

用综合指数量化各国的冠状病毒

大流行形势和应对措施

**Quantifying Every Country's COVID-
19 Pandemic Severity and Response
Through the Creation of a Relative
Composite Index**

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摘 要

新冠肺炎大流行突显了当前大流行病应对和遏制政策的缺陷。这是自 1918 年 H1N1 流感大流行以来规模最大的一次全球大流行；然而，伴随着新冠肺炎大流行的是大量的数据，这些数据详细说明了世界上几乎每一个国家的爆发严重程度和政府应对的严重程度。从这些数据中可以得出定量的结论，有可能指导决策者开始制定新的大流行病控制政策。通过我们的研究，我们将提出一种方法，从每个国家的新冠肺炎数据中提取高级指标，以定量地确定其大流行病爆发的严重程度。我们还将从各国政府的应对行动中得出指标。根据这两套指标之间的关系，还将计算出风险容忍度指标，以进一步增加各国采取行动抗击新冠肺炎大流行病的倾向性。根据这些指标，我们将建立一个综合指数，详细说明每个国家处理新冠肺炎大流行病的情况。此外，我们将进行混杂变量分析，目的是找到描述哪类国家处理大流行病爆发最好的量化因素。最后，作为这一分析的产物，我们将检查 2019 年 GHS 排名的准确性，因为它们与大流行病爆发有关，并将其与我们计算的指标进行比较，以进一步增加其结果的背景。

关键词：新冠肺炎疫情严重程度；非药物干预措施；政府大流行病应对措施；综合指数；量化指标

ABSTRACT

The COVID-19 Pandemic highlighted the shortcomings in current pandemic response and containment policy. It has been the largest global pandemic since the 1918 H1N1 Influenza Pandemic; however, the COVID-19 Pandemic is 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 conclusions can be drawn that have the potential to guide policy makers to as they begin the process of making new pandemic control policy. 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. 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 to combat the COVID-19 Pandemic. From these metrics, we will create a composite index that details every country's handling of the COVID-19 Pandemic. Furthermore, we will perform a confounding variable analysis with the goal of finding quantitative factors that describe the type of country that best handled the 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.

Keywords: COVID-19 Outbreak Severity; Nonpharmaceutical Interventions; Government Pandemic Response; Composite Index; Quantification Metrics

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LIST OF SYMBOLS AND ACRONYMS

AAPI	Asian Americans and Pacific Islanders
AfD	Alternative for Germany
ANOVA	Analysis of Variance
CDC	Center for Disease Control
COVID-19	A coronavirus disease caused by SARS-CoV-2
Ebola	A deadly disease with outbreaks that occur primarily in Africa
FPO	Freedom Party of Austria
G20	An international forum for the governments and central banks from 19 countries and the EU
GDP	Gross Domestic Product
GHS	Global Health Security Rankings
H1N1	A strain of the influenza A virus
H5N1	A strain of the influenza virus that primarily infects birds
IQR	Inter Quartile Range
ISO	International Organization for Standards
KMeans	A method of vector quantization that partitions n observations into k clusters
NPI	Nonpharmaceutical Intervention
OxCGRT	Oxford COVID-19 Government Response Tracker
PCHIP	Piecewise Cubic Hermite Interpolating Polynomial
SARS	Severe Acute Respiratory Syndrome
WHO	World Health Organization
ΔR_t	Rate of Transmission

CHAPTER 1 INTRODUCTION

In this section, I will briefly introduce the overall topic of my research. This will put my research in the proper context to provide more specific background information and other important factors to consider my research with.

1.1 The COVID-19 Pandemic

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 (Dong, Du, & Gardner, 2020) has exposed the vulnerability of the modern world to a global pandemic outbreak. The last pandemic of similar severity and scale was the 1918 H1N1 Influenza Pandemic that has been estimated to have killed 50 million people and infected about 500 million (Center for Disease Control and Prevention, 2020). However, even though the last major global pandemic outbreak had been over 100 years ago, the risk of a future global pandemic outbreak needs to be considered a serious threat going forward. Not only does the world have a significant moral obligation to do so, but failure to do so will likely result in severe negative economic consequences.

Since 2000, there have been pandemic outbreaks that have had measurable economic impact. The Global Preparedness Monitoring Board (2019) 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 (Jonas, 2013). In fact, these appear to have been underestimates as, despite COVID-19's severity being less than the 1918 H1N1 Influenza Pandemic, global GDP contracted by 4.3% in 2020 (World Bank, 2021). 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 (Global Preparedness Monitoring Board, 2019).

To put these economic figures into context, 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” (CNN Wire Staff, 2011) 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 (Samet, 2016). Therefore, the economic impact of COVID-19 are already 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 Nonpharmaceutical Interventions (NPIs)

Before COVID-19 vaccinations became available, every country's government response measures hinged upon NPIs. The CDC states that “NPIs are actions, apart from getting vaccinated and taking medicine, that people and communities can take to help slow the spread of illnesses ... NPIs are among the best ways of controlling pandemic flu when vaccines are not yet available” (Center for Disease Control and Prevention, 2020). Although somewhat obvious, NPIs are the only way to contain the spread of a global pandemic event and mitigate its negative effects. Thus, the research and understanding of the effectiveness of different NPIs will be critical in formulating the best response to future pandemic outbreaks.

At the start of the COVID-19 Pandemic, factors contributing to the acceleration of the COVID-19 virus were identified as follows (Schuchat & Team, 2020):

- “Continued travel-associated importations of the virus”
- “Large gatherings”
- “Introductions into high-risk workplaces/settings”
- “Crowding and high population density”
- “Cryptic transmission”

Possible NPI responses to combat these acceleration factors that could have been taken by governments were posed as follows (Schuchat & Team, 2020):

- “Travel notices, travel restrictions, and quarantines”
- “Restricting mass gatherings, transitioning to virtual events”
- “Restricting visitor access, establishing cohort units, contact tracing”
- “Stat-at-home orders, social distancing, face coverings”
- “Increasing testing, COVID-19 specific surveillance”

1.3 Social and Political Implications

In the wake of the COVID-19 Pandemic outbreak, there has been a rise in nationalism and racist incidents that are a cause for concern. In the United States, President Donald Trump famously referred to the COVID-19 virus as the China virus which was even reflected in a “photo showing ‘corona’ crossed out and replaced with ‘Chinese’ in Trump’s briefing notes” (Renton & Reynolds, 2020). Subsequently, there was an increase in Asian-American discrimination and hate crime incidents in the United States tracked by the Stop AAPI Hate website (Bieber, 2020). Similar sentiments have been observed in Europe where Germany’s AfD political party and Austria’s FPÖ political party have used the COVID-19 Pandemic to call for stricter immigration control (Jansen, 2020). Such incidents were not exclusive to the western world as noted by the Nigerian Government releasing an official statement “over allegations of continued racial discrimination against blacks and Africans, particularly Nigerians, resident in Guangzhou Province and other parts of the country” (Vanguard, 2020).

Governments have begun discussing possible policy changes post-COVID-19 and companies have begun discussing possible changes in supply chain strategies. In the wake of COVID-19, many countries and business are realizing just how much their supply chains relied on one geographic region: China (Javorcik, 2020). This has led to calls from some to make global supply chains more geographically diverse and become more decentralized. 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 (Miroudot, 2020). However, especially considering their discussion before the conclusion and full reflection from the COVID-19 Pandemic, these decisions may be a double-edged sword and may be motivated by other actors.

1.4 Research Objective

The objective of this research is to formulate and execute a method that will allow for every country’s COVID-19 Pandemic response to be accurately quantified so they can be compared. The COVID-19 Pandemic has presented an opportunity for the world to learn what was and was not effective in controlling a global pandemic so we can all be better prepared to combat a future global pandemic outbreak. Given this unique

opportunity, it is imperative that this method be quantitatively based so that takeaways from the COVID-19 Pandemic are as accurate and factual as possible. Furthermore, by making a quantitative method, systematic bias from such analysis can be removed so we can be assured the results are trustworthy and present the true picture of every country's handling of the COVID-19 Pandemic. Given the amount of lives at stake in a future global pandemic outbreak, the importance of this research cannot be understated. Through this research, to following questions will be explored or answered:

1. Which NPIs were the most effective in controlling the COVID-19 Pandemic and what is the consensus of their effectiveness?
2. How can advanced metrics be drawn from the real-world (and often messy) COVID-19 data?
3. How can an advanced metric extraction method be devised to maximize quantitation and minimize introduced bias?
4. Are there confounding variables that are correlated to a country's handling of the COVID-19 Pandemic?
5. Pandemic preparedness rankings have been formulated in the past. How accurate were they and what can we learn from them given the results of this research?

Although this research focuses on the broader issue of quantifying every country's COVID-19 Pandemic response, it is still incredibly important as it takes the crucial first step of parsing every countries' COVID-19. This acts as a vital guide to more specific and important pandemic research. For example, policy makers from governments around the world will undoubtedly reformulate their existing pandemic response policy in the wake of the COVID-19 Pandemic. Many will look for which countries handled the pandemic the best, try to derive the important takeaways, and use them as a blueprint for future pandemic policy. Without my research, this exploration process risks being bias and, therefore, not optimally effective. However, although my research would not definitely explain why one country's handling of the COVID-19 Pandemic was better than another's, it provide an integral roadmap that will allow everyone to quickly and accurately know where to start looking.

1.5 Structure

The remainder of the paper is structured as follows: in Chapter 2, I will conduct a

brief literature review to provide further context to the problem and detail my contributions. In Chapter 4, I will present a summarized version of the results. Then, in Chapter 5, I will draw conclusions from the results and place them in context. Finally, in Chapter 6, I will detail possible future work on this problem.

CHAPTER 2 LITERATURE REVIEW

In this chapter, I will present a comprehensive literature review about the study of NPIs and the COVID-19 Pandemic. I will examine specific NPIs and external factors that may affect NPI effectiveness. I will also provide further detail about two important datasets critical to my research.

2.1 Different Types of COVID-19 Pandemic Studies

In Perra's (2021) literature review, *Non-pharmaceutical interventions during the COVID-19 pandemic: a review*, she notes that the majority of research can be broken down into four main categories:

- Epidemic Models: “papers aimed at describing the unfolding of COVID-19 via epidemic models”
- Surveys: “papers aimed at characterizing the impact of NPIs on several areas of human activity and/or their adoption via surveys”
- Comments and/or Perspectives: “papers that offer a reflection/perspective on NPIs in particular contexts”
- Quantifying the Effects of NPIs: “papers aimed at characterizing the effects of NPIs on epidemic indicators, behaviors and activities”

In this respect, my research would fall into the *comments and/or perspectives* category. My research's focus is to identify the country's that did the most to combat the COVID-19 Pandemic with the idea that summarizing such information will allow a quantitative and systematic approach to policy exploration. One theme throughout this literature review is the fact that most studies, from every single category, heavily focus on a select few countries (e.g. the United States, China, Italy, etc.). Thus, the fact that my research seeks to analyze every country should make it impactful and meaningful.

2.2 Specific NPIs

In this section, I will review some of the literature on specific NPIs.

2.2.1 Lockdowns

Lockdowns are a NPI that involves ordering a country's population to cease certain activities for a period. Accordingly, they have a broad range of implementations including mandatory stay-at-home orders, national lockdowns, and only closing certain businesses. One study found that national lockdowns were one of the best NPIs for controlling the COVID-19 Pandemic with a reduction in ΔR_t of between 0.008 and 0.14 (Haug, et al., 2020). Another study has stated that lockdowns were the only effective NPI measure as “all the decrease of viral reproduction was attributed to the lockdown intervention in the 10 countries where it was effectuated. In those same 10 countries, the effects of the 5 other considered intervention categories [banning public events, school closures, self-isolation, and social distancing] were almost negligible” (Soltesz, et al., 2020). However, other studies have cast doubt on the necessity of total lockdowns in the presence of other NPIs. One study found that “when these interventions [closing schools and limiting gathering sizes] were already in place, issuing a stay-at-home order had only a small additional effect. These results indicate that, by using effective interventions, some countries could control the epidemic while avoiding stay-at-home orders” (Brauner, et al., 2021). In fact, another study came to a similar conclusion, finding that “by implementing effective NPIs, many countries can reduce ΔR_t below 1 without issuing a stay-at-home order” (Chae & Park, 2020). The same study also noted that “closing most businesses only has limited additional benefit”. One study also found that “lockdowns may work better when governments introduce penalties against those who ignore them” (Chae & Park, 2020).

2.2.2 Testing

Testing is an NPI that involves increasing the number of COVID-19 tests performed on a country's population. The theory is that increased testing provides decision makers a more accurate view of the state of their country's pandemic situation and reduces the risk of asymptomatic spread of the virus. However, the research appears mixed on the actual effectiveness of testing as an NPI. One study found that “a higher amount of testing resulted in a lesser spreading of the virus and better control. In most regions, countries that were conducting a large number of tests also seemed to have lower mortality rates” (Imtyaz, Haleem, & Javaid, 2020). Another study had similar findings stating, “higher early testing implementation, as indicated by more cumulative tests per case when

mortality was still low, was associated with longer accrual time for higher per capita deaths” (Kannoth, Kandula, & Shaman, 2021). However, another study found that “measures to enhance testing capacity or improve case detection strategy [were] among the least effective interventions” and did not reduce ΔR_t (Haug, et al., 2020). However, it has been noted that there may be ambiguity in such results as such measures lead to a short-term rise in cases.

