Performance Efficiency Evaluation of European Countries Healthcare Systems during the Pandemic (Covid-19) Using the Data Envelopment Analysis (DEA)

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ABSTRACT

In this paper, a non-parametric method known as Data Envelopment Analysis was used to analyse the efficiency of the healthcare systems of 48 European countries in managing the covid-19 pandemic. Using the constant returns to scale model of Charnes, Cooper and Rhodes (CCR) on input and output variables like total population, total covid-19 cases, total tests performed, total recoveries etc, the results showed that only 10 out of the 48 countries were optimally efficient in their management of the pandemic with some of the richest countries like France and Belgium being some of the poorest performers. Minimally developed countries like the Czech Republic, Andorra and Moldova were some of the best performers with Moldova being the most referenced optimal country in the benchmark test. It was shown that the inefficient countries like France and Belgium had to reduce the number of cases via distancing and lockdown measures to improve efficiency. The same goes for minimally efficient countries like the United Kingdom.

The results finally indicate that developmental indices like gross domestic product (GDP) had an insignificant impact on the efficiency of countries in managing the pandemic as very rich countries were poor performers, although their high populations likely skewed the efficiency ratios in comparison to high performing countries with low populations.

Keywords: Data Envelopment Analysis, DEA, CCR, European, Countries, Healthcare, Efficiency, Gross Domestic Product, Total Population, Covid-19, Tests

ÖZ

Bu makalede, Veri Zarflama Analizi olarak bilinen parametrik olmayan bir yöntem, covid-19 pandemisini yönetmede 48 Avrupa ülkesinin sağlık sistemlerinin etkinliğini analiz etmek için kullanılmıştır. Charnes, Cooper ve Rhodes'un (CCR) ölçek modeline göre sabit getiri modelini toplam nüfus, toplam covid-19 vakaları, gerçekleştirilen toplam testler, toplam geri kazanımlar gibi girdi ve çıktı değişkenleri üzerinde kullanarak, sonuçlar 48 ülkeden yalnızca 10'unun Fransa ve Belçika gibi en zengin ülkelerden bazıları en fakir performans gösteren ülkelerden bazıları ile pandemiyi idare etmede en iyi şekilde etkiliydi. Çek Cumhuriyeti, Andorra ve Moldova gibi minimal gelişmiş ülkeler, kıyaslama testinde en çok başvurulan optimal ülke olan Moldova ile en iyi performans gösteren ülkelerden bazılarıydı. Fransa ve Belçika gibi verimsiz ülkelerin verimliliği artırmak için mesafe ve tecrit tedbirleri yoluyla vaka sayısını azaltmak zorunda kaldığı gösterildi. Aynı durum Birleşik Krallık gibi minimum düzeyde verimli ülkeler için de geçerli.

Son olarak sonuçlar, gayri safi yurtiçi hasıla (GSYİH) gibi kalkınma endekslerinin, çok zengin ülkeler zayıf performans gösterenler olduğu için, ülkelerin pandemiyi yönetmedeki verimliliği üzerinde önemsiz bir etkiye sahip olduğunu göstermektedir.

Anahtar Kelimeler: Veri Zarflama Analizi DEA), CCR, Avrupa, Ülkeler, Sağlık Hizmetleri, Verimlilik, Gayri Safi Yurtiçi Hasıla, Toplam Nüfus, Covid-19, Pandemi, Testler

DEDICATION

I would like to dedicate this research work to my family.

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I truly appreciate you!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

In this introductory part of the thesis, the aim of the thesis, the nature of the problem and the aim of the thesis is discussed. The pandemic, its history, health care systems and health care efficiency are discussed.

1.1 Structure of the Thesis

The aim of this paper is to evaluate the efficiency of the healthcare systems of different countries in the coronavirus pandemic. This evaluation will be used to determine:

- Countries that were relatively efficient in the management of the pandemic with their healthcare systems.
- Introduce (Lambdas) benchmarks to determine and upgrade inefficient countries to be efficient.
- Output and input variables that are important to healthcare efficiency.
- Improving healthcare efficiency using the above variables.

The first chapter gave an introduction to the concept and terms employed in the paper. The second chapter will be a review of literature relevant to the study. The third chapter will detail the methodology used for the analysis. The fourth chapter will present the results and discuss the meaning of the results. The fifth chapter will be a conclusion.

1.2 The Problem

In late December 2019, a novel coronavirus known as the SARS-CoV-2 was discovered in Wuhan, China (He et al., 2020). By March 2020, the virus had spread from Wuhan to 153,517 people from 144 countries, causing 5,735 deaths (WHO, 2020). By January 2021, there have been 99,135,707 global cases with 2,127,963 deaths (URL2, 2021). Due to this level of spread and virulence, the virus is described as the “perfect storm (“wrong virus” at the “wrong time”). This “biological storm” has put unprecedented pressure on global healthcare systems, causing dramatic healthcare challenges and environmental contamination (Lippi et al., 2020). A report by the Chinese Center for Disease Control and Prevention clearly stated that SARS-CoV-2 will irreversibly derange the global healthcare system. In greater detail, although a majority of the cases will be mild (around 80%), up to 15% of the cases will be severe (needing at least ventilation support), whilst nearly 5% of all cases will develop critical illness, requiring intensive care (Wu et al., 2020). In providing support for patients of this syndrome in conjunction with patients of a virus like influenza, it is projected that nearly 208 million people will need mechanical ventilation support while 69 million people will need intensive care unit (ICU) admission worldwide. No health care system is prepared to face this virtually unpredictable challenge (Lippi et al., 2020). The management of highly limited healthcare resources by healthcare systems in the pandemic is thus a serious problem that must be analyzed.

1.3 The Coronavirus Pandemic

The coronavirus, also known as the Severe Respiratory Syndrome Coronavirus (SARS-CoV-2) is the causative agent of a respiratory syndrome. The disease was first discovered in late December 2019, in Wuhan, Hubei province, China (He et al., 2020). As of January 2021, according to the World Health Organization, the number of deaths due to the corona virus has exceeded 1.9 million. The coronavirus is primarily communicated through respiratory droplets and can thus pass between humans. The usual symptoms are fever, cough, labored breathing, and fatigue while rare symptoms include saliva and mucus production, headache, coughing of blood, and diarrhea. In China, COVID-19 cases had already passed 80,000 around March 2020, with the Hubei province of Wuhan accounting for over 80% of these cases and Wuhan itself accounting for over 60%. Globally, Germany, the United Kingdom, the United States, and 119 other countries have reported COVID-19 cases, majority of which spread by local transmission outside China (Wu et al., 2020). The exponential spread and virulence of this pandemic has put a heavy strain unprecedented on global health and economic systems, with global stock markets falling dramatically until governments began to intervene with financial packages to mitigate the shock (Nicola et al., 2020). This economic strain undoubtedly affected healthcare funding and spending, and also limited the availability of medical resources (Wu et al., 2020; Moss et al., 2020).

1.4 Healthcare Systems

The World Health Organization defines health systems as consisting of all organizations, people and actions whose primary intent is to promote, reet store or maintain health. This includes efforts to influence determinants of health as well as more direct health-improving activities (WHO, 2007). From the above definition, it is seen that health systems are responsible for managing the state of health at population level. This is extremely important in the case of a pandemic like SARS-CoV-2 which affects large swathes of the population at a high rate because, the efficiency of the health systems in the affected areas determines how well the pandemic can be contained.

Globally, different countries have different health systems which are strongly influenced by the fundamental prevalent societal norms and value in the respective countries (Lameire et al., 1999). There are three major types of healthcare systems globally which influences access to, quality and cost of healthcare. These systems are the Beveridge model, which is financed by taxation and public providers. The second is the Bismarck model or mixed model, financed by a social insurance system based on premiums consisting of a mixture of private and public providers. Finally, the 'Private Insurance model' which is only run by the United States of America. In the Beveridge model, access is nearly 100% while the private insurance model produces the highest cost but is least in access and quality (Lameire *et al*., 1999). The nature of these systems have had a great impact on health delivery and efficiency in the coronavirus pandemic.

1.5 Healthcare Efficiency

The efficiency of a healthcare system is generally synonymous to the the level of output (quality) from a given healthcare expenditure. This is especially true for economies with high and medium Human Development Index (HDI). Increasing the output derived from heath expenditure is the only option for overcoming age and tax related pressures (Asandului et al., 2014). This becomes more important due to the economic crash that accompanied the coronavirus pandemic. Managing productivity from expenditure involves a wide range of healthcare management facets such as maintaining efficient models for staffing, ensuring prompt procurement of equipment and optimal use of healthcare installations and infrastructure (Cantor and Poh, 2018).

Despite the importance of maximizing healthcare efficiency as it is useful in program management and policy making, it is difficult to measure and evaluate said efficiency using conventional techniques (Asandului et al., 2014; Huang and McLaughlin, 1989).

Historically, performance indicators and regression analysis have been used to evaluate efficiency related data (Cantor and Poh, 2018). But, due to the presence of multiple input and output variables in health efficiency data, a method based on mathematical programming was developed. This method is known as Data Envelopment Analysis (DEA). DEA is the most common method for analyzing health efficiency data.

1.6 Structure of the Thesis

The aim of this paper is to evaluate the efficiency of the healthcare systems of different countries in the corona virus pandemic. This study is important because it enables policy makers and health sector workers understand how they can optimize their operations and processes in this pandemic and in general health administration.

The first chapter gave an introduction to the concept and terms employed in the paper. The second chapter will be a review of literature relevant to the study. The third chapter will detail the methodology used for the analysis. The fourth chapter will present the results and discuss the meaning of the results. The fifth chapter will be a conclusion.

Chapter 2

LITERATURE REVIEW

2.1 Literature on Covid-19

Li et al., (2020) were the first in literature to describe the epidemiological and biological characteristics of the novel coronavirus known as the SARS-CoV-2 which causes covid-19, by analyzing the first 452 cases of the disease, which initially occurred in Wuhan, Hubei Province, China, in December 2019 and January 2020. On December 29, 2019, the first 4 cases reported, all linked to the Huanan (Southern China) seafood wholesale market. Fauci et al., (2020) recognized Covid-19 as a threat to global health, stating its similarity to the SARS and Middle Eastern Respiratory Syndrome (MERS) outbreaks. They predicted from the efficiency of transmission, a global spread of Covid-19, including in the United States, with a need for mitigation strategies such as isolating ill persons (including voluntary isolation at home), school closures, and telecommuting due to community spread as opposed to containment strategies. Guan et al., (2020) did work on the clinical symptoms of Covid-19 which included fever, cough and in severe cases, respiratory failure. Their study on 1099 patients showed a fatality rate of 1.3%. At this point, the WHO had declared covid-19 a global health emergency.

Velavan and Meyer (2020) observed that dense communities were at particular risk from the virus with Africa being the most vulnerable region due to:

- Dense traffic between China and Africa.

- Inadequacy of sufficient and appropriate diagnostic capacities among African countries, coupled with obvious health challenges exist to handle such outbreaks.

According to the authors, WHO has identified 13 top-priority countries (Algeria, Angola, Cote d'Ivoire, the Democratic Republic of the Congo, Ethiopia, Ghana, Kenya, Mauritius, Nigeria, South Africa, Tanzania, Uganda and Zambia) which either maintained direct links to China or a high volume of travel to China. Thus, trade proximity with China was identified as a factor that could determine rate of viral spread and cause potential pressure on health resources in Africa. The fragility of African health resources was emphasized in the quote "Given the fragile health systems in most sub-Saharan African countries, new and re-emerging disease outbreaks such as the current COVID-19 epidemic can potentially paralyse health systems at the expense of primary healthcare requirements. The impact of the Ebola epidemic on the economy and healthcare structures is still felt five years later in those countries which were affected. Effective outbreak responses and preparedness during emergencies of such magnitude are challenging across African and other lower-middle-income countries. Such situations can partly only be mitigated by supporting existing regional and sub-Saharan African health structures."

