SAFETY PERFORMANCE OF HEAVY AND LIGHT INDUSTRAL PROJECTS BASED ON ZERO ACCIDENT TECHNIQUES

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ABSTRACT

Worker safety continues to be a significant issue in the construction industry. Construction Industry Institute (CII) uses Zero Accidents Techniques (ZAT) best practice to create and implement safety plans in construction projects. This study uses a regression-based heterogeneity analysis to cluster construction projects in groups that are homogeneous in terms of their operational and environmental conditions. The performance of construction projects with respect to their level of implementation of ZAT inside each homogeneous group is then evaluated and compared using Data Envelopment Analysis (DEA) technique. We then use Meta-frontier framework to evaluate and compare performance of different groups of construction projects (defined based on their operational environment) with each other. Our results show there is a significant difference in safety performance between the Light Industrial and Heavy Industrial sectors.

INTRODUCTION

Background

The Construction Industry Institute (CII) is an organization of companies who all share the objective of performing or assisting in research to benefit the productivity and safety of the industry. There have been many efforts by the CII to improve performance of construction projects with respect to their cost, time, and more importantly human safety. Due to extreme financial cost of incidents as well as moral obligation to employees, creating the safest possible workplace is of utmost importance to CII.
The current best practice performed by CII for improving safety performance is called Zero Accidents Techniques (ZAT). The validations performed by CII on the effects of the safety best practice shows that as the ZAT best practice use in construction projects increases, their Recordable Incident Rate (RIR) decreases. However, most of the techniques performed are parametric. The objective of this paper is to present additional and/or new understanding regarding the degree of implementation of ZAT and its effect on safety outcomes in construction projects using a parametric approach called Data Envelopment Analysis (DEA). In this study we first identify sources of project heterogeneity with respect to safety performance, and then analyze the efficiency scores through DEA modeling to obtain an understanding of the relationship between ZAT implementation and safety performance.

The Zero Accident Techniques (ZAT)

The ZAT best practice includes thirteen components each of which has a weigh assigned by a panel of experts at CII. These components focus on: 1) Safety plan implementation, 2) Safety supervisor commitment, 3) Number of safety workers, 4) Extensiveness of safety orientation programs, 5) Presence of formal safety training, 6) Number of toolbox meetings, 7) Number of safety audits, 8) Pre-Employment Drug Screenings, 9) Frequency of drug screening, 10) Number of near-miss investigations, 11) Safety incentive use, 12) Use of safety performance criteria in contractor selection, and 13) Identifying safety risks.

The Recordable Incident Rate (RIR)

The Recordable Incident Rate (RIR) is a widely accepted measure of the level of safety on a job site. Equation 1 proposed by Bureau of Labor Statistics (BLS) [1] is designed to represent the average number of incidents present for 100 full time workers in one year, or for every 200,000 working hours.

$$RIR = \frac{\text{Total \# of Recordable Incidents}}{\text{Project Total Working Hours/200,000}} \tag{1}$$

Data Envelopment Analysis

DEA [2] is a "non-parametric" analysis technique that is used for examining the relative efficiency of a set of similar decision-making-units (DMUs) that are in charge of transforming a set of inputs to a set of outputs. DEA uses linear programming to define a frontier as the set of best performing DMUs that generate the maximum output given a specific input level or use the minimum input level to produce a given output level. The efficiency scores corresponding to all DMUs then are calculated in comparison with best performing DMUs. DEA does not need any assumption regarding the functional relationship between input and output variables to measure performance; instead DEA allows "the data to speak for itself". In addition, DEA also doesn't need all the factors to be reduced to a common unit, meaning they can have different scales [2].

DEA requires a prior definition of the modeling perspective, i.e., input orientation versus output orientation. An input-oriented DEA model calculates the level by which the inputs used by an organization can be reduced without altering the level of outputs produced by the organization, for example, how to lower inputs, such as budget or labor hours to maintain a certain standard, or level of outputs (cost growth, schedule growth, or safety performance). Alternatively, an output-oriented model calculates the level by which the outputs produced by an organization can be increased without altering the level by which inputs are used, for example, how to increase their performance in production quantities or quality using the same level of inputs. Moreover, DEA requires all the DMUs in each group to be similar, i.e., homogeneous, in terms of the nature of the operations they perform.

DEA has been widely used in the literature as a tool for performance measurement and evaluation in various application areas, such as, measuring performance of highway maintenance contractors [3,4], measuring performance of construction contractors [5], and measuring performance of contractors in the prequalification process [6]. This paper is believed to be among the first studies that apply DEA for measuring performance of safety best practices in construction industry.

