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COVID-19 Response and Prospects of Clean/Sustainable Energy Transition in Industrial Nations: New Environmental Assessment

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Abstract: Coronavirus Disease 2019 (COVID-19) became a pandemic around the world and has huge impacts on our economic and social systems, particularly on the healthcare system and the transportation and energy sectors. To examine a relationship between healthcare and energy sectors in the COVID-19 era, we propose a holistic application of Data Envelopment Analysis for Environmental Assessment (DEA-EA) to assess the COVID-19 response performance of 33 OECD (Organization for Economic Co-operation and Development) nations and investigate whether health insurance systems contribute to the performance. We also associate the performance with mobility, which is an energy consumption measure, to test the relationship through statistical analyses. In the DEA-EA, particularly, this study incorporates undesirable outputs (i.e., the number of confirmed cases and that of deaths) as well as desirable outputs (i.e., the number of total recovered people and that of total tested people) during April 2020 as the initial stage of COVID-19. While the former outputs need to be maximized, the latter ones need to be minimized in the assessment of healthcare system performance. This study finds that (a) the COVID-19 response performance of countries is varying and those with higher public health coverage have outperformed others with lower public coverage in terms of combating the COVID-19 outbreak, and (b) the healthcare system performance is significantly associated with mobility. Particularly, the second finding indicates that outperforming nations in the healthcare system are returning to the normal (with less volatility) while underperforming ones are still stagnating in terms of mobility. It implies that outperforming countries need to prepare for continuous commitment to clean/sustainable energy transition.

Keywords: coronavirus; energy; mobility; healthcare system; data envelopment analysis

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1. Introduction

Human and natural systems have interacted with each other in history. For instance, the transportation sector (particularly, fossil fuel-powered vehicles for mobility) has emitted an enormous amount of Greenhouse Gases (GHGs) that led to global warming and climate change. In return, they have affected transportation infrastructure adversely. In addition to the interplay of transportation and energy/environment, human beings are currently facing serious public health challenges stemming from the novel coronavirus disease 2019 (COVID-19) pandemic. By the nature of the infectious respiratory disease, many nations have sought to contain COVID-19 through confinement measures such as a lockdown or stay-at-home advisory. While those government policies impacted their economies negatively, they resulted in the reduction of trips that led to the lower volume of energy demand and supply but the improvement of the environment (e.g., better air quality) [1,2]. At this moment, it is not easy to predict how long those energy/environmental gains will last. However, it is important to explore the relationship between energy/environment, public health, and transport sectors. Specifically, examining how COVID-19 is related to mobility and energy consumption has many policy implications not only for public health but also for transportation and energy/environment decision-makers.

One of the policy issues related to the COVID-19 management is the provision of healthcare access, particularly to the marginalized populations who are more vulnerable to various health risks. For example, those who live in polluted areas are more likely to have COVID-19 confirmed cases or deaths [3,4]. Given that healthcare access is intertwined with health insurance systems, the COVID-19 crisis called attention to the role of health insurance systems. It was particularly true in nations with private health insurance systems (rather than public or universal health insurance systems). In the United States, for instance, redesigning its health insurance system recently aroused public opinion in battling COVID-19 [5]. It is also worth noting that health insurance systems determine the amount of medical resources, such as hospital personnel and medical space/supplies, which rely on energy [6].

Another policy concern is how COVID-19 will impact each nation's clean/sustainable energy transition (e.g., Green New Deal initiatives). Before COVID-19 took place, many countries, particularly the Organization for Economic Co-operation and Development (OECD) members, were on the trajectory of attaining sustainable development goals by decreasing their reliance on fossil fuels and increasing alternative energy sources. The Kyoto Protocol and the Paris Climate Agreement, as well as the United Nations Framework Convention on Climate Change (UNFCCC), were examples of those efforts. However, COVID-19 changed many things including the contexts surrounding the original sustainable development goals and implementation plans [7]. Because of the heterogeneity of each nation's COVID-19 containment measures and capacities, they undergo different levels of economic and health damages that may enable some countries to keep on track but may derail others from their original paths to sustainable development. Moreover, the higher priority of government spending on the response to the COVID-19 emergency may postpone investing in clean/sustainable energy transition. Given the complex impacts of this unprecedented situation on the clean/sustainable energy transition, it may require more holistic approaches to address policy concerns. A recently proposed concept, the healthcare–energy–environment nexus under climate change constraints [8], can be such an example.

In this vein, this study aims to explore the relationships between healthcare and mobility, and their implications on clean/sustainable energy transition at a national level; see Figure 1. Specifically, we examine the public health performance of OECD countries in preventing and controlling the COVID-19 crisis instead of using oversimplified metrics such as the number of cases or deaths. Then, we relate the national-level performance with mobility using Google's COVID-19 Community Mobility reports, which collect mobile phone users' location data. Moreover, we examine the moderating effect of health insurance systems in the relationship. Based on the results, lastly, we develop policy implications on outperforming OECD countries in containing COVID-19 and on underperforming countries.

To explore such concerns, this study takes a two-stage approach. We measure each nation's COVID-19 response performance by proposing a novel application of Data Envelopment Analysis for Environmental Assessment (DEA-EA) at the first stage. Then, we examine statistical relationships between the performance and mobility (as a proxy for energy consumption/supply) and consider that the transportation sector is a major consumer of energy and contributor to GHG emissions while being impacted the most by the COVID-19 prevention and control measures at the second stage. To partly deal with the methodological difficulty in the first-stage assessment, this research attempts to apply DEA-EA, as a practical method, which allows us to deal with multiple inputs and outputs (undesirable and desirable outputs) based on linear programming and to produce efficiency scores (generally between 0 and 1) as an indicator for performance. In the conventional use of DEA-EA, economic activities are characterized by multiple production factors such as

X (a vector of inputs), *G* (a vector of desirable outputs), and *B* (a vector of undesirable outputs). At the national level, for instance, population, Gross Domestic Product (GDP), and environmental pollution can represent *X*, *G*, and *B*, respectively. In the public health context of COVID-19, however, we need to incorporate different production factors, such as the number of hospital employees, the number of recoveries, and the number of deaths, in each nation's healthcare systems.

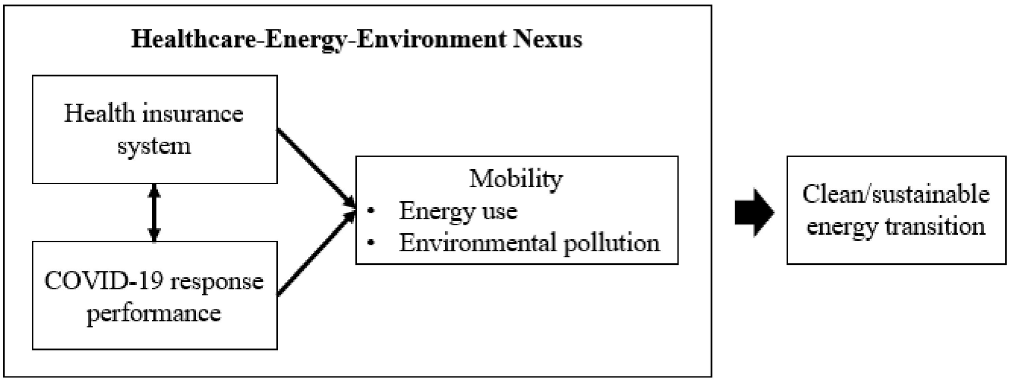


Figure 1. Relationships between healthcare–energy–environment nexus and clean/sustainable energy transition.

The remaining sections are organized as follows: Section 2 conducts a literature survey on the interplay of COVID-19 and energy/environment and the applications of DEA to public health along with a brief introduction of national health insurance systems. Section 3 demonstrates a preliminary analysis of COVID-19 and the energy market with a focus on the United States. Section 4 describes a proposed novel application of DEA-EA to healthcare systems. Section 5 summarizes our empirical results obtained in this research. Section 6 discusses the research outcomes in the COVID-19 context. Section 7 concludes this study along with future extensions.

2. Literature Review

For the purpose of this study, we have surveyed literature on three different realms: (a) the applications of DEA to the assessment of healthcare performance, (b) health insurance systems in OECD nations, and (c) interplay of COVID-19 and energy/environment. In the first realm of literature, we explore various DEA applications in the public health context and justify the use of the DEA-EA methodology for measuring performance of public health units and specific inputs and outputs in the analytic framework. In the second, we look into health insurance systems that play critical role in providing access to healthcare and, as an important context, may influence the healthcare performance. In the third, we associate COVID-19 (and its response) with energy market and environmental pollution. Based on those threads of literature, we constructed our research hypotheses. After the three surveys, this section describes a rationale on why our approach is important in exploring the relationship between COVID 19 and energy concerns.

2.1. Applications of DEA to Assessment of Healthcare Performance

Efficiency has been one of the important criteria in the various types of decision-making processes, particularly in evaluating the performance of Decision-Making Units (DMUs). Since DEA was developed to compute the efficiency scores of DMUs with multiple inputs and outputs and provide a holistic nonparametric approach, it has been applied to both public and private entities. Healthcare entities are one of the examples and DEA has been used for assessing the performance of hospitals/clinics at an organizational level, states/provinces at a regional level, and countries at a national level. Particularly, Table 1 summarizes previous DEA efforts to evaluate the performance of healthcare systems at a national level. For example, Zanakis and Alvarez [9] measured the efficiency of

116 countries in dealing with HIV/AIDS (Human Immunodeficiency Virus/Acquired Immunodeficiency Syndrome). Asandului et al. [10] looked into European nations to assess their public health system performance in maximizing life expectancy while minimizing the required numbers of doctors and beds.

As COVID-19 became a pandemic and has huge impacts on our societies, each country has been struggling in protecting its people from suffering and dying from COVID-19 symptoms [11]. They are desperate in forcing people to keep social distancing and securing not only human capital (e.g., doctors and nurses) but also materials (e.g., hospital beds) to prevent COVID-19 from spreading and to treat COVID-19 cases better. It requires a high degree of efficiency in many aspects. For instance, it is important to understand and determine how to triage patients, how to allocate healthcare personnel, and how to produce and distribute necessary goods such as respirators and masks more efficiently not only at a hospital level but also at a national level [12,13].

From this perspective, it makes sense to assess each nation's healthcare systems by efficiency in managing the COVID-19 crisis. It also suggests that DEA may act as a vehicle to measure the efficiency scores. Acknowledging the importance of such previous works, as summarized in Table 1; however, this study points out that the previous DEA studies applied to healthcare systems have a methodological problem. Their research tool was a standard DEA model, often referred to as ratio form, which can deal with desirable outputs only. For instance, most of the previous efforts have looked into the performance of country-level healthcare systems with a focus on maximizing life expectancy or survival rate (as a transformation of mortality rate that needs to be minimized). To address this issue, we need to separate outputs into desirable and undesirable categories, both of which have opposite directions for optimization. In our COVID-19 context, for example, the number of recoveries should be maximized but the number of deaths should be minimized. The two types of outputs are unified together in a DEA-EA that is different from the classical DEA and contains two different efficiency frontiers. One of the two frontiers is for desirable outputs and the other is for undesirable outputs. The type of DEA applications cannot be found in the conventional use of DEA models. To our best knowledge, furthermore, the DEA-EA approach has not been used in a healthcare context.