Gemelli (2020), although proposing an interdisciplinary approach, encompassing all aspects of internal medicine and geriatrics to the management of covid-19, infectious disease physicians, pneumologists, and intensive care physicians were identified as the medical specialists primarily involved in the management of the acute phase of covid-19. These are the main actors from the health sector in the pandemic.

In a novel approach, Pfefferbaum and North (2020) discussed the effect of the covid-19 pandemic on mental health. They posited that uncertain prognoses, scarcity of testing materials, treatment and protection of responders and health care providers from the pandemic, passage of unfamiliar public health schemes that trespass on individual liberties, increasing economic losses, and contradicting signals from authorities were major stressors that could trigger emotional distress and psychiatric illness associated with covid-19.

In another novel perspective, Daniel (2020) in his discussion on the effects of the pandemic on educational systems recognized the pandemic as the greatest challenge national educational systems have faced in the last 50 years. He proposed digital asynchronous learning as a way for colleges to ramp up teaching. He also proposed that as well as the normal classroom subjects, teaching should include varied assignments and work that puts COVID-19 in a global and historical context.

Anderson et al. (2020) posited that as the primary duty of government was to preserve the lives of the citizenry in the pandemic, government would not be able to do this without facing an economic downturn thus, measures to also cushion the effect of the economic downturn must also be implemented.

A host of other papers have been published on the intersection of covid-19 with different facets of life. Lisa Bowleg (2020) published on how the pandemic has disproportionately affected marginalized groups. In a positive outlook, Saadat et al., (2020) discussed on how the pandemic has led to a drop in air and water pollution globally due to lockdown and containment efforts, despite the ravaging effects of the pandemic on health and economic systems.

Haynes (2020) discussed that many intersecting factors led to the overwhelming of global health systems by cvid-19. The respiratory spread of SARS-CoV-2 and an inconsistent adherence to effective public health measures, including wearing masks and maintaining social distancing were mentioned. Also, persons infected with SARS-CoV-2 are frequently asymptomatic, yet having high respiratory viral load and were thus, major spreaders of the infection. Haynes posited that these factors led to the current explosion of Covid-19 hospitalizations and deaths, with Covid-19 being the major cause of deaths in the United States.

2.2 Literature on Measures against Covid-19

Different papers have been published on the protectionist, mitigating, and containment measures against covid-19 and the different facets in which its effects are felt.

According to Perlman (2020), "public health measures, including quarantining in the community as well as timely diagnosis and strict adherence to universal precautions in health care settings, were critical in controlling SARS and MERS. Institution of similar measures will be important and, it is hoped, successful in reducing the transmission of 2019-nCoV."

The primary medical measure that was taken and invested in for coid-19 containment and treatment was vaccination. Haynes (2020) stated that "Our only hope is safe and effective vaccines that can be widely deployed to provide herd immunity that can control viral (covid-19) spread". Le et al., (2020) gave an overview of the research and development landscape in the development of a covid-19 vaccine. The authors identified 78 vaccine developers, 56 being private developed, while 22 were government, academic and non-profit led. The authors also proscribed that high level cooperation between private developers, academics, public health bodies, regulatory bodies and governments would be needed to speed up development and ensure that vaccines get to low-income and low-resource regions. Polack et al., (2020) announced in December 31, 2020, the BNT162b2 mRNA Covid-19 Vaccine. A two-dose regimen of BNT162b2 conferred 95% protection against Covid-19 in persons 16 years of age or older. The vaccine's development was funded by BioNTech and Pfizer. Rubin and Longo (2020), noted the logistic challenges of manufacturing and delivering the BNT162b2 mRNA Covid-19 Vaccine as it requires storage at -70°C which was almost impossible for developmentally challenged regions and countries.

Funded by the Biomedical Advanced Research and Development Authority and the National Institute of Allergy and Infectious Diseases, Baden et al., (2020) announced in December 30, 2020 the mRNA-1273 SARS-CoV-2 Vaccine. The vaccine showed 94.1% efficiency. This was the second CDC approved covid-19 vaccine to be announced, commonly known as the Moderna vaccine.

Funded by Johnson & Johnson and the Biomedical Advanced Research and Development Authority of the Department of Health and Human Service, Sadoff et al., (2021) announced interim results for the Ad26.COV2.S Covid-19 Vaccine which proves which has given very promising results.

On December 30th 2020, the Oxford-AstraZeneca vaccine was approved for use (URL1, 2020). Voysey et al., (2020) determined the efficiency to be 90%. The vaccine is not CDC approved. Other vaccine options include the BBIBP-CorV from Sinopharm (Xia et al., 2020), BBV152 from Bharat Biotech (NHI, 2020), CoronaVac from

Sinovac (Zhang et al., 2020) and the Sputnik V from the Gamaleya Research Institute (Burki, 2020). These vaccines are not CDC approved.

Kavanagh et al., (2020) discuss how most African countries lack the funding and infrastructure to develop or procure testing and medical resources to combat the pandemic, and in cases with available funding, many African countries are unable to procure supplies needed as economically powerful countries mobilise eco-political and strategic power to procure supplies for their citizens. Nkengasong et al., (2020) in their paper discussed plans for covid-19 containment and vaccination in Africa. One of such measures mentioned is the COVID-19 Vaccine Global Access (COVAX) initiative. Co-led by the World Health Organization (WHO), the Coalition for Epidemic Preparedness Innovations (CEPI) and Gavi, the Vaccine Alliance and comprising of 167 member countries as at the time of publishing, the aim of the initiative is to speed up the development of COVID-19 vaccines and make sure they are distributed equitably among higher- and lower-income countries. The COVAX initiative has three pillars. The first is to accelerate African involvement in the clinical development of a vaccine. The second is to ensure that Africa can access a sufficient share of the global supply. The third is to remove barriers to widespread delivery and uptake of the vaccine across Africa.

Covid-19 testing is another key factor in controlling the spread of the corona virus (WHO, 2020). Beeching et al. (2020) discussed different testing strategies such as the reverse transcription polymerase chain reaction (RT-PCR) test, antibody tests and antigen detection tests. Schmitt-Grohé et al., (2020) analysed testing inequality in New York City, and found that although the number of tests administered was equal across all income groups, the number of negative test results was higher across wealthier income groups. This paper is important in analyzing healthcare resource distribution in poorer communities and countries. Piguillem (2020) found that testing was a better substitute for containment measures like widespread quarantine. BMJ (2020) also saw lockdowns as crude measures with great social and economic costs, advocating ramped up efficient testing over lockdowns.

Apart from vaccination, social distancing is the most important non-biological measure against covid-19. Greenstone *et al.*, (2020), using a simulation model projected that in three months beginning from March 2020, effective social distancing would have saved 1.7 million lives in the United States of America, with 670,000 of these lives saved due to an avoidance of the overwhelming of the health system. Mortality benefits from a 3 month lockdown was estimated at $8 trillion. The authors conclusively showed that social distancing measures against covid-19 had substantial economic benefits which is not the case for other measures like lockdowns or quarantine. Farboodi et al., (2020) also agree with economic and health benefits of social distancing.

Lewnard and Lo. (2020) in analyzing the scientific and ethical basis for social distancing interventions against covid-19 found that the most effective social distancing measure was one that included a mixture of specific initiatives like quarantine, school closure, and workplace distancing were combined. The authors discovered that stricter social distancing measures with greater the degree of compliance – as observed in China – had a greater effect on stopping the spread of the virus compared to lax measures as observed in western democracies. The authors also recognized the potential for abuse of such measures by government authorities and how it disproportionately marginalized communities.

Koren and Peto (2020) in a different approach quantified the economic cost of social distancing by analyzing it from the perspective of jobs from sectors whose market were based mainly on customer contact and where these contacts reduced the most: retail stores, leisure spots like hotels and restaurants, arts and entertainment and schools, due to the pandemic. The authors concluded that the main cost of social distancing was a reduction in division of labor.

Thunström et al., (2020) used epidemiological and economic forecasting to determine the net benefits of social distancing. The authors recognized that social distancing measures comes at an economic cost. Based on the model used by the authors, it is shown that the benefits derived from social distancing far outweigh the immediate economic costs by about $5.16 trillion.

Huremović (2019) in his paper "Social distancing, quarantine, and isolation" describes social distancing with its variants and psychological factors due to isolation and sigma to take into account when implementing social distancing measures. The paper also mentions other infection containment strategies like shelter-in-place, cordon sanitaire, or protective sequestration. In a similar vein, Venkatesh and Edirappuli (2020) also analysed the psychological effects of isolation and distancing measures, predicting frustration, boredom, low mood, and potentially depression and anxiety due to deprivation of personal liberties and altered routines. Worse of all, individuals with pre-existing mental illnesses could be deprived of interpersonal interactions and psychiatric help central to their management due to the "non-essential" nature of these services.

Ranney et al., (2020) discussed the shortage of protective equipment and ventilators which are key to the care of critically ill covid-19 patients in the United States. A decrease in efficiency of health systems due to this shortage was also discussed. Scanlon and Stephens (2020), recognizing the stress on healthcare structural resources like intensive care unit beds and ventilators, discuss how real time availability of health-related and covid-related data could be analysed and used to provide clearer pathways for treatment and alleviation of stress on resources. In a computing based approach like Scanlon and Stephens', Vaishya et al., (2020) discussed how Artificial Intelligence (A.I) could be applied in the fight against covid-19 and they identified seven applications from a review of literature. The authors mentioned that other computing concepts like the Internet of Things (IoT) and Machine Learning could also be applied. Siow et al., (2020) proposed pathways for managing healthcare resources in low-to-middle-income countries (LMIC). The authors recognized that as LMICs face constraints in capacity and accessibility during normal times, the pandemic would have enabled serious shortcomings in the health systems LMICs. This paper proposed alternative management measures because LMICs lack the financial capacity and time for swift uptake of conventional, modern solutions (vaccines, test kits etc). Solutions like open field hospitals in large public spaces to decongest local hopsitals are proposed in the paper with focused testing on symptomatic patients rather than random testing to make maximum utility of test kits and improvised continuous airway pressure systems to supplement limited ventilators.

Kim et al., (2020) described a three-phase approach developed by the University of Washington Medicine's (UWM's) Post-Acute Care (PAC) Network to help slow the spread of covid-19, support local nurses and nursing facilities from being overwhelmed and help decrease the burden on hospitals and healthcare systems. The three phases involved an Initial Phase which was designed to optimize communication, review infection control practices, and create a centralized process to track and test the target population. Next is a Delayed Phase with an aim to slow the spread of the disease once it is present in the skilled nursing facility by providing consistent education and reinforcing infection prevention and control practices to all staff. Last is the Surge Phase aimed to prepare facilities in response to an outbreak by deploying a "Drop Team" within 24 hours to the facility to expeditiously test patients and exposed employees, triage symptomatic patients, and coordinate care and supplies with local public health authorities.

2.3 Literature on Healthcare Systems

Numerous papers have been published on health systems, ranging from their structure to their performance, on a global scale and on a national scale. Yousuf et al., (2002) described the Saudi Health system as a three-tier system corresponding to primary, secondary and tertiary care. In the Saudi health structure, also exists the ministry of health that oversees public health centers, the private sector and other government health facilities like university and military hospitals. The authors noted that Saudi Arabia is a welfare petro-state and this reflects in their government backed health policy. A different health system structure from the Saudi model was described by Hsiao (1995) in his paper on the Chinese system. The author showed that although China ran a relatively disordered health system, there was no measurable decrease in the health status of the Chinese people. This could be explained by rising income which led to healthier living. China runs a different type of three-tier system for healthcare delivery comprising of village stations, township health centers, and county hospitals in the rural sector. In the urban sector, they are street health stations, community health centers, and district hospitals. The financing of these sectors is also complex, comprising a mixture of government determined and free market principles.

