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Managerial and Natural Disposability in Two-Stage Network Structure: A DEA-Based Approach

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Abstract

The traditional Data Envelopment Analysis (DEA) model on network-structured performance analysis normally considers desirable intermediate measures. In many real cases, the intermediate measures consist of both desirable and undesirable factors. The motivation of this paper is employing "Natural and managerial disposability" in two-stage network structures with undesirable intermediate measure. The non-cooperative game theory is proposed to study the two-stage structure. A real case of 34 OECD countries in 2012 has been illustrated to shed a light on applicability of the proposed methodology.

Keywords: Data Envelopment Analysis (DEA), Non -cooperative game theory, Natural disposability, Managerial disposability, Environmental efficiency, Two stage network structures.

1 | Introduction

Over the last two decades, increasing number of human activity and organizations have become involved in preserving, protecting, and mitigating negative effects on environment. Recently, the world commission on climate change has reported that the governments and production process are forced to adopt strategies aimed at reducing the amount of Green House Gases (GHG) emissions by 2050. Consequently, due to the new economic normal, Carbon neutrality, it is necessary to continuously optimize the economic structure, decline energy consumption as a proportion of Gross Domestic Product (GDP), and exhibit greater willingness in low-carbon green development in governing climate change. Since, climate change presents a grievous challenge, this challenge and pressure causes an inevitable interest in use of efficiency and productivity management taking undesirable and pollutant outputs into account. To address this issue, non-parametric technique, Data Envelopment Analysis (DEA), initiated by Charnes et al. [3] and extended by Banker et al. [2], has recently provided a substantial contribution in evaluating the relative efficiency of an entity or Decision making Units (DMUs) and analyzing undesirable outputs. DEA is a non- parametric technique for evaluating the relative efficiency of a set of homogeneous DMUs by using a ratio of the weighted sum of outputs to the weighted sum of inputs, subject to the condition that this ratio

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does not exceed one for any DMU. Also, conventional DEA models determine a set of weights such that the efficiency of a target DMU relative to the other DMUs is maximized. Because of the growing emphasis on sustainable green development, Sueyoshi et al. ([8]-[13], [14]-[20]) have developed a DEA approach for environmental assessment, which conceptually incorporates the two conflicting disposability assumption regarding environmental regulation and economic prosperity, i.e., managerial disposability and natural disposability. Of particular relevance to this paper are studies of different researchers from the sustainability perspective involving both economic and environmental indicators. For example, [23], [22], [1], [21], [5], [24] and many other articles. The methodological contribution of existing research on environmental issues has mostly conducted for some block box systems. In addition to such previous research efforts, Liuguo Shao et.al [7] has proposed a DEA-based approach for evaluating pollution treatment in a two-stage network structure. The authors employed Directional Distance Function (DDF) methodology for reduction of pollutant emissions. Mavi et al. [4] proposed an alternative approach in a two-stage network DEA based on goal programming to analyze the joint effects of eco-efficiency and eco-innovation, considering the undesirable inputs, intermediate products, and the outputs in the context of big data. Environmental status and performance assessment can be approached from several perspectives. Generally, environmental performance is dependent on the management of an organization or a country on its environmental aspects. In contrast to the extensive mode of environment growth and eco-efficiency evaluation, the motivation of this study is the application of natural disposability or managerial disposability to modeling network DEA with undesirable intermediate measures. We believe that the contribution of this paper is handling undesirable factors in a two- stage network production system. What's more, non-cooperative game theory is proposed to assess the relative performance of the DMUs. The paper aims to contribute in this direction. In the following section, a brief description of managerial and natural disposability is reviewed. Section 3 describes how to measure the efficiency of a two-stage network structure under natural and managerial disposability. Section 4 applies the before mentioned approaches on a real case study. The conclusion section will summarize the findings and implications of the study.

