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Abstract: In the ordinary macro-economic input-output tables, the industrial sector consists of several dozen industries and each industry in a certain sector is an aggregate of many companies in the sector. The sectoral statistics are the sum of statistics of companies in the respective sector. Usually, all sectors have the same set of inputs for producing outputs. For example, they have labour, capital and intermediate as input and amount of production as output. We can apply traditional DEA models for evaluation of efficiency regarding all sectors by means of these common input and output factors. However, there remain some insecure feelings in comparing all sectors as a *scratch* race. Some sectors are in fields with matured technologies, while others are in emerging fields. Some are labour intensive, while others are capital intensive. These situations lead us to compare sectors under a *handicap* race. In this paper, we propose a new DEA

model based on the non-convex frontiers that all associated sectors may exhibit and handicaps are derived from. We apply this model to Ethiopian industry.

1. Introduction

In the ordinary macro-economic input-output tables, the industrial sector consists of several dozen industries and each industry in a certain sector is an aggregate of many companies in the sector. The sectoral statistics are the sum of statistics of companies in the respective sector. Usually, all sectors have the same set of inputs for producing outputs. For example, they have labour, capital and intermediate as input and amount of production as output. We can apply traditional DEA models for evaluation of efficiency regarding all sectors by means of these common input and output factors. However, there remain some insecure feelings in comparing all sectors as a *scratch* race. Some sectors are in fields with matured technologies, while others are in emerging fields. Some are labour intensive, while others are capital intensive. These differences lead us to compare sectors under a *handicap* race. In this paper, we propose a new DEA model based on the non-convex frontiers that all associated sectors may exhibit and handicaps are derived from. Most DEA models assume convex set frontiers. However, there are non-convex frontiers as indicated by the S-shaped curves in production. Tone & Tsutsui (2013) proposed a new DEA model that can cope with non-convex frontiers. They classify all DMUs (decision-making units) into several clusters and define a new efficiency score, called the *SAS* (scale and cluster adjusted score), that can take into account non-convex frontiers. In this paper, we define the handicap of each industrial

sector using the SAS model. We modify inputs (outputs) by the handicaps and re-evaluate the efficiency scores. We apply this model to Ethiopian industry.

Several authors have discussed handicap-related topics in DEA. Yang & Paradi (2006) proposed a "Handicapped" Data Envelopment Analysis to Adjust for Corporate Strategic Effects for Canadian banks. They applied the index number originally proposed by Fixler & Zieschang (1993). Their index number is based on the tactical and strategic heterogeneity between banks. Olsen & Petersen (2009) discussed target and technical efficiency in DEA controlling for environmental characteristics. They extended Banker & Morey (1986) and incorporated allowable handicap values into the model along the same lines as specifications of assurance regions in standard DEA.

Our problem and approach differ from the preceding ones as follows. (1) We deal with industrial sectors which have a two-layered structure, i.e., each sector consists of many companies in the sectoral category and its inputs/outputs are the sum of these companies. (2) Although we wish to evaluate technical efficiency of sectors, there are handicaps among sectors, as mentioned above, which should be identified and be accounted in efficiency measurement. (3) For this purpose, we first find the VRS frontiers of each sector and project companies in the sector to their frontiers. (4) Then, we find the VRS meta-frontiers regarding the projected companies in all sectors. (5) If the best performer (company) in a sector is positioned on the meta-frontiers, then we classify the sector as having *no-handicap* Otherwise, if the best performer is off the meta-frontiers, we classify the sector as *with-handicap*. This indicates that this sector is in either emerging fields or unfavourable environments. (6) In order to gauge the degree of handicaps, we apply a non-convex frontier model developed by Tone & Tsutsui

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(2013) and decide the handicaps of *with-handicap* sectors. (7) Using handicaps, we adjust inputs (input-oriented case) and outputs (output-oriented case), and apply the CRS model to obtain the final sectoral efficiency score.

We would like to note that we are comparing sectoral efficiency as measured by the ratio input vs. output. For example, three sectors (food, textiles and motor) have the respective input (manpower) and output (profit) exhibited in Table 1. From this table, we see that the virtual (dual) value of input for Food is one tenth of that for Motor, but we do not intend to say that Food should reduce its input to 1, because the environments of three sectors are quite different. However, this kind of comparison is necessary and needed for understanding national and international economics.

Table 1: Three sectors

Sector	Input (Manpower)	Output (Profit)	Output/Input
Food	10	1	0.1
Textiles	5	1	0.2
Motor	1	1	1

This paper unfolds as follows: In Section 2 we introduce the basic framework and classify sectors into *no-handicap* and *with-handicap* groups. In Section 3 we set handicaps to *with-handicap* sectors. Then, we redefine sectoral inputs and outputs using the handicaps and obtain the final efficiency scores which take account of the sectoral handicaps in Section 4. In Section 5, we apply this model to Ethiopian industry. Section 6 concludes this paper.

2. Basic framework

In this section, we describe the basic materials in the paper.

