Assessing productivity changes using the bootstrapped Malmquist index: the case study of the Iranian construction industry

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Abstract

In this paper, productivity and the effective factors are determined in the Iranian construction industry over the period 2006-2012 by the DEA-based Malmquist indices. Moreover, the explanatory factors affecting productivity levels are determined using truncated regression method. The results show that the average of productivity levels has significantly decreased. Although sanction has had significant negative correlations with technology change and productivity change, it did not have an effect on efficiency change. Furthermore, it was observed that the economic recession only had a negative correlation with technology change. It was witnessed that construction companies suffer numerous issues in productivity and lesser flexibility in the execution of projects as they grow in size. It also was concluded that companies located in the capital have more potential to improve their productivity due to easier access to technological advancement.

Keywords

Malmquist productivity index, Construction industry, Bootstrap, Truncated regression, Explanatory factors

1. Introduction

Based on global statistics, the construction industry covers about 9% of the GDP and about 7% of the workers worldwide (Horta et al., 2013). Construction companies employ systematic methods for evaluating their performance in order to achieve sustainable growth, profitability, and competitive advantage (Horta et al., 2013). Analyzing the

productivity of companies will lead to the identification of the factors which influence their performance and state over time. A number of methods exist to assess productivity; one highly practical method for evaluating productivity is the use of the Malmquist Productivity Index (MPI). The main advantage of MPI is its ability to be decomposed into different components. Using this decomposition, more accurate information can be extracted about what resources have impact on growth or decline in productivity.

In calculating MPI, various approaches can be adopted to approximate the distance functions, which can be parametric, such as the stochastic frontier analysis method, or non-parametric, such as the Data Envelopment Analysis (DEA) method (Lovell et al., 1994; Fare et al., 1994). One advantage of DEA is the ability to model multi-input and multi-output technologies even when no price information is available. In addition, another desirable characteristic of the method is that there are no constraints on the form of the production function regarding the inputs and outputs (Charnes et al., 2013; Cooper et al., 2004). One disadvantage of the conventional DEA method was that it provided no information on the estimates' uncertainty levels (Odeck, 2009). In other words, using this method, it will not be possible to infer whether there are significant statistical differences between two or more estimates. To address this problem, (Simar and Wilson, 1998) introduced the bootstrap method (proposed by (Efron, 1992)) into DEA. This method has found applications in different fields such as power plants, airports and healthcare (Gharneh et al., 2014; Gitto and Mancuso, 2012; Chowdhury et al., 2014; Nabavieh et al., 2015; Ahnagaran et al., 2014).

In recent years, special attention has been directed towards obtaining efficiency and productivity using the Malmquist index and DEA in the construction industry in the United States (Topuz and Isik, 2009; Anderson et al., 2002), Australia (Li and Liu, 2010), and China (Hung Chiang et al., 2012; Xue et al., 2008), however, sample variation and its role did not have received enough attention when determining productivity. Hence this approach has been implemented to assess the significance of productivity. Furthermore, the impact of two new factors namely economic downturn and sanctions on productivity changes of construction companies will be evaluated.

Therefore, in this paper, using MPI, the levels of productivity for the largest construction holding companies listed in the Tehran Stock Exchange (TSE) will be studied; Then the bootstrap method will be employed to determine the stability of the extracted factors. Finally, using the Truncated Regression method, the effect of explanatory factors such as sanctions, recession, headquarter location, and age on Total Factor Productivity (TFP), Technology Change (TC), and Efficiency Change (EC) is analysed.

2. Literature review

In this section, some of the recent articles which examine efficiency and productivity in construction sectors using the Malmquist index and DEA are reviewed.

(Chau et al., 2005) evaluated the relative efficiency of Hong Kong construction firms between 1981 and 2001. The results indicated that fixed investment (land and machinery) would result in issues in the resources consumption management and would result in a loss of efficiency. Nevertheless, in the long-term, it would cause an increase in potential efficiency. It was also found that subcontracting would negatively affect the efficiency of the firms.

(You and Zi, 2007) examined different types of efficiency in the South Korean construction industry from 1996 to 2000, during which the country experienced an economic crisis. The results indicated that the efficiency measures had noticeably decreased during this period, and there was a great difference before and after the crisis of 1997.

(Xue et al., 2008) studied the productivity of construction in China between 1997 and 2003. The results indicated that except for the interval between 2001 and 2003, the industry witnessed a continual improvement. However, discrepancies in the levels of productivity existed among the western, central, eastern, and northern regions.

(Li and Liu, 2010) employed Malmquist index with Lovell's decomposition method to estimate the TFP of the Australian construction industry during the period 1990-2007. In addition, based on temporal and spatial comparisons, they analyzed the changes in productivity and its components. The results revealed a very slow growth in the levels of productivity and there were no significant differences in the productivity of different states.

