Using Data Envelopment Analysis for Environment Assessment

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*Abstract*—Data envelopment analysis (DEA), is a mathematical technique to evaluate the performance of various organization in public and private sector. DEA is a powerful nonparametric engineering tool for estimating technical efficiency and production capacity of service units. The healthcare organization is a basic factor for any community, as it highly acts on the socioeconomic development of any country. Beginning of coronavirus disease 2019 (COVID-19) was initial reported in December 2019. Until now, many medicines and plans have been used in the cure of the illness. The COVID-19 became a pandemic around the world and has giant effect on our industrial and social systems, particularly on the healthcare system. 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 OECD (Organization for Economic Co-operation and Development) nations and investigate whether health insurance systems contribute to the performance. In the DEA-EA, we should incorporate undesirable outputs, while the former outputs need to be maximized, the latter ones need to be minimized in the assessment of healthcare system performance.

Keywords—Data Envelopment Analysis, healthcare Systems, Environmental Assessment, COVID-19 Pandemic,

# Introduction

Data envelopment analysis (DEA) is a powerful technique in productivity management. It is a linear programming based methodology introduced by Charnes et al. [1] for measuring the relative efficiency of decision making units (DMUs). Specifically, DEA measures the efficiency of the i-th DMU under evaluation relative to the other DMUs of the set. DMUs use multiple inputs to produce multiple outputs, which can be measured in different units, such as financial institutions and health systems.

Covid-19 is an infectious disease, which initially appeared in Wuhan, in December 2019. This disease is a cause of novel coronavirus, which influences the respiratory system. It caused the outbreak of a Worldwide pandemic due to its fast spread and the unavailability of vaccines or specific treatment.

Indeed, the healthcare systems’ efficiency improvement has been one of the main concerns of all developed countries. It is worth studying the performance of these systems in facing Covid-19. DEA is an efficiency measurement method, which is incorporated in many applications, among these is comparing the healthcare systems’ performance of different 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 DEA 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 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.

# Literature

## Data Envelopment Analysis (DEA)

DEA, suggested by Charnes et al. [1], is a method for measuring the efficiency of DMUs using linear programming techniques to ‘‘envelop” observed input–output vectors as tightly as possible. One main advantage of DEA is that it allows several inputs and several outputs to be considered at the same time. The DEA models can provide efficiency scores scaled to a maximum value of 1 for efficient DMUs and can inform the DM of the amount of percentage by which an inefficient DMU should decrease its inputs and/or increase its outputs in order to become efficient. It also provides reference units known as composite or virtual units which lie on the efficient frontier and are used as target units for inefficient DMUs to benchmark against. The production process for each DMU involves using a set of inputs to produce a set of outputs. Each producer has varying levels of inputs and gives varying levels of outputs. DEA assumes that either making more output with the same input or making the same output with less input is a criterion of efficiency. In the presence of undesirable outputs, DMUs with more good (desirable) outputs and less bad (undesirable) outputs (relative to less input resources) should be recognized as efficient. For example, if there are inefficiencies in the production process, the outputs of wastes and pollutants (which are undesirable) should be reduced to improve the performance various transformation techniques have been proposed in the literature for dealing with desirable inputs and undesirable outputs. Consider an n-DMUs set, each consuming m different inputs to produce s different outputs. The relative efficiency of a DMU is defined as the ratio of its total weighted output to its total weighted input, subjected to lie between zero and the unity. Mathematically, the efficiency score of a particular DMU0, i.e., E0, is obtained by solving the following so-called CCR model:

 (1)

ur is the weight parameter for output *r* and *vi* the weight parameter for input *i*. *e*0 =1*/h*0 denotes the optimal technical efficiency score with a possible range of 0≤*e*0≤1 obtained from solving the DEA model. The efficiency score of *e*0 = 1 shows the *DMU* as technical efficient and 0*<e*0 *<*1 reveals the presence of technical inefficiency. Here, each *DMU* can be evaluated by setting itself as the optimal objective function of *DMU*0 and is allowed freedom by the DEA model in assigning the set of output weights *ur* and input weights *vi* , which will render the *DMU* as efficient as possible. In other words, the efficiency measure *e*0 is optimized within the constraints for each of the *n DMU*s. In the output-orientated *CCR* primal model (1), the weighted outputs are fixed to unity and the weighted inputs minimized. The output weights *ur* and input weights *vi* are adjusted accordingly to generate an efficiency score. While the *CCR* primal model can generate both an efficiency score and the optimal output weights *ur* and input weights *vi* , the *CCR* dual model can be used to generate not only the efficiency score but also the composite inputs and outputs that the observed *DMU*0 should benchmark against. The output-orientated *CCR* dual model is given as follows:

 (2)

In the output-orientated *CCR* dual model (2), for each observed *DMU*0 an imaginary composite unit is constructed that outperforms *DMU*0. is the reference weight for *DMUj*and means that *DMUj* is used to construct the composite unit for *DMU*0. The composite unit consumes at most the same inputs as *DMU*0 and produces outputs that are at least equal to a proportionof the outputs of *DMU*0. The parameter indicates by how much *DMU*0 has to proportionally increase its outputs to become efficient. The inverse of is the efficiency score of *DMU*0. The increase is employed concurrently to all outputs and results in a radial movement towards the envelopment surface.