Suppose that there are K sectors in the industry and each sector k $(=1,\ldots,K)$ has n_k DMUs with m inputs and s outputs. Let us denote a DMU in the sector k by $\left(\mathbf{x}_j^k, \mathbf{y}_j^k\right)$ where $\mathbf{x}_j^k \in R_+^m$ $(\mathbf{y}_j^k \in R_+^s)$ is the input (output) vector of the DMU. We define the set of DMUs in the sector k by $\left(\mathbf{X}^k, \mathbf{Y}^k\right)$ with $\mathbf{X}^k = \left(\mathbf{x}_1^k,\ldots,\mathbf{x}_{n_k}^k\right)^T$ and $\mathbf{Y}^k = \left(\mathbf{y}_1^k,\ldots,\mathbf{y}_{n_k}^k\right)^T$.

2.1   Evaluation of DMU within each sector and its projection onto frontiers of the sector

We evaluate each DMU in its belonging sector by using the variable returns-to-scale (VRS) model. In this paper, we use the input oriented SBM (slacks-based measure (Tone 2001)). However other models, e.g. radial models, can be applied as well. This can be attained as below.

For each DMU $\left(\mathbf{x}_o^k, \mathbf{y}_o^k\right)(o=1,\ldots,n_k)$ we solve the following LP:

$$
\begin{aligned}
&\min_{\lambda,\mathbf{s}_o^-,\mathbf{s}_o^+} 1 - \frac{1}{m}\sum_{i=1}^m \frac{s_{io}^-}{x_{io}^k} \\
&\text{subject to} \\
&\mathbf{X}^k\lambda + \mathbf{s}_o^- = \mathbf{x}_o^k \\
&\mathbf{Y}^k\lambda - \mathbf{s}_o^+ = \mathbf{y}_o^k \\
&\mathbf{e}\lambda = 1 \\
&\lambda \geq \mathbf{0}, \mathbf{s}_o^- \geq \mathbf{0}, \mathbf{s}_o^+ \geq \mathbf{0},
\end{aligned}
\tag{1}
$$

where λ is the intensity vector, and $\mathbf{s}_o^-$ and $\mathbf{s}_o^+$ are respectively input and output slacks.

Let an optimal solution to (1) be $(\lambda^*, \mathbf{s}_o^{-*}, \mathbf{s}_o^{+*})$. We project $\left(\mathbf{x}_o^k, \mathbf{y}_o^k\right)$ onto the efficient frontiers of sector k as follows:

$$\overline{\mathbf{x}}_o^k = \mathbf{x}_o^k - \mathbf{s}_o^{-*}, \ \overline{\mathbf{y}}_o^k = \mathbf{y}_o^k + \mathbf{s}_o^{+*}. \tag{2}$$

Thus, we obtain the set of DMUs $\left(\overline{\mathbf{X}}^k, \overline{\mathbf{Y}}^k \right) (k = 1, \dots, K)$ which are VRS-efficient with respect to the frontiers of sector k. See Figure 1.
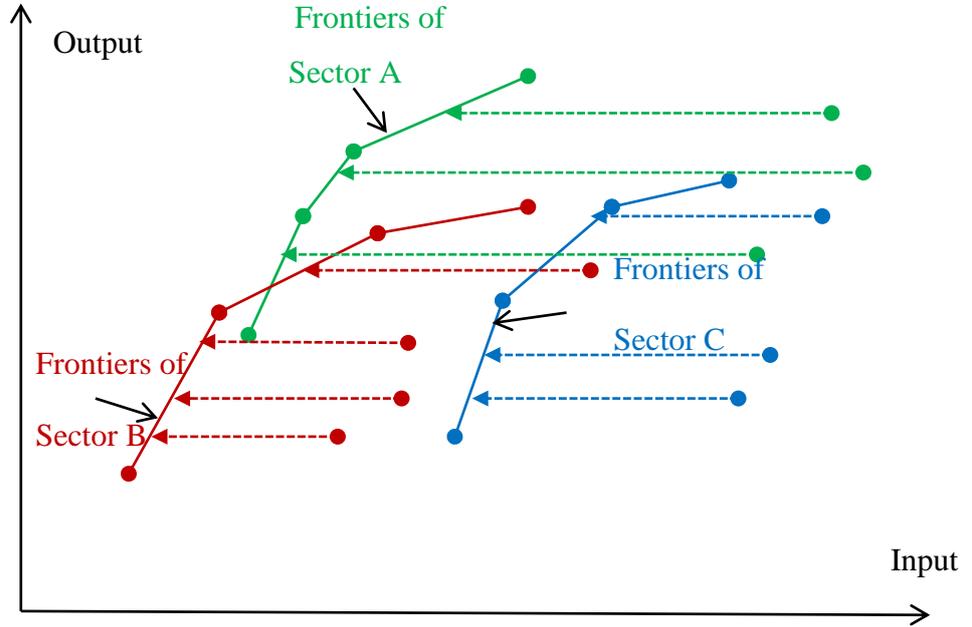