(Zheng et al., 2011) measured the performance and efficiency of 94 listed real-estate companies in Chinese stock markets in 2009. In their research, they used three DEA-based models, namely BCC-DEA, CCR-DEA and Super-Efficiency-DEA. The results indicated that 69% of the inefficient companies were classified as increasing return to scale and could improve their operating efficiency by scale expansion.

(Tsolas, 2011) utilized a new framework which integrates DEA and ratio analysis. In this study, profitability efficiency and effectiveness of 16 construction firms listed on the Athens Exchange were evaluated. The results indicated that Profitability inefficiency was explained by size and expenses to total revenue ratio, while effectiveness was explained only by expenses to total revenue ratio.

(Horta et al., 2012) studied the performance of Portuguese construction companies during the period 1997-2009 using the bootstrapped DEA. The results showed that the performance of the studied companies was strongly affected by the national economic conditions. The companies experienced a remarkable improvement in performance during the 1990s, but the trend slowed down in recent years.

(Hung Chiang et al., 2012) compared the efficiency of 20 construction companies listed in Hong Kong and China Mainland from 2004 to 2010. The results indicated that Hong Kong contractors had higher MPI than their Mainland counterparts, mainly due to higher efficiency scores in catch-up effect. It was also found that the main advantage of Hong Kong contractors over Mainland contractors was their managerial and strategic capabilities.

(Horta et al., 2013) aimed to assess the efficiency levels of construction companies' worldwide, and the effect of location and activity on the efficiency levels in particular. In order to correct the estimates obtained by DEA and MPI, the bootstrap method was used. The results showed that efficiency is higher in North American companies in comparison with Asian or European companies. However, it was noted that sample variation was not fully recognized for determining productivity.

3. Methodology

In this paper, productivity and the factors affecting it are measured in three stages. In the first stage, the data has been collected, the productivity, efficiency, and technology changes are measured using the DEA-based Malmquist productivity indices. In the second stage, the significance of the productivity indices is examined using a bivariate smoothing procedure. In the third stage, the explanatory factors affecting productivity levels are determined. Fig.1 shows the methodology of the study diagrammatically.
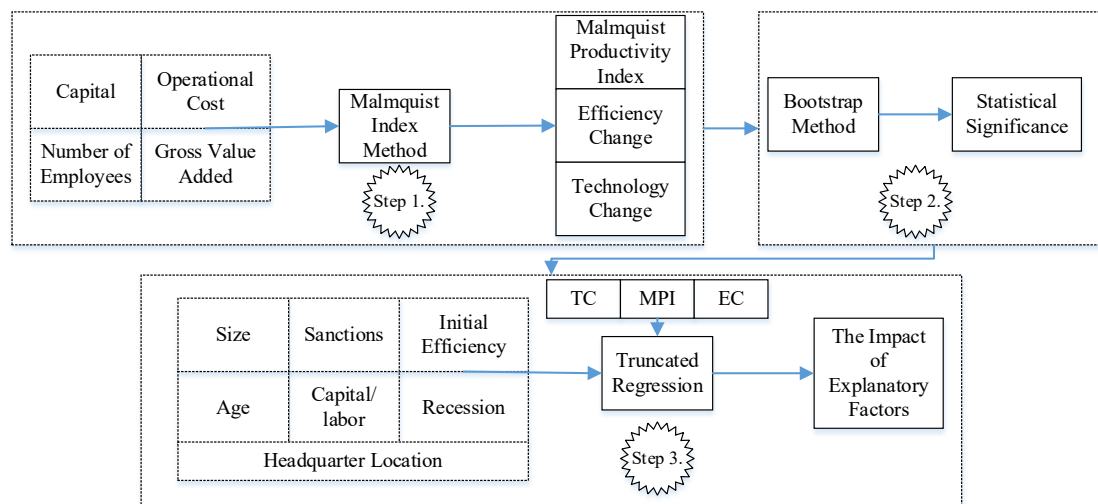

Fig. 1 Methodology of the study

3.1. Malmquist index

MPI measures the changes in the productivity of a unit between two different time periods. MPI can be estimated with different methods for the estimation of the distance function, such as DEA or SFA. It should be noted that other indices, such as the Tornqvist index or the Fihser index could be used for the estimation of productivity; one major issue with these indices, however, is that they are dependent on price data. Another advantage of MPI is the existence of various decomposition methods in the literature (Balk, 2001; Färe et al., 1994; Färe et al., 1997; Ray and Desli, 1997; Grifell-Tatjé and Lovell, 1999). In the present study, MPI is decomposed into the two components of changes in efficiency and technology because in the presence of non-constant return to scale, MPI does not accurately measures the changes in productivity (Grifell-Tatjé and Lovell, 1995). In general, MPIis calculated between years t and t+1 in

the form of the ratio of the distance functions for each year relative to a common technology. MPI for output distance functions in time period t is defined as in Eq. (1). Similarly, the output-oriented MPI based on the technology in time period t+1 is defined as in Eq. (2).