2.2. Health Insurance Systems in OECD Nations

Health insurance is a key to quality healthcare services in both public and private healthcare systems. While healthcare access matters in address public health issues, each nation has adopted different health insurance systems. There are some studies on the taxonomy of healthcare systems [17,18]. So, we largely classify them into public and private ones. The former includes (a) UGHS (Universal Government-funded Health System), (b) UPIS (Universal Public Insurance System), and (c) UPPS (Universal Public–Private Insurance System) while the latter includes (d) UPHS (Universal Private Health Insurance System and (e) NUIS (Non-Universal Insurance System). Table 2 summarizes the unique features of the five different healthcare insurance systems in OECD nations.

Table 1. Data Envelopment Analysis (DEA) applications to healthcare systems.

Author(s)	Country	Model	Summary	Inputs	Outputs
Zanakis et al. [9]	World	Regression analysis and DEA	This study identified social and economic determinants of HIV/AIDS and measured the efficiency of 116 countries in dealing with the pandemic.	Health system performance index with existing resources; health private expenditure; health public expenditure tax-funded; doctors per capita; nurses per capita; adult literacy rate; GNP per capita; radios per capita	Percentage of total adults living with HIV/AIDS; HIV/AIDS cases per capita; and AIDS-related death rate for adults and children
Spinks & Hollingsworth [14]	OECD countries	DEA	This study looked into the health production efficiency of 28 OECD countries.	The level of education; unemployment rate; GDP per capita; total health expenditure	Life expectancy
Asandului et al. [10]	European countries	DEA and censored regression analysis	This study explored the efficiency of 30 European countries' public health systems and the relationship between the efficiency, economic and demographic factors.	The number of radiotherapy units per 1,000,000 inhabitants; public health expenditures as a percentage of the GDP; and the number of hospital beds for 10,000 inhabitants	The incidence of tuberculosis; the number of deaths by ischemic diseases per 100,000 inhabitants; and the health adjusted life expectancy
Ortega et al. [15]	Developing countries	Robust DEA and regression analysis	This study measured the efficiency of 47 developing countries in enhancing the under-five survival rate and examined the relationship between efficiency, inequality, and government effectiveness.	Physician density per 10,000 people; and Total health expenditure as a percentage of the country's GDP	Under-five survival rate; and the Proportion of 1-year-old children immunization against measles
Abolghasem et al. [16]	World	Cross-efficiency DEA with a flexible measure	This study measured the average cross-efficiency of 120 countries' healthcare systems.	Population; Specialist surgical; birth rate; total fertility rate; hospital beds; nurses and midwives; physicians	Mortality; life expectancy (as a flexible measure)

Table 2. Description of five different health insurance systems.

Health Insurance System	Description	Example
Universal government-funded health system (UGHS)	All citizens, regardless of their income or employment status, are accessible to government-funded healthcare (or single-payer healthcare). Non-citizen residents may access healthcare in some countries or buy private insurance in other countries.	UK: Under the National Health Service (NHS) Act of 1946, all citizens are eligible for a comprehensive, free health service. Non-citizens can access only limited services such as emergency treatment. A primary NHS funding source is general taxes. The NHS places limitation on cost-sharing arrangements for free health services. Outpatient prescription drugs and dentistry services are subject to copayments whereas screening and vaccination are not. As of 2016, out-of-pocket health expenditures by households accounted for 15 percent of total expenditures.
Universal public insurance system (UPIS)	Employed workers carry social insurance based on tax levied by both employee and employer. Those who are not employed or cannot register as unemployed may be ineligible for public health care.	Japan: The combination of the statutory health insurance system (SHIS) and the Public Social Assistance Program cover all citizens and resident non-citizens. The SHIS is based on either employment or residence. Those who carry SHIS pay copayments and coinsurance without any deductibles, but marginalized people are exempt. As of 2015, out-of-pocket payments accounted for 14 percent of current health expenditures.
Universal public-private insurance system (UPPS)	Some people receive healthcare via primary private insurance. Others who are cannot afford to buy private insurance are benefitted from the government.	Germany: Health insurance became mandatory in 2007 via either statutory health insurance or private health insurance. Copayments are determined by federal legislation. For instance, there are no copayments for recommended preventive service (e.g., cancer screenings). As of 2017, out-of-pocket spending accounted for 13.5 percent of total health spending.
Universal private health insurance system (UPHS)	People receive healthcare via mandatory private insurance. Low-income citizens are eligible for government subsidy.	Switzerland: Under the Health Insurance Law in 1994, health insurance became mandatory, which is provided by many small private insurers. The insured pays 10 percent coinsurance for most services along with a minimum annual deductible of CHF 300 and a zero deductible for children. As of 2016, cost-sharing accounted for 5.3 percent of total health expenditures.
Non-universal insurance system (NUIS)	Some citizens carry private health insurance. Others are eligible for subsidized public health care. While health insurance is not mandatory, some are not insured at all.	U.S.A.: As of 2018, 8.5 percent of the population (i.e., 27.5 million people) are uninsured due to the non-universal insurance system. More than the half of population is covered by employment-based insurance. For the marginalized people, public insurance programs such as Medicare and Medicaid have been provided since 1965. The insured pays fully up to a deductible. As of 2018, out-of-pocket spending represented 10 percent of total health expenditures, which is particularly substantial for dental care and prescribed medicines.

Source: International Health Care System Profiles and the Commonwealth Fund.

Table 3 summarizes health insurance systems in 33 OECD nations. Although there are 36 member countries on the OECD member list, we have dropped three (New Zealand, Poland, and Sweden) due to their data limitations. The values in parenthesis represent the percentage of the population covered by primary public health insurance [19]. For example, the United States has 35.9% of the total population belonging to "Medicare", which is public healthcare insurance for old people more than 65.

Table 3. Health insurance systems of 33 OECD countries.

Health Insurance System	Universal and Public Health Insurance System			Non-Universal and Private Health Insurance System	
	UGHS (N = 12)	UPIS (N = 13)	UPPS (N = 5)	UPHS (N = 2)	NUIS (N = 1)
Country (public coverage, %)	Australia (100%) Canada (100%) Denmark (100%) Finland (100%) Greece (100%) Iceland (99.5%) Ireland (100%) Italy (100%) Norway (100%) Portugal (100%) Spain (99%) U.K. (100%)	Belgium (98.7%) Czech R. (100%) Estonia (94.1%) France (99.9%) Hungary (94%) Israel (100%) Japan (100%) Korea (100%) Latvia (100%) Lithuania (98.1%) Luxembourg (95.2%) Slovak R. (94.6%) Slovenia (100%)	Austria (99.9%) Chile (75.6%) Germany (89.4%) Mexico (89.3%) Turkey (99.2%)	Netherlands (0%) Switzerland (0%)	USA (35.9%)

Note: UGHS = Universal Government-funded Health System, UPIS = Universal Public Insurance System, UPPS = Universal Public-Private Insurance System, UPHS = Universal Private Health Insurance System, NUIS = Non-Universal Insurance System; and values in parenthesis represent the percentage of population covered by primary public health insurance. Source: OECD [19].

In this vein, we construct the following null hypothesis:

Hypothesis 1 (H1). *Each nation's COVID-19 responses are the same as their performance measures.*

They may vary across their different conditions and are dynamic over time. As an example of the heterogeneous conditions, we select each nation's different health insurance systems. Given that one of the critical determinants of COVID-19 response performance is people's access to quality healthcare, the performance may be affected by each nation's health insurance systems. Taking the progression of COVID-19 and governments' policy actions into account, in addition, the performance may be changing over time.

2.3. Interplay of COVID-19 and Energy/Environment

Table 4 summarizes previous studies between COVID-19 and energy/environment. With the emergence of the COVID-19 pandemic, a considerable number of attempts have explored not only public health but also energy/environment issues. As depicted in Table 4, scholars started researching the impact of COVID-19 on energy/environment at local, regional, national, and global levels. For instance, Collivignarelli et al. [20] and Adams [21] explored the impact of COVID-19-related government measures on the concentration of air pollutants that were primarily emitted from vehicle tailpipes and found a significant decrease in the concentration at the City of Milan, Italy, and the Province of Ontario, Canada, respectively.

Table 4. Studies of the interactions between COVID-19 and energy/environment.

Author(s)	Country	Summary
Collivignarelli et al. [20]	Italy	This study measured the effects of Italian local governments' lockdown order on air pollutants concentration primarily due to the reduced amount of traffic.
Adams [21]	Canada	This study examined the impact of the province of Ontario's emergency measures on the concentration of air pollutants (e.g., nitrogen oxide and dioxide) as a result of stay-at-home and fewer trips.
Malliet et al. [22]	France	This study evaluated the short- and long-term impact of lockdown measures on economy and environment with a focus on CO_2 emissions and carbon pricing implementation.
Lahcen et al. [23]	Belgium	This study quantified the macroeconomic impact of COVID-19 taking into account CO_2 emissions and government investments in eco-friendly construction projects.
Le Quéré et al. [24]	Europe, US, China, and India	This study explored how government policies (confinements) influence CO_2 emissions through changes in sectoral activities, particularly in the surface transport.
Ghiani et al. [25]	Italy	This study analyzed the impact of COVID-19 containment measures on load profiles, consumption, and market price in the electricity sector.
Ruan et al. [26]	US	This study assessed the short-term impact of COVID-19 on the electricity consumption along with social distancing and commercial activity.
Eryilmaz et al. [27]	US	This study looked into how the stay-at-home advisory impacts the amount and fuel mix of regional electricity generation.
Snow et al. [28]	Australia	This study researched household electricity consumption, controlling the weather conditions, over the COVID-19 pandemic.
Nyga-Łukaszewska & Aruga [29]	Japan and US	This study investigated how energy market (i.e., oil and gas prices) responded to the COVID-19 pandemic in two nations.
Kuzemko et al. [30]	World	This study shed light on the political implications of COVID-19 on the sustainable energy transitions in terms of energy system change, finance and investment, multi-scalar policy and politics, and social and political practices.

Malliet et al. [22] and Lahcen et al. [23] examined changes in the national-level CO_2 emissions due to the COVID-19 emergency measures in France and Belgium, respectively. Le Quéré et al. [24] expanded a research scope to include more countries and demonstrated that CO_2 emissions were significantly decreased primarily due to the curtailed volume of traffic. In the energy area, the references of [25–28] examined the effect of the COVID-19 confinement measures on the electricity market in Italy, US, and Australia. Other than electricity, Nyga-Łukaszewska and Aruga [29] investigated the dynamics of oil and gas prices over the COVID-19 pandemic. While the references of [20–29] employed quantitative methods such as direct measurements, auto-regressive distributive lag, and computable general equilibrium models, [30] took a qualitative approach to offer insights on the impact of COVID-19 on clean/sustainable energy transition taking political context into consideration.

To address these issues, some studies provided prospects of clean/sustainable energy transition drawing on qualitative assessment whereas others looked into the relationship between COVID-19 and the energy market through quantitative methods. While all of them are useful, their limitations lie in the oversimplification of the COVID-19 crisis. Existing literature tends to assess each nation's crisis management performance based on simple metrics, such as the number of COVID-19 cases or deaths, explore statistical associations between simple COVID-19 metrics and nations' complex energy market indicators, and forecast the future of clean/sustainable energy transition. Unlike those studies, this research first seeks to evaluate each nation's COVID-19 response performance in a refined analytic framework and then associate the performance with mobility (a paramount goal of transportation) to provide insights on the progress of clean/sustainable energy transition in the future.

