Financial Performance Assessment of Construction Firms by Means of RAM-Based Composite Indicators

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Abstract: This paper aims to provide a novel construct that is based on data envelopment analysis (DEA) range adjusted measure (RAM) of efficiency and demonstrate its practical implementation by evaluating the financial performance of a sample of three upper-class contracting license (Classes 5–7) Greek construction firms. In a two-step framework, firm efficiency (i.e., composite indicators (CIs)) is produced firstly by means of RAM using single financial ratios, which are selected by grey relational analysis (GRA), and then Tobit regression is employed to model the CIs. In light of the results, only 4% of the sampled firms are efficient, and the firm ranking is consistent with the ranking of Grey Relational Grande (GRG) values produced by GRA. Moreover, the firms with a contracting license of the highest level (Class 7) appear not to be superior in efficiency to their counterparts that belong to Classes 5–6.

Keywords: data envelopment analysis; grey relational analysis; composite indicators; construction firms; Tobit regression

1. Introduction

The managers of any company must measure the financial performance of the firm they manage. Assessing the performance of modern construction companies is a complex issue from both an international and local perspective [1]. The financial success of construction firms very much depends on the location [2], proper management [3], environmental characteristics [4], selected technologies [5], staff qualification [6], and specific circumstances [7,8]. Besides, at the project level, the influence of various factors on the project success may be responsible for the production of differently significant outcomes [9]. The managers can predict the data describing the projects accurately and determine them at certain intervals, or they should treat them as fuzzy data [10,11].

Management accounting information is mainly used for firm financial performance assessment. Since the early 1990s, management accounting has attracted studies from operations research that suggest frameworks or propose model building on methods, such as data envelopment analysis (DEA) (see Callen [12] and Malmi [13] for surveys). DEA [14] is a multicriteria evaluation method that can screen the most desirable alternatives (i.e., decision-making units (DMUs), e.g., firms) among large sets by means of mathematical programming. DEA provides for each DMU a composite score, which is referred to as efficiency using actual input–output data for a sample of them and this facilitates the complexity of analysis by evaluating the multicriteria [15]. DEA can be employed in a multiple input–multiple output setting and, in regard to model building, it avoids the prior assumption on weights of inputs and outputs; the weights are produced by the optimization process.

Firm assessment of financial performance using DEA deals with the analysis of financial statement data to distinguish a sample of firms into efficient and inefficient. DEA-based efficiency and inefficiency reflect good and bad financial conditions, respectively [16].

The current paper aims to employ a constructive research approach [17] by providing a novel construct that is based on DEA and demonstrate its practical applicability. Firm performance evaluation can be accomplished by means of a derived composite indicator (CI) using DEA [18]. The approach used for the derivation of a CI distinguishes from the conventional DEA in that it looks at the one side of DEA (i.e., on outputs or inputs only) using a set of single (individual) indicators. The use of DEA to derive CIs at the firm-level is promising since DEA can aggregate multiple firm performance dimension, expressed as single financial ratios, into a consolidated performance metric.

Horta et al. [18] recently employed DEA to evaluate construction enterprise performance by deriving firm CIs. The current study improves upon Horta et al. [18] by firstly employing GRA for the selection of financial ratios and then using a modified range-adjusted measure (RAM) of efficiency [19] suggested by Lozano and Gutierrez [20] for the derivation of firm CIs. Recent studies integrate models based on grey theory with DEA [21,22], and, for the case of robustness, the DEA results are compared with those of GRA. In a second step, the determinants (i.e., drivers) of firm overall performance (i.e., DEA-based CIs) are explored using regression techniques (i.e., censored Tobit regression). The practical applicability of the proposed RAM-Tobit regression modeling is demonstrated at the project-level for a group of construction projects performance evaluation [23]. In particular, this paper focuses on a sample of three upper-class contracting license (Classes 5–7) Greek construction firms with the aim to derive DEA-based performance scores (i.e., composite indicators (CIs)) using selected financial ratios.

GRA is based on grey theory and it is used to derive the relational degree of every attribute for a set of alternatives in a multicriteria decision-making (MCDM) problem where multiple variables and their interrelationships need to be taken into account. GRA produces for every alternative one single-attribute value by considering all multiple-attribute values to facilitate the whole process [24]. It is worth noting that the utilization of GRA in construction is not very widespread in terms of multicriteria analysis [25]. For other MCDM methods in construction, the interested reader is referred to the work of Jato-Espino et al. [25].

In this paper, the composite indicator construction is modeled as a decision-making problem with multi-attributes. Financial ratios are viewed as attributes for construction firms, and firms as alternatives.

This paper contributes to the existing literature by outlining a procedure that can be used by firms and consultants to aggregate single firm financial ratios into one CI and identify the drivers of performance. Firstly, GRA ranks the level of importance of the financial ratios, and then, based on selected ratios, firm CIs are constructed by means of a no-input RAM by allowing firms to adjust in the direction of greater output-like values (i.e., single financial ratios) as much as it is feasible in the DEA context; DEA and GRA results are also compared in terms of firm ranking. In this sense, a useful performance companion is provided when the goal of firms is the maximization of selected financial ratios. The incremental contribution of the current research over Tsolas [23] lies in the employment of a no-input RAM with the aim to pinpoint the drivers of firm performance in terms of DEA-based CIs and the integration of DEA with GRA. The identification of firm performance drivers will guide future studies for analyzing financial statement data of Greek construction firms.

The remainder of the paper is organized as follows: Section 2 provides a review on the use of DEA in management accounting. Moreover, it also reviews firm DEA studies in the construction industry as well as the relation of DEA with multicriteria methods. Section 3 describes the methods used for the analysis of data. Section 4 presents the dataset. Section 5 reports and discusses the results. Section 6 provides policy implications. Section 7 concludes.

2. Literature Review

DEA performance assessment in the field of management accounting research deals with the works of Turner [26] on manufacturing maintenance performance; Banker et al. [27] on nursing services; Deville [28] on branch banking network assessment; Deville et al. [29] on bank efficiency; Halkos and

Salamouris [30] on Greek commercial banks; and Rouse et al. [31] on aircraft maintenance (see also Callen [12] and Malmi [13] for surveys on that subject). It is worth noting that DEA can be integrated with other MCDM methods for financial performance purposes [32].

In the operations research literature, there are a few DEA works that are deemed as the first which make use of financial statement data [33–36]. Relevant are also the works by Feroz et al. [37] who employed the DuPont model in oil and gas, pharmaceuticals and primary metals industries; Rodriguez-Perez et al. [38] who provided a DEA-based performance assessment of insurance companies; and Demerjian et al. [39] who used DEA to quantify managerial ability. A recent review can be found in Harrison and Rouse [40].

