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Advertising efficiency in the Spanish beer industry: spending too much?

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Advertising efficiency in the Spanish beer industry: spending too much?

Purpose: The main goal of this paper is to estimate advertising efficiency in the Spanish beer industry and to analyse the effects of several environmental variables and brand portfolio scope on advertising efficiency scores.

Design/methodology/approach: A two-stage double bootstrap procedure is employed. In the first stage, advertising efficiency is estimated using a bootstrapped Data Envelopment Analysis on a multiple input-output model of advertising. In the second stage, a bootstrapped truncated regression model is estimated in order to identify the determinants of advertising efficiency. Both stages are estimated simultaneously. The empirical application is carried out on a sample of Spanish brewers between 2007 and 2014.

Findings: Results show low advertising efficiency scores and highlight the effects that environment and brand portfolio scope have on these estimates.

Originality: For the first time, this paper analyses the effect of environmental variables and brand portfolio scope on advertising efficiency in the beer industry.

KEYWORDS: Advertising; efficiency; branding; beer.

Article type: Research Paper

1. Introduction.

Firms annually spend a huge amount of money to implement their marketing strategy. However, little guidance is available to forms regarding the relative efficiency of their marketing expenditures (Ataman, Van Heerde, and Mela 2010).

From a budget perspective, the biggest part of marketing expenditures is usually devoted to advertising and promotion (Ambler 2000). Therefore, the assessment of advertising spending results is a critical component of the advertising strategy in any type of organization. Further, the increasing media space/time costs and the link between advertising and firm performance have led marketers to focus on the assessment of advertising spending (Ambler 2000; Sheth and Sisodia 2002; Cheong et al. 2014).

Particularly, an understanding of advertising effectiveness would contribute significantly to the productivity of advertisers in terms of the effective allocation of their marketing budgets. Furthermore, it would also contribute significantly to advertising agencies in terms of measuring objectively the effectiveness of the primary service they provide (Bendixen 1993). In this sense, there is a substantial volume of past research on advertising focused on advertising effectiveness (Kim et al. 2001). Although it is a critical issue, we must go beyond it and investigate the concept of advertising productivity (Kim et al. 2001). Recently, advertising efficiency has emerged as a strategic concept that aims to estimate the goodness of the decisions undertaken in the field of advertising spending.

Broadly speaking, advertising efficiency can be estimated as the ratio between the output of the advertising process (in terms of profits, sales, or the number of target audience reached) and the cost of the advertising investment. This approach was applied in early research on assessing advertising performance, which was mainly focused on the estimation of the return on advertising investment and on the advertising cost/sales ratio (Assmus, Farley, and Lehmann 1984; Smith and Park 1992). In an attempt to improve the evaluation of advertising spending, some researchers have argued that competition should be taken into account when evaluating advertising efficiency as firms do not make decisions in a vacuum (Fare et al. 2004; Lohtia, Donthu, and Yaveroglu 2007). In fact, Rust et al. (2004) argue that firm performance is fundamentally affected by competition and it is necessary to capture it when evaluating marketing productivity.

As an alternative, relative advertising efficiency is a new approach to estimate advertising performance which considers a firm relative to the best performers rather than the average performers as the traditional absolute measures. Following this latter approach, there is an increasing use of Data Envelopment Analysis (a non-parametric technique to estimate efficiency) to specifically analyse advertising efficiency (e.g., Luo and Donthu 2001; Fare et al. 2004; Büschken 2007; Pergelova, Prior, and Rialp 2010). However, the number of papers analysing the drivers of advertising efficiency is scarce.

In this paper we also focus on branding literature, which holds that brand value improves company productivity by reducing marketing costs and improving margins (Keller and Lehman 2003; Rust et al. 2004).

Specifically, we analyse the relationship between brand portfolio scope and advertising efficiency. Advertising effectiveness and branding papers have been active in the field of firms' brand extensions into new product areas, which act as an umbrella for several brands belonging to the same firm (Smith and Park 1992; Nijssen 1999). These papers find that brand extensions increase advertising productivity measured in terms of the advertising cost–sales ratio. Furthermore, Morgan and Rego (2009) analyse the relationship between several brand portfolio characteristics and marketing efficiency (ratio of advertising spending to sales), showing that a firm's brand portfolio strategy explains marketing performance. This paper contributes to this stream of research by analyzing the relationship between advertising efficiency and brand portfolio scope.

Otherwise, it is well recognized that efficiency estimates which do not account for the operational environment have only a limited value. In fact, the ability of a firm to transform inputs into outputs is influenced not only by its efficiency but also by the external operating environment (Fried, Schmidt, and Yaisawarng 1999). In this context, the term “environment” is used to describe factors which could influence the efficiency of a firm, where such factors are not traditional inputs and are assumed to be not under the control of the manager. Therefore, if the firms in a given sample are influenced by this environment the efficiency analysis should take into account this heterogeneity. Although the literature has proposed several approaches to incorporate the exogenous environment in efficiency analysis, none of these techniques have been applied in the field of advertising efficiency. This paper tries to fill this gap by considering the impact of several environmental variables related to where the firms develop their activities in order to obtain accurate efficiency estimations.

To summarize, the main contributions of this paper are: (1) to extend the stream of research aimed at examining advertising efficiency; (2) to test the effect of environmental variables and brand portfolio scope on this efficiency.