Paim et al., (2011) describes a different structure in Brazil, which is driven by civil society rather than by governments, political parties, or international organisations. In France, as in many western European countries, healthcare is a mix of public and private providers and insurers, each having compulsory and voluntary components as noted by Chevreul et al., (2010). Barr (2016) discuss how the United States of America, despite having some of the best physicians globally, runs one of the most inequitable healthcare systems based on free-market insurance and provision principles. Thus, it is clear that different countries have different systems, with the core defining variance centered around private financing versus government financing. Hacker (1998) underscored the importance of government funded health systems in the quote "few social programs involve the state so directly in the workings of the economy and the practice of a powerful profession. Few entangle the interests of so many diverse and resourceful groups. And few casts in such stark relief the ideological principles at stake. Although the participants in conflicts over health policy have differed from nation to nation, no country has acquired national health insurance without a fierce and bitter political fight".

For Africa, Mills et al., (2012) analyzed the journey of Ghana, South Africa and Tanzania towards universal health coverage. Despite important financial and economic disparities and differences between these countries, they all operate a similar health structure on a broad level, comprising of the Ministry/Department of Health at the national level, and regions/provinces and districts below that. An important component of the health sector in many African countries are religious organizations.

Tambo et al., (2016) recognized how foreign governments and organizations play a huge role in the structure and policies of African health systems.

Health system performance is another well discussed aspect in the literature. Arah et al., (2003) discussed the frameworks and indicators that government in OECD countries use to analyze performance. Performance assessment is needed to improve effectiveness, equity, efficiency, and quality. It was found that efficiency was usually measured as an outcome dependent variable instead of a process-dependent variable. Conrad and Shortell (1996) discuss the performance of vertically integrated health systems which they describe as more efficient than multi-hospital systems. The authors demanded increased accountability by the players in these systems optimum performance as opposed to just saving lives. Kruk and Freedman (2008), in their review on African health systems describe the indicators used for assessing performance in literature. Indicators were in three categories: effectiveness, equity, and efficiency. Indictators of effectiveness were health status increase, access to care and quality of said care and, increasingly, satisfaction of patients. Measures of equity included the ease of access to care for disadvantaged groups together with fair financing, protection from risks and increased accountability. Measures of efficiency were optimal funding, the cost-effectiveness of interventions, and good administration.

Schoen et al., (2007) in a different approach to assessing performance from user perspective, documented the experiences of healthcare users across seven countries: Australia, Canada, Germany, the Netherlands, New Zealand, the United Kingdom, and the United States. They found that a medical home which is accessible and helps to coordinate care was associated with a more positive experience. Barriers due to cost were most commonly found in the United States.

2.4 Health System Efficiency and DEA

Multiple papers have been published on the use of data envelopment analysis (DEA) for evaluation of efficiency in the health sector. Hollingsworth et al. (2008) divided health system efficiency studies into two: Micro-level studies and Macro-level studies. Micro-level studies concentrate on Hospitals and Clinics as the Decision-Making Units (DMUs) while Macro-level studies consider the overall Health System.

Cantor and Poh in 2017 wrote a review in which they analyzed the need for healthcare efficiency. They stated the 2008 financial crisis which led to spending cut in the health sector as a reason for resurgence in the calls for healthcare efficiency. Due to the financial crisis, spending in the health sector slowed down from a growth rate of 4% to a growth rate of 0.1%. Asandului et al. in 2014 they noted that the health status of citizens affects their productivity level thus, increasing the efficiency of health systems is a priority for nations with low or medium human development index. States with a high human development index are obliged to maintain a high-quality health system.

Hadad et al. in 2013 also note that the increasing burden of healthcare consumption on countries limited resources has brought about a clear policy implication of maximizing health care productivity from limited output. Sam Mirmirani in his 2008 paper, analyzing the efficiency of healthcare systems in transition economies noted that there has been a steady increase in healthcare costs in these economies. This has led to a competition for limited funds among the healthcare system, social systems, and industrial systems. The paper stated that in 2001, transition economies had a mean per-capital health expenditure of $130.5, an increase of 16.7% from 1997. This is lower than what is gotten in the OECD countries. This indicates that resources in the healthcare system must be managed efficiently.

Top *et al*. in their 2020 paper analyzing the technical efficiency of healthcare systems across African countries posited that for a health care system to be efficient, it must provide quality healthcare at an economically equitable rate. They used a benchmarking system to compare healthcare systems across socio-economically similar countries. Nepomuceno *et al*. also in 2020, stated that the covid-19 pandemic led to an exponential increase in the number of critically ill patients. This increase put great pressure on hospital resources like hospital beds and ventilators. Therefore, the efficiency of the distribution of these resources must be analyzed to make sure that the healthcare system is not overrun.

A 2011 study by Halkos and Tzeremes on the Greek healthcare system evaluated for inefficiencies in the system of Greek health prefectures due to the failure of the 2002 reformation of the Greek healthcare system. Jimenez and Smith in their 1996 study on the British National Health System (NHS) analysed for indicators of quality in the health system and also, the extent to which DEA gave insight into the NHS's performance in terms of quality. Breitenbach et al. (2020) noted that most data published on the variables associated with the covid-19 pandemic are based on mortality and infection rates. They noted that there is a void in the literature on the efficient use of health resources towards flattening the curve in the first 100 days of the pandemic. The authors noted that the question of resource use in the pandemic must be answered to enable more optimal medical response.

Stefko et al. (2018) noted that in the Slovakian healthcare system, serious disparities in the technical efficiencies of healthcare systems at regional level were becoming a serious constraint. To quantify the extent of these disparities, window DEA was used. Due to the highly autonomous nature of the Italian Health System and the presence of alternative reimbursement systems, Nicola et al. (2014), used DEA to evaluate if this autonomy results in difference in efficiencies of the health organizations and the extent of these differences.

Ahmed et al. (2019), noted that in Asia, personal health expenses and out-of-pocket payments for health services are a major source of poverty as 78 million people are pushed into poverty due to out-of-pocket spending on healthcare in a study of 11 Asian countries by Doorslaer et al. (2006). As governments in the South-Asia region spend about 1% of Gross Domestic Product (GDP) on healthcare, it is very imperative that the health resources are ustilised very efficiently.The authors used DEA analysis to evaluate for technical efficiency in the health systems of 46 Asian countries.

Pelone et al. (2014) suggested that since health systems aim to maintain, restore and improve the health status of a population, it is crucial to assess the achievement of goals such as effectiveness, equity, and responsiveness in relation to quantity of healthcare resources consumed.

In measuring healthcare efficiency, different forms of DEA are used. Top et al. combined DEA with a Tobit regression analysis. The healthcare systems of the 36 countries were compared with DEA after which the inputs in the DEA were used as the independent variable and the transformed DEA score was used as a dependent variable. Inputs with statistically significant effects on DEA score were identified.

Halkos and Tzeremes (2011) used input oriented Constant-Return-to-Scale (CRS) and Variable-Return-to-Scale (VRS) models were used to estimate efficiency in the DEA. A bootstrap test was used to evaluate what efficiency values will be adopted. Stefko et al. (2018) used DEA window analysis because the DMUs was limited in number in individual periods and to changes in efficiency had to be analysed over time.

Nicola et al. (2014) used truncated regression to estimate effects of exogenous variables on health system efficiency. Nepomuceno *et al*. (2020) used a two-step approach consisting of using an input-oriented VRS DEA model to analyse the full production capacity of each hospital using hospital admissions as an output and hospital beds as a discriminatory resource. Step 2 involved using the Brazilian Health System's Complexity of needs prioritization model to reallocate and prioritize the optimal number of beds based on medical specialty and complexity of needs.

2.5 DEA and Covid-19

Due to the recent arrival of the pandemic – 2019 – literature on the use of DEA in analyzing COVID-19-related efficiency of healthcare systems is sparse.

Using a three-staged method, comprised of a more recent and advanced form of DEA, Aydin and Yurdakul (2020) analysed the efficiency of 142 countries in covid-19 management. In their method, machine learning was integrated with machine learning to refine the data using clustering analyses. A novel model of DEA, the weighted stochastic imprecise data envelopment analysis (WSIDEA) was then used to determine efficiency. 20 countries out of 142 countries were fully effective, and 36% of them were found to be effective at a rate of 90%. Strangely enough, data such as GDP, smoking rates, and the rate of diabetes patients did not affect the effectiveness level of the countries. Mariano et al., (2020), in a regional level approach, used Network Data Envelopment Analysis (NDEA) to compare the performance of federal health units and the Brazilian states. Using intermediate variables, in addition to input variables and an output variable, the authors were able to determine and visualize inefficient regions, which could assist policy makers.

Shirouyehzad et al., (2020) using the number of confirmed cases and the condition of the countries to determine how seriously affected the countries are, the authors used DEA to determine the effectiveness of medical treatment in these most seriously affected countries. Ghasemi et al., (2020), observed that the comparison of country performance based on the statistics of virus spread and mortality alone without considering the contextual variables, could be misleading,used dynamic DEA to calculate the performance of 19 countries in two parameters: inefficiency of preventing coronavirus spread and inefficiency of preventing coronavirus deaths from February 2 to April 12. They found that the inefficiency in preventing spread in Singapore, was decreasing while the inefficiency of other countries, which of course were increasing with different slopes. Australia, experienced less inefficiency in preventing deaths caused by coronavirus compared to other countries.

da Silveira Pereira and de Mello (2021) used multi-criteria DEA(MCDEA) for a slightly similar case of analyzing the efficiency of domestic airline operations in the pandemic using their response to lower demand as an indicator. Airlines with a better mix of aircrafts were shown to have greater efficiency compared to their counterparts.

Malik and Senjiati (2020), using the VRD DEA method analysed the efficiency of covid-19 handling services in zakat institutions and found the efficiency to be very low around 22%. Adabavazeh et al., (2020) in a similar study to this thesis evaluated the performance of the world health systems dealing with the pandemic using parametric techniques for indicators such as population, GPD Per Capita, total recovered, total cases, and total deaths. They found that most of the studied countries operated inefficiently due to sub-optimal resource usage with the authors calling the attention of the world health organisation in promoting health culture during the crisis management.

Nepomuceno et al., (2020), focusing on hospital beds as a healthcare resource, used DEA to determine optimal allocation and reallocation of bed spaces in the pandemic. Inefficient health units with bed spaces had those space reallocated to patients presenting severe conditions. This was done based on a complexity of needs approach. The study found 3772 beds feasible to be evacuated by 64% of the analyzed health units in Brazil, of which more than 82% are moderate complexity evacuations. Ibrahim et al. (2020), due to the shortcomings of current health management systems in managing the pandemic employed DEA to evaluate efficiency in 58 countries. 89.6% of countries were inefficient in pandemic control and 79% were inefficient in treatment measures. The authors identified a lack of a global public health database support system and uniform response as a factor that compounded inefficiency. Breitenbach et al. (2020) in a more time focused study evaluated the efficiencies of the 31 most infected countries in flattening the covid-19 infection cure in the first hundred days of the pandemic. They found that 12 of the 31 countries were efficient and 19 inefficient in the use of resources to manage the flattening of their covid-19 contagion curves. The richest countries were some of the most inefficient.

Chapter 3

METHODOLOGY

3.1 Data Collection

To determine the efficiency of healthcare systems in European countries during the pandemic, data on the total population per country, total number of covid-19 cases per country, number of covid-19 tests done per country, gross domestic product (GDP), total number of deaths due to the pandemic, total number of recovered patients from covid-19 and total number of covid-19 patients in intensive care unit (ICU) were taken. This data will enable us to analyse how efficiently the different healthcare systems are able to manage the pandemic judging from the degree of casualty the pandemic inflicted on the countries and the degree of resources the systems had to expend to bring about the recorded amount of recoveries. Rather than try to measure efficiency from the aspect of health resources (human and infrastructural), we choose to directly look at the health outcomes of the pandemic (ICU, death and recovery) and the frequency of these outcomes as indicators of efficiency.

This data was collected for 48 European countries, starting from the date of the first covid-19 case recorded in each country, up till the 4th of December, 2020.

