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Title: Using every country's COVID-19 data to create a composite index ranking their relative attractiveness for geographic supply chain diversification to combat the risk of a future pandemic outbreak

题目: 利用每个国家的 COVID-19 数据建立一个综合指数，对其地理供应链多样化的相对吸引力进行排名，以应对未来大流行病爆发的风险

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Abstract

The COVID-19 pandemic presented the world to a new type of black swan supply chain risk: a global pandemic outbreak. The COVID-19 pandemic and the actions taken to control it caused massive supply chains disruptions on a scale never seen; the fact these disruptions occurred across nearly every industry made the outbreak even more unique. Through these disruptions, the COVID-19 pandemic brought to light the shortcomings of current supply chain resilience techniques and highlighted the lack of geographic diversification in current global supply chains. It has been the largest global pandemic outbreak since the 1918 Spanish Flu; but unlike the Spanish flu outbreak, it accompanied by an abundance of data detailing the outbreak severity and government response severity for nearly every country in the world. From this data, quantitative conclusion can be made that could help global supply chains combat the risk of future pandemic outbreaks and become more resilient. Through our research, we will propose a method for extracting advanced metrics from every country's COVID-19 data to quantitatively determine the severity of their pandemic outbreak. We will also derive metrics from countries' government response actions that would specifically effect the performance of global supply chains. From the relationships between these two sets of metrics, risk tolerance metrics will also be calculated to further add context to every country's propensity to take actions that would have negative consequence for global supply chains. From these metrics, we will create a composite index that details every country's relative attractiveness for geographic supply chain diversification to make global supply chains more pandemic resilient. Furthermore, we will perform a confounding variable analysis with the goal of finding quantitative factors that describe the type of country that is the best target for geographic supply chain diversification to combat the risk of a future pandemic outbreak. Finally, as a product of this analysis, we will examine the accuracy of the 2019 GHS rankings as they relate to pandemic outbreaks and compare them to the metrics we calculated to add further context to their results.

Contents

1 Introduction

1.1 Pandemic Severity and Economic Effects

The global pandemic brought upon by the COVID-19 virus, which has killed over 2.3 million people and infected over 100 million more on every continent in the world [1], has highlighted and exposed the threat of a new black swam risk - a global pandemic disease outbreak - to global supply chains. In the past, the typical black swan risks considered in supply chain management were mainly war, floods, storms, and terrorist or cyberattacks [2]. Indeed, the last such pandemic outbreak of similar severity and scale was the 1918 Spanish Influenza pandemic that has been estimated to have killed 50 million people and infected about 500 million [3]. Despite the fact that the last global pandemic event occurred over 100 year ago, the risk of a global pandemic outbreak needs to be considering the strategic supply chain management planning process going forward.

Since 2000, there have been pandemic outbreaks that have had measurable economic impacts. In September 2019, the *Global Preparedness Monitoring Board* outlined these specific pandemic outbreaks in their annual report on global preparedness for health emergencies. Four of these pandemic outbreaks (SARS, H5N1, H1N1, and EBOLA) had measurable economic impacts at or exceeding \$40 million USD. In fact, it had been estimated that a pandemic outbreak on the scale of the 1918 Spanish Flu outbreak could cause the world's economy \$3 trillion USD (4.8% of global GDP) whereas the cost of even a moderate influenza pandemic would be 2.2% of global GDP. In fact, these appear to be underestimates as, despite COVID-19's severity being less than the 1918 Spanish Flu pandemic, global GDP contracted by 4.3% in 2020 [5]. Finally, the risk of a global pandemic outbreak is not likely to go away as between 2011 and 2018, WHO tracked 1483 epidemic events in 172 countries [6].

Despite their infrequency, the risk of a global pandemic outbreak must be considered in strategic supply chain decision making due to their immense economic impact. For comparison, the most expensive natural disaster in recorded history was the 2011 Tōhoku earthquake and tsunami in Japan. " Japan' s government says the total cost of the damage caused by the tsunami could reach 25 trillion yen–or U.S. \$309 billion" [7] which would equate to \$353 million today. The most expensive man-made disaster was the 1986 Chernobyl Nuclear Disaster. The high-end estimate of the 30-year cost of the Chernobyl Nuclear Disaster is \$700 billion [8]. Therefore, the economic impact of COVID-19 is expected to be nearly 13 times more expensive than the 2011 Tōhoku earthquake and tsunami and 6.5 times more expensive than the 1986 Chernobyl Nuclear Disaster.

1.2 Supply Chain Effects

The effects of the COVID-19 pandemic, asides from work stoppages and nationwide lockdowns, were probably most noticeable in the form of supply chain disruptions. While the shortages of toilet paper, hand sanitizer, and medical personal protective equipment made for newsworthy headlines, COVID-19's disruption was drastic on all supply chains. On April 14, 2020, the *Institute for Supply Management(ISM)* released its second wave of research on COVID-19' s impacts on businesses and their supply chains [9]. Some of the most notable takeaways, which capture COVID-19's first wave's effects on the global supply chains, included:

- 95% of organizations will be or have already been impacted by coronavirus supply chain disruptions
- Average lead times for inputs are at least twice as long as compared to "normal" operations,for Asian , European, and domestically sourced (USA) inputs
- US manufacturing is operating at 79% of normal capacity. Chinese and European manufacturing is at about one-half normal capacity, 53% and 50% respectively

It was not only the severity of the COVID-19 Pandemic that made it notable, but also the fact that its disruption characteristics varied greatly from past large-scale disruption events. In particular, the differing effects of the COVID-19 pandemic on supply chain disruption can best be described amongst the following dimensions [10][11]:

1. Geographic: COVID-19's impact was global whereas most other supply chain disruptions are regional
2. Industry: COVID-19 affected nearly every industry's supply chains whereas most supply chain disruptions disproportionately affect only a few industries
3. Demand vs Supply: COVID-19 affected both supply and demand whereas most disruptions only effect supply
4. Duration: COVID-19's effects are much more long-term than typical supply chain disruptions
5. Prior Planning and Experience: there is little to no experience with global pandemic outbreaks and their effects on global supply chains, while the literature about other supply disruptions is plentiful
6. Financial System: COVID-19 was highly correlated with global financial systems, most other supply chain disruption have only a low to moderate correlations with global financial systems
7. Human Impact and Behavior: COVID-19 cause widespread and long-term fear whereas most other supply chain disruptions caused localized and short-term fear

Now that the end of the COVID-19 pandemic is in sight, more reflective statistics exist to quantify COVID-19's effect on global supply chains. *Capgemini's Fast Forward* report provides such statistics [12]:

- 68% of organizations have taken more than three months to recover from supply chain disruptions caused by COVID-19

- 66% believe their supply chain strategy will need to change significantly in order to adapt to a new normal post COVID-19
- 57% of organizations are increasing their investments in improving supply chain resilience
- 68% are actively investing in diversifying their supplier base (i.e. shifting from single to multi-sourcing wherever possible)
- 62% are actively investing in diversifying their manufacturing base (i.e. reducing their reliance on a single geographic region)

1.3 Improving Global Supply Chains

Many approaches have been proposed for businesses to pursue to combat the new black swan risk of a global pandemic outbreak from causing such significant supply chain disruptions in the future. In the wake of COVID-19, many countries and business are realizing just how much their supply chains relied on one geographic region: China [13, paper 8]. This has led to many proposals about how to adapt global supply chains to improve their resiliency and robustness including: geographic diversification and dual sourcing [14], reducing the amount of irretrievable investment abroad [15], segmenting or regionalizing the supply chain [16], focusing on increasing supply chain visibility and information sharing [12], and the usage of digital technologies [17]. In short, the types of improvements can be broken into two categories: geographic and technological.

Within the geographic dimension, two main methodologies, regionalization and diversification, have become two of the most prominent solutions. In fact, the *UNCTAD World Investment Report* already predicts that reshoring, diversification, and regionalization will dominate global value chain restructuring in the coming years [18]. While for essential goods, like medical equipment, a regionalization approach may become the new normal [14], the question of whether to regionalize the other global supply chains is more complicated. Due to the fact that supply chain cost remains the highest metric for companies even after COVID-19 [12] the questions about how to actually go about regionalizing vs. diversifying the global supply chain is much more complicated than just considering the effects of COVID-19 [19] as "the risks of the interdependencies of economies has [long] been the source of growth and development".

Regardless of the approach companies take to make their supply chains robust and resilient to the black swan risk of a global pandemic outbreak, it is without question that research must be done to determine how such changes to global supply chains need to be made to mitigate future disruptions and risk.

1.4 Outline

The remainder of the paper is structured as follows: in Section 2, we present the specific problem we will solve. In Section 3, we will conduct a brief literature review to provide further context to our problem and detail our contributions. In Section 4, we will explain the methods we used to solve the problem. In Section 5, we will present a summarized version of our results. Finally, in Section 6 we will draw conclusions from our results and place them in context. Finally, in Section 7, we will detail possible future work on this problem.

2 Problem Statement

Given that companies will likely pursue a variety of methods to make their supply chains more resilient and robust post-COVID-19 and that geographic supply chain diversification will be one possible solution avenue, it is imperative that research be done on geographic supply chain diversification to hedge the risk of a global pandemic outbreak. Given that the last global pandemic outbreak of sufficient scale was the 1918 Spanish Flu pandemic, there was never enough quality data to conduct such an analysis. However, given the wealth of COVID-19 data available from nearly every country on the planet, such an analysis can finally occur. Additionally, it is critical that any such analyses heavily utilize the COVID-19 data because, if they do not, it cannot be assured that any conclusions can be drawn about the effect of different geographic supply chain diversification decisions have against combating the risk of another global pandemic outbreak.

In this paper, we propose a comprehensive analysis of every country's COVID-19 data and government response data in order to create a composite index that will detail the relative attractiveness of every country in terms of geographic supply chain diversification to hedge against the risk of a future global pandemic outbreak. From every country's COVID-19 case and death data, advanced metrics (i.e. rate of cases growth during an outbreak as opposed to simply the total number of cases) will allows us to quantify the the severity of the COVID-19 pandemic in every country. Additionally, by analyzing government response metrics that would be directly related to global supply chain performance, we can determine how much every country hampered global supply chains that ran through their country. Additionally, by drawing relationships between the COVID-19 data and government response data, we can derive risk tolerance metrics that describe the propensity of a country to enact stricter measures that hinder supply chain performance based on their observed outbreak severity (i.e. the growth rate in cases before instituting a total lockdown).

Additionally, we will perform statistical correlation analyses between the COVID-19 case and death data / government response metrics and possible confounding variables / prior pandemic preparedness metrics to create a general profile of a country whose handling of the pandemic is more attractive in terms of future geographic supply chain diversification. Additionally, such analyses can serve to determine the accuracy of these prior pandemic preparedness metrics. These results will complement the results of the composite index and they can place them in context and, in the event of the this research's application, it can help narrow the list of country's to begin considering for geographic supply chain diversification.