2.2.3 School Closings

School closings are NPIs that involve closing primary, secondary, and university education. Initial research seemed to suggest that school closings were an ineffective NPI noting that school closure only lead to an 8% reduction in the number of new cases (Banholzer, et al., 2020). Some newer research suggests that school closings may be one of the most effective NPIs. One study noted that school closings resulted in the reduction of ΔR_t between 0.15 and 0.21 (Haug, et al., 2020). Another study found that school closings resulted in a posterior median reduction in ΔR_t of over 35% (Brauner, et al., 2021). These newer studies attribute the early date of prior studies as being a possible contributing factor in the conclusions about school closings being an ineffective NPI. However, it is important to note that some newer research has maintained that school closings “were not correlated to a significant control of the [pandemic] growth rate” (Duhon, Bragazzi, & Kong, 2021).

2.2.4 Gathering Limitations

Gathering Limitations are an NPI that involves limiting the total size of any type of group gathering. Many studies separate this NPI into different subgroups based on their severity (e.g. limiting gathers to less than 1000, 100, or 10 people). However, most of the research is unanimous in declaring gathering limitations as one of the most effective NPIs. One study noted that “banning gatherings was effective, with a large effect size for limiting gatherings to 10 people or less, a moderate-to-large effect for 100 people or less, and a small-to-moderate effect for 1000 people or less” (Brauner, et al., 2021). Another showed that small gathering cancellations was the most effective NPI and reduced ΔR_t of between 0.22 and 0.35 (Haug, et al., 2020).

2.2.5 Border Restrictions

Border Restrictions are an NPI that involve restricting entry into a country from those currently outside of it. These can range in severity from a total border closure to only banning the entry of people from certain countries. One study ranked border restrictions as being one of the most effective unanimous NPIs and reducing ΔR_t between 0.057 and 0.23 (Haug, et al., 2020). However, another study had found that travel restrictions were not “statistically significant at the 95% confidence level” (Chen & Qiu, 2020) when it came to mitigating the pandemic outbreak. That study noted that, in many cases, early border restrictions were ineffective because they only restricted passengers from China which allowed “people who were infected could still come across the border by connecting to a third country” (Chen & Qiu, 2020).

2.2.6 Education

Education is an NPI that aims to inform the public of the dangers of the COVID-19 Pandemic and explain the necessity of different pandemic control measures. One study found that “Romanian authorities initiated a nationwide information campaign through various media channels, including television and social media [along with the] Romanian Orthodox Church followed the recommended measures and advised all believers and clerics to take appropriate precautions” (Dascalu, 2020). These educational measures, the study claimed, were contributing factors towards Romania's control of the COVID-19 Pandemic. Additionally, another study found that “risk-communication activities to inform and educate the public” reduced ΔR_t of between 0.008 and 0.14 (Haug, et al., 2020).

2.2.7 Face Masks

Face Masks are an NPI that involves mandating or recommending members of the public to wear face masks which cover the mouth and nose in certain or all public settings. One study concluded that “wearing a mask in combination with social distancing and other measures is promising to replace the shelter-in-place orders and significantly reduce the COVID-19 burden on society” (Li, Liu, Li, Qian, & Dai, 2020). Another study that focused exclusively on Canada suggested that “mandating indoor masks nationwide in early July could have reduced the weekly number of new cases in Canada by 25 to 40 percent in mid-August, which translates into 700 to 1,100 fewer cases per week”

(Karaivanov, Lu, Shigeoka, Chen, & Pamplona, 2020). In addition to the effectiveness of face masks in general, another study has suggested that “the necessity of wearing masks by the public during COVID-19 is under-emphasized” (Wang, Pan, Tang, Ji, & Shi, 2020).

2.2.8 Environmental Factors

Environmental Factors are a NPI that aim to eliminate or reduce the amount of the COVID-19 virus in an area (e.g. sanitizing surfaces). One study found that “[environmental] measures are ineffective in (almost) all methods and datasets—for example, environmental measures to disinfect and clean surfaces and objects in public and semi-public places” (Haug, et al., 2020). Although the study notes that this NPI is more difficult to track, due to a lack of government reporting data, it is significant because their findings contradict the advice of WHO. Although this study claimed that the effectiveness of such measures was unobservable, the tested effectiveness of some environmental factors as NPIs is apparent. One study found that “instant hand wiping using a wet towel soaked in water containing 1.00% soap powder, 0.05% active chlorine, or 0.25% active chlorine from sodium hypochlorite removed 98.36%, 96.62%, and 99.98% of the virus from hands, respectively” (Ma, et al., 2020). However, other possible environmental factors were deemed highly ineffective. One study noted that “spraying of outside spaces such as streets or marketplaces is not recommended as the disinfectant is inactivated by dirt and cannot have enough contact time to kill the pathogen” (Odusanya, Odugbemi, Odugbemi, & Ajisegiri, 2020).

2.2.9 Nonbinding Measures

One of the most interesting takeaways from the research of specific NPIs was that nonbinding and/or less disruptive NPIs can be just as effective as more stringent NPIs. For example, one study indicated “that a suitable combination of NPIs is necessary to curb the spread of the virus. Less disruptive and costly NPIs can be as effective as more intrusive, drastic, ones (for example, a national lockdown)” (Haug, et al., 2020). These findings are important because, as the authors have noted, the effects of the most drastic NPIs can be very severe including, interrupting learning, increasing rates of domestic violence, and restricting access to long-term healthcare (Haug, et al., 2020). Another aspect of nonbinding measures is public participation. One study found that “the value of collaboration among local citizens, civil society including community-based groups, and

regional government to fill gaps in public services” (Miao, Schwarz, & Schwarz, 2021) (referred to as community volunteerism and coproduction) played a large role in China's COVID-19 Pandemic response.

2.3 Factors Affecting NPI Effectiveness

In this section, I will review some of the other factors identified in the research that contribute to the effectiveness of implemented NPIs.

2.3.1 Response Speed

Research has shown that the faster NPIs are implemented, the more effective they are at controlling the spread of the COVID-19 Pandemic. One such study noted that “the management of the COVID-19 crisis in Romania illustrates the importance of a fast initial response” (Dascalu, 2020). Additionally, another study that focused solely on the United States found that “advancing the date of NPI adoption by one day lowers the COVID-19 death rate by 2.4%” (Amuedo-Dorantes, Kaushal, & Muchow, 2020). Such a conclusion makes logical sense as, the earlier NPIs are implemented, the smaller size of the outbreak that they must control and mitigate.

2.3.2 Politics

Some studies have found that the political climate of a country's government can have effects on the effectiveness or stringency of the NPIs that are implemented. One article made the claim that “the [USA's] response has been handicapped by deficient political commitment and unclear goals, dysfunctional institutional dynamics” (Carter & May, 2020). However, it is important to note that this article was qualitative in nature. However, more quantitative research has also been conducted. One study, which had noted a link between NPI adoption speed and death rate, also found that “NPI adoption speed has less relevance in Republican counties—a possible byproduct of skepticism and reluctance to apply or fully comply with NPIs” (Amuedo-Dorantes, Kaushal, & Muchow, 2020). Another studied also showed that “for every 10% increase in Republicans in a state, mobility restriction declines 8%” (Hsiehchen, Espinoza, & Slovic, 2020). Although these studies are focused specifically on the United States, it is not unreasonable to think the idea that politics may play a role in the effectiveness of NPIs exists elsewhere.

2.3.3 Local Context (Culture)

Throughout the research, authors made note of the fact that local context (e.g. culture) can play a significant role in NPI effectiveness and should play a role in which NPIs are implemented. One such study noted “the fact that gross domestic product is overall positively correlated with NPI effectiveness whereas the governance indicator ‘voice and accountability’ is negatively correlated might be related to the successful mitigation of the initial phase of the epidemic of certain south-east Asian and Middle East countries showing authoritarian tendencies” (Haug, et al., 2020). One study has even found that “demographic, climatic, and social variables play a greater role in the initial growth rate of the virus [than NPIs]” (Duhon, Bragazzi, & Kong, 2021).

2.3.4 Government Approaches

There has also been research on exactly how different governmental approaches to controlling the COVID-19 Pandemic can affect its effectiveness. One such study analyzed the expected cost of implementing one of three different NPI strategies: laissez-faire, herd immunity approach, and aggressive approach. “Somewhat surprisingly, we find that the aggressive approach achieves the lowest costs for the society both for low and high values of statistical life” (Ugarov, 2020). It also noted that the herd immunity approach was better than laissez-faire. However, most interesting might be the conclusion that an “infection fatality rate of 0.15% and lower doing nothing [i.e. laissez-faire] would minimize total societal costs” (Ugarov, 2020).

Another study looked at how the concepts of adaptive and agile governance affected the Dutch response to COVID-19. It concluded that “agility and adaptivity can go hand in hand, but they can also conflict in practice. Hence, agile and adaptive governance should not be mixed up, as they have different origins, purposes, and implications” (Janssen & van der Voort, 2020). Its overall conclusions revolve around the idea that the Dutch response was hindered by the fact they tried to integrate agile governance into their existing adaptive government framework. In essence, the takeaway was that, given the shortcoming of the existing governmental style, trying new styles that may be better suited for a new situation could be counterproductive.

Another study found that weak governmental actions had adverse effects on their population outside of them potentially not controlling the COVID-19 Pandemic optimally. It found that “decisive actions from policy-makers, we find, have the ability to alter how

people perceive their governments and other citizens, and in turn improve mental health” (Fetzer, et al., 2020). Thus, reluctance to take strong governmental actions could result in further increasing government distrust and internal strife, which is already higher than normal due to the pandemic situation.

2.4 GHS 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])” (The Global Health Security Index, 2019). 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) (Wong, Huang, Wong, Kwok, & Teoh, 2020), 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 (Haider, et al., 2020), not be a predictor of effective pandemic control when viewing total cases, total deaths, recovery rate, and total tests performed (Abbey, et al., 2020), and were not a significant factor in a country’s testing rate. Additionally, the GHS Rankings were inversely correlated to the COVID-19 data (Aitken, Chin, Liew, & Ofori-Asenso, 2020). 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 capacity and performance (Ravi, et al., 2020). 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 severity in different countries (Razavi, Erondur, & Okereke, 2020).

2.5 OxCGRT 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” (Hale, et al.). 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's response at the early stage of the pandemic was correlated with reducing the deaths (Dergiades, Milas, & Panagiotidis, 2020) 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) (Zhu, Mishra, Ma, & Han, 2020). 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 (Harder & Harder, 2020)

CHAPTER 3 METHODS

In this section, I will describe the methods I used for my research. This will range from discussing the data sources to the creation of the composite index.

3.1 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 entirety of every country's COVID-19 outbreak and response before the first mass distribution of vaccines began.

3.1.1 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 were obtained from the *Johns Hopkins Whiting School of Engineering's Center for Systems Science and Engineering's* GitHub page (Dong, Du, & Gardner, 2020). The data is formatted as a cumulative time series, contained data on a country and state/provincial level, and was updated daily. The COVID-19 test data was obtained from the *Our World in Data's* GitHub page (Hasell, et al., 2020). The data was formatted as both a daily and cumulative time series, contained data on a country level, and was updated twice weekly, however the number of countries and the quality of the data made the derivation of advanced metrics unsuitable. The full COVID-19 case, death, and test datasets can be found in Appendix ____.

3.1.2 Government Response Data

The government response data was obtained from the *OxCGRT* GitHub page (Hale, et al.). 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” (Hale, et al.) and the full dataset can be found in Appendix _____. 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 behavior”

3.1.3 Pandemic Preparedness Data

The pandemic preparedness data was obtained from the *The Global Health Security Index* (2019). It ranked 195 countries’ pandemic preparedness across six different dimensions as well as providing an overall score. In addition to the quantitative ranking, a categorical score was given to every country across each dimension and in the overall. The full dataset can be found in Appendix _____. 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”

3.1.4 Healthcare Performance Data

The healthcare performance data was obtained from a *World Health Organization* report titled *Measuring Overall Health System Performance for 191 Countries* (Tandon, Murray, Lauer, & Evans, 2000). 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. The full dataset can be

found in Appendix ____.

3.1.5 Global Economic Data

The economic data was obtained from the International Monetary Fund's (2020) *World Economic Outlook Database*. From this data, three key metrics were 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 was not available for every country. The full dataset can be found in Appendix ____.

3.1.6 Population Data

The population data was obtained from the *United Nations Department of Economic and Social Affairs World Population Prospects 2019 Report* (Desa, 2019). Three key metrics were collected for later analyses: total population (in thousands), population density (per square kilometer), and average median age (of a country's population). The full dataset can be found in Appendix ____.

3.1.7 Press Freedom Data

The press freedom data was obtained from the Reporters Without Borders (2020) *World Press Freedom Index Rankings*. It gave every country a score, numeric rank, and categorical rank in terms of their measured/observed press freedom. The full dataset can be found in Appendix ____.

3.2 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 (2020). 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 incident rates per million (e.g. from daily cases to daily cases per million).

3.3 Data Smoothing

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.

3.3.1 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 list of all identified outliers can be found in Appendix ____.

The outlier removal algorithm was composed of two separate algorithms: a New Value algorithm and a Redistribution algorithm. The New Value Algorithm determined 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 determined 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 algorithms is shown in Figure ____ and the pseudocode for both algorithms can be found in Appendix ____.

