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Combined Role of Manpower Ethics and Physical Space Facilities of Bank Branches in Productivity Analysis

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Abstract
Productivity growth and efficiency improvements are the major sources of economic development. Pure efficiency, scale efficiency, and technology are basic factors, and rules and regulations and balance are recently known factors affecting the productivity growth. This paper focuses on the effect of manpower ethics and physical space facilities of bank branches as two factors affecting the Malmquist productivity index in the bank branches evaluation. The proposed model uses assurance region weight restrictions to increase discrimination power of basic data envelopment analysis models for the constant return to scale technologies. The validity of the proposed model and the extended Malmquist index is confirmed with an empirical case study of 74 branches of aspecializedbank in thehousing sector of Iran in two time periods of 2017 and 2018. The results for both traditional and extended indicesand the effects of manpower ethics and physical space facilities are analyzed.

Keywords
Data envelopment analysis; Malmquistproductivity growth management; Manpower ethics.

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Introduction

Data envelopment analysis (DEA) defines the efficiency of a given Decision Making Unit (DMU) as the ratio of the weighted sum of outputs to the weighted sum of inputs. By DMUs, we mean firms, plants, branches, hospitals, or other units that are being evaluated. They should have the same inputs and outputs. Complete freedom of DMUs in selecting input and output weights may result in ignoring some of the inputs/outputs or assigning a zero weight to them. Most methodological extensions of DEA followed an application-driven path as a result of the application of the method in solving real life problems. The desire to incorporate restrictions on the weights attached to the inputs/outputs of DMUs is one of the areas of development in DEA.One way to avoid such a situation is to restrict the weights. By incorporating absolute upper and lower bounds, assurance region type I (ARI) and type II (ARII), and virtual weight restrictions, the analyst can make the model more realistic and improve the discrimination of basic DEA models. For literature ondifferent types of weight restrictions and value judgments in DEA, see Thanassoulis, Portela, and Allen (2004). Weight restriction is also a way of reflecting the manager's or modeler's prior views or information about the relative importance of individual inputs and outputs or imposing a specific relation between them involving cost or price considerations. In addition to weight restrictions, there are other methods for improving discrimination power of DEA models such as trade-offs, selective proportionality, and the creation of unobserved DMUs (Podinovski&Thanassoulis,2007).

The literature on operations research (OR) and ethics has roots extending at least back to the 1960s, and is increasing in breadth and vigor (Wenstøp, 2010). When we reviewed the literature of consideration of ethical issues in OR (and specifically in DEA), we found two types of studies. As Figure 1 shows, the first is studies that discuss the necessity of adherence of OR modelers and researchers to some ethical principles.Since this paper doesn’t address this type of study, we just refer the reader to the survey of Ormerod and Ulrich (2013) for further study in this area.The second type, that is, the subject of our paper,are studies thatwant to model ethical subjects in terms of some ethical indices, criteria, variables, or constraints. Very few studies have focused on this area. Probably, one of the reasons for the literature weakness on this area is considerable challenges of incorporating qualitative variables such as ethics into the analysis.

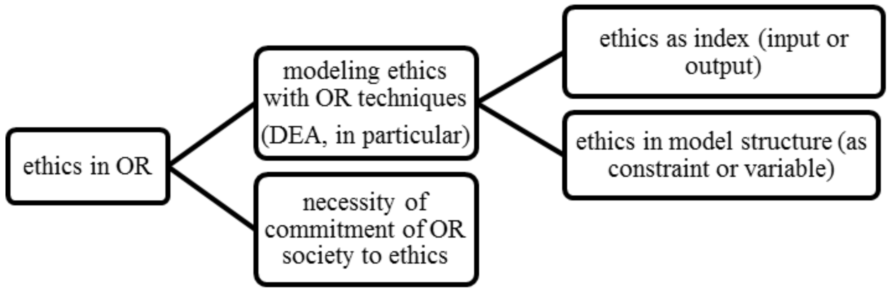

Fig. 1. Areas of intervention of ethical subjects in OR (and DEA in particular)