To reach these goals, the methodology employed comprises a two-stage double bootstrap efficiency analysis (Simar and Wilson, 2007). In the first stage, advertising efficiency is estimated using a bootstrapped Data Envelopment Analysis on a multiple input-output model of advertising. In the second stage, a bootstrapped truncated regression model is estimated in order to identify the determinants of advertising efficiency. Both stages are estimated simultaneously. The empirical application has been carried out using data from the largest firms operating in the Spanish beer industry between 2007 and 2014. This industry represents an interesting case study because it is an intensive advertising spending sector and a key economic activity within the agribusiness sector, being one of the main drivers of the national economy (Calvo-Porral and Levy-Mangin, 2015). In addition, it also faces the challenge of the craft brewing industry, which has experienced major growth in most Western countries where craft breweries compete now with larger beer companies (Duarte-Alonso et al., 2017). The rest of the paper is structured as follows. The next section reviews the previous literature on this topic. Section 3 presents the research methodology, the data and the variables used. In section 4 the empirical results are reported and, finally, section 5 presents the main conclusions, implications and limitations of the paper.

2. Literature review.

2.1. Advertising efficiency.

In the past two decades, media spending patterns and advertising formats have changed dramatically (Dahlen and Rosengren, 2016). Simultaneously, there has been a growing demand to demonstrate the returns of advertising spending. Some of the early studies on this topic consider the returns on advertising investment approach to estimate advertising efficiency, measuring it by the advertising cost/sales ratio (e.g., Smith and Park 1992). Under this view, companies evaluate their productivity by comparing themselves to similar companies (benchmarking) to learn from the best-performing organizations (Donthu, Hershberger, and Osmonbekov 2005).

Recently, Data Envelopment Analysis (DEA), a non- parametric technique to estimate efficiency, has been increasingly used to estimate advertising efficiency (e.g., Luo and Donthu 2001, 2005; Büschken 2007; Cheong et al. 2014). Table 1 summarizes previous research on advertising efficiency. Given the different inputs and outputs employed, the different nature of industries and countries considered, and the different periods of time analysed, direct comparison of results among previous studies is challenging. However, it is worth noting that most of them show high levels of advertising inefficiency among firms. Thus, there is a growing need to understand and identify the drivers that affect advertising efficiency. The present study adds to this literature and examines to what extent the brand portfolio scope and the environment influences advertising efficiency.

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2.2. Brand portfolio strategy and advertising efficiency.

Brand literature maintains a certain consensus around the idea that the value of a brand improves the efficiency of the company by reducing marketing costs and improving prices and margins (Keller and Lehman 2003, 2006; Fernández-Barcala and González-Díaz 2006; Smith and Park 1992). Two reasons could explain this relationship. First, a very reputable brand virtually guarantees success with lower investment (Aaker, 1991; Keller, 2002). On the one hand, due to the fact that better differentiated brands can develop more efficient marketing programs because their customers are more sensitive to advertising and promotion (Rust et al., 2004). On the other hand, brands help consumers to interpret and to process the information on the product and they influence consumer confidence when making the purchase decision. According to the Signalling Theory (Erdem and Swait 1998), a brand represents the classic signal of quality used in many markets to guarantee the quality of a company. Consequently, knowledge of a brand created in consumers' minds through a company's investment in pre-marketing programs is a very valuable asset to improve marketing productivity (Rust et al. 2004).

This paper focuses on one of the key aspects of the brand portfolio strategy: the scope of the portfolio, which considers the number of brands the firm owns and markets.

Some pioneer studies, such as Smith and Park (1992) and Collins-Dodd and Louviere (1999), examine the empirical relationship between the efficiency of advertising and the brand extensions strategy into new product areas. They assume that brand extensions increase the efficiency of a company's investment in marketing communications by generating a greater level of sales from a given advertising investment or by achieving a target level of sales with less investment than would be needed if the same products were launched with a new brand name (Aaker 1990; Anderson 2002).

Further, theoretical developments derived from the agency perspective would allow us to understand the effect of brand knowledge on advertising efficiency. The Signalling Theory refers to the role of brand reputation as a quality indicator that reduces the perception of risk in conditions of asymmetric information on quality in the market (Erdem and Swait 1998). Basically, this theory assumes the existence of imperfect and asymmetric information in markets. When these information asymmetries refer to quality, high and low-quality products can co-exist in the market (Akerlof 1970), which means that consumers have to make ex-ante evaluations of the quality of the products they are considering. This makes choice a problematic and costly exercise, as the consumers have doubts over product quality and do not know a priori which product they are going to buy. Thus, we can expect them to try to make good purchases and to reduce risk, which means that the purchase decision process will be based on all the intrinsic and/or extrinsic signals that reveal the quality of the product.

One of the most analysed signals to reduce these asymmetries in the consumer markets is brand reputation. This argument is coherent with marketing literature, where the value of a brand is defined by the utility it provides to the consumer as an information signal, so the main determinant of brand value would be the credibility that consumers assign to it, which could contribute to the improvement of the product's quality perception and to reduce both the search costs and the risk associated with purchasing the product.

