Assessment of performance and innovation of Portuguese construction companies

Isabel M. Horta[a*], Ana S. Camanho[b], Jorge M. Costa[c]

[a]Faculdade de Engenharia da Universidade do Porto, Porto, Portugal
imhorta@fe.up.pt

[b]Faculdade de Engenharia da Universidade do Porto, Porto, Portugal
acamanho@fe.up.pt

[c]Faculdade de Engenharia da Universidade do Porto, Porto, Portugal
jmfcosta@fe.up.pt

[*]Corresponding Author

Abstract

This paper evaluates the performance of Portuguese construction companies between 1996 and 2007. The purpose of the paper is to explore the trends in construction industry performance, and identify the factors that promote excellence and innovation in the sector. From a methodological perspective, this study enhances the construction of composite indicators by using Data Envelopment Analysis to aggregate the key performance indicators of the construction companies. The statistical significance of the results obtained is ensured by the use of bootstrapping. This paper also proposes an enhanced approach to assess innovation within the industry, enabling the identification of innovative companies and the extent of innovation.

Keywords: Composite indicators, Innovation, Construction Industry.

1- Introduction

In recent years, it is well-known that the competitive environment of the Construction Industry (CI) has become increasingly fierce. The construction companies are aware of the challenges imposed by this context and attempt to implement systematic methods of performance assessment in order to achieve competitive advantage. The research described in this paper intends to promote sustainable performance improvements for CI companies, and to encourage excellence in the sector.

Performance assessment in the CI has been subject to a considerable amount of research over the past 15 years (see Bassioni et al., 2004 for a literature review). Following the publication of the seminal reports, such as the Egan (1998), construction companies have been mostly concerned with benchmarking systems based on key performance indicators (KPIs). These systems are usually available in the internet, and enable collecting data and produce real-time results concerning performance levels. Costa et al. (2006) describe the scope of the four most well known web-based benchmarking programs focused on construction company performance measurement, carried out in Brazil, Chile, United Kingdom and United States.

More recently, the literature on performance measurement has described successful applications of the Data Envelopment Analysis (DEA) technique to the CI. El-Mashaleh et al. (2007) considered DEA a tool that can offer significant improvements over web-based benchmarking systems for the CI. According to the authors, the existing benchmarking systems have limitations in their ability to guide the industry towards more efficient and effective performance. The DEA models proposed allow construction firms to be evaluated on a company-wide basis and to identify specific areas of improvement. Horta et al. (2010) developed a methodology for assessing company performance combining the use of KPIs and DEA. The models proposed evaluate the relative efficiency of the companies and provide performance improvement targets for all companies, even for the best-practice companies. This is achieved by the specification of virtual companies, whose activity reflects the decision maker preferences.

The purpose of this paper is to evaluate the financial performance and competitive environment of the construction industry in Portugal in the recent past, between 1996 and 2007. In particular, we explored the trends concerning performance improvement and decline, and identified the companies that were able to innovate during this period. This was followed by a study of the factors promoting excellence in the sector. We explored the relationship between performance and company size, location of the headquarters, engagement in Research and Development (R&D) and the evolution of the national economic environment.

The remainder of this paper is organized as follows. Section 2 describes the methods used. Section 3 includes the data used in the study, and Section 4 discusses the results obtained. The last section concludes and suggests recommendations for future research.

2- The methodology

2.1 Performance Assessment

DEA, first introduced by Charnes et al. (1978), is a linear programming technique for comparing the efficiency of a relatively homogeneous set of organizational decision making units (DMUs) in their use of multiple resources (inputs) to produce multiple outcomes (outputs). DEA derives a single summary measure of efficiency for each DMU, which is based on the comparison with other DMUs in the sample. This assessment is relative, as the DMUs are compared to others within a sample. DEA identifies a subset of efficient DMUs, considered as examples of best practices or benchmarks. For the inefficient DMUs, the magnitude of their inefficiency is derived by the distance to the frontier constructed from the benchmark DMUs. The efficient DMUs obtain a performance score equal to 100%, and the inefficient ones obtain a score lower than 100%. The comparison with the benchmarks also allows determining the input and output targets corresponding to efficient operation.