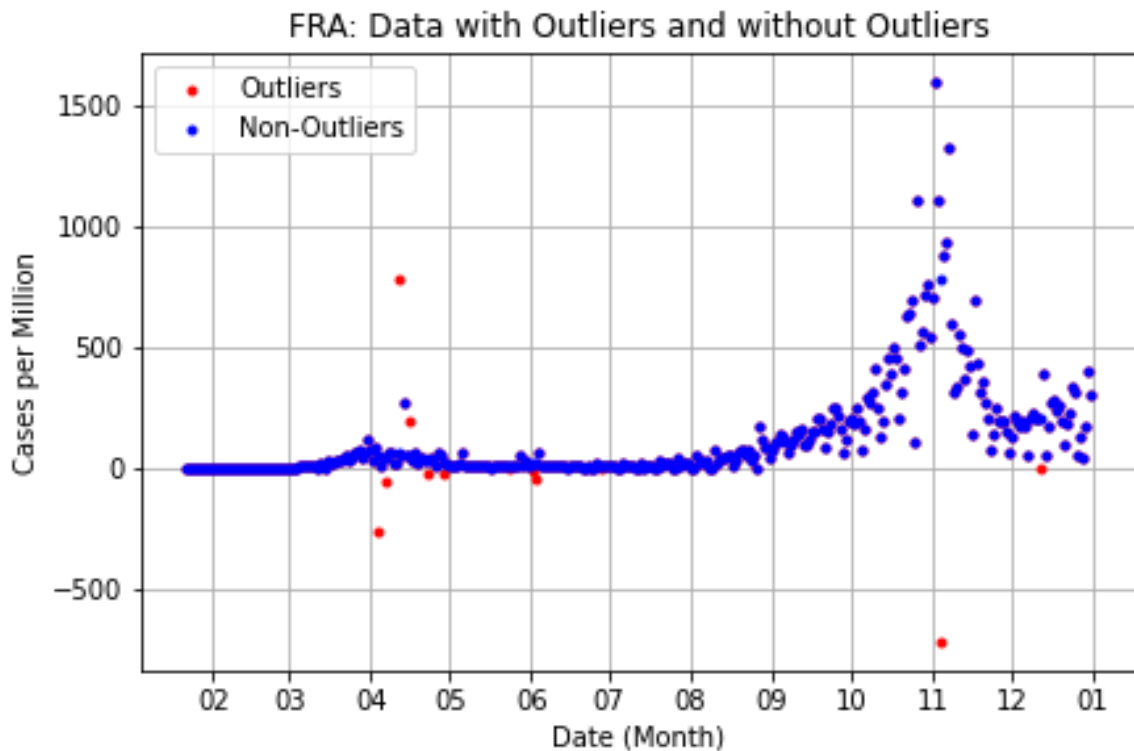


Figure 1 Outlier Removal Algorithm Results

3.3.2 Smoothing

Most countries' COVID-19 incident data exhibited weekly periodicity. For example, for any given week the USA's COVID-19 cases tended 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 were removed and the seven-day moving average was 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 (Savitzky & Golay, 1964) was applied to the COVID-19 data. This allowed 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 was 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 Figure _____. The graphs of every county's raw, moving average, and smoothed data can be found in Appendix _____.

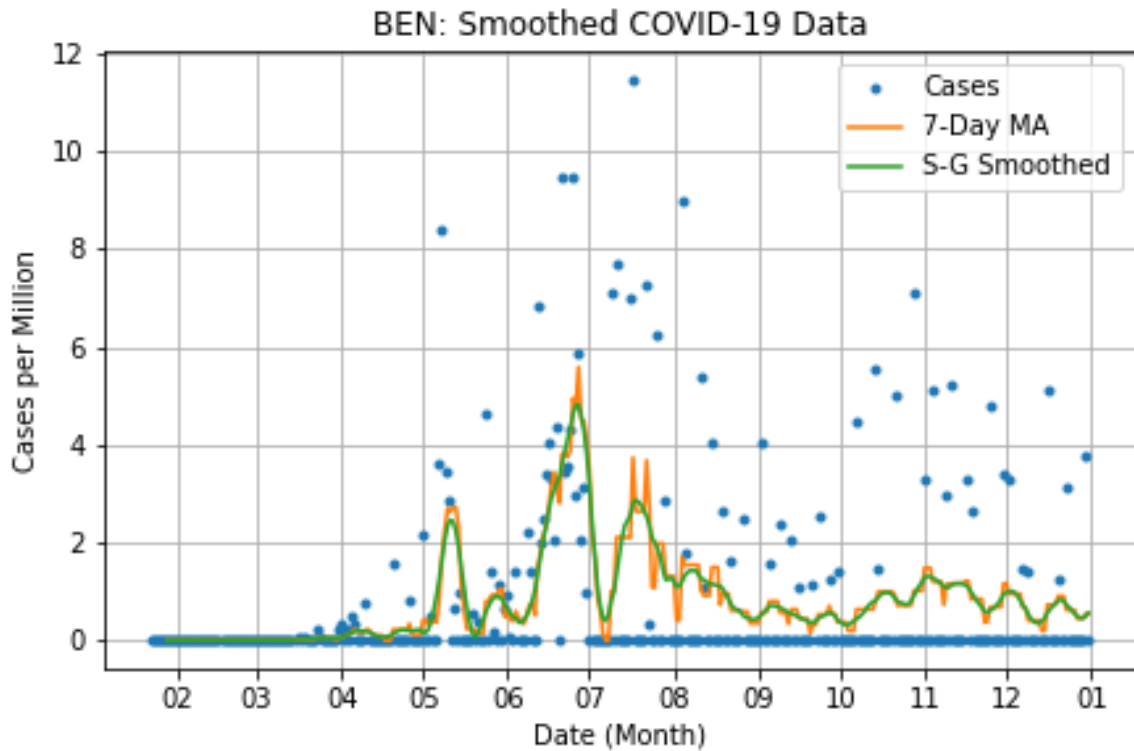


Figure 2 Data Smoothing Results

3.4 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 (the results of these algorithms can be found in Appendix ____). Then, a key point addition algorithm was used to add more points to improve the quality of the subsequent interpolation (the results of this algorithm can be found in the Appendix ____). The key point selection algorithm was made up of four sub-algorithms: Initial Peaks Algorithm, Peak Pruning Algorithm, Final Pruning Algorithm, and Valley Finding Algorithm.

3.4.1 Initial Peaks Algorithm

The Initial Peaks Algorithm worked in two main steps. First, points were 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 maximums, one solves the problem of the data between peaks and valleys not being strictly increasing or decreasing.

The second step was to determine if a peak was a plateau and only to keep the middle point if it was. For example, especially for countries with less COVID-19 incidents, 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 datasets) where two small peaks of equal size appear next to each other. An example of this algorithm is shown in Figure ___ and the pseudocode can be found in Appendix ___.

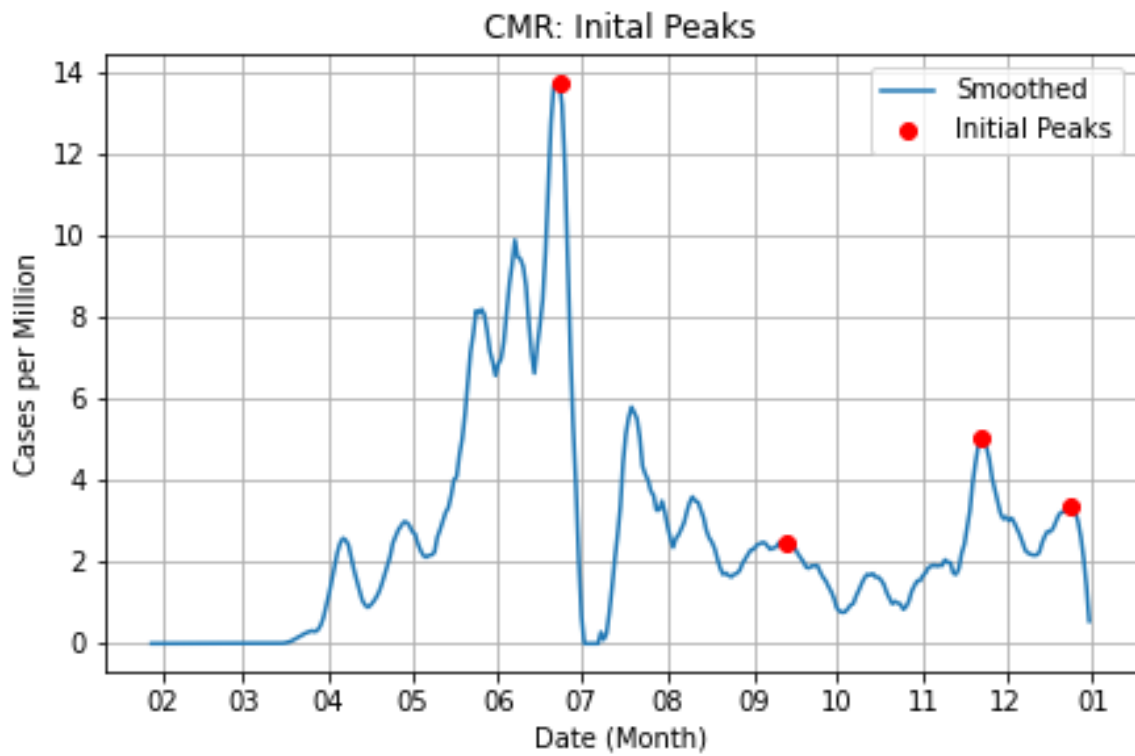


Figure 3 Initial Peaks Algorithm Results

3.4.2 Valley Finding Algorithm

The Valley Finding Algorithm was 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 Figure ____ and the pseudocode can be found in Appendix ____.

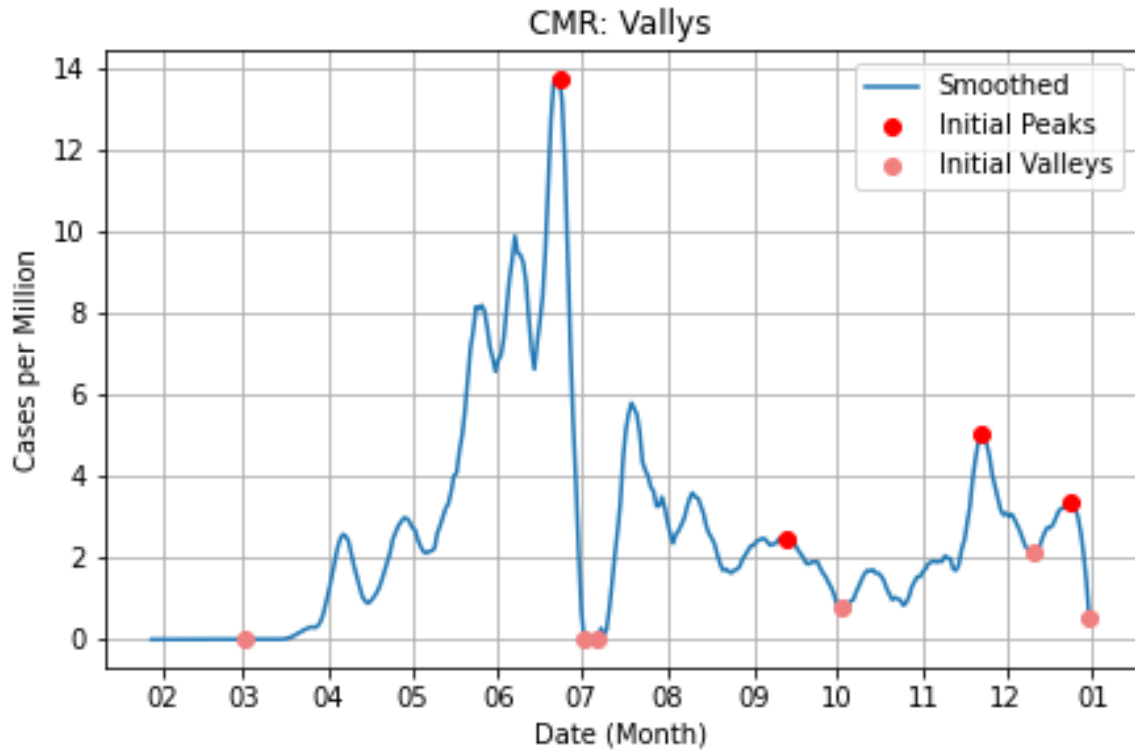


Figure 4 Valley Removal Algorithm Results

3.4.3 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 was performed to ensure it was appropriate that it was included. An example of this algorithm is shown in Figure ____ and the pseudocode can be found in Appendix ____.

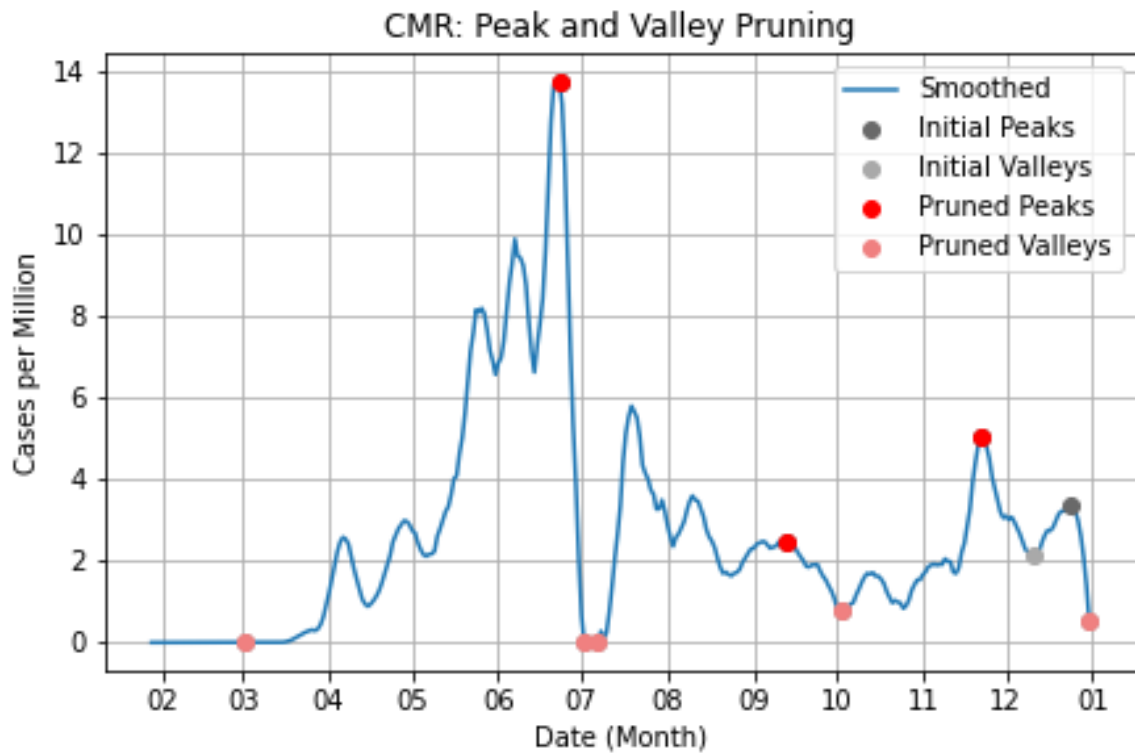


Figure 5 Peak Pruning Algorithm Results

3.4.4 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 was used in the rare instance that a country's COVID-19 incident data had a significant drop in cases over a noticeably short time period (e.g. a couple of days). When this happened, it could cause valleys to be improperly identified, and thus, a final correction was needed. An example of this algorithm is shown in Figure ___ and the pseudocode can be found in Appendix ___.