Although there is almost no ethics-based DEA study, from a general point of view, we can say that two approaches for taking ethics-based performance evaluation into account may be considered: As illustrated in Figure 1, one straightforward procedure is to define an ethics index in an appropriate way, make it quantitative using questionnaire or another method, and then consider it as an extra input or output in different basic DEA models. Another novel approach adopted in this study is to incorporate ethical concepts into the model structure, for example, by adding additional constraint(s) to the basic models or by changing the relationship between the variables in a way that suggests the respective ethical purpose of doing research. Basso and Funari (2003,2007) assessed ethical mutual funds in which an ethical measure, as the ethical level of the fund obtained through questionnaires, is considered as an additional output along with other inputs and outputs of basic DEA models. We found only these two papers in the literature of ethics-based DEA studies. Unfortunately, there is no research in conjunction with the second view. In this paper, we impose ethics of human resources (HR) and physical space (PS) in the form of weight restrictions on the basic DEA models to reach a performance evaluation based on these ethical subjects in the level of bank branches.

Productivity is viewed as the most important long-run driver of economic growth in both economic theory and empirical research

(Ding, Guariglia,&Harris,2016). Therefore, understanding the factors affecting productivity is very important. Economists often use total factor productivity estimates as proxies for management (Triebs&Kumbhakar,2018). In recent years, the measurement and analysis of productivity change has attracted many researchers. The Malmquist index (MI), first introduced as a quantity for use in the analysis of input consumptions, is a prominent index measuring productivity change over time. It was first used in productivity literature by Caves, Christensen, and Diewert(1982). Fare, Grosskopf, Lindgren, and Roose (1992) developed a DEA-based decomposition of the Malmquist index, known as FGLR decomposition, consisting of two components, technology change (TC) and efficiency change (EC), over two time periods. Three-component decomposition of the index was developed by Fare, Grosskopf, Norris, and Zhang(1994) regarding both CRS and VRS technologies involving pure efficiency change (PEC), scale efficiency change (SEC), and technological change. This decomposition is called FGNZ. These decompositions were conducted using basic models of CCR and BCC. In this context, there are two more studies that apply new technologies as a basis. In order to improve the meaning of efficiency using expanded production possibility set (PPS), Alirezaee and Afsharian (2010) presented an extended Malmquist index (EMI) using trade-off technology aligned with two basic models. Also, in order to take into account the effect of imposed strategies on DMUs' behavior, Alirezaee and Rajabi Tanha (2015) proposed a balance model for assessing balance factor of DMUs and developed another extended Malmquist index. A new Malmquist productivity index, that takes the links between the inputs and the outputs into account, was proposed by Walheer (2019). Indeed, plants use inputs that are differentially linked to each type of electricity production. Next, the methodology hasbeen developed which allows defining and decomposing output-specific Malmquist productivity index. In multi-output settings, different types of inputs are simultaneously used to produce the outputs. On the one hand, some inputs are jointly used to produce all (or a subset of) the outputs. These inputs give rise to economies of scope, which form a prime economic motivation to produce multiple outputs. On the other hand, some inputs can also be allocated to specific output productions (walheer, 2019).Considering these links between inputs and outputs, one can extend the method proposed here to include thesedata structures in DEA. This is a proposition for future work.

In line with these studies, here we claim that the way the branch staff interacts with customers and also the appearance of branch physics and facilities available in the branch are contributing factors in its productivity growth. Examples of ethical behavior of the personnel are customer guidance and assistance in doing his/her demand, orderly appearance, and customer appreciation. We believe that branch physics can indirectly be ethical or unethical. Convenient counter, suitable furniture, parking, decoration, facilities for entering disabled persons with wheelchair can indicate branch physics and location to be ethical.We, first, use weight restrictions in the form of ARI in the proposed models of Human ResourceEthics (HRE) and Physical Space Facilities (PSF), that is so-called HRE&PSF, and then define HRE&PSFfactorsfor each under- assessment branch. In applying ARI restrictions, we utilize predefinedHRE and PSF scores obtained during periodic annual evaluations carried out by Plan and Program managementof bank. We treat the scores as the relative value of the inputs of HR and location index in multiplier forms of DEA models.Then the proposed models are used in developing an extended Malmquist index (EMI) to determine the combined role of HRE&PSF as a contributing factor in branch productivity growth or decline. The EMI will be decomposed into two components of extended efficiency change (EEC) and extended technology change (ETC). Regarding bothethics-based and CRStechnologies, we define new component of HRE&PSF factor change and propose a three-component decompositionincluding EC and ETC. Also, if we consider VRS technology alongside ethics-based and CRS technologies, a new four-component decomposition of EMI consisting of SEC, PEC, HRE&PSF factor change, and ETC will be obtained. The novel decomposition provides us new insight about the contribution of ethics-related categoriesalong with other known factors in productivity changes.