In this vein, we construct the following null hypothesis:

Hypothesis 2 (H2). *People's mobility scores in each nation are not associated with their COVID-19 response performance measures.*

Specifically, we hypothesize that "there is no relationship between mobility and the performance measures". We expect the positive relationship because the effective and efficient government policies can contain COVID-19 within the manageable capacity of their healthcare systems and, as a consequence, people in outperforming countries feel free to make more trips than those in underperforming countries do.

2.4. Contribution to Existing Literature

As an extension of the previous studies, this study considers policy insights about the energy and environment sectors that are now in highly uncertain times (characterized by the COVID-19 pandemic). We combine a new methodological application of DEA-EA in the public health context, which is used together with a Linear Growth Model (LGM: measuring a mobility level of transportation as a measure of major energy consumption). We empirically examine the associations between the COVID-19 response performance, health insurance systems, and mobility at a national level so that this research explores the relationship between COVID-19 and energy issues. Prior to the COVID-19 crisis, there has been a paucity of literature on the relationship between the public health sector and the energy and environment sectors because most diseases tend to be epidemic or endemic (locally confined) rather than pandemic (globally spread). They had relatively minimal effects on these sectors in a global scale. Meanwhile, COVID-19, among other diseases, had unique impacts on them through the transportation sector (by reducing mobility). In the aftermath of the pandemic, for instance, international mobility (e.g., via air transportation) has dramatically decreased and the consumption of airplane fuel and the greenhouse gas emission from the airline industry both have curtailed.

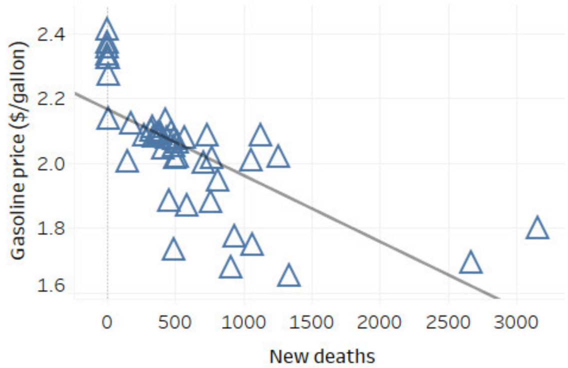
On the other hand, while technological innovations (e.g., new vaccines for COVID-19) and some nations' stringent policy measures (e.g., strict mask-wearing and social distancing) show some promising perspectives of managing COVID-19, they add more uncertainty in predicting the nations' future of clean/sustainable energy transition. In such an uncertain era, this study employs DEA-EA in conjunction with a statistical model (i.e., LGM) to explore the dynamic COVID-19 response performance of OECD nations in April 2020 (at the culmination of the first wave of COVID-19) and then relate it to people's mobility to develop policy implications for the energy and environment sectors. To the best knowledge, the application of DEA-EA in the public health setting linked to energy is the first attempt although the conventional use of DEA is somewhat popular (see Table 1). In addition, this study is different from the existing literature in which we consider the role of health insurance systems in the relationship between the COVID-19 response performance and people's mobility. The aspect of this study may bridge a gap in the existing literature that seeks to shed light on the connections between the public health sector and the energy sector due to mobility.

3. Preliminary Analysis: A Case of the United States

Prior to our proposed two-stage analyses (i.e., DEA and statistical analysis), we conduct a preliminary analysis of the relationships between COVID-19 and the energy market. Considering the availability of recent energy prices and consumption, we select the United States as a testbed for our analysis. Our interim purpose is to examine if there are statistically significant relationships and, in a broader context, if the healthcare concerns are associated with social systems including economy and energy consumption.

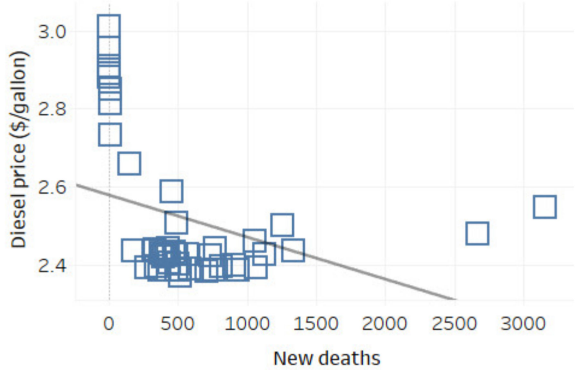
Using COVID-19 death data from the US Center for Disease Prevention and Control (CDC) and energy data from the US Energy Information Administration (EIA), we prepare four charts in Figure 2, whose x-axis indicates new deaths due to COVID-19 and the y-axis represents (a) weekly regular conventional retail gasoline prices (dollars per gallon), (b) weekly diesel retail prices (dollars per gallon), (c) weekly petroleum products supplied (thousand barrels), and (d) weekly finished motor gasoline (thousand barrels) over the period of 45 weeks from 27 January 2020 to 30 November 2020. Petroleum products include finished motor gasoline, kerosene-type jet fuel, distillate fuel oil, residual fuel oil, propane/propylene, and other oils. Figure 1 demonstrates that there are hypothesized relationships between COVID-19 and the energy market, suggesting the importance of healthcare study in discussing the change of energy components. It also implies that the future of energy sectors may depend at least partly upon whether we can prevent and control COVID-19 effectively and efficiently.

(**a**)



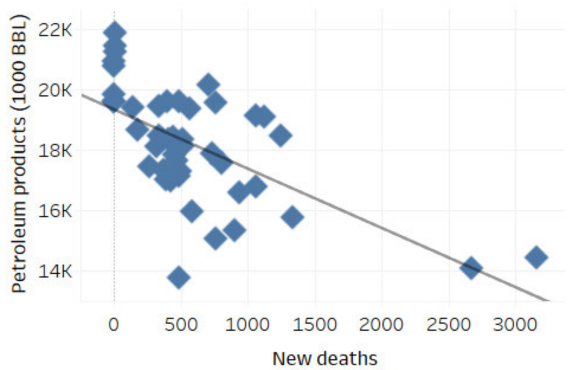
Gasoline price = −0.0002 & New deaths + 2.165
R-squared = 0.464; p-value < 0.0001

(**b**)



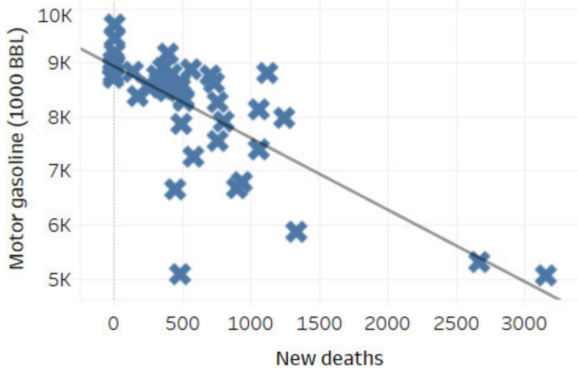
Diesel price = −0.0001 & New deaths + 2.578
R-squared = 0.131; p-value = 0.015

(**c**)



Petroleum product = −1.963 & New deaths + 19353
R-squared = 0.400; p-value < 0.0001

(**d**)



Motor gasoline = −1.331 & New deaths + 8939
R-squared = 0.545; p-value < 0.0001

Figure 2. Relationships between new COVID-19 deaths and energy sectors. Note: (**a**) Gasoline price, (**b**) diesel price, (**c**) petroleum products supplied, and (**d**) motor gasoline supplied. In the four charts, the x-axis indicates new deaths due to COVID-19 and the y-axis represents (**a**) weekly regular conventional retail gasoline prices (dollars per gallon), (**b**) weekly diesel retail prices (dollars per gallon), (**c**) weekly petroleum products supplied (thousand barrels), and (**d**) weekly finished motor gasoline (thousand barrels) over the period of 45 weeks from 27 January 2020 to 30 November 2020. Petroleum products include finished motor gasoline, kerosene-type jet fuel, distillate fuel oil, residual fuel oil, propane/propylene, and other oils.

4. Methods

In the two-stage analytic framework, we first apply DEA-EA to assess each nation's COVID-19 management performance and then a linear growth modeling approach to test statistical associations between the COVID-19 response performance and mobility. At the first stage, particularly, we use DEA-EA, one of the nonparametric techniques, which has some advantages over other parametric techniques. For instance, the approach does not assume any specific functional forms relating inputs and outputs. Furthermore, DEA-EA obtains a frontier (based on efficient DMUs) that acts as a benchmark for inefficient ones while parametric techniques tend to focus on means (demonstrating general tendency). In this study that seeks to evaluate DMU's performance, the advantages of DEA-EA are capitalized on. An important research question, particularly in the application of DEA-EA to public health context, is why the proposed approach can unify desirable (e.g., recoveries from COVID-19) and undesirable outputs (e.g., deaths induced by COVID-19), both of which have opposite directional vectors for performance betterment. This section mathematically describes the rationale. We also explain differences between efficiency and index measures. On occasion, DEA generates too many efficient DMUs, which make it difficult to rank DMUs, so that we introduce indexes as well as efficiencies.

Note that the Appendix A of this study lists the nomenclatures, along with abbreviations, used for the formulations discussed in this study. The references [31,32] have discussed a new type of applications of DEA-EA.

4.1. Unified Efficiency

This research summarizes abbreviations and nomenclatures used for DEA-EA at the end of this article. To formulate unified efficiency measures, this study specifies the following three types of data ranges (R) according to the upper and lower bounds of production factors:

$$R_i^x = (m+s+h)^{-1}\left(\max_j\{x_{ij}|j=1,\ldots,n\} - \min_j\{x_{ij}|j=1,\ldots,n\}\right)^{-1},$$
$$R_r^g = (m+s+h)^{-1}\left(\max_j\{g_{rj}|j=1,\ldots,n\} - \min_j\{g_{rj}|j=1,\ldots,n\}\right)^{-1} \&$$
$$R_f^b = (m+s+h)^{-1}\left(\max_j\left\{b_{fj}\middle|j=1,\ldots,n\right\} - \min_j\left\{b_{fj}\middle|j=1,\ldots,n\right\}\right).$$

The purpose of the three ranges is that computation results can avoid an occurrence of zero in dual variables. Such an occurrence implies that corresponding production factors (i.e., X: Inputs, G: Desirable outputs, and B: Undesirable outputs) are not fully utilized in the proposed assessment. The occurrence is problematic so that we incorporate the data ranges into the proposed formulations.

