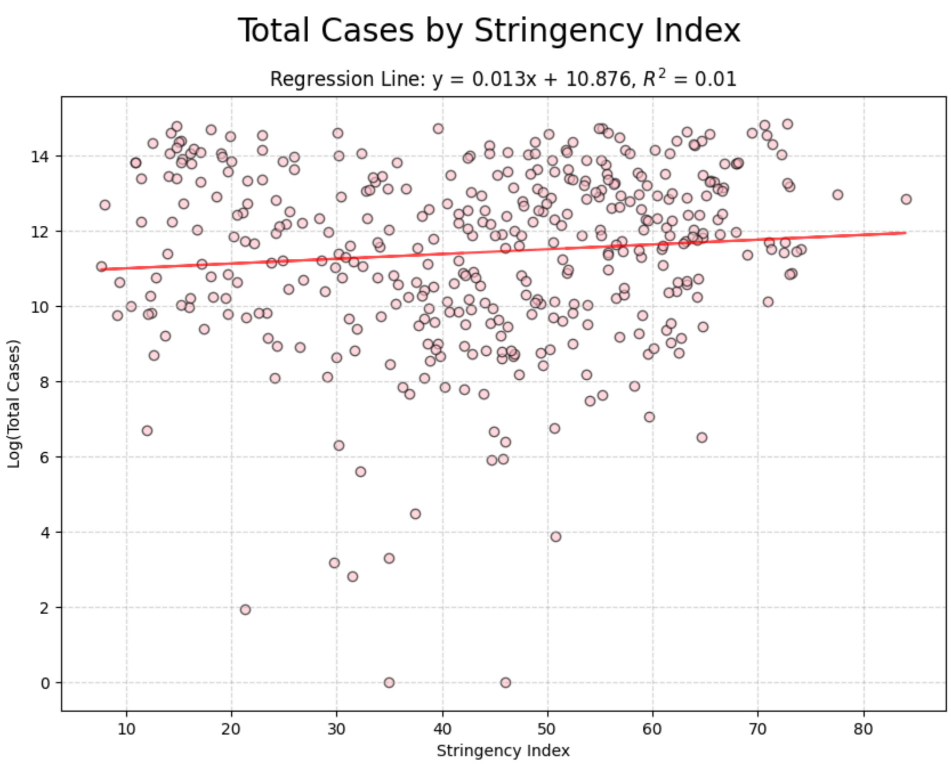


A similar trend to daily deaths was observed in the average daily new cases boxplot, seen above. Again, a large increase in daily new cases was observed between 2020 and 2021, with medians 80.24 cases and 405.18 cases respectively, and a large decrease in daily new cases was observed between 2021 and 2022, with a median of 212.76 cases in 2022. However, it should be noted that the decrease in daily new cases is not as sharp as the decrease in daily deaths.

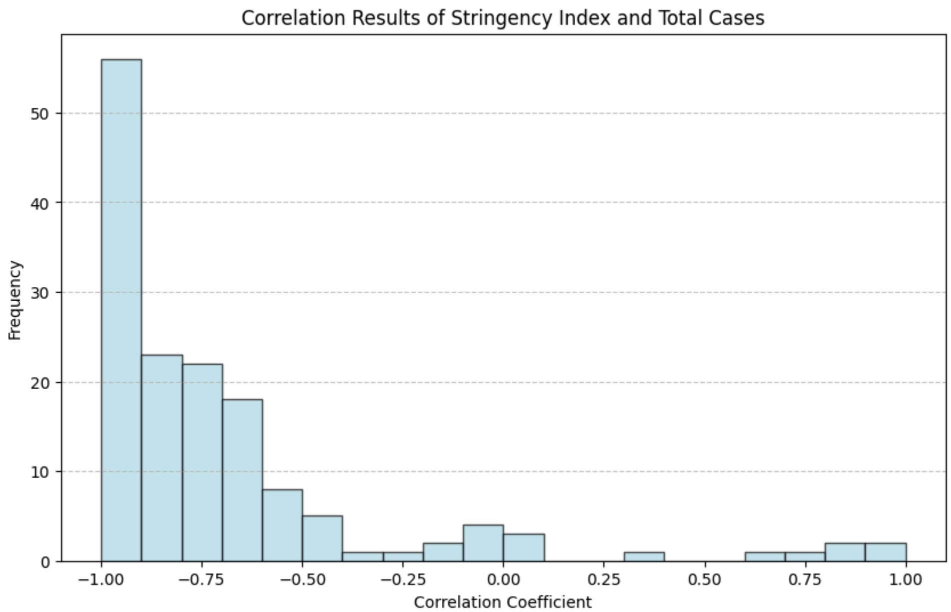
These trends could be due to a multitude of reasons, but one of the most probable reasons is the effect of vaccination. By February of 2022, 54.52% of the world was fully vaccinated against COVID-19, and 62.19% of the world had at least one dose (Zhou et. al., 2022). **Therefore, the sharp decrease in deaths and new cases in 2022 could be due to increased global resistance to COVID-19, which could also have led to the large decrease in Stringency Index as governments relaxed their policies in response to lowered death rates.** In addition, the difference between the decrease in average new cases and the decrease in average daily deaths could be due to a combination of the Stringency Index falling and vaccination rates increasing. With policies relaxed, the existence of asymptomatic superspreaders (persons affected by COVID-19 but experiencing no symptoms who unknowingly spread the virus quickly) may have increased the number of cases even with vaccinations at a high level (Kault, 2020).