$$M_0^t = \frac{\Delta_o^t\left(x^{t+1}, y^{t+1}\right)}{\Delta_o^t\left(x^t, y^t\right)} \quad (1) \qquad M_0^{t+1} = \frac{\Delta_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{\Delta_o^{t+1}\left(x^t, y^t\right)} \quad (2)$$

To obtain an ideal index from the formulation of Fisher , (Fare et al., 1994) have shown that the output-oriented Malmquist index can be defined as the geometric mean of the t and t+1 Malmquist indices. The output-oriented Malmquist index between t and t+1 is decomposed as follows Eq. (4).

$$M_o = \sqrt{M_o^t \times M_o^{t+1}} = \sqrt{\frac{\Delta_o^t\left(x^{t+1}, y^{t+1}\right)}{\Delta_o^t\left(x^t, y^t\right)} \times \frac{\Delta_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{\Delta_o^{t+1}\left(x^t, y^t\right)}} \quad (3)$$

$$M_o^{t,t+1} = \frac{\Delta_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{\Delta_o^t\left(x^t, y^t\right)} \times \left[\frac{\Delta_o^t\left(x^{t+1}, y^{t+1}\right)}{\Delta_o^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{\Delta_o^t\left(x^t, y^t\right)}{\Delta_o^{t+1}\left(x^t, y^t\right)}\right] = EC^{t,t+1} \times TC^{t,t+1} \quad (4)$$

Where EC and TC denote the changes in efficiency and technology, respectively. $M_o > 1$ (TC or EC) denotes an increase in productivity (technology or efficiency). $M_o < 1$ (TC or EC), on the other hand, indicates that productivity (technology or efficiency) has decreased. A value of $M_o = 1$ (TC or EC) is an indicator of constant productivity (technology or efficiency) between the two periods.

Following (Färe et al., 1994) in order to calculate MPI, four output-oriented distance functions need to be estimated via DEA by solving linear programming models. Eq. (5) estimates the within-period distance functions under assumption of constant returns-to-scale (CRS). The adjacent-period distance functions are obtained by solving the linear programming in Eq. (6).

$$\left[\Delta_o^s\left(x^s, y^s\right)\right]^{-1} \quad (s : t, t+1)$$
$$\max_{\phi, \lambda}(\phi)$$
$$subject\,to : X^s\lambda \leq x_o^s \quad (5)$$
$$\phi y_o^s \leq Y^s\lambda$$
$$\lambda \geq 0$$

$$\left[\Delta_o^s\left(x^r, y^r\right)\right]^{-1} \quad (s, r : t, t+1, s \neq r)$$
$$\max_{\phi, \lambda}(\phi)$$
$$subject\,to : X^s\lambda \leq x_o^r \quad (6)$$
$$\phi y_o^r \leq Y^s\lambda$$
$$\lambda \geq 0$$

3.2. Bootstrapping Malmquist indices

Since DEA uses linear programming for estimating the frontiers and is non-stochastic, the possibility of random errors or noise is not taken into account. Therefore, DEA is not able to determine the validity of the efficiency estimates or to provide a statistical foundation for the estimated frontiers.

In the context of DEA, bootstrap means resampling the estimated efficiency scores. Nevertheless, the nature of DEA-efficiency scores imposes some complexity on the bootstrap process. (Simar and Wilson, 1998) proposed the smooth bootstrap procedure. Specifically, they proposed a Gaussian kernel density estimator and applied the reflection method. To estimate confidence intervals for the Malmquist indices, bootstrap procedure DEA was modified. In order to take into account possible temporal correlations that arise from the characteristics of the panel data, (Simar and Wilson, 1999) proposed a consistent method using a bivariate kernel density estimate. This method accounts for the temporal correlation via the covariance matrix of data from two adjacent years. The idea is that a company operating at a low efficiency level in one period might increase the probability that this company will also operate at the same low levels in the adjacent period.

The bootstrap procedure proposed by (Simar and Wilson, 1999) can be summarized in the following steps:

1. Computing the Malmquist productivity index $\left(\hat{M}_i^{t,t+1}, i = 1, 2, ..., n\right)$ for each company using the DEA model described in (Fare et al., 1994; Färe et al., 1995).