Several researchers argue that companies develop reputational capital through individual brand names, to address the information asymmetry between producer and consumer (Fernández-Barcala and González-Díaz 2006). Thus, in the case of an experience good, in which quality cannot be discerned prior to purchase (see McQuade, Salant, and Winfree, 2012), and especially for experience products, producers repeatedly supply the promised quality to show that they are not exploiting their information advantage in terms of the actual quality. Thus, producers create an individual reputation for their brand names that will be used as a guarantee for future consumers.

Our interest in testing the relationship between brand knowledge and advertising efficiency arises from its important implications for managers' decisions regarding the effectiveness of brands in creating added value for companies and, thus, on whether to use different brands (expanding the length of the portfolio) or whether to use few brands in favour of independent promotion of the familiar individual brand. As stated by Morgan and Rego (2009) owning a larger number of brands enables a firm to attract and retain the best brand managers, to build a greater market share, to enjoy grater power and to deter new market entrants. However, larger brand portfolios might be inefficient because they lower manufacturing and distribution economies, and dilute marketing expenditures. Moreover, they are a potential cause of weakened brand loyalty and they increased price competition, suggesting more potential cost associated with larger brand portfolios.

3. Methodology, sample and variables.

3.1. Methodology.

In this paper, the two-stage double bootstrap methodology proposed by Simar and Wilson (2007) is employed. This methodology is based on the non-parametric technique of Data Envelopment Analysis (DEA) to estimate efficiency. Further, it considers regression analysis to estimate the effect of environmental variables on efficiency. Besides, both steps are estimated simultaneously.

DEA was firstly developed by Charnes et al. (1978, 1981) based on linear programming techniques. The underlying idea of DEA is to identify a firm as efficient when no other firm is capable of producing a higher output from the same level of input (output-oriented model) or, alternatively, of producing the same output using a lower level of input (input-oriented model). Thus, to evaluate efficiency every firm is directly compared against a peer or combination of peers. The underlying assumption is that each firm uses the same set of inputs to produce the same set of outputs, but the inputs are consumed and outputs are produced in various amounts.

In this paper, an input-oriented model is used because the firms involved are subject to market demand and the inputs are under the control of the firms. Although beer firms try to maximize their revenues, the volume of beer sold in the Spanish market is steady at around 35.5-million hectolitres over the last ten years (Cerveceros, 2015), acting as an important constraint for beer firms. In any case, it should be stressed that both model orientations identify the same efficient breweries.

DEA considers the existence of n firms (in the jargon of DEA known as decision-making units (DMU_i; i = 1,...,n)) which employ a vector of m inputs $X_i = (x_{1i},x_{2i},...,x_{mi})$ to obtain a vector of s outputs $Y_i = (y_{1i},y_{2i},...,y_{si})$. For each DMU, the following linear programming model (Banker et al. 1984) must be solved:

$$\max \left\{ \begin{array}{l} z_0 = \delta + \varepsilon \sum_{r=1}^{s} s_r^+ + \varepsilon \sum_{j=1}^{m} s_j^- \;\; s.t. \sum_{i=1}^{n} x_{ji}\lambda_i + s_j^- = x_{r0}; \\ \sum_{i=1}^{n} y_{ri}\lambda_i - s_r^+ = \delta y_{j0}; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i, s_r^+, s_j^- \geq 0 \end{array} \right\} (1)$$

Where i=1,..,n; r=1,..,s; and j=1,..,m. $\hat{\delta}_i$ is the Farrel's efficiency estimate obtained for the DMU analysed. A DMU is considered efficient if $\hat{\delta}_i = 1$ and all the slacks are zero. If $\hat{\delta}_i <$ 1, then the DMU is inefficient. The lower the index the lower the efficiency. Thus, we use Farrell's (1957) definition of efficiency, as the efficiency score is estimated by the radial distance. The above model assumes variable returns to scale (VRS). When eliminating the restriction of convexity, we obtain the constant returns to scale (CRS) model. Under VRS models, changes in outputs are not necessarily proportional to the changes in inputs, therefore, the VRS model is more flexible as the CRS model is a special case of the VRS model.

One of the main disadvantages of this DEA model is its deterministic nature. The measurement of input and output values is subject to errors and noise. Since DEA is an extreme point technique, noise (even symmetrical noise with zero mean) such as measurement error can cause bias, as the frontier is very sensitive to these errors. Further, the noise in data usually leads to mistakes in production frontier specification and efficiency scores. To overcome this limitation, the bias-corrected data envelopment analysis approach is employed in this paper. Simar and Wilson (1998, 2000a, 2000b) use a bootstrap approach to develop a consistent estimator of the unknown data generating process.

In order to examine the determinants of efficiency estimates, a second-stage truncated regression model is estimated. From the efficiency DEA estimates ($\hat{\delta}_i$) a regression model, which considers these estimates as the dependent variable and a set of Z_i variables as independent variables, is estimated:

$$\hat{\delta}_i = f(Z_i, \beta_i) + \varepsilon_i \quad (2)$$

Where ε_i is a random variable distributed $N(0, \sigma_i)$. The estimation of the parameters $\hat{\beta}_i$ might allow us to identify the effect of the Z_i variables on efficiency. However, as the efficiency estimates in the first stage (dependent variable) are built from all the data set, this estimation could be biased as the DEA efficiency scores are correlated (Simar and Wilson 2011). Thus, the two-stage double bootstrap methodology proposed by Simar and Wilson (2007) is employed (Algorithm 2, page 42). In this methodology, both stages (efficiency estimation and effect of environment) are estimated simultaneously, avoiding the problems that might arise with the separate estimation of the two steps.