3 Literature Review

3.1 COVID-19 and Supply Chain Resilience

The COVID-19 pandemic has proven that no business sector is immune to a COVID-19 level disruption, with global supply chains being particularly vulnerable. A firm's recovery from such a disruption is be dependent on their ability to quickly remobilize their supply chain [20]. Early in the pandemic, the most common response to new market developments was changing operating volumes, however the most successful measure was developing new supply chain partnerships [21]. Calls for supply chain diversification and regionalization have come before (especially after natural disasters or terrorist attacks), but have never been seriously adopted; however, COVID-19 will likely be different [22]. However, these decisions may be a double-edged sword and may be motivated by other actors. Supplier diversification was a key component of firm success during COVID-19 and there was a shift towards regionalization (especially when China was the source of a supply chain). However, such regionalism will likely remain to complement existing global supply chain infrastructure leading to diversification as opposed to leaving China [23]. Regionalization post-COVID-19 would likely be a temporary and inferior choice compared to further geographic diversification because geographic diversification also lowers unsystematic risk in the supply chain [24]. Supply chain resilience to extraordinary events must be considered at a viability level going forward, with Intertwined Supply Networks (ISN) being a possible solution [25]. The usages of a Viable Supply Chain model (VSC) has also been proposed as it would help firms re-build after a global, long-term crisis [26]. Additionally, methods to integrate geographic diversification into supply chain resilience models to make them more robust has been proposed through the usage the uncertainty in pandemic spread and recovery patterns [27].

3.2 Global Health Security Rankings

"The Global Health Security (GHS) Index is the first comprehensive assessment and benchmarking of health security and related capabilities across the 195 countries that make up the States Parties to the International Health Regulations (IHR [2005])" [28]. Accordingly, its results have been a topic of research in relation to the COVID-19 pandemic. While the GHS Rankings were found to be a significant predictor of COVID-19 pandemic control when analyzing the maximum 14-day cumulative incident rate per 100,000 and rate of incidence increase per 100,000 starting from a date when 100 confirmed cases had been reported (early in the pandemic) [29], it has been a poor predictor of outbreak severity overall. The GHS Rankings were shown to not predict countries' COVID-19 detection times and morality outcome [30], not be a predictor of effective pandemic control when viewing total cases, total deaths, recovery rate, and total tests performed [31], and were not a significant factor in a country' s testing rate. Additionally, the GHS Rankings were inversely correlated to the COVID-19 data [32]. However, it has been claimed that one cannot and should not use the GHS Rankings to predict how countries respond to outbreaks, nor how many cases or deaths a country will report during an outbreak. Some have claimed that this is not a proper use of the GHS Rankings, which should be used as entry points into deeper analysis of health system capacities and performance [33]. Additionally, it has been noted that [the GHS] while comprehensive, has questions about the skew of some indicators towards high income countries, the validity of some indicators, and the scoring and weighting system. These concerns are independent of GHS' s accuracy in the COVID-19 pandemic [34].

3.3 Oxford Government Response Index

"The Oxford COVID-19 Government Response Tracker (OxCGRT) systematically collects information on several different common policy responses that governments have taken to respond to the pandemic on 18 indicators such as school closures and travel restrictions" [35]. This index has allowed for several interesting takeaways to be drawn about the nature of governments' response' s in relation to the COVID-19 pandemic. It has been shown that the greater the strength of a government response at the early stage of the pandemic was correlated with reducing the deaths [36] and that The early start of high-level response is associated with early arrival of the peak number of daily new cases (the turning point in the pandemic outbreak) [37]. It has even led to research about how the characteristics of government have shaped pandemic response. For example, Amongst OECD countries, there was no evidence that female leaders enacted stricter measures than male leaders; however, they did enact their maximum shutdown measures earlier [38].

3.4 Contributions

Our research contributes the following:

- It is the first work that explicitly seeks the create a composite index or ranking system to rank every country's attractiveness for geographic supply chain diversification to combat the new black swan risk of a global pandemic outbreak.
- It is the first work that also seeks to create a generalized profile of a country that would be best for geographic supply chain diversification to combat the new black swan risk of a pandemic outbreak.
- Through the utilization of a longer timeframe of COVID-19 data (from January 2020 to December 2020), the metrics derived will better encapsulate the entirety of every country's COVID-19 outbreak severity while excluding the effect of vaccine distribution.
- By calculating new metrics that describe the severity of a country's pandemic outbreak, further conclusions about possible confounding variables and the appropriate usage of the GHS rankings can be established.
- The derivation of metrics from the OxCGRT indexes that causally relate the disruption of supply chains via governmental actions allow for a quantitative analysis of the magnitude and duration of (indirect) government sanctioned supply chain disruption.
- The calculation of new relational metrics between the COVID-19 data and the OxCGRT indexes will allow for the relative risk tolerance of every country to be expressly calculated and ranked.

In summary, this research, at minimum, provides a crucial key step in utilizing the massive amount of COVID-19 data to quantitatively consider which countries to target for geographic supply chain diversification and, at maximum, can be immediately applied in the strategic supply chain decision making process.

4 Methods

4.1 Data Sources

A key factor in the paper is the collection and usage of COVID-19, government response, and other data. In this section, the data sources used in this research will be discussed. For time series data, the collection period spanned from January 1, 2020 (or the first start date of the data collection) and ended on December 31, 2020. This range of data captures the entirely of every country's COVID-19 outbreak and response before the first mass distribution of vaccines began.

4.1.1 COVID-19 Incident Data

The COVID-19 incident data can be broken down into three different categories: cases, deaths, and tests. The COVID-19 case and death data are obtained from the *Johns Hopkins Whiting School of Engineering's Center for Systems Science and Engineering's* GitHub page [1]. The data is formatted as a cumulative time series, contains data on a country and state/provincial level, and is updated daily. The COVID-19 test data was obtained from the *Our World in Data's* GitHub page [39]. The data is formatted as both a daily and cumulative time series, contains data on a country level, and is updated twice weekly, however the number of countries and the quality of the data made the deviation of advanced metrics unsuitable.

4.1.2 Government Action Data

The government action data was obtained from the *The University of Oxford's COVID-19 Stringency Index* GitHub page [35]. For this data "the data from 19 indicators is aggregated into a set of four common indices, reporting a number between 1 and 100 to reflect the level of government action" [Citation Needed]. The four common indices are:

- **Overall Government Response**: "records how the response of governments has varied over all indicators in the database, becoming stronger or weaker over the course of the outbreak"
- **Containment and Health**: "combines 'lockdown' restrictions and closures with measures such as testing policy and contact tracing, short term investment in healthcare, as well investments in vaccine"
- **Economic Support**: "records measures such as income support and debt relief"
- **Stringency**: "records the strictness of 'lockdown style' policies that primarily restrict people's behaviour"

4.1.3 Pandemic Preparedness Data

The pandemic preparedness data is obtained from *Johns Hopkin's 2019 Global Health Security Rankings* [28]. It ranks 195 country's pandemic preparedness across six different dimensions as well as providing an overall score. In addition to the quantitative ranking, a categorical score is given to every country across each dimension and in the overall. The six dimensions are:

- **Prevention**: "prevention of the emergence or release of pathogens"
- **Detection and Reporting**: "early detection and reporting for epidemics of potential international concern"
- **Rapid Response**: "rapid response to and mitigation of the spread of an epidemic"
- **Health System**: "sufficient and robust health system to treat the sick and protect health workers"
- **Compliance with International Norms**: "commitments to improving national capacity, financing plans to address gaps, and adhering to global norms"
- **Risk Environment**: "overall risk environment and country vulnerability to biological threats"

4.1.4 Healthcare Performance Data

The healthcare performance data is obtained from a *World Health Organization* report titled *Measuring Overall health System Performance for 191 Countries* [40]. This report generated an index score for the quality of every country's healthcare system in terms of the quality of level, equity of distribution, efficiency of health, responsiveness, and fairness in financing.

4.1.5 Global Economic Data

The economic data is obtained from the *International Monetary Fund's 2020 World Economic Outlook Database* [41]. From this data, three key metrics are selected to be used in this research: general government net lending/borrowing (percent of GDP), GDP (current prices in purchasing power parity), and unemployment rate (percent of total labor force). The unemployment rate is not available for every country.

4.1.6 Population Data

The population data is obtained from the *United Nations Department of Economic and Social Affairs World Population Prospects 2019 Report* [42]. Three key metrics are collected for later analyses: total population (in thousands), population density (per square kilometer), and average median age (of a country's population).

4.2 Data Preparation

In order to maintain consistency and to formalize the later data analyses, every country's data across all data sets were labeled according to their *ISO 3166-1 alpha-3* code as published by the *International Organization for Standardization* [43]. For data where countries were not originally labeled with the *ISO 3166-1 alpha-3* code, the codes needed to be applied manually. Then all the time series data was converted into daily instances (e.g. from cumulative cases to daily cases). Finally, to ensure equitable comparisons could be made between countries, all time series data was also converted from their raw form into incidence rates per million (e.g. from daily cases to daily cases per million).

4.3 Data Smoothening

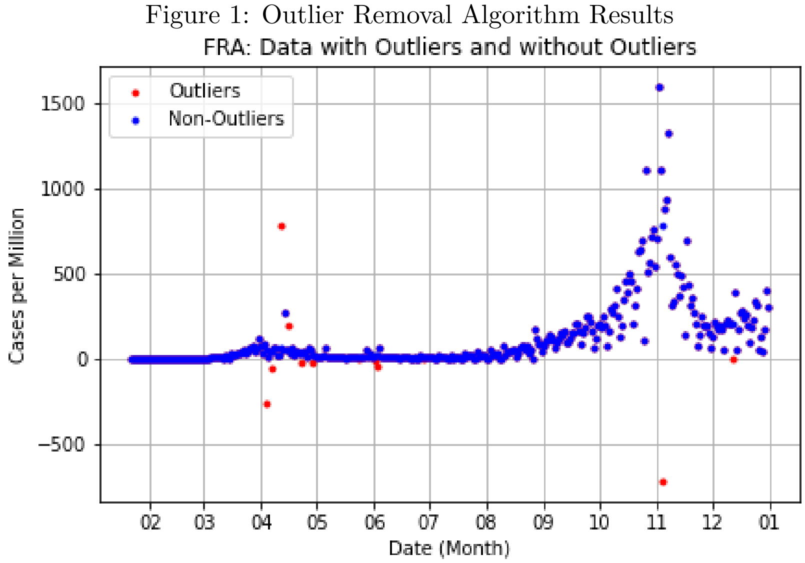
This section describes the steps to smooth every country's data in order to ensure it could be used for metric generation in later analyses.