2. constructing a pseudo-dataset $\{(x_{i,t}^*, y_{i,t}^*); i = 1, 2, ..., n; t = 1, 2\}$ to obtain the reference bootstrap technology using a bivariate kernel density for which the bandwidth is selected based on the normal reference rule.

3. computing the bootstrapped estimate of the Malmquist index $\widehat{M_{i,b^*}^{t,t+1}}$ for each of the companies using the pseudo-sample obtained in Step 2.

4. Repeating Steps 2 and 3, B times (bootstrap iterations) to obtain the bootstrapped Malmquist index estimates $\hat{M}_{i,1^*}^{t,t+1}, \hat{M}_{i,2^*}^{t,t+1}, ..., \hat{M}_{i,B^*}^{t,t+1}$.

5. computing the bias-corrected estimates using the obtained bootstrapped Malmquist index estimates and calculating the confidence intervals with appropriate percentiles.

The bias-corrected estimate of the Malmquist index is obtained from Eq. (7):

$$\hat{M}_i^{t,t+1} = \hat{M}_i^{t,t+1} - \hat{bias} = 2\hat{M}_i^{t,t+1} - B^{-1}\sum_{b=1}^{B}\hat{M}_{i,b^*}^{t,t+1} \qquad (i = 1, 2, ..., n) \qquad (7)$$

Correcting bias will introduce extra noise into the estimates. This will result in an increase in the variance of the estimators. Therefore, as a rule-of-thumb, (Simar and Wilson, 1999) suggest that the bias-corrected estimators be used when $|\widehat{bias}| > \sqrt{3}\widehat{std}(\hat{M}_{i,b^*}^{t,t+1})$ where $\widehat{std}(\hat{M}_{i,b^*}^{t,t+1})$ is the sample standard deviation of the bootstrap values.

To construct the confidence interval, first the sequence $\{\hat{M}_{i,b^*}^{t,t+1} - \hat{M}_i^{t,t+1}\}_{b=1}^{B}$ is sorted in ascending order. Then $\frac{\alpha}{2} \times 100$ elements are removed from either end of the sorted sequence. The $(1 - \alpha)\%$ estimate of the confidence interval for the Malmquist index is obtained from the Eq. (8).

$$\hat{M}_i^{t,t+1} + \hat{a}_\alpha^* \leq \hat{M}_i^{t,t+1} \leq \hat{M}_i^{t,t+1} + \hat{b}_\alpha^* \qquad (8)$$

where $\widehat{a_\alpha^*}$ and $\widehat{b_\alpha^*}$ $(\widehat{a_\alpha^*} < \widehat{b_\alpha^*})$ are the endpoints of the ordered sequence after the removal of the tails.

If the value 1 is not in this interval, the Malmquist index for the ith company is significantly different from unity at the $\alpha\%$ level, which means that the productivity of the company has increased or decreased. For estimating the confidence intervals for the components of MPI, similar steps will be followed.

3.3. Truncated regression

(Simar and Wilson, 2007) pointed out that the efficiency scores obtained through DEA are statistically dependent. This in turn means that the error term in the regression model is not independently distributed. In addition, environmental factors are correlated with the efficiency and productivity scores, this would be motivation for a second-stage analysis. This in turn denotes the correlation of the error term with the environmental variables. Therefore, using productivity and efficiency scores to study management-related issues in the second-stage regression analysis violates the basic assumptions required by the regression model. To solve this problem, (Simar and Wilson, 2007) proposed a double bootstrapping procedure. Since then, several researches have used this approach to study the effect of environmental variables on efficiency and productivity (Odeck, 2009; Assaf, 2010; Barros and Peypoch, 2009).

This approach is described by Eq. (9):

$$\hat{m}_i = z_i\beta + \varepsilon_i \qquad (9)$$

where z_i is the vector of environmental variables, β denotes the vector of estimated parameters, and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ is the noise term. Since it is assumed that $Corr(\varepsilon_i, z_i) = 0$ for the regression analysis, if either the ordinary least square or Tobit method is used for parameter estimation, problems will arise in estimation as this assumption will be violated.

This procedure can be summarized in the following steps:

1. Calculating the productivity scores for each Company using the output-oriented MPI model.

2. Using the Maximum Likelihood Estimation (MLE) method for estimating the truncated regression of $\hat{m}_i$ on z_i and estimating $\hat{\beta}$ from β and $\hat{\sigma}_\varepsilon$ from $\hat{\sigma}_\varepsilon$.