Natural Disposability: We use Model (1) to measure the degree of unified efficiency of the kth DMU under natural disposability (N) where the first priority is betterment of desirable outputs and the second priority is reduction of undesirable outputs. In many previous studies that used the concept of natural disposability in the context of economic development, the maximization of operational aspects (e.g., gross domestic product) was placed in a preferred position over the minimization of environmental ones (e.g., carbon emissions). In our public health context, the former was replaced by the positive aspects of COVID-19 response (e.g., the number of tests and recoveries) resulting from better diagnosis and higher-quality treatment while the latter is replaced by the negative aspects of COVID-19 response (e.g., the number of confirmed cases and deaths) stemming from a lower level of compliance to governments' COVID-19 measures and worse resource production/allocation. Under natural disposability, in other words, the maximization of desirable COVID-19 response outputs overrides the minimization of undesirable COVID-19 response outputs. To reflect on natural disposability, we particularly incorporate the status of constant returns to scale (RTS: desirable outputs proportionally increase with inputs) [31]:

$$
\begin{aligned}
\text{Maximize} \quad & \xi + \varepsilon_s\left(\sum_{i=1}^{m} R_i^x d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right) \\
\text{s.t.} \quad & \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^{x-} = x_{ik} \ (i = 1, \ldots, m), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g - \xi g_{\mathrm{rk}} = g_{\mathrm{rk}} \ (r = 1, \ldots, s), \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b + \xi b_{\mathrm{fk}} = b_{\mathrm{fk}} \ (f = 1, \ldots, h), \\
& \lambda_j \geq 0 \ (j = 1, \ldots, n), \xi : URS,\ d_i^{x-} \geq 0 (i = 1, \ldots, m), \\
& d_r^g \geq 0 (r = 1, \ldots, s) \ \&\ d_f^b \geq 0 (f = 1, \ldots, h).
\end{aligned} \tag{1}
$$

Here, it is important to note two concerns on Model (1). One of the two is that the efficiency frontier consists of $\sum_{j=1}^{n} x_{ij}\lambda_j$, $\sum_{j=1}^{n} g_{rj}\lambda_j$ and $\sum_{j=1}^{n} b_{fj}\lambda_j$ in (1), located on the position of maximizing the components of G (e.g., total recovered and tests from COVID-19) and minimizing the components of B (e.g., total cases and deaths due to COVID-19). Model (1) attains the optimization by reducing the inputs (X: e.g., health expenditure). The other is that the optimization is based upon G and B, both of which have opposite vectors and thereby be unified as in Model (1). In other words, the degree ξ is an output-based measure that unifies G-based maximization and B-based minimization within the framework of Model (1).

We measure the degree of unified efficiency (UEN_c^R) of the kth DMU under natural disposability by

$$
UEN_c^R = 1 - \left[\xi^* + \varepsilon_s\left(\sum_{i=1}^{m} R_i^x d_i^{x-*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}\right)\right], \tag{2}
$$

where the inefficiency measure and all slack variables are determined on the optimality of Model (1). Thus, the equation within the parenthesis is resulted from maximizing the objective while satisfying constraints in Model (1). The unified efficiency (UEN_c^R) is obtained by subtracting the level of inefficiency from unity.

Managerial Disposability: In a great body of existing literature that has used the concept of managerial disposability in the context of sustainable development, the minimization of environmental ones (e.g., carbon emissions) was placed in a preferred position over the maximization of operational aspects (e.g., GDP). In our public health context, the minimization of undesirable COVID-19 response outputs overrides the maximization of desirable COVID-19 response outputs. Shifting to managerial disposability that has an opposite priority, we change Model (1) under constant damages to scale (DTS: Undesirable outputs proportionally increase with inputs) as follows [32]:

$$
\begin{aligned}
\text{Maximize} \ & \xi + \varepsilon_s\left(\sum_{i=1}^{m} R_i^x d_i^{x+} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right) \\
\text{s.t.} \quad & \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^{x+} = x_{ik} \ (i = 1, \ldots, m), \\
& \textit{the same as in Model (1)}, \\
& \lambda_j \geq 0 \ (j = 1, \ldots, n), \xi : URS,\ d_i^{x+} \geq 0 (i = 1, \ldots, m).
\end{aligned} \tag{3}
$$

Model (3) changes $+d_i^{x-}$ of Model (1) to $-d_i^{x+}$ in Model (3). The unified efficiency under managerial disposability is measured by the following Equation:

$$UEM_c^R = 1 - [\xi^* + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_i^{x+*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*})], \quad (4)$$

where the inefficiency score and all slack variables are determined on the optimality of Model (3). The equation within the parenthesis is obtained from the optimality of Model (3). The unified efficiency under managerial disposability (UEM_c^R) is obtained by subtracting the level of inefficiency from unity.

4.2. Unified Index

Natural Disposability: To handle an occurrence of many efficient DMUs, this study use "sensitivity analysis", which measures an index of each efficient DMU, not inefficiency, to determine the order of all DMUs. To explain the index measurement, we use a new model that pays attention to the efficient DMU {a} whose efficiency status was previously determined by Model (1).

The model for index measurement under constant RTS becomes as follows:

$$\begin{aligned}
\text{Maximize} \quad & \xi + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b) \\
s.t. \quad & \sum_{j \in J-a} x_{ij}\lambda_j + d_i^{x-} = x_{ia} \ (i = 1, \ldots, m), \\
& \sum_{j \in J-a} g_{rj}\lambda_j - d_r^g - \xi g_{ra} = g_{ra} \ (r = 1, \ldots, s) \\
& \sum_{j \in J-a} b_{fj}\lambda_j + d_f^b + \xi b_{\mathrm{fa}} = b_{\mathrm{fa}} \ (f = 1, \ldots, h), \\
& \lambda_j \geq 0 \ (j \in J-a), \xi : URS, \ d_i^{x-} \geq 0 (i = 1, \ldots, m), \\
& d_r^g \geq 0 (r = 1, \ldots, s) \ \& \ d_f^b \geq 0 (f = 1, \ldots, h).
\end{aligned} \quad (5)$$

The unique feature of Model (5) is that it drops efficient DMU {a} from a frontier as formulated from the left-hand side and then measure the index of the DMU as formulated in the right-hand side. As a consequence, Model (5) measures the index of the DMU that may have the magnitude more than unity. So, it is not an efficiency score (between 0: Fully inefficient and 1: Fully efficient) anymore, rather being an index measure that implies how much above the efficiency frontier.

The degree of the index measure is determined by the following equation:

$$UIN_c^R = 1 - [\xi^* + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_i^{x-*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*})], \quad (6)$$

where the inefficiency score and all slack variables are determined on the optimality of Model (5). The ξ^* may become negative on the optimality of Model (5). The equation within the parenthesis is obtained from the optimality. The unified efficiency under natural disposability (UIN_c^R) is obtained by subtracting the level of inefficiency from unity.

Managerial Disposability: To shift the index measure under managerial disposability, this study measures an index of each efficient DMU to determine the order of all DMUs as we discuss previously on Model (5). We use the following new model that pays attention to only the efficient DMU {a} whose efficiency status was previously determined by Model (5).

The proposed model under constant DTS becomes as follows:

$$\begin{aligned}
&Maximize\ \xi + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_i^{x+} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b) \\
&s.t. \quad \sum_{j \in J-a} x_{ij}\lambda_j - d_i^{x+} \quad = x_{ia}\ (i\ =\ 1,\ \ldots\ ,\ m), \\
&\qquad the\ same\ as\ in\ Model\ (5), \\
&\qquad \lambda_j \geq 0\ (j \in J - a), \xi : URS,\ d_i^{x+} \geq 0 (i = 1, \ldots, m), \\
&\qquad d_r^g \geq 0 (r = 1, \ldots, s)\ \&\ d_f^b \geq 0 (f = 1, \ldots, h).
\end{aligned} \tag{7}$$

The important feature of Model (7) is that it changes $+d_i^{x-}$ of Model (5) to $-d_i^{x+}$ in order to attain the status of managerial disposability. It also drops DMU {a} from an efficiency frontier as formulated from the left-hand side and then measures the index of the DMU as formulated in the right-hand side. As a consequence, Model (7) measures the index of the DMU that may have the magnitude more than unity. So, it is not an efficiency score (between 0: Fully inefficient and 1: Fully efficient) anymore, rather being an index measure that implies how much above the efficiency frontier.

The degree of the index measure is determined by the following equation:

$$UIM_c^R = 1 - [\xi^* + \varepsilon_s(\sum_{i=1}^{m} R_i^x d_i^{x+*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*})], \tag{8}$$

where the degree of ξ^* may become positive and/or negative on the optimality of (7).

4.3. Computational Flow

Figure 3 depicts the computational flow of the proposed approach. We first apply Models (1) and (3) to all DMUs to compute their unified efficiency measures.

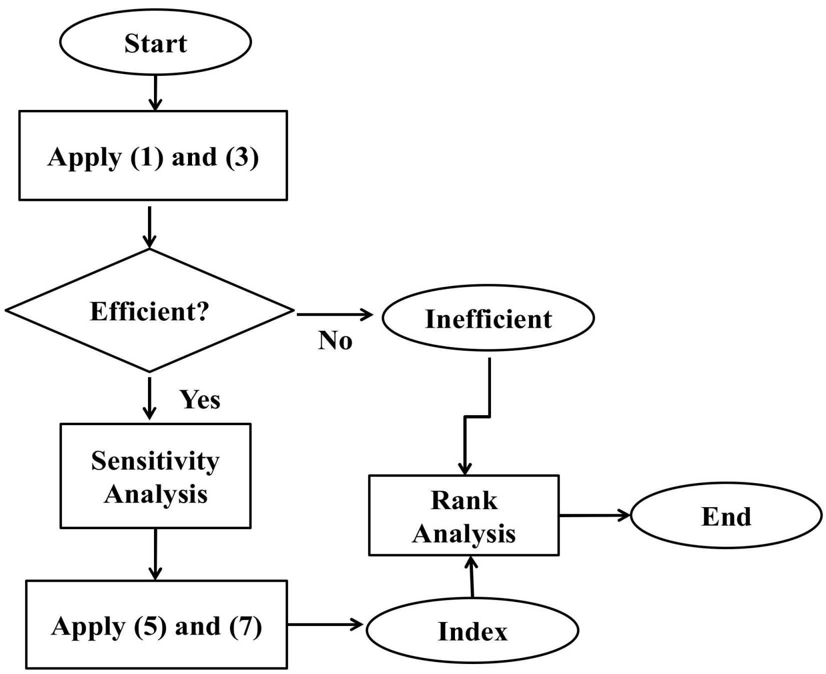


Figure 3. Computational process.

Of them, we apply Models (5) and (7) to efficient DMUs only to compute their unified index measures. Based on two-stage process, we rank all DMUs: Efficient ones by unified index measures and inefficient ones by unified efficiency measures. In the figure, we need to note that the indexes measured by Models (5) and (7) assume constant RTS and DTS to avoid an occurrence of computational infeasibility, respectively. The index measurement is conventionally referred to as sensitivity analysis. However, the previous literature does not include the existence of undesirable outputs and a directional vector of observed production factors in the framework. In the regard, the proposed approach is different from them.

5. Empirical Result

5.1. Data

This study has kept track of 33 OECD countries over the period in which COVID-19 progressed dramatically. Specifically, we have measured variables at three different time points: 4 April 2020, 10 April 2020, and 16 April 2020. A rationale on why we select April 2020 is as follows: After the World Health Organization (WHO) declared COVID-19 pandemic on March 11, 2020, there has been significant COVID-19 progression in April, particularly in the OECD countries such as Italy, South Korea, and Spain. On 4 April, the number of confirmed cases reached 1 million worldwide. Then, 9 April was the time when 100 days had passed since the first COVID-19 case ("pneumonia with unknown cause" at that time) was reported. With the dramatic growth of COVID-19 cases and deaths, on 16 April, WHO started to recommend more aggressive measures such as lockdowns. See WHO COVID-19 Timeline [33] for a detailed report. The selection of the three days is subjective. Therefore, the first hypothesis to be examined in this study confirms the validity on whether the selection does not produce any major difference in our empirical results.