The remainder of this article is organized as follows: Section 2 describes the proposed HRE&PSF modeland defines HRE&PSF factor of a given branch. An extended MI and its different decompositions including HRE&PSF change is presented in section

3.In section 4, we use a real-world case study at the bank branch level to demonstrate the applicability and efficacy of the proposed methods in calculating EMI with its decompositions. We will analyze and compare MI and EMI for two time periods in this section. Concluding remarks and future directions willappear in section 5.

The proposed HRE&PSF model

Suppose that we have n DMUs with m inputs and s outputs denoted by $X_j = (x_{1j}, x_{2j}, \ldots, x_{ij}, \ldots, x_{mj})$ and $Y_j = (y_{1j}, y_{2j}, \ldots, y_{rj}, \ldots, y_{sj})$ respectively for DMU_j, $j = 1, \ldots, n$. It is assumed that $X_j \geq 0$ and $Y_j \geq 0$ with $X_j \neq 0$ and $Y_j \neq 0$ for all DMUs. The multiplier forms of input-oriented basic DEA models of CCR and BCCfor measuring technical efficiency(TE) and pure efficiency (PE)fora given DMU_k aredefinedrespectively as follows:

$$
\begin{aligned}
&\theta_{CCR} = \max \sum_{r=1}^{s} u_r y_{rk} \\
&s.t. \sum_{i=1}^{m} v_i x_{ik} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \; j = 1, \ldots, n \\
&u_r \geq \varepsilon, r = 1, \ldots, s \\
&v_i \geq \varepsilon, i = 1, \ldots, m
\end{aligned}
\tag{1}
$$

And

$$
\begin{aligned}
&\theta_{BCC} = \max \sum_{r=1}^{s} u_r y_{rk} - u_0 \\
&s.t. \sum_{i=1}^{m} v_i x_{ik} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0, \; j = 1, \ldots, n \\
&u_r \geq \varepsilon, r = 1, \ldots, s, u_0 \; \textit{is free} \\
&v_i \geq \varepsilon, i = 1, \ldots, m
\end{aligned}
\tag{2}
$$

where u_r and v_i are weights assigned to output r and input i, respectively, and $\varepsilon > 0$ is a non-Archimedean infinitesimal applied to avoid zero weights.The above CCR and BCC models will be used in the following.

Production efficiency is one of the most significant dimensions of bank branch performance. In bank branch analyses, the production model commonly views bank branches as producers of services using labor and other physical resources as inputs and providing services for taking deposits, making loans and others (number of transactions or document processing) as outputs (Paradi&Zhu,2013). Consider Figure 2 production model:

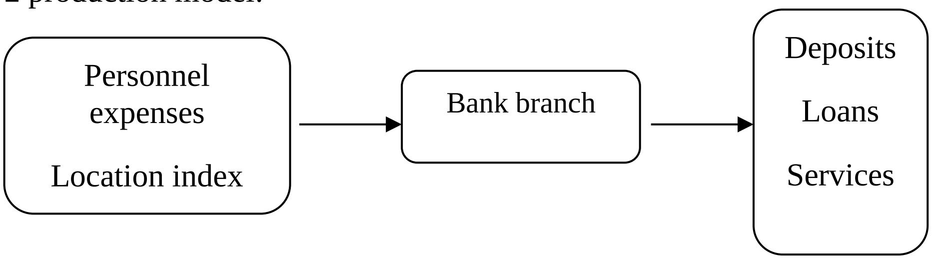

Fig. 2. DEA production model

We will develop the proposed models based on this input-output structure, but one mayadd other inputs to personnel expenses and location index or consider different outputs. Note that since the physical space and manpower ethics are related to the inputs of the above production model, we consider an input-oriented model in this paper. Simply, one can consider output orientation models and do the same discussion.