3. Repeating the next steps (steps (a)-(d)) B times for obtaining the bootstrapped estimates $\{\hat{m}_{i,b}, b = 1, 2, ..., B\}$.

    a)   Drawing ε_i from $N(0, \sigma_\varepsilon^2)$ with left truncation at $(1 - \hat{\beta} z_i)$.

    b)   Calculating $m_i^* = z_i \hat{\beta} + \varepsilon_i$.

    c)   Constructing a pseudo-dataset of n bootstrapped samples $(x_i, y_i), i = 1,2 \dots, n$ and constructing (x_i^*, y_i^*) with $x_i^* = x$ and $y_i^* = y_i \widehat{m_i}/m_i^*$.

    d)   Calculating the new MPI, m_i^*, using the dataset (x_i^*, y_i^*).

4. Calculating the bias-corrected estimate $\widehat{m}_i = \hat{m}_i - \widehat{bias}_i$ where $\widehat{bias}_i$ is the bootstrapped estimator of bias, which can be obtained from $\widehat{bias} = (\frac{1}{B}) \sum_{b=1}^{B} (\hat{m}_{i,b}^* - \hat{m}_i)$.

5. Using the MLE method for estimating the truncated regression of $\widehat{m}_i$ on z_i and obtaining the estimates $(\hat{\hat{\beta}}_i, \hat{\hat{\sigma}}_i)$ of (β, σ).

6. Repeating the next steps (steps (a)-(c)) B times for obtaining the bootstrapped estimates $\{\hat{\beta}^*, s\widehat{igma}_b^a, b = 1,2, \dots, B\}$.

    a)   Drawing ε_i from $N(0, \hat{\sigma}_\varepsilon^2)$ with left truncation at $(1 - \hat{\beta} z_i + \varepsilon_i)$.

    b)   Calculating $m_i^{**} = \hat{\beta} z_i + \varepsilon_i$.

    c)   Using the MLE method again for estimating the truncated regression of m_i^{**} on z_i and obtaining the estimates $(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*)$.

7. Using the bootstrapped results of the above procedure for constructing confidence intervals for the MPI values.

The smooth bootstrap procedure for productivity and truncated regression analysis were implemented using the FEAR package (Wilson, 2008).

4. Data

The selection of appropriate data is crucial to DEA models (Charnes et al., 2013). The processes of variable selection and data selection started with an extensive review of the existing literature on the subject. The existing literature indicates the need for sound inferences about the efficiency and productivity characteristics of the construction industry. The input/output variables selected from the literature which have already been used in most of the researches. Experts also consulted for examining and selecting the list of variables. As can be seen in Table 1, the variables of the number of employees, operational costs, and capital were taken as inputs and value added was selected as the output variable.

Table 1. Selection of inputs/outputs

Study	Input variables	Output variables
Chan and Walker (1988)	Labour, Material, Plant and equipment, Overhead	Building works in terms of gross output
Odech (1996, 2001)	Labour, Capital, Material	Construction volume
Chen (2003)	Labour, Capital	Gross output value
Chau et al. (2005)	Labour, Capital, Construction material, Office overhead expense	Total value of work (revenue) less payment to subcontractor
Xue et al. (2008)	Total assets, Employees of the industry	Industrial value added amount
Qi and Jia (2010)	Total asset, Employee 's salaries	Operation income and profit
Zheng et al. (2011)	Registered capital, Asset value, Employee number, Operation cost	Revenue, Profit
Wei et al. (2011)	Annual investment, New operated area, Employee	Completed area, Sales
Chiang et al. (2012)	Total asset value, Number of employees, Cost of goods sold and salaries plus expenses	Total revenue and total profit
Peng Wong et al. (2012)	Total assets value, Capital, Labour and costs	Profit and revenue
Horta et al. (2012)	Total current liabilities, Shareholders' funds, cost of goods sold	Net value of sales

Li et al. (2013)	Assets and employees	Revenue
In this paper	Employees, operational costs, capital	value added

Considering the importance of the years 2006-2012 in Iran's economy, this interval was selected for the study. The data used in this paper were collected from the Codal database (http://www.codal.ir) which contains the financial statements of the companies. Ten companies selected for this study are the largest active companies in the construction industry in Iran in the interval between 2006 and 2012 (This data set contains balanced panel data out of 70 observations). The data regarding the companies under study is presented in Table 2.

Table 2. Companies' data

No.	Company	Headquarter location	Age (>10;=1, 0=else)	No.	Company	Headquarter location	Age
1	Sakhteman Isfahan	Isfahan	0	6	Toseh Sakhteman	Tehran	1
2	Sakht Azhand	Tehran	1	7	Omran Fars	Shiraz	1
3	Sar Toosgostar	Mashhad	0	8	Sar Samangostar Isfahan	Isfahan	0
4	Sar Sakhteman	Tehran	0	9	Abadgaran	Mashhad	1
5	Sar Maskan	Tehran	1	10	Nosazi va Sakhteman	Tehran	0

The operational costs variable used in this paper matches the soft cost used in (Gitto and Mancuso, 2012) and is defined as the costs which are not directly related to capital or personnel. The capital variable is taken to be equal to the book value of assets. The gross value added variable indicates the end results of construction production activities and measures gross production by the construction industry (Li and Liu, 2010). All monetary variables have been divided by the GDP deflator provided by Iran's Central Bank .