While our study time window is relatively narrow, testing the first hypothesis is still meaningful because (a) as aforementioned, April 2020 was a critical time point for nations to take appropriate actions and actually many policy measures were implemented for the short time period [34], which reflects the dynamic change of governments' interventions. (b) At the beginning of the COVID-19 crisis (January or February 2020), the disease did not reach the level of global pandemic yet so a comparative study may be too early to be conducted and relevant statistics (e.g., the number of cases or deaths) were neither fully reliable nor consistent across nations. (c) By the nature of infectious disease, it is pivotal to perform initial response to contain the disease within nations' healthcare capacity and the initial performance may, at least partly, determine the overall performance of the nations by the path-dependency theory [35,36]. Lastly, (d) before the second wave of COVID-19 started, April 2020 data may have sufficient predictive power for the future (at least for the near future) so some studies (e.g., COVID-19 prediction models using S-curve or logistic functions) were based on a relatively short timeframe.

For our DEA-EA application in the frame of inputs and desirable and undesirable outputs, we have collected a data set from two sources: (a) COVID-19 data from Worldometer, Johns Hopkins University, and Our World in Data and (b) health system data from OECD Health Database and WHO Global Health Expenditure Database.

This research uses three inputs: Current Health Expenditure (CHE), Total Hospital Employment (THE), and Total Hospital Beds (THB). The CHE is measured at per-capita purchasing power parity (PPP) while both THE and THB are measured in per 1000 populations. Those inputs correspond with the input factors (i.e., labor and capital) of general production function. THE, as a labor, includes medical workforce, such as doctors and nurses, which are responsible for taking care of COVID-19 patients. CHE and THB both represent capital that medical workforce can utilize. CHE is related to access to high-quality healthcare, particularly in nations with private health insurance systems. THB is an indicator of nations' healthcare capacity so securing the sufficient number of beds is critical for controlling COVID-19. Those input factors are widely used in other healthcare studies (see Table 1).

There are two desirable outputs: COVID-19 Total Recovered (CTR) and Total Tests (CTT) as well as two undesirable outputs COVID-19 Total Cases (CTC) and Total Deaths (CTD). Four outputs are measured in per 1 million populations. CTR indicates the result of quality healthcare in that it requires the effective triage and timely treatment of COVID-19 patients. CTT points out not only nations' COVID-19 diagnosis capacity but also their willingness to track and monitor COVID-19 cases, which is essential for preventing and controlling infectious disease. CTC is a bad output stemming from the lack of nations' COVID-19 managing capacity or their unwillingness to respond to COVID-19 (particularly if they seek the herd immunity without any serious government intervention). It may be a result from their citizens' incompliance to government measures (e.g., social distancing and face mask wearing). CTD, as an ultimate toll of the COVID-19 crisis, should be avoided. Nations' healthcare systems should prevent COVID-19 at best and, otherwise, convert confirmed cases into recoveries. It is important to note that the inputs are considered as the same in April 2020, but the desirable and undesirable outputs change on April 4th, 10th, and 16th; see Table 3 that classifies the types of insurance systems in OECD nations.

Table 5 provides a data set and descriptive statistics. Countries are listed in alphabetical order of their names. The first row of the table contains POP: Population (1000 s); CHE: Current health expenditure (per capita in PPP); THE: Total hospital employment (per 1000 POP); THB: Total hospital beds (per 1000 POP); CTC: Total cases (per 1 million POP); CTD: Total deaths (per 1 million POP); CTR: Total recoveries (per 1 million POP); and (h) CTT: Total tests (per 1 million POP).

On average, 33 OECD countries have approximately 14 hospital employees and 5 hospital beds per 1000 populations and their individuals spend more than US $4000 in health care annually. As of 16 April 2020, on average, they conduct approximately 17,000 COVID-19 tests and have 1500 confirmed cases, 80 deaths, and 400 recovered per 1 million populations, respectively.

5.2. Efficiency and Index Measures

This research first measures efficiency and index measures as of 4, 10, and 16 April 2020, respectively, as summarized in Tables 6 and 7. We document the unified efficiencies and indexes under natural and managerial disposability. The former table lists UEN_C measured by Model (1) and UEM_C measured by Model (3) while the latter table lists UIN_C measured by Model (5) and UIM_C measured by Model (7).

The efficiency and index measures have both their degrees and ranks based upon a descending order with parenthesis. Efficient nations in both UEN_C and UEM_C include Australia, Iceland, Korea, and Latvia. The efficient nations only in UEM_C contain Japan and Slovak R. The other nations contain some level of inefficiency. The average of UEN_C (0.63) is slightly greater than that of UEM_C (0.59). All inefficiency measures shift to UIN_C and UIM_C as shown in Figure 2. Meanwhile, we apply Models (5) and (7) on efficient nations to determine their UIN_C and UIM_C measures. As of 4 April 2020, for example, Japan has 0.39 (81th) in UIN_C and 1.69 (1st) in UIM_C, so being influenced by a shift from natural to managerial disposability due to less infected case and death with the smaller number of tests. The finding can be found in their average measures. The average of UIN_C is 0.64, which is greater than that of UIM_C (0.60).

Table 5. Data and descriptive statistics.

Country	CHE (per Capita in PPP)	THE (per 1000 POP)	THB (per 1000 POP)	CTC (per 1 M POP)			CTD (per 1 M POP)			CTR (per 1 M POP)			CTT (per 1 M POP)		
				4/4/20	4/10/20	4/16/20	4/4/20	4/10/20	4/16/20	4/4/20	4/10/20	4/16/20	4/4/20	4/10/20	4/16/20
Australia	4816.15	17.98	3.81	218	245	254	1.0	2.1	2.0	23.93	73.86	153.25	11,247	13,696	14,902
Austria	5617.40	13.41	7.37	1308	1506	1605	21.0	35.4	44.0	285.77	752.78	1024.29	11,562	16,052	17,410
Belgium	5119.07	18.92	5.66	1590	2301	3003	111.0	260.5	419.0	286.04	527.32	666.15	6040	9982	11,588
Canada	4928.63	17.52	2.52	369	586	752	6.0	15.1	27.0	70.85	179.91	245.17	8425	10,679	12,393
Chile	2228.56	6.72	2.11	218	340	461	1.0	3.4	5.0	29.24	103.24	162.67	2543	4134	4806
Czech R.	2753.38	14.49	6.63	418	535	589	6.0	11.1	16.0	7.37	38.85	78.55	6926	11,767	13,634
Denmark	5510.00	20.60	2.61	704	1005	1188	28.0	42.6	55.0	223.18	340.07	525.85	7816	11,691	14,223
Estonia	2153.34	12.23	4.69	783	948	1081	10.0	18.1	27.0	44.85	70.69	101.09	14,392	23,326	27,156
Finland	4255.22	18.01	3.28	340	500	608	5.0	8.7	14.0	54.32	54.32	307.79	5234	8251	8970
France	5011.20	19.62	5.98	1378	1389	2265	116.0	202.2	263.0	231.09	395.05	463.37	3436	6217	5114
Germany	5922.64	16.48	8.00	1147	1404	1619	17.0	30.4	46.0	319.92	695.58	933.09	10,962	19,737	20,629
Greece	2295.33	9.14	4.21	161	193	212	7.0	8.6	10.0	7.24	24.98	24.98	2153	3364	4871
Hungary	1979.40	10.77	7.02	70	136	171	3.0	8.8	15.0	5.92	11.74	20.31	2011	3322	3984
Iceland	4721.43	20.79	3.06	4152	4908	5061	12.0	20.5	23.0	1182.00	2510.26	3214.69	69,276	102,591	109,558
Ireland	5544.68	13.15	2.96	932	1638	2541	28.0	58.1	90.0	5.23	5.23	16.09	6119	13,364	18,358
Israel	3014.65	10.90	3.02	907	1202	1455	5.0	11.0	16.0	51.31	161.15	315.33	10,443	17,740	21,634
Italy	3619.70	10.33	3.18	2061	2441	2732	254.0	311.8	358.0	346.53	536.96	628.69	10,870	16,294	18,481
Japan	4563.46	16.50	13.05	25	42	68	0.6	0.7	1.0	4.03	5.98	7.07	339	592	745
Korea	2980.16	7.47	12.27	198	204	207	3.0	4.1	4.0	124.06	142.07	152.15	8875	9911	10,509
Latvia	1682.34	10.77	5.57	270	324	358	0.5	1.1	3.0	0.51	8.20	29.23	10,275	14,684	16,595
Lithuania	2132.61	15.42	6.56	283	367	414	4.0	6.2	11.0	2.46	18.96	62.50	7852	13,487	17,829
Luxembourg	5956.48	15.77	4.66	4360	5149	5388	50.0	86.3	110.0	846.50	846.50	890.52	36,412	47,960	49,080
Mexico	1035.59	6.98	1.38	15	30	45	0.6	1.8	3.0	4.90	4.90	16.45	122	190	311
Netherlands	5513.10	15.23	3.32	970	1348	1705	96.0	146.5	193.0	14.64	14.64	14.64	4401	6765	8634
Norway	6518.87	21.62	3.60	1024	1152	1254	11.0	17.0	28.0	6.09	6.09	6.09	19,528	22,805	24,020
Portugal	2917.36	12.67	3.39	1032	1517	1848	26.0	42.7	62.0	7.27	25.80	47.82	7952	12,364	20,430

Table 5. *Cont.*

Country	CHE (per Capita in PPP)	THE (per 1000 POP)	THB (per 1000 POP)	CTC (per 1 M POP)			CTD (per 1 M POP)			CTR (per 1 M POP)			CTT (per 1 M POP)		
				4/4/20	4/10/20	4/16/20	4/4/20	4/10/20	4/16/20	4/4/20	4/10/20	4/16/20	4/4/20	4/10/20	4/16/20
Slovak R.	2184.20	7.62	5.82	86	131	179	0.2	0.4	1.0	1.84	4.23	30.72	2497	5031	6311
Slovenia	2960.59	11.09	4.50	470	558	610	11.0	21.6	29.0	38.24	71.64	84.22	13,040	16,739	18,344
Spain	3468.69	12.10	2.97	2699	3358	3910	256.0	338.9	409.0	735.45	1270.40	1607.57	7593	13,745	19,896
Switzerland	8216.96	25.16	4.53	2369	2799	3089	77.0	93.0	147.0	761.92	1437.13	1829.08	17,729	21,913	23,849
Turkey	1180.64	9.02	2.81	284	558	823	6.0	11.9	18.0	9.73	36.72	70.27	1913	4060	5664
U.K.	4338.37	20.11	2.54	617	1035	1519	64.0	132.0	202.0	2.05	5.22	12.83	2698	4004	6152
U.S.A.	10,246.14	20.02	2.71	941	1515	1965	26.0	56.7	99.0	45.69	96.38	151.30	4933	8043	9899
Mean	4102.62	14.50	4.72	982	1254	1484	38.3	60.9	83.3	175.16	317.48	421.03	10,170	14,985	17,151
Max	10,246.14	25.16	13.05	4360	5149	5388	256.0	338.9	419.0	1182.00	2510.26	3214.69	69,276	102,591	109,558
Min	1035.59	6.72	1.38	15	30	45	0.2	0.4	1.0	0.51	4.23	6.09	122	190	311
S.D.	2041.63	4.85	2.64	1078	1277	1390	64.6	91.6	119.5	292.90	541.46	681.13	12,659	18,092	19,094

Table 6. *UENc* and *UEMc* over the three periods.