One important remaining question is how environmental variables might affect the production process. In the model presented by Simar and Wilson (2007), environmental variables affect the shape (i.e., mean, variance, etc.) of the distribution of inefficiencies, but not the support of input or output variables. However, environmental variables might affect the production possibilities themselves. In this sense, Simar and Wilson (2007) model rationalizes second-stage regression of efficiency estimates on some environmental variables, but does not allow for the possibility that environmental variables might affect the production possibilities. If they do, then a different model is needed, and second-stage regression is not appropriate. In this sense, the Dairaio, Simar and Wilson (2015) proposal is employed to test separability. The sample is randomly split into two independent parts, and two independent statistics are computed to test the null hypothesis of separability. Following this one-sided test, the hypothesis of separability is rejected when the difference between them is "too big".

To implement the methodology the rDEA library (Simm and Besstremyannaya 2016), which is based on the statistical package R, is employed. In this package, efficiency is measured in terms of Shephard's (1970) distance function, which is the reciprocal of Farrell's measure. In this case, Shephard's estimates range from one to infinity. However, results can be transformed into Farrel's distance measure in a straightforward manner.

Finally, the number of bootstrap replications to compute the bias-corrected efficiency scores is set to 100, while the number of bootstrap replications to compute the confidence intervals is set to 2000. Confidence intervals are estimated at 95%.

3.2. Sample and variables.

The empirical analysis is performed on a sample of companies operating in the Spanish beer sector between 2007 and 2014. This experience goods industry has been chosen as an interesting case study because it is an intensive advertising spending sector. Furthermore, the beer industry in Spain is a key economic sector and activity within the agribusiness sector, being one of the main drivers of the national economy (Calvo-Porral and Levy-Mangin, 2015). For the sample selection, we use the population of brewing companies registered in paragraph 1105 of CNAE-2009 ("Fabricación de cerveza"), which is the equivalent of code 2082 of the US SIC classification ("Malt beverages"). The final sample used for the empirical study is made up of 6 beer firms continuously operating from 2007 to 2014 (8 years). Data is computed on a quarterly basis (a total of 192 observations). The six firms included in the sample are *Mahou-San Miguel*, *Heineken España*, *Grupo Damm*, *Hijos De Rivera*, *Compañia Cervecera de Canarias*, and *La Zaragozana*, which are the main beer brewing companies in Spain. Despite the small number of firms included in the sample size, the final sample represents 99.7% of the total beer sales in the Spanish market in 2014. Moreover, it comprises all the firms that continually invested in advertising during the whole time period, with a total of over 1,671 million euros invested on advertising.

In this paper, two different model specifications are considered (see Table 2). In the first model (Model 1), four advertising inputs are included: (1) Print (newspapers + magazines + Sunday supplements); (2) Broadcast (TV + cinema + radio); (3) Internet; and (4) Outdoor. Data on advertising are obtained from the INFOADEX (Information for Advertising Expenditures) database, which provides detailed information on advertising expenditures in Spanish media. All the variables are expressed in monetary units. In the second model (Model 2), two additional inputs are included: (1) Labour (number of full time employees); and (2) Capital (plants+equipment), measured in millions of euros. Data on these latter variables are obtained from the SABI database (the Iberian version of the Bureau Van Dijk database)

Regarding the outputs, the same two variables are considered in both models: (1) Total sales revenue, measured in millions of euros; and (2) Total beer sales, measured in millions of litres and obtained from "Cerveceros de España" (The Brewers of Spain), which is the association that since 1922 represents practically the whole of the beer production in Spain.

In order to explain advertising efficiency, we consider the following variables.

Firstly, three environmental variables related to the market: (1) Number of tourists arriving in Spain (measured in millions of people and obtained from the Frontur database (http://estadisticas.tourspain.es); (2) Average quarterly temperature (measured in degrees Celsius and obtained from Aemet (www.aemet.es), the Spanish national meteorological agency; and (3) Gross Domestic Product, measured in thousands of millions of euros and obtained from INE (www.ine.es), the Spanish National Statistics Institute. These three variables are widely reported by Cerveceros' annual reports as the main variables that could affect the seasonality of beer sales. Although these variables affect all six firms in the same way, their inclusion allows us to find out whether brewers are efficient because of clever management or they are efficient because they benefit from a positive environment. In fact, these variables might affect the ability of brewers to transform their inputs into outputs. If we did not include these variables brewers might appear as "efficient" when there are simply benefiting from a positive environment (derived from the effect of these variables on beer sales).

Secondly, two company characteristics. (1) Brand portfolio scope, measured through the number of brands included in the firm's brand portfolio, which is obtained from the companies' annual reports; and (2) A dummy variable that takes the value 1 if the firm has invested in the Internet in the quarter and 0 otherwise. As this is a relatively new input, not all the firms invested in the Internet throughout the whole time period. Furthermore, the amount of investment in the Internet is lower than the amount invested in other media. Thus, this dummy variable acts as a control variable.