Once the Malmquist indices have been calculated, it is important to estimate the influence of the factors which are outside management control but may affect the productivity. In the present study, the effect of such factors on productivity is determined through regression analysis. This technique summarizes effects of the factors on productivity, efficiency, and technology in a single coefficient. It should be noted that this is impossible using DEA.

 In this paper, seven explanatory factors of sanctions, size, capital-labour ratio, recession, initial efficiency, headquarter location, and age were considered. A look at the literature of the field shows that little attention has been paid to these variables.The variable sanctions is a dummy variable, considered equal 1 since 2010. In the meantime, sanctions against Iran have also been tightened so that the country has experienced a sharp decline in economic growth, which has affected the whole industrial sectors, including the construction industry. According to the data published by Iran's Central Bank, the interval between 2008 and 2010 has been marked as a period of recession (dummy variable).

The variable of size has a great influence on the changes in productivity (Li and Liu, 2010). Little research has been done on the correlation between the size of a company and its productivity (Horta et al., 2012). For example, (Kale and Arditi, 1998) have concluded that size can be one of the major factors in predicting failure in business. In addition, (Li and Liu, 2010) have pointed out that size and the scope of production activities are two major influential factors in the growth of productivity in the construction industry. Regarding the size of construction companies, (Zhi et al., 2003) consider the fluctuation of the size of labor force in construction firms is an important factor.

Initial efficiency is calculated using the DEA method for each period. The age of company is another dummy variable which is considered in this paper. The capital-labour ratio is defined as the ratio of fixed assets to number of employees.

The last parameter under study is the headquarter location parameter, which denotes where the headquarters of the observed companies are located. In a similar study, (Horta et al., 2012) investigate the effect of this parameter on the performance of Portuguese construction companies. In the present study, the aim is to investigate the relationship

between the geographical locations of the companies and their respective levels of productivity. In this paper, based on the economic and political circumstances in the capital (Tehran), this variable is also considered as a dummy.

A summary of the inputs, outputs, and explanatory factors is presented in Table 3. The gross value added obtained by some companies in the sample is over 50 times that achieved by others. Similar differences exist for the input parameters as well. For the initial efficiency parameter it should be pointed out that on average there is approximately $|(0.712\text{-}1)|\times100 \approx 29\%$ potential in output expansion for construction companies in each individual year.

Table 3. Summary statistics, 2006-2012

Variable	Define	Min	Max	Mean
Gross value added*	The value of outputs less the value of intermediate consumption	170.5	9900.8	2352.3
Number of employees	It consist of company permanent forces in person	137	6716	1234
Operational costs*	Soft cost (Gittoand Mancuso, 2012)	2.7	495.9	77.9
Capital*	Book value of total assets	1377.5	106623.4	16289.9
Size	Log (Fix asset)	0.204	3.1	2.001
Capital-labour	The ratio of fixed assets to labour costs	0.032	20.300	3.092
Initial efficiency	The efficiency based on variable returns to scale	0.101	1.00	0.713

* In 100 Million Rials

5. Results

In this paper, the results were obtained by using the smooth bootstrap procedure. The purpose of employing this method was to obtain confidence intervals for the productivity, efficiency, and technology changes. Three input variables and an output variable were used based on the data of 10 companies with output-oriented and CRS assumptions. The obtained bootstrapped MPI and their components for the interval 2006-2012 are presented in Table 4 and Fig.2 (It has used B=2000 bootstrap replication). It is also indicated in the table whether or not the changes are statistically significant.

Table 4. Summary of results for each company between 2006 and 2012

Company	MPI	MPI˜	EC	EC˜	TC	TC˜
1	0.590	0.550**	0.686	0.698**	0.945	0.949
2	0.881	0.898**	1.089	1.117**	0.901	0.872**
3	1.001	1.012**	0.971	0.895**	1.0541	1.077
4	0.961	0.955	1	1.068	0.960	0.982
5	0.893	0.920**	1.001	1.052	0.888	0.903**
6	1.121	1.127	1.132	1.105	0.905	0.885
7	0.829	0.799**	0.874	0.915**	1.012	1.056**
8	0.663	0.673**	0.729	0.689**	0.930	0.941**
9	1.048	1.052	1.069	1.093**	0.925	0.916**
10	0.836	0.847**	1.197	1.221**	0.894	0.889**
Improvement	3	1	5	3	2	1
No change	0	3	1	3	0	4
Decline	7	6	4	4	8	5
Geometric mean	0.905	0.799	0.961	0.926	0.939	0.928

˜ = bias correction. ** Significance at 5% level.