In regard to relevant DEA studies in the construction sector, the works at the firm-level are classified as standard, two-stage, and series two-stage DEA studies. The standard studies focus on the relative efficiency of DMUs. The two-stage DEA studies aim not only to derive the efficiency metrics but also to identify the drivers of performance, whereas the series two-stage studies distinguish two stages with output from the first stage becoming input to the second stage. The works in the first and second strands can be classified further into studies that are based on production theory and studies that use DEA models to produce synthetic performance indicators.

In the first strand (i.e., standard DEA studies) lie a lot of relevant works. Pilateris and McCabe [41] use conventional DEA (e.g., CCR [14] and BCC [42]) models to evaluate contractors. McCabe et al. [43] and El-Mashaleh et al. [44,45] employ DEA to prequalify and evaluate contractors, respectively. Sueyoshi and Goto [46] use DEA as a discriminant tool. Horta et al. [47] employ DEA models with and without weight restrictions, and Horta and Camanho [48] combine DEA with other data mining techniques.

In the second strand (i.e., two-stage DEA modeling) lies the work by Horta et al. [18] who first derive DEA-based composite performance indicators by means of an equivalent to CCR model and then identify the drivers of performance.

In the third strand, i.e., series two-stage DEA modeling, firstly proposed by Seiford and Zhu [49] lie the DEA studies by Tsolas [50,51] on the evaluation of listed Greek construction enterprises and Hu and Liu on the Australian [52] and Chinese construction industry [53].

As for the Greek construction industry, DEA firm-level studies are the works by Tsolas [50,51] and Christopoulos et al. [54]. In the above studies [34,38] DEA is integrated with ratio analysis in a two-stage framework [50] or employed to provide metrics that stem from models that use financial ratios and financial statement data separately [54].

Using DEA, the derivation of composite performance metrics is based on the methodological relation between multicriteria decision analysis (MCDA) and DEA. The connection between the two approaches is that if all criteria in MCDA can be defined as benefit (i.e., maximizing) or cost (i.e., minimizing) criteria, outputs and inputs are equivalents of these in DEA terminology. Thus, if a criterion is defined as minimizing or maximizing, it can be considered in the DEA model as input or output. The basic function of DEA is to classify the units under evaluation in efficient and inefficient ones; in MCDA, these can be regarded as non-dominated and dominated alternatives, respectively. For more on the methodological relation between DEA and MCDA, the interested reader is referred to previous relevant studies [55–58].

GRA studies in construction are scarce [25]. There are mainly GRA studies at the project level on pre-evaluation of engineering design [59] and bid evaluation [60].

Two-stage DEA is performed by firstly calculating DEA efficiency ratings and then regressing them on explanatory variables using Tobit or ordinary least squares (OLS) regression. Simar and Wilson [61] suggest the use of an integrated with bootstrapping truncated regression rather than Tobit regression. They bootstrap the efficiency scores to produce bias-corrected efficiency ratings and then they regress these corrected ratings on explanatory variables using bootstrapped truncated regression. As to which regression method is the most appropriate to employ in the second stage of analysis is a subject that is the interest in a lot of studies. Banker and Natarajan [62] argue that the above methods

are all appropriate. McDonald [63] supports the use of OLS instead of Tobit regression. Moreover, new methods have been proposed such as fractional regression [64], partial least squares regression [65], or other efficiency estimators [66]. For a recent review the interested reader is referred to Liu et al. [66].

Banker et al. [67] argue that Simar and Wilson's [61] procedure precludes statistical noise and it is inconsistent with the modeling of production functions. In the light of the simulation results of their study [67] the DEA-OLS and DEA-Tobit procedure dominate the DEA-bootstrapped truncated regression. The results hold whether explanatory and other variables are independent or correlated, and whether there is no statistical noise.

The DEA-bootstrapped truncated regression cannot be applied to slack-based models, such as RAM. To the best of the author's knowledge, there has not been developed yet a bootstrapping procedure for slacks-based models along the lines of Simar and Wilson [61]. Therefore, in the current paper the DEA-Tobit procedure will be employed. Moreover, for the case of robustness the results of DEA-OLS approach will be also discussed.

Another problem with two-stage DEA modeling is relative to the separation of the space of the input/output variables used in first stage DEA and the space of the explanatory factors used as independent variables in the second stage of analysis. Simar and Wilson [61] found that regression techniques such as Tobit and OLS were inappropriate in the second stage and proposed bootstrapped truncated regression, despite understanding that this technique may suffer from the same problem. According to Daraio et al. [68], if the separability condition does not hold, the second stage results would have drawbacks [69].

The separability assumption of Simar and Wilson [61] is strong [67,70] and it is unlikely to be satisfied in real applications [67,71]. Despite the strong nature of this assumption the tests presented in a proceeding research by Daraio et al. [68,71,72] may be employed to confirm the separability condition. In cases where the separability assumption is rejected, models of conditional efficiency may be used. For a recent survey on that issue the reader is referred to Henriques et al. [69]. Due to unavailability of a test code, Benito et al. [73] propose the comparison of outcomes based on the bootstrapped truncated regression [61] procedure, as well as on the conditional efficiency measures [71]; results produced by the two methods are considered robust if there is consistency of outcomes, otherwise it may be possible that the separability condition does not hold. Most of the previous two-stage DEA studies, although may comment on the reality of the above separability condition, take its fulfillment for granted [73]. Therefore, in the current paper as in most of the previous relevant works separability appears as a taken-for-granted assumption.

The contribution of the current research is manifold. First, this paper distinguishes from previous construction industry DEA works that use the same two-stage framework (e.g., [23]) in that it focuses on financial firm performance. Second, it documents how to derive CIs for financial firm performance by integrating GRA with a no-input RAM of efficiency. The employment of conventional DEA models, such as the CCR and the BCC model, may be problematic when financial statement-based ratios are used due to the presence of negative values, and therefore, by employing the RAM for the derivation of construction firm Cis, the current study improves upon Horta et al. [18]. Moreover, the GRA and DEA results, in terms of firm ranking, are also compared. Third, the two-stage modeling adopted herein involves a DEA model (i.e., RAM) that firstly uses a set of single financial ratios to produce firm CIs and then the firm CIs produced are regressed on a set of explanatory variables such as size, geographical location and class of the firm. The latter variable reflects the complexity of firm projects and characterizes the structure of the Greek construction industry [51], whereas the other two variables have also been used by other researchers [18]. As regards the class of the firm, the current research uses a sample that represents about 88 percent of the total population and therefore this sample feature aids to generalize results.