4.3.1 Handling Outliers

When analyzing every country's COVID-19 case and death data, it was apparent that some outliers existed. Three types of outliers were identified: Known, Negative, and Manual. Known outliers were explicitly noted and tracked by their original data sources. Negative outliers were apparent because, when plotted, they appear as negative daily incidents (which is a physical impossibility). Manual outliers were outliers that, although not explicitly tracked or negative, clearly skewed the moving average of a country's data series. These outliers were identified and tracked manually and determined based on their value compared to surrounding data points, the variance of their surrounding data points, and their effects on a moving average.

The outlier removal algorithm was composed of two separate algorithms: a New Value algorithm and a Redistribution algorithm. The New Value Algorithm determines the new value of incidents to set on the date of the outlier. It functions by determining the average number of incidents on dates before and after the date with the outlier. This served to keep the signal of the distribution as intact as possible after the outlier was removed. It then returned the number of incidents to remain on that date (e.g. the new value) and the number of incidents to be redistributed (e.g. the excess incidents). The Redistribution Algorithm determines how to redistribute the excess incidents after the outlier has been removed. It does so on a proportional basis over the prior 30 days. This means that dates with more incidents will get slightly more incidents added or removed than dates with less incidents and ensures that, after removing cases, the number of incidents on each date remains positive. This helps minimize the changes in the signal of the overall distribution. An example of the results of these algorithm is shown below and the psuedocode for both algorithms can be found in Appendix A.

Figure 1: Outlier Removal Algorithm Results



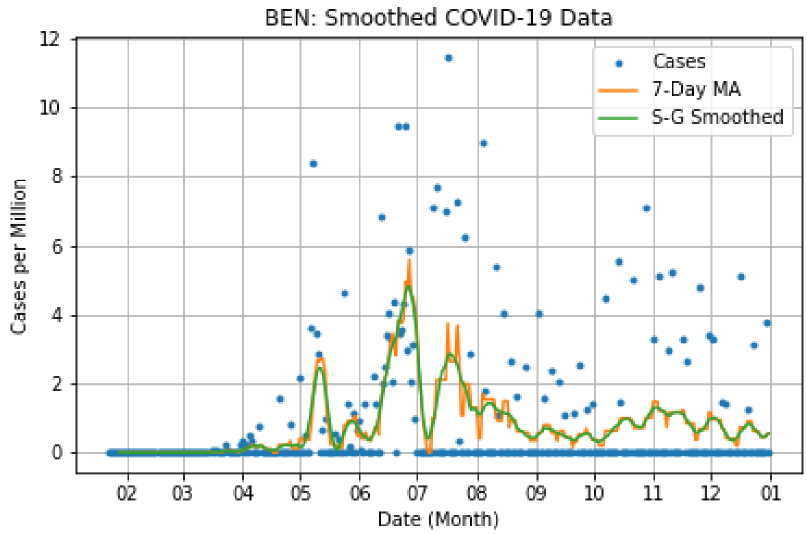
4.3.2 Smoothening

The vast majority of countries' COVID-19 incident data exhibits weekly periodicity. For example, for any given week the USA's COVID-19 cases tend to be higher on Friday than Monday. To remove this periodicity and further smooth the COVID-19 data, a seven-day moving average was applied to the COVID-19 data. A seven-day moving average was chosen because there are seven days in a week.

Even after the outliers are removed and the seven-day moving average is applied, the data for some countries may still contain sudden spikes that result in a time series that is not smooth. These spikes can be considered as noise as, although they do not affect the overall signal of the data, they could cause issues with later data analysis. To correct this, a Savitzky-Golay filter [Citation

Needed] was applied to the COVID-19 data. This allows for the noise in the COVID-19 data to be removed while preserving the overall signal. Every country's COVID-19 case and death data awas smoothed using a Savitzky-Golay filter with a window length of 15 (days) and a third-order polynomial. The results of these two smoothing methods are shown in the figure below.

Figure 2: Data Smoothening Results



4.4 Interpolation Fitting

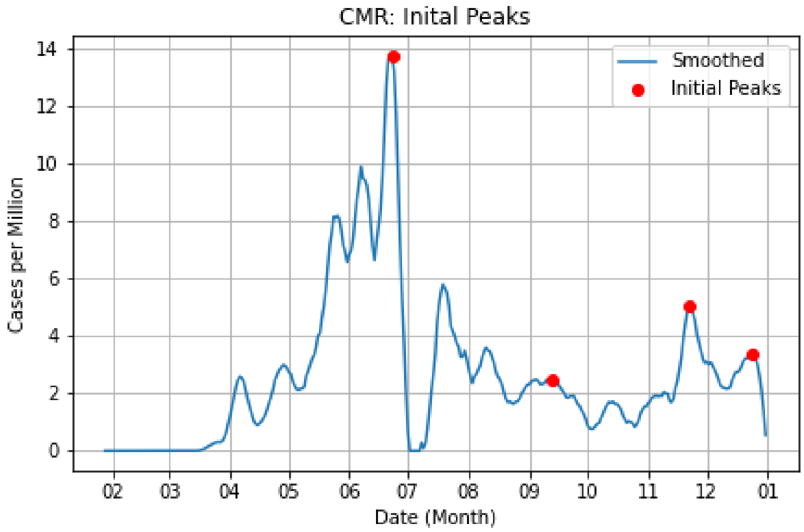
One of the things that makes this research unique and important is the ability to extract advanced metrics from every country's COVID-19 data. To do so, it was crucial to fit every country's data with interpolated functions. However, this required only a few key points from the dataset to be selected from every country's time series data to later be interpolated. Naturally, these key points would include the start, peak, and end of every outbreak in a country's time series data. Thus, it was imperative to develop a key point selection algorithm to find these key points for every country's COVID-19 case and death data. Then, a key point addition algorithm was used to add more points to improve the quality of the subsequent interpolation. The key point selection algorithm was mad up of four sub-algorithms: Initial Peaks Algorithm, Peak Pruning Algorithm, Final Pruning Algorithm, and Valley Finding Algorithm.

4.4.1 Initial Peaks ALgorthm

The Initial Peaks Algorithm works in two main steps. First, points are analyzed to determine if they dominate over a specific window of points. Note that this is different than determining whether points are relative maximums. For example, it is possible for a point to be a relative maximum while not dominating over a range of points (of sufficient size). Thus, by searching for dominating points instead of relative maxes, one solves the problem of the data between peaks and valleys not being strictly increasing or decreasing.

The second step is to determine if a peak is a plateau and only to keep the middle point if it is. For example, especially for countries with less COVID-19 incidences, a peak will be at a certain level for multiple days (e.g. a plateau). Keeping every point in a plateau is redundant, so only the middle point on a plateau should be kept. The algorithm also accounts for the instance (usually only present in smaller data sets) where two small peaks of equal size appear next to each other. An example of this algorithm is shown below and the psuedocode can be found in Appendix B.1.

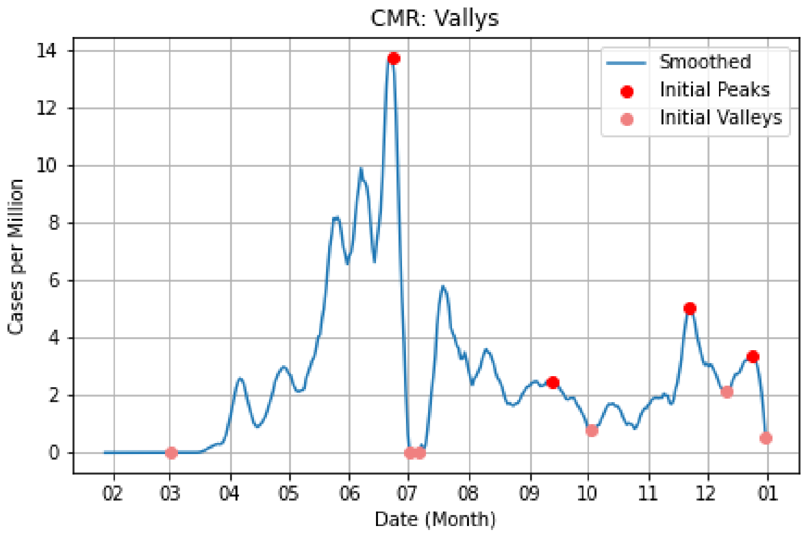
Figure 3: CMR: Initial Peaks



4.4.2 Valley Finding Algorithm

The Valley Finding Algorithm is run after every step of the overall peak finding algorithm (e.g. after the Initial Peaks Algorithm, Peak Pruning Algorithm, and Final Pruning Algorithm). It works by looking for the absolute minimums between peaks and endpoints of the COVID-19 incident data. It does so peak by peak, which allows for instances where ranges of dates that contain zero incidents to be preserved in the data. Duplicate valleys are removed at the end. An example of this algorithm is shown in the figure below and the pseudocode can be found in Appendix B.2.

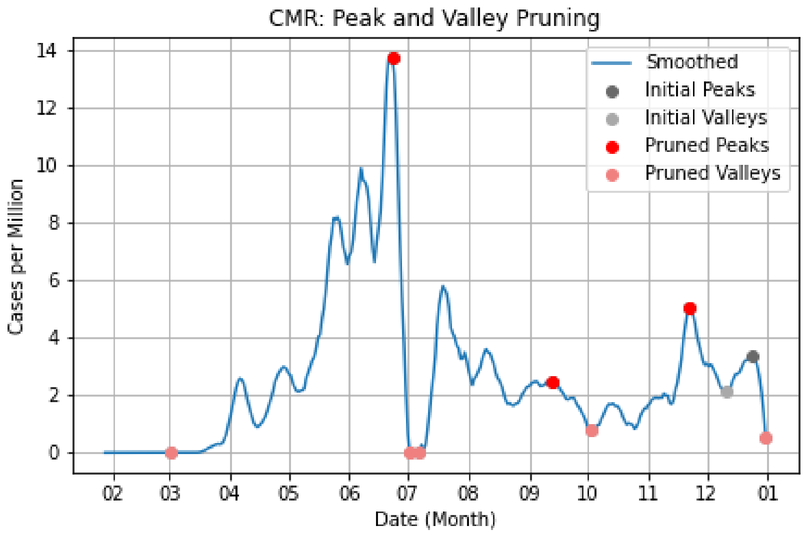
Figure 4: CMR: Valleys



4.4.3 Peak Pruning Algorithm

The Peak Pruning Algorithm prunes peaks based on the peak's width, relative height (height above neighboring valleys), width percentage, height percentage, and relative height percentage (where percentage refers to the percent of that value of the summation of all values, e.g. $Peak\ i\ Width\ /\ All\ Peak\ Widths$). The combination of these metrics allows the conditional removal of peaks that are not large enough to be considered true peaks in the COVID-19 data. Furthermore, the inclusion of the percentage metrics allows for the function to be universally applied to every country's COVID-19 incident data. An additional check on the first peak in the data to ensure it is appropriate that it is included. An example of this algorithm is shown in the figure below and the psuedocode can be found in Appendix B.3.

