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Bootstrapping assessment in exporting companies competitiveness

Evaluación del bootstrapping en la competitividad de las empresas exportadoras

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Abstract

This investigation article presents the result of a scientific research carried out to the Exporting Companies of the Agricultural Sector in the state of Michoacan. Its general objective is to determine the interrelationships between the critical variables that define the International Competitiveness of companies that export agricultural products to the United States market, located in the state of Michoacan. A theoretical review was made, which identified the variables -quality, price, training, indices, and indicators that were integrated into a questionnaire composed of 38 items and applied to the identified exporting companies in the sector. Once the information was processed, different statistical techniques were used, and with the results obtained a Structural Model was identified that describes how these variables are interrelated, based on the Partial Least Square Modeling Statistical Technique (PLS) and the Bootstrapping model. After applying the questionnaire to agricultural exporting companies, the processing of the data of each of the surveyed companies was continued, through parametric statistics and the application of variance correlation.

Keywords: Competitiveness, Exporting Companies, Partial Least Square, Bootstrapping

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Introduction

Agriculture is a vulnerable sector in Mexico and therefore in the state of Michoacan, so its development represents an economic and social balance. To the extent that quality, price, technology, training and distribution channels affect the competitive development of the state; exporting companies will be more profitable and the sector will be in constant growth, since, the international markets day by day become more demanding and the normativity coupled with the quality, represents a challenge for the local offer.

The problems of the industrial sector and the process of trade opening adopted by Mexico from the 1980s. He showed challenges and opportunities to Mexican companies, as companies were accustomed to working in protected markets. These distortions had serious social effects related to business competitiveness. A key issue for the Mexican avocado industry has been US import regulations, which have often been denounced as "green barriers". These standards relate to the use of agricultural pesticides, as well as quality and maturity standards.

It is important to mention that the avocate sector of the state of Michoacan is not organized, nor is it disciplined and the technification in the production and marketing of Michoacan avocado has lagged that used in other producing countries such as Israel, Chile, the United States of America and Spain. There has been little research on the competitive success factors of Mexican companies, by identifying the competitiveness factors of Mexico's avocado exporting companies, this article will show the current knowledge on the competitiveness variables of avocado exporting companies to the US, and structural models (Bonales, Ochoa, & Cortéz, 2013).

Based on the above, exporting companies in the state of Michoacan, require to determine their competitive level when entering the US market, using structural techniques that apply to their indicators and variables; so their problem to solve, is: What are the interrelated variables that determine the International Competitiveness of Michoacán state companies that export agricultural products such as avocado to the USA, through structural models?

Methodology

Partial Least Squares, PLS

Research in social areas has been supported by increasingly sophisticated statistical tools. With this, it is possible to use increasingly complex models with the emergence of techniques such as Structural Equation Modeling (SEM) that allows multiple regressions between latent variables (Batista Foguet & Coenders Gallart, 2000).

Conceptually, what is intended is to reflect in a model the way in which internal and external factors affect competitiveness indices, considering the way in which these variables may be interrelated.

With the results obtained, a model is constructed to be able to see the interrelationships between the variables, in this case the PLS technique is used, a technique of Modeling Structural Equations, which focuses on maximizing the variance of the dependent variables explained by the independent variables (Loehlin, 1998).

This model seeks to contribute to the understanding of the interrelationships between variables that determine the competitive performance of a company; and this knowledge could directly affect the performance of the business, as they suggest (Johnson, 1997). In addition, the results of their analysis will allow the identification of the factors that most impact each of the indices, so that managers can support their subjective assessments when evaluating various action plans during strategic planning.

The PLS, being an SEM technique, is a methodology that assumes that each construct plays the role of a theoretical concept represented by its indicators, and the relations between constructs must be established considering previous knowledge (theory) of the analyzed phenomenon (Loehlin, 1998). The PLS is based on an iterative algorithm in which parameters are calculated by a series of least squares regressions and the partial term is due to the iterative procedure involving separating parameters rather than estimating them simultaneously (Batista Foguet and Coenders Gallart, 2000).