3. Methods

3.1. Grey Relational Analysis (GRA)

The calculating process of GRA application is as follows [74]:

Let X_0 be the referential sequences with $r = 1, \ldots, k$ attributes (i.e., financial ratios) of $X_1, X_2, \ldots, X_n$ ($j = 1, \ldots, n$ firms). These sequences are the attribute ideal values that are necessary to define a baseline (i.e., reference point) to evaluate the alternatives. Then,

$$X_0 = x_0(1), x_0(2), \ldots, x_0(r), \ldots, x_0(k) \tag{1}$$

where k and x_0 are the number and the ideal (i.e., target) values of the attributes, respectively.

The problem decision matrix is set using a $j = 1, \ldots, n$ series:

$$X_j = x_j(1), x_j(2), \ldots, x_j(r), \ldots, x_j(k), \; j = 1, \ldots, n \tag{2}$$

The grey relational coefficient (GRC) between the sequences X_j and the referential sequences of X_0 at the rth attribute is derived as

$$\xi_{0r}(r) = \frac{\Delta \min + p\Delta \max}{\Delta x_{0r}(r) + p\Delta \max} \tag{3}$$

where

$$\Delta x_{0r}(r) = \left| x_0(r) - x_j(r) \right| \tag{4}$$

$$\Delta \max = \max_j \max_r \Delta_{0r}(r) \tag{5}$$

$$\Delta \min = \min_j \min_r \Delta_{0r}(r) \tag{6}$$

and $p = 0.5$.

The original data should be normalized before the GRC calculation according to [74]:

(i) Larger-the-better principle and (ii) smaller-the-better principle using Equations (7) and (8), respectively:

$$x_j^*(r) = \frac{x_j(r) - \min_r x_j(r)}{\max_r x_j(r) - \min_r x_j(r)} \tag{7}$$

$$x_j^*(r) = \frac{\max_r x_j(r) - x_j(r)}{\max_r x_j(r) - \min_r x_j(r)} \tag{8}$$

where $\max_r x_j(r)$ and $\min_r x_j(r)$ are the rth attribute maximum and minimum value, respectively.

The grey relational grade (GRG) for the sequences X_j is given as:

$$\Gamma_{0j} = \sum_{r=1}^{k} w_r \xi_{0r}(r) \tag{9}$$

where w_r is the weight of the rth attribute. In the current analysis equal weights are used.

3.2. Range Adjusted Measure (RAM) of Efficiency

Given a group of construction firms n, $j = 1, \ldots, n$, for which of them there is a set of selected single indicators (i.e., output-like values) that should be maximized and the values of the rth output

indicators of the jth firm are denoted by y_{rj}, the following RAM Model (10) with no inputs is used to produce the construction firm inefficiency metric P (see also: [19]):

$$
\begin{aligned}
&P = Max \frac{1}{k} \sum_{r=1}^{k} \frac{s_r^{*+}}{R_r^+} \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rj_0} \quad r = 1, 2, \ldots, k \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j, s_r^+ \geq 0 \quad \forall j, r
\end{aligned}
\tag{10}
$$

where P ($0 \leq P \leq 1$) is a metric of inefficiency, $R_r^+ = max_j[y_{rj}] - min_j[y_{rj}] \geq 0$ is the range of the r output indicators and λ_j is an intensity variable.

The firm under assessment (i.e., firm "0") is efficient if and only if $P = 0$ and the slacks $s_r^{+*} = 0 \ \forall r$, where superscript "*" indicates an optimum value for Model (10).

The metric Γ is the efficiency score according to Equation (11):

$$
0 \leq \Gamma = 1 - P \leq 1
\tag{11}
$$

RAM of efficiency is expressed with $\Gamma = 1$ and if and only $s_r^{+*} = 0 \ \forall r$. Firm inefficiency, $\Gamma < 1$, is present when there are non-zero slacks.

The selection of RAM is justified due to the drawbacks of conventional DEA models in ranking firms according to their efficiency. RAM assesses each DMU (i.e., firm) by reference to all of the DMU performance (i.e., the R_r^+ is used for all DMUs) compared to the conventional DEA models that use different reference sets [75]. RAM is invariant to linear transformations and belongs to a family of models that are extensions of the additive model [76]. This family of models includes: slacks-based measure (SBM [77]), Russell model (RM [78]), and enhanced Russell graph measure (ERGM [79]). From the above models, the SBM has not the invariance property and the ERGM is equivalent to SBM [80]. In addition, RAM works equally well as RM and ERGM and, moreover, in regard to translation invariance RAM is superior to RM and ERGM [81]. From the above, the use of RAM is also justified in the case of negative values in the dataset.

In the current research, the RAM (Model (10)) is employed using financial ratio data of year 2010 for a sample of the Greek construction firms to produce a CI for each firm. If the derived firm CI is equal to unity, it indicates the most excellent performance and the firm is efficient; when the firm CI value is less than one the firm is deemed inefficient.

3.3. Tobit Regression

The current study integrates Tobit regression [82] with DEA (see also [83]) to model the CIs produced by the RAM of efficiency and identify the drivers of performance.

The Tobit model (12) is established when the dependent variable is censored at zero:

$$
P_j^* = \begin{cases} \beta Z_j + \varepsilon_j & P_j^* > 0 \\ 0 & P_j^* \leq 0 \end{cases}
\tag{12}
$$

where P_j is the dependent variable (i.e., the metric of inefficiency of the jth firm that stems from Model (10)) measured using a latent variable P_j^* for positive values and censored otherwise ($P_j = P_j^*$ if $P_j^* > 0$ and $P_j = 0$ if $P_j^* \leq 0$), Z_j, β are respectively the vectors of explanatory (independent) variables and unknown parameters, and ε_j is the term for random error. Some factors that may have an effect on inefficiency are selected as independent variables.

4. Dataset and Financial Ratio Selection

4.1. Dataset

Greece's construction activity can be classified into private, public, and joint private-public structures. The Greek construction firms are categorized into classes (Classes 1–7). This categorization of licensure grants different rights to firms reflecting the complexity of projects they can undertake [84].

Data on 96 Greek construction firms of three upper-class contracting license (Classes 5–7) are used. Data refer to the year 2010. Details of the process on firm selection sample are depicted in Table 1.

Table 1. Greek construction enterprises sample selection.

License Class	Sampled Firms [a]	Registered Firms [b]	% of Registered Firms [c]
7th	9	11	81.82%
6th	35	37	94.59%
5th	52	61	85.25%
Total	96	109	88.07%

Sources: [a] The current research; [b] Association of Greek Contracting Companies (SATE) (2010); [c] The current research.