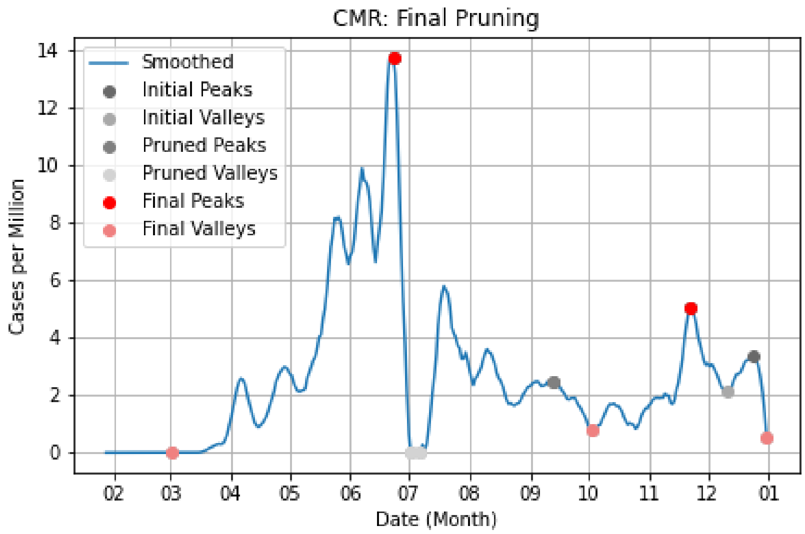
Figure 5: CMR: Peak Pruning



4.4.4 Final Pruning Algorithm

The Final Pruning Algorithm works by pruning peaks, and their corresponding valleys, if they do not dominate over their range (e.g. if a point larger than the peak appears between it and a neighboring valley). This algorithm is used in the rare instance that a country's COVID-19 incidence data had a significant drop in cases over a noticeably short time period (e.g. a couple of days). When this happens, it can cause valleys to be improperly identified and thus a final correction is needed. An example of this algorithm is shown in the figure below and the psuedocode can be found in Appendix B.4.

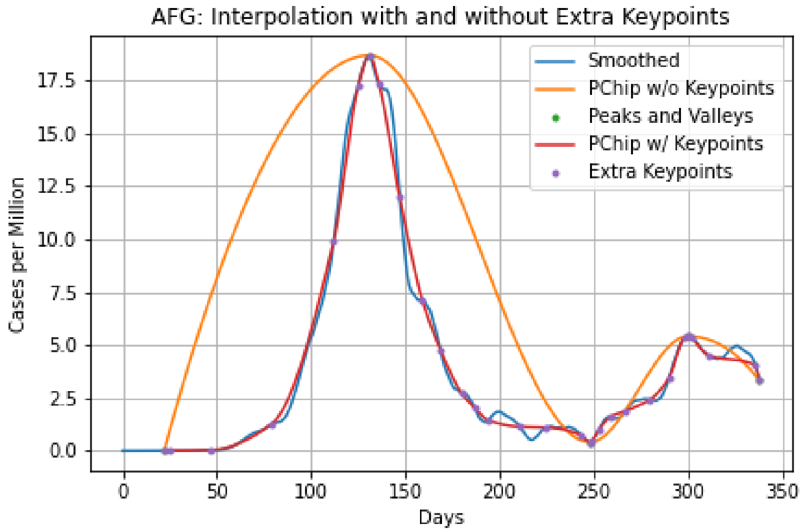
Figure 6: CMR: Final Pruning



4.4.5 Key Point Addition Algorithm

The Key Point Addition Algorithm is used to add additional points to the peak and valley points to increase the accuracy of the interpolation. It works by fitting a cubic polynomial between every single peak-valley pair. It then searches for all the points in the peak-valley range where the COVID-19 incident data and the cubic polynomial intersect. Then, based on whether the data is increasing or decreasing, points are pruned based on whether their neighboring points increase or decrease. This process ensures that the data between the peaks and valleys will always be purely increasing or decreasing while greatly improving the accuracy of the final interpolation. An example of this algorithm is shown in the figure below and the psuedocode can be found in Appendix C.

Figure 7: AFG: Interpolation with and without Extra Key Points



4.4.6 Interpolation

A Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) [44] was chosen as the interpolation method over other interpolation methods (like splines). This is because PCHIP interpolation does not overshoot data and it includes less oscillation, which is important due to the wide variety of data distributions for which it is performed on. Additionally, PCHIP interpolation is able to handle instances of flat data, which is important as it would not be unexpected for flat data ranges (e.g. consecutive days with zero new COVID-19 cases) to occur in a country's COVID-19 data. This interpolation created a continuous and derivable equation from which advanced metrics (e.g. the rate of growth of the nth outbreak) could be derived.

4.5 Metric Generation

This section will detail the different types of metrics that were generated via the analysis of the different datasets and their interactions. A table of all the calculated metrics and their characteristics can be found in Appendix D.

4.5.1 Summation Metrics

A *summation* metric is a metric where all values over the entire range of a time series dataset are summed together (e.g. total cases per million). It is performed on a per country basis.

4.5.2 Ratio Metrics

A *ratio* metric is a metric where two summation metrics are compared against one another as a ratio. It is performed on a per country basis (e.g. cases per million to deaths per million ratio).

4.5.3 Maximum Value Metrics

A *maximum value* metric is a metric where the maximum value over the entire range of a given time series data is determined (e.g. Maximum Government Response). It is performed on a per country basis.

4.5.4 Number of Peaks Metrics

A *number of peaks* metric is a metric that indicates how many peaks occurred in a country's COVID-19 data (e.g. the number of peaks in cases).

4.5.5 Rate of Growth Metrics

A *rate of growth* metric is a metric where the rate of growth of COVID-19 data between a peak and its preceding valley is calculated. It is calculated both in term of the average rate of growth rate and the maximum rate of growth over that range. These metrics are also broken down into all peaks and the first peak. It is calculated for every single peak in a country's COVID-19 data and on a per country basis (e.g. average rate of growth of cases).

4.5.6 Rate of Submission Metrics

A *rate of submission* metric is a metric where the rate of growth (which in this case is negative) of COVID-19 data between a peak and its succeeding valley is calculated. It is calculated both in terms of the average rate of submission and the maximum rate of submission over that range. These metrics are also broken down into all peaks and the first peak. It was calculated for every single peak in a country's COVID-19 data and on a per country basis (e.g. Average rate of submission of cases).

4.5.7 Length of Time Metrics

A *length of time* metric is a metric where the length of a specific observation relating to the COVID-19 data is recorded. Three length of time metrics were calculated for every peak in the COVID-19 data on a per country basis: length of growth (the amount of time between a peak and it's preceding valley), length of submission (the amount of time between a peak and its succeeding valley), and total peak length (a peak's length of growth and length of submission).

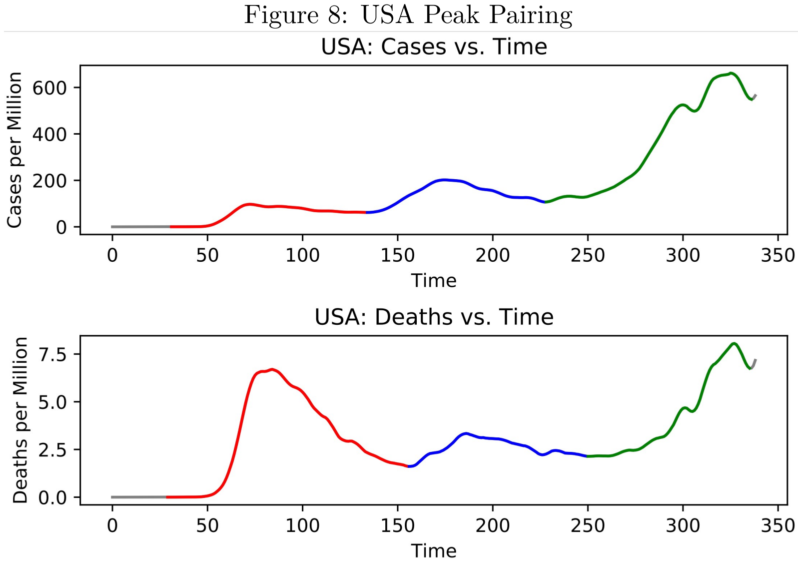
4.5.8 Peak/Valley Value Metrics

A *peak/valley value* metric is a metric that measures the number of new incidents observed at either a peak or valley in a country's COVID-19 data. The peak value metric measures the worst severity of a given peak and the valley value metrics measure how submitted the COVID-19 outbreak actually was. These metrics were calculated for every peak and every peak's succeeding valley on a per country basis (e.g. Peak Value of Cases).

4.5.9 Case-Death Pair Peak Ratio

A *case-death pair peak ratio* metric is a metric that compares the ratio between the peak number of cases and the peak number of deaths of a country's corresponding COVID-19 case peak and death peak. KMeans clustering was used to pair peaks in cases with peaks in deaths [45]. A KMeans clustering was used because the number of case peaks and death peaks is not guaranteed to match in quantity or location. This could be due to several factors. For example, one case peak could be related to two death peaks in the situation where ICU's reach capacity (i.e. a peak in deaths occurs), but a better treatment method is found (i.e. the number of daily deaths begin to fall), yet the number of daily cases continues to grow (i.e. the ICU's begin to fill up again and another peak in deaths occurs). The data used for the KMeans clustering was a peak's start date, peak date, and end date. The optimal number of clusters to use was calculated by finding the optimal silhouette value of different sized clusters. The resulting clusters were the case-death peak pairings. Note that this algorithm does not necessarily force the pairing of case and death peaks. Thus, it is possible for a "paring" to only be a single case or death peak. The final part is an algorithm that will calculate the case-death pair peak ratios. It does so by, after ensuring there is at least one case peak and one death peak in a pairing, finding the maximum case and death peak value over the ranges. An example of the peak paring algorithm is shown in the figure below.

Figure 8: USA Peak Pairing



4.5.10 Days Above Sub-index Level

A *days above sub-index level* metric is a metric that tracks the total number of days that the level of one of *Oxford's Stringency* indexes [35] are at or above a specified level (e.g. number of days all non-essential sectors closed). Each level in a sub-index corresponds to a certain stringency that can be tracked. For example, one of the sub-indexes that is used to calculate a country's containment policy index is workplace closings, of which a level 2 corresponds to some sectors being closed. Some of these sub-indexes have a great deal of direct importance to this research, thus the necessity of these metrics.

4.5.11 Total and Rate before Sub-Index Level Metrics

A *total and rate before sub-index level* metric is a metric that describes the total number of incidents, and the rate of growth of instance, before the first time a specified sub-index level was reached (e.g. Average Rate of Growth in Cases before some sectors closed). The rate of growth is captured by both an average rate and a maximum rate.