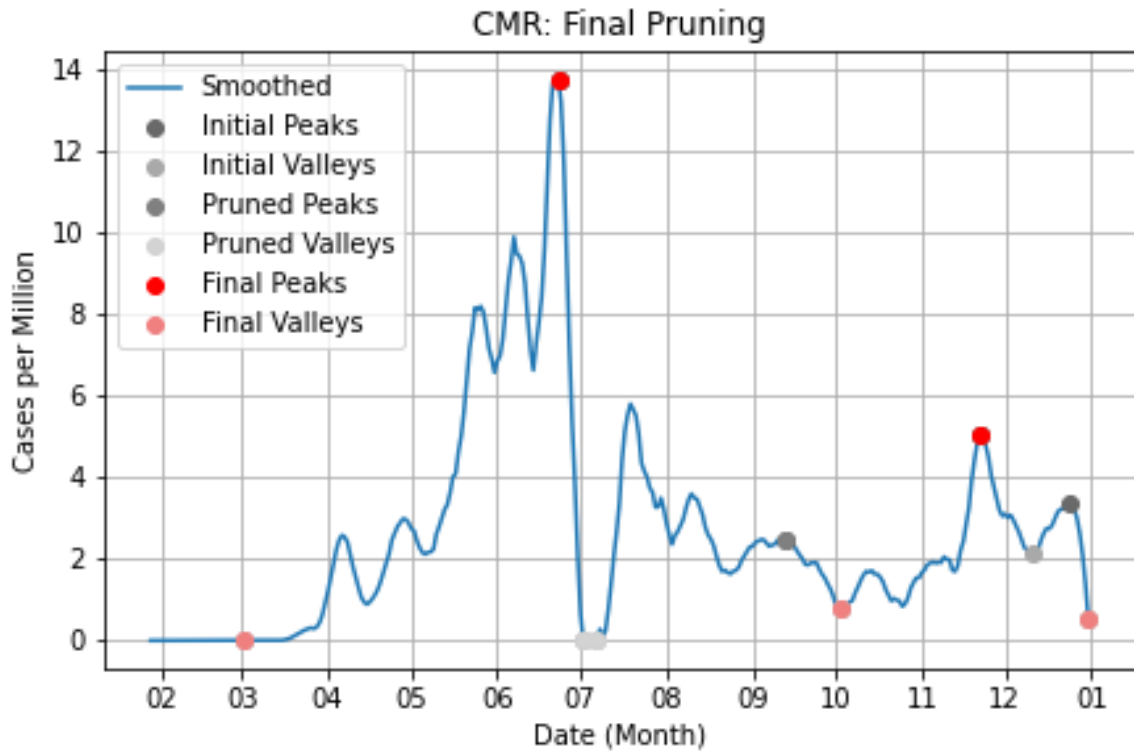


Figure 6 Final Pruning Algorithm Results

3.4.5 Key Point Addition Algorithm

The Key Point Addition Algorithm was used to add additional points to the peak and valley points to increase the accuracy of the interpolation. It worked by fitting a cubic polynomial between every single peak-valley pair. It then searched 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 was increasing or decreasing, points were pruned based on whether their neighboring points increase or decrease. This process ensured 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 Figure ___ and the pseudocode can be found in Appendix ___.

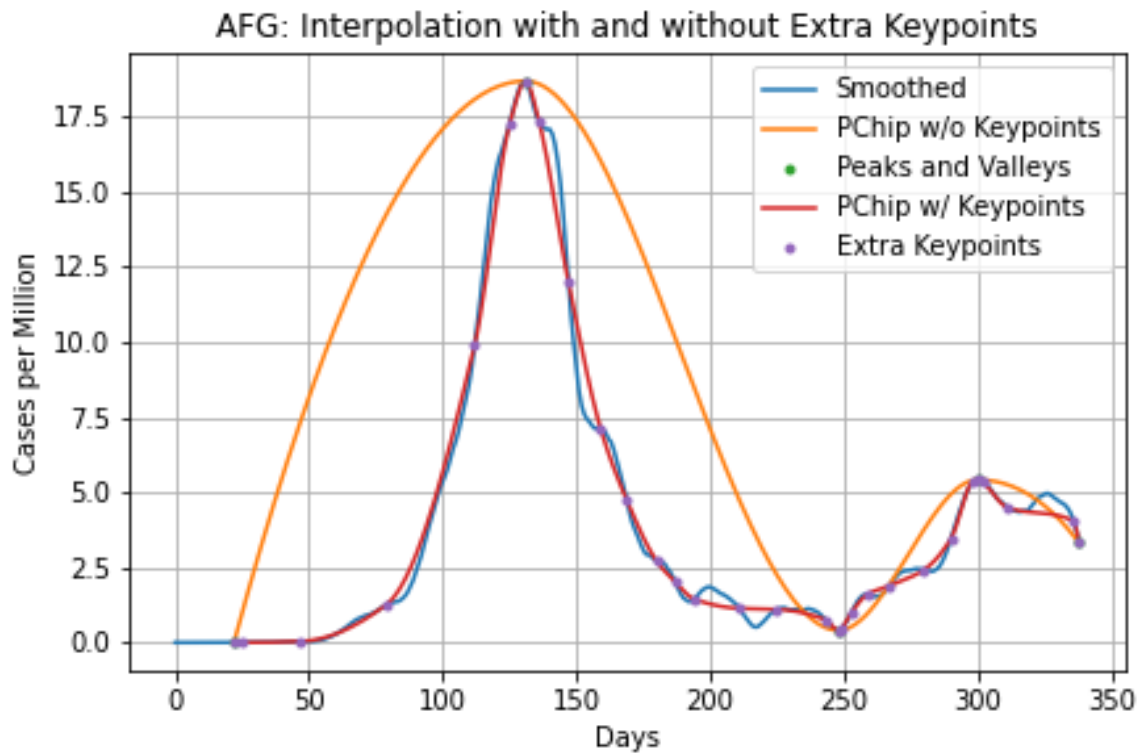


Figure 7 Interpolation with and without Extra Key Points

3.4.6 Interpolation

A Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) (Fritsch & Carlson, 1980) was chosen as the interpolation method over other interpolation methods (like splines). This was 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 n th outbreak) could be derived.

3.4.7 Peak-Pairing Algorithm

To relate a country's COVID-19 case and death data, a peak-pairing algorithm was created. This algorithm sought to pair peaks in a country's COVID-19 case data with peaks in their COVID-19 death data. This was done using a KMeans clustering (MacQueen & others, 1967). A KMeans clustering was used because the number of case peaks and death peaks was 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. An example of the result of this algorithm is shown in Figure __. All the peak paring graphs can be found in Appendix __.

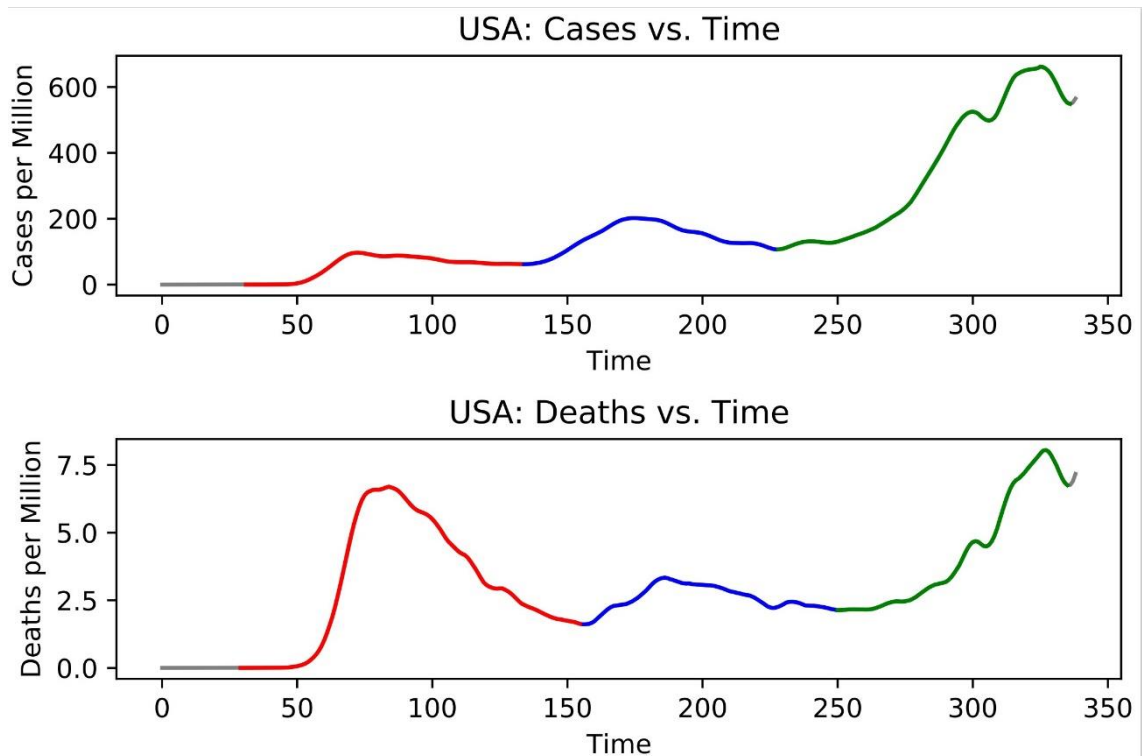


Figure 8 Peak Pairing Algorithm Example

3.5 Metric Data

In this section, the data used to calculate all of the different metrics will be explained.

3.5.1 Outbreak Data

After performing the data preparation, data smoothening, and interpolation fitting on

every country's COVID-19 case, death, and test data, the following data had been prepared could be used for metric calculations. Note that every item in this list exists for every country.

- $R(t)$: Raw COVID-19 Incident Data
 - A function that accepts an input of a *specific day*, t , and outputs the number of new COVID-19 incidents, $R(t)$, that occurred on that day (after outliers had been removed). This function exists for COVID-19 cases, deaths, and tests.
- $S(t)$: Smoothed COVID-19 Incident Data
 - A function that accepts an input of a *specific day*, t , and outputs the number of new COVID-19 incidents, $S(t)$, that occurred on that day (after the original function, $R(t)$, had been smoothed with a Savitzky-Golay Filter). This function exists for COVID-19 cases and deaths.
- $F(t)$: Fitted COVID-19 Incident Data
 - A function that accepts an input of a *specific day*, t , and outputs the number of new COVID-19 incidents, $F(t)$, that occurred on that day (after the smoothed function, $S(t)$, had been fitted via PCHIP Interpolation). This function exists for COVID-19 cases and deaths.
- $P \in \{p_1, p_2, \dots, p_n\}$: Set of COVID-19 Incident Peaks
 - A set of days where peaks in the COVID-19 incident data occurred. This data exists for COVID-19 cases and deaths.
- $V \in \{v_1, v_2, \dots, v_n\}$: Set of COVID-19 Incident Valleys
 - A set of days where valleys in the COVID-19 incident data occurred. This data exists for COVID-19 cases and deaths.
- $B \in \{(\{c_1, \dots, c_n\}, \{d_1, \dots, d_n\}), \dots, (\{c_{n+1}, \dots, c_m\}, \{d_{n+1}, \dots, d_m\})\}$: Set of COVID-19 Case-Death Peak Pairs
 - A set of case-death peak pairs that links the a country's COVID-19 case data to its death data.

3.5.2 Government Response Data

The following Government Response Data was also available for metric calculations. Note that every item in this list exists for every country.

- $M(t)$: Main Index Data

- A function that accepts an input of a *specific day*, t , and outputs the index value of the four Main OxCGRT Indexes, $M(t)$, observed on that day. This function exists for the Containment Health, Economic Support, Government Response, and Stringency Index.
- $N(t)$: Subindex Data
 - A function that accepts an input of a *specific day*, t , and outputs the index value of one of the OxCGRT Subindexes, $N(t)$, observed on that day. This function exists for the Facial Coverings, International Travel, Movement Restrictions, Public Information Campaign, Restrictions on Gatherings, School Closings, Stay at Home Requirements, and Workplace Closings subindexes.

3.6 Metric Calculation

In this section, the metric calculation procedures will be described. Note that every metric described was calculated for every single country. All of the metrics and their values can be found in Appendix __. A generalized equation for every metric is shown after each metric is introduced. The functions and set used in these equations if reflective of the metric data discussed in Chapter 3.5.