The research sample used covers about 82 percent of the Class 7 firms, about 95 percent of Class 6 firms, and about 85 percent of Class 5 firms. The sample firms cover about 88 percent of the three upper-class registered firms by the Association of Greek Contracting Companies (SATE [85]).

In this paper DEA is used to evaluate the financial performance of the sampled construction firms. The single financial ratios chosen aim to capture the multi dimensional firm performance. Based on the relevant studies [18,41,86], it is evident that the single financial ratios that used for measuring construction firm performance should reflect: liquidity, profitability, and leverage. Although in a recent study by Horta et al. [18], gross value added per employee is also used as a productivity indicator, in the current analysis, productivity is not considered. This is justified by the fact that there is evidence that construction firms which generate profits support their high productivity level [87]. Therefore, the DEA model used includes representative financial ratios of liquidity, profitability, and financial autonomy (see also [18]).

4.2. Financial Ratio Selection

In the DEA context the selected single indicators (i.e., financial ratios) should be correlated as low as possible. This is because related indicators deliver a huge part of the same information in the derivation process of the composite indicator. GRA based on GRG values provides clusters of (related) indicators, except for each cluster's representative indicators [88–90].

The procedure in order to select the appropriate indicators is as follows:

Previous studies suggest that representative financial ratios of liquidity, profitability, and financial autonomy should be used (see also: [18]).

The initial indicators used include the following financial ratios: current ratio, quick ratio, gross margin, net margin, return on equity (ROE), return on assets ROA, debt to equity ratio, and equity to assets ratio (Table 2).

Table 2. Financial ratios.

Indicator No.	Financial Ratio	Category	Ideal Value
I1	Current ratio	Liquidity	Maximum
I2	Quick ratio	Liquidity	Maximum
I3	Gross margin	Profitability	Maximum
I4	Net margin	Profitability	Maximum
I5	Return on equity (ROE)	Profitability	Maximum
I6	Return on assets (ROA)	Profitability	Maximum
I7	Debt to equity ratio	Financial autonomy	Maximum
I8	Equity to assets ratio	Financial autonomy	Maximum

Using the calculating procedure of GRA as described in Section 3.1 GRGs between every pair of indicators are calculated. The results are depicted in Table 3.

Table 3. Grey relational matrix.

Reference/Sequences	Comparative Sequences							
Reference Indicator	I1	I2	I3	I4	I5	I6	I7	I8
	1	2	6	7	8	11	9	10
I1	-	**0.90**	**0.77**	0.46	0.59	0.47	0.54	**0.85**
I2	**0.90**	-	**0.77**	0.45	0.50	0.51	0.53	**0.83**
I3	**0.77**	**0.77**	-	0.48	0.58	0.55	0.57	**0.77**
I4	0.48	0.47	0.50	-	0.66	0.78	0.73	0.47
I5	0.69	0.67	0.70	0.56	-	0.68	0.71	0.67
I6	0.55	0.54	0.59	**0.80**	**0.82**	-	**0.92**	0.54
I7	0.54	0.53	0.57	0.70	0.51	**0.87**	-	0.52
I8	**0.84**	**0.83**	**0.77**	0.45	**0.86**	0.51	0.52	-

Values over 0.75 are in bold.

The ranks for each indicator from the largest to the least GRG are shown in Table 4.

Table 4. Grey relational grade (GRG) rank.

Reference/Sequence Rank	Comparative Sequence Rank						
Reference	1	2	3	4	5	6	7
I1	**I2**	**I8**	**I3**	I5	I7	I6	I4
I2	**I1**	**I8**	**I3**	I7	I6	I5	I4
I3	**I1**	**I8**	**I2**	I5	I8	I6	I4
I4	**I6**	I7	I5	I3	I1	I2	I8
I5	I7	I5	I4	I7	I6	I2	I4
I6	**I7**	**I4**	I5	I3	I1	I8	I2
I7	**I6**	I4	I3	I1	I2	I2	I5
I8	**I5**	**I1**	**I2**	I3	I7	I6	I4

Indicators in bold are referred to their values over 0.75 (Table 3).

There are two clusters of financial ratios: I1, I2 and I8 (first cluster); I6, I7 and I4 (second cluster). In the first cluster I1 appears to be first in sequences most of the times whereas in second cluster I6 appears to be first in sequences. Therefore, I1 and I6 may be considered as the representative indicators of the first and second cluster, respectively. Moreover, there is evidence that indicators I5 and I1 are also related.

The selection process starts from an independent indicator which does not belong to the above two clusters and then indicators that they should correlated as low as possible and belong to the above clusters are added into the analysis. I5 is regarded as an independent indicator. In regard to profitability, the focus of the current study is on equity shareholders; thus, I5 is first selected and

because I6 is correlated with it (Pearson correlation coefficient: 0.91 (Table 5)), I6 is omitted. Since I5 appears to be related with I7, I7 is omitted. The last indicator of the second cluster, I4 is also correlated with I5 (Pearson correlation coefficient: 0.85 (Table 5)), so I4 is omitted.

Table 5. Pearson correlation coefficients.

Indicator No.	I1	I2	I3	I4	I5	I6	I7
I2	0.81						
I3	0.39	0.43					
I4	0.41	0.41	0.45				
I5	0.40	0.43	0.57	0.85			
I6	0.42	0.44	0.54	0.88	0.91		
I7	0.34	0.34	0.34	0.57	0.52	0.65	
I8	0.49	0.43	0.48	0.27	0.42	0.42	0.37

From the first cluster of indicators, as it stems from Table 5, I8 has a lower Pearson correlation coefficient (0.43) with I2, compared with I1 (0.49) and since I1 is highly correlated with I2 (Pearson correlation coefficient: 0.81), I1 is omitted and I8, I2 are used in the analysis. Thus, the selected indicators are: I5 (ROE), I8 (equity to asset ratio), and I2 (quick ratio).

The DMUs assessed in this study correspond to the sampled Greek construction firms, which characterized by the above three financial ratios that all of which are intended to be maximized.

Table 6 reports the descriptive statistics for variables in the first stage analysis.

Table 6. Construction firm financial ratios: Descriptive statistics.

Descriptive Statistics	Quick ratio, Times	Return on Equity (ROE), %	Equity to Asset Ratio, %
Mean	1.25	0.75	2.60
Standard deviation	1.19	23.17	2.56
Median	0.85	2.03	1.88
Min	0.02	−90.68	−0.09
Max	7.14	71.95	14.03

From Table 6, it is evident that the firms analyzed are relatively homogeneous, as it stems from the standard deviation for quick ratio and equity to asset ratio. Profitability, as expected, is the indicator with the greatest variation (see also [18]).