The location index of the branch is an index to show the branch status in terms of many qualityand quantity factors. The factors are classified into three categories: branch customers' characteristics,physical locations of the branch, and branch staff characteristics. Computing the location index for allof the bank's branches was done as part of the research project 'Model design and Implementation for Maskan Bank Branches Location', contract No. 48-90-2612, dated 13/07/2011, which was prepared bythe authors. This index is of vital importance toboth the evaluation of branches from the operationalperspective and as an index of the potential capital of the bank in terms of its geographical location.

Weuse this index as an input for the evaluation of the branches (Alirezaee&RajabiTanha,2015).

Plan and program management of bank assigns scores to each branch's staff and physical location ethicsby conducting periodic evaluations over a year. Consider P_j^{min} and P_j^{max} as the minimum and maximum HRE scores of DMU$_j$. Also, suppose $P_j^{'min}$ and $P_j^{'max}$ are the minimum and maximum PSF scores.All of the scoresare nonnegative values between 0 and 1.

Here we propose HRE&PSF model as

$$\begin{aligned} &\theta_{HRE\&PSF} = \max \sum_{r=1}^{3} u_r y_{rk} \\ &s.t. \sum_{i=1}^{2} v_i x_{ik} = 1 \\ &\sum_{r=1}^{3} u_r y_{rj} - \sum_{i=1}^{2} v_i x_{ij} \le 0,\ j = 1,\dots,n \\ &\frac{P_k^{\min}}{P_k^{'max}} \le \frac{v_1}{v_2} \le \frac{P_k^{\max}}{P_k^{'min}} \\ &u_r \ge \varepsilon, r = 1,2,3. \end{aligned} \tag{3}$$

Model(3) takes the role ofHRE&PSF into account inDEA assessmentby adding a constraint that uses the related ethics scores as the ratio of input weights$v_1$and v_2.In model (3), the relative weights of inputs are set as their ethics scores and thus, an ethics-based evaluation of DMUs is implemented. The weight restrictions used in model (3) impose an upper and lower bounds to ratio of $v_1$and v_2. The attached constraint is in the form of ARI and as Charnes, Cooper, Huang & Sun (1990) and Thompson, Langemeier, Lee, Lee, and Thrall (1990) noted; when imposing ARI there will always exist at least one efficient DMU. Moreover, whether the output or input orientation is used, a DEA model incorporating ARI produces the same relative efficiency scores. Therefore, there remains no question about the feasibility of model (3).

In order to investigate the role of HRE&PSF changes in Malmquist productivity change index, which is discussed in the next section, here we define new concepts called HRE&PSF Factor ((HRE&PSF)F) as follows:

Definition 1.The (HRE&PSF)Fof a DMU is respectively defined as the ratio of the HRE&PSF to the CCR efficiency score.

Among the basic DEA models, the CCR model has the most discrimination power. The efficiency measure obtained from it is lower or equal to the BCC measure. In order to propose a new model that hasmore discrimination power relative to basic DEA models based on HRE&PSF considerations, we use CCR model in Definition 1 (see Figure 1).In order to demonstrate the effect of adding HRE&PSF weight restrictions and the concept of(HRE&PSF)F, consider the PPS generated by DMUs A to G with one input and two outputs under CCR and HRE&PSF technologies in Figure 3.By Definition 1, the gap between two drawn efficient frontiers shows the (HRE&PSF)F of each DMU. This difference measures the efficiency status before and after taking the weight restrictions into consideration. Considering DMU C, θ_{CCR}, $\theta_{HRE\&PSF}$, and (HRE&PSF)F are as follows:

$$\theta_{CCR} = \frac{OC}{OC'}, \quad \theta_{HRE} = \frac{OC}{OC''}, \quad \text{HREF} = \frac{OC'}{OC''}.$$

Obviously, both the θ_{CCR} and $\theta_{HRE-PSF}$ measures obtained for DMU C are less than 1, so it is neither technically nor ethically efficient, and its (HRE&PSF)F is less than 1. The (HRE&PSF)F for DMU A is equal to 1, meaning that it is efficient under both technologies. Hence, DMU A is ethically and technically efficient. DMU B is technically but not ethically efficient, and its(HRE&PSF)F is less than 1. In this Figure, it is DMU A that still remains on the frontier after adding new ethical constraints.