4.2 Effectiveness of Policies on Total Cases

To answer our first research question: **How does the COVID-19 Stringency Index correlate with the total number of COVID-19 cases across countries?**, a scatterplot between total cases and stringency index was generated, as well as the correlation between each individual country's stringency index and total cases. Because of the large discrepancy between each country's population and the resulting discrepancy in total cases, the total cases data was log transformed along the y axis.



Above is the scatter plot generated. While there was a weak positive correlation as indicated by the slope of 0.013, there was little to no correlation found between stringency index and total cases, as indicated by the R^2 value of 0.01. Therefore, we can conclude that **on a global scale, there was no trend between stringency index and total cases**. However, investigation into individual countries may reveal more about this relationship.

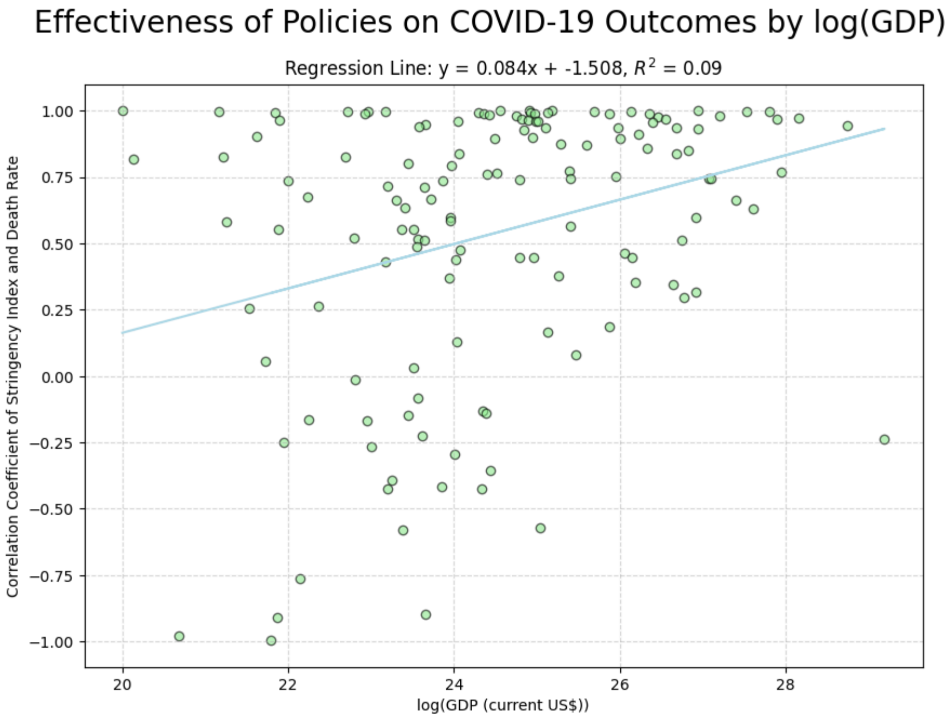


Above is a histogram showing the distribution of correlation coefficients for each individual country. Correlation values closer to 1 indicate that as the Stringency Index rose, total cases rose as well, and correlation values closer to -1 indicate that as the Stringency Index rose, total cases fell. **The large majority of countries showed a negative correlation between the Stringency Index and total cases, which indicated that enforcing stricter policies led to positive outcomes in most countries.** Among the strongest correlations were Singapore, Italy, and Australia, all highly developed countries.

However, some outliers had a positive correlation between the Stringency Index and total cases, indicating that enforcing stricter policies actually led to negative outcomes in these countries. This could be due to a number of reasons, but looking at these outliers individually reveals more about these countries. The majority of countries with positive correlations are smaller, less developed countries, such as Burundi, Tonga, and the Solomon Islands. The one outlier in these positively correlated countries is China, which may be due to the fact that the outbreak originated from there.