Country	*UENc*						*UEMc*					
	4/4/2020		4/10/2020		4/16/2020		4/4/2020		4/10/2020		4/16/2020	
Australia	1.00	(2)	0.98	(11)	1.00	(1)	1.00	(3)	0.98	(11)	1.00	(2)
Austria	0.50	(68)	0.87	(24)	1.00	(10)	0.47	(66)	0.81	(25)	0.93	(15)
Belgium	0.43	(74)	0.53	(63)	0.51	(64)	0.39	(76)	0.48	(65)	0.46	(67)
Canada	0.65	(49)	0.66	(46)	0.68	(41)	0.57	(51)	0.60	(47)	0.62	(42)
Chile	0.48	(70)	0.64	(50)	0.71	(37)	0.55	(56)	0.63	(40)	0.69	(32)
Czech R.	0.47	(71)	0.61	(52)	0.67	(43)	0.45	(69)	0.55	(55)	0.57	(52)
Denmark	0.66	(47)	0.69	(40)	0.82	(29)	0.61	(43)	0.63	(41)	0.75	(29)
Estonia	0.67	(44)	0.90	(21)	0.94	(18)	0.48	(62)	0.59	(48)	0.60	(46)
Finland	0.42	(77)	0.44	(73)	0.88	(23)	0.44	(72)	0.44	(70)	0.82	(24)

Table 6. *Cont.*

Country	*UENc*						*UEMc*					
	4/4/2020		**4/10/2020**		**4/16/2020**		**4/4/2020**		**4/10/2020**		**4/16/2020**	
France	0.41	(79)	0.61	(53)	0.48	(69)	0.37	(78)	0.56	(54)	0.44	(73)
Germany	0.60	(55)	0.87	(25)	0.95	(17)	0.57	(53)	0.81	(26)	0.88	(20)
Greece	0.37	(83)	0.46	(72)	0.56	(61)	0.40	(75)	0.48	(64)	0.58	(50)
Hungary	0.66	(48)	0.59	(56)	0.57	(60)	0.75	(30)	0.63	(39)	0.60	(45)
Iceland	1.00	(2)	1.00	(8)	1.00	(4)	0.90	(16)	0.96	(14)	1.00	(4)
Ireland	0.20	(93)	0.42	(76)	0.43	(75)	0.21	(90)	0.24	(83)	0.22	(89)
Israel	0.50	(67)	0.69	(39)	0.73	(36)	0.36	(81)	0.40	(74)	0.49	(59)
Italy	0.42	(78)	0.51	(66)	0.53	(62)	0.37	(79)	0.46	(68)	0.48	(63)
Japan	0.39	(81)	0.39	(82)	0.31	(86)	1.00	(1)	0.88	(19)	0.64	(37)
Korea	0.95	(15)	0.98	(12)	1.00	(5)	0.97	(13)	0.98	(12)	1.00	(6)
Latvia	1.00	(6)	1.00	(9)	1.00	(6)	1.00	(7)	1.00	(5)	0.88	(18)
Lithuania	0.70	(38)	0.87	(26)	0.97	(13)	0.66	(36)	0.78	(27)	0.85	(21)
Luxembourg	0.51	(65)	0.58	(58)	0.57	(59)	0.44	(71)	0.37	(77)	0.37	(80)
Mexico	0.62	(51)	0.37	(84)	0.68	(42)	0.99	(10)	0.58	(49)	0.77	(28)
Netherlands	0.14	(97)	0.16	(95)	0.21	(91)	0.16	(97)	0.16	(95)	0.16	(96)
Norway	0.74	(35)	0.79	(31)	0.79	(33)	0.49	(61)	0.50	(58)	0.49	(60)
Portugal	0.29	(87)	0.40	(80)	0.58	(57)	0.23	(85)	0.24	(84)	0.32	(82)
Slovak R.	0.84	(27)	0.95	(16)	0.81	(30)	1.00	(8)	1.00	(9)	0.84	(22)
Slovenia	0.79	(32)	0.90	(20)	0.93	(19)	0.64	(38)	0.68	(35)	0.68	(34)
Spain	0.60	(54)	0.75	(34)	0.84	(28)	0.54	(57)	0.68	(33)	0.72	(31)
Switzerland	0.67	(45)	0.89	(22)	0.96	(14)	0.61	(44)	0.82	(23)	0.89	(17)
Turkey	0.21	(92)	0.29	(88)	0.33	(85)	0.22	(87)	0.22	(88)	0.22	(86)
UK	0.14	(98)	0.12	(99)	0.16	(96)	0.16	(94)	0.14	(98)	0.13	(99)
US	0.16	(94)	0.24	(90)	0.26	(89)	0.20	(92)	0.19	(93)	0.20	(91)

Table 6. *Cont.*

Country	*UENc*						*UEMc*					
	4/4/2020		**4/10/2020**		**4/16/2020**		**4/4/2020**		**4/10/2020**		**4/16/2020**	
Descriptive statistics												
Mean	0.55	(58)	0.64	(49)	0.69	(43)	0.55	(55)	0.59	(49)	0.61	(46)
Max	1.00	(98)	1.00	(99)	1.00	(96)	1.00	(97)	1.00	(98)	1.00	(99)
Min	0.14	(2)	0.12	(4)	0.16	(1)	0.16	(1)	0.14	(5)	0.13	(4)
S.D.	0.25	(28)	0.26	(28)	0.26	(29)	0.27	(30)	0.26	(28)	0.26	(29)
Kruskal-Wallis rank test												
Rank sum	1371		1686		1893		1498		1675		1777	
H-statistic	5.076 (p = 0.0790)						1.464 (p = 0.4809)					

Note: *UENc* = unified efficiency under natural disposability and constant returns to scale, *UEMc* = unified efficiency under managerial disposability and constant damages to scale; and the values in parenthesis indicate each country's rank.

Table 7. *UINc* and *UIMc* over the three periods.

Country	*UINc*						*UIMc*					
	4/4/2020		**4/10/2020**		**4/16/2020**		**4/4/2020**		**4/10/2020**		**4/16/2020**	
Australia	1.02	(8)	0.98	(11)	1.15	(3)	1.09	(6)	0.98	(11)	1.16	(4)
Austria	0.50	(68)	0.87	(24)	1.00	(10)	0.47	(66)	0.81	(25)	0.93	(15)
Belgium	0.43	(74)	0.53	(63)	0.51	(64)	0.39	(76)	0.48	(65)	0.46	(67)
Canada	0.65	(49)	0.66	(46)	0.68	(41)	0.57	(51)	0.60	(47)	0.62	(42)
Chile	0.48	(70)	0.64	(50)	0.71	(37)	0.55	(56)	0.63	(40)	0.69	(32)
Czech R.	0.47	(71)	0.61	(52)	0.67	(43)	0.45	(69)	0.55	(55)	0.57	(52)
Denmark	0.66	(47)	0.69	(40)	0.82	(29)	0.61	(43)	0.63	(41)	0.75	(29)
Estonia	0.67	(44)	0.90	(21)	0.94	(18)	0.48	(62)	0.59	(48)	0.60	(46)
Finland	0.42	(77)	0.44	(73)	0.88	(23)	0.44	(72)	0.44	(70)	0.82	(24)

Table 7. *Cont.*

Country	*UINc*						*UIMc*					
	4/4/2020		**4/10/2020**		**4/16/2020**		**4/4/2020**		**4/10/2020**		**4/16/2020**	
France	0.41	(79)	0.61	(53)	0.48	(69)	0.37	(78)	0.56	(54)	0.44	(73)
Germany	0.60	(55)	0.87	(25)	0.95	(17)	0.57	(53)	0.81	(26)	0.88	(20)
Greece	0.37	(83)	0.46	(72)	0.56	(61)	0.40	(75)	0.48	(64)	0.58	(50)
Hungary	0.66	(48)	0.59	(56)	0.57	(60)	0.75	(30)	0.63	(39)	0.60	(45)
Iceland	1.06	(6)	1.01	(9)	1.22	(1)	0.90	(16)	0.96	(14)	1.10	(5)
Ireland	0.20	(93)	0.42	(76)	0.43	(75)	0.21	(90)	0.24	(83)	0.22	(89)
Israel	0.50	(67)	0.69	(39)	0.73	(36)	0.36	(81)	0.40	(74)	0.49	(59)
Italy	0.42	(78)	0.51	(66)	0.53	(62)	0.37	(79)	0.46	(68)	0.48	(63)
Japan	0.39	(81)	0.39	(82)	0.31	(86)	1.69	(1)	0.88	(19)	0.64	(37)
Korea	0.95	(15)	0.98	(12)	1.04	(7)	0.97	(13)	0.98	(12)	1.03	(7)
Latvia	1.19	(2)	1.14	(4)	1.06	(5)	1.20	(3)	1.00	(9)	0.88	(18)
Lithuania	0.70	(38)	0.87	(26)	0.97	(13)	0.66	(36)	0.78	(27)	0.85	(21)
Luxembourg	0.51	(65)	0.58	(58)	0.57	(59)	0.44	(71)	0.37	(77)	0.37	(80)
Mexico	0.62	(51)	0.37	(84)	0.68	(42)	0.99	(10)	0.58	(49)	0.77	(28)
Netherlands	0.14	(97)	0.16	(95)	0.21	(91)	0.16	(97)	0.16	(95)	0.16	(96)
Norway	0.74	(35)	0.79	(31)	0.79	(33)	0.49	(61)	0.50	(58)	0.49	(60)
Portugal	0.29	(87)	0.40	(80)	0.58	(57)	0.23	(85)	0.24	(84)	0.32	(82)
Slovak R.	0.84	(27)	0.95	(16)	0.81	(30)	1.52	(2)	1.02	(8)	0.84	(22)
Slovenia	0.79	(32)	0.90	(20)	0.93	(19)	0.64	(38)	0.68	(35)	0.68	(34)
Spain	0.60	(54)	0.75	(34)	0.84	(28)	0.54	(57)	0.68	(33)	0.72	(31)
Switzerland	0.67	(45)	0.89	(22)	0.96	(14)	0.61	(44)	0.82	(23)	0.89	(17)
Turkey	0.21	(92)	0.29	(88)	0.33	(85)	0.22	(87)	0.22	(88)	0.22	(86)
UK	0.14	(98)	0.12	(99)	0.16	(96)	0.16	(94)	0.14	(98)	0.13	(99)
US	0.16	(94)	0.24	(90)	0.26	(89)	0.20	(92)	0.19	(93)	0.20	(91)

Table 7. *Cont.*

Country	***UINc***						***UIMc***					
	4/4/2020		**4/10/2020**		**4/16/2020**		**4/4/2020**		**4/10/2020**		**4/16/2020**	
Descriptive statistics												
Mean	0.56	(58)	0.65	(49)	0.71	(43)	0.60	(54)	0.59	(49)	0.62	(46)
Max	1.19	(98)	1.14	(99)	1.22	(96)	1.69	(97)	1.02	(98)	1.16	(99)
Min	0.14	(2)	0.12	(4)	0.16	(1)	0.16	(1)	0.14	(8)	0.13	(4)
S.D.	0.27	(28)	0.26	(28)	0.28	(29)	0.37	(30)	0.26	(28)	0.27	(29)
Kruskal-Wallis rank test												
Rank sum	1370		1683		1897		1506		1668		1776	
H-statistic	5.161 (p = 0.0758)						1.357 (p = 0.5075)					

Note: *UINc* = unified index under natural disposability and constant returns to scale, *UIMc* = unified index under managerial disposability and constant damages to scale; and the values in parenthesis indicate each country's rank.