Figure 1: Sectoral frontiers and projections

2.2　　**Global evaluation of the projected DMUs**

We merge the set $\left(\overline{\mathbf{X}}^k, \overline{\mathbf{Y}}^k \right) (k = 1, \dots, K)$ and denote it by $\left(\overline{\mathbf{X}}, \overline{\mathbf{Y}} \right)$ which consists of $n_1 + \cdots + n_K$ DMUs. We evaluate the VRS efficiency of $\left(\overline{\mathbf{x}}_o^k, \overline{\mathbf{y}}_o^k \right)$ with respect to $\left(\overline{\mathbf{X}}, \overline{\mathbf{Y}} \right)$

and denote its VRS score by $\bar{\theta}_o^k$. Further, we define the maximum of $\bar{\theta}_o^k$ among sector k as,

$$\bar{\bar{\theta}}^k = \max_{o=1,\dots,n_k} \left\{ \bar{\theta}_o^k \right\}. \tag{3}$$

If $\bar{\bar{\theta}}^k = 1$, the best performer of sector k is located on the global VRS frontiers (*meta-frontiers*) of $\left(\overline{\mathbf{X}}, \overline{\mathbf{Y}} \right)$. We judge that this sector k has no handicap and classify k to the *no-handicap* group. However, if $\bar{\bar{\theta}}^k < 1$, the best performer of sector k is inferior to the best performers in the *no-handicap* group, we classify k to the *with-handicap* group. See Figure 2 where Sectors A and B belong to the *no-handicap* group and Sector C to the *with-handicap* group.
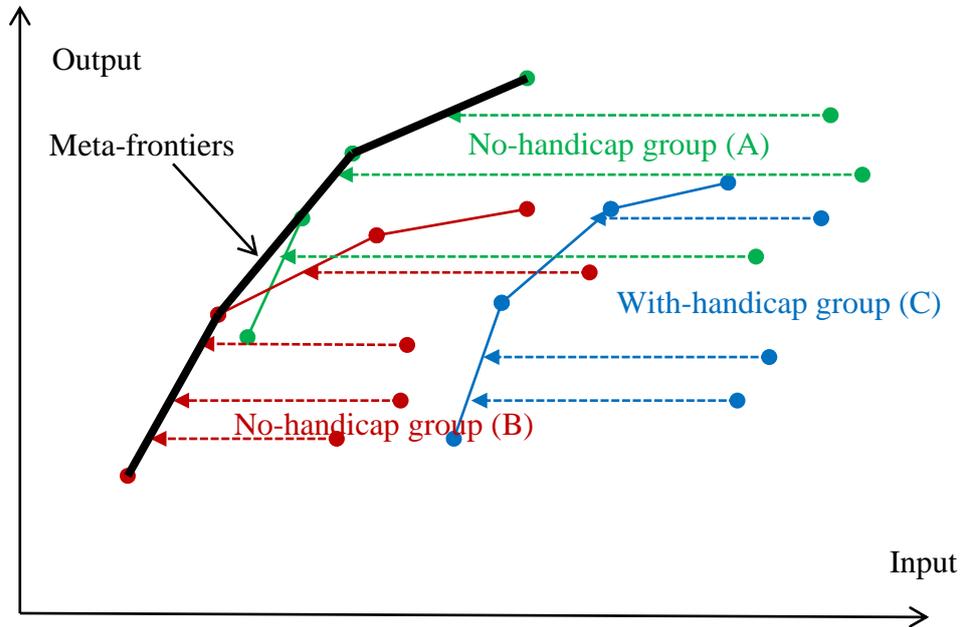

Figure 2: Meta-frontiers and handicaps

3. Handicaps

In this section we describe the scheme how to set handicap to *with-handicap* group.

3.1 Sectoral inputs and outputs

Sectoral inputs and outputs can be defined as the aggregates of VRS-projected DMUs in the sector as follows:

$$\text{Input to Sector } k: \quad x_i^k = \sum_{j=1}^{n_k} \overline{x}_{ij}^k \quad (i=1,\ldots,m; k=1,\ldots,K)$$
$$\text{Output from Sector } k: \quad y_l^k = \sum_{j=1}^{n_k} \overline{y}_{lj}^k \quad (l=1,\ldots,s; k=1,\ldots,K)$$

$$(4)$$

Input/output vectors of sector k are defined by

$$\mathbf{x}^k = \left(x_1^k, \ldots, x_m^k\right)^T \text{ and } \mathbf{y}^k = \left(y_1^k, \ldots, y_s^k\right)^T \tag{5}$$

We deal with K DMUs defined by $\left(\mathbf{x}^k, \mathbf{y}^k\right) \quad (k=1,\ldots,K)$.

3.2 Clustering

We classify K sectors in several clusters. First, sectors belonging to *no-handicap* go to cluster "NHD", while sectors in *with-handicap* hold its sector name as the cluster name. For example, if a sector "Machinery and equipment" belongs to the *with-handicap* group, its cluster name is "Machinery and equipment".

The characteristics of industrial sectors are diverse. Some are in mature fields while others are in emerging fields. This suggests the existence of S-shaped (non-convex) frontiers as exhibited in Figure 3. Tone & Tsutsui (2013) proposed a method for solving non-convex frontiers based on clusters.

Figure 3: S-shaped frontier

3.3 Solving the non-convex model

We solve the dataset $\left(\mathbf{x}^{k}, \mathbf{y}^{k}\right)$ ($k = 1, \dots, K$) with cluster name using the above non-convex model and obtain the scale and cluster adjusted efficiency score, *SAS*, which takes into account the effect of non-convex frontiers.