5. Results

5.1. First-step DEA Results

In the light of the first-step DEA results, only 4 out of 96 firms (about 4% of the total) are efficient (i.e., they have a CI equal to unity) and thus, the RAM of efficiency has a high discriminating power. The mean efficiency is 0.71 (median efficiency: 0.68) (Table 7) and this finding is in line with the mean firm efficiency (0.64) presented by Horta et al. [18].

Table 7. Descriptive statistics of range adjusted measure (RAM) of efficiency ratings, number, and percentage of efficient firms.

Descriptive Statistics (All Firms), Number and Percentage of Efficient Firms	Efficiency (Γ)	GRG
Mean	0.71	0.58
Standard deviation	0.12	0.05
Median	0.68	0.58
Min	0.43	0.40
Max	1.00	0.79
Efficient firms, Number (%)	4 (4%)	

For the case of robustness, the DEA efficiency scores are compared with the GRGs produced by GRA using equal weights for the three finally selected indicators (Table 7). According to Spearman's correlation coefficient (0.74) the results of both methods are satisfactory in terms of firm ranking.

5.2. Second-step Tobit Regression Results

The construction firm RAM inefficiencies P are regressed using Tobit model (12) to pinpoint the effect of the possible drivers of performance listed in Table 8.

Table 8. Explanatory variables: Descriptive statistics.

Descriptive Statistics	Size	Location	Class Dummy
Mean	16.42	0.73	0.09
Standard deviation	1.23	0.45	0.29
Median	16.17	1.00	0.00
Min	14.00	0.00	0.00
Max	20.10	1.00	1.00

Notes: Size = natural logarithm of sales revenue; Location = a dummy variable with values of "1" for firms located in Attica area and "0" for other areas; Class dummy = a dummy variable with values of "1" for upper class firms (Class 7) and "0" for other firm classes.

The possible drivers of performance (i.e., explanatory variables) are the firm size, geographic location [18], and a class dummy variable [51].

Firm size (=natural logarithm of sales revenue) is included as a variable in the analysis to investigate the presence of economies of scale and test whether large firms are superior in performance to small firms [18]. Geographic location (i.e., a dummy variable with values of "1" for firms located in Attica area (i.e., in the city of Athens, the capital of Greece, and close to it) and "0" for other areas is also included to test whether construction firms located in Attica area are more efficient than the firms located outside it. Moreover, a class dummy with values of "1" for upper class firms (Class 7) and "0" for other firm classes is also included to investigate whether there is a difference in performance between the firms of the highest class (Class 7) and the firms that belong to Classes 5–6 [51].

In light of Tobit regression results, there may be a link of performance with only class dummy (Table 9). The effect of the class dummy variable is significant in explaining inefficiency. This finding shows that the Class 7 contracting license firms seem to not be superior in efficiency to their counterparts that belong to Classes 5–6. It is worth noting that the conclusion drawn from the analysis here is consistent with that by Tsolas [51] in regard to profitability efficiency of Greek listed firms.

Table 9. Results of Tobit regression for firm inefficiency.

Variable	Coefficient	Standard Error	T-Value (*p*-Value)
Constant	0.4883	0.1914	2.55 (0.012)
Size	−0.0146	0.0119	−1.23 (0.221)
Location	0.0425	0.0269	1.58 (0.117)
Class dummy	0.1261	0.0498	2.53 (0.013)

Notes: Log Likelihood = 63.107; Dependent variable: P; Explanatory variables: Size = natural logarithm of sales revenue; Location = a dummy variable with values of "1" for firms located in Attica area and "0" for other areas; Class dummy = a dummy variable with values of "1" for upper class firms (Class 7) and "0" for other firm classes.

Somewhat surprisingly, the effects of size and location are insignificant in explaining performance. Therefore, these explanatory variables and the relevant hypotheses, i.e., whether firm size is related to financial performance and whether the firms located in Attica area outperform the other firms should be investigated further in a future research.

For the case of robustness, except for Tobit regression the OLS method is also used after transforming the DEA estimates of efficiency using their natural logarithm values [61]. OLS results are in line with those of Tobit regression. The OLS results are available upon request from the author.

6. Policy Implications

The implications of the current research are as follows: In the first step, GRA is employed for the financial ratio selection process and the firms under assessment are classified by means of RAM into efficient (i.e., best) and inefficient, with a CI that equals to unity or takes values less than unity, respectively. The GRA based GRGs support the firm ranking provided by RAM scores. In the second stage, the results show that the Class 7 contracting license firms seem to not be superior in efficiency to their counterparts that belong to Classes 5–6.

In regard to managerial implications, the RAM of efficiency produces the performance metric of each one of the sampled firms. The produced scores of RAM of efficiency can serve for firm managers as they reflect the level of firm overall performance; the derived GRGs can be seen as an alternative measure of performance. Moreover, among firm-related variables, the firms that belong to upper class (Class 7) do not have a comparative advantage compared to the firms of other classes.

The implication to consultants is that in a prequalification process they should take into account this factor. As for construction firms, they should put their efforts towards the delivery of financial outcomes as they expressed by the selected single financial ratios.

7. Conclusions

The current research employs the RAM-Tobit modeling for the performance evaluation of a sample of Greek construction firms. The data on selected financial ratios of the sampled firms are used to demonstrate the practical implementation of the suggested approach.

In the first step of analysis, scores of firm RAM of efficiency are produced using quick ratio, ROE, and equity to asset ratio as ratios that should be maximized. In the financial ratio selection process, GRA is employed. The RAM provides for each of the sample firms a CI that reflects the overall firm performance in liquidity, profitability, and financial autonomy, whereas the produced GRGs can be seen as an alternative measure of performance. In the light of the RAM results, only 4% of the sampled firms are efficient, compared to the rest of the firms and the produced GRGs support the firm ranking provided by RAM results. Moreover, the Class 7 contracting license firms seem to not be superior in efficiency to their counterparts that belong to Classes 5–6. Since there is no evidence for difference in performance between the firms with the highest class (Class 7) contracting license and their counterparts that belong to Classes 5–6, future studies on the financial statement data of Greek construction firms of the three upper-class contracting license (Classes 5–7) should analyze

them together and not separately. It may be argued that the results of the study have potential for generalization in the three upper-class contracting license (Classes 5–7) Greek construction firms.