To statistically examine whether the differences in efficiency and index measures have occurred among the three periods, we applied the Kruskal–Wallis rank-sum tests. For the test, all the datasets in the three periods were pooled. The tests do not reject the null hypotheses that there are no differences in *UENc/UEMc* and UIN_C/UIM_c at the level of 5% significance. For the former, the bottom of Table 6 exhibits the *H*-statistic of 5.076 (*p*-value = 0.0790) and 1.464 (*p*-value = 0.4809), respectively. For the latter, the bottom of Table 7 exhibits the *H*-statistic of 5.161 (*p*-value = 0.0758) and 1.357 (*p*-value = 0.5075.)

Here, it is worth noting Japan and the United Kingdom (UK) as illustrative discussions. Japan has a declining trend in both *UINc* and *UIMc*. For example, Japan had 0.39, 0.39, and 0.31 in UIN_C and 1.69, 0.88, and 0.64 in UIM_C over the three periods. The decreasing trend was particularly serious in UIM_C. The UK is more undesirable than Japan. The nation showed 0.14, 0.12, and 0.16 in UIN_C and 0.16, 0.14, and 0.13 in UIM_C over the same period. The results imply that the two nations did not pay serious attention to the pandemic response in April 2020. For example, Hunter [37] discussed that the UK lacked the number of hospital beds and had a limited number of medical staff and protection equipment (e.g., face masks). The medical insufficiency and lack of government measures may be applicable to Japan as well [38].

Note that Tables 6 and 7 have overviewed the COVID-19 response performance measures and ranks of 33 OECD nations. There are stark contrasts between outperforming and underperforming nations in terms of efficiency/index measures. As indicated by *H*-statistics, on the other hand, each nation's COVID-19 response performance measures were not significantly changed over time, specifically in the beginning to mid-April 2020. It may be due to our short period analysis time windows. If we extend the analysis period, the result may be different. Anyway, we tentatively and cautiously conclude that each nation's performance tends to be path-dependent so it may be critical for each nation's public health authorities to take aggressive actions at the beginning to maintain their performance in the COVID-19 prevention and control.

Additionally, we have analyzed the relationship between the performance and health insurance systems (as one of the different conditions of OECD countries). Supposing that different health insurance systems provide citizens (particularly socio-economically vulnerable populations) with different levels of healthcare access, which is critical in increasing the numbers of tests and recovered patients while decreasing the number of deaths, we have hypothesized that the performance indexes (*UINc* and *UIMc*) of countries with higher public coverage (e.g., UGHS, UPIS, and UPPS) are statistically greater than those of countries with lower public coverage (e.g., UPHS and NUIS).

5.3. Mobility and Efficiency/Index Measures

Our second hypothesis concerns the relationships between mobility and efficiency/index measures. To test the relationships, we first provide an array of charts showing the difference in mobility measures between efficient and inefficient nations and then some statistics confirming the difference. Additionally, we run a linear growth modeling to examine how COVID-19 management performance influences mobility measures. For the mobility measures, we refer to Google's COVID-19 Community Mobility reports.

As shown in Figure 4, COVID-19-based mobility change of underperforming nations (in orange) tends to be more volatile than that of outperforming ones (in blue) is, except for the beginning of October when the COVID-19 second wave started, at four different locations: Grocery and pharmacy, residential, retail and recreation, and workplaces. It is also supported by the higher standard deviation (SD) of underperforming nations (see Table 8 for efficiency and Table 9 for index). According to Pearson correlation, it is found that outperforming and underperforming nations show relatively similar patterns at residential and transit stations, positively related with mobility measures and a public health insurance system can play a significant role in changing mobility measures.

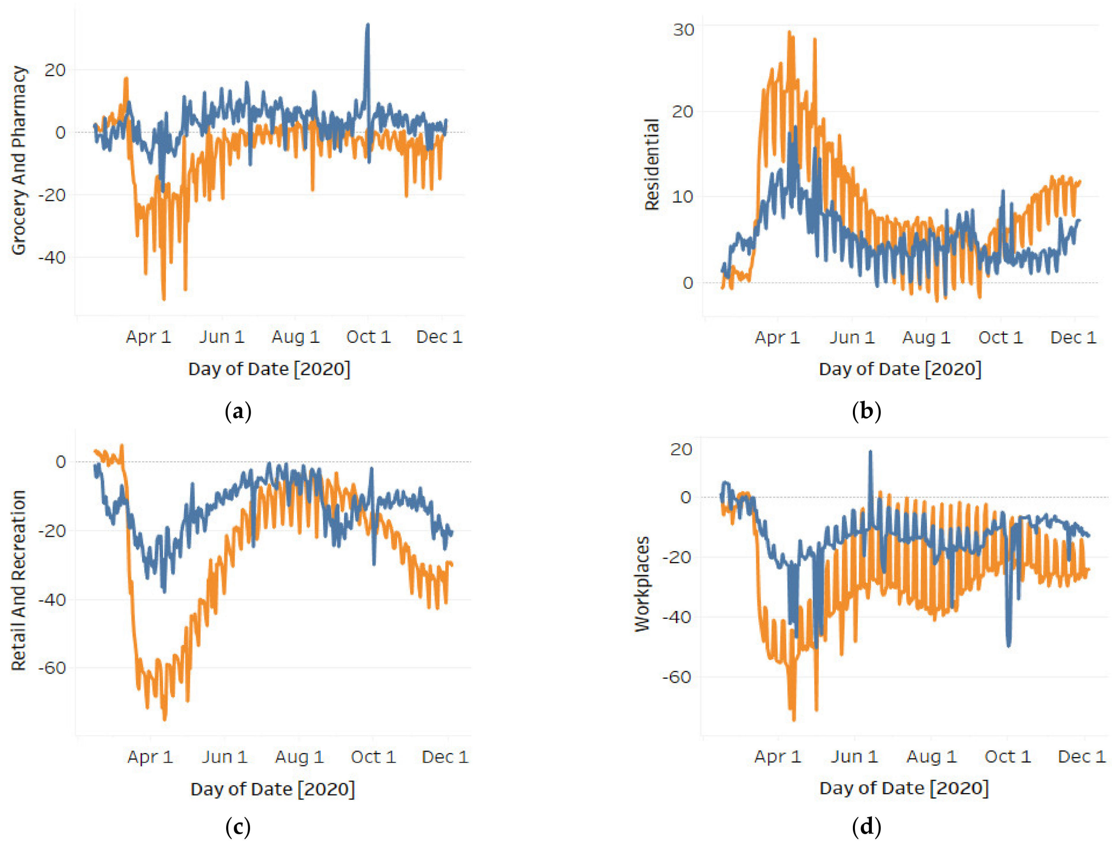


Figure 4. Mobility measures over Time by *UENc/UINc*: Efficient (in blue) and inefficient nations (in orange) at (**a**) grocery, (**b**) residential, (**c**) retail and recreation, and (**d**) workplaces. Note: Mobility measures in four difference places indicate the percent change from the baseline (before COVID-19 took place).

Table 8. Differences in mobility between efficient and inefficient nations by *UENc/UINc*.

UENc/UINc		Grocery & Pharmacy	Parks	Residential	Retail & Recreation	Transit Stations	Workplaces
SD	Inefficient	10.54	44.98	6.81	19.98	16.66	16.27
	Efficient	5.71	21.99	3.27	7.60	7.32	9.06
Pearson correlation		0.38	0.62	0.81	0.70	0.81	0.68

Note: SD = standard deviation.

Table 9. Differences in mobility between efficient and inefficient nations by *UEMc/UIMc*.

UEMc/UIMc		Grocery & Pharmacy	Parks	Residential	Retail & Recreation	Transit Stations	Workplaces
SD	Inefficient	10.72	46.28	6.99	20.30	16.96	16.75
	Efficient	6.06	22.17	3.57	9.70	8.84	8.97
Pearson correlation		0.67	0.82	0.90	0.90	0.92	0.82

Note: SD = standard deviation.

Table 10 presents a correlation table between mobility and index measures. In addition to the Pearson correlation, we calculated a partial correlation controlling time. Because it adjusted time effect, partial correlation coefficients are smaller than Pearson correlation coefficients. However, there are statistically significant relationships between (a) *UINc* and all mobility measures (except for retail and recreation, and grocery and pharmacy), and (b) *UIMc* and all mobility measures (without any exception) at the 5% significance level.

Table 10. Correlations between mobility and COVID-19 performance measures.

	GRR	GGP	GPK	GTS	GWP	GRD	*UINc*	*UIMc*
GRR	1.000							
GGP	0.816 ***	1.000						
GPK	0.695 ***	0.674 ***	1.000					
GTS	0.777 ***	0.720 ***	0.712 ***	1.000				
GWP	0.863 ***	0.786 ***	0.796 ***	0.880 ***	1.000			
GRD	−0.705 ***	−0.660 ***	−0.837 ***	−0.796 ***	−0.895 ***	1.000		
UINc	0.260 *	0.168 *	0.319 ***	0.396 ***	0.336 ***	−0.377 ***	1.000	
UIMc	0.434 ***	0.277 ***	0.341 ***	0.498 ***	0.536 ***	−0.472 ***	0.775 ***	1.000

Note: GRR = retail and recreation, GGP = groceries and pharmacies, GPK = parks, GTS = transit stations, GWP = workplaces, GRD = residential; *UINc* = unified index under natural disposability and constant returns to scale, *UIMc* = unified index under managerial disposability and constant damages to scale; and *** = statistically significant at 1%, ** = 5%, and * = 10%.

6. Discussion

This section discusses the two hypotheses presented in the literature review section along with statistical evidence.

On Hypothesis 1: Each nation's COVID-19 response performance measures are varying across their different conditions and are dynamic over time.

To empirically test the hypothesis, we have first checked the normality of *UINc* and *UIMc*. A skewness and kurtosis test (listed at the end of this article) was conducted to determine if *UINc* and *UIMc* are normally distributed, respectively. Based on the test, we reject the hypotheses that *UINc* and *UIMc* are normally distributed, respectively, $\chi^2(2) = 5.20$ (p = 0.0744) and $\chi^2(2) = 10.38$ (p = 0.0056). Because of non-normality, we conduct the Kruskal–Wallis tests to determine if there are differences in *UINc* and *UIMc* between (a) the two groups (high public vs. low public coverage) and (b) the five groups (UGHS, UPIS, UPPS, UPHS, and NUIS) with different health insurance systems.

Table 11 summarizes indexes and the sum of ranks of (a) the two groups and (b) the five groups of healthcare insurance systems. In the *H*-statistic columns of the table, *UINc* and *UIMc* are statistically different across health insurance systems, respectively, *H*-statistic = 5.181 (p = 0.023) and *H*-statistic = 5.808 (p = 0.016) for the two groups; and *H*-statistic = 9.975 (p = 0.041) and *H*-statistic = 11.843 (p = 0.019) for the five groups. We reject the null hypotheses (i.e., no difference among (a) the two groups (high and lower coverages) and (b) the five groups of health insurance systems). Thus, the indexes of nations with higher public coverage under UGHS, UPIS, and UPPS are statistically greater than those of countries with lower public coverage under UPHS and NUIS.

Table 11. Summary of the Kruskal–Wallis tests.

Performance Index	(a) (N = 90)	(b) (N = 9)	*H*-statistic	(c) (N = 36)	(d) (N = 39)	(e) (N = 15)	(f) (N = 6)	(g) (N = 3)	*H*-statistic
UINc	0.660 (4687)	0.411 (263)	5.181 *	0.624 (1739)	0.714 (2246)	0.606 (702)	0.506 (236)	0.220 (27)	9.975 *
UIMc	0.626 (4698)	0.376 (252)	5.808 *	0.549 (1622)	0.700 (2257)	0.623 (819)	0.467 (228)	0.195 (24)	11.843 *

Note: (a) Health insurance system with higher public coverage; (b) Health insurance system with lower public coverage; (c) UGHS = Universal Government-funded Health System; (d) UPIS = Universal Public Insurance System; (e) UPPS = Universal Public-Private Insurance System; (f) UPHS = Universal Private Health Insurance System; and (g) NUIS = Non-Universal Insurance; and * stands for statistical significance at 10%.