3.4 Handicap

We define the handicap h_{k} of sector k as follows:

$$h_{k} = 1, \text{ if the sector belongs to the } \textit{no-handicap} \text{ group.} \tag{6}$$

$$h_{k} = \text{SAS score}, \text{ if the sector belongs to the } \textit{with-handicap} \text{ group.} \tag{7}$$

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4. Global issues

In this section, we redefine sectoral inputs and outputs using the above defined handicap and obtain the overall efficiency score of industries.

4.1 Input (Output) under handicap

In the input-oriented case, we define sectoral inputs and outputs as follows:

$$\text{Sectorial input } \xi_i^k = h_k \sum\nolimits_{j=1}^{n_k} x_{ij}^k \quad (i=1,\ldots,m : k=1,\ldots,K)$$
$$\text{Sectorial output } \eta_l^k = \sum\nolimits_{j=1}^{n_k} y_{lj}^k \quad (l=1,\ldots,s : k=1,\ldots,K)$$

(8)

Further we define input/output vectors for each sector as follows:

$$\boldsymbol{\xi}_k = \left(\xi_1^k,\ldots,\xi_m^k\right)^T \text{ and } \boldsymbol{\eta}_k = \left(\eta_1^k,\ldots,\eta_s^k\right)^T \quad (k=1,\ldots,K)$$

(9)

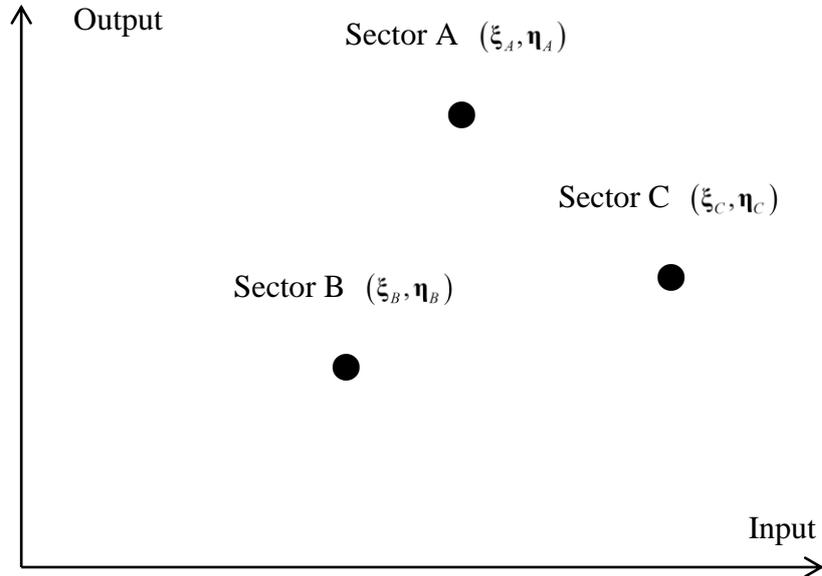See Figure 4 for an example.

Figure 4: Handicapped input and output

4.2   Solving the CRS model

In the non-radial SBM model case, we solve the following LP and obtain the sector-specific efficiency score $\theta_o^*(o=1,\ldots,K)$ under handicap.

$$
\theta_o^* = \min_{\lambda,\mathbf{s}^-,\mathbf{s}^+} 1 - \frac{1}{m}\sum_{i=1}^m \frac{s_{io}^-}{\xi_i^o}
$$

$$
st.
$$

$$
\sum_{k=1}^K \xi_k \lambda_k + \mathbf{s}_o^- = \xi_o \tag{10}
$$

$$
\sum_{k=1}^K \eta_k \lambda_k - \mathbf{s}_o^+ = \eta_o
$$

$$
\lambda \geq \mathbf{0}, \mathbf{s}_o^- \geq \mathbf{0}, \mathbf{s}_o^+ \geq \mathbf{0}
$$

Let an optimal solution to (10) be $\left(\lambda^*, \mathbf{s}_o^{-*}, \mathbf{s}_o^{+*}\right)$. Then we have the projection to the SAS efficient frontiers as follows:

$$
\text{Projected input: } \xi_o^* = \xi_o - \mathbf{s}_o^{-*}
$$
$$
\text{Projected output: } \eta_o^* = \eta_o + \mathbf{s}_o^{+*}. \tag{11}
$$

5. Application to Ethiopian industry

In this section, we describe the characteristics of the manufacturing sector and our data, and apply our model to 14 industrial groups which largely dominate the Ethiopian manufacturing sector.

5.1   On Ethiopian industry

5.1.1 The manufacturing sector

Ethiopia's industrial sector has not yet taken off. Its contribution to GDP has been stagnating for long periods of time, amounting to between 13 and 14 percent. Particularly, the share of the manufacturing sub-sector remained stagnant. The

manufacturing sector is dominated by simple agro-processing activities and production of basic consumer goods. All manufacturing exports are agriculture-based, which include clothing, semi-processed hides, footwear, beverages and others. However, Ethiopia has great potential to jump-start its manufacturing sector. Ethiopia has abundant low-cost labour, which gives it a comparative advantage in less-skilled, labour-intensive sectors such as light manufacturing which includes textile, wood products, leather products and apparel industries (Dinh et al., 2012; Sonobe, 2009). This provides a good opportunity for low-cost manufacturing exports. Moreover, Ethiopia has abundant natural resources including cattle, which can be used as an input for making leather and leather products; forests, which can be used in the furniture industry; cotton, which can be expanded to further develop the garments industry; and land for the agribusiness industry. On the policy side, the government, with an aim of transforming the country from agrarian to industrialised nation, has been preparing an environment conducive to attracting direct foreign investment and domestic investment. To tap into all of these opportunities, many foreign companies including those from China, India, Japan and Turkey are currently flocking into the country.