3.6.1 Outbreak Severity Metrics

In this section, the calculation procedure for the outbreak severity metrics will be described. A full breakdown of all the outbreak severity metrics, including their type, can be found in Appendix __.

3.6.1.1 Total Incidents Metrics

A total incidents metric is a metric that calculated the total number of COVID-19 incidents that occurred over the duration of the observed data. Examples include *Total Cases per Million*, *Total Deaths per Million*, and *Total Tests per Million*.

$$Total\ Incidents = \sum_t R(t) \quad (3.1)$$

3.6.1.2 Summation Ratio Metrics

A summation ratio metric is a metric that calculates the ratio relationship between two total incidents metrics. Examples include *Total Cases per Million*, *Total Deaths per Million*, and *Total Tests per Million*.

$$\text{Summation Ratio} = \frac{\sum_t R_1(t)}{\sum_t R_2(t)} \quad (3.2)$$

3.6.1.3 Peak Pair Ratio Metrics

A peak pair ratio metric is a metric that calculated the ratio between the number of COVID-19 cases and deaths from a paired case-death peak. An example would be the *Case-Death Pair Peak Ratio* metric.

$$\text{Peak Pair Ratio} = \frac{\frac{1}{n} \sum_{t \in B_n} S(t)}{\frac{1}{n} \sum_{t \in B_n} S(t)} \quad (3.2)$$

3.6.1.4 Number of Incident Peaks Metrics

A number of incident peaks metric is a metric that counts the number of peaks in the COVID-19 incident data (this can also be thought of as the number of outbreak). Examples would include *Number of Case Peaks* and *Number of Death Peaks*. They were calculated using the cardinality of the set P .

$$\text{Number of Incident Peaks} = |P| \quad (3.2)$$

3.6.1.5 Rate of Growth Metrics

A rate of growth metric is a metric that describes the rate of growth of COVID-19 incidents leading up to a peak in COVID-19 incidents. This metric can be calculated as an average or as a maximum. Examples include *Cases Average Growth Rate*, *Cases Maximum Growth Rate*, *Deaths Average Growth Rate*, etc.

$$\text{Average Growth Rate} = \frac{1}{p_n - v_n} \int_{v_n}^{p_n} F'(t) dt \quad (3.2)$$

$$\text{Maximum Growth Rate} = \max_{v_n \leq t \leq p_n} \left[\frac{dF(t)}{dt} \right] \quad (3.2)$$

Note that these metrics, when used in later analyses, were broken into two categories: aggregated across all peaks and only the first peak (e.g. the average rate of growth of the first outbreak and the average rate of growth across all outbreaks). In the case of aggregation, a simple average was used to calculate the new metric.

3.6.1.6 Rate of Submission Metrics

A rate of submission metric is a metric that describes the rate of submission of COVID-19 incidents after a peak in COVID-19 incidents. This metric can be calculated as an average or as a maximum. Examples include *Cases Average Submission Rate*, *Cases Maximum Submission Rate*, *Deaths Average Submission Rate*, etc. These metrics were aggregated during later analyses like the rate of growth metrics.

$$\text{Average Submission Rate} = \frac{1}{v_{n+1} - p_n} \int_{p_n}^{v_{n+1}} F'(t) dt \quad (3.2)$$

$$\text{Maximum Submission Rate} = \min_{p_n \leq t \leq v_{n+1}} \left[\frac{dF(t)}{dt} \right] \quad (3.2)$$

3.6.1.7 Length of Outbreak Metrics

A length of outbreak metric describes the amount of time a peak in a country's COVID-19 incident data was observed (e.g. how long an individual outbreak lasted). This metric is composed of two different length metrics: *Length of Growth* and *Length of Submission*. Like the rate of growth metrics, these metrics could be aggregated during later analyses.

$$\text{Length of Growth} = p_n - v_n \quad (3.2)$$

$$\text{Length of Submission} = v_{n+1} - p_n \quad (3.2)$$

$$\text{Total Outbreak Length} = v_{n+1} - v_n \quad (3.2)$$

3.6.1.8 Incident Peak Value Metrics

An incident peak value metric is a metric that describes the number of COVID-19 incidents that occurred at either a peak or valley. Examples include *Case Peak*, *Death Peak*, *Case Valley*, etc.

$$Peak Value = F(p_n) \quad (3.2)$$

3.6.2 Government Response Metrics

In this section, the calculation procedure for the government response metrics will be described. A full breakdown of all the government response metrics, and their type, can be found in Appendix __.

3.6.2.1 Maximum Index Value Metrics

A maximum index value metric describes the maximum values observed in one of the four main OxCGRT indexes over the time period used in this research. An example is *Maximum Stringency*.

$$Maximum Main Index Value = \max_t M(t) \quad (3.2)$$

3.6.2.2 Index Ratio Metrics

An index ratio metric is a metric that relates the scores across one of the OxCGRT main indexes to another in a ratio format. An example is *Economic Support to Containment Health Ratio*.

$$Main Index Ratio = \frac{\sum_t M_1(t)}{\sum_t M_2(t)} \quad (3.2)$$

3.6.2.3 Length of Elevated Response Metrics

A length of elevated response metric is a metric that counts the number of days where one of the OxCGRT subindexes was at an elevated level of response (above a threshold T). Examples include *Number of Days Public Transport Closed*, *Number of Days Facial Coverings in all Public Places*, *Number Days Restricting Gatherings (<100)*, etc.

$$Length of Elevated Response = \sum_t \begin{cases} \text{if } N(t) \geq T & 1 \\ \text{otherwise} & 0 \end{cases} \quad (3.2)$$

3.6.3 Risk Tolerance Metrics

In this section, the calculation procedure for the risk tolerance metrics will be described. A full breakdown of all the risk tolerance metrics, and their type, can be found

in Appendix ____.

3.6.3.1 Number of Incidents before Index Peak Metrics

A number of incidents before peak index metric is a metric that counts the number of COVID-19 incidents that occurred before the first peak in one of the four main OxCGRT indexes occurred. After the date of the first peak in one of the OxCGRT indexes was determined (p_1), the total prior incidents were calculated. Some examples of this type of metric include *Number of Cases before Peak Stringency* and *Number of Deaths before Peak Containment Health*.

$$\text{Number of Incidents before Main Index Peak} = \sum_0^{p_1} S(t) \quad (3.2)$$

3.6.3.2 Incident Growth Rate before Index Peak Metrics

An incident growth rate before index peak metric is a metric that calculates the growth rate (average and maximum) of COVID-19 incidents before the first peak in one of the four main OxCGRT indexes. After the first peak in one of the OxCGRT indexes was calculated (p_1), the preceding growth rate can be calculated. Examples of this metric include *Average Case Growth before Peak Government Response* and *Maximum Death Growth before Peak Economic Support*.

$$\text{Average Growth Rate before Main Index Peak} = \frac{1}{p_1 - 0} \int_0^{p_1} F'(t) dt \quad (3.2)$$

$$\text{Maximum Growth Rate before Main Index Peak} = \max_{0 \leq t \leq p_1} \left[\frac{dF(t)}{dt} \right] \quad (3.2)$$

3.6.3.3 Index Peak to Preceding Incidents Ratio Metrics

An index peak to preceding incidents ratio metric is a metric that describes the ratio between the first peak in one of the four OxCGRT Indexes and the number of incidents that preceded it. An example of this metric is *First Maximum Economic Support to Preceding Deaths Ratio*.

$$\text{Incidents before Main Index Peak to Main Index Peak Ratio} = \frac{\sum_0^{p_1} R(t)}{M(p_1)} \quad (3.2)$$

3.6.3.4 Number of Incidents before Subindex Threshold Metrics

A number of incidents before subindex threshold metric calculated the number of COVID-19 incidents observed before the level of one of the OxCGR's subindexes exceeded a threshold (T on day d). An example of this metric is *Number of Cases Before Facial Coverings in Some Public Places*.

$$\text{Number of Incidents before Subindex Peak} = \sum_0^d S(t) \quad (3.2)$$

3.6.3.5 Incident Growth Rate before Subindex Threshold Metrics

An incident growth rate before subindex threshold metric calculates the growth rate of COVID-19 incidents observed before the level of one of the OxCGR's subindexes exceeded a threshold (T on day d). Some examples of this metric include *Avg Cases Rate Before Stay-at-Home Total Lockdown* and *Max Death Rate Before All Schools Closed*.

$$\text{Average Growth Rate before Subindex Threshold} = \frac{1}{d-0} \int_0^d F'(t) dt \quad (3.2)$$

$$\text{Maximum Growth Rate before Subindex Threshold} = \max_{0 \leq t \leq d} \left[\frac{dF(t)}{dt} \right] \quad (3.2)$$

3.7 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.

3.7.1 Test Selection Procedure

There were five different types of statistical test that could have been performed between different sets of metrics: Pearson Correlation (Pearson, 1895), Spearman Correlation (Myers, Well, & Lorch, 2010), Kendall Association (Kendall, 1938), ANOVA (Fisher, 1919), and Kruskal–Wallis (Kruskal & Wallis, 1952). The type of significance test performed depended both upon the metrics' scale classification and normality. The

normality of ratio and interval scaled metrics was done by conducting a Shapiro-Wilkes Test (Shapiro & Wilk, 1965). 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 in Figure __.

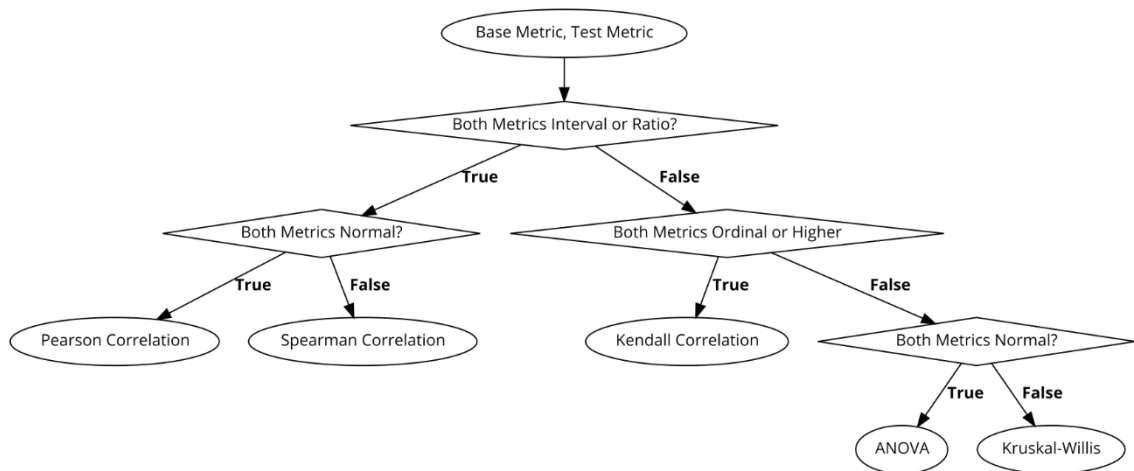


Figure 9 Statistical Test Selection Procedure

3.7.2 Confounding Variable vs Outbreak Severity Metrics

Statistical testing, following the test selection procedure, was performed between the possible confounding variables and the calculated outbreak severity metrics to determine the relationships between them and whether or not they were significant (i.e. if possible confounding metrics could be found). A full breakdown of all the confounding variables, and their types, can be found in Appendix __.

3.7.3 GHS Rankings vs Outbreak Severity Metrics

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

variables.

3.7.4 Confounding Variables vs Government Response Metrics

Statistical testing, following the test selection procedure, was performed between the possible confounding variables and the calculated government response metrics. This was done to see if any confounding variables could be identified as possible predictors as to the severity of a country's COVID-19 government response.

3.7.5 GHS Rankings vs Government Response Metrics

Statistical testing, following the test selection procedure, was performed between the *GHS Rankings* and the calculated government response metrics (from the OxCGR Index). This was done to determine if the GHS Rankings could act as predictors as to the severity of a country's COVID-19 government response.

3.7.6 Confounding Variables vs Risk Tolerance Metrics

Statistical testing, following the test selection procedure, was performed between the possible confounding variables and the calculated risk tolerance metrics. This was done to see if any confounding variables could be identified as possible predictors as to the observed risk tolerance country's demonstrated in response to the COVID-19 Pandemic.

3.7.7 GHS Rankings vs Risk Tolerance Metrics

Statistical testing, following the test selection procedure, was performed between the *GHS Rankings* and the calculated risk tolerance metrics. This was done to see if the GHS Rankings could be used as possible predictors as to the observed risk tolerance country's demonstrated in response to the COVID-19 Pandemic.

3.8 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. The detailed index breakdown can be found in Appendix

—.

3.8.1 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. Within each subindex, the metrics were broken into different groups where each group was given the same weight. For example, under the *Initial Outbreak: Cases* subindex, the two metrics *Cases Average Growth Rate* and *Cases Maximum Growth Rate* were in the same group, which was weighted the same as the group containing the length of outbreak metrics (*Cases Growth Length*, *Cases Submission Length*, *Cases Total Length*).

3.8.2 Response Severity

The response severity subindex was made up of three equally weighted subindexes: severity, relative economic support, and length of elevated response. It was composed of metrics derived from the OxCGRT index data. Within each subindex, similar to the outbreak severity index, similar metrics were grouped together and every group was weighted the same within each subindex.

3.8.3 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 up of two equally weighted subindexes: strict measures and most strict measures.

3.8.4 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.

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 to be 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 performance within the metrics.

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In this section the results of the statistical tests and the rankings will be discussed. 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. At the end, I will also present a case to highlight my research.

4.1 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 relationships to the base metric are given.

4.1.1 Confounding Variables vs Outbreak Severity Metrics

The 42 outbreak severity metrics derived from every country's COVID-19 data were tested against the possible confounding variables. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix ____.