Thirdly, given the panel data nature of the data, firm specific dummy variables and quarterly dummy variables are also included to capture specific firm effects and seasonality.

All the monetary variables are deflated by the GDP deflator index (2007–2014) and converted into constant 2014 monetary units. Descriptive statistics and correlations between the variables are presented in Table 2 and Table 3, respectively.

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4. Results.

Advertising efficiency is estimated using two different models. The first model (Model 1) considers only inputs related to the advertising activity of the brewer, while the second model (Model 2) considers also two inputs related to the traditional production process. In addition, each specification is estimated through the traditional input-oriented DEA model with variable returns to scale (hereafter called DEA model), and through the bias-corrected DEA model (hereafter called BC model).

The results obtained (see Table 5) show that the average advertising efficiency for the companies considered between 2007 and 2014 varies between 0.471 (DEA model) and 0.343 (BC model) in Model 1, which reflects a high degree of inefficiency. These values imply that, on average, the companies could have obtained the same levels of outputs using 52.9% lower resources under the DEA model or, alternatively, using 65.7% lower resources under the BC model. This advertising inefficiency represents a potential saving between 884 and 1,097 million euros for the whole period. Although efficiency scores estimated under the BC model are lower than the efficiency scores estimated under the traditional DEA model, results evidence a high correlation between these estimates (Pearson correlation coefficient=0,993; p=0.000). However, the Wilcoxon test detected significant differences between the median levels of efficiency (Z= -11,995; p=0,000). In any case, given that the bias-corrected bootstrap estimates of efficiency are more robust than the traditional estimates of efficiency, results highlight a huge advertising overspend in the considered period of time.

In Model 2, the obtained results show that the average efficiency for the firms considered varies between 0.931 (DEA model) and 0.897 (BC model) between 2007 and 2014. As expected, and although the results are not comparable, the efficiency estimates in Model 2 are higher than in Model 1, as the later model includes a larger number of inputs. Under this assumption, DEA loses its discriminatory power as firms can specialize in any of the inputs to become efficient.

Regarding the advertising efficiency of the individual firms in Model 1, *Grupo Damm* shows the highest level of efficiency for the period analysed (0.568 in the DEA model and 0.408 under the BC model), while *CC. Canarias* shows the lowest level (0.405) in the DEA model and *La Zaragozana* shows the lowest level (0.297) in the BC model. In Model 2, *Mahou-San Miguel* is the most efficient firm for the considered time period (0.970 in the DEA model and 0.945 under the BC model), while *Hijos De Rivera* is the less efficient firm (0.845 in the DEA model and 0.792 under the BC model). These results highlight the idea that managers should be aware of the efficiency of their advertising activity.

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Regarding the evolution of the efficiency over time, data shows a slight decrease of efficiency over time within Model 1. This drop is especially pronounced in 2012. In Model 2 the evolution of efficiency is steady during this period.

Table 6 shows the bias, and the lower and upper bounds of the efficiency confidence intervals estimated with bootstrapping. The biases are substantial for all the firms and the confidence intervals estimated are wide in Model 1, which shows the high statistical variability of the efficiency estimates. Further, some of the intervals overlap, which suggests that only some of the rankings indicated by point traditional DEA estimates are confirmed.

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Table 7 shows the results of the truncated bootstrapped regression. Despite the results are not directly comparable (given the models employ different dependent variables), results are very similar among the different specifications. Furthermore, the Dairaio, Simar and Wilson (2015) proposal is employed to test separability. The joint test (p=0.889 in Model 1 and P=0.801 in Model 2) indicates that there is no evidence against separability. This result is not surprising given the low correlation indexes between the environmental variables and the inputs and outputs.

As can be seen, the intercept term and all the explanatory variables are statistically significant in all the models. At this point, it must be stressed that the dependent variable represents the mode of inefficiency (Shepard's estimate), thus a parameter with negative sign indicates a positive effect on efficiency while a positive sign indicates a negative effect on efficiency.

Overall, results suggest that the environmental variables considered have a significant effect on the efficiency of firms. As can be seen, the number of tourists and temperature have a positive effect on efficiency in all models. Concretely, these variables positively affect beer sales and, although these sales could be wrongly attributed to a clever use of advertising inputs, results suggest that firms benefit from environment. Otherwise, GDP is negatively associated with advertising efficiency in Models 1a and 1b but positively associated in Model 2. In this sense, it must be reminded that the dependent variable is different in Models 1 and 2. In any case, it highlights the importance of including these variables in the analysis.

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Regarding brand strategy scope, results show a negative effect of the brand portfolio on firms' advertising efficiency. As the width of the brand portfolio increases, inefficiency increases or, alternatively, efficiency decreases. This result implies that firms using a wide portfolio decrease their advertisement efficiency in marketing communications. Therefore, when a firm launches a new product (brand) into the market, it seems that it must make a bigger advertisement investment to obtain a certain level of sales than would be needed if the product had been launched with the same brand name as previous products.

Finally, the variable reflecting the effect of Internet advertising on efficiency is also significant. As could be expected, Internet investment has a positive effect on efficiency, which is consistent with Pergelova et al. (2010). One of the advantages of the Internet is its cost-effectiveness, which allows firms to target interested consumers with a lower cost.