2 | Managerial and Natural Disposability

Any activity carried out at any scale often generates undesirable impacts on the environment. Following the concept of sustainable development, the initial goals of the relevant governments or industries include reducing these hazards. One of the researches made the contribution to literature have examined by Sueyoshi et al. [13], [14]-[18], exploring the concept of "natural and managerial disposability" in DEA. Assume that there are n DMUs and for $DMU_j(j=1,\dots,n)$ data on the vectors of input, desirable output and undesirable output are $(x_{1j},\dots,x_{mj})\geq 0,(v_{1j},\dots,v_{Nj})\geq 0$ and $(w_{1j},\dots,w_{Fj})\geq 0$, respectively. Furthermore, assume that x_j, v_j and $w_j\neq 0$. "Natural disposability", indicates that a firm decreases the vector of inputs to decrease the vector of undesirable outputs. Given the decreased vector of undesirable outputs and that of inputs, the firm attempts to increase the vector of desirable outputs as much as possible. The production technology can be represented as follows:

$$P^n(x)=\{(v,w)\left|\sum_{j=1}^{n}\lambda_j v_j\geq v,\sum_{j=1}^{n}\lambda_j x_j\leq x,,\sum_{j=1}^{n}\lambda_j w_j\leq w,,\sum_{j=1}^{n}\lambda_j=1,\lambda_j\geq 0,j=1,\dots,n\right.\}.$$

It should be pointed out that the natural disposability discusses the importance of adapting the environmental regulation and economic prosperity for reducing undesirable factors in a mathematical framework based on DEA. The inequality constraint on input vectors declares a short-run environmental effort to reduce the pollutants. As Porter Hypothesis [6] states environmental regulation provides firms with a new business Opportunity to produce new products. Hence, technology innovation and altering management strategies cause to reduce the production of undesirable outputs. Equipped with this concept, "managerial disposability" covers both environmental regulation and economic prosperity. This type of disposability indicates that a firm increases the vector of inputs to increase the vector of desirable outputs but to simultaneously decrease the vector of undesirable outputs. The production technology can be expressed as follows:

$$P^m(x)=\{(v,w)\left|\sum_{j=1}^{n}\lambda_j v_j \ge v,\sum_{j=1}^{n}\lambda_j x_j \ge x,,\sum_{j=1}^{n}\lambda_j w_j \le w,,\sum_{j=1}^{n}\lambda_j =1,\lambda_j \ge 0, j=1,\dots,n\right.\}.$$

The most important feature of these concepts is the difference on input inequality constraint. Under "natural disposability" the firm decreases the input vector to decrease the undesirable output. This type of strategy has been followed up because of incapability in technology innovation and financial problems. In contrast, "managerial disposability" is a strategy for environmental protection. Looking for environmental performance, equipped with managerial strategy, firms can deal with various pollution issues by technology innovation and/or new management. These technologies are used to modeling undesirable intermediate measures in a two-stage production process.

3 | Natural and Managerial Disposability in Two-Stage Decision Process

In this section, a two-stage decision process is introduced within which the intermediate measures consist of desirable and undesirable outputs. Consider a two-stage production process as shown in *Fig. 1*.

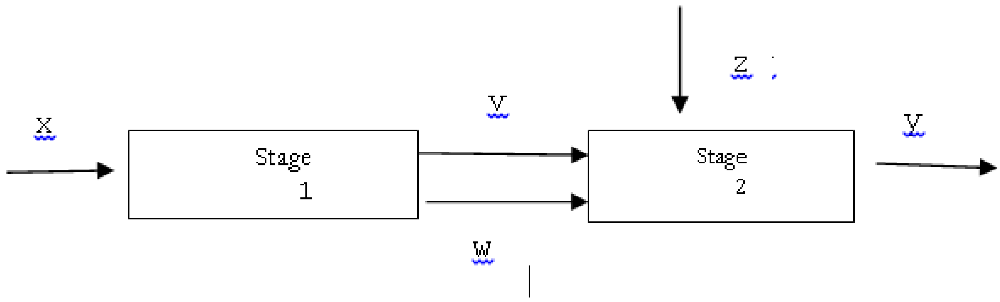

Fig. 1. Two stage process of DMU_j .