The results show that the geometric mean of bias corrected MPI is 0.799; this means that the level of productivity decreased by approximately $(0.799\text{-}1)\times100 \approx -20\%$. In this period, only one company was able to increase its productivity and six other companies had TFP decreases that amongst them the first company had the highest level of productivity loss. In addition, three companies did not experience any statistically significant productivity change. As described before, a change in MPI is composed of two components, thus we investigate the sources of the significant change in the MPI. The geometric mean of the bias corrected efficiency change is equal to 0.927. This indicates a decline of about $(0.927\text{-}1)\times100 \approx -7.3\%$ in efficiency. In this period, three companies experienced improvements in efficiency, three companies experienced no significant changes, and four companies observed a decline in efficiency.
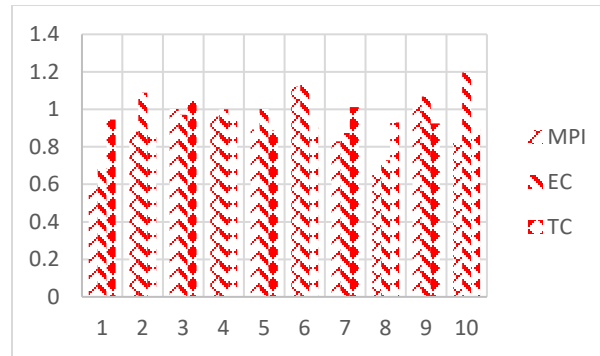
Fig. 2 MPI, EC and TC of companies between 2006 and 2012

The negative changes in TFP could be also derived by the significant decreases in the individual technologies of company. The geometric mean of the bias corrected technology change is equal to 0.928, which indicates a decrease of about (0.928-1)×100 ≈ -7.2% in technology. In this period, one company experienced an improvement in technology statistically, three companies did not experience any significant changes, and four companies experienced a decrease in technology.

Thus, in the future, new technological investments and effective utilization of resources should be carried out by the construction companies in order to increase their productivity.

After estimating MPI and its components, the truncated regression was employed to calculate the sources of changes in productivity levels. Seven variables were considered as explanatory factors. As mentioned previously, these are: capital-labour ratio (KL), size (S), sanctions (T), age (A), recession (R), headquarter location (H), and initial efficiency (IE). Three variables were selected to be dependent variables, namely efficiency change (EC), technology change (TC), and productivity change (MPI) .

Table 5 presents the final results of using the truncated regression method, based on the Eq. (10):

$$MPI_{it}|EC_{it}|TC_{it} = \alpha_0 + \alpha_1 T_{it} + \alpha_2 KL_{it} + \alpha_3 H_{it} + \alpha_4 IE_{it} + \alpha_5 S_{it} + \alpha_7 R_{it} \tag{10}$$

Table 5. Parameter estimates of explanatory variables-Malmquist indices

	Variable	Constant	T	R	IE	KL	H	S	A
	Coefficient	1.513	-0.404	-0.408	0.444	-0.064	0.243	-0.239	0.158
MPI	T-value	3.620**	- 1.072	- 2.317**	1.528	-1.725*	0.692	- 1.651*	0.943
	STD error	0.418	0.183	0.156	0.223	0.035	0.187	0.141	0.217
	Coefficient	1.782	0.095	-0.199	0.168	- 0.369	- 0.093	- 0.134	0.385
EC	T-value	3.500**	1.323	-0.744	1.087	-1.694*	-0.649	-1.525*	1.043
	STD error	0.453	0.231	0.194	0.299	0.044	0.214	0.173	0.356
	Coefficient	0.969	- 0.246	- 0.159	- 0.121	0.198	0.366	0.169	- 0.425
TC	T-value	6.759**	- 2.193**	- 2.552**	- 1.638*	1.527*	1.804*	0.782	-0.844
	STD error	0.123	0.066	0.05	0.079	0.012	0.004	0.051	0.532

Note: * and ** indicate the significance at 10 and 5% levels, respectively.

The effect of explanatory factors on MPI, EC and TC is also shown by spider diagram in Fig.3. According to the obtained results from Table 5, there was a negative significant correlation between sanctions and technology change. This correlation seems obvious because a great portion of the technology employed in the construction industry is imported. If the sanctions are remained, it is expected that the industry faces technological difficulties. This parameter did not exhibit a significant correlation with the efficiency and productivity changes. Recession was significantly correlated with the technology change in a negative way. Since during times of recession, there will be less economic activity, companies will not be able to use their technological resources and equipment thoroughly. In addition, the tendency of companies to enter new fields and invest in more advanced equipments and technologies decreases. This parameter did not demonstrate a significant relationship with the efficiency change. The effect of this factor on the productivity change was statistically significant. The correlation was also negative; (Ngowi et al., 2005) have also confirmed the influence of economic circumstances on the performance of companies in the construction industry. The results indicated that initial efficiency had a negative significant correlation with the technology change. This implies that companies with lower initial efficiency levels try to cover their weakness by using better technology in order to achieve an ideal position in the market. This parameter did not exhibit a significant statistical relationship with efficiency change and productivity change. The capital-labour ratio was significantly correlated with all indices.