PLS could deal with very complex models with a large number of constructions and interrelationships, allows working with relatively small samples, and makes less stringent assumptions about data distribution, being able to work with nominal data, ordinal or interval. Moreover, the mathematical methods of the PLS have proven to be quite rigorous and robust. In short, PLS can be a powerful tool for minimal demands on measurement scales, sample size and residual distributions.

Bootstrapping

Bootstrapping is a resampling technique that extracts many subsamples from the original data (with substitution) and estimates models for each subsample. It is used to determine the standard errors of the coefficients to evaluate their statistical significance without relying on distributive assumptions (Hair Jr, Hult, Ringle, & Sarstedt, 2016).

So, it estimates properties (such as their variance) by measuring those properties when the sampling is of a rough distribution. In the case where it can be assumed that a set of observations comes from an independent and identically distributed population, it can be implemented by constructing a series of resellers with replacement of the observed data set.

It can also be used to construct a hypothesis test. It is often used as an alternative to statistical inference based on the assumption of a parametric model when that assumption is in doubt, or when parametric inference is impossible or requires complicated formulas for standard error calculation.

The bootstrap procedure is a nonparametric inference technique that randomly extracts several subsamples (e.g., 5000). The removal of a sample of data from an indirect effect is necessary to obtain information on the distribution of the population, which is then the basis for hypothesis testing. Therefore, bootstrapping routines do not require assumptions about the shape of the variable distribution (Chin, 2010). In the first step in PLS, data for each measurement item is bootstrapped. In the next step, bootstrap results are used separately to estimate the underlying PLS path model. The different model estimates provide the distribution of the trajectory coefficients for the internal trajectory model (Nitzl, Roldan, & Cepeda, 2016).

Boot routines in PLS software often provide boot results for at least direct effects (e.g., path a and path b). However, for a more detailed analysis of mediation, particularly in more complex model structures (e.g., multiple mediators), it is often necessary to compute the results of bootstrapping for the combination of a b of certain indirect effect with the help of a spreadsheet. For each subsample of bootstrap, the results of route a must be multiplied by route b to create the product term b of the indirect effect in a new column (Chernick, González-Manteiga, Crujeiras, & Barrios, 2011).

(MacKinnon, Lockwood, & Williams, 2004) and (Wood, 2005) stated that more valid information is obtained on the characteristics of the distribution of mediating effects by calculating a confidence interval (ci) for a b than with a pseudo-value. To calculate a confidence interval (ci), the subsamples (k) for a b of the boot procedure must be organized from lower to higher (Hayes, 2009).

PLS, being a Structural Equations (SEM) technique, is a multivariate data analysis methodology that provides a framework for analyzing multiple relationships between constructs. It is assumed that each construct plays the role of a theoretical concept that is represented by its indicators, and the relations between constructs must be established considering the prior knowledge (theory) of the phenomenon under analysis. PLS is based on an iterative algorithm in which parameters are calculated by a series of Least Squares regressions and the term Partial is due to the iterative procedure involving separating parameters rather than estimating them simultaneously (Roldán & Sánchez-Franco, 2012).

The PLS approach (based on variance) is more appropriate for variable prediction, high complexity, and theory development (exploratory analysis) (Chin, 2010). This method focuses on maximizing the variance of the dependent variables explained by the independent variables, instead of reproducing the empirical covariance matrix (Haenlein & Kaplan, 2004). In addition, because the approach estimates latent variables as linear combinations of measurements.

The PLS could deal with very complex models with many constructs and interrelationships, allows working with relatively small samples, and makes less stringent assumptions about the distribution of data, being able to work with nominal data, ordinal or interval (Duarte & Raposo, 2010).

Questionnaire

A questionnaire was built to measure the relationship between the various factors and the competitiveness of avocado exporting companies.