4.5.12 Total, Rate, and Incident-to-Index Ratio Before First Peak in Index

A *total and rate before first peak in index* metric is a metric describes that the total number of instances and the rate of growth in COVID-19 incidents before the first peak in one of Oxford's four main indexes was reached (e.g. total cases before first peak in stringency). The rates are calculated by both an average rate and a maximum rate. The ratio is made between the number of incidents and the index level at its first peak.

4.5.13 Index-to-Index Ratio Metrics

A *index-to-index ratio* metric is a metric that creates a ratio between the values in one of Oxford's indexes to another (e.g. Economic Support to Containment Health Ratio). The ratio is calculated by finding the average level of both indexes over the recording time frame, then creating the ratio between the resulting averages.

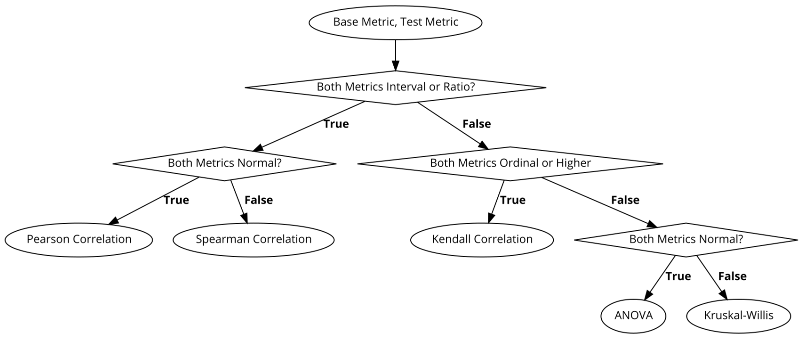
4.6 Statistical Analysis

This section contains some details of the statistical analyses that will be performed to uncover relationships in and evaluate the COVID-19 data between countries and other datasets.

4.6.1 Test Selection Procedure

There were five different types of statistical test that could have been performed between the two different sets of metrics: Pearson Correlation [Citation Needed], Spearman Correlation [Citation Needed], Kendall Association [Citation Needed], ANOVA [Citation Needed], and Kruskal–Wallis [Citation Needed]. The type of significance test run depended both upon the metrics' scale classification and normality. The normality of ratio and interval scaled metrics was done by conducting a Shaprio-Wilkes Test [Citation Needed]. If both metrics were a ratio or interval scale and were normally distributed, a Pearson Correlation test was performed. If both metrics were a ratio or interval scale, but one or both was not normally distributed, a Spearman Correlation test was performed. If one or both metrics was ordinal, a Kendall Association test was performed. If one of the metrics was categorical and was normally distributed, an ANOVA test was performed. In the event the metric was not normally distributed, a Kruskal-Wallis test was performed. A flowchart detailing this procedure is shown below.

Figure 9: Statistical Test Selection Procedure



4.6.2 Confounding Variable Exploration

Statistical testing, following the test selection procedure, was performed between outside metrics and the calculated COVID-19 metrics to determine the relationships between them and whether or not they were significant (i.e. if possible confounding metrics could be found).

4.6.3 Pandemic Preparedness Rankings to COVID-19 Data Accuracy

Statistical testing, following the test selection procedure, was performed between the *GHS Rankings* and the calculated COVID-19 metrics in order to determine how accurately the can be used as predictors as the effectiveness of a country's COVID-19 response. The analyses were performed on all the quantitative and categorical metrics against the same COVID-19 metrics used when analyzing possible confounding variables.

4.6.4 Pandemic Preparedness to Oxford Stringency Analysis

The *GHS Rankings* were compared to the *OxCGRT Index* in order to determine how accurately the GHS rankings were at predicting the magnitude of a country's COVID-19 response following the test selection procedure. The overall and sub-indices of the global health security rankings will be compared to the four main Oxford indices.

4.6.5 COVID-19 Data to Oxford Stringency Index Analysis

The COVID-19 data will be compared with the *OxCGRT Index* to quantity an compare the thresholds required for a country to increase the severity of their action to combat COVID-19 following the test selection procedure. This will help determine every country's observed risk tolerance, which would be causally related to their desirability as being a new geographical location for supply chain diversification in a future pandemic scenario.

4.7 Index Generation

This section will detail the construction of the composite index. It was broken down into three different and equally weighted main subindexes: Outbreak Severity, Response Severity, and Risk Tolerance.

4.7.1 Outbreak Severity

The outbreak severity subindex was composed of two equally weighted subindexes: initial outbreak severity and total outbreak severity. It was composed of metrics derived from the COVID-19 case and death data. The Initial Outbreak subindex was made up of two equally weighted sub-indexes: cases and deaths. The Total Outbreak subindex was made up of three equally weighted subindexes: aggregate data, case data, and death data. The detailed subindex breakdown can be found in Appendix E.1.

4.7.2 Response Severity

The response severity subindex was made up of three equally weighted subindexes: severity, relative economic support, and length of elevated responses related to supply chain factors. It was composed of metrics derived from the OxCGRT index data. The detailed subindex breakdown can be found in Appendix E.2.

4.7.3 Risk Tolerance

The risk tolerance subindex was made up of two equally weighted subindexes: outbreak severity before actions taken and outbreak severity before highest first actions taken. It was derived from interaction metrics between the COVID-19 case and death data and the OxCGRT index. The outbreak severity before actions taken subsection was made of two equally weighted subindexes: strict measures and most strict measures. The detailed subindex breakdown can be found in Appendix E.3.

4.7.4 Scaling Methods and Outlier Handling

For every metric used in every subindex, the metric values were rescaled from their original values to a 0 to 1 scale (e.g. if the range of total cases was 100 per million and 1.500 per million, the data was rescaled so 100 per million was zero and 1,500 per million was 1). For every metric, the scaling was also adjusted so that 1 would be considered the best score and zero would be the worst. For example, having less cases is better than having more cases, so if the range before scaling was 100 per million and 1,500 per million, 100 per million would become 1 and 1,500 per million would become 0).

In order to ensure reasonable results could be drawn from the calculated metrics, outliers needed to be handled. If outliers were not handled, there would be no parity within the scaled metrics which would limit their useability and the conclusions that could be drawn from them. For example, it was not uncommon for countries with exceptionally low populations (e.g. Vatican City) to have extremely high case growth rates. This would completely overshadow the rest of the case growth rates, so it had the dealt with.

Outliers were handled using the interquartile range method. the IQR would be calculated for a single metric and the outliers would be identified using the Q75/Q25 and a k-value of 3 times the IQR. These values would then be considered the possible limits of the metric and any specific metric values outside of this range would be appropriately adjusted to be either the minimum or maximum of this new range. Thus, when the metrics were scaled, reasonable parity existed while still capturing every country's performed within the metrics.

5 Results

In this section the results of the statistical tests and the rankings will be discusses. For every type of test, the p-value was set at 0.05 and the correlation strength was determined via the specific test's testing procedures.

5.1 Statistical Correlation Analysis

The tables in this section will detail the overall results of the statistical correlation tests performed. The number and percentage of test metrics that had both relatively strong or stronger relationship to the base metric are given.

5.1.1 Confounding Variables vs COVID-19 Data

42 test metrics derived from the COVID-19 data were tested against base metrics (e.g. confounding variables). the following tables present the results based on the scaling method of the metrics. A table summarizing the results of this analysis is below and the full results can be found in Appendix F.

Table 1: Ratio/Integer Metrics

Base Metric	# of Test Metrics	% of Test Metrics
GDP	6	14.3%
Government Net Lending/Borrowing	1	2.4%
Median Age	19	45.2%
Press Freedom Score	2	4.8%
WHO Healthcare Index Score	22	52.4%

As one can see from the table above, a country's GDP, Government Net Lending/Borrowing, and Press Freedom Score do not serve as reliable indicators for the outbreak severity of a country's COVID-19 pandemic. However, Median Age and the WHO Healthcare Index Score did appear to provide some correlation to the severity of a country's COVID-19 outbreak. Median Age in particular had a relatively strong correlation to many of the metrics that would be expected given the nature of the COVID-19 virus like total cases, total deaths, case growth rate (both for the first outbreak and overall), and death growth rate (both for the first outbreak and overall). However, despite the WHO Healthcare Index Score having a relatively strong correlation to a country's COVID-19 outbreak severity, across many metrics the correlation was the opposite of expectation. Relatively strong correlations between higher (i.e. better-quality healthcare systems) and higher cases, deaths, case growth rates (for both first and total outbreaks), and death growth rates (for both the first and total outbreaks) were found to be the opposite of expectation. However, relatively strong correlations did exist in the direction of expectation for other metrics like case submission rate (for both first and total outbreaks) and death submission rate (both first and subsequent outbreaks). Furthermore, a strong correlation was found between the total number of tests perform and a country's WHO Healthcare Index Score.

Table 2: Ordinal Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Press Freedom Rank	0	0%
WHO Healthcare Index Rank	0	0%

No significant correlations were found between a country's press freedom rank or WHO healthcare index rank and the severity of a country' s COVID-19 pandemic outbreak.

Table 3: Nominal Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Categorical Income Level	33	78.6%
Geographic Region	38	90.5%
Press Freedom Category	31	73.8%

There proved to be a significant difference between the severity of the COVID-19 outbreak in a country based on its categorical income level, geographic region, and press freedom category. The higher the categorical income of a country, the more total cases, deaths, and tests a country had/performed. Additionally, their case and death growth and submission rates were higher than countries with lower categorical incomes along with longer case and death outbreaks. The geographic region results were of particular interest because, across nearly all significant metrics (total cases, deaths, case and death growth rate, case and death submission rate, and outbreak length), North America, Europe, Latin America, and Western Asia performed worse than Africa, Southern Asia, Southeastern Asia, Central Asia, and Eastern Asia. The Press Freedom Ranking's results were also interesting as, across most metrics, the worst a country's press freedom (e.g. the less free the press is) the less severe the country's COVID-19 outbreak was.

Overall, the difference of the correlation between the ratio/integer and nominal metrics' correlation to COVID-19 outbreak severity (e.g. Press Freedom Score did not have a significant correlation but there was a significant difference between categorical groups) would indicate that there was a high degree of variability amongst the severity of a country's COVID-19 outbreak.

5.1.2 GHS Rankings vs COVID-19 data

42 test metrics derived from the COVID-19 data were tested against the GHS's overall index and six subindexes. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix G.