Suppose again that there are n DMUs and for the first stage of DMU_j the observed data on the vectors of inputs, desirable outputs and undesirable outputs are $x_j=(x_{ij},x_{2j},\dots,x_{mj})\ge 0$, $v_j=(v_{ij},v_{2j},\dots,v_{Nj})\ge 0$ and $w_j=(w_{1j},w_{2j},\dots,w_{Fj})\ge 0$, respectively. The first stage outputs (v_j,w_j) are used as the inputs for the second stage. The second stage fed up with the intermediate measure (v_j,w_j) and external input vector $z_j=(z_{1j},z_{2j},\dots,z_{Tj})$. The final product of DMU_j is represented by $y_j=(y_{1j},x_{2j},\dots,y_{sj})\ge 0$. In what follows, two different strategies for handling undesirable outputs to this two-stage decision process is employed. In the first approach, "natural disposability" is introduced and the second one considers "managerial disposability". To describe the DEA environmental assessment, the non-cooperative game theory is proposed. The theory describes a preference on leader and follower. Such a requirement is confirmed by the optimal solutions of the leader. Based on the efficient statues of the leader the follower identifies the optimality. Without less of generality, assume that the first stage is leader and the second stage is follower. According to "natural disposability" approach for dealing with undesirable factors, the following formulation in the first stage measures the DEA environmental assessment:

$$
\begin{aligned}
&\text{Min } \theta, \\
&\text{s.t.} \\
&\sum_{j=1}^{n}\lambda_j x_{ij} \le \theta x_{io}, \ i=1,\dots,m, \\
&\sum_{j=1}^{n}\lambda_j v_{kj} \ge v_{ko}, \ k=1,\dots,N, \\
&\sum_{j=1}^{n}\lambda_j w_{fj} \le \theta w_{fo}, \ f=1,\dots,F, \\
&\sum_{j=1}^{n}\lambda_j = 1, \\
&\lambda_j \ge 0, \quad j=1,\dots,n.
\end{aligned} \tag{1}
$$

Employing model (1) θ stands for efficiency measure and $\lambda_j (j=1,\dots,n)$ referred to as structural variables. Also the objective function minimizes the equal proportional reduction factor for both undesirable outputs and input while preserving the desirable outputs. Clearly, *model (1)* is always feasible and bounded. Reduction of inputs as well as undesirable output accompanied with augmentation of desirable output shortfalls can improve the first stage. Having obtained the efficiency of the first stage, the second stage has been evaluated through preserving the efficiency statues of the first stage. Hence, employing the optimal solutions of the first stage, the second stage treats the triple (v^*, w^*, z) as its input to generate the final output y. Applying the

Optimal solution of the first stage insures that the efficiency of the first stage remain unchanged. On the basis of first stage optimal solution, DEA environmental efficiency for the second stage can be defined as follows:

$$
\begin{aligned}
&\text{Min } \theta', \\
&\text{s.t.} \\
&\sum_{j=1}^{n}\mu_j z_{tj} \le \theta' z_{to}, \ t=1,\dots,T, \\
&\sum_{j=1}^{n}\mu_j v_{kj} = \sum_{j=1}^{n}\lambda_j v^*_{kj}, \ k=1,\dots,N, \\
&\sum_{j=1}^{n}\mu_j w_{fj} = \sum_{j=1}^{n}\lambda_j w^*_{fj}, \ f=1,\dots,F, \\
&\sum_{j=1}^{n}\mu_j y_{rj} \ge y_{ro}, \ r=1,\dots,s, \\
&\sum_{j=1}^{n}\mu_j = 1, \\
&\mu_j \ge 0, \quad j=1,\dots,n.
\end{aligned} \tag{2}
$$

In this model, the second stage treats N desirable intermediate inputs and F undesirable intermediate inputs as the term $\sum_{j=1}^{n}\lambda_j v^*_{kj}$ and $\sum_{j=1}^{n}\lambda_j w^*_{fj}$ respectively. These values are the optimal output values of the first stage for under evaluated DMU_o. The external input z and final output y are recorded in the *model (2)* under the "natural disposability" hypothesis. It is worth to note the objective function identifies the feasible and bounded solution as an abatement factor of external input for the second stage. Returning to concept of regulation, "managerial disposability" belongs to a strategic concept that is widely accepted by many corporate strategists. Generally, environmental performance is dependent on the management of an organization or a country on its environmental aspects.