Table 1 Confounding Variables vs. COVID-19 Data - Ratio/Integer Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
GDP	6	14.3%
Government Net Lending/Borrowing	1	2.4%
Median Age	19	45.2%
Population Density	0	0%
Press Freedom Score	2	4.8%
Unemployment Rate	0	0%
WHO Healthcare Index Score	22	52.4%

As shown in Table __, only Median Age and WHO Healthcare Score were a significant and relatively strong or strong predictors of the severity of a country's COVID-19 Pandemic outbreak. The fact that Median Age was a significant predictor across many metrics appears to confirm other researcher's findings and conforms with the notion that the COVID-19 virus disproportionately affects the elderly. However, the results that a

country's WHO Healthcare Score was a significant predictor of a country's COVID-19 outbreak severity was surprising because, in many cases, there was a significant and strong relationship in the opposite of expectation. One would expect countries with higher WHO Healthcare Scores to have a less severe pandemic outbreak. However, across COVID-19 Incident, Incident Growth Rate, and Outbreak Length metrics, country's with higher WHO Healthcare Scores were shown to have more COVID-19 incidents, higher incident growth rates, and longer outbreaks than countries with lower WHO Healthcare Scores. However, when it came to Incident Submission metrics, the significant relationships existed in the direction of expectation.

Table 2 Confounding Variables vs. Outbreak Severity Metrics - Ordinal Metrics

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

As shown in Table ___, a country's Press Freedom Rank nor its WHO Healthcare Rank had any significant and relatively strong or strong relationships with a country's Outbreak Severity.

Table 3 Confounding Variables vs. Outbreak Severity Metrics - Nominal Metrics

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

As shown in Table ___, across a majority of metrics, significant differences existed between the groups of Categorical Income Level, Geographic Region, and Press Freedom Category in relation to the outbreak severity. In terms of Press Freedom, countries with categorically lower Press Freedom Ranks experienced less COVID-19 incidents, shorter outbreaks, less severe growth rates, and fast submission rates compared with country's with categorically higher press freedom ranks. In terms of Geographic Region, North America, Europe, and Latin America experienced more COVID-19 Incidents than the rest of the world where Oceania, Eastern Asia, Central Asia, Africa, Southeastern Asia, and Southern Asia experienced less COVID-19 incidents. Europe, North America, and Western Asia experienced higher growth rates while Africa, Central Asia, Eastern Asia, Oceania, Southeastern and Southern Asia experienced lower growth rates. However, this

relationship was inverted when it came to submission rates. Then, in terms of Outbreak Length, Africa, Central Asia, Eastern Asia, Europe, North America, Southern Asia, and Western Asia experienced longer outbreaks whereas Latin America, Oceania, and Southeastern Asia experienced shorter outbreaks. Finally, higher income countries experienced more COVID-19 incidents, longer outbreaks, and higher growth rates than lower income countries. However, this relationship was inverted when it came to submission rates.

4.1.2 GHS Rankings vs Outbreak Severity Metrics

The GHS Rankings were tested against the Outbreak Severity metrics. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix ____.

Table 4 GHS Rankings vs. Outbreak Severity Metrics - Ratio/Integer Metrics

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

As shown in Table __, only the risk index score was a significant predictor of a country's outbreak severity. In the case of risk, countries with higher (better) risk scores had higher COVID-19 incidents, growth rates, and longer outbreaks compared to countries with lower (worse) risk scores. However, this relationship was inverted in the case of submission rates.

Table 5 GHS Rankings vs. Outbreak Severity Metrics - Nominal Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Overall	32	76.2%
Detect	35	83.3%
Health	37	88.1%

Norms	6	14.3%
Prevention	37	83.3%
Respond	27	64.3%
Risk	32	76.2%

As shown in Table __, all but the Norms index proved to be a significant predictor for a majority of metrics when the GHS Rankings were interpreted categorically. As with the conclusions from the ratio/integer metrics, across the overall, detect, health, prevention, respond, and risk scores, countries with higher categorical ranks were associated with higher COVID-19 incident, growth rates, and outbreak length, but higher submission rates compared to countries with lower categorical ranks.

4.1.3 Confounding Variables vs Government Response Metrics

The Confounding Metrics were tested against the 25 Government Response metrics. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix __.

Table 6 Confounding Variables vs. Government Response Metrics - Ratio/Integer Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
GDP	0	0%
Government Net Lending/Borrowing	0	0%
Median Age	5	20%
Population Density	0	0%
Press Freedom Score	3	12%
Unemployment Rate	0	0%
WHO Healthcare Index Score	4	16%

As shown in Table __, none of the confounding variables proved to be a significant and relatively strong or strong predictor of the severity of a country's government response.

Table 7 Confounding Variables vs. Government Response Metrics - Ordinal Metrics

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

As shown in Table __, none of the confounding variables, when considered ordinally, proved to be a significant predictor of the severity of a country's government response.

Table 8 Confounding Variables vs. Government Response Metrics - Nominal Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Categorical Income Level	21	84%
Geographic Region	21	84%
Press Freedom Category	11	44%

As shown in Table __, Categorical Income Level and Geographic Region showed significant different between categorical groups in terms of government response. In terms of Geographic Region, Asian regions had the most stringent government responses and held the most strict measures the longest compared to Africa and Oceania, which were the least strict and held lockdown measures the shortest. In terms of categorical income, richer countries tended to give more economic support, and held strict measures for less time compared to lower middle income and upper middle-income countries. Although low income countries did not provide a lot of economic support, their length of maintaining of strict measures was similar to high income countries.

4.1.4 GHS Rankings vs Government Response Metrics

The GHS Rankings were tested against the 25 Government Response metrics. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix __.

Table 9 GHS Rankings vs. Outbreak Severity Metrics - Ratio/Integer Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Overall	5	20%
Detect	0	0%
Health	3	12%
Norms	0	0%
Prevention	3	12%
Respond	3	0%

Risk	5	20%
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As shown in Table ___, none of the GHS Ranking's Indexes proved to be a significant and relatively strong or strong predictor of the severity of a country's government response.

Table 10 GHS Rankings vs. Outbreak Severity Metrics - Nominal Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Overall	18	72%
Detect	11	44%
Health	12	48%
Norms	2	8%
Prevention	19	76%
Respond	10	40%
Risk	21	84%

As shown in Table ___, the categorical rank of the Overall, Prevention, and Risk indexes proved to be a significant predictor of when significant differences between categorical groups in terms of government response existed. Furthermore, the Detect, Health, and Respond Indexes did so to a lesser extent. Across these categories, countries ranked as more prepared held strict measures longer than both most and least prepared countries. In terms of maximum response severity and economic response severity compared to other severity measures, most prepared countries had the lowest maximum response severity while the least prepared countries had the highest; this relationship held true for the relative severity of a countries economic response compared to other measures.

4.1.5 Confounding Variables vs Risk Tolerance Metrics

The possible confounding variables were tested against the 140 different risk tolerance metrics. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix ___.

Table 11 Confounding Variables vs. Risk Tolerance Metrics - Ratio/Integer Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
GDP	11	7.9%
Government Net Lending/Borrowing	1	0.7%

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Median Age	86	61.4%
Population Density	0	0%
Press Freedom Score	18	12.9%
Unemployment Rate	0	0%
WHO Healthcare Index Score	101	72.1%

As shown in Table ____, only Median Age and WHO Healthcare Index Score proved to be significant predictors of the observed risk tolerance countries demonstrated in handling the COVID-19 Pandemic. Across most risk tolerance metrics, countries with higher median ages tended to enact strict measures after experiencing higher COVID-19 incidents and growth rates compared to countries with lower median ages. Accordingly, countries with higher Median Ages strictest index-measured response was lower (when compared on a ratio basis) to the number of COVID-19 instances they had already experienced. The same findings were found when it came to WHO Healthcare Scores as countries with high healthcare scores also observed higher COVID-19 incidents and growth rates before enacting stricter pandemic control measures.

Table 12 Confounding Variables vs. Risk Tolerance Metrics - Ordinal Metrics

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

As shown in Table ____, both a country's Press Freedom and WHO Healthcare ordinal rank both did not serve as a significant and relatively strong or strong indicator of a country's observed risk tolerance during the COVID-19 Pandemic.

Table 13 Confounding Variables vs. Risk Tolerance Metrics - Nominal Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Categorical Income Level	134	95.7%
Geographic Region	128	91.4%
Press Freedom Category	108	77.9%

As shown in Table ____, across the majority of risk tolerance metrics, there were significant differences between the categorical groups for Categorical Income Level, Geographic Region, and Press Freedom Category. Across nearly all significant relationships, the better the categorical grouping in terms of Press Freedom Categories

corresponded to enacting strict control measures later (in terms of outbreak severity) when compared with worse categorical groupings of press freedom rankings. Generally, North American, European, and Western Asian countries waited the longest (in terms of pandemic severity) to enact stricter pandemic control measures while Southern Asia, Southeastern Asia, and Africa were some of the quickest. Similarly, countries with higher categorical income prove the most reluctant to enact strict pandemic control measures while low income and middle-income countries were quicker to do so.

4.1.6 GHS Rankings vs Risk Tolerance Metrics

The GHS Rankings were tested against the 140 Risk Tolerance metrics. The following tables present the results based on the scaling method of the metrics. The full results can be found in Appendix ____.

Table 14 GHS Rankings vs. Risk Tolerance Metrics - Ratio/Integer Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Overall	51	36.4%
Detect	2	1.4%
Health	61	43.6%
Norms	0	0%
Prevention	55	39.3%
Respond	1	0.7%
Risk	106	75.7%

As shown in Table ____, only the Risk score proved to be a significant indicator as to the observed risk tolerance demonstrated by a country in a majority of metrics. The Overall, Health, and Prevention scores were lesser indicators and were significant for less than 50% of calculated risk metrics. Across the risk tolerance metrics for which the Overall, Health, Prevention, and Risk scores were significant indicators, countries with higher (better) scores were shown to implement strict measures later (in terms of pandemic outbreak severity) compared to countries with lower (worse) scores.

Table 15 GHS Rankings vs. Risk Tolerance Metrics - Nominal Metrics

Base Metric	# of Significant Metrics	% of Significant Metrics
Overall	113	80.7%
Detect	102	72.9%

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Health	139	99.4%
Norms	33	23.6%
Prevention	123	87.9%
Respond	92	65.7%
Risk	126	90%

As shown in Table ____, when countries in the GHS Rankings were split into different categorical groups, across the Overall, Detect, Health, Prevention, Respond, and Risk indexes, there were significant differences between categorical groups in relation to the Risk Tolerance metrics. As observed with the ratio/integer metrics, the countries that were labeled as being most prepared demonstrated significantly higher risk tolerance (in terms of enacting strict pandemic control measures later in terms of their observed outbreak severity) compared to countries labeled as least prepared. Such a relationship was observed across nearly all significant relationships.

4.2 Index Results

In this section the results of the composite index and three main subindexes will be detailed. All G20 members will be listed for each index in Table ____. The full index is in the Appendix ____.

Table 16 Indexes of G20 Countries

Country	<u>Composite</u>		<u>Outbreak Severity</u>		<u>Response Severity</u>		<u>Risk Tolerance</u>	
	Index	Rank	Index	Rank	Index	Rank	Index	Rank
China	.7915	10	.6864	62	.7600	2	.9280	62
India	.7564	37	.5389	141	.7341	6	.9962	6
Indonesia	.7052	80	.6114	113	.6483	52	.8558	94
Australia	.6874	90	.7086	38	.5679	95	.7857	110
Argentina	.6754	96	.3856	172	.7359	5	.9047	70
South Korea	.6681	101	.6873	60	.5348	114	.7822	112
Saudi Arabia	.6635	103	.5314	147	.6521	47	.8071	106
Russia	.6591	107	.5223	148	.6180	70	.8370	99
South Africa	.6480	110	.4549	162	.5947	84	.8945	75

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Mexico	.6445	115	.4705	159	.7052	16	.7576	118
Japan	.6097	128	.6668	87	.2470	172	.9158	67
Canada	.5980	134	.5659	128	.5356	113	.6926	130
Turkey	.5567	149	.5846	121	.5498	103	.5355	152
Brazil	.5476	151	.4052	169	.6715	36	.5661	149
France	.5242	154	.4931	154	.5923	88	.4873	156
Germany	.5164	156	.5825	125	.6034	78	.3632	166
United States	.5049	157	.4029	170	.6064	76	.5053	155
Italy	.5039	158	.4359	167	.6566	43	.4193	161
Great Britain	.4937	159	.4673	160	.4898	128	.5239	153

4.2.1 Composite Index

The composite index can be used to analyze the handling of the COVID-19 Pandemic in every country through the equal weight of outbreak severity, response severity, and risk tolerance. Countries that perform well in this index have relatively less severe outbreaks, more severe responses, and low-risk tolerance compared to countries that do not perform well on this index.

4.2.2 Outbreak Severity Index

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.

4.2.3 Response Severity Index

The response severity index details the relative severity of the government response actions taken to combat COVID-19. Countries that do well in this index will have relatively higher government response values, stringency values, high economic support values, economic support ratios, and more time in lockdowns than countries that do not do well in this index.

4.2.4 Risk Tolerance Index

The risk tolerance index details which countries had a relatively lower risk tolerance towards government response considering the pandemic severity in their country at the time. Countries that perform well in this index will have relatively better pandemic severity metrics before the enactment of strict measures (both for the first outbreak and subsequent outbreaks) when compared to countries that do not do well in this index

4.3 A Case Example

A Time article titled *The Best Global Responses to the COVID-19 Pandemic, 1 Year Later* (Bremmer, 2021) provides an interesting comparison to contrast with the results of my research. This article, when describing the countries that it deems the have handled the pandemic the best, lists the number of COVID-19 cases and deaths from both June 2020 and February 2021. It specifically names eight countries as having handled the pandemic the best: Singapore, South Korea, New Zealand, Australia, Canada, Germany, Iceland, and the UAE. For the sake of comparison, let us compare these country's index rankings to four other countries: China, Eritrea, Vietnam, and the USA. These rankings are shown in Table ____.