Table 4: Ratio/Integer Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Overall Score	9	21.4%
Detect Score	4	9.5%
Health Score	9	21.4%
Norms Score	0	0%
Prevention Score	7	16.7%
Respond Score	1	2.4%
Risk Score	23	54.8%

As one can see from the table above, except for the Risk score, none of the scores from the GHS Rankings had significant correlations to most of the outbreak severity metrics. Furthermore, in the instances where correlations were significant (e.g. total cases and overall score) the relationship were the opposite of what would've been expected (e.g. the higher the country's overall score, the more cases they had). However, this was not the case with testing where, there was a significant correlation between countries with higher overall, prevention, and health scores conducting more tests. The risk score was notable as it was a has a relatively strong relationship with the severity of a country ' s COVID-19 outbreak. Although the relationships between a higher risk score (which is good) and total cases, deaths, case growth rate, and death growth rate were the opposite of expectation, the case submission rate and death submission rate were that of expectation (e.g. a high risk score indicated that a country was able to submit their outbreaks at a faster rate).

Table 5: Nominal Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Overall Score	32	76.2%
Detect Score	35	83.3%
Health Score	37	88.1%
Norms Score	5	11.9%
Prevention Score	37	88.1%
Respond Score	27	64.3%
Risk Score	32	76.2%

As we saw in the prior set of statistical analyses, when the GHS Rankings were divided categorically, the number of significant relationships across all index score increased. However, the overall trend from the ratio/integer metrics analysis still held. For significant relationships, higher categorical index rankings were associated with a more server pandemic outbreak.

5.1.3 GHS Rankings to OxCGRT

The overall and six subindexes of the GHS Rankings were tested against 95 test metrics calculated from the OxCGRT and COVID-19 interaction metrics. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix H.

Table 6: Ratio/Integer Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Overall Score	37	38.9%
Detect Score	2	2.1%
Health Score	39	41.1%
Norms Score	0	0%
Prevention Score	38	40%
Respond Score	0	0%
Risk Score	64	67.4%

As seen in the table above, only the GHS overall, health, prevention, and risk score had relatively strong correlations between the index score and the metric calculated from the OxGRT metrics and OxGRRT to COVID-19 data metrics. Of note from the metrics calculated purely from the OxGRT index, countries with higher overall, prevention., health, and risk scores provided more proportional economic support compared to their containment health, stringency, and overall government response actions. Furthermore, when looking at the metrics calculated from the relationship between the OxGRT index and COVID-19 data (i.e. the risk tolerance metrics), the higher the overall, health, prevention, and risk score, the higher the risk tolerance observed. For example, a relatively strong correlation was found as the higher the overall, health, prevention, and risk scores were, the higher the average rate was before some and all non-essential sectors were closed.

Table 7: Nominal Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Overall Score	78	82.1%
Detect Score	73	76.8%
Health Score	87	91.6%
Norms Score	16	16.8%
Prevention Score	83	87.4%
Respond Score	63	66.3%
Risk Score	87	91.6%

As with the prior statistical analysis, the significance between the categorical index rankings and the calculated metrics increased compared with the quantitative index rankings. However, the results found remained inline with the findings from the ratio/integer metrics tests: that higher GHS rankings were correlated with a higher risk tolerance. However, with this analyses, further correlations between the GHS rankings and metrics calculated solely form the OxGRT index could be drawn. In the case of the maximum government response and stringency the higher categorical GHS rankings were corelated with a lower QxGRT index scores.

5.1.4 Confounding Variables to OXGRT

95 test metrics derived from the OxGRT index and COVID-19 data interactions were tested against base metrics (e.g. confounding variables). the following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix I.

Table 8: Ratio/Integer Metrics

Base Metric	# of Test Metrics	% of Test Metrics
GDP	10	10.5%
Government Net Lending/Borrowing	1	1.1%
Median Age	50	52.6%
Press Freedom Score	9	9.5%
WHO Healthcare Index Score	56	58.9%

As seen in the table above, only the median age and WHO healthcare score had a relatively strong correlation with the metrics calculated from the OxGRT index. Similar the statical analysis between the GHS Rankings and the OxGRT metrics, country's with higher median ages and who healthcare scores tended to resort to stricter measures (i.e. closing some scores or all non-essential sectors) after experiencing higher case and death growth rates compared with countries with lower median ages and lower WHO healthcare index scores.

Table 9: Ordinal Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Press Freedom Rank	0	0%
WHO Healthcare Index Rank	5	5.3%

As one can see from the table above, the press freedom rank and Who healthcare index rank had very few relatively strong correlations with the OxGRT metrics.

Table 10: Nominal Metrics

Base Metric	# of Test Metrics	% of Test Metrics
Categorical Income Level	95	100%
Geographic Region	88	92.6%
Press Freedom Category	69	72.6%

As with prior analyses, once countries are categorically grouped by income level, geographic region, and press freedom category, more significant relationships are found when analyzed against the OxGRT index scores. In terms of Categorical Income two interesting trends emerged. The first was that higher income countries enacted strict lockdown measures after experience higher case and death growth rates. However, both high- and low-income countries tended to maintain stricter measures for significantly less time than lower middle and upper middle-income countries. Furthermore, the countries with higher categorical income tended to reach their peak strictness after more cases and deaths were observed. In terms of geographic region, one can observed that North American and European higher risk tolerance when it came to taking strict measures to control the virus. Additionally, they tended to hold less strict measure for linger than other regions of the world. Overall, regions like Africa and Southern Asia tended to hold strict and less strict lockdown measures for the shortest amount of time. In terms of press freedom, countries with a better categorical press freedom ranking tended to have lower maximum stringency and government response steps than those with worse press freedom rankings. Additionally, countries with better press freedom tended to hold strict and most strict lockdown measures for shorter times than countries with worse categorical press freedom rankings. Finally, higher press freedom ranking was associated with higher risk tolerances than those with worse press freedom rankings.

5.2 Index Results

In this section the results of the composite index and three main subindexes will be detailed. The top five, bottom five, and all G20 members will be listed for each index. The full index is in the appendix.

5.2.1 Composite Index

The composite index can be used to analyze the relative attractiveness of different countries for supply chain diversification through the equal weight of outbreak severity, response severity, and risk tolerance. Countries that perform well in this index relatively less severe outbreaks, less severe responses, and high-risk tolerance compared to countries that did not perform well on this index. The full index can be found in Appendix J.1.

Table 11: Composite Index

Ranking	Score	Country
1	.7552	Iceland
2	.7516	Faroe Islands
3	.7082	Macao
4	.6792	Luxembourg
5	.6786	Andorra
20	.6139	Japan
25	.6022	France
27	.5990	Germany
34	.5813	Great Britain
45	.5558	Canada
50	.5389	South Korea
72	.4954	Turkey
74	.4945	Australia
82	.4814	Brazil
95	.4652	United States
118	.4302	Italy
133	.4091	Saudi Arabia
144	.3951	China
146	.3942	Indonesia
162	.3664	South Africa
167	.3581	Russia
170	.3443	Mexico
171	.3396	India
172	.3286	Georgia
173	.3250	Kuwait
174	.3211	Libya
175	.3206	Chile
176	.3177	Argentina

5.2.2 Outbreak Severity

The outbreak severity index details the relative outbreak severity of every country in the list. Countries that score well in this index will tend to have less cases and deaths, more tests, lower case and death growth rates, higher case and death submission rates, and shorter outbreaks compared to countries that do not score well in this index. The full index can be found in Appendix J.2.

Table 12: Composite Index

Ranking	Score	Country
1	.9159	Solomon Islands
2	.9136	Laos
3	.9092	Timor-Leste
4	.9061	Greenland
5	.9033	Cambodia
75	.6829	Japan
78	.6809	Australia
82	.6750	South Korea
96	.6587	China
112	.6356	Indonesia
126	.6061	Turkey
130	.5988	Germany
133	.5796	Canada
146	.5568	India
150	.5409	Saudi Arabia
151	.5325	Russia
156	.5132	France
160	.4973	Mexico
163	.4825	Great Britain
172	.4330	Brazil
173	.4253	Colombia
174	.4235	United States
175	.4123	Argentina
176	.3994	Chile

5.2.3 Response Severity

The response severity index details the relative severity of the government response actions taken to combat COVID-19 with a special emphasis on measures that that would negatively affect supply chain performance in a country. Countries that do well in this metrics will have relatively lower government response values, stringency values, high economic support values, economic support rations, and less time in lockdown measure that would negatively affect supply chains that countries that do not do well in this index. The full index can be found in Appendix J.3.

Table 13: Composite Index

Ranking	Score	Country
1	.8705	Macao
2	.8265	Iceland
3	.8206	Faroe Islands
4	.8066	Andorra
5	.8001	Japan
23	.6518	Great Britain
54	.5695	Turkey
59	.5537	France
66	.5342	South Korea
67	.5323	Canada
86	.4876	Australia
89	.4808	United States
96	.4631	South Africa
97	.4591	Germany
106	.4345	Italy
114	.4101	Saudi Arabia
115	.4067	Indonesia
116	.4063	Russia
131	.3846	Mexico
142	.3638	Brazil
158	.3312	India
166	.2963	Argentina
172	.2705	China
173	.2693	Eritrea
174	.2653	Kazakhstan
175	.2602	Palestine
176	.1503	Libya

5.2.4 Risk Tolerance

The risk tolerance index detail which countries had a relatively higher risk tolerance towards government response considering the pandemic severity in their country at the time. Countries that perform well in this metric will have relatively worse pandemic severity metrics before the enactment of strict measure that would negatively effect supply chains (both for the first outbreak and subsequent outbreak) when compared to countries that do not do well in this index. The full index can be found in Appendix J.4.

Table 14: Composite Index

Ranking	Score	Country
1	.8950	San Marino
2	.8565	Ireland
3	.7969	Iran
4	.7913	Luxembourg
5	.7844	Netherlands
8	.7396	France
9	.7390	Germany
15	.6473	Brazil
17	.6096	Great Britain
23	.5555	Canada
29	.4913	United States
55	.4074	South Korea
58	.3998	Italy
63	.3588	Japan
77	.3149	Australia
78	.3106	Turkey
86	.2763	Saudi Arabia
91	.2562	China
97	.2446	Argentina
127	.1566	South Africa
129	.1511	Mexico
137	.1402	Indonesia
145	.1355	Russia
152	.1309	India
172	.1073	Central Africa Republic
173	.1031	Serbia
174	.0988	Yemen
175	.0922	Syria
176	.0527	Kyrgyzstan

6 Conclusions

6.1 GHS Rankings

The GHS Rankings did not prove to be a proper predictor of the COVID-19 outbreak severity in a country. When it came to key quantitative metrics (e.g. total cases, total deaths, case growth rate. death growth rate, etc.), across the six subindexes and the overall index, the correlations were either negligible or the opposite of expectation (e.g. a higher overall score was correlated with more cases). However, it is important to note that in other metrics (e.g. total tests, case submission rate, death submission rate, etc.) significant and relatively strong correlations were found in some of the indexes. Furthermore, when the countries were grouped categorically, these trends became more pronounced.