On Hypothesis 2: People's mobility scores in each nation are associated with their COVID-19 response performance.

A series of charts and correlation tables in Section 5.3 supported our second hypothesis on the relationship between each nation's COVID-19 response performance and mobility measures. Specifically, outperforming nations tend to show more stable mobility than underperforming ones. In addition, mobility measures in the latter return to the baseline level whereas those in the latter still stagnate. While the second or later waves of COVID-19 may impact mobility measures in the future, it implies that outperforming nations need to prepare for back-to-the-normal strategies, which include clean/sustainable energy transition, for their sustainable development. This is particularly important and timely since we observed previous incidents where energy (particularly, fossil fuels) consumption soared up even higher than the baseline level after economic recessions (e.g., the financial crisis of 2008) were recovered. Once the COVID-19 crisis is addressed, it may end up with much more trips that lead to more energy consumption and more GHG emissions. That is why it is critical for OECD nations (particularly high-performing nations in managing COVID-19) to lead clean/sustainable energy transition through a continuous commitment to their Green New Deal initiatives (e.g., more deployment of alternative fuel-powered vehicles).

Tables 12 and 13 summarize LGM (linear growth modeling) results by *UINc* and *UIMc*. Here, it stands for a special example of hierarchical linear modeling or multilevel modeling with time as a first level variable. Instead of explaining all models in the two tables, we select one model from each table as an example: GRR under *UINc* and GGP under *UIMc*. The model with GRR as a dependent variable in Table 12, particularly, indicates that (a) the average GRR is estimated to be about −68% in the middle of the time points, implying that COVID-19 has a significantly negative impact on mobility, (b) GRR has improved by about 7% each time point, and (c) in the case of nations with public health insurance systems (i.e., INS = 1), a one-unit increase in *UINc* is associated with about 45% increase in mobility when holding all other variables constant. The model with GGP as a dependent variable in Table 13 points out that (a) the average GGP is estimated to be about −11% in the middle of the time points, implying that COVID-19 has a significantly negative impact on mobility (but not so much as GRR under *UINc*), (b) GGP has improved by about 16% each time point, and (c) a one-unit increase in *UIMc* is associated with about 28% increase in mobility when holding all other variables constant. Overall, in the two models with a focus on the mobility at retail and recreation and grocery and pharmacy, we find that COVID-19 response performance is positively related with mobility measures and public health insurance system can play a significant role in changing mobility measures.

Table 12. LGM analysis results: *UINc*.

Model Parameters	GGP	GPK	GRD	GRR	GTS	GWP
Fixed Effect						
For Intercept						
Base	−12.758	−0.391	13.712 ***	−68.450 ***	−53.974 ***	−39.934 ***
INS	−19.610	−29.807	2.154	1.540	−8.128	−2.716
For Growth Rate						
Base	15.584 ***	19.905 ***	0.096	6.932**	6.102 **	3.646
INS	−5.085	−15.872 **	1.198	−5.270 *	−4.248	−5.910 **
For *UINc* slope						
Base	18.703	32.078	3.139	−36.522	7.463	−12.937
INS	−6.162	14.170	−12.278	45.025 *	10.258	31.695
Random Effect						
Intercept	330.560 ***	1149.094 ***	25.276 ***	341.119 ***	154.423 ***	141.535 ***
Level-1 error	133.883	185.719	7.039	27.144	29.981	25.813

Note: *** = statistically significant at 1%, ** = 5%, and * = 10%. INS: health insurance system (0 = private; 1 = public).

Table 13. LGM Analysis Results: *UIMc.*

Model Parameters	GGP	GPK	GRD	GRR	GTS	GWP
Fixed Effect						
For Intercept						
Base	−10.704 *	3.733	13.585 ***	−67.212 ***	−52.910 ***	−39.545 ***
INS	−21.590 ***	−33.298	2.228	0.266	−9.115	−3.067
For Growth Rate						
Base	15.653 ***	19.894 ***	0.208	5.674 **	6.077 **	3.211
INS	−4.327	−12.656 *	0.483	−3.489	−3.066	−4.270 *
For *UIMc* slope						
Base	27.668 ***	50.097	2.571	−30.960	12.115	−11.186
INS	−18.430	−31.884	−9.350	41.045 *	2.154	28.228
Random Effect						
Intercept	319.450 ***	1232.379 ***	23.628 ***	312.607 ***	145.253 ***	113.155 ***
Level-1 error	134.885	194.047	7.105	26.670	28.937	25.127

Note: *** = statistically significant at 1%, ** = 5%, and * = 10%. INS: health insurance system (0 = private; 1 = public).

7. Conclusions and Future Extensions

The COVID-19 became a global pandemic and has deep impacts on our economic and social systems, including healthcare, mobility, and energy/environment. In this context, this study sought to better understand the relationships among them. Particularly, we aimed to explore how health insurance systems of OECD nations were associated with their COVID-19 response performance and then how the performance scores were related to their mobility scores. Drawing on the statistical examination of those relationships, we attempted to consider policy implications about the link to clean/sustainable energy transition. The future or success of the transition (and broader sustainable development) may depend upon how efficiently nations can prevent and control COVID-19.

The two implications are summarized as follows: First, we tested a null hypothesis that there was no difference in the unified efficiencies/indexes across nations or among the three time windows (4, 10 and 16 April 2020). We also looked into the role of the health insurance systems among OECD nations in coping with the COVID-19 pandemic. The examination of the first hypothesis indicated that there was a significant difference in the performance scores across countries but no major difference among the three periods. We found that the COVID-19 response performance scores were static rather than dynamic, implying that the performance (e.g., resulted from governments' strict measures) tended to be path-dependent and it was critical for nations to take appropriate initial response. We also found that there were significant differences in the performance among groups of nations decomposed by their health insurance systems. Specifically, countries with higher public coverage (e.g., UGHS, UPIS, and UPPS) outperformed those with lower public coverage (e.g., UPHS and NUIS).

Second, we examined another null hypothesis that there was no relationship between COVID-19 response performance and mobility measures. We considered two different types of efficiency/index measures (*UENc*/*UINc* vs. *UEMc*/*UIMc*) and mobility measures depending on six different types of locations (retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential). Testing the second hypothesis resulted in statistically significant relationships between the COVID-19 performance and mobility measures in our study nations. Specifically, there were positive relationships between the performance measures and mobility measures at all locations, except for residential (which had negative relationships with the performance measures). The results imply that outperforming nations are returning to the normal while underperforming ones are still stagnating in terms of mobility. The mobility measures of underperforming nations are also more vulnerable to external shocks such as governments' COVID-19 regulations. Additionally, the results of linear growth models reaffirmed that there were statistically significant relationships between COVID-19 response performance, health insurance systems, and mobility measures.

At the end of this section, this study notes two drawbacks. One of the two is that this study documents the DEA-EA practicality in offering policy implications about restructuring the healthcare system [5] and preparation for clean/sustainable energy transition post-COVID-19 [30], which has some limitations. We have discussed health insurance systems as a different condition at a national level, believing that healthcare access or coverage is a key to the better COVID-19 response performance. We know that there are a multitude of factors, such as social distance practices, government actions, and national cultures [39], which make some nations, stand out from others. The other is that our DEA-EA analysis time windows were short. While April 2020 is meaningful in terms of the WHO announcement, COVID-19 progression, and government lock-down measures, it would be desirable if we could extend the analysis timeframe. A possible future direction of this study may be found in [40,41].

In conclusion, it is hoped that this study makes a contribution to DEA-EA applied to COVID-19 and energy studies. We look forward to seeing future extensions as specified in this study.

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Appendix A

(a) Abbreviations on DEA-EA (Data Envelopment Analysis-Environmental Assessment) are summarized as follows:
DMU: Decision Making Unit.
DTS: Damages to Scale.
GDP: Gross Domestic Product.
RTS: Returns to Scale.
R (superscript): Radial measurement.
c (subscript): Constant RTS or DTS.
UEN_c^R: Unified Efficiency under Natural disposability and Constant RTS.
UEM_c^R: Unified Efficiency under Managerial disposability and Constant DTS.
UIN_c^R: Unified Index under Natural disposability and Constant RTS, and
UIM_c^R: Unified Index under Managerial disposability and Constant DTS.

(b) Nomenclatures are summarized as follows:
x_{ij}: an observed i-th input of the j th DMU ($i = 1, \ldots, m$ and $j = 1, \ldots, n$),
g_{rj}: an observed r-th desirable output of the j th DMU ($r = 1, \ldots, s$ and $j = 1, \ldots, n$),
b_{fj}: an observed f-th undesirable output of the j th DMU ($f = 1, \ldots, h$ and $j = 1, \ldots, n$),
d_i^x: an unknown slack variable of the i-th input,
d_r^g: an unknown slack variable of the r-th desirable output,
d_f^b: an unknown slack variable of the f-th undesirable output,

λ_j: an unknown j-th intensity (or structural) variables,
ε_s: a prescribed very small number and J: a set of all DMUs.

(c) Kruskal-Wallis Rank Sum Test: To examine the null hypothesis (a group of observations distributes randomly among multiple groups), we use the Kruskal-Wallis rank sum test. The entire observed data is separated into T groups. To compute the Kruskal-Wallis statistic (H), we combines all observations ($n = \sum_{t=1}^{T} n_t$) in T groups. Then, we rank them from the greatest to the least by these efficiency/index scores. Let R_{jt} denote the rank of the j-th nation in the t-th group. The rank sum of all plants in the t-th group is $R_t = \sum_{j=1}^{n_t} R_{jt}$. Then, the statistic (H) is determined by $H = 12/n(n+1)\sum_{t=1}^{T}[R_t^2/n_t - 3(n+1)]$. The statistic follows the χ^2 distribution with a degree of freedom (df = $T - 1$). See Sueyoshi & Goto [31] that have discussed how to use the H statistic to DEA results.

(d) Linear Growth Modeling: For LGM, we use the following formula based on the assumption that mobility measures are associated with time, COVID-19 response performance, and health insurance system:
Level-1 model:
$MOBIL_{ti} = \pi_{0i} + \pi_{1i}{*}(TIME_{ti}) + \pi_{2i}{*}(PERM_{ti}) + e_{ti}$
Level-2 Model:

$$\pi_{0i} = \beta_{00} + \beta_{01}{*}(INS_i) + r_{0i}$$
$$\pi_{1i} = \beta_{10} + \beta_{11}{*}(INS_i) + r_{1i}$$
$$\pi_{2i} = \beta_{20} + \beta_{21}{*}(INS_i) + r_{2i}$$

where *MOBIL* = mobility measures at six different locations: Grocery & Pharmacy (GGP), Parks (GPK), Residential (GRD), Retail & Recreation (GRR), Transit Stations (GTS), and Workplaces (GWP); *TIME* = time points on April 4, 10, and 16 in 2020; *PERM* = performance measures (*UINc* and *UIMc*); *INS* = health insurance systems (1 = public insurance, and 0 = private insurance); π = level-1 parameters; β = level-2 parameters; e = level-1 error term; and r = level-2 error term.

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