IMPLEMENTATION

Data

CII has created a questionnaire of 550 questions pertaining to all aspects of project planning and execution, best practice implementations, and project outcomes. A representative from each of the 1800 projects completed this 550-question survey. For this study, we were provided with data of 226 industrial projects from this database. Each project contains information on project type, location, major classification, project delivery method, and various other characteristics which are required for this study. We filtered the data to include only those projects that had recorded their number of recordable incidents. Next, the ZAT data was checked for completeness. The projects that did not answer all 13 ZAT questions were removed from the dataset because they would be unusable in this study. At the completion of these criteria checks, there were 59 projects remaining in the data set for use in this study.

The Model

As it was mentioned before, this paper focuses on the application of DEA to evaluate the performance of CII's ZAT. The DMUs in this paper are construction projects which are concerned with transforming a set of inputs (resources) to a set of outputs (associated with the outcomes after implementing ZAT). The input used in this paper is a weighted average index of the thirteen elements that make up ZAT; this aggregated index is known as the Best Practice Implementation Score (BPIS). In order to calculate the input variable, we combine all of the 13 separate elements that comprise the ZAT into one aggregate Best Practice Implementation Score. This score is one final number that represents the level of overall ZAT implementation that was conducted by the project. The method for calculating the BPIS was developed by CII and the same method and weightings were utilized in this study. Taking the survey responses from each of the 13 questions, and translating them to a scale of 0-1, with 0 being no implementation and 1 being the highest level of implementation of that specific action is the first step of calculating the aggregated Best Practice Implementation Score. Moreover, each component of the ZAT has been assigned a weighting by a panel of experts at CII. To calculate the aggregated ZAT BPIS, each component's score for each project is multiplied by the weight of that component and are added up. For reasons that will be explained later, the output used is the inverse of the RIR.

To define the type of DEA model to use for this study, we need to decide on the orientation of the model (i.e., input or output orientation) as well as its return to scale (i.e., variable or constant return to scale). DEA assumes data to be isotonic, meaning as inputs increase, outputs increase as well [7]. An output-oriented DEA model used to assess safety would calculate the amount of improvement in the safety performance (or output) that can be achieved using the same amount of input, or safety practice implementation level. In this study we have an undesirable output, i.e., RIR; hence our analysis uses the inverse of the output, i.e., 1/RIR, which is maximized by minimizing the RIR. By using the inverse of the RIR as the output variable we make sure that our data shows the isotonic behavior required in DEA analysis [8]. In terms of the return to scale (i.e., variable return to scale (VRS) or constant return to scale (CRS)) of the DEA model, the output variable that represents the number of injuries (RIR) cannot be improved past zero incidents. Thus, a VRS frontier is needed, since a CRS frontier continues extending linearly without taking any boundary constraint into account [3]. Consequently, we use the ‘‘BCC model’’ of DEA, as introduced in [8], to appropriately account for the VRS behavior.

Heterogeneity Analysis

DEA assumes groups of DMUs to be homogeneous. This means that DMUs are expected to be involved in similar activities, use a common set of inputs, produce a common set of outputs, and operate in comparable environments [9]. During review of possible sources of heterogeneity among construction projects, it was determined that potential sources of heterogeneity among projects are: 1) Location (Domestic, International); 2) Major Classification (Light Industrial, Heavy Industrial, Infrastructure,

Buildings); 3) Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location); 4) Project Delivery Method (Design-Build, Multiple Design-Build, CM at Risk, Traditional D-B-B, Parallel Primes, Other); 5) Fast Tracked (yes, no); 6) Complexity (1-10); 7) Project Cost; 8) Project Duration; 9) Worker Density = Total Work Hours /(Project Duration * Project Cost).
To test the level of influence each of the nine project characteristics has over the safety performance, a regression analysis was used using the RIR as a dependent variable and each of these nine project characteristics as independent variables. The RIR data was analyzed and it was determined that this frequency distribution most closely resembles a Zero Inflated Poisson's distribution. The distribution of this data is zero inflated because of the extreme number of times zero recordable incidents occurs.

The Poisson (or log-linear) regression is chosen for this application because it is designed to be used when the dependent variable (total recordable incidents) consists of only natural, integer values [10]. The total number of recorded incidents is a "counted" variable because the only possible values are integers from 0 to infinity. The Poisson regression equation does normalize the total number of recordable incidents for the length of the project by defining the dependent variable as the log(count/time). This is important so that longer projects are not penalized for having more time in which incidents can possibly occur. The statistically significant results are shown in Table 1. The parameters in this regression model all contain a Chi Squared (shown as Pr>ChiSq in the column heading) value of less than 0.05, which defines the variable as statistically significant. The statistically significant variables to the Normal Poisson group are: 1) Project Location (Domestic, International); 2) Major Classification (Light Industrial, Heavy Industrial); 3) Characteristic (Grass Roots, Modernization, Addition, Brownfield or Co-Location); and 4) Project Cost.