Although they dint' predict the pandemic outbreak severity, and often the inverse was found, concluding that the GHS Rankings are heavily flawed or useless may not be entirely correct. The evidence from this come from the statistical analysis between the GHS Rankings and the risk tolerance metrics. Across many of the risk tolerance metrics, a high overall, health, prevention, and risk score had relatively strong correlation to having higher (worse) pandemic severity metrics before enacting strict lockdown controls. This correlation could possibly imply that country's with higher GHS Rankings (e.g. those that would be expected to perform better in a pandemic outbreak) were able to delay enacting strict measure because their healthcare system and other protocols were better prepared to handle a pandemic outbreak. This correlation is given further credence as the WHO healthcare index scores were often also inversely correlated with key pandemic severity metrics, except for total tests.

Logically, it makes sense that delaying stricter control measures would lead to higher infection rates and more deaths. This would match up with the inversely correlations found between some GHS indexes and many of the case and death metrics. However, the fact that relatively strong correlations were found between test metrics and some GHS indexes and the WHO healthcare index would seemingly imply the healthcare systems and infrastructure in these countries were prepared and capable to handle a pandemic outbreak (which is what the GHS rankings measured). Thus, while the statement: the GHS Rankings were an insufficient predictor of pandemic outbreak severity is technically correct, it may be too simplistic to capture the entirely of the COVID-19 pandemic situation. Rather, through the analysis performed in our research, a more apt conclusion statement may be: country's with better GHS rankings were more likely to delay the enactment of stricter control measures (possibly due to the knowledge of their advanced healthcare systems and infrastructure), which lead to a more severe observable pandemic outbreak.

6.2 Confounding Variables

The fact that out the metrics we calculate and statistically evaluate found that median age was a confounding/predicting factor for the severity of a country's COVID-19 pandemic outbreak should serve as a proof of the validity and usability of the metrics were calculated and the subsequent analyses we performed. This is because it has been well established that the COVID-19 virus effects the elderly significantly more than the younger members of the population [46]. Thus, it would make sense that the median age of a country would have some correlation to the overall severity of that country's pandemic outbreak (which our analyses found to be the case). Additionally, this would seem to be further supported by the fact that geographic regions with lower median ages (e.g. Africa, Western Asia, and Southern Asia) tended to have less severe pandemic outbreaks compared to regions with high median ages (e.g. North America and Europe).

Another interesting confounding/predicting variable founding was categorical income level. Significance differences between the outbreak severity, response severity, and risk tolerance metrics were found between countries with different categorical income levels. Due to the previous conclusions, the fact that higher categorical income levels were correlated with more sever pandemic outbreaks is not particularly new and significant. However, the fact that low- and high-income countries maintained strict and most strict lockdown measure shorter than lower middle and upper middle-income countries is interesting. This is because, it would seemingly imply that low- and high-income countries would have caused less disruption to their supply chain compared to lower middle and upper middle-income countries. This results, regardless of its cause, could have significant implications for geographic supply chain diversification decisions in the future.

Finally, the correlation between the press freedom rankings, especially when it came to the categorical classification were interesting. Firstly, it was found that, overall, countries with lower press freedom rankings had less sever pandemic outbreaks than countries with higher press freedom rankings. Secondly, it was found that countries with lower press freedom rankings also enacted stricter lockdown measure, and held them for longer, than countries with higher press freedom rankings. Although some might speculate that a possible reason as to why countries with lower press freedom scores had less severe pandemic outbreaks was because they just underreported their data (after all, it would make intuitive sense that a country with a less free press would be more likely to falsify their COVID-19 data) the fact that these countries also tended to enact strict lockdown polices earlier and longer provides a more grounded explanation. Although this relationship may become a more prominent discussion topic after the COVID-19 pandemic is over, it is important to note it does make sense based on the available data available today.

6.3 Country Profile

Based upon the results of the statistical analyses that we conducted, we can construct a profile containing general characteristics that describe countries' that are most attractive mor geographic supply chain diversification. This profile, unlike the composite index, which is based on the calculated metrics, is more based on the relationships observed between the confounding metrics and the outbreak severity, response severity, and risk tolerance metrics. The profile is as follows:

- Outbreak Severity
  - Country's with higher WHO healthcare scores and median ages correlated with more severe pandemic outbreaks
  - High income countries had more severe pandemic outbreaks than low income countries
  - North America, Europe, and Latin America had the most severe pandemic outbreak while Africa, Southern Asia, Southeastern Asia, and Eastern Asia had the least severe pandemic outbreaks.
  - Country ' s with the worst press freedom scores had the least severe pandemic outbreaks
- Response Severity
  - high- and low-income countries maintain strict lockdowns for less time than lower middle and upper middle-income countries
  - North America and Europe took the longest to enact stricter lockdown measures
  - Africa and Southern Asia maintained strict lockdown measures for the shortest amount of time
  - Countries with the worst press freedom rankings enacted the strictest lockdown policies for the longest amount of time

- Risk Tolerance
  - Countries with higher median ages and WHO healthcare scores enacted shutdown latest (in terms of pandemic severity)
  - Countries with high income tended to enact strict lockdown measures latest
  - Countries with high press freedom rankings enacted strict lockdown measure latest

Thus, the profile of an ideal country for supply chain diversification to combat the risk of a global pandemic outbreak would have a low Who healthcare score, low median age, low income, and be located in Africa or southern Asia. However, it is important to discuss the limitation of such a profile. Throughout each of the statistical analyses involving confounding variables, more correlation could be drawn between categorical groups than the quantitative measures. This would indicate that, although the averages between categorical groups (like the ones defined in this country profile) are significant, there does exist variability within each categorical group. Therefore, just choosing a country that fit this profile is far from guarantee that it is the best choice for geographic supply chain diversification to combat against the risk of a global pandemic outbreak. Rather, such a profile should only be used as a first step to potentially guide the usage of the composite and subindexes that have been calculated.

6.4 Index Takeaways

Based off the sheer amount of calculated metrics and number of statistical analysis performed, it is necessary to create an index system, so the results of the research are useful and actionable. Furthermore, by creating a composite index composed of three main subindexes (outbreak severity, response severity, and risk tolerance) supply chain managers have the option to examine the results in more detail and weight the subindexes as they see appropriate. Although the current composite index provides and equal weight and well-rounded of view of the pandemic and government response actions, if, for example, a supply chain manager only wished to know about the response severity of a given country, they can exclusive use the response severity subindex as a decision making tool.

Additionally, it is imperative to put the results of the indexes in context. These indexes purely rank countries on a relative and absolute manner. Thus, the index is most approbatively used as an ordinal or integer tool rather than a ratio tool. For example, in the composite index France scored a 0.6021 and the USA scored a .4652. A proper takeaway could be "the France is more attractive for supply chain diversification to combat the risk of a future global pandemic outbreak than the USA" (an ordinal takeaway). The interval takeaway, "France is .1369 points better than the USA for geographic supply chain diversification to combat the risk of a future pandemic outbreak", while correct, lacks meaning because the index is unitless. Accordingly, a ratio-based comparison, like "France is 25% more attractive than the USA for geographic supply chain diversification to combat the risk of a global pandemic outbreak", would be an inpatriate conclusion.

The indexes themselves have enough parity for practical use. The composite index ranges from .3177 to .7552, the outbreak severity index ranges from .3994 to .9159, the response severity index ranges from .1503 to .8705, and the risk tolerance index ranges from .0527 to .8950. Furthermore, the results of the sub-indexes make intuitive enough sense for their results to be trusted. For the outbreak severity, both the USA and Brazil (who have been noted for severe outbreaks) ranked 174 and 172 respectively (out of 176). For the response severity index, Japan (who has been noted for less severe government response and lockdowns) was 5 (out of 176) and China (who has been noted for having strict lockdown) was 172 (out of 176). For the risk tolerance index, Sweden (who was noted as willing to have little government action as the first pandemic outbreak began) was 10 (out of 176).

6.5 A Case Example

To demonstrate the utility of the indexes for geographic supply chain diversification, let us analyze Apple's and their supplier's decision to shift some of their production to both India and Vietnam [47]. Although the COVID-19 pandemic was not the only factor behind these decisions, the US-China trade war and rising labor prices are also a contributing factor, making the supply chain pandemic proof was certainly somewhat of a consideration. The table below details China's, India' s and Vietnam's scores across the composite and three subindexes:

Table 15: China, India, and Vietnam Index Scores and Ranks

	Composite		Outbreak		Response		Risk Tolerance	
Country	Score	Rank	Score	Rank	Score	Rank	Score	Rank
China	.3951	146	.6587	96	.2705	172	.2562	91
India	.3396	171	.5568	146	.3312	158	.1310	152
Vietnam	.3871	151	.6982	56	.3366	154	.1265	157

As one can see from the table above, it would not appear that Apple and their suppliers - purely from a global pandemic risk - geographically diversified their supply chain in the most optimal manner (of course, there are certainly other factors they are considering). On can see that China, in the composite index, is the most attractive of the three countries. While China did have the more severe government response, they also had the highest risk tolerance of the three countries. While Vietnam did have a less severe outbreak than China, India had a worse outbreak. Thus, Apple and their suppliers placed more weight on the severity of government response compared to outbreak severity and risk tolerance.

The next question would be if there was a better country to consider (purely from a global pandemic outbreak risk point of view)? If we make the assumption that Apple and their supplier wish that production stayed in south or southeast Asia (which is reasonable because they chose India and Vietnam), were there other countries in that region that performed better int eh indexes? The answer is yes, and the countries are Iran, Thailand, Cambodia, and Laos. The table below adds their information to the previous table.

Table 16: Other Countries Index Scores and Ranks

	Composite		Outbreak		Response		Risk Tolerance	
Country	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Cambodia	.5650	39	.9033	5	.6578	20	.1340	150
China	.3951	146	.6587	96	.2705	172	.2562	91
India	.3396	171	.5568	146	.3312	158	.1310	152
Iran	.6421	12	.5722	135	.5572	58	.7969	3
Laos	.5274	55	.9136	2	.5393	64	.1292	155
Thailand	.6080	22	.7188	32	.6780	15	.4261	49
Vietnam	.3871	151	.6982	56	.3366	154	.1265	157

As one can see from the table able, all four of these countries outperform China, India, and Vietnam across nearly every index (the risk tolerance index is the exception). It is also the magnitude at which Cambodia, Iran, Laos, and Thailand outperform China, India, and Vietnam that is notable. For example, in the response index, Laos had the worst rank of the four new countries but was still ranked 90 countries ahead of Vietnam (who had the best response score of the three original countries considered). Furthermore, if we consider the response severity index as being the most important (which was potentially the case with Apple and their suppliers) all four new countries posed viably better options than Vietnam and India.