5. Conclusions, implications, limitations and further research.

The assessment of advertising efficiency provides useful information to managers about differences in performance among firms and the potential for improvement. For this reason, the goal of this paper is to estimate advertising efficiency. This topic is crucial in a competitive environment as inefficient advertising spending contributes to lower profit margins and sales losses (Luo and Donthu 2005). Further, the effects of environmental variables and brand strategy are considered.

Overall, the results of the empirical application carried out on a sample of Spanish brewers show a high degree of advertising inefficiency. Further, the environment, the brand portfolio scope and the internet strategy have a significant effect on these estimates. Thus, the effect of these variables cannot be ignored without introducing some bias to the analysis.

The results obtained in this paper have significant implications for managers. It should not be forgotten that Spanish brewers invest a huge amount of money on advertising to promote their brands and also to attract consumers. This fact increases managers' responsibility for a clever advertising investment and it highlights the importance of monitoring advertising performance. In this sense, the estimation of advertising efficiency might be used as external benchmarking. From a managerial perspective, the process of benchmarking requires measuring the difference between the current performance level of a firm and the best possible practice. Afterwards, firms must identify the underlying causes of this difference. In terms of efficiency, this process implies that an (advertising) inefficient brewer should examine the reasons why other brewers are more efficient. This paper offers some interesting insights on this topic.

First, the results show a significant effect on advertising efficiency for each of the exogenous variables included in the analysis. This illustrates that when estimating efficiency one should not only be limited to advertising-related variables, but also control for exogenous factors that could affect the ability of the firm to transform inputs into outputs. Although one might think that all the firms included in the analysis face the same operational environment, there are seasonal environmental changes that have an effect on the heterogeneity of the efficiency estimates. In fact, efficiency estimates which do not account for the operational environment have only a limited value. Therefore, if the firms in a given sample are influenced by environmental variables, which are out of the control of managers, the efficiency analysis should take into account this circumstance.

Secondly, the results of this paper show a negative effect of brand portfolio on advertising efficiency. In terms of the effectiveness of brand portfolios in creating value-added for firms, this result suggests that reinforcing the promotion of the individual familiar brand might be preferred to fostering a strategy with a wider portfolio. Results suggest that a larger brand portfolio decreases the efficiency of a company's investment in advertising by reaching a certain level of sales with a bigger level of investment than would be needed if the same product was launched by the company with an individual brand. It seems that larger brand portfolios are inefficient because they lower scale economies and dilute marketing expenditures (Morgan and Rego, 2009).

Thirdly, results show that Internet advertising has a positive effect on efficiency. This result reinforces the advantages this cost-effectiveness strategy. In this sense, although Internet is a young advertising medium (compared to traditional medium such as TV or print advertising), it is interesting for managers to note that brewers can obtain efficiency gains thorough this medium. Its interactivity and its ability to transmit information quickly and inexpensively to interested consumers (Pergelova et al., 2010) implies that managers should make a big effort in order to implement effective online campaigns.

Of course, this paper has also several limitations. First, one of the limitations of the study is the potential generalisation of the conclusions to other sectors, which must be done with care, since only one industry has been analysed. Moreover, although this paper considers three environmental factors that affect advertising efficiency, it would be possible to include other relevant variables which may also affect efficiency. However, lack of information impedes the analysis of other efficiency determinants. Thirdly, in this paper the separability condition between the inputs/outputs and the environmental variables is assumed and tested. Obviously, failure to reject the null hypothesis of separability does not imply by itself that separability holds. In fact, failure to reject might be due to other factors (e.g. insufficient data or too many dimensions).

Finally, future research should try to overcome these limitations. This paper provides a starting point for the further study of other factors causing the observed efficiency differences. In particular, instead of employing general environmental variables, which affect all the firms in the same manner, future research might include specific environmental variables for each firm included in the sample. These variables could be related to the level of competition the firm faces or the strength of the brands advertised. Brand strength is one of the central components of brand equity, and not only can brand strength be conceptualized in terms of consumers' attitude towards the brand with respect to quality, but it also integrates behavioural dimensions such as brand loyalty and brand share across the markets in which the brand competes; so it is expected that brand strength might influence advertising efficiency.

Ultimately, future studies are also encouraged to replicate and to validate the proposed model in different countries and different contextual settings.