Four input and three output variables were used in this research. The input variables are total population per country, total number of covid-19 cases per country, number of covid-19 tests done per country and gross domestic product (GDP) while the output variables are total deaths due to covid-19, total number of covid-19 patients in intensive care unit (ICU) and total number of recovered covid-19 cases. As observed, this choice of variables indicates an outcome-dependent model, rather than a process-dependent model. A higher covid-19 related death rate compared to other countries if other variables like total population and number of tests are factored for, will indicate relative inefficiency as death is a non-desirable outcome. The same holds for ICU cases. The opposite holds for recovery cases as recovery is a desirable outcome. This approach greatly simplifies efficiency evaluation as opposed to analyzing the use of healthcare resources and indicators of patient behavior.

Total population: The human population in each country is the main target of the pandemic. From the total population, all other data, relating to the pandemic's outcome is derived.

Total number of cases: The total number of cases is the section of the human population that has ever been infected with the virus up till December 4, 2020 in each country. From here, data on death and death rate is derived.

Number of tests: Covid-19 testing is one of the major means of managing the pandemic. It involves the use of healthcare resources (human and material), and thus, this parameter, when viewed in light of other outcome variables is a useful indicator of efficiency.

Gross domestic product (GDP): This is an exogenous variable that is outside the control of the health system, but indicates the economic state of the country and thus, the health system at large.

Total Deaths: The total deaths per country indicates the number of individuals that died due to the viral infection from the date of the first confirmed case in that country up till December 4, 2020.

Total in ICU: This represents the number of patients that have had to be placed in ICU due to an infection from the corona virus. It gives an idea of the expenditure of emergency healthcare resources (human and material) and can thus serve as an indicator for efficiency in the healthcare sector.

In this analysis, 48 DMUs were used for the DEA, with each DMU representing a European country. 48 DMUs were chosen because the researcher believes the sample size is large enough and actively involved in the management and prevention of the pandemic, with an availability of reliable and updated data.

DEA is a mathematical technique that was developed by Charnes, Cooper and Rhodes in 1978. This technique has grown immensely in popularity because of its ability to handle multiple inputs and outputs, and also provide other data like relative efficiency ratio and the quantity and source of relative inefficiencies in decision making units (Huang and McLaughlin, 1989).

One of the common schemes for evaluating efficiency of DMUs is Data Envelopment Analysis (DEA), which is a non-parametric method, using linear programming techniques to identify an efficiency frontier on which only the efficient Decision-Making Units (DMUs) are then located. The first DEA model is known in the literature as the CCR model, after its authors, Charnes, Cooper and Rhodes, presented in 1978, who introduced constant returns to scale (CRS), where all decision-making Units

(DMUs) are operating at their optimal scale. Thus, by using linear programming and nonparametric methods of frontier evaluation, the DMU efficiency can be evaluated through comparison with the recognized efficiency frontier. A DEA model is either input or output oriented. An output oriented DEA model evaluates towards output maximization of DMUs while keeping inputs constant, whilst the input oriented models works towards input minimization, where the inputs are used for processing the determined amount of outputs (Asandului et al., 2014).

The second major DEA model is the BCC model developed in 1984 by Banker, Charnes and Cooper. Here, they introduced the variable returns to scale (VRS) efficiency measurement model, allowing the breakdown of efficiency into technical and scale efficiencies in DEA. In this paper, the CCR model would be used.

There are some important parameters that need to be understood in DEA analyses and they are:

n = number of DMUs

m = Number of inputs used in each DMU

s = Number of outputs produced in each DMU

θ = Efficiency

u_r = Output weight ($r = 1...s$)

v_i = Input weight ($i = 1…m$)

y_{r0} = Amount of output r produced by the observed DMU_0

x_{io} = Amount of input i used by the observed DMU_0

y_{rj} = Amount of output r produced by the observed DMU_j

x_{ij} = Amount of input i used by the observed DMU_j.

DMU_j, where j = 1,2,3…n

DMU_0 is the desired DMU being evaluated, where 0 = 1…n.

3.2 Efficiency

Efficiency is extremely important in very private and government run sector, including the health sector. There are different coinciding reasons for a resurgence in the call for efficiency in the health sector and the measurement of this efficiency. Spending cuts in the healthcare sector due to the 2008 financial crises which slowed down health spending in OECD countries to 0.1% from a growth rate of 4% pre-financial crises made OECD countries to focus on productivity growth via optimization of performance and decrease in financial "wastage" (Cantor and Poh, 2018). The covid-19 pandemic which ravaged even the most developed healthcare systems globally due to the pressure it placed on human and infrastructural healthcare resources gives a greater case for the need of efficiency and its measurements in the health sector.

Global healthcare institutions seeking to improve performance and maximize health outcomes must first address the question of how to measure performance and how to identify determinants involved in the health production function.

The three methods for measuring business performance using efficiency related data are the performance indicators, the regression analysis (traditional methods) and the data envelopment analysis (DEA) (Cantor and Poh, 2018).

Basically, efficiency can be evaluated as the ratio of output to input and this efficiency can be increased either by minimizing the input amount (input oriented DMUs) or by increasing the output amount (Output oriented DMUs). Thus, efficiency can be represented mathematically as:

$$Efficiency = \frac{Output}{Input} \tag{3.1}$$

Figure 3.1: Single input-output model

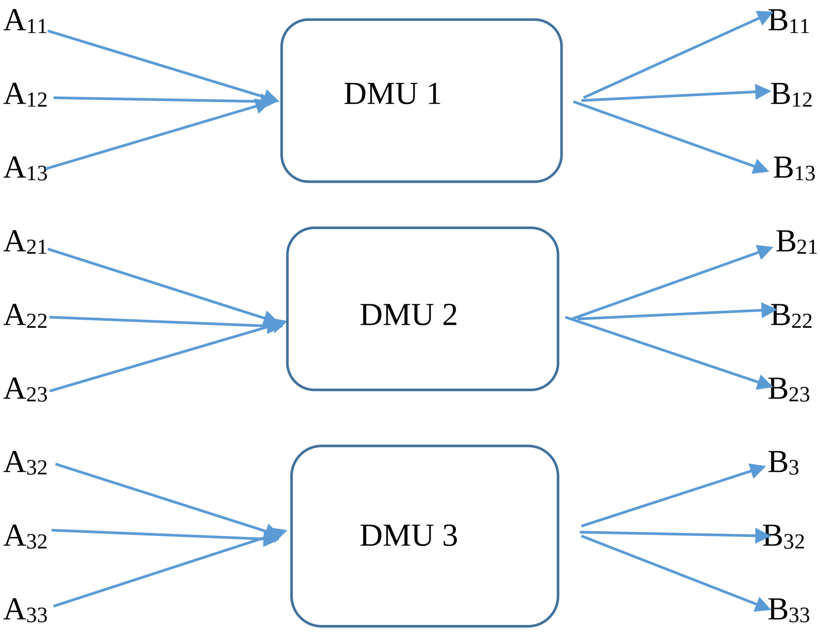

Figure 3.2: Multi input-output model of homogenous DMUs

In figure 3.1, equation 3.1 is perfectly suited to calculate efficiency. But in a multiple input-ouput system of homogenous DMUs like in equation 3.2, CCR is the programming technique that is suitable.

3.3 CCR Model

The CCR model is a linear programming model that evaluates efficiencies of DMUs using the weights of input and output variables, with 1 being the maximum limit for efficiency (θ) that can be reached in every DMU when θ is represented as a ratio between output weights ($u_{r)}$) and input weights (v_i) as shown in equations 3.1 and 3.2. Equations 3.4 and 3.5 are the non-negativity conditions for the input and output weights.

$$\theta_{max} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{3.2}$$

given that: $\theta_{max} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$ where j = 1…n (3.3)

$v_i \geq 0$ where i = 1…m (3.4)

$u_r \geq 0$ where r = 1…s (3.5)

The model above is the fractional program (FP_0) of the CCR model. The linear form, also known as the linear program (LP_0) is equivalent to and derived from the fractional model. Below is the formulation of the linear program.

$$\theta_{max} = \sum_{r=1}^{s} u_r\, y_{ro} \tag{3.6}$$

given that: $\sum_{i=1}^{m} v_i\, x_{io} = 1$ (3.7)

$\sum_{r=1}^{s} u_r\, y_{rj} = \sum_{i=1}^{m} v_i\, x_{ij} \leq 0$ j = 1…n (3.8)

$v_i \geq 0$ where i = 1…m (3.9)

$u_r \geq 0$ where r = 1…s (3.10)

Another formulation is the vector form of the linear programming model. u and v variables are the row vectors as output and input multipliers respectively.

$$uy_{0max} \tag{3.11}$$

given that: $vx_0 = 1$ (3.12)

$uY = vX \leq 0$ (3.13)

$u \geq 0$ (3.14)

$v \geq 0$ (3.15)

Where:

$$X = \begin{matrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{matrix} = \text{(m by n) matrix,} \tag{3.16}$$

$$X = \begin{matrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{s1} & \cdots & y_{sn} \end{matrix} = \text{(s by n) matrix,} \tag{3.17}$$

3.4 CCR Efficiency Conditions

In using CCR to evaluate efficiency of DMUs;

- If θ* =1, and at least one of the optimal inputs or outputs (v* or u*) is greater than zero, then the DMU is said to be efficient. Otherwise, it is said to be inefficient.
- If θ* =1 and U*, V* ≥ 0 and at least U* = 0 or V* = 0, then the DMU is CCR weak efficient.
- If either θ* ≤ 1 and at least v* = 0 or u* = 0.

Inefficient DMUs can be upgraded to efficient DMUs in DEA by either decreasing the input or increasing the output. In this research, the model was input-oriented. The data downloaded from the World Health Organisation and the International Monetary Fund websites for the purpose of this research are represented in table 3.1 below.

Table 3.1: Input and output data

Country	Total Population	Total Number of Cases	Number of Test	Total Ggdpa ($$)	Total Deaths	Total Recovered Cases	Total in Icu
Russia	141,961,200	2,402,949	201,769,463	1,464,078	42,176	1,888,752	2,300
Germany	83,783,942	1,131,828	29,141,172	3,780,553	18,303	868,600	3,957
United Kingdom	68,037,738	1,674,134	44,416,420	2,638,296	60,113	1,554,000	1,315
France	65,335,131	2,257,331	20,787,734	2,551,451	54,140	166,940	3,425
Italy	60,461,826	1,664,829	22,561,071	1,848,222	58,038	846,809	3,597
Spain	46,762,516	1,693,591	22,992,742	1,247,464	46,038	1,605,000	2,440
Ukraine	43,733,762	787,891	4,528,772	142,250	13,195	397,809	117
Poland	37,828,876	1,041,846	6,396,712	580,894	19,359	666,413	1,961
Romania	19,182,526	500,273	4,205,480	248,624	12,052	390,212	1,275

Netherlands	17,151,047	538,050	4,043,482	886,339	9,565	487,000	507
Belgium	11,611,101	584,857	6,012,323	503,416	17,033	38,577	788
Czech Republic	10,708,981	537,663	3,131,585	241,975	8,641	468,302	586
Greece	10,401,201	111,537	2,432,614	194,376	2,706	9,989	622
Portugal	10,196,709	307,618	4,675,744	221,716	4,724	229,018	525
Sweden	10,099,265	272,643	3,457,247	529,054	7,007	234,000	249
Hungary	9,660,351	238,056	1,876,274	149,939	5,513	68,525	639
Belarus	9,447,994	141,609	3,335,788	57,708	1,181	118,924	125
Austria	9,006,398	297,245	3,209,340	432,894	3,651	243,775	642
Serbia	8,722,276	199,158	1,844,731	51,999	1,765	31,536	288
Switzerland	8,681,501	344,497	2,836,245	707,868	5,221	260,600	480
Bulgaria	6,948,445	155,193	999,867	67,917	4,503	57,141	523
Denmark	5,800,894	85,140	7,653,700	339,626	858	67,416	38
Finland	5,544,394	26,758	2,033,123	267,856	408	18,100	21
Slovakia	5,460,772	113,392	1,115,246	101,892	957	77,142	246
Norway	5,439,235	37,371	2,350,736	366,386	354	27,414	38
Ireland	4,961,126	73,228	1,998,479	399,064	2,080	23,364	32
Croatia	4,094,389	143,370	790,883	56,768	2,032	117,148	262
Moldova	4,029,947	112,307	472,705	11,241	2,363	97,549	302
Bosnia and Herzegovia	3,280,819	91,539	428,822	18,893	2,812	56,050	77
Albania	2,876,453	40,501	192,663	14,034	852	20,484	27
Lithuania	2,705,865	69,582	1,304,400	55,064	590	27,760	132
North Macedonia	2,083,337	65,231	341,261	12,510	1,847	41,656	138
Slovenia	2,078,938	81,349	538,770	51,802	1,592	59,469	195