In this paper, the DEA model used followed the research line proposed by Cherchye et al. (2004), which popularized the concept of composite indicators estimated recurring to optimization techniques. The main difference between a traditional DEA efficiency analysis and the construction of a composite indicator as proposed by Cherchye et al. (2004) is that the latter only looks at achievements, without explicitly taking into account the resources used. The rationale of using a DEA model to obtain a composite indicator is to aggregate a set of KPIs into a single summary measure of performance. Nevertheless, these KPIs must be carefully specified, as they must reflect the outputs achieved normalised by the resources used, as otherwise the comparison between companies would be impaired. The advantage of using DEA is to allow each company to select its own weighting system for the performance evaluation, recurring to optimization techniques that emphasize the company strengths. The linear programming (LP) model for deriving the composite indicator C_{j_0} for a company j_0 is shown in (1).

$$
\begin{aligned}
C_{j_0} = max \sum\nolimits_{r=1}^{s} & \mathrm{u_r y_{rj_0}} \\
\text{s.t.} \sum\nolimits_{r=1}^{s} & \mathrm{u_r y_{rj}} \leq 1 \qquad j = 1, \dots, n \\
& \mathrm{u_r} \geq 0 \qquad\qquad r = 1, \dots, s
\end{aligned}
\tag{1}
$$

In model (1), y_{rj_0} corresponds to the value of the output indicator r (r=1,...,s) in company j (j=1,...,n), with higher values corresponding to better performance. Model (1) is equivalent to the original DEA constant returns to scale model of Charnes et al. (1978), with all indicators considered as outputs and a "dummy input"[1] with the same value for all companies. We run model (1) including a pooled sample of the Portuguese CI companies, comparing the financial indicators of each company in each year with a frontier representing the best practices of the period analyzed.

The rationale basis of this procedure to evaluate the construction companies is easy to explain: since it is difficult to identify a priori a set of weights that all companies would agree that reflects adequately the relative importance of each indicator y_r, we let each company select its own weights, such that its composite indicator is as high as possible compared to the composite indicator of other companies evaluated with similar weights. If we impose an upper bound of one to the highest composite indicator obtained across all companies, a value of the composite indicator equal to one signals best performance (i.e., benchmarks). Under these conditions, if a company does not achieve the maximum score, even when evaluated with a set of weights that intends to maximize its performance score, it provides irrefutable evidence that other companies performed better during the period considered.

After computing the composite indicators, we used bootstrapping to obtain unbiased performance estimates. Bootstrapping is based on the idea of resampling from an original sample of data to create replicate datasets from which we can make statistical inference. Performance estimates computed by model (1) are truncated, with an upper value equal to one, and there may exist several estimates close to unity. Consequently, resampling directly from the original data (naive bootstrap) provides a poor estimate of the data generating process. The common approach is to nonparametrically estimate the original densities of the performance scores using kernel smoothing methods, combined with a reflection method. Simar and Wilson (1998} proposed the smoothed bootstrap method which deals with all the particular features of DEA-based performance scores when mimicking the data generating process. This was the procedure adopted in this paper, which was implemented using the statistical package R including the FEAR library, developed by Wilson (2008).

2.2 Explaining Performance

To explore the factors that may be associated with good performance levels of the construction companies, we used a panel data truncated model controlling both for company and time effects. The model was specified as follows

$$C_{jt} = \alpha_0 + \delta_j + \mu_t + z_{jt}\beta + \varepsilon_{jt} \qquad (2)$$

Subscript j represents the jth company (j=1,...,n), subscript t represents the time period (t=1,...,l), α_0 is an intercept, δ_j is a vector of dummy variables for each company, μ_t is a vector of dummy variables for each year, z_{jt} represents the set of regressors: company size, geographic location, R&D engagement, and national Gross Domestic Product (GDP) per capita, β denotes the regression coefficients and $\varepsilon_{jt} \sim N(0,\sigma^2_\varepsilon)$ is the error term. Note that C_{jt} corresponds to the performance level of company j in year t, estimated using model (1) and corrected by bootstrapping.