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TABLE 1

Summary of previous papers estimating advertising efficiency

Authors	Sample	Technique	Inputs	Outputs	Results
Luo and Donthu (2001)	63 U.S. advertisers in 1997 and 1998 23 outdoor campaigns	DEA	3 inputs (expenditure): print, broadcast, and outdoors 4 inputs (Concepts. Words, colour, graphics)	2 outputs: sales, operating income 2 outputs: recall, evaluation	33 firms had advertising efficiency levels below 20% 6 campaigns were efficient. Average efficiency 70%
Färe et al. (2004)	6 US beer firms from 1983 to 1993	DEA cost model	3 inputs (expenditure): print, television, and radio	1 output: sales (millions of barrels)	Low cost efficiency levels
Luo and Donthu (2005)	Top 100 US advertisers in 1997 and 1998	DEA and Stochastic Frontier	3 inputs (expenditure): print (Magazine and Newspaper), broadcast (Spot TV, Cable TV Networks, Network Radio, and National Spot Radio), and outdoors	1 output: sales revenue	High levels of inefficiency. Firms could bring in 20% more sales
Büschken (2007)	35 car brands operating in Germany between 1998 and 2001	DEA	5 inputs (expenditure): television, radio, outdoor, magazine, and newspaper	4 outputs: brand familiarity, sympathy, brand consideration, and brand purchase intention	13 firms are efficient. 8% of a brand's advertising budget wasted. Advertising spending efficiency increases as size of an organization's product portfolio expands
Lohtia et al. (2007)	37 banner advertisements	DEA	6 inputs (coded by five independent judges): incentives, emotional appeals, colour, interactivity, animation, message length	3 outputs: click-through-rate (CTR), attitude towards the ad, recall	A large number of advertisements were efficient
Pergelova et al (2010)	18 car firms operating in Spain from 2001 to 2007	Bootstrap bias-corrected DEA and truncated regression	4 inputs (expenditure): print, broadcast internet, outdoor	2 outputs: sales revenue (income), number of cars sold	Online advertising improves the efficiency
Brown and Cheong (2013)	26 companies in 2009	DEA	8 inputs (expenditures): Sports media spending, non-sports media spending, magazines, national spot radio, network television, cable television, spot television.	2 outputs: gross profits and brand value	Half of the companies were inefficient. 20% overspending.
Kim et al. (2013)	Super Bowl advertisers from 2005 to 2010	DEA	4 inputs: Advertising expenditure, frequency, total ad length, number of brands promoted	2 outputs: AdMeter rating and Nielsen viewership scores	Advertising efficiency is positively associated with abnormal stock returns.
Cheong et al. (2014)	100 top U.S. advertisers from 1985 to 2012	DEA	6 inputs (expenditure): magazines, newspapers, TV, radio, outdoor, Internet	1 output (income): total sales	Overall increase in inefficiency over time. 61% of top advertisers are inefficient. 34% overspending

TABLE 2

Estimated models

	Inputs	Outputs
Model 1	Outdoor Print Broadcast Internet	Beer sales (euros) Beer sales (Hl)
Model 2	Outdoor Print Broadcast Internet Employees Capital	Beer sales (euros) Beer sales (Hl)

TABLE 3

Descriptive statistics (2007-2014, quarterly basis, n=192)

	Mean	S.D.	Max	Min
Beer sales (million euros)	145.29	123.18	396	10
Beer sales (1000s Hl)	1391.96	1253.76	3853	104
Outdoor advertising (1000s euros)	460.49	767.47	3875	1
Print advertising (1000s euros)	416.18	540.54	2413	0
Broadcast advertising (1000s euros)	9,004.08	12,468.45	57,754.58	5.14
Internet advertising (1000s euros)	33.12	75.25	497.31	0
Employees (number)	262.69	203.64	771	19
Capital (Plants+Equipment) (million euros)	99.22	82.43	402	5
Brands (Number)	19.67	8.621	36	5
Tourists (Millions pax)	14.37	4.67	24.35	8.78
Temperature (Celsius)	15.463	5.5523	24.0	7.2
GDP (Million euros)	266,958	10,378	288,429	249,652

TABLE 4

Pearson correlation indexes among variables

	Sales (€)	Sales (Hl)	Outdoor	Print	Broad.	Internet	Employ.	Capital	Brands	Tourist	Temp.	GDP
Sales (€)	1											
Sales (Hl)	0.987a	1										
Outdoor	0.453a	0.520a	1									
Print	0.582a	0.599a	0.558a	1								
Broad.	0.564a	0.576a	0.660a	0.581a	1							
Internet	0.382a	0.402a	0.410a	0.260a	0.292a	1						
Employ.	0.966a	0.982a	0.498a	0.592a	0.541a	0.353a	1					
Capital	0.902a	0.923a	0.561a	0.607a	0.506	0.337	0.939a	1				
Brands	0.830a	0.861a	0.604a	0.609a	0.591a	0.377a	0.817	0.821	1			
Tourist	0.185b	0.167b	-0.063	-0.093	-0.231a	0.062	0.186a	0.181b	0.031	1		
Temp.	0.153b	0.142b	-0.154b	-0.051	-0.295a	-0.022	0.164b	0.153b	0.004	0.807a	1	
GDP	-0.036	-0.007	0.004	-0.060	-0.022	-0.084	0.032	-0.011	-0.113	-0.191a	0.096	1

a: p< 0.01; b: p< 0.05

TABLE 5

Evolution of firms' efficiency score (original DEA and bias-corrected DEA) per firm and year.