Table 1 Operationalization of Latent Variable

Variable	*Dimension*	*Indicator*	*Key*
Quality	Quality standards	Objective	QQSOB
		Customers	QQSCU
		Raw Materials	QQSRM
		Competition	QQSCO
		Communication	QQSCM
	Quality control systems	Customers	QQCCU
		Standards	QQCST
	Quality Inspection Systems	Customers	QQICU
		Raw material	QQIRM
		Thread Tools	QQITT
Price	Market	Price management	PMRMP
		Supervision	PCPSU
	Production costs	Competitors	PCPCO
		Competitive diagnosis	PCPDC
		Price integration	PCPIP
	Marketing Costs	Competitive prices	PCPPC
		Elements	PCCEL
Technology	Machinery and equipment	Use of resources	TMEUR
		Modernity	TMEMO
	Technical assistance	Consulting	TATAC
		Investment	TATIN
	Infrastructure	Competitors	TINCO
		Export	TINEX
Training	Education	Vocational training	CEDFP
		Education level	CEDNE
	Training systems	Capacitation program	CSCPC
		Training Techniques	CSCTC
		Support material	CSCMA
	Investment	Previous training	CSCFP
		Training Hours	CINHC
		Investment in sales	CINIV
		Client	DDCCL
Distribution	Design of the distribution channel	Contract	DACCO
		Intermediary	DACIN
	Distribution Channel Management	Competition	DACCM
		Normativity	DACNO
		Distance	DEMDI
	Shipment	Batch Optimization	CEMOL

Source: Obtained information of theorical framework

Results and discussions

When performing the process of each of the indicators using the PLS-SEM technique, the factors that affect each index are shown, considering those with a total effect greater than 0.15, see Table 2 and Figure 1.

Based on the above information, the following competitiveness indices were obtained, using the PLS technique, Table 2. Therefore, the indices were grouped, leaving the variables as seen in Table 6. In which it is observed that the Technology Variable is the most significant, since it has a positive association with each of the independent variables (Quality, Training, Distribution and Price).

Table 2 Factors affecting each index, considering total effect greater than 0.15

Key	*Distribution*	*Price*	*Quality*	*Tecnology*	*Training*
CEDFP					0.700
CEDNE					0.622
CINHC					0.656
CNCCL			0.772		
CNCCM			0.496		
CNCCP			0.699		
CNCMP			0.604		
CSCCC			0.433		
CSCCE			0.577		
CSCFP					0.638
CSCMA					0.778
CSCPC					0.621
CSCTC					0.695
CSICC			0.570		
CSICH			0.453		
CSICM			0.478		
DACCO	0.532				
DACIN	0.635				
DACNO	0.447				
DDCCL	0.504				
DEMDI	0.773				
DEMOL	0.540				
PCCEL		0.474			
PCPCO		0.554			

PCPDC	0.801	
PCPIP	0.659	
PCPPC	0.735	
PCPSU	0.663	
PMRMP	0.635	
TATAC		0.742
TATIN		0.742
TMEMO		0.870
TMEUR		0.755

Source: Obtained information of field investigation

In the distribution, the information obtained by applying the questionnaires to avocado exporting companies was to have a good knowledge of the distribution channels that the companies manage. 50% of companies are above (median) 21 points. On average, companies are at 20.56 points. Likewise, they deviate from the average 3.34 points. 10 companies (40%) rated their distribution channels as excellent, none of the companies reached the maximum value of 28. The bias presented in the distribution channels of the surveyed companies was -0.054 points, representing a negative bias because the average is lower than the median. As for dispersion of the data was 11.17 points.

Table 3 Correlation of PLS variances

Variable	*I*	*II*	*III*	*IV*
I. Distribution				
II. Price	0.158			
III. Quality	0.284	0.698		
IV. Tecnology	0.444	0.582	0.839	
V. Training	0.397	0.529	0.579	0.500

Source: Obtained information of field investigation

The process followed for the use of the PLS was as follows: first, the weights of the relationships, which link the indicators to their respective latent variables are estimated; second, case values are calculated for each latent variable based on a weighted average of its indicators. Finally, these case values are used in a group of regression equations to determine the parameters of paths or structural coefficients (Haenlein and Kaplan, 2004). The algorithm returns again to the ratios of the measurement model where new weights (outer weights) are calculated, and the process continues iteratively until the convergence of the weights is reached, see figure 1.