5.1.2 The data

The data used in this application was extracted from the Central Statistical Agency (CSA) of Ethiopia database. CSA conducts annual census (covering the entire population) of large and medium sized power driven manufacturing firms of the country that employ 10 persons or more. We use data from the 2008 census that comprises relevant outputs and inputs. Based on the literature and data availability, we use a single-output and 3-input production technology for Ethiopian manufacturing. Output is

measured by the gross value of all outputs produced by the firm. The inputs include: (i) the number of employees measured by the sum of permanent and temporary workers, (ii) capital input measured by the net value of fixed assets at the end of the survey year, (iii) intermediate inputs aggregated as the sum of the values of raw materials, fuel and lubricating oil, electricity, wood and charcoal for energy for each establishment and other industrial costs. The types of industries for which our model applies include manufacture of: (1) *Food and beverage*, (2) *Textiles*, (3) *Wearing apparel*, (4) *Tanning, leather and footwear*, (5) *Wood and wood products*, (6) *Paper and printing*, (7) *Chemical and chemical products*, (8) *Rubber and plastics products*, (9) *Non-metallic mineral products*, (10) *Fabricated metal products* (11) *Basic iron and steel*, (12) *Machinery and equipment*, (13) *Motor vehicles* and (14) *Furniture*.

For the purpose of this application, the firm level data were aggregated to 2-digit level industries according to the "International Standard Industrial Classification of All Economic Activities" (ISIC). Prior to data aggregation, we have made super-efficiency procedures to detect outliers in the data. According to the findings, three firms with super-efficiency greater than or equal to three were found as outliers and we deleted them from the data leaving the total of firms from which data was aggregated to industry level 11,213. Moreover, since inflation in 2008 was at its peak in Ethiopia, the data was adjusted for price changes. All inputs (except labour) and output were deflated

by their respective sectoral price deflator taking year 2000 as the base year. Finally, to avoid data fluctuations, we also smooth the data using a four-year moving average[1].

5.2   Main statistics

We begin by presenting the original (non-handicapped) dataset in Table 2. The summary statistics of this dataset is exhibited in Table 3. The summary statistics in Table 3 represent the Min/Max inputs and output of the industry.

Table 2: Original dataset for the year 2008[2]

Industry	Companies	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Food and beverage	349	35391.1458	1788168221	1495232246	4068003497
Textiles	21	18363.7916	381057469	395188377	692187774
Wearing apparel	26	4815.79165	104353732	65318032.1	129750825
Tanning, leather &footwear	62	7887.5625	363361747	561064968	890647967
wood	28	1959.81248	6871141.31	20176600.1	56729660.1
Paper and printing	96	7967.64585	180550018	320157164	638558017
Chemicals	61	6426.50001	286834161	482231522	818780598
Rubber and plastics	75	7083.16665	361385672	417657829	727078679
Non-metals	243	10300.75	677356667	576183151	1377392696
Basic iron and steel	14	1821.60418	212223001	633340164	1002609408
Fabricated metals	49	2482.89584	88309646.7	189549991	342615766
Machinery and equipment	9	1303.5	92018536.2	67075028.3	116429874
Motor vehicles	10	1214.41666	60968765.8	233431786	327031850
Furniture	170	4529.18749	93204031.8	87966624.3	189933023

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[1] The 2008 data is part of the big dataset (covering 2000 to 2009) we had. We first made a four-year moving average adjustment using the 2000 to 2009 dataset and then extracted the 2008 data for the purpose of this application.

[2] "I" and "O" stand for input and output, respectively. The value of capital, intermediate inputs and output are measured in Ethiopian Birr (ETB), Ethiopia's currency. The current exchange rate of ETB against USD is about Birr 19.41 to 1 USD. Labour is measured by the number of annual temporary and permanent workers. Moreover, to consider price changes in our study, inputs (except labour) and output were deflated by their respective implicit sectoral GDP deflator at 2000 price.

Table 3: Industry level summary statistics (non-handicapped data)

Statistics	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Minimum	1214.417	6871141.31	20176600.1	56729660.1
Average	7967.698	335475915	396040963	812696402
St. Dev.	9133.455	454726832	378329529	1014420298
Maximum	35391.15	1788168221	1495232246	4068003497

5.3   Evaluation of DMU within each sector and projection

Utilising the scheme described in Section 2.1, we evaluate each DMU in their respective industry to obtain sectoral frontiers and projections. To this end, we use the VRS input oriented SBM. The development of the handicap model begins with the utilisation of the projected inputs and output where all the DMUs are on their efficient frontier in their respective industry. In Table 4, we provide the industry level summary statistics of the projected inputs and output.