	2007	2008	2009	2010	2011	2012	2013	2014	2007-2014
Mahou-San Miguel									
Model 1: DEA	0.802	0.553	0.528	0.578	0.694	0.430	0.394	0.373	0.544
Model 1: BC	0.582	0.416	0.379	0.401	0.475	0.301	0.288	0.286	0.391
Model 2: DEA	1.000	0.964	0.972	0.977	1.000	0.967	0.881	1.000	0.970
Model 2: BC	0.963	0.940	0.951	0.954	0.972	0.946	0.861	0.974	0.945
Heineken España									
Model 1: DEA	0.748	0.210	0.384	0.268	0.617	0.643	0.452	0.536	0.482
Model 1: BC	0.581	0.167	0.260	0.209	0.423	0.455	0.316	0.342	0.344
Model 2: DEA	0.850	0.802	0.857	0.850	0.946	0.950	0.896	0.907	0.882
Model 2: BC	0.818	0.785	0.816	0.831	0.883	0.893	0.861	0.853	0.842
Grupo Damm									
Model 1: DEA	0.703	0.412	0.463	0.634	0.625	0.441	0.631	0.634	0.568
Model 1: BC	0.512	0.306	0.342	0.448	0.431	0.311	0.454	0.461	0.408
Model 2: DEA	0.999	0.944	0.880	0.975	0.987	0.973	0.976	1.000	0.967
Model 2: BC	0.970	0.928	0.861	0.946	0.961	0.955	0.955	0.971	0.943
Hijos De Rivera									
Model 1: DEA	0.670	0.557	0.328	0.554	0.604	0.240	0.178	0.225	0.419
Model 1: BC	0.502	0.389	0.253	0.394	0.412	0.176	0.140	0.173	0.305
Model 2: DEA	0.850	0.779	0.759	0.940	0.929	0.846	0.807	0.853	0.845
Model 2: BC	0.775	0.706	0.725	0.854	0.845	0.806	0.789	0.835	0.792
C.C. Canarias									
Model 1: DEA	0.476	0.642	0.601	0.379	0.255	0.262	0.315	0.306	0.405
Model 1: BC	0.378	0.477	0.452	0.296	0.195	0.206	0.240	0.231	0.309
Model 2: DEA	0.962	0.981	0.937	0.949	0.898	0.927	0.992	1.000	0.956
Model 2: BC	0.929	0.937	0.901	0.923	0.873	0.905	0.948	0.960	0.922
La Zaragozana									
Model 1: DEA	0.577	0.429	0.471	0.503	0.522	0.263	0.238	0.265	0.409
Model 1: BC	0.397	0.309	0.320	0.359	0.399	0.200	0.189	0.213	0.298
Model 2: DEA	1.000	0.930	0.906	0.979	1.000	0.984	0.948	1.000	0.968
Model 2: BC	0.960	0.899	0.879	0.952	0.964	0.946	0.925	0.961	0.936
Global									
Model 1: DEA	0.662	0.467	0.462	0.486	0.553	0.380	0.368	0.390	0.471
Model 1: BC	0.492	0.344	0.334	0.351	0.389	0.275	0.271	0.284	0.343
Model 2: DEA	0.944	0.900	0.885	0.945	0.960	0.941	0.916	0.960	0.931
Model 2: BC	0.902	0.866	0.856	0.910	0.916	0.908	0.890	0.925	0.897

TABLE 6

Efficiency estimates, bias and confidence interval bounds (2007-2014).

	Efficiency (DEA)	Efficiency (BC)	Bias	Lower Bound	Upper Bound	Bound difference
Model 1						
Mahou-San Miguel	0.544	0.391	0.153	0.318	0.487	0.169
Heineken España	0.482	0.344	0.138	0.285	0.409	0.125
Grupo Damm	0.568	0.408	0.160	0.330	0.508	0.178
Hijos de Rivera	0.419	0.305	0.114	0.259	0.358	0.099
CC. Canarias	0.405	0.309	0.095	0.262	0.371	0.109
La Zaragozana	0.409	0.298	0.110	0.248	0.352	0.104
Mean	0.471	0.343	0.128	0.284	0.414	0.131
SD	0.337	0.232	0.112	0.187	0.291	0.110
Min	1.000	0.785	0.438	0.663	1.019	0.415
Max	0.059	0.042	0.015	0.037	0.049	0.012
Model 2						
Mahou-San Miguel	0.970	0.945	0.025	0.923	0.994	0.071
Heineken España	0.882	0.842	0.040	0.812	0.895	0.083
Grupo Damm	0.967	0.943	0.024	0.922	0.992	0.069
Hijos de Rivera	0.845	0.792	0.054	0.754	0.851	0.098
CC. Canarias	0.956	0.922	0.034	0.894	0.972	0.078
La Zaragozana	0.968	0.936	0.033	0.907	0.989	0.082
Mean	0.931	0.897	0.035	0.869	0.949	0.080
SD	0.092	0.086	0.029	0.085	0.103	0.059
Min	1.000	0.991	0.174	0.984	1.128	0.291
Max	0.553	0.534	0.007	0.521	0.549	0.013

Total number of iterations = 2000

TABLE 7

Determinants of inefficiency: estimation on bias corrected efficiency estimates.
(dependent variable = mode of inefficiency).

Variable	Model 1a Coefficient	Model 1b Coefficient	Model 2 Coefficient
Intercept	3.040 e+00*	-6.095 e+00*	1.096 e+00*
Number of tourists	-1.122 e-02*	-3.064 e-03*	-3.888 e-05*
Temperature	-1.289 e-01*	-5.115 e-02*	-2.692 e-04*
GDP	2.958 e-06*	2.605 e-06*	-1.358 e-07*
Brand portfolio	7.717 e-01*	7.695 e-01*	1.310 e-02*
Internet	-1.067 e+01*	-4.183 e+00*	-1.193 e-01*
Dummies for quarters	No	Yes	Yes
Dummies for firms	No	Yes	Yes
Variance	9.617	6.088	0.1435

* $p<0.05$; Total number of iterations = 2000