Latvia	1,877,202	19,993	658,086	33,015	242	1,849	46
Estonia	1,326,535	13,939	499,566	30,468	125	8,549	17
Montenegro	628,066	36,932	139,029	4,943	516	25,866	68
Luxemborg	630,266	36,429	1,407,284	68,613	339	27,356	41
Malta	442,044	10,320	439,477	14,290	149	8,120	18
Iceland	342,184	5,462	396,283	20,805	27	5,223	2
Andorra	77,318	6,904	168,635	3,238	77	6,066	20
Monaco	39,360	630	51,953	7,188	3	570	5
Liechtenstein	38,128	1,339	14,040	6,215	17	1,169	15
San Marino	33,961	1,714	18,364	1,410	46	1,356	11
Cyprus	1,211,164	12,451	639,047	23,246	61	2,057	15
Armenia	2,965,652	142,344	530,225	12,813	2,344	117,649	24
Kazakhstan	18,873,514	136,983	4,206,738	165,730	2,034	120,799	221
Azerbaijan	10,178,675	146,679	1,837,001	41,666	1,632	88,497	28
Turkey	84,730,672	828,295	19,691,845	9,043	14,900	431,253	5,805

The normalised input and output data is shown below in table 4.2, and it was computed from table 4.1 by dividing each variable value by the maximum value that variable has taken in any DMU. This makes sure that the highest value for any input or output variable is 1 and makes the data fit for calculating efficiency via DEA. Table 4.2 below shows this normalised data with input 1 representing total population, input 2 representing total number of cases, input 3 representing number of tests and input 4 representing total $GDPA. Output 1 represents total deaths, output 2 represents total recovered cases and output 3 represents total in ICU. The DMUs in table 4.2 are the countries in table 4.1.

Table 3.2: Normalised data

DMU	Input 1	Input 2	Input 3	Input 4	Output 1	Output 2	Output 3

DMU 01	1	1	1	0.387	0.0004	0.0008	1
DMU 02	0.59	0.471	0.144	1	0.0009	0.0005	0.461
DMU 03	0.479	0.697	0.22	0.698	0.0002	0.001	0.823
DMU 04	0.46	0.938	0.103	0.675	0.0003	0.0005	0.088
DMU 05	0.426	0.693	0.112	0.489	0.0002	0.0005	0.448
DMU 06	0.329	0.705	0.114	0.332	0.0003	0.0008	0.851
DMU 07	0.308	0.328	0.022	0.038	0.001	0.0171	0.211
DMU 08	0.266	0.434	0.032	0.154	0.0008	0.001	0.0353
DMU 09	0.135	0.208	0.021	0.066	0.0004	0.0015	0.207
DMU 10	0.121	0.224	0.02	0.234	0.0005	0.003	0.258
DMU 11	0.121	0.243	0.03	0.133	0.0009	0.002	0.0204
DMU 12	0.082	0.224	0.016	0.064	0.001	0.003	0.248
DMU 13	0.075	0.047	0.012	0.051	0.006	0.003	0.005
DMU 14	0.073	0.128	0.023	0.058	0.003	0.0038	0.121
DMU 15	0.071	0.113	0.017	0.141	0.002	0.008	0.123
DMU 16	0.068	0.099	0.0093	0.041	0.003	0.003	0.035
DMU 17	0.067	0.059	0.017	0.015	0.0141	0.016	0.063
DMU 18	0.063	0.124	0.016	0.114	0.004	0.0031	0.129
DMU 19	0.061	0.083	0.009	0.014	0.009	0.006	0.017
DMU 20	0.061	0.143	0.014	0.187	0.003	0.0041	0.138
DMU 21	0.049	0.064	0.005	0.018	0.003	0.0038	0.03
DMU 22	0.041	0.035	0.041	0.091	0.0019	0.052	0.0357
DMU 23	0.039	0.011	0.01	0.073	0.042	0.0952	0.009
DMU 24	0.038	0.047	0.006	0.027	0.018	0.0081	0.041
DMU 25	0.038	0.016	0.012	0.097	0.048	0.0536	0.015
DMU 26	0.035	0.03	0.01	0.106	0.008	0.063	0.012
DMU 27	0.029	0.06	0.004	0.015	0.008	0.0076	0.062
DMU 28	0.028	0.047	0.002	0.002	0.007	0.0066	0.052
DMU 29	0.023	0.038	0.0021	0.004	0.006	0.026	0.0296
DMU 30	0.02	0.017	0.001	0.003	0.019	0.074	0.011
DMU 31	0.019	0.029	0.007	0.015	0.029	0.0152	0.015
DMU 32	0.015	0.027	0.002	0.003	0.009	0.0145	0.022
DMU 33	0.014	0.034	0.003	0.014	0.011	0.0102	0.031
DMU 34	0.013	0.0083	0.003	0.008	0.07	0.0434	0.0009
DMU 35	0.009	0.0056	0.002	0.008	0.136	0.1176	0.004
DMU 36	0.0044	0.015	0.001	0.001	0.033	0.0294	0.013
DMU 37	0.004	0.0151	0.007	0.018	0.05	0.049	0.014
DMU 38	0.0031	0.0043	0.002	0.003	0.114	0.111	0.004
DMU 39	0.0031	0.0023	0.002	0.005	0.627	1	0.002
DMU 40	0.00054	0.0029	0.0008	0.0008	0.22	0.1	0.0032
DMU 41	0.00028	0.00026	0.0003	0.001	0.559	0.4	0.0003
DMU 42	0.00027	0.00056	0.00007	0.001	1	0.133	0.0006
DMU 43	0.00024	0.00071	0.00009	0.0003	0.373	0.182	0.0007
DMU 44	0.009	0.0052	0.003	0.006	0.278	0.133	0.001
DMU 45	0.021	0.059	0.003	0.003	0.007	0.0834	0.062
DMU 46	0.133	0.057	0.02	0.044	0.008	0.009	0.064
DMU 47	0.072	0.061	0.009	0.011	0.0103	0.0714	0.047
DMU 48	0.597	0.345	0.12	0.002	0.0113	0.0003	0.228

Chapter 4

RESULTS AND DISCUSSION

In this chapter, we present and discuss the CCR efficiency results, CCR cross-efficiency results, benchmarks (Lambdas) of the CCR result, weight of the CCR variables, and the results for input and output targets of CCR.

4.1 CCR Efficiency

The efficiency of every decision-making unit (DMU) which is shown below in table 4.1 was gotten based on the multiplier form of the CCR model, using the PIM-DEA software.

Table 4.1: CCR efficiency results

DMU	Efficiency (%)	DMU	Efficiency (%)	DMU	Efficiency (%)
DMU 01	84.22	DMU 17	92.37	DMU 33	80.71
DMU 02	81.08	DMU 18	88	DMU 34	9
DMU 03	97.82	DMU 19	18.03	DMU 35	59.23
DMU 04	8.07	DMU 20	84.55	DMU 36	94.1
DMU 05	53.56	DMU 21	41.22	DMU 37	81.87
DMU 06	100	DMU 22	84.5	DMU 38	77.14
DMU 07	57.25	DMU 23	67.81	DMU 39	73.28
DMU 08	7.17	DMU 24	73.94	DMU 40	100
DMU 09	86.07	DMU 25	77.68	DMU 41	100
DMU 10	100	DMU 26	33.14	DMU 42	100
DMU 11	7.14	DMU 27	92.52	DMU 43	100
DMU 12	100	DMU 28	100	DMU 44	16.04
DMU 13	8.81	DMU 29	69.75	DMU 45	100
DMU 14	78.59	DMU 30	57.92	DMU 46	93.02
DMU 15	90.82	DMU 31	42.85	DMU 47	67.71
DMU 16	30.71	DMU 32	72.81	DMU 48	100

The efficiency of every decision-making unit (DMU) which is shown below in table 4.1 was gotten based on the multiplier form of the CCR model, using the PIM-DEA software.

Table 4.1 above shows the efficiency results for each DMU. From the table, it can be seen that DMU 06 (Spain), DMU 10 (Netherlands), DMU 12 (Czech Republic), DMU 28 (Moldova), DMUs 40 to 43 (Andorra, Monaco, Liechtenstein and San Marino respectively), DMU 45 (Armenia) and DMU 48 (Turkey) have the highest efficiency. These countries are on the efficiency frontier and can be said to have handled the covid-19 pandemic most effectively by having the least deaths and ICU cases with the most recoveries. Also, these countries could have had the most recoveries. DMU 4 (France), DMU 8 (Poland), DMU 11 (Belgium), DMU 13 (Greece), DMU 19 (Serbia) and DMU 34 (Latvia) had the lowest efficiency scores. This indicates a poor management of the pandemic indicated by high death rates, ICU cases or low recoveries. DMU 01 (Russia), DMU 02 (Germany), DMU 03 (United Kingdom), DMU 09 (Romania), DMU 14 (Portugal), DMU 15 (Sweden), DMU 17 (Belarus), DMU 18 (Austria), DMU 20 (Switzerland), DMU 22 (Denmark), DMU 27 (Croatia), DMU 28 (Moldova) DMU 33 (Slovenia), DMU 36 (Montenegro), DMU 37 (Luxemborg) and DMU 46 (Kazakhstan) had close to maximum efficiency ranging be ≥ 80% and < 100%. Little optimization will be needed for these DMUs to achieve maximum efficiency in the management of the pandemic.

4.2 Lambdas of CCR

The lambda values of the CCR, also known as benchmark values, are the raw efficiency weights assigned to peer DMUs compared to each other. In this context, benchmarking involves computing the most efficient DMUs and using them as a measure of comparison for other DMUs as indicated in the table below. This was implemented by solving equation 3.16 using the PIM-DEA software, to obtain benchmark results that would be compared to moderately efficient and inefficient DMUs with a goal to upgrading them.