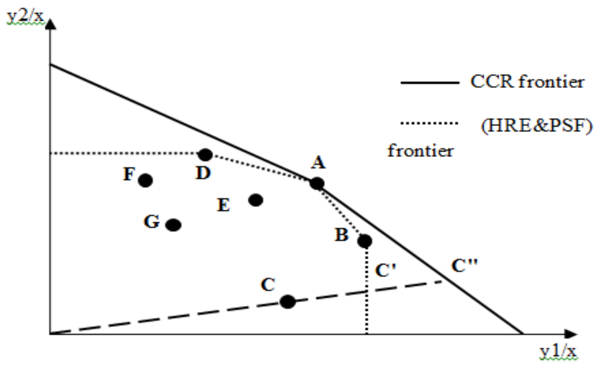

Fig. 3. CRS and HRE&PSF efficiency frontiers for sample DMUs.

Extending MI

In this section, first we have a brief review of the traditional Malmquist index in subsection 3.1 and then use the proposed models of previous sectionfor developing EMI in subsection 3.2.

1. MI and its decompositions

Let$(x_k^t, y_k^t)$and (x_k^{t+1}, y_k^{t+1}) be inputs and outputs of DMU$_k$ observed at two time periods,$t$and $t+1$. The (input-oriented) Malmquist productivity index can be expressed as

$$MI = \left[\frac{D^t\left(x_k^{t+1}, y_k^{t+1}\right)}{D^{t+1}\left(x_k^t, y_k^t\right)} \times \frac{D^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{D^t\left(x_k^t, y_k^t\right)} \right]^{1/2} \tag{4}$$

Calculation of MI requires two single-period and two mixed-period measures.The two single-period measures are $D^t(x_k^t, y_k^t)$and $D^{t+1}(x_k^{t+1}, y_k^{t+1})$,which refer to the distance of (x_k^t, y_k^t) and $(x_k^{t+1}, y_k^{t+1})$from efficient frontiers of time periods t and $t+1$, respectively. Also, the two mixed-period measures are $D^{t+1}(x_k^t, y_k^t)$and $D^t(x_k^{t+1}, y_k^{t+1})$, which refer to the distance of (x_k^t, y_k^t) and (x_k^{t+1}, y_k^{t+1}) from different efficient frontiers constructed in time periods $t+1$ and t, respectively.These four measures are called distance functions. All of the required distance functions in the MI formula can be obtained from DEA models. Assuming input-oriented CRS technology, $D^t(x_k^{t+1}, y_k^{t+1})$could be obtainedas follows:

$$\begin{aligned}
&\left[D_{CRS}^t\left(x_k^{t+1}, y_k^{t+1}\right)\right] = \max \sum_{r=1}^{s} u_r^t y_{rk}^{t+1} \\
&s.t. \sum_{i=1}^{m} v_i^t y_{ik}^{t+1} = 1 \\
&\sum_{r=1}^{s} u_r^t y_{rj}^t - \sum_{i=1}^{m} v_i^t x_{ij}^t \le 0, j = 1, \ldots, n \\
&u_r^t \ge \varepsilon, r = 1, \ldots, s \\
&v_i^t \ge \varepsilon, i = 1, \ldots, m.
\end{aligned} \tag{5}$$

The other three distance functions can be computed similarly. FGLR two-component decomposition of MI, which presents EC and TC, is

$$MI = \frac{D_{CRS}^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right)}\left[\frac{D_{CRS}^{t}\left(x_k^{t+1}, y_k^{t+1}\right)}{D_{CRS}^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)} \times \frac{D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right)}{D_{CRS}^{t+1}\left(x_k^{t}, y_k^{t}\right)}\right]^{\frac{1}{2}} = EC \times TC \tag{6}$$

Considering two CRS and VRS technologiesand using CCR and BCC models, FGNZ decomposition breaks down MI into three components, PEC, SEC, and TC..We note that SE is defined as the ratio of CCR to BCC efficiency scores.