4.3 GDP and Effectiveness of Policies on Death Rate

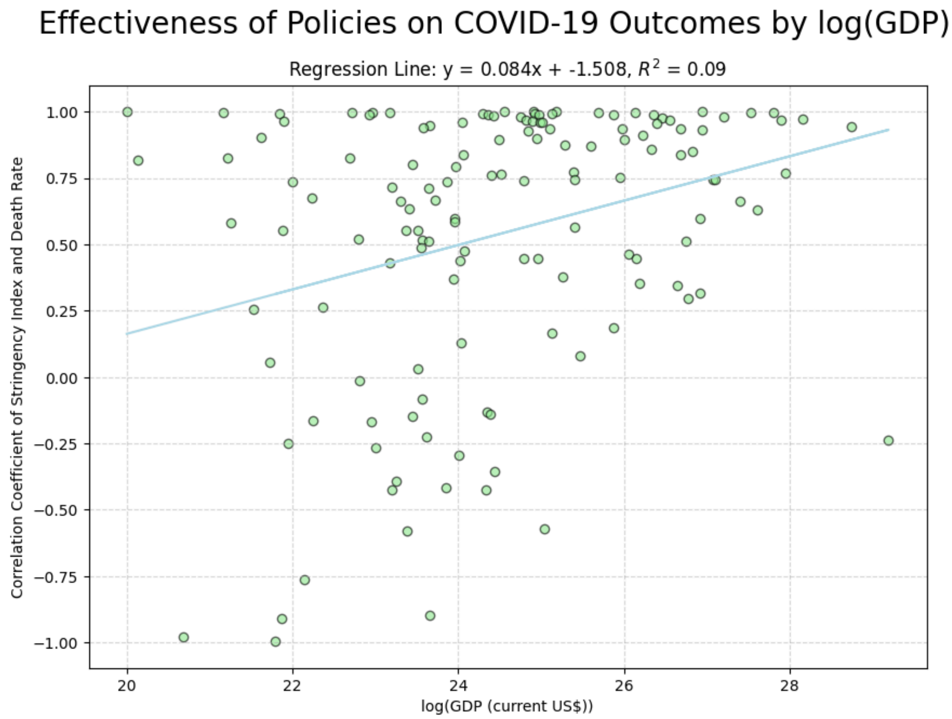
To answer our second research question: **What is the relationship between GDP and the effectiveness of COVID-19 policies in reducing mortality rates?**, the death rates of each country were calculated (from total deaths and total cases), and the correlation coefficient between this and the country's Stringency Index was then calculated. These correlation coefficients were then plotted against each country's GDP. Because of the large discrepancy in GDP between countries, the data was log-transformed on the x-axis.



The scatter plot above shows a weak positive correlation between GDP and the effectiveness of policies on death rates on a global scale, as indicated by the slope of 0.084 and the R^2 value of 0.09. This indicates that with each one percent increase in GDP, the correlation rose by 0.00084 (the slope divided by 100, as the x-axis was log-transformed). GDP measures a country's economic output, and more developed countries therefore have a larger GDP. **Therefore, if a country is more successful economically, the effectiveness of its policies on affecting the death rate increases.**

4.4 Economic Disparities and Policy Strictness

Finally, to answer our third research question: **How do economic disparities influence the duration and intensity of COVID-19 policy implementation across countries?**, a scatterplot between GDP and Stringency Index was generated. Because of the large discrepancy in GDP between countries, the data was log-transformed on the x-axis.



The scatterplot shows a weak positive association as indicated by the slope of 0.977. However, the R^2 value was 0.01, indicating that the fit of this association was very weak. Therefore, we can conclude that **a country's economic output does not affect the strictness of governments on COVID-19 policies**.

5. Conclusion

The COVID-19 pandemic made a profound impact on societies, economies, and healthcare systems around the world, and in response to these severe impacts, governments responded with different degrees of policy strictness. This study examined the relationship between the COVID-19 Stringency Index, GDP, and health outcomes, analyzing the influence of economic disparities on pandemic responses. While there was no strong correlation found between the stringency and total COVID-19 cases, it was revealed that stringent policies generally showed more reduction in cases in countries with higher GDP. However, there were outliers present, such as smaller and economically weaker nations that demonstrated the complexity of policy impacts, which can be influenced by factors such as healthcare infrastructure, cultural compliance, and population density.

Additionally, the analysis showed a weak but positive correlation between GDP and the effectiveness of policies in reducing mortality rates. This suggests that nations of higher GDP may benefit from wealthier resources to implement policies more effectively, which may result in improved health outcomes. However, there is still little evidence to support that GDP significantly impacted policy strictness, indicating that factors other than economic output influenced government decisions to enforce restrictions.

The result also shows that vaccinations played a pivotal role in reducing mortality and daily cases. These findings highlight the importance of effective vaccine distribution globally and the need for adaptive strategies to overcome unique challenges faced by countries with diverse economic and social backgrounds. By understanding such interactions between economic disparities and policy outcomes, governments and health organizations globally can make better preparations for future health crises, ensuring more effective responses worldwide.

5. Works Cited

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