Table 1: SAS Software Results Output for Zero Inflated Poisson Regression

Analysis Of Maximum Likelihood Parameter Estimates								
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept		1	-12.022	0.1904	-12.3952	-11.6487	3984.82	<.0001
country_r	**International**	1	-1.2116	0.1095	-1.4263	-0.9969	122.35	<.0001
country_r	**United States**	0	0	0	0	0	.	.
majorcls	**Heavy Industrial**	1	-1.0795	0.1205	-1.3157	-0.8433	80.22	<.0001
majorcls	**Light Industrial**	0	0	0	0	0	.	.
char	**Addition**	1	0.4544	0.1963	0.0697	0.839	5.36	0.0206
char	**Brownfield or Co-location**	1	1.2104	0.2329	0.7539	1.667	27	<.0001
char	**Grass Roots**	1	0.6375	0.1839	0.277	0.9979	12.01	0.0005
char	**Modernization**	0	0	0	0	0	.	.
projectcost1		1	0.0008	0.0001	0.0007	0.001	112.86	<.0001

The statistically significant factors accounting for heterogeneity were used by a statistical software package named JMP to cluster the projects accordingly. JMP uses a hierarchical process to take the smallest clusters of one project, and combine them with other clusters until the desired number of groups is obtained. JMP assigns a "distance" between the values of each variable and then combines groups of projects having the least total "distance" between them. The selected clustering scenario that provides the maximum level of homogeneity while keeping the cluster sizes large enough to perform DEA is shown below in Table 2. These four clusters were subjected to DEA analysis, the results of which are presented in the next section.

DEA RESULTS AND DISCUSSION

Once the clusters of DMUs (projects) are formed, we run the BCC DEA model for each cluster separately. Table 3 shows the summary statistics for the DEA scores of projects in all four clusters. The advantage of this clustering step is that each project is compared with the projects that have similar operational conditions. Thus their estimated efficiency scores are obtained as a result of a fair comparison. However, another important question is how these groups of DMUs have performed in comparison with each other, in terms of using the available resources and improving performance of projects with respect to their safety practices. A Meta-Frontier analysis [11,12] is used to compare homogeneous groups of DMUs with each other and to investigate inherent differences among the groups.

Table 2: Characteristics of the Four Clusters.

Cluster	*# of Projects*	*Location*	*Major Classification*	*Characteristic*
1	22	Domestic	Heavy	Modernization Grass Roots Brownfield Addition
2	15	Domestic	Light	Modernization Addition
3	10	Domestic	Light	Grass Roots
4	12	International	Light Heavy	Modernization Grass Roots Addition

The meta-frontier framework was implemented by first analyzing each group and estimating an efficient frontier for each homogeneous cluster of DMUs (as performed and shown in Table 3). Next the DMUs are all pooled together irrespective of their clusters and an estimate of a Meta-Frontier is calculated. The result of such analysis has been shown in the last column of Table 3. Once we calculate the efficiency of each DMU (construction project) with respect to its group frontier and also meta-frontier, then we can calculate the so-called meta-technology ratio (MTR) as the ratio of the efficiency score of each DMU with respect to its group frontier to the efficiency of that DMU with respect to the meta-Frontier. This meta-technology ratio can be used to identify which homogeneous groups are closer to the meta-frontier and are outperforming others or which homogeneous groups seem to have some inherent differences to other groups.

Table 3: DEA Results Tables

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**All clusters**
Average Efficiency Score	0.382	0.414	0.696	0.600	0.283
Median Efficiency Score	0.182	0.269	0.756	0.619	0.141
Standard Deviation	0.370	0.361	0.320	0.381	0.310
Maximum Efficiency Score	1	1	1	1	1
Minimum Efficiency Score	0.036	0.066	0.152	0.028	0.013
Number of Efficient DMUs	4	3	4	4	7
Number of Inefficient DMUs	18	12	6	8	52

Table 4 shows the MTR for all clusters. As you can see average MTR for cluster 4 is larger than other clusters. This shows that cluster 4 forms a major part of the meta-frontier and on average projects that are in cluster 4 (i.e., projects that are international, light heavy, modernization/grass roots/addition) have performed better that other groups of projects in terms of performing the ZAT best practice and reducing their recordable incidents. Projects in the first cluster (i.e., projects that are domestic, light, modernization/addition) have the second rank in terms of their performance for implanting ZAT best practice. Overall looking at the results in Table 4 shows that Cluster 1 and 4 which are mainly related to Heavy industrial projects have performed better than clusters 2 and 3 that are related to Light industrial projects.

Table 4: Efficiency Scores and MTRs of All DMUs

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**
Average MTR	0.763	0.547	0.176	0.946
Median MTR	0.937	0.436	0.186	1.000
Standard Deviation	0.302	0.249	0.059	0.075
Maximum MTR	1	1	0.237	1
Minimum MTR	0.026	0.348	0.030	0.810

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