Table ____

Country	<u>Composite</u>		<u>Outbreak Severity</u>		<u>Response Severity</u>		<u>Risk Tolerance</u>	
	Index	Rank	Index	Rank	Index	Rank	Index	Rank
Eritrea	.8577	1	.8787	9	.7043	17	.9902	15
Vietnam	.7982	8	.7260	27	.6704	38	.9983	3
China	.7915	10	.6864	62	.7600	2	.9280	62
UAE	.6946	87	.6711	80	.5933	86	.8193	102
Australia	.6874	90	.7086	38	.5679	95	.7857	110
New Zealand	.6835	91	.7341	20	.4397	149	.8767	84
South Korea	.6681	101	.6873	60	.5348	114	.7822	112
Singapore	.6635	103	.5314	147	.6521	47	.8071	106
Canada	.5980	134	.5659	128	.5356	113	.6926	130
United States	.5049	157	.4029	170	.6064	76	.5053	155

Iceland	.4535	166	.6634	89	.2985	171	.3986	162
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When comparing the conclusions from this article to the results of my research, the importance of my research becomes apparent. This article appears to demonstrate how, when only looking at the most basic COVID-19 metrics (e.g. total cases and deaths) and considering government response qualitatively, one may choose the wrong countries to study more in-depth for new pandemic control policy creation. My research prevents such a problem by considering more COVID-19 data metrics to obtain a fuller picture of a country's COVID-19 outbreak severity. Additionally, by considering government response quantitatively, while also introducing the idea of risk tolerance, it produces a much clearer view of which country's government response is worth further study.

Without my research, policy makers may be inclined to focus on Germany for new pandemic control policy. However, when examined quantitatively, Germany's responses were remarkably similar, quantitatively when aggregated, compared to the United States. Additionally, none of the countries identified in this article were elite in the composite index or any of the subindexes. The only top 50 rankings in any index was New Zealand and Australia, who ranked 20th and 38th in Outbreak Severity respectively. In short, this article demonstrates how the absence of detailed quantitative analysis and an overreliance on qualitative inferences leads to misconceptions about which countries best handled the COVID-19 Pandemic.

Additionally, the takeaways from this article appears to heavily favor countries with closer cultural and economic ties to the western world. Despite that Africa, quantitatively speaking, was one of the best geographic regions to handle the COVID-19 Pandemic, not a single African country was included on this list. This article appears biased towards high income countries as every country it includes would be considered a developed country. Two countries that would be considered developing or under-developed: Eritrea and Vietnam, both vastly outperformed every country this article listed.

Finally, it is important to acknowledge how China may not be getting its due credit for its handling of the COVID-19 Pandemic. Despite vastly outperforming every country included in this article, when speaking quantitatively, this article only credited China with having strong leadership during the COVID-19 Pandemic. Based on my research, China's entire pandemic response is worthy of future research in terms of future pandemic control policy. China was faced with, what may have been, the hardest challenge of any country in the world as the COVID-19 Pandemic originated in Wuhan. Thus, the fact that,

according to my research, China had one of the best COVID-19 responses in the world highlights how they are not being given their due credit on the international stage.

CHAPTER 5 CONCLUSIONS

In this section, I will discuss the possible conclusions that can be drawn from my research.

5.1 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 did not 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 for this comes 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) delayed enacting strict measures 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 inverse 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 entirety of the COVID-19 pandemic situation. Rather, through the analysis performed in my 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 led to a more severe observable pandemic outbreak.

5.2 Confounding Variables

The fact that the metrics I calculated and statistically evaluated found that median age was a confounding/predicting factor for the severity of a country's COVID-19 pandemic outbreak should serve as proof of the validity and usability of the metrics that were calculated and the subsequent analyses that were 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 \citep{davies2020age}. 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 my 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 finding was Categorical Income Level. Significant 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 severe pandemic outbreaks is not particularly new and significant. However, the fact that low- and high-income countries maintained strict and most strict lockdown measures shorter than lower middle and upper middle-income countries is interesting. This is because, it would seemingly imply that low-income countries were somewhat forced to have short lockdowns because of the inability to afford longer shutdowns and thus their response mirrored that of high-income countries who had short

lockdowns due to their strong trust in their current health systems.

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 severe pandemic outbreaks than countries with higher press freedom rankings. Secondly, it was found that countries with lower press freedom rankings also enacted stricter lockdown measures, 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 policies 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 current available data.

5.3 Country Profile

Based upon the results of the statistical analyses that I conducted, I can construct a profile containing general characteristics that describe countries' that best handled the COVID-19 Pandemic. 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 outbreaks 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 maintained 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 shutdowns latest (in relation to their observed pandemic outbreak severity).
 - Countries with high income tended to enact strict lockdown measures latest.
 - Countries with high press freedom rankings enacted strict lockdown measures latest.

Thus, the profile of a country that best handled the COVID-19 Pandemic outbreak would have a low WHO Healthcare Score, low median age, low income, and be located in Africa or Asia. However, it is important to discuss the limitations of such a profile. Throughout each of the statistical analyses involving confounding variables, more correlations 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 fits this profile is far from a guarantee that it is the best choice to model future pandemic control policy after. 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.

5.4 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) policy makers have the option to examine the results in more detail and weight the subindexes as they see appropriate. Although the current composite index provides an equally weighted and well-rounded view of the pandemic and government response actions, if, for example, a policy maker only wished to know about the response severity of a given country, they can exclusively 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 appropriately used as an ordinal tool rather than an integer or ratio tool. For example, in the composite index France scored a 0.5242 and the USA scored a .5049. A proper takeaway could be "overall, the USA handled the COVID-19 pandemic outbreak worse than France" (an ordinal takeaway). The interval takeaway, "the USA handled the COVID-19 Pandemic Outbreak 0.0193 points worse than France", while correct, lacks meaning because the index is unitless. Accordingly, a ratio-based comparison, like "the USA handled the COVID-19 Pandemic 3.75% worse than France", would be an inappropriate conclusion.

The indexes themselves have enough parity for practical use. The composite index ranges from .3490 to .8577, the outbreak severity index ranges from .3776 to .9159, the response severity index ranges from .2039 to .7720, and the risk tolerance index ranges from .1298 to .9997. 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 170 and 169 respectively (out of 174). For the response severity index, Japan (who has been noted for less severe government response and lockdowns) was 172 (out of 174) and China (who has been noted for having strict lockdowns) was 2 (out of 174). For the risk tolerance index, Sweden (who was noted as willing to have little government action as the first pandemic outbreak began) was 163 (out of 174).

5.5 Contributions

In terms of the overall research on this topic, my research contributed the following:

1. It is the first work that explicitly created a composite index or ranking system that quantitatively described every country's handling of the COVID-19 Pandemic.

2. By analyzing every country, it has resulted in a generalized profile that summarized the characteristics of country's that best handled the COVID-19 Pandemic.
3. The utilization of a longer timeframe (January 2020 to December 2020) allowed for a more complete view of every country's handling of the COVID-19 Pandemic to be created.
4. The methodology on how to derive advanced metrics from every country's COVID-19 data introduced a biased minimized approach to do so while working on every country's data.
5. The calculation of risk tolerance metrics is unique and captures another important lens in which pandemic policy can be viewed and measured.

CHAPTER 6 FUTURE WORK

In this section, topics for future research are discussed and how they relate to the research conducted.

6.1 Incorporating Vaccine Distribution

For my research, I stopped raw data collection on December 31, 2020 as that is approximately when vaccine distribution began in some countries on a large scale. I primarily wanted to focus on how countries handled the pandemic outbreak and will be vital in formulating policy to combat the next pandemic outbreak. However, vaccine distribution will prove pivotal in allowing countries to truly return to normal operation like before the COVID-19 Pandemic. Furthermore, the uneven 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” (UN News, 2021). The effects of this, and how other countries who have not reached herd immunity respond after other countries have, will also be important to consider. It is likely a range of responses, from a country without herd immunity lifting all restrictions to countries with herd immunity to maintaining all restrictions, are possible and can be quantified into a relative attractiveness ranking. Thus, vaccine distribution will likely prove to be a whole different research problem in itself.

6.2 Industry Specific Applications

The indexes I calculated were relative in nature and although they allow for important conclusions to be drawn and can be use actionably, they come with limitations. Because they are relative in natures, their application in specific industries, as opposed to being a starting point for policy research, is limited. However, if the indexes were able to be tied to direct data, these limitations could be overcome. For example, a company who was looking to geographically diversify their supply chain to combat the risk of a future pandemic outbreak may find my research interesting. If they were able to tie their company's data directly into my indexes, tangible and actionable geographic supply chain

diversification decisions could be made. However, such research may have difficulty occurring academically due to large companies' general sensitivity with sharing such intimate data publicly. Thus, this avenue of research is much more likely to take place internally.

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APPENDIX A DATA SOURCES

In this section, link to my GitHub that contain the data sources I used in this research are provided.

A.1 COVID-19 Incident Data

- COVID-19 Case Data:
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/Case_Data.csv
- COVID-19 Death Data:
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/Death_Data.csv
- COVID-19 Testing Data:
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/covid-testing-all-observations.csv

A.2 Government Response Data

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/OxCGRT_timeseries_all.xlsx

A.3 Pandemic Preparedness Data

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/GHS%20Rankings.csv

A.4 Healthcare Performance Data

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/GHS%20Rankings.csv

[end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/WHO%20Healthcare%20Rankings.csv](https://github.com/theo-tsinghua/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/WHO%20Healthcare%20Rankings.csv)

A.5 Global Economic Data

[https://github.com/theo-tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/IMF%20Economic%20Rankings.csv](https://github.com/theo-tsinghua/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/IMF%20Economic%20Rankings.csv)

A.6 Population Data

https://github.com/theo-tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/Population_Data.csv

A.7 Press Freedom Data

https://github.com/theo-tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/Press%20Freedom%20Rankings.csv

APPENDIX B OUTLIERS

In this section, I have provided links to my GitHub with the outliers removed through my outlier removal algorithms. I have also provided pseudocode for these algorithms.

B.1 Known Outliers

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/Known_Outliers.csv

B.2 Negative Outliers

- COVID-19 Negative Case Outliers
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cases_Negative_Instances.csv
- COVID-19 Negative Death Outliers
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Deaths_Negative_Instances.csv

B.3 Manual Outliers

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Read%20Files/Manual_Outliers.csv

B.4 New Value Algorithm

B.5 Redistribution Algorithm

APPENDIX C SMOOTHENING, INTERPOLATION, & PAIRING

In this section, links to my GitHub where graphs detailing the smoothed and interpolated data will be provided. The pseudocode for the peak finding algorithms will also be provided.

C.1 Raw, Moving Average, and Smoothed Data Graphs

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Basic_Data_Graphs.pdf

C.2 Peak Finding Graphs

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Peak_Finding_Graphs.pdf

C.3 Key Point Addition Graphs

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Interpolation_Graphs.pdf

C.4 Initial Peaks Algorithm

C.5 Valley Finding Algorithm

C.6 Peak Pruning Algorithm

C.7 Final Pruning Algorithm

C.8 Key Point Addition Algorithm

C.9 Peak Pairing Graphs

https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Peak_Pairing_Graphs.pdf

APPENDIX D CALCULATED METRICS

The link to the master excel sheet that contain all of the calculated metrics for every single country can be found at the following link.

- https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Country_Metrics.xlsx

APPENDIX E METRIC CLASSIFICATION

In this section, classification lists for all the calculated metrics are provided. These detail how each specific metric was calculated within each metric category. For example, *Total Cases per Million* is classified as a Total Incidents Metric under the Outbreak Severity Metric category. Therefore, it is calculated using the Total Incident Metrics equation.