Table 4.2: Lambdas/Benchmark result

DMU	DMU 06	DMU 10	DMU 12	DMU 28	DMU 40	DMU 41	DMU 42	DMU 43	DMU 45	DMU 48
DMU 01	0.96	0	0	3.51	0	0	0	0	0	0
DMU 02	0.54	0	0	0	0	0	0	0	0	0
DMU 03	0.97	0	0	0	0	0	0	0	0	0
DMU 04	0.04	0.17	0.05	0.03	0	0	0	0	0	0
DMU 05	0.53	0	0	0	0	0	0	0	0	0
DMU 06	1	0	0	0	0	0	0	0	0	0
DMU 07	0.05	0	0	3.31	0	0	0	0	0	0
DMU 08	0.01	0.03	0	0.39	0	0	0	0	0	0
DMU 09	0.12	0.06	0	1.76	0	0	0	0	0	0
DMU 10	0	1	0	0	0	0	0	0	0	0
DMU 11	0.01	0.02	0	0.05	0	0	0.01	0	0	0
DMU 12	0	0	1	0	0	0	0	0	0	0
DMU 13	0.01	0	0	0	0	0.01	0	0	0	0
DMU 14	0.14	0	0	0.09	0	0.01	0	0	0	0
DMU 15	0.12	0.07	0	0	0	0	0.06	0	0	0
DMU 16	0.01	0.03	0	0.28	0	0	0.01	0	0	0
DMU 17	0.04	0	0	0.59	0	0.03	0	0	0	0
DMU 18	0.08	0.22	0	0	0	0	0.02	0	0	0
DMU 19	0.01	0	0	0.23	0	0.01	0	0	0	0
DMU 20	0.04	0.11	0.29	0	0	0	0.02	0	0	0
DMU 21	0.01	0.02	0	0.35	0	0	0.01	0	0	0
DMU 22	0.04	0	0	0	0	0.13	0	0	0	0
DMU 23	0.01	0	0	0	0	0.24	0	0	0	0
DMU 24	0.03	0.04	0	0.09	0	0	0.06	0	0	0
DMU 25	0.02	0	0	0	0	0.13	0	0	0	0
DMU 26	0.01	0	0	0	0	0.16	0	0	0	0
DMU 27	0.01	0.02	0.11	0.5	0	0	0.03	0	0	0
DMU 28	0	0	0	1	0	0	0	0	0	0
DMU 29	0	0	0	0.5	0	0	0.17	0	0	0
DMU 30	0	0	0	0.17	0	0	0.55	0	0	0
DMU 31	0.02	0	0	0	0	0.05	0	0	0	0
DMU 32	0	0	0	0.34	0.39	0	0	0	0	0
DMU 33	0.01	0.02	0.08	0.02	0	0	0.07	0	0	0
DMU 34	0	0	0	0	0	0.13	0	0	0	0
DMU 35	0	0	0	0	0	0.29	0	0	0	0
DMU 36	0	0	0	0	0.48	0	0	0	0.18	0

DMU 37	0	0	0	0	3.07	0	0	0	0	0
DMU 38	0	0	0	0	0	0.28	0	0	0	0
DMU 39	0	0	0	0	0	2.5	0	0	0	0
DMU 40	0	0	0	0	1	0	0	0	0	0
DMU 41	0	0	0	0	0	1	0	0	0	0
DMU 42	0	0	0	0	0	0	1	0	0	0
DMU 43	0	0	0	0	0	0	0	1	0	0
DMU 44	0	0	0	0	0	0.5	0	0	0	0
DMU 45	0	0	0	0	0	0	0	0	1	0
DMU 46	0.08	0	0	0	0	0.02	0	0	0	0
DMU 47	0.02	0	0	0.6	0	0.17	0	0	0	0
DMU 48	0	0	0	0	0	0	0	0	0	1

The result obtained in table 4.1 showed that DMU 06, DMU 10, DMU 12, DMU 28, DMU 40, DMU 41, DMU 42, DMU 43, DMU 45 and DMU 48 has the optimum efficiency, which made them the suitable benchmark for comparing all other DMUs for inefficiency determination and upgrading inefficient DMUs to efficient. This comparison is what was done in table 4.2a above. A cursory analysis of table 4.2 shows that DMU 01 can be compared to DMU 06 and DMU 28, but it is best compared with DMU 28. This implies that DMU 28 is the best DMU among all optimal DMUs that DMU 01 can be compared with in upgrading the efficiency of its health systems in the management of the covid-19 pandemic. Likewise, DMU 02 can only be compared with DMU 06 and cannot be compared with any of the other optimal DMUs because they are zero values. Thus, the inefficient DMUs can be compared with the positive and non-zero lambda value optimum DMUs, and the greatest lambda from this optimum DMUs is the best benchmark. Table 4.2b below gives a more detailed comparison of the DMUs and their lambdas, showing the best DMU for each benchmark and from it, figure 4.1 is derived which shows the frequency of each optimal DMU as the best benchmark.

Table 4.3: Best benchmark per DMU

DMU	Best Benchmark	DMU	Best Benchmark	DMU	Best Benchmark
DMU 01	DMU 28	DMU 17	DMU 28	DMU 33	DMU 40
DMU 02	DMU 06	DMU 18	DMU 10	DMU 34	DMU 12
DMU 03	DMU 06	DMU 19	DMU 28	DMU 35	DMU 41
DMU 04	DMU 10	DMU 20	DMU 12	DMU 36	DMU 40
DMU 05	DMU 06	DMU 21	DMU 10	DMU 37	DMU 40
DMU 06	DMU 06	DMU 22	DMU 28	DMU 38	DMU 41
DMU 07	DMU 28	DMU 23	DMU 41	DMU 39	DMU 41
DMU 08	DMU 28	DMU 24	DMU 41	DMU 40	DMU 40
DMU 09	DMU 28	DMU 25	DMU 28	DMU 41	DMU 41
DMU 10	DMU 10	DMU 26	DMU 41	DMU 42	DMU 42
DMU 11	DMU 28	DMU 27	DMU 41	DMU 43	DMU 43
DMU 12	DMU 12	DMU 28	DMU 28	DMU 44	DMU 41
DMU 13	DMU 06 and 41	DMU 29	DMU 28	DMU 45	DMU 45
DMU 14	DMU 06	DMU 30	DMU 28	DMU 46	DMU 06
DMU 15	DMU 06	DMU 31	DMU 42	DMU 47	DMU 28
DMU 16	DMU 28	DMU 32	DMU 41	DMU 48	DMU 48

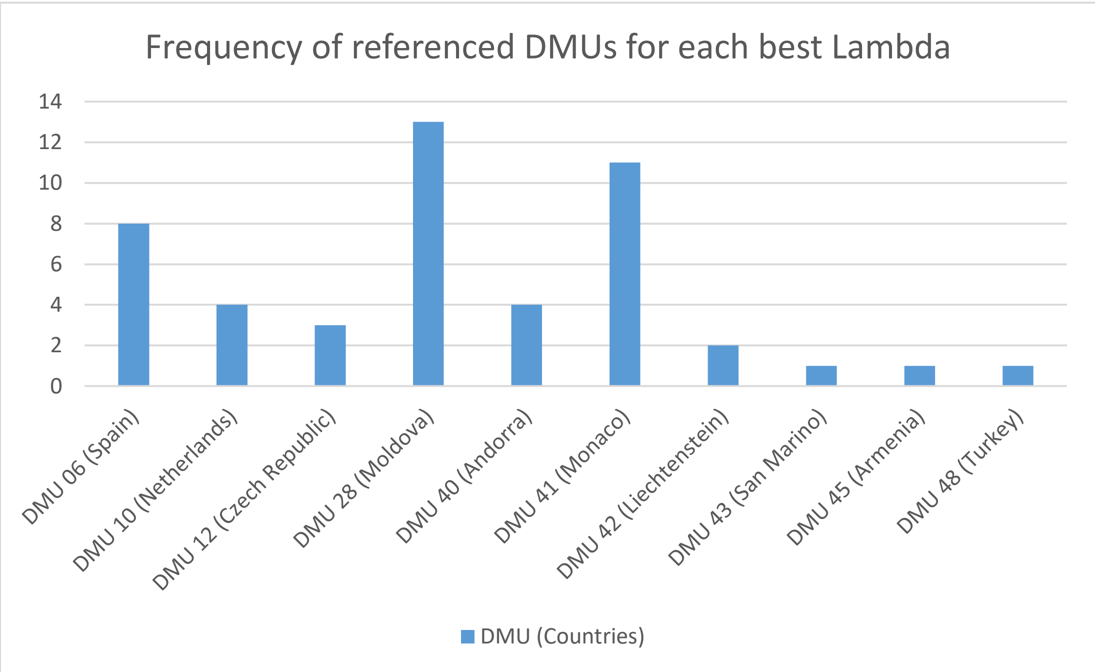

Figure 4.2: Frequency of referenced DMU per Optimum Lambda

From the figure above, it is seen that Moldova is the most frequently referenced country in terms of healthcare efficiency during the pandemic, followed by Monaco.

San Marino, Armenia and Turkey are the least frequently referenced countries out of the optimally efficient countries.

4.3 Weights of CCR

The significance and contribution of each output and input parameter in the evaluation of efficiency of each decision making unit. Table 4.3 below shows the weight of each variable.

Table 4.4: Weights of variables in CCR

Name	Input 1	Input 2	Input 3	Input 4	Output 1	Output 2	Output 3
DMU 01	0	0.92	0	0.2	0	0	0.84
DMU 02	0	2.12	0	0	0	0	1.76
DMU 03	0	1.43	0	0	0	0	1.19
DMU 04	0.11	0.91	0.87	0.01	0	0	0.92
DMU 05	0	1.3	0.91	0	0	0	1.2
DMU 06	0	1.29	0	0.28	0	0	1.18
DMU 07	0	2.97	0	0.64	0	0	2.71
DMU 08	0	2.18	1.67	0.01	0	0	2.03
DMU 09	0	4.45	3.41	0.03	0	0	4.16
DMU 10	0	4.15	3.18	0.03	0	0	3.88
DMU 11	0.44	3.47	3.33	0.03	0	0	3.5
DMU 12	0.59	3.95	3.48	0.16	0	0	4.03
DMU 13	0	21.28	0	0	0	0	17.63
DMU 14	0	7.12	0	1.53	0	0	6.49
DMU 15	0	8	5.64	0	0	0	7.38
DMU 16	0	9.4	7.19	0.06	0	0	8.77
DMU 17	0	16.07	0	3.44	0	0.01	14.66
DMU 18	0	7.39	5.21	0	0	0	6.82
DMU 19	0	11.63	0	2.49	0	0	10.61
DMU 20	0.99	6.02	5.68	0	0	0	6.13
DMU 21	0	14.72	11.26	0.1	0	0.01	13.74
DMU 22	0	28.57	0	0	0	0	23.67
DMU 23	0	90.91	0	0	0	0	75.31
DMU 24	0	19.32	14.78	0.13	0	0.01	18.03
DMU 25	0	62.5	0	0	0	0	51.78
DMU 26	0	33.33	0	0	0	0	27.61
DMU 27	1.86	14.79	14.21	0.12	0	0.01	14.92
DMU 28	0	21.08	0	4.52	0	0.01	19.23
DMU 29	0	25.23	19.3	0.17	0	0.01	23.55
DMU 30	0	56.23	43.01	0.37	0	0.03	52.49
DMU 31	0	34.48	0	0	0	0	28.57
DMU 32	5.64	32.85	0	9.48	0	0	33.09
DMU 33	3.25	25.8	24.78	0.2	0	0.01	26.03

DMU 34	0	120.48	0	0	0	0	99.81
DMU 35	0	178.57	0	0	0	0.01	147.94
DMU 36	190.73	0	160.79	0	0	0	72.38
DMU 37	21.61	60.5	0	0	0	0	58.48
DMU 38	0	232.56	0	0	0	0.01	192.66
DMU 39	0	434.78	0	0	0	0.01	360.19
DMU 40	106.07	325.08	0	0	0.02	0.02	310.31
DMU 41	0	428.85	0	888.5	0.98	1.13	0
DMU 42	0	134.69	0	924.58	1	0	0
DMU 43	89.92	1248.62	0	306.34	0.27	0.38	1188.67
DMU 44	0	192.31	0	0	0	0	159.31
DMU 45	3.96	15.12	4.62	3.69	0	0.01	16.11
DMU 46	0	17.54	0	0	0	0	14.53
DMU 47	0	15.78	0	3.38	0	0.01	14.4
DMU 48	0	2.59	0	53.47	0	0.08	4.39

Analysing the table above, it is seen that only input 2 (number of covid-19 cases), input 4 ($GDP) and output 3 (recovered cases) contributed to the efficiency of DMU 1 (Russia). This means that inputs like tests done per country and total population did not affect the efficiency of the DMU, which is why they had zero weight. This is different from DMU 45 in which all the inputs contributed significantly with only one output contributing significantly. Generally, variables in a DMU with zero weight do not contribute to the efficiency of that DMU and the higher the weight, the more significant the contribution of that variable.