Table 4: Industry level summary statistics of the projected data

Statistics	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Minimum	942.0572	3140337.5	18952775	57420822.6
Average	4461.147	158798402	285544233	871889484
St. Dev.	4508.271	226084166	219213081	1150917694
Maximum	18689.76	870850327	821789723	4544356485

5.4   Global evaluation of the projected DMUs

The efficiency scores in Table 5 were calculated according to the procedure outlined in Section 2.2. After merging the projected inputs and output, we evaluated DMUs with the VRS model from which the maximum score $\overline{\overline{\theta}}^k$ of DMUs in their respective sector was defined to judge whether the industry belongs to the *no-handicap* group or

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with-handicap group. Accordingly, we see in Table 5 that *Wearing apparel, Tanning, Leather and footwear, Paper and printing,* and *Machinery and equipment* industries are in the *with-handicap* group while the remaining industries are in the *no-handicap* group. We also exhibit inputs and output of a sample company with the maximum score $\overline{\overline{\theta}}^k$ for each industry. An industry with $\overline{\overline{\theta}}^k = 1$ belongs to the meta-frontiers.

Table 5: *No-handicap* group and *with-handicap* group before non-convex adjustment

Industry	$\overline{\overline{\theta}}^k = \max\limits_{o=1,\dots,n_k}\left\{\overline{\theta}_o^k\right\}$	A sample company with max θ				Meta-frontier(Y/N)[3]
		(I)Labour	(I)Capital	(I)Intermediate	(O)Output	
Food and beverage	1	12.35922	140318.8	177992.6516	8041129	Y
Textiles	1	1725	32069.7	21700000	37900000	Y
Wearing apparel	0.343418	13.16667	4321.956	66919.76	87352.65	N
Tanning, leather and footwear	0.909345	10.5	1823.441	12303.54	60075.27	N
Wood	1	40	2111.534	205487.8	1042979	Y
Paper and printing	0.488351	12	3216.459	43311.45	97698.5	N
Chemicals	1	21.23822	435970.9	2246884.544	6319859	Y
Rubber and plastics	1	62	6717595	1254564	74600000	Y
Not-metals	1	91.58334	170206.5	6084128	18100000	Y
Fabricated metals	1	19	832519.9	26876.57	2437786	Y
Basic iron and steel	1	290	2863552	102000000	182000000	Y
Machinery and equipment	0.447216	177.0833	3709670	27800000	48100000	N
Motor vehicle	1	148	6583011	177000000	217000000	Y
Furniture	1	12.33333	36995.28	2078167	5568806	Y

5.5   Handicaps

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[3] While "Y" indicates the sector is on the Meta-frontier (belonging to the *no-handicap* group), "N" implies the sector is off the Meta-frontier (belonging to the *with-handicap* group).

5.5.1 Sectoral inputs and outputs

Table 6 presents sectoral inputs and outputs aggregated from the VRS-projected

DMUs in the sector according to Section 3.1.

Table 6: Aggregates of inputs (output) of VRS-projected DMUs in the sector

Industry	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Food and beverage	18689.76	870850327	821789723	4544356485
Textiles	5477.866	37291624	191300303	363220956
Wearing apparel	5713.199	139074482	112307222	220631685
Tanning, leather and footwear	5005.315	186313400	469860107	800649505
Wood	2325.809	3140337.5	18952775	57420822.6
Paper and printing	5693.758	88431187	267162146	614123385
Chemicals	2788.107	82517926	442951464	1028226007
Rubber and plastics	2374.122	174408612	174512573	956744221
Not-metals	6230.622	379273000	490968503	1782276024
Fabricated metals	2052.191	74160812	223054964	460355315
Basic iron and steel	942.0572	46086368	392698767	659006974
Machinery and equipment	1046.282	60668080	59152487	114955660
Motor vehicle	1313.834	50655770	262797476	397401292
Furniture	2803.14	30305709	70110758	207084441

5.5.2 Solving non-convex models

Here, we solve the non-convex nature of the data using the data in Table 6 and classify the scale

adjusted scores (SAS) of each sector. In Table 7 "a" stands for *non-handicapped* group. We

found that all *with-handicap* sectors belong to non-convex (S-shaped) frontiers.

Table 7: *No-handicap* group and *with-handicap* group after non-convex
adjustment

Industry	(I)Labour	(I)Capital	(I)Intermediate	(O)Production	Cluster	SAS
Food and beverage	18689.8	870850327	821789723	4544356485	a	1
Textiles	5477.87	37291624	191300303	363220956	a	0.5931
Wearing apparel	5713.2	139074482	112307222	220631685	Wearing apparel	0.768

Industry					Industry	
Tanning, leather and footwear	5005.31	186313400	469860107	800649505	Tanning, leather and footwear	0.9923
Wood	2325.81	3140337.5	18952775	57420822.6	a	1
Paper and printing	5693.76	88431187	267162146	614123385	Paper and printing	0.9715
Chemicals	2788.11	82517926	442951464	1028226007	a	1
Rubber and plastics	2374.12	174408612	174512573	956744221	a	1
Not-metals	6230.62	379273000	490968503	1782276024	a	0.7429
Fabricated metals	2052.19	74160812	223054964	460355315	a	0.664
Basic iron and steel	942.057	46086368	392698767	659006974	a	1
Machinery and equipment	1046.28	60668080	59152487	114955660	Machinery and equipment	0.5433
Motor vehicle	1313.83	50655770	262797476	397401292	a	0.6274
Furniture	2803.14	30305709	70110758	207084441	a	0.6622

5.5.2 Handicap

The final (after non-convex adjustment) handicap scores are reported in Table 8.