2.3 Assessment of Innovation

The final stage of the performance assessment is related to the evaluation of innovation. In this study, a company is considered an innovator if it shifts the best-practice frontier of a given year to better levels than those observed in previous time periods. This means that an innovator company is able to introduce better practices in the industry. The other companies (i.e. the followers, hereafter) can improve their performance by copying the practices observed in the innovators.

The assessment of innovation using DEA models was originally proposed by Fare et al. (1994), and served as the basis for the analysis described. In this study, the concept of innovation was adapted to an evaluation of performance based on composite indicators. Another enhancement of our approach concerns the comparison of the achievements of a company in year t with the practices observed in all previous years, up to year t, whereas the concept of innovation proposed by Fare et al. (1994) only involved a comparison of practices between two consecutive years.

To be able to identify the innovators, we run a LP model comparing the performance of each company, in a given year t, with the performance of all other companies, including observations from the same year and from previous years. As proposed by Tulkens and Vandeneeckaut (1995), a frontier that results from an assessment whose production possibility set is defined including observations from a given year as well as from previous periods is called a sequential frontier. This frontier is based on the idea that what was feasible in the past remains achievable in any later period. We consider that a necessary condition to be innovator in year t is to be located in the best practice sequential frontier, which implies having a composite indicator equal to one in a sequential frontier assessment.

To quantify the magnitude of the performance enhancement of innovative companies in relation to previous years, we run a second LP model comparing the performance of the innovators in year t, with all other companies in previous years, up to t-1. The estimate obtained using this procedure is called innovation score hereafter. Note that this second LP model differs from the previous assessment due to the exclusion of observations from year t. The innovation score can either be equal to one, meaning that the achievement of company j in year t is identical to what was observed in previous years, or greater than one, meaning that the company has actually moved the frontier to more productive levels than those previously observed.

The final stage of the analysis of innovation consisted on the study of the factors that promote innovation in the CI. For this purpose, we constructed a logistic regression model, where the dependent variable characterizes the companies as innovators or followers. In particular, a value of one for the dependent variable represents the companies that innovated in at least one of the years analyzed, and zero represents the remaining companies - the followers. The logistic model predicts the odds of being innovator, given known values of the independent variables. The odds is defined as the ratio of the probability of being innovator to the probability of being follower. The logistic model can be specified as follows:

$$ln\left(\frac{P_j}{1-P_j}\right) = \alpha_0 + z_j\beta \quad (3)$$

In the expressions above, P_j is the predicted probability of being innovator for the j[th] company, and z_j represents the set of regressors: company size, geographic location, R&D engagement, liquidity, financial autonomy, value added and profitability. Companies with P_j values above 0.5 are classified in the innovators group, and companies with P_j values below 0.5 in the followers group. The classification accuracy of the model is obtained by comparing the actual with the predicted status.

3- The data

This paper used a sample of 90 companies corresponding to major Portuguese contractors laboring on public works. The longitudinal assessment reported covers the time period between 1996 and 2007. The data used came from the database of the 500 larger Portuguese companies, in terms of value of sales, published every year in the *Exame* magazine. The construction companies sampled vary from one year to the other, which is explained by the volatility of the market. In particular, new companies enter the market, and others may cease activity, merge or not provide data in some years. This implies that the assessment explores an unbalanced panel data sample.