Figure 4.3 below shows the most significant input and output variables in evaluating healthcare efficiency in covid-19, based on their cumulative weights. It shows that input 2 (total number of covid-19 cases per country) is the most significant variable in determining the efficiency of a healthcare system in the pandemic, followed by input 4 ($GDPA). Output 3 (number of recoveries) is the most significant output variable in efficiency evaluation and is also the second most significant variable overall. Outputs 1 and 2 (number of deaths and ICU cases) have negligible impact on efficiency, while inputs 1 and 2 (total population and total tests) have a slightly important impact in healthcare efficiency evaluation in relation to covid-19.

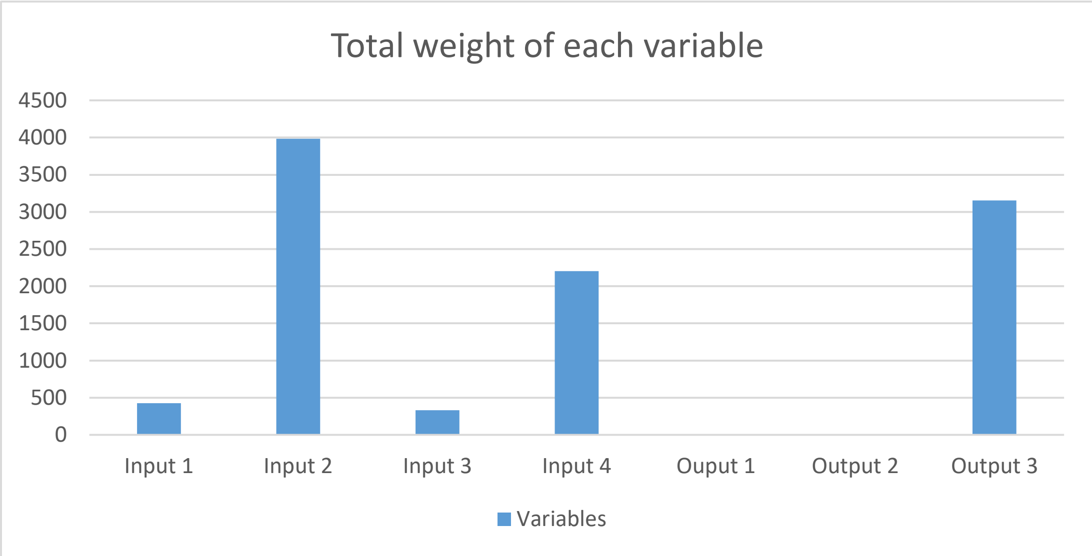

Figure 4.3: Total weight of each variable to determine significance

4.4 Target of CCR

Table 4.4a, 4.4b and 4.4c below shows the input weights, a target and the gain (%). These parameters are based on the fact stated discussed in the methodology section of the theses that to upgrade the efficiency of a DMU, the input weight has to be decreased or the output weight increased. The table shows the percentage increment or decrement necessary to meet the target value which is necessary for efficiency upgrade.

Table 4.5: CCR variable targets

Name	Input 1 Value	Input 1 Target	Input 1 Gain(%)	Input 2 Value	Input 2 Target	Input 2 Gain(%)
DMU 01	1	0.41	-58.57	1	0.84	-15.78
DMU 02	0.59	0.18	-69.79	0.47	0.38	-18.92
DMU 03	0.48	0.32	-33.58	0.7	0.68	-2.18
DMU 04	0.46	0.04	-91.93	0.94	0.08	-91.93
DMU 05	0.43	0.17	-59.33	0.69	0.37	-46.44
DMU 06	0.33	0.33	0	0.7	0.71	0
DMU 07	0.31	0.11	-65.02	0.33	0.19	-42.75

DMU 08	0.27	0.02	-93.44	0.43	0.03	-92.83
DMU 09	0.14	0.1	-29.44	0.21	0.18	-13.93
DMU 10	0.12	0.12	0	0.22	0.22	0
DMU 11	0.12	0.01	-92.86	0.24	0.02	-92.86
DMU 12	0.08	0.08	0	0.22	0.22	0
DMU 13	0.08	0	-97.42	0.05	0	-91.19
DMU 14	0.07	0.05	-34.95	0.13	0.1	-21.41
DMU 15	0.07	0.05	-30.89	0.11	0.1	-9.18
DMU 16	0.07	0.02	-75.9	0.1	0.03	-69.29
DMU 17	0.07	0.03	-56.71	0.06	0.05	-7.63
DMU 18	0.06	0.05	-13.42	0.12	0.11	-12
DMU 19	0.06	0.01	-86.31	0.08	0.01	-81.97
DMU 20	0.06	0.05	-15.45	0.14	0.12	-15.45
DMU 21	0.05	0.01	-70.04	0.06	0.03	-58.78
DMU 22	0.04	0.01	-66.29	0.04	0.03	-15.5
DMU 23	0.04	0	-90.98	0.01	0.01	-32.19
DMU 24	0.04	0.02	-54.07	0.05	0.03	-26.06
DMU 25	0.04	0.01	-84.68	0.02	0.01	-22.32
DMU 26	0.04	0	-86.67	0.03	0.01	-66.86
DMU 27	0.03	0.03	-7.48	0.06	0.06	-7.48
DMU 28	0.03	0.03	0	0.05	0.05	0
DMU 29	0.02	0.02	-32.96	0.04	0.03	-30.25
DMU 30	0.02	0.01	-71.58	0.02	0.01	-42.08
DMU 31	0.02	0.01	-69.43	0.03	0.01	-57.15
DMU 32	0.02	0.01	-27.19	0.03	0.02	-27.19
DMU 33	0.01	0.01	-19.29	0.03	0.03	-19.29
DMU 34	0.01	0	-97.17	0.01	0	-91
DMU 35	0.01	0	-82.28	0.01	0	-40.77
DMU 36	0	0	-5.9	0.02	0.01	-17.99
DMU 37	0	0	-18.13	0.02	0.01	-18.13
DMU 38	0	0	-48.65	0	0	-22.86
DMU 39	0	0	-61.83	0	0	-26.72
DMU 40	0	0	0	0	0	0
DMU 41	0	0	0	0	0	0
DMU 42	0	0	0	0	0	0
DMU 43	0	0	0	0	0	0
DMU 44	0.01	0	-94.8	0.01	0	-83.96
DMU 45	0.02	0.02	0	0.06	0.06	0
DMU 46	0.13	0.02	-81.39	0.06	0.05	-6.98
DMU 47	0.07	0.02	-68.11	0.06	0.04	-32.29
DMU 48	0.6	0.6	0	0.34	0.35	0

Name	Input 3 Value	Input 3 Target	Input 3 Gain(%)	Input 4 Value	Input 4 Target	Input 4 Gain(%)
DMU 01	1	0.12	-88.35	0.39	0.33	-15.78
DMU 02	0.14	0.06	-57.11	1	0.18	-82.01
DMU 03	0.22	0.11	-49.89	0.7	0.32	-54
DMU 04	0.1	0.01	-91.93	0.68	0.05	-91.93
DMU 05	0.11	0.06	-46.44	0.49	0.18	-64.2
DMU 06	0.11	0.11	0	0.33	0.33	0
DMU 07	0.02	0.01	-46.27	0.04	0.02	-42.75
DMU 08	0.03	0	-92.83	0.15	0.01	-92.83
DMU 09	0.02	0.02	-13.93	0.07	0.06	-13.93
DMU 10	0.02	0.02	0	0.23	0.23	0
DMU 11	0.03	0	-92.86	0.13	0.01	-92.86
DMU 12	0.02	0.02	0	0.06	0.06	0
DMU 13	0.01	0	-94.4	0.05	0	-96.16
DMU 14	0.02	0.02	-31.44	0.06	0.05	-21.41
DMU 15	0.02	0.02	-9.18	0.14	0.06	-59.21
DMU 16	0.01	0	-69.29	0.04	0.01	-69.29
DMU 17	0.02	0.01	-67.48	0.02	0.01	-7.63
DMU 18	0.02	0.01	-12	0.11	0.08	-30.14
DMU 19	0.01	0	-87.09	0.01	0	-81.97
DMU 20	0.01	0.01	-15.45	0.19	0.06	-68.62
DMU 21	0	0	-58.78	0.02	0.01	-58.78
DMU 22	0.04	0	-88.25	0.09	0.01	-84.57
DMU 23	0.01	0	-87.33	0.07	0	-94.9
DMU 24	0.01	0	-26.06	0.03	0.02	-26.06
DMU 25	0.01	0	-82.96	0.1	0.01	-93.85
DMU 26	0.01	0	-83.52	0.11	0	-95.45
DMU 27	0	0	-7.48	0.02	0.01	-7.48
DMU 28	0	0	0	0	0	0
DMU 29	0	0	-30.25	0	0	-30.25
DMU 30	0	0	-42.08	0	0	-42.08
DMU 31	0.01	0	-71.1	0.02	0.01	-60.68
DMU 32	0	0	-29.9	0	0	-27.19
DMU 33	0	0	-19.29	0.01	0.01	-19.29
DMU 34	0	0	-94.9	0.01	0	-94.23
DMU 35	0	0	-69.39	0.01	0	-77.25
DMU 36	0	0	-5.9	0	0	-5.9
DMU 37	0.01	0	-56.94	0.02	0	-77.3
DMU 38	0	0	-69.6	0	0	-39.82
DMU 39	0	0	-54.13	0	0	-40.25
DMU 40	0	0	0	0	0	0
DMU 41	0	0	0	0	0	0
DMU 42	0	0	0	0	0	0
DMU 43	0	0	0	0	0	0

DMU 44	0	0	-91.23	0.01	0	-86.18
DMU 45	0	0	0	0	0	0
DMU 46	0.02	0.01	-57.1	0.04	0.02	-43.21
DMU 47	0.01	0	-62.86	0.01	0.01	-32.29
DMU 48	0.12	0.12	0	0	0	0

Name	Output 5 Value	Output 5 Target	Output 5 Gain(%)	Output 6 Value	Output 6 Target	Output 6 Gain(%)
DMU 01	0	0.02	6115.53	0	0.02	2892.27
DMU 02	0	0	0	0	0	92.22
DMU 03	0	0	203.21	0	0	0
DMU 04	0	0	20.22	0	0	77.61
DMU 05	0	0	255.41	0	0	0
DMU 06	0	0	0	0	0	0
DMU 07	0	0.02	2219.61	0.02	0.02	28.04
DMU 08	0	0	245.65	0	0	169.53
DMU 09	0	0.01	3000.23	0	0.01	693.97
DMU 10	0	0	0	0	0	0
DMU 11	0	0.01	1268.69	0	0	0
DMU 12	0	0	0	0	0	0
DMU 13	0.01	0.01	0	0	0	43.23
DMU 14	0	0.01	66.67	0	0	0
DMU 15	0	0.06	2793.91	0.01	0.01	0
DMU 16	0	0.01	229.03	0	0	0
DMU 17	0.01	0.02	49.09	0.02	0.02	0
DMU 18	0	0.02	349.39	0	0	0
DMU 19	0.01	0.01	0	0.01	0.01	0
DMU 20	0	0.02	627.99	0	0	0
DMU 21	0	0.01	344.02	0	0	0
DMU 22	0	0.07	3722.93	0.05	0.05	0
DMU 23	0.04	0.13	216.75	0.1	0.1	0
DMU 24	0.02	0.06	210.96	0.01	0.01	0
DMU 25	0.05	0.07	56.02	0.05	0.05	0
DMU 26	0.01	0.09	1000.39	0.06	0.06	0
DMU 27	0.01	0.03	312.2	0.01	0.01	0
DMU 28	0.01	0.01	0	0.01	0.01	0
DMU 29	0.01	0.17	2803.2	0.03	0.03	0
DMU 30	0.02	0.55	2789.05	0.07	0.07	0
DMU 31	0.03	0.03	0	0.02	0.02	36.59
DMU 32	0.01	0.09	880.44	0.01	0.04	184.65
DMU 33	0.01	0.07	571.62	0.01	0.01	0
DMU 34	0.07	0.07	0	0.04	0.05	15.41
DMU 35	0.14	0.16	20.84	0.12	0.12	0
DMU 36	0.03	0.11	226.25	0.03	0.06	116.86
DMU 37	0.05	0.67	1249.31	0.05	0.31	525.85