The analysis performed here involves only static snapshot results to demonstrate the practical implementation of the proposed framework. These results can be complemented in the future by analyzing firm time series by means of dynamic DEA. Since the GRA in the current study uses equal weights for the attributes; this can be seen as a limitation of the study that can be addressed in future research by using other suitable methods that are able to produce attribute weights. Moreover, since the separability assumption is very important another avenue for future research would be the investigation of applicability of conditional efficiency models for the case of construction firms.

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References

1. Zolfani, H.S.; Zavadskas, E.K.; Turskis, Z. Design of products with both International and Local perspectives based on Yin-Yang balance theory and SWARA method. *Econ. Res. Ekon. Istraživanja* **2013**, *26*, 153–166. [CrossRef]
2. Turskis, Z.; Lazauskas, M.; Zavadskas, E.K. Fuzzy multiple criteria assessment of construction site alternatives for non-hazardous waste incineration plant in Vilnius city, applying ARAS-F and AHP methods. *J. Environ. Eng. Landsc. Manag.* **2012**, *20*, 110–120. [CrossRef]
3. Erdogan, S.A.; Šaparauskas, J.; Turskis, Z. Decision making in construction management: AHP and expert choice approach. *Procedia Eng.* **2017**, *172*, 270–276. [CrossRef]
4. Bagočius, V.; Zavadskas, E.K.; Turskis, Z. Multi-person selection of the best wind turbine based on the multi-criteria integrated additive-multiplicative utility function. *J. Civ. Eng. Manag.* **2014**, *20*, 590–599. [CrossRef]
5. Ruzgys, A.; Volvačiovas, R.; Ignatavičius, Č.; Turskis, Z. Integrated evaluation of external wall insulation in residential buildings using SWARA-TODIM MCDM method. *J. Civ. Eng. Manag.* **2014**, *20*, 103–110. [CrossRef]
6. Karabasevic, D.; Zavadskas, E.K.; Turskis, Z.; Stanujkic, D. The framework for the selection of personnel based on the SWARA and ARAS methods under uncertainties. *Informatica* **2016**, *27*, 49–65. [CrossRef]
7. Stanujkic, D.; Zavadskas, E.K.; Karabasevic, D.; Turskis, Z.; Keršulienė, V. New group decision-making ARCAS approach based on the integration of the SWARA and the ARAS methods adapted for negotiations. *J. Bus. Econ. Manag.* **2017**, *18*, 599–618. [CrossRef]
8. Chalekaee, A.; Turskis, Z.; Khanzadi, M.; Ghodrati Amiri, G.; Keršulienė, V. A new hybrid model with grey numbers for the construction delay change response problem. *Sustainability* **2019**, *11*, 776. [CrossRef]
9. Turskis, Z.; Dzitac, S.; Stankiuviene, A.; Šukys, R. A fuzzy group decision-making model for determining the most influential persons in the sustainable prevention of accidents in the construction SMEs. *Int. J. Comput. Commun. Control* **2019**, *14*, 90–106. [CrossRef]
10. Turskis, Z.; Keršulienė, V.; Vinogradova, I. A new fuzzy hybrid multi-criteria decision-making approach to solve personnel assessment problems. Case study: Director selection for estates and economy office. *Econ. Comput. Econ. Cybern. Stud. Res.* **2017**, *51*, 211–229.
11. Zemlickienė, V.; Turskis, Z. Evaluation of the expediency of technology commercialisation: A case of information technology and biotechnology. *Technol. Econ. Dev. Econ.* **2020**, *26*, 271–289. [CrossRef]
12. Callen, J.L. Data Envelopment Analysis: Partial Survey and Applications for Management Accounting. *J. Manag. Account. Res.* **1991**, *3*, 35–56.
13. Malmi, T. Managerialist studies in management accounting: 1990–2014. *Manag. Account. Res.* **2016**, *31*, 31–44. [CrossRef]
14. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]

15. Kadoya, S.; Kuroko, T.; Namatame, T. Contrarian investment strategy with data envelopment analysis concept. *Eur. J. Oper. Res.* **2008**, *189*, 120–131. [CrossRef]

16. Kuo, K.C.; Lu, W.M.; Dinh, T.N. Firm performance and ownership structure: Dynamic network data envelopment analysis approach. *Manag. Decis. Econ.* **2020**, *41*, 608–623. [CrossRef]

17. Kasanen, E.; Lukka, K.; Siitonen, A. The constructive approach in management accounting research. *J. Manag. Account. Res.* **1993**, *5*, 243–264.

18. Horta, I.M.; Camanho, A.S.; da Costa, J.M. Performance assessment of construction companies: A study of factors promoting financial soundness and innovation in the industry. *Int. J. Prod. Econ.* **2012**, *137*, 84–93. [CrossRef]

19. Cooper, W.W.; Park, K.S.; Pastor, J.T. RAM: A range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. *J. Product. Anal.* **1999**, *11*, 5–42. [CrossRef]

20. Lozano, S.; Gutierrez, E. Data envelopment analysis of the human development index. *Int. J. Soc. Syst. Sci.* **2008**, *1*, 132–150. [CrossRef]

21. Tsolas, I.E. Utility exchange traded fund performance evaluation. A comparative approach using GRA and DEA modelling. *Int. J. Financ. Stud.* **2019**, *7*, 67.

22. Nguyen, H.K. Combining DEA and ARIMA models for partner selection in the supply chain of Vietnam's construction industry. *Mathematics* **2020**, *8*, 866. [CrossRef]

23. Tsolas, I.E. Construction project monitoring by means of RAM-based composite indicators. *J. Oper. Res. Soc.* **2013**, *64*, 1291–1297. [CrossRef]

24. Kuo, Y.; Yang, T.; Guan-Wei, H. The use of grey relational analysis in solving multiple attribute decision-making problems. *Comput. Ind. Eng.* **2008**, *55*, 80–93. [CrossRef]

25. Jato-Espino, D.; Castillo-Lopez, E.; Rodriguez-Hernandez, J.; Canteras-Jordana, J.C. A review of application of multi-criteria decision making methods in construction. *Autom. Constr.* **2014**, *45*, 151–162. [CrossRef]

26. Turner, L.D. Improved Measures of Manufacturing Maintenance in a Capital Budgeting Context: An Application of Data Envelope Analysis Efficiency Measures. *J. Manag. Account. Res.* **1990**, *2*, 127–142.

27. Banker, R.D.; Chang, H.; Das, S. Standard estimation, standard tightness, and benchmarking: A method with an application to nursing services. *J. Manag. Account. Res.* **1998**, *10*, 133–152.

