Journal of Scientific & Industrial Research
Vol. 79, June 2020, pp. 534-536

Identifying Industrial Productivity Factors with Artificial Neural Networks

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Received 27 March 2020; revised 30 April 2020; accepted 4 May 2020

Productivity is an important issue in recent literature because it encourages cost savings and efficiency in the use of industrial resources in all countries. However, the study of the factors that explain the productivity levels reached by the companies presents controversy, and the existing research demands new analysis models that can more accurately identify the causes of industrial productivity. The present study aims to develop a new model that allows determining with high accuracy the factors that explain productivity in the construction industry. For this, an important sample of industrial companies and techniques of artificial neural networks has been used. The results obtained provide levels of accuracy that exceed those obtained by the previous literature, and have allowed us to identify that the aspects related to turnover, liquidity, and growth of companies provide an excellent strategy for promoting industrial productivity.

Keywords: Multi-Layer Perceptron, Construction Industry, Industrial Analysis

Introduction

Industry productivity plays an important role in the economy of all countries, as it promotes cost savings and efficiency in the use of resources. In recent decades, the analysis of productivity and the factors associated with it has been the most important concern in developed and underdeveloped countries.[1,2] In this sense, the concept of productivity has been the subject of different approaches adopted by researchers, giving rise to a wide variety of definitions of productivity.[3,4] However, most definitions refer to a comparison of inputs versus outputs, that is, the use of factors concerning for to production. Many studies have investigated factors that affect productivity in the industry. These factors can be classified into four categories: management, technical, labour, and external.[5] However, the importance of these factors varies from country to country, and the existing results emerge from measurement models that do not offer high levels of accuracy.[5,6] To shed light on the importance of factors that explain productivity in construction industry, this study focuses on management factors, providing an analysis of economic and financial variables that explain levels of industrial productivity with a high level of accuracy, using a Multi-Layer Perceptron model.

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Methodology

Multi-Layer Perceptron (MLP) is an artificial neural network model with one layer of input units, another layer of output units, and some intermediate layers called hidden layers, that have no connection to the outside. Each input unit is connected to the units of the hidden layer, and these in turn to those of the output layer. The network aims to establish a correspondence between a set of input data and a set of desired outputs, determining a function that correctly represents the training patterns and allows a generalization process for data not analyzed during said training.[7] Learning in MLP is a special case of functional approximation in which no previous hypotheses about the relationship between variables are necessary.[8–10] MLP uses Eq. (1) to provide an adjustment for weights W of a data set that minimizes training error, $E(W)$.

$$\boldsymbol{min_W\, E(W) = min_W \sum_{i=1}^{p} \varepsilon(W, x}_i, y_i) \qquad \ldots (1)$$

Where, $\{(x1, y1), (x2, y2) \ldots (xp, yp)\}$ represents the set of pairs of training patterns, and $\varepsilon\ (W, X, Y)$ is the error function. As a complement to the MLP model, the present study applies a sensitivity analysis of the independent variables.[11] This sensitivity analysis aims to quantify the impact of the variables in explaining the problem under study. Therefore, the objective is to know to what measure the oscillations in input values or parameters influence the output results of this. And it is exactly through the analysis of these variations by which it is possible to determine the importance of each variable seeing as each one of them has a proportional representation in the model. In this sense, one variable is considered more significant than another if the variance increases compared to the set of variables, using the Sobol[12] method, which decomposes the variance of the total output *V(Y)* according to the Eq. (2).

$$\boldsymbol{V}(\boldsymbol{Y}) = \sum_{\boldsymbol{i}} \boldsymbol{V_i} + \sum_{\boldsymbol{i}} \sum_{\boldsymbol{j>i}} \boldsymbol{V_{ij}} + \cdots + \boldsymbol{V_{1,2,\ldots k}} \qquad \ldots(2)$$

$$V_i = V(E(Y|X_i)$$

$$V_{ij} = V(E(Y|X_i, X_j))\text{-}V_i\text{-}V.$$

Sensitivity indexes are determined by $Si = V_i / V$ and $S_{ij} = V_{ij} / V$, being S_{ij} the effect of the interaction between two factors.