This ratio reveals whether a certain company is capital-oriented or labour-oriented. Naturally, this parameter had a positive influence on the changes in technology. As a matter of fact, the results of this analysis indicate that the more capital-oriented and mechanized companies had a greater tendency to improve their technology from one period to the next. The correlation coefficient for the efficiency change was negative. One of the reasons that can explain this effect is that generally it is difficult to maintain a high level of fixed asset utilization; an increase in fixed assets can be accompanied by a high level of idle capacity. As a result of the fluctuations in the volume of activities which construction companies face, their fixed assets will not be fully utilized at all times. In addition to this, these idle fixed assets cannot be avoided because a certain level of fixed assets is required for the companies to be able to take part in auctions for public sector construction contracts. Furthermore, it is not possible for construction companies to predict the future demand and the volume of their activities accurately. The labor force inputs can be distributed with greater flexibility in the construction industry. Consequently, under similar circumstances, companies with higher capital-labour ratio are expected to be less efficient in the short term. The results obtained by (Chau et al., 2005) also confirm the above observations. This parameter showed a negative influence on the productivity change. The reason is that as a result of the technology required by the market, Iranian companies cannot in general make full use of the technology available to them and consequently, efficiency plays a bigger role in productivity change than technology. Therefore, the parameter of capital-labour ratio affects the productivity negatively. The parameter of size did not have a significant correlation with the technology change. This parameter exhibited statistical significances for both the efficiency and productivity change. The effect on the efficiency change was negative. The reason is that as size increases, the level of supervision on the execution of projects will generally decrease and result in a lower efficiency. Sometimes an increase in size will cause a reduction in efficiency due to the fact that the bureaucracy in these companies will increase. The effect of this parameter on the productivity change was also negative. In fact, Iranian companies suffer numerous issues in productivity and flexibility in the execution of projects as they grow in size. One solution of this is the establishment of small subsidiaries by large companies. The parameter of age did not have any significant correlation with productivity levels. The parameter of headquarter location exhibited a positive relationship with changes in technology. The reason for this is the availability of technology in the capital(Tehran) . This parameter did not show any significant correlations with changes in efficiency or productivity.
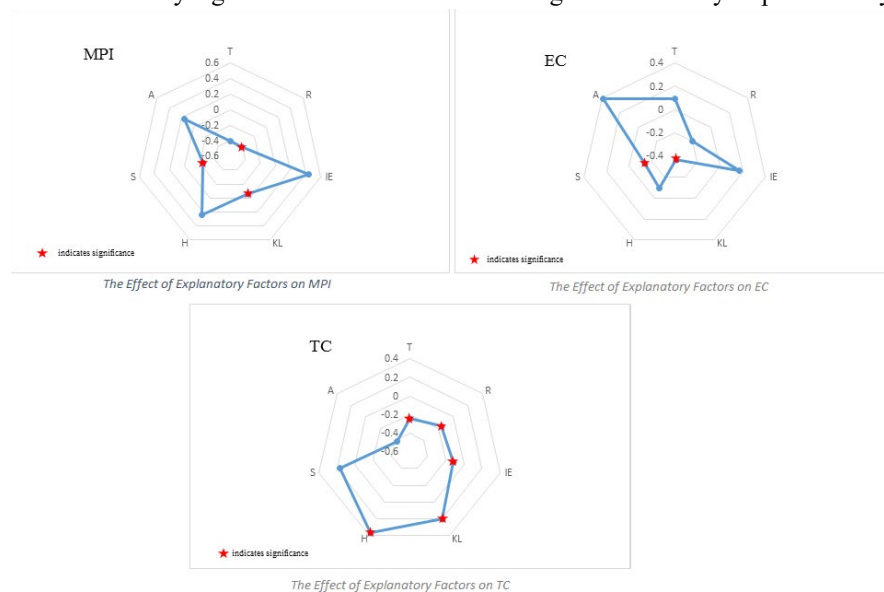

The Effect of Explanatory Factors on MPI

The Effect of Explanatory Factors on EC

The Effect of Explanatory Factors on TC

Fig 3. Effect of Explanatory factors on MPI, EC and TC

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