28. Deville, A. Branch banking network assessment using DEA: A benchmarking analysis–A note. *Manag. Account. Res.* **2009**, *20*, 252–261. [CrossRef]

29. Deville, A.; Ferrier, G.D.; Leleu, H. Measuring the performance of hierarchical organizations: An application to bank efficiency at the regional and branch levels. *Manag. Account. Res.* **2014**, *25*, 30–44. [CrossRef]

30. Halkos, G.E.; Salamouris, D.S. Efficiency measurement of the Greek commercial banks with the use of financial ratios: A data envelopment analysis approach. *Manag. Account. Res.* **2004**, *15*, 201–224. [CrossRef]

31. Rouse, P.; Putterill, M.; Ryan, D. Integrated performance measurement design: Insights from an application in aircraft maintenance. *Manag. Account. Res.* **2002**, *13*, 229–248. [CrossRef]

32. Alimohammadlou, M.; Bonyani, A. A comparative analysis of dynamic and cross-sectional approaches for financial performance analysis. *Am. J. Financ. Account.* **2018**, *5*, 253–275. [CrossRef]

33. Oral, M.; Yalalan, R. An empirical study on measuring operating efficiency and profitability of bank branches. *Eur. J. Oper. Res.* **1990**, *46*, 282–294. [CrossRef]

34. Smith, P. Data envelopment analysis applied to financial statements. *Omega Int. J. Manag. Sci.* **1990**, *18*, 131–139. [CrossRef]

35. Yeh, Q.-J. The application of data envelopment analysis in conjunction with financial ratios for bank performance evaluation. *J. Oper. Res. Soc.* **1996**, *47*, 980–988. [CrossRef]

36. Bowlin, W.F. An analysis of the financial performance of defense business segments using Data Envelopment Analysis. *J. Account. Public Policy* **1999**, *18*, 287–301. [CrossRef]

37. Feroz, E.H.; Kim, S.; Raab, R.L. Financial statement analysis: A data envelopment analysis approach. *J. Oper. Res. Soc.* **2003**, *54*, 48–58. [CrossRef]

38. Rodriguez-Perez, G.; Slof, J.; Sola, M.; Torrent, M.; Vilardell, I. Assessing the impact of fair-value accounting on financial statement analysis: A data envelopment analysis approach. *Abacus* **2011**, *47*, 61–84. [CrossRef]

39. Demerjian, P.; Lev, B.; Mcvay, S. Quantifying managerial ability: A new measure and validity tests. *Manag. Sci.* **2012**, *58*, 1229–1248. [CrossRef]

40. Harrison, J.; Rouse, P. DEA and accounting performance measurement. In *Handbook of Operations Analytics Using Data Envelopment Analysis*; Hwang, S.-N., Lee, H.-S., Zhu, J., Eds.; Springer Science + Business Media: New York, NY, USA, 2016; pp. 385–412.

41. Pilateris, P.; McCabe, B. Contractor financial evaluation model (CFEM). *Can. J. Civ. Eng.* **2003**, *30*, 487–499.

42. Banker, R.D.; Charnes, A.; Cooper, W.W. Models for estimating technical and scale efficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]

43. McCabe, B.; Tran, V.; Ramani, J. Construction prequalification using data envelopment analysis. *Can. J. Civ. Eng.* **2005**, *32*, 183–193. [CrossRef]

44. El-Meshaleh, M.S.; Minchin, R.E., Jr.; O'Brien, W.J. Management of construction firm performance using benchmarking. *J. Manag. Eng.* **2007**, *23*, 10–17. [CrossRef]

45. El-Mashaleh, M.S.; Rababeh, S.M.; Hyar, K.H. Utilizing data envelopment analysis to benchmark safety performance of construction contractors. *Int. J. Proj. Manag.* **2010**, *28*, 61–67. [CrossRef]

46. Sueyoshi, T.; Goto, M. DEA-DA for bankruptcy-based performance assessment: Misclassification analysis of the Japanese construction industry. *Eur. J. Oper. Res.* **2009**, *199*, 576–594. [CrossRef]

47. Horta, I.M.; Camanho, A.S.; da Costa, J.M. Performance assessment of construction companies integrating key performance indicators and data envelopment analysis. *J. Constr. Eng. Manag.* **2010**, *136*, 581–594. [CrossRef]

48. Horta, I.M.; Camanho, A.S. Competitive positioning and performance assessment in the construction industry. *Expert Syst. Appl.* **2014**, *41*, 974–983. [CrossRef]

49. Seiford, L.M.; Zhu, J. Profitability and marketability of the top 55 U.S. commercial banks. *Manag. Sci.* **1999**, *45*, 1270–1288. [CrossRef]

50. Tsolas, I.E. Modelling profitability and effectiveness of Greek-listed construction firms: An integrated DEA and ratio analysis. *Constr. Manag. Econ.* **2011**, *29*, 795–807. [CrossRef]

51. Tsolas, I.E. Modeling profitability and stock market performance of listed construction firms on the Athens Exchange: Two-Stage DEA approach. *J. Constr. Eng. Manag.* **2013**, *139*, 111–119. [CrossRef]

52. Hu, X.; Liu, C. Profitability performance assessment in the Australian construction industry: A global relational two-stage DEA method. *Constr. Manag. Econ.* **2016**, *34*, 147–159. [CrossRef]

53. Hu, X.; Liu, C. Measuring efficiency, effectiveness and overall performance in the Chinese construction industry. Engineering. *Constr. Archit. Manag.* **2018**, *25*, 780–797. [CrossRef]

54. Christopoulos, A.G.; Dokas, I.G.; Katsimardou, S.; Vlachogiannatos, K. Investigation of the relative efficiency for the Greek listed firms of the construction sector based on two DEA approaches for the period 2006–2012. *Oper. Res.* **2016**, *16*, 423–444. [CrossRef]

55. Belton, V.; Vickers, S.P. Demystifying DEA-A visual interactive approach based on multiple criteria analysis. *J. Oper. Res. Soc.* **1993**, *44*, 883–896.