Note that the above models are based on constant returns to scale (CRS). This, however, disregards economies of scale. Variable returns to scale in efficiency analysis were taken into account in another version of DEA model developed by Banker et al. [2], called the BCC model which is different from the CCR model in that the former has an additional convexity constraint of all  restricted to sum to 1 in the dual case. Note, the *CCR* and *BCC* models only provide the radial measure of technical efficiency. Since the very beginning of DEA studies, various extension of the CCR model have been proposed, among which the BCC (Banker-Charnes-Cooper) model is representative. The BCC model has its production possibility set and production frontiers different from CCR model BCC model is presented as follows:

## (3)

BCC introduced variable returns to scale (VRS) which envelops data more tightly than constant returns to scale (CRS). This model is an output-oriented BCC model where an efficiency score is generated for a DMU by maximizing outputs with limited inputs and for each observed DMUp an imaginary composite unit is constructed that outperforms DMUp. Also,  represents the proportion for which DMUj is used to construct the composite unit for DMUp. In model (3), the composite unit consumes at most the same levels of inputs as DMUp and produces outputs that are at least equal to a proportion  of the outputs of DMUp with . The inverse of  is the efficiency score of DMUp. If  > 1, DMUp is not efficient and the parameter bp indicates the extent by which DMUp has to increase its outputs to become efficient. There is no unique model in the literature for handling DEA problems with coexisting desirable and undesirable outputs. In the variable return to scale environment, Seiford and Zhu(2002) have proposed a method that first multiplies each undesirable output by -1 and then finds a proper translation vector to let all negative undesirable outputs be positive. This approach is very simple and easy to understand. Also, it maintains the current property of production. Therefore, we employ this approach in the MOLP method proposed in this study Suppose we have n DMUs and each DMUj produces s1 desirable outputsand s2 undesirable outputs  using m inputs xij(i = 1, 2, . . . , m).

 (4)

Where 

For each inefficient DMUP, we define a reference set Is the optimal solution of (4), in this case, the following point on the efficient frontier is used to evaluate the performance of DMUP and can be regarded as a target unit for the inefficient unit DMUPThis target unit usually does not include a DM's preference structure or value judgments. An interactive MOLP could be used to address this deficiency.

## 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.

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 [2]. 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 [3,4].

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. 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.

In this study we consider 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.

# Method

## DEA-EA

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.

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) [5]:

 (5)

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In other words, the degree *x* is an output-based measure that unifies G-based maximization and B-based minimization within the framework of Model (5), We measure the degree of unified efficiency (UENRC ) of the kth DMU under natural disposability by

 (6)

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 (5) under constant damages to scale (DTS: Undesirable outputs proportionally increase with inputs) as follows [6]:

 (7)

The unified efficiency under managerial disposability is measured by the following Equation:

 (8)

where the inefficiency score and all slack variables are determined on the optimality of Model (7). The equation within the parenthesis is obtained from the optimality of Model (7). The unified efficiency under managerial disposability UENRC is obtained by subtracting the level of inefficiency from unity. The model for index measurement under constant RTS becomes as follows:

 (9)

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

 (10)

where the inefficiency score and all slack variables are determined on the optimality of Model (10). The xmay become negative on the optimality of Model (10). The equation within the parenthesis is obtained from the optimality. The unified efficiency under natural disposability (UENRC) is obtained by subtracting the level of inefficiency from unity.

The proposed model under constant DTS becomes as follows:

 (11)

Model (3) 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



## Computational Flow

Figure 3 depicts the computational flow of the proposed approach. We first apply Models (5) and (7) to all DMUs to compute their unified efficiency measures.

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 (9) and (11) 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.

**Conclusion**

The COVID-19 became a global pandemic and has deep impacts on our economic and social systems, including healthcare, mobility, and energy/environment. We considered two different types of efficiency/index measures (UENc/UINc vs. UEMc/UIMc) and mobility measures 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. 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. 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 and preparation for clean/sustainable energy transition post-COVID-19, 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.

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استفاده از تحلیل پوششی داده ها برای ارزیابی محیطی

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چکیده تحلیل پوششی داده ها (DEA، یک تکنیک مدیریتی برای برآورد ارزیابی سازمان های مختلف خصوصی و عمومی می باشد. DEA یک ابزار مهندسی قوی برای براورد کارایی تکنیکی و ظرفیت تولید واحدهای تحت ارزیابی می باشد. سازمان های مراقبت سلامتی از فاکتور های اصلی هر کشور می باشد، به طوری که بیشترین تاثیر را بر روی توسعه اقتصاد هر کشور می گذارد. کووئید 19 برای اولین بار در سال2019 گزارش شد، تا کنون روش ها و دارو های بسیاری برای درمان این بیماری مورد استفاده قرار گرفته است. کووئید 19 در کل جهان گسترش و فراگیر شد به طوریکه بیشترین تاثیر را بر روی سیستم های اقتصادی و اجتماعی بویژه سیستم درمان داشته است. با بررسی رابطه بین بخش های انرژی و تلاش جهت درمان در ویروس کرونا ، یک برنامه کلی تحلیل پوششی داده ها برای ارزیابی محیطی (DEA-EA) و بررسی کووئید 19 در واکنش به اجرای سازماندهی به منظور تحلیل عملکرد اقتصادی جامعه و بررسی اینکه سیستم های سلامت چه سهمی در اجرای ان داشته اند. در تحلیل پوششی داده ها برای ارزیابی محیطی، خروجی های نامطلوب مورد استفاده قرار می گیرند، در حالی که در مدل های پیشین خروجی را ماکسیمم مینمودیم اما در این تحقیق ، در ارزیابی کارایی سیستم های سلامت کاهش خروجی نیز بررسی می گردد.

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**کلید واژگان:** تحلیل پوششی داده ها، ارزیابی محیطی، سیستم های سلامتی، پاندمی کووید 19