Based on the processes to carry out the modeling with the PLS, it resulted in a structural model in graphical form that represents the relationships between constructs that are hypothesized in the proposed model. To analyze the structural model with PLS, it must be posed as a recursive model, which means that loops are not allowed in structural relationships. Because the primary objective of the PLS is prediction, the goodness of the model is evaluated by two main indices: structural paths coefficients and combined predictability (R2) of endogenous constructs (Chin, 2010). (Duarte & Raposo, 2010), used the criterion that the explained variance (R2) for endogenous variables should be greater than 0.1

As can be seen in Figure 2, Technology is the variable that presents a significant and relevant impact in almost all the indexes analyzed. This is consistent with what was shown in the models EFQM (2003), BNQP (2008), (Bassioni, Price, & Hassan, 2005), which place it as the driver of the other factors and results of the Exporting Companies.

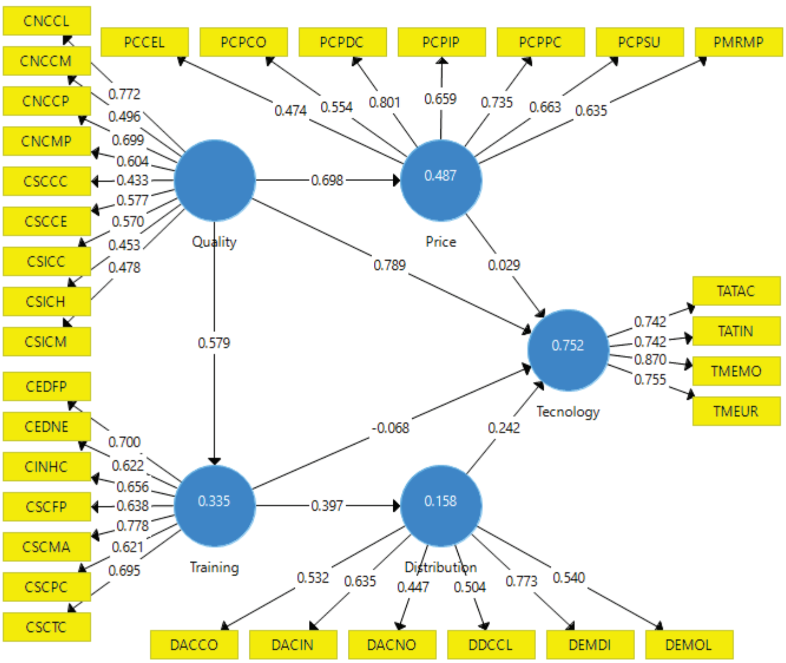
Table 4 Coefficient of Determination

Variable	R^2	R^{2Aj}
Distribution	0.158	0.121
Price	0.487	0.465
Tecnology	0.752	0.702
Trainning	0.335	0.306

Source: Obtained information of field investigation

In Table 4, it is described that the variable Technology is the one that presents the highest indicators, the R2 by 0.752 and the R2aj 0.702, can also be seen graphically in Figure 2.

Figure 1 Model of interrelationships of competitiveness variable



Source: Obtained information of field investigation

Table 5 Path Coefficients

Variable	*I*	*II*	*III*	*IV*	*V*
I. Distribution				0.242	
II. Price				0.029	
III. Quality		0.698		0.789	
IV. Tecnology					0.579
V. Training	0.337			-0.068	

Source: Obtained information of field investigation

In table 5 shows the results obtained when processing the Path Bootstrapping coefficients with 2000 observations, and the most significant relationships are: the quality price variable by 0.698 and technology quality by 0.789.

Table 6 f^2

Variable	I	II	III	IV	V
I. Distribution				0.194	
II. Price				0.002	
III. Quality		0.951		1.115	
IV. Tecnology					0.503
V. Training	0.187			0.011	