$$\begin{aligned} MI &= \frac{PE^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{PE^{t}\left(x_k^{t}, y_k^{t}\right)} \times \frac{SE^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{SE^{t}\left(x_k^{t}, y_k^{t}\right)} \\ &\times \left[\frac{D_{CRS}^{t}\left(x_k^{t+1}, y_k^{t+1}\right)}{D_{CRS}^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)} \times \frac{D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right)}{D_{CRS}^{t+1}\left(x_k^{t}, y_k^{t}\right)}\right]^{\frac{1}{2}} = PEC \times SEC \times TC \end{aligned} \tag{7}$$

where

$$PE^{t}\left(x_k^{t}, y_k^{t}\right) = D_{VRS}^{t}\left(x_k^{t}, y_k^{t}\right), SE^{t}\left(x_k^{t}, y_k^{t}\right) = \frac{D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right)}{D_{VRS}^{t}\left(x_k^{t}, y_k^{t}\right)}$$

and

$$\begin{aligned} &\left[D_{VRS}^{t}\left(x_k^{t}, y_k^{t}\right)\right] = \max \sum_{r=1}^{s} u_r^t y_{rk}^t - u_0^t \\ &s.t. \sum_{i=1}^{m} v_i^t y_{ik}^t = 1 \\ &\sum_{r=1}^{s} u_r^t y_{rj}^t - \sum_{i=1}^{m} v_i^t x_{ij}^t - u_0^t \le 0, j = 1, \dots, n \\ &u_r^t \ge \varepsilon, r = 1, \dots, s, u_0^t \ is \ free \\ &v_i^t \ge \varepsilon, i = 1, \dots, m. \end{aligned} \tag{8}$$

It is noteworthy that in all decompositions above, an MI quantity greater than, equal to, or less than 1 means that productivity has grown, remained unchanged, or declined during periods t and $t+1$.

Similar resultsare held about growth or decline of individual components in various MI decompositions.

2. Developing EMIusing HRE&PSFconcept

If we consider HRE&PSF model as the base technology in (4),the novelEMI will be obtained as (9):

$$EMI^{HRE\&PSF}=\left[\frac{D^{t}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)}{D^{t+1}_{HRE\&PSF}\left(x^{t}_{k},y^{t}_{k}\right)}\times\frac{D^{t+1}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)}{D^{t}_{HRE\&PSF}\left(x^{t}_{k},y^{t}_{k}\right)}\right]^{1/2} \tag{9}$$

where $\left(x^{t}_{k},y^{t}_{k}\right)$ and $\left(x^{t+1}_{k},y^{t+1}_{k}\right)$ are the observed inputs and outputs of DMU$_k$ in time periods t and $t+1$,respectively. $D^{t}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)$ is calculated by solving model (10).

$$\begin{aligned}&\left[D^{t}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)\right]=\max\sum_{r=1}^{3}u^{t}_{r}y^{t+1}_{rk}\\&s.t.\sum_{i=1}^{2}v^{t}_{i}x^{t+1}_{ik}=1\\&\sum_{r=1}^{3}u^{t}_{r}y^{t}_{rj}-\sum_{i=1}^{2}v^{t}_{i}x^{t}_{ij}\leq 0,\ j=1,\ldots,n\\&\frac{P^{\min,t}_{k}}{P'^{max,t}_{k}}\leq\frac{v^{t}_{1}}{v^{t}_{2}}\leq\frac{P^{\max,t}_{k}}{P'^{min,t}_{k}}\\&u^{t}_{r}\geq\varepsilon,r=1,2,3\end{aligned} \tag{10}$$

Now we can develop other versions of EMI decompositions regarding CCRand HRE&PSF technologies. Two-component EMI can be written as

$$EMI^{HRE\&PSF}=EEC^{HRE\&PSF}\times ETC^{HRE\&PSF} \tag{11}$$

Where

$$EEC^{HRE\&PSF}=\frac{D^{t+1}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)}{D^{t}_{HRE\&PSF}\left(x^{t}_{k},y^{t}_{k}\right)}, \tag{12}$$

$$ETC^{HRE\&PSF}=\left[\frac{D^{t}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)}{D^{t+1}_{HRE\&PSF}\left(x^{t+1}_{k},y^{t+1}_{k}\right)}\times\frac{D^{t}_{HRE\&PSF}\left(x^{t}_{k},y^{t}_{k}\right)}{D^{t+1}_{HRE\&PSF}\left(x^{t}_{k},y^{t}_{k}\right)}\right]^{1/2}$$

which are obtained by substituting HRE&PSF technology instead of CCR in (6).Using(HRE&PSF)F concepts developed in Definition 1, the novel three-component decompositions that specify(HRE&PSF)F Change ((HRE&PSF)FC)portion in productivity change is developed as follows:

$$EMI^{HRE\&PSF} = EC \times \left(HRE\,\&\,PSF\right)FC \times ETC^{HRE\&PSF} \tag{13}$$