56. Stewart, T.J. relationships between data envelopment analysis and multicriteria decision analysis. *J. Oper. Res. Soc.* **1996**, *47*, 654–665. [CrossRef]

57. Cook, W.D.; Kress, M.A. multiple criteria decision model with ordinal preference data. *Eur. J. Oper. Res.* **1991**, *54*, 191–198. [CrossRef]

58. Cook, W.D.; Kress, M.A.; Seiford, L.M. Data envelopment analysis in the presence of both quantitative and qualitative factors. *J. Oper. Res. Soc.* **1996**, *47*, 945–953. [CrossRef]

59. Wang, J.; Xu, Y.; Li, Z. Research on project selection system of pre-evaluation of engineering design project bidding. *Int. J. Proj. Manag.* **2009**, *27*, 584–599. [CrossRef]

60. Hong-Yan, Y. The construction project bid evaluation based on gray relational model. *Procedia Eng.* **2011**, *15*, 4553–4557. [CrossRef]

61. Simar, L.; Wilson, P.W. Estimation and inference in two-stage, semi-parametric models of productive processes. *J. Econom.* **2007**, *136*, 31–64. [CrossRef]

62. Banker, R.; Natarajan, R. Evaluating contextual variables affecting productivity using data envelopment analysis. *Oper. Res.* **2008**, *56*, 48–58. [CrossRef]

63. McDonald, J. Using least squares and tobit in second stage DEA efficiency analyses. *Eur. J. Oper. Res.* **2009**, *197*, 792–798. [CrossRef]

64. Ramalho, E.; Ramalho, J.; Henriques, P. Fractional regression models for second stage DEA efficiency analyses. *J. Product. Anal.* **2010**, *34*, 239–255. [CrossRef]

65. Guan, J.; Chen, K. Modeling the relative efficiency of national innovation systems. *Res. Policy* **2012**, *41*, 102–115. [CrossRef]

66. Liu, J.S.; Lu, L.Y.Y.; Lu, W.-M. Research fronts in data envelopment analysis. *Omega* **2016**, *58*, 33–45. [CrossRef]

67. Banker, R.; Natarajan, R.; Zhang, D. Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using Data Envelopment Analysis: Second stage OLS versus bootstrap approaches. *Eur. J. Oper. Res.* **2019**, *278*, 368–384. [CrossRef]

68. Daraio, C.; Simar, L.; Wilson, P.W. Central limit theorems for conditional efficiency measures and tests of the 'separability' condition in non-parametric, two-stage models of production. *Econom. J.* **2018**, *21*, 170–191. [CrossRef]

69. Henriques, I.; Sobreiro, V.A.; Kimura, H.; Mariano, E.B. Two-stage DEA in banks: Terminological controversies and future directions. *Expert Syst. Appl.* **2020**, *161*. [CrossRef]

70. Simar, L.; Wilson, P. Two-stage DEA: Caveat emptor. *J. Product. Anal.* **2011**, *36*, 205–218. [CrossRef]

71. Daraio, C.; Simar, L.; Wilson, P. *Testing Whether Two-Stage Estimation is Meaningful in Non-Parametric Models of Production*; Discussion paper #1031; Institut de Statistique, Universite Catholique de Louvain: Louvain-la-Neuve, Belgium, 2010.

72. Daraio, C.; Simar, L.; Wilson, P. *Testing the "Separability" Condition in Two-Stage Nonparametric Models of Production, LEM Papers Series 2015/21*; Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies: Pisa, Italy, 2015.

73. Benito, B.; Solana, J.; Moreno, M.-R. Explaining efficiency in municipal services providers. *J. Product. Anal.* **2014**, *42*, 225–239. [CrossRef]

74. Lin, C.-T.; Chang, C.-W.; Chen, C.-B. The worst ill-conditioned silicon wafer slicing machine detected by using grey relational analysis. *Int. J. Adv. Manuf. Technol.* **2006**, *31*, 388–395. [CrossRef]

75. Cooper, W.W.; Ruefli, T.W.; Deng, H.; Wu, J.; Zhang, Z. Are state-owned banks less efficient? A long-vs. short-run Data Envelopment Analysis of Chinese banks. *Int. J. Oper. Res.* **2008**, *3*, 533–556. [CrossRef]

76. Charnes, A.; Cooper, W.W.; Golany, B.; Seiford, L.; Stutz, J. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *J. Econom.* **1985**, *30*, 91–107. [CrossRef]

77. Tone, K. A slacks based measure of efficiency in Data Envelopment Analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]

78. Färe, R.; Lovell, C.A.K. Measuring the technical efficiency of production. *J. Econ. Theory* **1978**, *19*, 150–162. [CrossRef]

79. Pastor, J.T.; Ruiz, J.L.; Sirvent, I. An enhanced DEA Russell graph efficiency measure. *J. Oper. Res. Soc.* **1999**, *115*, 596–607. [CrossRef]

80. Cooper, W.W.; Seiford, L.M.; Tone, K.; Zhu, J. Some models and measures for evaluating performances with DEA: Past accomplishments and future prospects. *J. Product. Anal.* **2007**, *28*, 151–163. [CrossRef]

81. Sueyoshi, T.; Sekitani, K. An occurrence of multiple projections in DEA-based measurement of technical efficiency: Theoretical comparison among DEA models from desirable properties. *Eur. J. Oper. Res.* **2009**, *196*, 764–794. [CrossRef]

82. Tobin, J. Estimation of relationships for limited dependent variables. *Econom. J. Econom. Soc.* **1958**, *26*, 24–36. [CrossRef]

83. Tsolas, I.E.; Charles, V. Green exchange-traded fund performance appraisal using slacks-based DEA models. *Oper. Res. Int. J.* **2015**, *15*, 51–77. [CrossRef]

84. Karousos, E.; Vlamis, P. The Greek construction sector: An overview of recent developments. *J. Eur. Real Estate Res.* **2008**, *1*, 254–266. [CrossRef]

85. Association of Greek Contracting Companies (SATE). *Concise Guide of Greek Contracting Companies*; SATE: Athens, Greece, 2010. (In Greek)

86. Kangari, R.; Farid, F.; Elgharib, H.M. Financial performance analysis for construction industry. *J. Constr. Eng. Manag.* **1992**, *118*, 349–361. [CrossRef]

87. Choi, K.; Haque, M.; Lee, H.W.; Cho, Y.K.; Kwak, Y.H. Macroeconomic labour productivity and its impact on firm's profitability. *J. Oper. Res. Soc.* **2013**, *64*, 1258–1268. [CrossRef]

88. Wang, S.; Ma, Q.; Guan, Z. Measuring Hospital Efficiency in China Using Gray Relational Analysis and Data Envelopment Analysis. In Proceedings of the 2007 I.E. International Conference on Gray Systems and Intelligent Services, Nanjing, China, 18–20 November 2007.

89. Jiang, P.; Hu, Y.-C.; Yen, G.-F. Applying grey relational analysis to find interactions between manufacturing and logistics industries in Taiwan. *Adv. Manag. Appl. Econ.* **2017**, *7*, 21–40.

90. Feng, C.-M.; Wang, R.-T. Performance evaluation for airlines including the consideration of financial ratios. *J. Air Transp. Manag.* **2000**, *6*, 133–142. [CrossRef]