DMU 38	0.11	0.16	36.07	0.11	0.11	0
DMU 39	0.63	1.4	122.89	1	1	0
DMU 40	0.22	0.22	0	0.1	0.1	0
DMU 41	0.56	0.56	0	0.4	0.4	0
DMU 42	1	1	0	0.13	0.13	0
DMU 43	0.37	0.37	0	0.18	0.18	0
DMU 44	0.28	0.28	0	0.13	0.2	49.57
DMU 45	0.01	0.01	0	0.08	0.08	0
DMU 46	0.01	0.01	56.45	0.01	0.01	0
DMU 47	0.01	0.1	855.58	0.07	0.07	0
DMU 48	0.01	0.01	0	0	0	0

Name	Output 7 Value	Output 7 Target	Output 7 Gain(%)
DMU 01	1	1	0
DMU 02	0.46	0.46	0
DMU 03	0.82	0.82	0
DMU 04	0.09	0.09	0
DMU 05	0.45	0.45	0
DMU 06	0.85	0.85	0
DMU 07	0.21	0.21	0
DMU 08	0.04	0.04	0
DMU 09	0.21	0.21	0
DMU 10	0.26	0.26	0
DMU 11	0.02	0.02	0
DMU 12	0.25	0.25	0
DMU 13	0	0	0
DMU 14	0.12	0.12	0
DMU 15	0.12	0.12	0
DMU 16	0.04	0.04	0
DMU 17	0.06	0.06	0
DMU 18	0.13	0.13	0
DMU 19	0.02	0.02	0
DMU 20	0.14	0.14	0
DMU 21	0.03	0.03	0
DMU 22	0.04	0.04	0
DMU 23	0.01	0.01	0
DMU 24	0.04	0.04	0
DMU 25	0.02	0.02	0
DMU 26	0.01	0.01	0
DMU 27	0.06	0.06	0
DMU 28	0.05	0.05	0
DMU 29	0.03	0.03	0
DMU 30	0.01	0.01	0
DMU 31	0.02	0.02	0
DMU 32	0.02	0.02	0
DMU 33	0.03	0.03	0

DMU 34	0	0	0
DMU 35	0	0	0
DMU 36	0.01	0.01	0
DMU 37	0.01	0.01	0
DMU 38	0	0	0
DMU 39	0	0	0
DMU 40	0	0	0
DMU 41	0	0	0
DMU 42	0	0	0
DMU 43	0	0	0
DMU 44	0	0	0
DMU 45	0.06	0.06	0
DMU 46	0.06	0.06	0
DMU 47	0.05	0.05	0
DMU 48	0.23	0.23	0

From table 4.4a, it is seen that in order for DMU 1 (Russia) to upgrade efficiency, a certain target has to be met. Its input 1 (total population) has to decrease its weight by a gain of -58.57% to a value of 0.41, input 2 (total cases) has to be decreased by -15.78% to 0.84, input 3 (tests done) has to be decreased by -88.35% to 0.12 and input 4 ($GDP) by -15.78 to 0.33. This decreases in input will drive efficiency. On the output side, there is no observable change in gain as most of the output weights are zero, and the only significant output cannot be increased further above 1.

Output 3 in the DMUs show no reasonable quantifiable gain because the target needed to meet efficiency is equal to the actual value. The significance of output 3 in driving efficiency can be deduced from figure 4.3. Gains for output 1 and 2 are usually very high because their original values are low, sometimes zero. This is why they have a low impact on efficiency from figure 4.3.

DMUs that are optimally efficient and are on the frontier of efficiency show zero change in gain. This is because no further improvements can be made. DMU 06

(Spain), DMU 10 (Netherlands), DMU 12 (Czech Republic), DMU 28 (Moldova), DMUs 40 to 43 (Andorra, Monaco, Liechtenstein and San Marino respectively), DMU 45 (Armenia) and DMU 48 (Turkey) show zero adjustments in gain despite differing values for their input and outputs.

Chapter 5

CONCLUSION, RECOMMENDATION AND SUGGESTION

In this section of the research, the efficiency of the healthcare systems of 48 European countries during the pandemic is evaluated by considering some health and population variables (total population, amount of covid-19 tests done, number of recovery cases), which is important considering the extreme pressure the pandemic imposed on health resources. DEA was used in analyzing the data, and conclusion was made based on the results obtained using CCR model as the methodology in analyzing the data downloaded from the World Health Organisation and the International Monetary Fund.

5.1 Conclusion

The covid-19 pandemic, which originated in China, 2019 has spread globally. Global health systems have been responsible for discovering and implementing measures for mitigating, preventing and possible curing the disease. Thus, the health system is the primary system responsible for battling the pandemic and securing society from the effects of the pandemic. This implies that nations have had to amass their health resources (human and material) to address the pandemic. Rising inflation, international insecurity and increasing poverty, especially in developing countries has led to an increase in the fragility of health system due to falls in government and private spending on healthcare. These issues were discussed in chapter 1 of this thesis which was an introduction to the core concepts of the topic and in chapter 2 of the thesis which was a review of literature relevant to the topic.

Health systems, which were fragile pre-covid, have now been further ravaged by the pandemic with an unprecedented pressure on health resources. Scarcity of protective medical equipment like masks and bio-hazard suits, inadequate ventilators for handling critical cases, insufficient ICUs, unavailability of test kits for many countries, and currently, a great scarcity of vaccines, with low income countries having zero access to these vaccines and protective measures have made it necessary for health systems to evaluate their performance and efficiency and also determine how efficiency can be optimized to ensure optimal performance delivery and prevent wastage. In chapter 3, the methodology used was explained, with the mathematical framework for the development of the methodology's model given. Also, the raw data on covid-19 death rates and recovery rates among others was obtained from the World Health Organisation's website, while the data on Gross Domestic Product (GDP) was obtained from the International Monetary Fund's website. This data was presented in chapter 3, with the variables and the reasons for the choice of variables explained in that chapter. In chapter 4, the normalised data, which was derived from the raw data was presented and this normalised data was run through the PIM-DEA software based on the CCR model for DEA analysis. The results and a brief explanation of the various results were given in chapter 4.

From table 4.1, the efficiency data gave 10 countries that were optimally efficient. They were Spain, Netherlands, Czech Republic, Moldova, Andorra, Monaco, Liechtenstein, San Marino, Armenia and Turkey. It is observed from this list that countries on the efficiency frontier of managing the pandemic are mixture of highly developed and developing countries. This is further reflected in countries that have close to optimal efficiency like Russia, the United Kingdom and Germany which are highly advanced countries with Kazakhstan and Belarus which are not as developed. This indicates that development is not a really significant variable in determining efficiency of health systems is relation to the pandemic. The inefficient countries, with efficiency scores less than 20% were France, Poland, Belgium, Greece, Serbia and Latvia. The surprising inclusions here are France, Belgium and Poland. This further reinforces the fact of societal advancement and development playing a minimal role in controlling the pandemic. Although, this is a rather broad interpretation because highly developed countries on the lower side of efficiency tend to have higher populations which affects their efficiency in the management of the pandemic.

To account for the effect of population on efficiency measurement, the countries are classified into three groups; low population, medium population and high population in table 5.1, with the comparison of efficiencies done based on this classification. Based on the data from table 3.1, countries with population greater than 50 million are classified as high population, countries with a population between 10 million and 5 million are moderately populated and countries with a population less than 5 million are low population countries.

Table 5.1: Population based classification

High Population	Moderate Population		Low Population	
Russia	Spain	Belarus	Ireland	Luxemborg
Germany	Ukraine	Austria	Croatia	Malta
United Kingdom	Poland	Serbia	Moldova	Iceland
France	Romania	Switzerland	Bosnia and Herzegovia	Andorra
Italy	Netherlands	Bulgaria	Albania	Monaco
Turkey	Belgium	Denmark	Lithuania	San Marino

	Czech Republic	Kazakhstan	North Macedonia	Armenia
	Greece	Azerbaijan	Slovenia	Iceland
	Portugal	Hungary	Latvia	Montenegro
	Sweden	Slovakia	Estonia	Liechtenstein
	Finland	Norway		

Comparing table 5.1 with table 4.1, it is noted that most high population countries are close to the efficiency frontier with Turkey having maximum efficiency, and Italy having average efficiency. France is the only high population country with low efficiency. France's low efficiency could be due to a high number of Covid-19 cases and ICU cases relative to other high population countries.

Among moderately populated countries, Spain, Netherlands and the Czech Republic have maximum efficiency, with Poland, Belgium, Greece and Serbia having low efficiency. Countries like Romania, Sweden, Portugal, Belarus, Denmark, Kazakhstan etc operated close to the efficiency of frontier, while Finland had average efficiency. The mixture of countries across all development levels in every efficiency grade is observed strongly among the moderately populated countries.

Low population countries have Moldova, Andorra, Monaco, Liechtenstein and San Marino at the frontier of efficiency. With $GDP thousands of times smaller than France which had low efficiency, the defining difference was the low ICU cases in these low population countries, which can be accounted for by their low population.

Table 4.2 presents the lambdas which are the benchmark results that will be compares to the countries that are not optimally efficient. This data serves to see how inefficient countries compare to the optimally efficient ones. Surprisingly, Moldova which is the least advanced country of the optimal countries was the most referenced lambda from figure 4.2. This means most inefficient countries took Moldova as the benchmark for efficiency, even advanced inefficient countries like Russia and Belgium. Turkey, although being the largest and most developed lambda was the least referenced, serving as a benchmark for itself alone. This reinforces the point in the previous paragraph.

Weights of each variable in determining efficiency in table 4.3 gives greater insight into why Moldova is highly efficient. The input variable "Number of cases" has a weight of 21.08 and the output "Recovery rate" has a weight of 19.23. These are the most significant variables for Moldova and the whole DMUs thus, Moldova is able to serve as a benchmark for countries with the same sort of significant variables. Turkey's most significant variable is "$GDP", thus making it a omitted benchmark because covid-19 based parameters are the variables that link all the DMUs. Countries with almost optimum efficiencies like Sweden, Denmark, Croatia and Montenegro had better spread of weights across all variables. Figure 4.3 gives the total significance of each variable based on its cumulative weight across all DMUs. Inefficient countries like France, Denmark and Poland had low weights across all variables. This indicates low recovery rates and low testing rates.

Table 4.4 is a table of the target values for each variable to reach per DMU for efficiency to be achieved. It is gotten from the PIM-DEA software, using the CCR model. For inefficient countries like France, Poland, Belgium, Greece, Serbia, Latvia to improve their efficiencies, they all need to reduce their inputs (number of cases, population) by around 90%. Although the data proposes an increase in outputs for upgrading efficiency, increasing the outputs which are negative outcomes is unwise. Moderately efficient countries need to increase efficiency by an average of 50% to upgrade their efficiencies. To improve efficiency, inputs can either be reduced or output increased. From the nature of these variables, an input decrease at the level proposed by table 4.4 is advised rather than an output increase.

5.2 Recommendation and Suggestion

The primary aim of this thesis is to determine the efficiency levels of national healthcare systems in the covid-19 pandemic. From the data, only 10 countries are optimally efficient. The covid-19 pandemic is a global scourge that is still causing increasing death rates and because of this, the author recommends some measures to improve efficiencies in countries both in Europe and outside Europe. The researcher noted that although the data implies that countries like Andorra and Moldova with the least populations were more efficient than countries like Russia, Germany and France which are more developed, using table 5.1 for further analysis shows how population disparities among countries greatly skews the efficiency ratios. Thus, further efficiency studies that correct for the population disparity should be conducted. These studies could use variables that are population independent. Table 5.1 serves as a good guide for population classification. The researcher also recommend that the Government and policy makers must initiate programs that will keep population growth to a minimal while making sure that measures that keep the spread down like social distancing, lockdowns, remote work, wearing of face masks are implemented. This will reduce the number of cases and improve efficiency as indicated from table 4.4.

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