The performance assessment model specified in this paper characterizes companies mainly from a financial perspective. The indicators used are: i) Profitability - to measure the profit of the company before tax and interest; ii) Value added - to measure the value-added per employee; iii) Financial Autonomy - to measure the contribution of equity on company funding; iv) Liquidity - to measure the company capacity to face short-term commitments. The value added indicator was deflated using the Gross Domestic Product (GDP) deflator, available in the World Bank's World Development Indicators database (http://data.worldbank.org/), considering 1996 as the base year. The last two indicators have minimum obligatory requirements to allow contractor activity in Portugal (at least 110% on Liquidity and 15% on Financial Autonomy).

4- Empirical Results

4.1 Performance Assessment

The first stage of the assessment was intended to explore whether the performance level of Portuguese construction companies improved over time. This required the estimation of a composite performance indicator for each company in each year, which was based on a comparison with a pooled frontier representing the best practices observed in the 12 years analyzed.

Table 1 reports the summary results for the composite indicator obtained using model (1). It also indicates the number of companies with a composite indicator equal to one in each of the years. These observations can be considered the benchmarks, as they correspond to the best financial results for the years studied. The bootstrap results are also shown in the middle panel of the table, including the average of the bias-corrected estimates, bias, standard deviation, and 95% confidence intervals for the bias-corrected composite indicator in the corresponding year.

Table 1 – Results of original and bootstrapped performance estimates

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Original Sample												
Performance score	0.555	0.563	0.591	0.618	0.636	0.617	0.650	0.694	0.682	0.697	0.705	0.678
No. of benchmarks	0	0	0	0	0	0	0	2	1	1	6	1
Bootstrap Sample	0.530	0.533	0.560	0.588	0.605	0.588	0.617	0.653	0.642	0.648	0.650	0.639
Bias-corrected score	0.025	0.030	0.031	0.030	0.031	0.029	0.033	0.041	0.039	0.049	0.055	0.039
Bias	0.025	0.030	0.031	0.030	0.031	0.029	0.033	0.041	0.039	0.049	0.055	0.039
St. Dev.	0.011	0.013	0.014	0.013	0.014	0.013	0.014	0.018	0.017	0.021	0.022	0.016
Lower Bound	0.514	0.516	0.543	0.571	0.587	0.570	0.598	0.633	0.623	0.629	0.633	0.619
Upper Bound	0.549	0.555	0.584	0.611	0.628	0.610	0.641	0.684	0.673	0.686	0.694	0.668

From the bootstrapped results, we can observe that the bias-corrected estimate is within relatively narrow confidence intervals, i.e. the lower and upper bounds of the intervals are relatively close. This provides statistical confidence for the bias-corrected estimate. Moreover, as the estimated bias is much larger than the standard deviation for all the companies, we conclude that the bias-corrected estimates should be preferred to the original estimates, as explained in Fried et al. (2008, p.467). Thus, the bias-corrected estimates were used in all analysis reported hereafter.

From Table 1 we can conclude that the performance estimates exhibited an increasing trend across years, although in 2001, 2004 and 2007 the performance levels suffered a decline in relation to the previous year. Comparing the average bias-corrected performance score of 2007 with the value of 1996, we can conclude that the financial performance of the Portuguese construction companies increased approximately 20% during this period, which is a remarkable improvement. It is also interesting to note that although the confidence intervals from consecutive years overlap, it is possible to observe a significant performance improvement between the first years analyzed (from 1996-1999) and recent years (from 2003-2007). This leads us to the conclusion that the Portuguese construction companies improved their financial performance during the period analyzed, at a statistically significant degree.