Offering "managerial disposability" for the first stage, allows for input increment to increase desirable output and at a same time undesirable output decreasing. The following formulation specifies the managerial disposability:

$$
\begin{aligned}
&\text{Min } \theta_1, \\
&\text{s.t.} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \ge \theta_1 x_{io}, \ i=1,\dots,m, \\
&\sum_{j=1}^{n} \lambda_j v_{kj} \ge v_{ko}, \ k=1,\dots,N, \\
&\sum_{j=1}^{n} \lambda_j w_{fj} \le \theta_1 w_{fo}, \ f=1,\dots,F, \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0 \ \ j=1,\dots,n.
\end{aligned} \tag{3}
$$

In a similar manner, after obtaining an optimal solution from *model (3)*, it can determine the efficiency measure θ_1^* for the first stage. A difference between *models (1)* and *(3)* is that the constraint for inputs of *model (1)* is expressed by $\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}$, $i = 1,\dots,m$ and the constraints in *model (3)* are presented by inequality constraints $\sum_{j=1}^{n} \lambda_j x_{ij} \ge \theta_1 x_{io}$, $i = 1,\dots,m$. Equipped with the optimal solution of the first stage, to examine the efficiency of second stage under managerial disposability, following model has been specified:

$$
\begin{aligned}
&\text{Min } \theta_2, \\
&\text{s.t.} \\
&\sum_{j=1}^{n} \mu_j z_{tj} \ge \theta_2 z_{to}, \ \ t=1,\dots,T, \\
&\sum_{j=1}^{n} \mu_j v_{kj} = \sum_{j=1}^{n} \lambda_j v^*_{kj}, \ k=1,\dots,N, \\
&\sum_{j=1}^{n} \mu_j w_{fj} = \sum_{j=1}^{n} \lambda_j w^*_{fj}, \ f=1,\dots,F, \\
&\sum_{j=1}^{n} \mu_j y_{rj} \ge y_{ro}, \ r=1,\dots,s, \\
&\sum_{j=1}^{n} \mu_j = 1, \\
&\mu_j \ge 0, \ \ j=1,\dots,n.
\end{aligned} \tag{4}
$$

Considering the optimal solutions of the first stage as the term $\sum_{j=1}^{n} \lambda_j v^*_{kj}$ and $\sum_{j=1}^{n} \lambda_j w^*_{fj}$ the efficiency of first stage remains unchanged. The first inequality $\sum_{j=1}^{n} \mu_j z_{tj} \ge \theta_2 z_{to}$, $t = 1,\dots,T$ treats external input z under the hypothesis of managerial disposability. Clearly, *model (4)* is a linear programming problem and it is always feasible and bounded. It should be pointed out that a system is efficient if and only if the two component processes are efficient.

4 | Numerical Example

In order to shed a light on the applicability of the proposed methodology in two-stage process a real data set consisting of 34 OECD countries in 2012 are examined. The data set are taken from Mavi et al. [4]. *Table 1* reports the data set.

Table 1. Data set for OCDE countries.