Source: Obtained information of field investigation

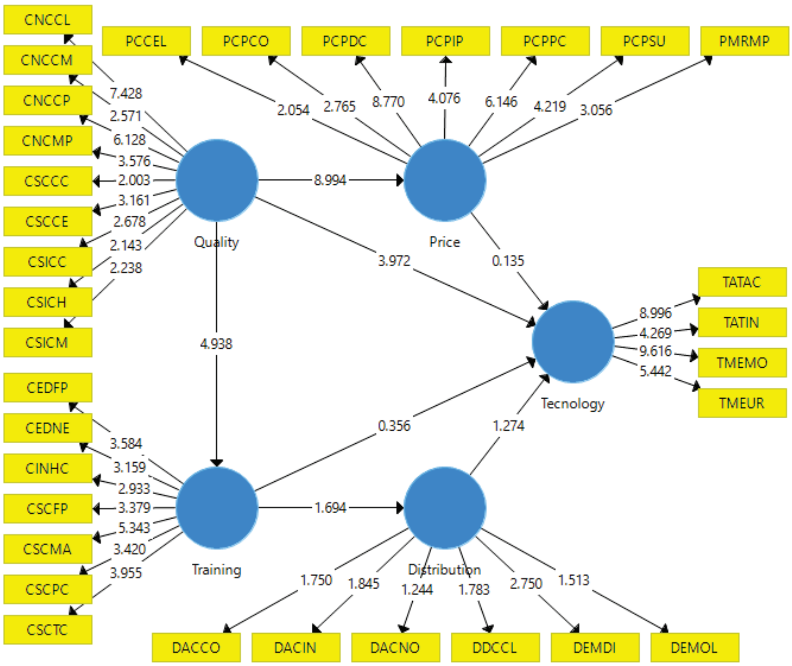
Table 7 Construct Reliability and Valilidity

Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted
Distribution	.612	.616	.748	.338
Price	.780	.822	.836	.427
Quality	.741	.762	.811	.330
Tecnology	.784	.787	.860	.607
Trainning	.803	.799	.853	.456

Source: Obtained information of field investigation

After processing the Bootstrapping technique with 2000 observations, the following results are presented in figure 2: the index of the variable quality at price is 8.994; from quality to training 4.938; from quality to technology 3.972. The variable training to technology index is 0.356; from training to distribution is 1.694. The index of the variable price to technology is 0.135 and distribution to technology is 1.274. So, the ratio of most significant variables is from quality to price by 8.994

Figure 2 Bootstrapping algorithm (2000 observations)



Source: Obtained information of field investigation

Table 8 Path Bootstrapping coefficients (2000 observations).

Variable	*Muestra original*	*Media de la muestra*	*2.5%*	*97.5%*
Distribution -Tecnology	0.242	0.246	-0.208	0.554
Price - Tecnology	0.029	0.064	-0.382	0.451
Quality - Price	0.698	0.748	0.581	0.878
Quality - Tecnology	0.789	0.752	0.369	.1.127
Quality -Training	0.579	0.626	0.371	0.806
Training - Distribution	0.397	0.514	-0.340	0.800
Training - Tecnology	-0.068	-0.072	-0.475	0.294

Source: Obtained information of field investigation

Conclusions

The agricultural sector has been a central axis within the economic impulse of the same, mainly in fruit and vegetable products, which is currently highly positioned in international markets. The industrialization of agricultural products is an essential part of the economic and social evolution of the sector.

The objective of this research was to determine the interrelationships between the critical variables that define the International Competitiveness of companies that export agricultural products to the United States market, located in the state of Michoacan, using the Pearson Correlation statistical technique.

The general hypothesis is tested, because it was demonstrated that, with the applied statistical models, there is a correlation with the independent variables proposed in addition to the coefficient of determination showed that quality, price, training, technology and distribution channels explain the competitiveness of exporting companies.

The analysis of the proposed model presented measures of good fit and in accordance with the different empirical rules established in the literature and that were reviewed. The model estimate validated, for an Alpha of 0.904, 38 relationships out of a total of 67 hypothetical relationships, and another 12 could be considered as marginally significant or almost significant ($p<0.15$).

From the results obtained it was demonstrated that the variable Technology establishes a significant impact with the variable: quality 0.839, training 0.500, distribution 0.444 and price 0.582.

So, we conclude that this article showed how the Modeling of Structural Equations with the PLS-SEM technique and the resamples that were made with the Bootstrapping (2000 observations) can be successfully applied to complex models that attempt to explain the reality of aspects of Exporting Companies. Such models will help to understand and explain the relationships between different factors that affect the performance of exporting companies.

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