4.2 Drivers of good performance

The purpose of this section is to explore the determinants of good performance. In particular, we explored the impact of the economic context, geographic location, company size and engagement on R&D projects on company financial performance. The national economic context was characterized by GDP per capita, measured in US dollars. The data was taken from the World Bank's World Development Indicators database. This variable was deflated using the GDP deflator, considering 1995 as the base year. The regression model included two factors related to GDP: the GDP per capita of the same year as the composite performance indicator used as dependent variable, as well as the GDP per capita of the previous year. The one year lag was included in the regression model to test the hypothesis that the economic context of a given year affects the industry performance in the following year. The company size variable was measured by the value of sales, in real terms. The square of the value of sales was also included in the model to allow for the existence of variable returns to scale. The geographic location of companies corresponds to the location of headquarters. To explore if companies with headquarters located in the capital or its vicinity outperform the other companies, we considered a dummy variable distinguishing this region from the others. The engagement on R&D projects corresponds to a dummy variable distinguishing between "engaged" or "not engaged" on R&D projects. This qualitative information was provided by CI academic experts routinely involved in conducting R&D projects in many CI companies, with a deep knowledge of the Portuguese CI and its players. Table 2 reports the estimates from the panel data truncated model, the coefficients, standard errors, and p-values. The total number of observations included in the model was 494, corresponding to all observations analyzed in all years. Note that we also used time and company dummies to control for time and company effects. The overall regression model was found to be statistically significant (χ^2 test with p-value of 0.000).

Table 2 – Regression results for the drivers of performance

Variable	Coefficient	Standard error	*p*-value
Size	-0.114	0.022	0.000
Size squared	0.014	0.003	0.000
GDP	-0.014	0.011	0.206
GDP (1 year lag)	0.039	0.014	0.005
Lisbon area	0.035	0.085	0.682
R&D engagement	0.018	0.111	0.873
Constant	0.403	0.097	0.000

From the results of Table 2, we can conclude that the national economic context has an impact on the performance of CI companies with a lag of one year. This impact is positive, meaning that a higher GDP promotes better performance of the CI one year latter. The current economic context has no significant impact on the financial performance of companies. Company size is related to performance nonlinearly, as both the first and the second order coefficients are statistically significant. Performance is U-shaped in relation to size. In particular, performance first decreases as company size increases, and for a value of sales greater than 421 million euros, performance starts to increase as size further increases. This means that the best performance levels tend to be achieved by small specialized companies, as well as by large companies. We reject the hypothesis that the engagement on R&D projects has a direct impact on financial performance. However, the long-term impact of R&D engagement on performance still remains an open question. The geographic location is not influential as well. This means that companies with their headquarters located in the capital or its surrounding area did not outperform the other companies. This could be expected due to the small dimension of Portugal, enabling a nationwide company activity.

4.3 Companies that innovated

This section explores innovation among CI companies in the period 1996 to 2007. Innovation in the context of this study reflects the ability of the CI companies to shift the frontier of financial achievements to better levels than those observed in previous years.

This analysis revealed that 22 companies from the 90 included in the sample were considered innovators in at least one year. Several companies (10) were considered innovative just in one year. Only 6 companies were considered innovators in more than half the years for which data was available for their evaluation. This suggests that keeping in the cutting edge of innovation for long periods is a difficult task. Nevertheless, it is interesting to note that there were innovators in all years studied. The years with the lowest innovation score were 2002 and 2007, both with a score of 1.05. These years coincide with some of the years that occurred a performance decline in the industry. Concerning the years with the highest innovation score (1997 and 2004), both with a score of 1.44, it can be concluded that a good innovation score for a few companies does not necessarily coincide with years of particularly good performance for the whole industry. Analyzing the performance pattern of innovator companies over time, we can conclude that high levels of performance typically precede the innovative status of companies. In particular, the companies that were innovative more than once during the period studied (12) were able to keep high levels of performance in most years for which data was available.

Next, we explored the factors that promote innovation. We used a logistic regression, where the dependent binomial variable represented the company status: innovators (1) or followers (0). The regressors were company size, location, R&D engagement, as well as the average value of the KPIs related to the financial status of the company in the period analyzed (i.e., the average value of liquidity, financial autonomy, value added and profitability). Table 3 reports the estimates from the logistic model, the coefficients, standard errors, Wald statistics, and p-values.