As previously stated, Apple and their suppliers certainly considered other factors than the risk of a global pandemic outbreak when geographically diversifying their supply chain and Vietnam and India may have far outperformed Cambodia, Iran, Laos and Thailand in these metrics to the point where the fact they performed better in combating the risk of a global pandemic outbreak was irrelevant. however, based on the results of this research, Apple and their supplier's decision to as to where to geographically diversify their supply chain has not necessarily put them in a significantly better position to combat the next pandemic outbreak and there were countries in the same region where, if they have diversified their supply chain there, they would have.

7 Future Work

In this section, two topic for future research are discusses and how they relate to the research conducted.

The indexes we calculated were relative in nature and although they allow for important conclusions to be drawn and can be use actionably, they came with limitations. Currently, although one can make conclusion about which countries are better candidates for geographic supply chain diversification to combat the risk of a global pandemic outbreak, the magnitude of the difference between countries is a little ambiguous. To be able to make stronger conclusions, the index we created would need to be linked to specific economic and supply chain data. For example, two useful points of information would be about how lead times changes during the COVID-19 pandemic, and for how long, as well as the change in revenue firms saw during such supply chain slowdowns. The difficulty in obtaining this data comes from the fact that it would have to be collected on a firm level, from multiple firms in multiple different industries, from as many different countries as possible, and then aggregated across different industries. Additionally, because many firms realized how much their supply chains relied on china during the COVID-19 pandemic, obtaining enough data from countries that may be locations for geographic supply chain diversification may prove difficult. More than likely, such a task would be conducted internally within a firm of sufficient size using their data and the indexes we created through our research.

7.1 Incorporating Vaccine Distribution

For our research, we stopped raw data collection on December 31, 2020 as that is approximately when vaccine distribution began in some countries on a large scale. For our research, we primarily wanted to focus on the how countries handled the pandemic outbreak and how that reflects their attractiveness for supply chain diversification to combat the risk of a future pandemic outbreak. After all, the most publicized supply chain shortages and disruptions occurred at the start of the COVID-19 pandemic. However, vaccine distribution will prove pivotal in allowing countries to truly return to normal operation like before the COVID-19 pandemic. Furthermore, the evened distribution of COVID-19 vaccines will likely make this another important issue to consider. UN Secretary-General António Guterres has remarked, "Just 10 countries have administered 75 per cent of all COVID-19 vaccines. Meanwhile, more than 130 countries have not received a single dose" [48]. This effects of this, and how other countries who have not reached herd immunity respond after other countries have, will have supply chain implication. It is likely a range of responses, from a country without herd immunity lifting all restriction to countries with herd immunity to maintaining all restriction, are possible and can be quantified into a relative attractiveness ranking. Research will need to be conducted to see if such effect is significant enough to be seriously considered ins strategic supply chain planning.

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A Outlier Handling Algorithms

A.1 New Value Algorithm

Algorithm 1: New Value Algorithm

$Outlier\_Date, First\_Date, Last\_Date, Incident\_Data$
$Avg\_Before\_Outlier = MEAN(Incident\_Data[Outlier\_Date - 7 : Outlier\_Date))$
$Avg\_After\_Outlier = MEAN(Incident\_Data(Outlier\_Date : Outlier\_Date + 7])$
$New\_Value = (Avg\_Before\_Outlier + Avg\_After\_Outlier)/2$
$Excess\_Value = Incident\_Data(Outlier\_Date) - New\_Value$
$Incident\_Data(Outlier\_Date) = New\_Value$

A.2 Redistribution Algorithm

Algorithm 2: Redistribution Algorithm

$New\_Value, Excess\_Value = New\_Value\_Algorithm(Outlier\_Date, First\_Date, Last\_Date, Incident\_Data)$
$Incidents\_Over\_Range = SUM(Incident\_Data[Outlier\_Date - 30 : Outlier\_Date])$
$Range\_Weight = Incident\_Data[Outlier\_Date - 30 : Outlier\_Date]/Incidents\_Over\_Range$
$Range\_Adjustments = Range\_Array * Excess\_Value$
$New\_Range\_Data = Incident\_Data[Outlier\_Date - 30 : Outlier\_Date] - Range\_Adjustments$

B Peak Finding Algorithms

B.1 Initial Peaks Algorithm

Algorithm 3: Initial Peaks Algorithm

```
Incident_Data, Window_Length, Peaks
for i ∈ Incident_Data do
    max_value = 0
    max_value = MAX(Incident_Data[i − Window_Length/2 : i + Window_Length/2])
    if Incident_Value(i) = max_value AND max_value > 0 then
        Peaks.append(i)
end
for j ∈ Peaks do
    if Peaks(j).index = Peaks(j + 1).index − 1 then
        if j + 2 = Peaks(last).index then
            n = 1
            plateau_points.append(Peaks(j : j + n).index)
        else
            n = 0
            while k + n < Peaks(last).index AND Peaks(j + n).index = Peaks(j + n +
              1).index − 1 do
                plateau_points.append(Peaks(j + n).index)
                n = n + 1
            end
        end
    else if Peaks(j + 1).index − Peaks(j).index < 15 AND Peaks(j + 1).index =
      Peaks(j).index then
        plateau_points.append(Peaks(j + 1).index)
end
Peaks = Set_Diff(Peaks, plateau_points)
```

B.2 Valley Finding Algorithm

Algorithm 4: Valley Finding Algorithm

```
Peaks, Incident_Data
for i ∈ Peaks do
    min_points.append(MIN(Incident_Data[i : i + 1]).index)
    min_points.append(MIN(Incident_Data[i − 1 : i]).index)
end
min_peaks.unique_values
```

B.3 Peak Pruning Algorithm

Algorithm 5: Peak Pruning Algorithm

```
Peaks, Incident_Data
for i ∈ Peaks do
    if i's Width is Too Thin AND i's Width % is Too Small then
        if i's Height % is Too Low then
            Prune(i)
    if i's Height % is Too Small then
        if i's Width % is Too Small then
            Prune(i)
    if i's Relative Height is Too Short then
        if i's Relative Height % is Too Small then
            Prune(i)
    if i is the first peak AND i's Height % is Too Small then
        Prune(i)
end
```

B.4 Final Pruning Algorithm

Algorithm 6: Final Pruning Algorithm

```
Peaks, Valleys, Incident_Data
for i ∈ Peaks do
    max_point = MAX(Incident_Data(i's Left Valley : i's Right Valley)
    if max_point > Incident_Data(i) then
        Removed_Peaks.append(i)
        Prune(i)
end
for j ∈ Removed_Peaks do
    if i < i + 1 then
        if Next Two Valleys = 0 then
            Remove Next Two Valleys
        else
            Remove Next Valley
        end
    else if i > i + 1 then
        if Last Two Valleys = 0 then
            Remove Last Two Valleys
        else
            Remove Last Valley
        end
end
```

C Key Point Addition Algorithm

Algorithm 7: Key Point Addition Algorithm

$Peaks\_and\_Valleys, Incident\_Data$
for $i \in Peaks\_and\_Valleys$ **do**
    $data\_direction = 0$
    if $Incident\_Data(i) < Incident\_Data(i+1)$ **then**
        $data\_direction = -1$
    else if $Incident\_Data(i) > Incident\_Data(i+1)$ **then**
        $data\_direction = 1$
    $Create\ Cubic\ Polynomial\ using\ Incident\_Data(i : i + 1)$
    $Identify\ Intersection\ Point\ between\ Cubic\ Polynomial\ Data\ and\ Incident\_Data$
    for $j \in Intersection\_Points$ **do**
        if $direction = 1ANDj > j+1$ **then**
            $Removej + 1$
        else if $direction = -1ANDj < j+1$ **then**
            $Removej + 1$
    end
end
$min\_peaks.unique$

D Metric Qualities List

This table contains every metrics and it's characteristics used in this analysis.

E Detailed Subindex Description

This section contains tables that describes the metrics that composed subindexes and their weights.

E.1 Outbreak Severity

Table 17: Other Countries Index Scores and Ranks

Index	Weight	Index	Weight
Initial Outbreak	**.5**	**Total Outbreak**	**.5**
Cases	*.5*	*Total Handling*	*.33*
Cases Avg. Growth Rate(First Outbreak)	.1	Total Cases per Million	.167
Cases Max. Growth Rate(First Outbreak)	.1	Total Deaths per Million	.167
Cases Growth Length(First Outbreak)	.067	Total Tests per Million	.167
Cases Avg. Submission Rate(First Outbreak)	.1	Case-Death Ratio	.167
Cases Max. Submission Rate(First Outbreak)	.1	Test-Case Ratio	.167
Cases Submission Length(First Outbreak)	.067	Case-Death Pair Peak Ratio	.167
Cases Total Length(First Outbreak)	.067	*Case Handling*	*.33*
Cases Peak Value(First Outbreak)	.2	Number of Cases Peaks	.2
Cases Valley Value(First Outbreak)	.2	Cases Avg. Growth Rate	.1
Deaths	*.5*	Cases Max. Growth Rate	.1
Deaths Avg. Growth Rate(First Outbreak)	.1	Cases Growth Length	.067
Deaths Max. Growth Rate(First Outbreak)	.1	Cases Avg. Submission Rate	.5
Deaths Growth Length(First Outbreak)	.067	Cases Max. Submission Rate	.5
Deaths Avg. Submission Rate(First Outbreak)	.1	Cases Submission Length	.067
Deaths Max. Submission Rate(First Outbreak)	.1	Cases Total Length	.067
Deaths Submission Length(First Outbreak)	.067	Cases Peak Value	.2
Deaths Total Length(First Outbreak)	.067	Cases Valley Value	.2
Deaths Peak Value(First Outbreak)	.2	*Death Handling*	*.33*
Deaths Valley Value(First Outbreak)	.2	Number of Deaths Peaks	.2
		Deaths Avg. Growth Rate	.1
		Deaths Max. Growth Rate	.1
		Deaths Growth Length	.067
		Deaths Avg. Submission Rate	.1
		Deaths Max. Submission Rate	.1
		Deaths Submission Length	.067
		Deaths Total Length	.067
		Deaths Peak Value	.2
		Deaths Valley Value	.2

E.2 Response Severity

E.3 Risk Tolerance

F Confounding Variables vs COVID-19 Data

F.1 Ratio/Interval Metrics

F.2 Ordinal Metrics

F.3 Nominal Metrics

G GHS Rankings vs COVID-19 data

G.1 Ratio/Interval Metrics

G.2 Nominal Metrics

H GHS Rankings to OxCGRT

H.1 Ratio/Interval Metrics

H.2 Nominal Metrics

I Confounding Variables to OXGRT

I.1 Ratio/Interval Metrics

I.2 Ordinal Metrics

I.3 Nominal Metrics

J Indexes

J.1 Composite Index

J.2 Outbreak Severity Subindex

J.3 Response Severity Subindex

J.4 Risk Tolerance Subindex