Country	Inputs			Intermediate input/output		Outputs			
	Total labor force (´000)	Energy use (kg of oil equivalent)/ $1000 GDP	Land area (sq. km)	GDP (10^7 current US$)	Total greenhouse gas emissions (kt of CO_2 equivalent)	Researchers in R & D (per million people)	High-technology exports (10^6 current US$)	ISO 14001 certificates/bn PPP$ GDP	Electricity production (10^6kWh)
	x_{1j}	x_{2j}	x_{3j}	z_{1j}	z_{2j}	y_{1j}	y_{2j}	y_{3j}	y_{4j}
Australia	12,241.40	130.38	7,682,300	156,395.10	531,325.6	3408.385	4565.211	2.10	13,090.00
Austria	4429.89	88.97	82,531	42,824.84	80,150.24	4763.259	18,412.394	2.80	8368.00
Belgium	4955.98	124.63	30,280	52,009.18	119,380.7	4156.244	41,673.751	1.70	11,187.00
Canada	19,516.48	170.55	9,093,510	183,744.35	729,206.9	4518.514	29,025.962	1.20	17,347.00
Chile	8603.14	101.21	743,532	27,707.87	109,908.8	335.284	507.844	2.10	6323.00
Czech Rep.	5337.98	141.75	77,230	20,940.24	129,749.8	3249.889	21,044.499	15.60	6575.00
Denmark	2901.68	72.54	42,256	33,892.71	56,087.33	7088.553	9226.707	4.80	15,976.00
Estonia	689.70	179.37	42,390	2508.12	21,856.28	3338.510	1307.609	13.10	1194.00
Finland	2721.26	155.72	303,890	26,998.01	63,138.29	7187.926	3724.745	6.00	12,772.00
France	30,052.00	103.08	547,557	280,851.12	487,262.7	4169.848	113,250.612	3.50	26,040.00
Germany	42,755.65	91.51	348,880	375,251.35	945,186	4399.672	193,799.441	2.00	129,368.00
Greece	4979.89	88.19	128,900	23,986.20	102,436.8	2643.854	855.057	1.80	8003.00
Hungary	4388.16	99.92	90,530	13,468.05	57,400.82	2522.846	14,470.677	8.10	2575.00
Iceland	190.09	443.62	100,250	1537.66	4461.415	5679.519	93.401	0.80	5248.00
Ireland	2184.31	61.50	68,890	23,927.12	57,922.48	3605.941	21,914.723	3.50	5027.00
Israel	3696.04	94.86	21,640	29,331.48	79,338.09	8255.404	9634.614	2.00	579.00
Italy	25,474.18	76.40	294,140	213,049.13	440,470.2	1943.470	29,711.963	11.40	59,238.00
Japan	65,559.50	100.46	364,560	490,886.28	1,406,855	5201.317	105,075.614	6.80	57,269.00
Korea, Rep.	26,119.54	160.73	97,466	130,560.50	696,523	6456.626	130,460.428	7.00	4494.00
Luxembourg	260.06	81.33	2590	6179.45	11,213.64	4594.529	714.838	0.70	251.00
Mexico	54,475.98	95.69	1,943,950	126,198.17	632,880.1	241.802	45,418.667	0.50	12,098.00
Netherlands	8998.33	101.51	33,690	86,668.00	195,406.6	4561.231	69,039.552	2.40	9076.00
New Zealand	2397.65	130.26	263,310	19,069.09	79,397.17	4008.711	723.215	1.50	2270.00
Norway	2695.09	101.42	365,245	52,274.62	53,527.82	5569.446	4818.883	3.00	14,628.00
Poland	18,294.71	110.70	306,210	52,421.48	393,515.6	1850.717	12,220.495	2.50	15,741.00
Portugal	5397.24	80.73	91,600	22,607.35	64,325.35	3615.146	1964.368	3.40	1505.00
Slovak Rep.	2736.15	122.98	48,088	9847.83	42,885.65	2717.589	7574.416	9.10	481.00
Slovenia	1017.24	121.51	20,140	4768.86	18,340.85	4216.835	1466.834	7.10	71,887.00
Spain	23,419.92	80.17	500,210	136,926.17	322,873.5	2652.551	16,346.454	11.60	21,327.00
Sweden	5118.45	118.16	407,340	57,874.20	55,537.4	6670.028	17,096.659	10.50	2264.00
Switzerland	4700.91	60.17	39,516	68,483.50	52,523.47	4481.074	53,294.078	6.80	2264.00
Turkey	27,797.25	83.67	769,630	82,325.66	442,170.5	1168.599	2176.908	1.20	9800.00
United Kingdom	32,772.20	79.81	241,930	271,950.95	568,763.8	4185.689	69,223.897	6.70	48,971.00
United States	159,815.82	135.93	9,147,420	1,669,151.70	6,680,052	4117.674	148,530.552	0.30	270,735.00