Table 3 shows that company size, R&D engagement, and location are not statistically significant at a 5% level. Concerning the financial status, the most critical factor to promote innovation is profitability, followed by value added. The overall model is statistically significant (χ^2 test with p-value of 0.000), with a Nagelkerke R^2 of 39.9%. The overall percentage of observations classified correctly was 82.2% ((10+64)/90). This value is considerably larger that the proportional chance criterion of 39.8% ($(22/90)^2+(68/90)^2$), which shows that the logistic regression is a good option to model the factors that promote innovation.

Table 3 – Logistic regression estimates

Variable	Coefficient	Standard error	Wald statistic	*p*-value
Size	-0.269	0.468	0.329	0.566
R&D engagement	0.151	0.668	0.051	0.822
Lisbon area	0.403	0.636	0.402	0.526
Profitability	0.390	0.177	4.850	0.028
Value added	0.063	0.035	3.198	0.074
Financial autonomy	0.025	0.042	0.370	0.543
Liquidity	0.012	0.009	1.875	0.171
Constant	-6.928	2.071	11.194	0.001

5- Conclusions

The purpose of this paper was to develop a quantitative approach to evaluate the financial performance of construction companies, and to identify the factors that promote performance improvements and innovation. To assess contractors performance we used a composite indicator calculated using DEA, and complemented with bootstrapping to obtain a robust estimate of performance. The study revealed that the performance of Portuguese construction companies increased during the years analyzed. Regarding the factors considered more influential, we concluded that company performance is affected by the national economic context with a one year lag, and that small specialized companies and large companies tend to achieve the best performance levels.

Concerning the assessment of innovation, this paper proposed an enhanced approach to identify innovative companies, to quantify the extent of innovation, and to explore the factors that drive innovation. It was concluded that keeping the innovative status for long periods is difficult, although a few companies were able to keep their innovative status in consecutive years. It was also found that high levels of performance typically precede the innovative status of companies. Concerning the factors that promote innovation, the results of the assessment suggest that the innovators are typically companies with high profitability.

5- References

Bassioni, H.A., Price A. D., and Hassan T. M. (2004). "Performance Measurement in Construction," *Journal of Management in Engineering* 20 (2): 42-50.

Charnes, A. Cooper W. W., and Rhodes E. (1978). "Measuring Efficiency of Decision Making Units," *European Journal of Operational Research* 2 (6): 429-444.

Cherchye L., Moesen W., and Puyenbroeck T.V. (2004). "Legitimately Diverse, yet Comparable: On Synthesizing Social Inclusion Performance in the EU," *Journal of Common Market Studies* 42(5): 919-955.

Costa D., Formoso C., Kagioglou M., Alarcon F. and Caldas H. (2006). "Benchmarking Initiatives in the Construction Industry: Lessons Learned and Improvement Opportunities.," *Journal of Management in Engineering* 22 (4): 158-167.

Egan J. (1998). *Rethinking Construction*. Technical report, Dept. of the Environment, Transport and the Regions, London.

El-Mashaleh M., Minchin R., and O'Brie W. (2007)., "Management of Construction Firm Performance Using Benchmarking," *Journal of Management in Engineering* 23 (1): 10-17.

Fare R., Grosskopf S., Norris M., and Zhang Z. (1994). "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *The American Economic Review* 87(5): 1040-1043.

Fried H.O., Lovell C.A.K., and Schmidt S.S. (2008), *The measurement of productive efficiency and productivity growth*. Oxford University Press US, New York.

Horta I.M., Camanho A.S., and Moreira Costa J. (2010). "Performance Assessment of Construction Companies Integrating Key Performance Indicators and Data Envelopment Analysis," *Journal of Construction Engineering and Management* 136 (5): 581-594.

Simar L. and Wilson P.W. (1998). "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models," *Management Science* 44(1): 49-61.

Tulkens H. and Vandeneeckaut P. (1995). "Nonparametric efficiency, progress and regress measures for panel-data - methodological aspects," *European Journal of Operational Research* 80(3): 474-499.

Wilson P.W. (2008). "FEAR: A package for frontier efficiency analysis with R," *Socio-Economic Planning Sciences* 42(4): 247-254.