Where

$$EC = \frac{D_{CRS}^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right)},$$

$$\left(HRE\,\&\,PSF\right)FC = \frac{\left(HRE\,\&\,PSF\right)F^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{\left(HRE\,\&\,PSF\right)F^{t}\left(x_k^{t}, y_k^{t}\right)} \tag{14}$$

$$= \left[\frac{D_{HRE\&PSF}^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)}{D_{CRS}^{t+1}\left(x_k^{t+1}, y_k^{t+1}\right)} \times \frac{D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right)}{D_{HRE\&PSF}^{t}\left(x_k^{t}, y_k^{t}\right)}\right]$$

which is obtained from (12), according to the relation $D_{HRE\&PSF}^{t}\left(x_k^{t}, y_k^{t}\right) = D_{CRS}^{t}\left(x_k^{t}, y_k^{t}\right) \times (\,HRE\,\&\,PSF\,)F^{t}\left(x_k^{t}, y_k^{t}\right)$.

In addition, if we consider VRS technology in addition to CRS andHRE&PSF, other novel four-component decompositionsof EMI will be obtainedas follows:

$$EMI^{HRE\&PSF} = PEC \times SEC \times \left(HRE\,\&\,PSF\right)FC \times ETC^{HRE\&PSF} \tag{15}$$

The components PEC and SEC were defined in (7). We use the relation $EC = PEC \times SEC$ in (13). Also, from Definition 1, we have $\theta_{HRE\&PSF} = \theta_{CCR} \times \left(HRE\,\&\,PSF\right)F$. Then, $EEC^{HRE\&PSF} = EC \times \left(HRE\,\&\,PSF\right)FC$ in relation (11).

Case study

In this section, we calculate and analyze the proposed EMInovel decompositions for 74 branches of Maskan Bank of Iran located inthe west region of Tehran for two time periods of 2017 and 2018as a real-world case study. It is noted that Maskan Bank is the largest Iranian governmental bank operating in the housing sector. It has more than 1300 branches in 38 regions in Iran.

1. Input and output data

The robustness of the results of a DEA analysis relies on the availability and quality of data (Sowlati&Paradi, 2004). The descriptive statistics of inputs and outputsdata for two time periods are given in Table 1. Measurement unit of personnel expenses is 1000000 Rials. Other indices have no units because they are normalized. The data are taken directly from the Bank's Plan and Program management.

Descriptive statistics of HRE and PSF scores for the two time periods are given in Table 2. Information of Tables 1 and 2 are the data of empirical case study provided by Plan and Program office.

Table 1. Data statistics

	2017				2018			
	Min	**Max**	**Mean**	**STD.**	**Min**	**Max**	**Mean**	**STD.**
Inputs								
Personnelexpenses	1384.62	13332.97	4364.46	2019.71	1898.48	18396.58	5870.05	2792.48
Location index	384	1212	926.8	164.64	384	1212	926.8	164.64
Outputs								
Deposits	86.8	5491	1524.86	1054.86	154.5	5620	1417.97	881.074
Loans	62.53	16127	1509.30	2063.145	111.9	18300	1648.76	2269.94
Services	69.05	18942	1404.53	2330.88	169.9	22045	1448.92	2649.23

Table 2. Descriptive statistics of HRE and PSF scores

	2017				2018			
	Min	**Max**	**Mean**	**STD.**	**Min**	**Max**	**Mean**	**STD.**
HRE Min scores	0.008	0.337	0.089	0.065	0.009	0.419	0.081	0.059
HREMax scores	0.031	1	0.348	0.226	0.035	1	0.315	0.184
PSF Min scores	0.007	0.339	0.090	0.064	0.009	0.419	0.082	0.058
PSF Max scores	0.028	1	0.352	0.224	0.034	1	0.320	0.183

2. EMI$^{HRE\&PSF}$ Results

Here, we examine the combined role of HRE- PSFin the new EMI$^{HRE\&PSF}$productivity index and consider its components in the new decomposition using the model (10) and the relation (15). At first, the descriptive statistics of EMI$^{HRE\&PSF}$ results and its differences with MI are as Table 3.