Sample and Variables

To have a database that provides significant and homogeneous information in the industry, this study has selected a sample of Spanish companies in the construction industry. The construction industry is a key sector of the national economy for countries around the world, as it traditionally occupies a large part of employment and contributes significantly to the nation's global income.[13,14] Furthermore, productivity is one of the important aspects of the construction industry, as it helps its survival and growth.[15] Specifically, a random sample of 500 Spanish companies operating in the construction industry in 2019 has been selected. Economic and financial information on variables related to their productivity levels has been obtained from the SABI Database of Bureau Van Dijk. Additionally, the sample set has been divided into two sub-samples, one for model training (80% of the data), and the other for testing (20% of the data). For their part, the variables used in the present study appear in Table 1 and have been selected from the previous literature on industrial productivity.[16] Of the set of selected variables, two correspond to the measurement of productivity, Value-added/number of employees (PRO1), and Gross revenues/number of employees (PRO2). For this, it has been taken into account that the definition of productivity respect to the construction industry is the measurement of the production of goods and services per unit of work.[5] These two variables have given rise to the dependent variable in the developed MLP model, which has a dichotomous character, and which is equal to 1 when a company has values in PRO1, and PRO2 higher than the sample mean, and 0 otherwise. On the other hand, the independent variables include aspects related to liquidity, performance, turnover, and growth.

Results

The results obtained with the MLP model are given in Tables 2. The classification level in the training sample is 97.21%, and in the test sample, 94.87%. Furthermore, the ROC curve also indicates a robust classification (0.981).

For its part, Fig. 1 shows the sensitivity of the variables used in the study. The variables TUR1 and TUR2 appear with the highest sensitivity, indicating

Table 1 — Econometric variables

Category	**Code**	**Definition**
Liquidity	LIQ1	Liability/total assets*100
	LIQ2	Current assets/current liability*100
Performance	PER1	Current net profit/total assets*100
	PER2	Current net profit/gross revenues*100
Turnover	TUR1	Gross revenues/total assets
	TUR2	Gross revenues/Average receivables
Growth	GRO	(Current gross revenues-previous gross revenues)/previous gross revenues*100
Productivity	PRO1	Value-added /number of employees
	PRO2	Gross revenues /number of employees

Table 2 — Results of the estimated MLP model

Classification (%)		RMSE		ROC Curve	Significant variables
Training	Testing	Training	Testing		
97.21	94.87	1.29	1.41	0.981	TUR1, TUR2, LIQ1, GRO

RMSE: Root mean squared error; Significant variables: Normalized important > 60%

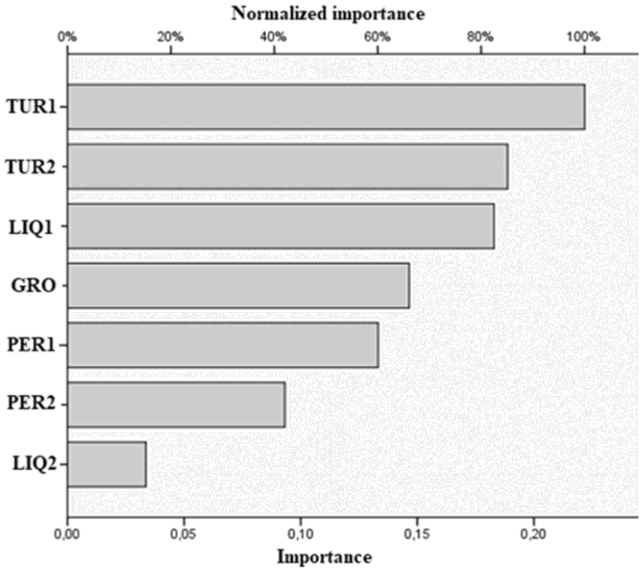

Fig. 1 — Variables sensitivity

that turnover measures such as Gross revenues/Total assets, and Gross revenues/Average receivables largely explain the productivity levels of the companies in the sample. On the other hand, there is a group of variables that also appear with high sensitivity. These variables are related to liquidity (LIQ1) and revenue growth (GRO). Therefore, the sensitivity results indicate that the levels of turnover, liquidity and growth are associated with the productivity of industrial companies.

Conclusions

The present study was carried out to find which variables explain the productivity levels in industrial companies. Our results indicate that management-related variables significantly explain the productivity levels of companies in the construction industry. Also, aspects related to turnover, liquidity and growth are the most sensitive. So as industrial companies improve their management, we find that they increase their productivity levels, so construction industry executives must identify the causes of high productivity in the company's overall economic and financial performance. The results also suggest that the analysis of economic and financial information may become a strategy to improve productivity. Therefore, the results of this study provide insights for industrial managers to analyze the evidence of productivity provided by the financial statements.

The MLP model developed has been limited to identifying with high precision the management factors that have a significant effect on industry productivity. Future studies could investigate the accuracy of artificial neural network models including other productivity factors such as human capital, innovation, and internationalization.

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