Table 8: Handicap score after non-convex adjustment

Industry	Handicap
Food and beverage	1
Textiles	1
Wearing apparel	0.768
Tanning, leather and footwear	0.9923
Wood	1
Paper and printing	0.9715
Chemicals	1
Rubber and plastics	1
Not-metals	1
Fabricated metals	1
Basic iron and steel	1
Machinery and equipment	0.5433
Motor vehicle	1
Furniture	1

5.6   Global issue

5.6.1 Input (output) under handicap

In this section, we apply the scheme outlined in Section 4.1 to obtain the handicapped data. Since we are using the input-oriented model, the inputs of the original dataset of each sector were multiplied by the handicap scores given in Table 8 to arrive at the data in Table 9.

Table 9: Handicapped Inputs and output

Industry	(I)Labour	(I)Capital	(I)Intermediate	(O)Production
Food and beverage	35391.15	1788168221	1495232246	4068003497
Textiles	18363.79	381057469	395188377	692187774
Wearing apparel	3698.528	80143666.2	50164248.7	129750825
Tanning, leather and footwear	7826.828	360563862	556744768	890647967
Wood	1959.812	6871141.31	20176600.1	56729660.1
Paper and printing	7740.568	175404343	311032684	638558017
Chemicals	6426.5	286834161	482231522	818780598
Rubber and plastics	7083.167	361385672	417657829	727078679
Not-metals	10300.75	677356667	576183151	1377392696
Fabricated metals	1821.604	212223001	633340164	1002609408
Basic iron and steel	2482.896	88309646.7	189549991	342615766
Machinery and equipment	708.1915	49993670.7	36441862.9	116429874
Motor vehicle	1214.417	60968765.8	233431786	327031850
Furniture	4529.187	93204031.8	87966624.3	189933023

5.6.2 Solving the CRS model

So far, we have been adjusting the original data in order to account for the handicap industry. In Table 10, we report the efficiency scores of each industry obtained after

making handicap adjustments. To obtain the efficiency scores reported in Table 10, we used the dataset given in Table 9.

Table 10: Efficiency score *with handicap* model

Industry	Score	Rank
Food and beverage	0.8357	6
Textiles	0.5192	14
Wearing apparel	0.5727	13
Tanning, leather and footwear	0.5836	12
Wood	1	1
Paper and printing	0.8722	5
Chemicals	0.6640	9
Rubber and plastics	0.5899	11
Non-metals	0.7839	8
Fabricated metals	1	1
Basic iron and steel	0.834	7
Machinery and equipment	1	1
Motor vehicle	1	1
Furniture	0.6019	10

5.6.3 Comparisons with *no-handicap* model

The scores in Table 11 were obtained using the original (*non-handicapped*) dataset reported in Table 2. Figure 5 compares the scores from the *no-handicap* and *with-handicap* models where the heading (H) indicates the *with-handicap* sector.

Table 11: Efficiency sore with *no-handicap* model

Industry	Score	Rank
Food and beverage	1	1

Textiles	0.5359	13
Wearing apparel	0.5037	14
Tanning, leather and footwear	0.5776	11
Wood	1	1
Paper and printing	0.8918	7
Chemicals	0.6943	8
Rubber and plastics	0.6216	10
Non-metals	0.9304	5
Fabricated metals	1	1
Basic iron and steel	0.9215	6
Machinery and equipment	0.5401	12
Motor vehicle	1	1
Furniture	0.6627	9

5.7   Observations

In Figure 5, we see that of the 3 handicapped industries, *Wearing apparel*, *Tanning*,

and *Machinery and equipment* have seen improvements in efficiency after handicap

adjustment was made, with *Machinery and equipment* industry becoming efficient. There

is a slight decline in efficiency score in the *Paper and printing* industry (handicapped)

and the *no-handicap* industries as compared to *no-handicap* model. The decrease of

efficiency scores in *Paper and printing* and other sectors might have been caused by the

increase of *Machinery and equipment* score (it has the smallest handicap and is efficient

now). The emergence of this efficient sector affects all other sectors.