In order to carry out the proposed approach for OCDE performance, two processes can be investigated: the first stage related to Eco-efficiency and the second stage related to Eco-innovation. Three inputs for the first stage are characterized by labor force (x_1), energy consumption (x_2) and land areas (x_3). Final outputs are recorded as researchers in research and development (y_1), high technology export ($y_2)$, ISO 14001 certificate (y_3) and Electricity production (y_4).The desirable intermediate measure is GDP ($v_1)$. One undesirable intermediate factors are reported as total greenhouse gas emission (GHG) (w_1). The undesirable factor does not leave the first stage and along with desirable measure are recorded as intermediate input factor for second stage. *Fig. 2* depicts the two-stage system of eco efficiency and eco-innovation.

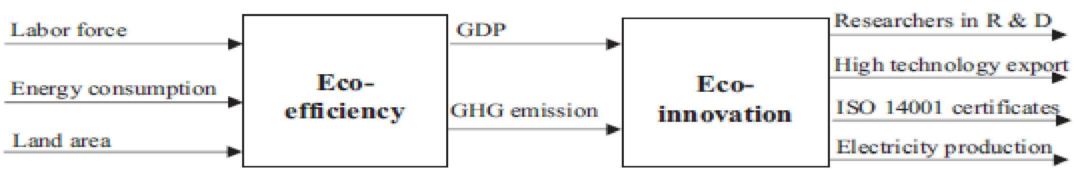

Fig. 2. Two-stage process.

To assess the environmental efficiency, the first stage or Eco-efficiency stage is assumed as leader. Employing the hypothesis "natural disposability" for handling undesirable factor for the first stage (leader stage), efficiency scores for first stage and second stage along with the overall efficiency are reported in *Table 2*. The efficiency score for stage 1 obtained with *model (1)* are recorded in the second column of *Table 2*. As *Fig. 2* shows, the intermediate undesirable factor has not left the first stage. Hence, *model (2)* takes the optimal values of both desirable and undesirable intermediate measure (v_1^*, w_1^*) into consideration. The results of *model (2)* for the second stage are summarized in the third column of *Table 2*.

Table 2. Efficiency score for stage 1 and stage 2 (natural disposability).

DMU	First stage (E_1^*)	Second stage (E_2^*)	$E_{overall} = \frac{(E_1^* + E_2^*)}{2}$
1	1	0.02	0.51
2	0.71	0.49	0.6
3	0.85	1	0.925
4	0.79	0.09	0.44
5	0.59	0.10	0.345
6	0.47	1	0.735
7	0.92	0.35	0.635
8	0.51	1	0.755
9	0.55	0.35	0.45
10	1	1	1
11	1	1	1
12	0.69	0.10	0.395
13	0.68	0.52	0.6
14	1	1	1
15	1	0.64	0.82
16	0.77	0.50	0.635
17	0.97	0.16	0.565
18	1	0.28	0.64
19	0.72	1	0.86
20	1	0.45	0.725
21	0.66	0.25	0.455
22	1	0.71	0.855
23	0.56	0.18	0.37
24	1	0.18	0.59
25	0.54	0.30	0.42
26	0.77	0.15	0.46
27	0.60	0.56	0.58
28	0.67	0.73	0.7
29	0.82	0.13	0.475
30	0.81	0.52	0.665
31	1	1	1
32	0.73	0.06	0.395
33	1	0.29	0.645
34	1	1	1
Average	0.805294	0.503235	0.654265
variance	0.031601	0.12074	0.041566

As *Table 2* shows, under "natural disposability" when the Eco-efficiency process is leader, there are twelve efficient units. As *model (1)* admits the efficiency score lays between zero and unity. Employing *model (2)* for the second stage, without any external input to produce final desirable products, the results show that the number of efficient units reduced to nine units in the second stage. Generally, there are five overall efficient units. That is, units#34, 31, 14, 10 and 11 are overall efficient. As the results show the proposed "natural disposability" can handle intermediate undesirable measure with references to their role. That is, both input and undesirable outputs are decreased, while the desirable output increases. The last two rows in *Table 2* highlight the average and dispersion of the efficiency scores. The maximum of average goes to first stage, 0.805294, while the dispersion of efficiency scores meets the greatest number 0.041566, which belongs to overall efficiency. Running "managerial disposability" on the data set of *Table 1*, the results are presented in *Table 3*.