As can be seen from Table 3, the average ofEMI-MI is equal to 0.03 which shows that EMI$^{HRE\&PSF}$ has less variation than EMI^{HRE} and EMI^{PSF} relative to MI. The mean of EMI$^{HRE\&PSF}$ is equal to 0.81, while the mean of EMI^{HRE} and EMI^{PSF} are 0.90 and 0.93, respectively.Again, the greatest decline in EMI relative to MIbelongs to the 60th branch. Also,branch 18 has the greatest increase in EMI relative to MI which is equal to 0.46.

The results of $EMI^{HRE\&PSF}$ components for selected branches are presented in Table 4.

Table 3. Data statistics of $EMI^{HRE\&PSF}$ results

	Min(#branch)	Max(#branch)	Mean	STD.
$ETC^{HRE\&PSF}$	0.55(6)	1.12(18)	0.65	0.09
(HRE&PSF)FC	0.95(37)	1.12(1)	0.98	0.02
$EMI^{HRE\&PSF}$	0.49(36)	1.83(71)	0.81	0.18
$EMI^{HRE\&PSF}$-MI	-0.34(60)	0.46(18)	0.03	0.08

Table 4. MI, $EMI^{HRE\&PSF}$, and their components for selected branches

Branches	(HRE&PSF)FC	PEC	SEC	$ETC^{HRE\&PSF}$	TC	MI	$EMI^{HRE\&PSF}$
1	1.12	0.88	0.95	0.68	0.84	0.71	0.64
3	0.99	0.94	1.00	0.86	0.66	0.63	0.81
6	0.98	1.23	1.20	0.55	0.58	0.85	0.80
16	0.98	0.83	1.11	0.61	0.60	0.74	0.74
18	0.98	1.11	0.97	1.12	0.54	0.43	0.89
23	0.98	1.03	1.08	0.58	0.57	0.64	0.64
36	0.96	0.83	0.89	0.69	0.58	0.43	0.49
37	0.95	1.24	1.12	0.56	0.53	0.73	0.74
42	0.98	1.02	1.02	0.73	0.55	0.57	0.74
60	1.00	1.00	1.00	1.00	1.34	1.34	1.00
68	0.98	1.00	1.67	0.60	0.58	0.98	0.98
71	0.98	1.21	2.47	0.62	0.60	1.79	1.82
74	1.00	0.97	2.60	0.56	0.54	1.36	1.41

The value of $EMI^{HRE\&PSF}$for branches 1, 6, and 60 has decreased relative to MI. This is due to the fact that $ETC^{HRE\&PSF}$component of $EMI^{HRE\&PSF}$ for the branches has been decreased relative to TC.However inbranch 1, we see (HRE&PSF)FC growth of 12%.The value of $EMI^{HRE\&PSF}$for branches 16, 23, 37, and 68 is equal to MI.The status of branches 60,71, and 74 remains productive.

Branch 3 has 20% increase in $ETC^{HRE\&PSF}$ relative to TC which has led to an increase in $EMI^{HRE\&PSF}$. $ETC^{HRE\&PSF}$ of branch 18 has been more than doubled compared to TC, and as result, $EMI^{HRE\&PSF}$ has been more than doubled to MI.Because (HRE&PSF)FC of branch 42 is approximately 1, so the increase in $ETC^{HRE\&PSF}$ relative to TC causes an increase in $EMI^{HRE\&PSF}$ relative to MI. In general, changes in $EMI^{HRE\&PSF}$ relative to MI are most likely due to changes in $ETC^{HRE\&PSF}$ relative to TC.

Conclusion

Productivity change is affected by a variety of factors.The more the number of factors involved in measurement, the more accurate the productivity rateobtained. Beside technology, efficiency, and scale, the paper backs the combined role of human resources ethics and physical space facilities factors in calculating an extended Malmquist productivity index in the bank branch level. In this paper, a new model has been developed to compute the distance functions of the extended Malmquist productivity index. The human resource and physical space ethics factor of each branch was defined as the ratio of the new modelsto CCR efficiency scores.The new three- and four-component decompositions of extended Malmquist index were developed to provide us with useful information about the sources of productivity growth or decline. The proposed method was applied to a real-world case study of bank branches.

Ethical issues of Operational Research clearlydeserve further work of theoretical, methodological,and applied nature. Here, we mention that as a recommendation for future work, the contribution of HRE and PSF to productivity growth,individually, can be the subject of future studies in this regard.

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