E.1 Outbreak Severity Metrics

- Total Incidents Metrics
 - Total Cases per Million
 - Total Deaths per Million
 - Total Tests per Million
- Summation Ration Metrics
 - Case-Death Ratio
 - Test-Case Ratio
- Peak Pair Ratio Metrics
 - Case-Death Pair Peak Ratio
- Number of Incident Peaks Metrics
 - Number of Cases Peaks
 - Number of Deaths Peaks
- Rate of Growth Metrics
 - Cases Average Growth Rate
 - Cases Maximum Growth Rate
 - Cases Average Growth Rate (First Outbreak)
 - Cases Maximum Growth Rate (First Outbreak)
 - Deaths Average Growth Rate
 - Deaths Maximum Growth Rate
 - Deaths Average Growth Rate (First Outbreak)
 - Deaths Maximum Growth Rate (First Outbreak)
- Rate of Submission Metrics

- Cases Average Submission Rate
- Cases Maximum Submission Rate
- Cases Average Submission Rate (First Outbreak)
- Cases Maximum Submission Rate (First Outbreak)
- Deaths Average Submission Rate
- Deaths Maximum Submission Rate
- Deaths Average Submission Rate (First Outbreak)
- Deaths Maximum Submission Rate (First Outbreak)
- Length of Outbreak Metrics
 - Cases Growth Length
 - Cases Submission Length
 - Cases Total Length
 - Cases Growth Length (First Outbreak)
 - Cases Submission Length (First Outbreak)
 - Cases Total Length (First Outbreak)
 - Deaths Growth Length
 - Deaths Submission Length
 - Deaths Total Length
 - Deaths Growth Length (First Outbreak)
 - Deaths Submission Length (First Outbreak)
 - Deaths Total Length (First Outbreak)
- Incident Peak Values Metrics
 - Cases Peak Value
 - Cases Valley Value–Cases Peak Value (First Outbreak)
 - Cases Valley Value (First Outbreak)
 - Deaths Peak Value–Deaths Valley Value
 - Deaths Peak Value (First Outbreak)
 - Deaths Valley Value (First Outbreak)

E.2 Government Response Metrics

- Maximum Index Value Metrics
 - Maximum Stringency
 - Maximum Government Response

- Maximum Containment Health
- Maximum Economic Support
- Index Ratio Metrics
 - Economic Support to Containment Health Ratio
 - Economic Support to Stringency Ratio
 - Economic Support to Government Response Ratio
- Length of Elevated Response Metrics
 - Number of Days Some Sectors Closed
 - Number of Days All Non-Essential Sectors Closed
 - Number of Days Public Transport Closed
 - Number of Days Stay-at-Home except for Essential Trips
 - Number of Days Stay-at-Home Total Lockdown
 - Number of Days Internal Movement Restricted
 - Number of Days International Bans for some Countries
 - Number of Days International Bans Total Border Closure
 - Number of Days Public Information Campaign
 - Number of Days Facial Coverings in Some Public Places
 - Number of Days Facial Coverings in All Public Places
 - Number of Days Facial Coverings Mandate
 - Number of Days Some Schools Closed
 - Number of Days All Schools Closed
 - Number of Days Public Events Cancelled
 - Number of Days Restricting Gatherings (<1000)
 - Number of Days Restricting Gatherings (<100)
 - Number of Days Restricting Gatherings (<10)

E.3 Risk Tolerance Metrics

- Number of Incidents before Index Peak Metrics
 - Number of Cases Before Peak Containment Health
 - Number of Cases Before Peak Economic Support
 - Number of Cases Before Peak Government Response
 - Number of Cases Before Peak Stringency
 - Number of Deaths Before Peak Containment Health

- Number of Deaths Before Peak Economic Support
- Number of Deaths Before Peak Government Response
- Number of Deaths Before Peak Stringency
- Incident Growth Rate before Index Peak Metrics
 - Average Case Growth Before Peak Containment Health
 - Average Case Growth Before Peak Economic Support
 - Average Case Growth Before Peak Government Response
 - Average Case Growth Before Peak Stringency
 - Average Death Growth Before Peak Containment Health
 - Average Death Growth Before Peak Economic Support
 - Average Death Growth Before Peak Government Response
 - Average Death Growth Before Peak Stringency
 - Maximum Case Growth Before Peak Containment Health
 - Maximum Case Growth Before Peak Economic Support
 - Maximum Case Growth Before Peak Government Response
 - Maximum Case Growth Before Peak Stringency
 - Maximum Death Growth Before Peak Containment Health
 - Maximum Death Growth Before Peak Economic Support
 - Maximum Death Growth Before Peak Government Response
 - Maximum Death Growth Before Peak Stringency
- Index Peak to Preceding Incidents Ratio Metrics
 - First Maximum Containment Health to Preceding Cases Ratio
 - First Maximum Containment Health to Preceding Deaths Ratio
 - First Maximum Economic Support to Preceding Cases Ratio
 - First Maximum Economic Support to Preceding Deaths Ratio
 - First Maximum Government Response to Preceding Cases Ratio
 - First Maximum Government Response to Preceding Deaths Ratio
 - First Maximum Stringency to Preceding Cases Ratio
 - First Maximum Stringency to Preceding Deaths Ratio
 - Number of Incidents before Subindex Threshold Metrics
 - Number of Cases Before All Non-Essential Sectors Closed
 - Number of Cases Before All Schools Closed
 - Number of Cases Before Facial Coverings in All Public Places

APPENDIX E METRIC CLASSIFICATION

- Number of Cases Before Facial Coverings in Some Public Places
- Number of Cases Before Facial Coverings Mandate
- Number of Cases Before Internal Movement Restricted
- Number of Cases Before International Bans for some Countries
- Number of Cases Before International Bans Total Border Closure
- Number of Cases Before Public Events Cancelled
- Number of Cases Before Public Information Campaign
- Number of Cases Before Public Transport Closed
- Number of Cases Before Restricting Gatherings (<10)
- Number of Cases Before Restricting Gatherings (<100)
- Number of Cases Before Restricting Gatherings (<1000)
- Number of Cases Before Some Schools Closed
- Number of Cases Before Some Sectors Closed
- Number of Cases Before Stay-at-Home except for Essential Trips
- Number of Cases Before Stay-at-Home Total Lockdown
- Number of Deaths Before All Non-Essential Sectors Closed
- Number of Deaths Before All Schools Closed
- Number of Deaths Before Facial Coverings in All Public Places
- Number of Deaths Before Facial Coverings in Some Public Places
- Number of Deaths Before Facial Coverings Mandate
- Number of Deaths Before Internal Movement Restricted
- Number of Deaths Before International Bans for some Countries
- Number of Deaths Before International Bans Total Border Closure
- Number of Deaths Before Public Events Cancelled
- Number of Deaths Before Public Information Campaign
- Number of Deaths Before Public Transport Closed
- Number of Deaths Before Restricting Gatherings (<10)
- Number of Deaths Before Restricting Gatherings (<100)
- Number of Deaths Before Restricting Gatherings (<1000)
- Number of Deaths Before Some Schools Closed
- Number of Deaths Before Some Sectors Closed
- Number of Deaths Before Stay-at-Home except for Essential Trips
- Number of Deaths Before Stay-at-Home Total Lockdown

- Incident Growth Rate before Subindex Threshold Metrics
 - Average Case Rate Before All Non-Essential Sectors Closed
 - Average Case Rate Before All Schools Closed
 - Average Case Rate Before Facial Coverings in All Public Places
 - Average Case Rate Before Facial Coverings in Some Public Places
 - Average Case Rate Before Facial Coverings Mandate
 - Average Case Rate Before Public Events Cancelled
 - Average Case Rate Before Public Information Campaign
 - Average Case Rate Before Restricting Gatherings (<10)
 - Average Case Rate Before Restricting Gatherings (<100)
 - Average Case Rate Before Restricting Gatherings (<1000)
 - Average Case Rate Before Some Schools Closed
 - Average Case Rate Before Some Sectors Closed
 - Average Cases Rate Before Internal Movement Restricted
 - Average Cases Rate Before International Bans for some Countries
 - Average Cases Rate Before International Bans Total Border Closure
 - Average Cases Rate Before Public Transport Closed
 - Average Cases Rate Before Stay-at-Home except for Essential Trips
 - Average Cases Rate Before Stay-at-Home Total Lockdown
 - Average Death Rate Before All Non-Essential Sectors Closed
 - Average Death Rate Before All Schools Closed
 - Average Death Rate Before Facial Coverings in All Public Places
 - Average Death Rate Before Facial Coverings in Some Public Places
 - Average Death Rate Before Facial Coverings Mandate
 - Average Death Rate Before Public Events Cancelled
 - Average Death Rate Before Public Information Campaign
 - Average Death Rate Before Restricting Gatherings (<10)
 - Average Death Rate Before Restricting Gatherings (<100)
 - Average Death Rate Before Restricting Gatherings (<1000)
 - Average Death Rate Before Some Schools Closed
 - Average Death Rate Before Some Sectors Closed
 - Average Deaths Rate Before Internal Movement Restricted
 - Average Deaths Rate Before International Bans for some Countries

APPENDIX E METRIC CLASSIFICATION

- Average Deaths Rate Before International Bans Total Border Closure
- Average Deaths Rate Before Public Transport Closed
- Average Deaths Rate Before Stay-at-Home except for Essential Trips
- Average Deaths Rate Before Stay-at-Home Total Lockdown
- Maximum Case Rate Before All Non-Essential Sectors Closed
- Maximum Case Rate Before All Schools Closed
- Maximum Case Rate Before Facial Coverings in All Public Places
- Maximum Case Rate Before Facial Coverings in Some Public Places
- Maximum Case Rate Before Facial Coverings Mandate
- Maximum Case Rate Before Internal Movement Restricted
- Maximum Case Rate Before International Bans for some Countries
- Maximum Case Rate Before International Bans Total Border Closure
- Maximum Case Rate Before Public Events Cancelled
- Maximum Case Rate Before Public Information Campaign
- Maximum Case Rate Before Public Transport Closed
- Maximum Case Rate Before Restricting Gatherings (<10)
- Maximum Case Rate Before Restricting Gatherings (<100)
- Maximum Case Rate Before Restricting Gatherings (<1000)
- Maximum Case Rate Before Some Schools Closed
- Maximum Case Rate Before Some Sectors Closed
- Maximum Case Rate Before Stay-at-Home except for Essential Trips
- Maximum Case Rate Before Stay-at-Home Total Lockdown
- Maximum Death Rate Before All Non-Essential Sectors Closed
- Maximum Death Rate Before All Schools Closed
- Maximum Death Rate Before Facial Coverings in All Public Places
- Maximum Death Rate Before Facial Coverings in Some Public Places
- Maximum Death Rate Before Facial Coverings Mandate
- Maximum Death Rate Before Internal Movement Restricted
- Maximum Death Rate Before International Bans for some Countries
- Maximum Death Rate Before International Bans Total Border Closure
- Maximum Death Rate Before Public Events Cancelled
- Maximum Death Rate Before Public Information Campaign
- Maximum Death Rate Before Public Transport Closed

APPENDIX E METRIC CLASSIFICATION

- Maximum Death Rate Before Restricting Gatherings (<10)
- Maximum Death Rate Before Restricting Gatherings (<100)
- Maximum Death Rate Before Restricting Gatherings (<1000)
- Maximum Death Rate Before Some Schools Closed
- Maximum Death Rate Before Some Sectors Closed
- Maximum Death Rate Before Stay-at-Home except for Essential Trips
- Maximum Death Rate Before Stay-at-Home Total Lockdown

APPENDIX F CONFOUNDING VARIABLE CLASSIFICATION

The list the detail the scaling classification (i.e. ratio, integer, ordinal, or nominal) of all the confounding variables is shown below.

- Ratio/Integer Metrics
 - GDP
 - Government Net Lending/Borrowing (% of GDP)
 - Median Age
 - Population Density (per sq km)
 - Press Freedom Score
 - Unemployment Rate
 - WHO Healthcare Index Score
- Ordinal Metrics
 - Press Freedom Rank
 - WHO Healthcare Rank
- Nominal Metrics
 - Categorical Income Level
 - Geographic Region
 - Press Freedom Category

APPENDIX G DETAILED SUBINDEX DESCRIPTION

A link to my GitHub page that contains a detailed breakdown of every index and subindex that was calculated to make the composite index can be found at the link below. It has the relative and absolute weight of every metric used in each index.

- https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Index_Weighting_System.xlsx

APPENDIX H STATISTICAL CORRELATION TESTING

This section contains links to my GitHub where the excel files and graphical files detailing the results of all of the statistical correlation testing can be found. The excel files are contain the type of test performed between every metric, its results, and its significance.

H.1 Confounding Variables vs Outbreak Severity Metrics

- Excel File
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/C_onfounding_Variable_COVID_19_Metrics.xlsx
- Graphical Results
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/C_onfounding_Variable_COVID_19_Metrics.pdf

H.2 GHS Rankings vs Outbreak Severity Metrics

- Excel File
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/P_andemic_Preparedness_COVID_19_Metrics.xlsx
- Graphical Results
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/P_andemic_Preparedness_COVID_19_Metrics.pdf

H.3 Confounding Variables vs Government Response Metrics

- Excel File
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/C_onfounding_Variable_COVID_19_Metrics.xlsx

[end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cofounding_Variables_vs_Oxford_Indices_Tables.xlsx](https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cofounding_Variables_vs_Oxford_Indices_Tables.xlsx)

- Graphical Results
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cofounding_Variables_vs_Oxford_Indices_Graphs.pdf

H.4 GHS Rankings vs Government Response Metrics

- Excel File
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Pandemic_Preparedness_Rankings_vs_Oxford_Index_Metrics_Tables.xlsx
- Graphical Results
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Pandemic_Preparedness_Rankings_vs_Oxford_Index_Metrics_Graphs.pdf

H.5 Confounding Variables vs Risk Tolerance Metrics

- Excel File
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cofounding_Variables_vs_Risk_Tolerance_Tables.xlsx
- Graphical Results
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cofounding_Variables_vs_Risk_Tolerance.pdf

H.6 GHS Rankings vs Risk Tolerance Metrics

- Excel File
 - https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Cofounding_Variables_vs_Risk_Tolerance_Tables.xlsx

[end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Pandemic_Preparedness_Rankings_vs_Risk_Tolerance_Tables.xlsx](#)

- Graphical Results

- [https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Pandemic_Preparedness_Rankings_vs_Risk_Tolerance.pdf](#)

APPENDIX I FULL INDEX RESULTS

A link to my GitHub where the full index results can be found is located at the link below.

- https://github.com/theo-end/Tsinghua_Masters_Thesis/blob/main/Indices/Output%20Files/Composite_Index.xlsx

APPENDIX J CODE

A link to my GitHub where the full code I wrote to execute my research can be found at the link below.

- https://github.com/theo-end/Tsinghua_Masters_Thesis/tree/main/Code/Thesis%20Analysis

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声 明

本人郑重声明：所呈交的学位论文，是本人在导师指导下，独立进行研究工作所取得的成果。尽我所知，除文中已经注明引用的内容外，本学位论文的研究成果不包含任何他人享有著作权的内容。对本论文所涉及的研究工作做出贡献的其他个人和集体，均已在文中以明确方式标明。

签 名：_____日 期：_____

RESUME

Theodore Alexander Endresen (安多) was born on 31st October 1996 in Traverse City, Michigan, United States of America.

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RESOLUTION OF THESIS DEFENSE COMMITTEE

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