Table 3. Efficiency score for stage 1 and stage 2(managerial disposability).

DMU	First stage (E_1^*)	Second stage (E_2^*)	$E_{overall} = \frac{(E_1^* + E_2^*)}{2}$
1	1	0	1
2	0.43	0	0.43
3	0.34	0	0.34
4	1	0	1
5	0.24	0	0.24
6	0.14	0	0.14
7	0.49	0	0.49
8	0.24	0	0.24
9	0.38	0	0.38
10	1	0	1
11	0.95	0	0.95
12	0.20	0	0.20
13	0.23	0	0.23
14	1	0	1
15	0.35	0	0.35
16	0.31	0	0.31
17	0.79	0	0.79
18	1	0	1
19	0.26	0	0.26
20	0.70	0	0.70
21	1	0	1
22	0.46	0	0.46
23	0.21	0	0.21
24	0.92	0	0.92
25	0.10	0	0.10
26	0.33	0	0.33
27	0.24	0	0.24
28	0.37	0	0.37
29	0.77	0	0.77
30	1	0	1
31	1	0	1
32	0.19	0	0.19
33	0.82	0	0.82
34	1	0	1
Average	0.572353	0	0.572353
variance	0.1116	0	0.1116

As *Table 3* records, equipped with "managerial disposability" when the Eco-efficiency process is leader, there are nine efficient units in the first stage. In contrast, the second stage records no efficient unit. What's more, the second stage deals with optimal solutions of first stage (intermediate desirable and undesirable measure) without any external input to produce final desirable products. Intermediate undesirable output is not the final output for the first stage and they have not left the process. The results of employing *model (4)* for handling the intermediate undesirable output shows no efficient unit in the second stage. At a rational sight, it might appear that the results are not logical, but the intermediate measure (v^*, w^*) is a good product of the system that can be used by the system itself. So, it seems to be rational that under "managerial disposability" the optimal increased good product for the whole system remains unchanged to increase the final desirable outputs. Hence, if we want to measure the efficiency of DMU_o in terms of abatement potential in undesirable outputs and increasing potential in desirable outputs and inputs the efficiency measures might meet zero. Generally, the overall efficiency is calculated as the average scores of two stages. Comparing the last two rows of *Table 2* and *Table 3* declares that the average of efficiencies catches the minimum quantity (0.572353) which belongs to the first stage employing "managerial disposability". Whilst, the minimum number of dispersion (0.031601) is seen in the first stage equipped with "natural disposability".

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4 | Conclusion

Aiming at determining environmental efficiency, considerable attention has pointed to two-stage network analysis. The existing studies on two-stage network structure just consider desirable intermediate measure. Since, in real occasions, the intermediate measure consists of both desirable and undesirable measures. The proposed approach employs two different disposabilities to handle undesirable factors. That is, "Managerial disposability "and "Natural Disposability". These two concepts ensure to decrease the undesirable factors from the environmental regulation and economic prosperity perspective. This paper employed these two concepts foe dealing with intermediate undesirable factors in a two-stage network structure. The contribution of this paper was applying a non-cooperative game theory in determining environmental efficiency in presence of desirable and undesirable intermediate measure. An illustrative example of 34 OCDE countries in 2012 revealed the applicability of the proposed method.

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Conflicts of Interest

This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript. The corresponding author will complete and submit the manuscript via Editorial Manager or to the Journal's Editorial Office, on behalf of all authors. I certify that there is no actual or potential conflict of interest in relation to this article.

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