In this application, we tried to standardize different industries of different nature

which use different inputs to produce different outputs.   However, we believe that the

model can also be applied to sectors (DMUs) in the same industry such as banks and electric power industry. Given that these industries provide similar services to their respective customers, the only difference remains the environment in which they operate. Some of the DMUs may enjoy advantages such as location and infrastructure while others do not. Unlike the traditional DEA which assumes DMUs enjoy similar environment, our model takes these environmental differences into account. Moreover, we can even make regional and/or international comparisons of DMUs producing similar products but they differ only in their environmental set up.
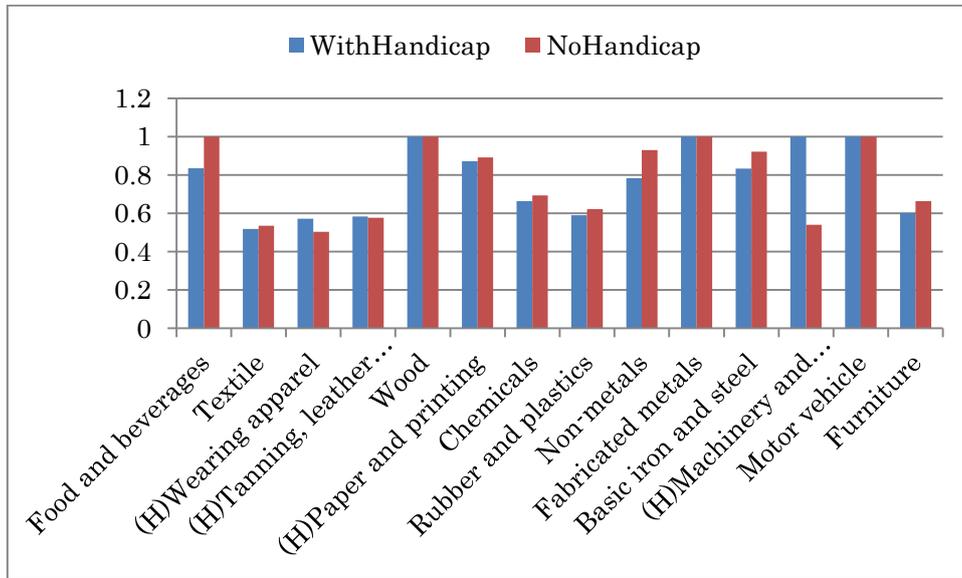

Figure 5: Comparison of handicap and *no-handicap* models

5.8 Policy implications

Besides the contribution of this study to handicap modelling in DEA, its application to Ethiopian industrial sector has certain policy implications. From policy perspective, the study of efficiency in the industrial sector may be helpful to allocate resources in a more efficient and productive way. This study can also be used as an input for policy

makers to formulate policies that are sector specific by identifying the best and worst performing industries. For instance, despite the strong belief that Ethiopia can be an industrial hub in labour-intensive light manufacturing such as *Textiles*, *Wearing apparel*, *Tanning, leather and leather products* and *Furniture* industries, the performance of these sectors remained poor in the period under study. While we suggest that concerned bodies should take further studies to investigate as to why low performance is registered in these sectors, it is also possible to cite factors such as poor input supply chain, lack of international exposure and poor technology might have contributed to the poor performance of the mentioned sectors.

For instance, it is often reported that there is difficulty in accessing quality hides and skins that would be used in the *Leather and leather products* industry. Hence, given that Ethiopia has a comparative advantage in providing ample inputs to boost these sectors, we suggest that the government needs to engage itself in reforming the input industries to achieve maximum efficiency in the sectors. We suggest that the government should introduce proper incentives in the input market. Provision of marketing information and marketing channels should be encouraged. As Ethiopian domestic investors are less competitive in the international arena, foreign direct investment may be helpful in bringing international experience, thereby improving the efficiency and competiveness of the sectors. The poor performance of the sectors might also indicate that firms in these sectors are using some older techniques of production (outdated machinery) in the production process. Hence, improving the existing techniques of production and/or introduction of modern machineries may improve the efficiency level. The *Machinery*

and equipment sector, in particular, has the potential to be the top industry, if innovation in inputs were executed.

6. Conclusions

In this paper, we proposed a handicap setting method for fair evaluation of industrial sectors and applied it to Ethiopian industry. The Manufacturing industry comprises many sectors which include many companies in the category. Thus, there is a "two-layered" structure. The statistics of a sector is the sum of those of its member companies. In order to evaluate the relative efficiency of industrial sectors, we need to take account of performance of their membership companies. For this purpose, we evaluated sectoral frontiers and projected member companies to their respective frontiers. We then merged the projected companies and found the meta-frontiers of all projected companies in the industry. If a member of a certain sector is on the meta-frontiers, we classified this sector to the *no-handicap* group, whereas if all members of a sector are off the meta-frontier, we classified the sector to the *with-handicap* group. Then we applied the non-convex model proposed in Tone & Tsutsui (2013) for deciding handicaps of *with-handicap* sectors. Actually, most of them belong to no-convex (S-shaped) frontiers. We modify inputs (in the input-oriented case) or outputs (in the output-oriented case) using the handicaps and re-evaluate the sectoral efficiency. As for the developing industry of Ethiopia, several sectors are in emerging fields. We found four sectors belonged to the *with-handicap* group; (1) *Wearing apparel* (handicap=0.768), (2) *Tanning, leather and footwear* (handicap=0.9923), (3) *Paper and printing* (handicap=0.9715), and (4) *Machinery and equipment* (handicap=0.5433). The most handicapped one is the *Machinery and equipment* sector. If this sector was

improved by innovation, it would become the top sector, while the other three handicapped sectors remain inefficient even after taking account of handicaps. The sectors in the *no-handicap* group could not increase the relative efficiency. This might be caused by the emergence of the *Machinery and equipment* sector as the efficient one.

Further research subjects include cost, revenue and profit-related extensions of this approach.

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