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2016

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Análise de eficiência de uma cadeia de lojas de Retalho de Moda e Acessórios

Efficiency analysis of a Retail Stores chain of Fashion & Accessories

Universidade de Aveiro
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Departamento de Economia, Gestão, Engenharia Industrial e Turismo

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Efficiency analysis of a Retail Stores chain of Fashion & Accessories

Tese apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Economia da Empresa, realizada sob a orientação científica do Professor Doutor Victor Manuel Ferreira Moutinho, Professor Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro e sob co-orientação científica da Professora Doutora Celeste Amorim Varum, Professora Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro.

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palavras-chave

DEA, Benchmarking, Determinates da eficiência, Regressão linear quantile, Brand equity, Shoppings.

resumo

O objetivo deste estudo é a avaliação da eficiência de uma cadeia de lojas de retalho que representa várias marcas internacionais de prestígio no mercado Português e a identificação dos determinantes que influenciam a eficiência. O estudo compara o desempenho das lojas compostas por 3 diferentes marcas do segmento Brand Equity e propõe melhorias no âmbito da melhoria da performance. Para avaliar a eficiência e os seus determinantes a análise é realizada em duas fases: na primeira fase a metodologia Análise Envoltória de Dados (DEA) é usada para determinar os níveis de eficiência e na segunda fase, os resultados obtidos na primeira fase são estimados através de uma regressão linear quantile de forma a determinar os determinantes da eficiência. Os principais resultados revelam que o número de lojas eficientes aumenta quando estamos perante retorno variável à escala e quando a variável renda é inserida no modelo DEA. As marcas e a localização comercial das lojas são os determinantes da eficiência.

keywords

DEA, Benchmarking, Determinants of efficiency, Quantile regression, Brand equity, Shoppings.

abstract

This study aims to assess efficiency of a retail stores chain of Fashion & Accessories that represents several international prestigious brands in the Portuguese market and to identify the driving forces that influence efficiency. The study compares the performance among the stores of 3 different brands of the Brand equity market and provides insights into ways of improving performance. To evaluate the efficiency and its determinants we use a two-approach methodology: first Data Envelopment Analysis methodology (DEA) is used to determine the efficient scores and then a Quantile linear regression to determine the efficiency drivers. Main results show that the number of efficient stores increase under variable return to scale and when the variable rent is included in the DEA model. The brands and the retail commercial location are the factors that explain efficiency.

Table of Contents

Index of Tables

Index of Figures

Glossary

CRS: Contant Returns to Scale

DEA: Data Envelopment Analysis

DMU: Decision Making Unit

INE: Intituto Nacional de Estatística (National Statistical Institute)

OLS: Ordinary Least-Squares regression

PPS: Production Possibility Set

VRS: Variable Returns to Scale

1. Introduction

Over the last two decades, the Portuguese retail market in general and the Fashion retail market in specific undergone profound transformation.

During these decades, the evolution of the concept of physic distribution led retailers to recognize gradually the advantages associated to this type of commerce. In the Fashion retail market, consumers became more selective regarding expenses, looking for better design, quality and price (Cantista et. al., 2011). In a market where consumers don't buy clothes by necessity and where the competition is fierce, the strategy is not only to propose the right product at the right time, but also to propose a different product (Institute Français de la Mode, 2004).

The transition from a "product market" for a "brand market" in Fashion retail market associated to the reduction of the operational costs of distribution led to the specialization of several retailers in this type of commerce.

Driven by the social and economic development and the extension of Fashion brands segmentation, this phenomenon become more evident in Portugal in the 90's. The Portuguese market opened for to retailers that commercialize fundamentally international fashion brands which are positioned in the premium market segment. The entrance of high mono-brand retailers in the Portuguese market set multi-brand retailers in crisis. (ATP – Associação Textil e Vestuário de Portugal, 2011).

Additionally, "New Distribution" based in Shopping Centers, Supermarkets and other Great surfaces emerged with new concepts and distribution practices. Several large shopping centers opened across the country in just over a decade, with an enormous impact on the Portuguese buying habits. In a study provided by one of the leader's companies of consultancy in real estate market (Jones Lang-la Salle, 2015), Shopping's are the first choice of Portuguese consumers and represents 80% of the global retail offer in Portugal. The retail sector has been the protagonist of the real estate market in Portugal since the 90's. The management of major shopping centers favored brands belonging to international groups and national retailers with mono-brand store structure. Under this type of real estate, spaces are rented to retailers.

Competition in retail has become even more intense in recent years. Some retailers specialized in distribution while others remained as producers. The clothing industry in Portugal is a recurrent topic for studies performed by Portuguese entities as Banco de Portugal, Associação Têxtil e de Vestuário, Agência de Investimento e Comércio Externo de Portugal, among others. However, the distribution sector seems to be a under research topic. Also, the increasing demand of retailers of this type of commercial locations, as Shopping Centers and other specialize retail locations, increased the value of those spaces (rents).

These challenges propelled us to conduct an efficiency analysis applied to the distribution fashion retail market. The study is applied to a Portuguese retail chain positioned at the brand equity segment, which distributes several international brands in the Portuguese market. All the stores are in retail commercial locations as referred above and are rented. The study is pursued by a two-stage approach: first, an analysis of efficiency is conducted using Data Envelopment Analysis (DEA, hereafter); second, it is applied a quantile regression estimation to explore the determinants of efficiency.

The assessment of corporate performance has been an issue of importance for economics for decades. Several studies have, however, several limitations. First, most studies select one-dimensional measure of outcome (Mateo et al., 2006; Barth, 2007; De Jorge Moreno, 2008; Vaz et al., 2010; Moreno and Sanz-Triguero, 2011; Ghandi and Shankar, 2014, 2016) which is a limited assessment. An alternative approach is to use an index resulting from the aggregation of different variables (Ket and Chu, 2003). Nonetheless, the sum of the multiple variables is based on a subjective system of weights that could vary. A method of overcoming these problems is to measuring relative performance in a way which is well-known from the efficiency analysis literature, the DEA method, first introduced by Charnes et al. in 1978.

A major technique that has been used to describe retail performance is Data Envelopment Analysis (DEA). DEA is a “data oriented” approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs (Cooper, Seiford and Zhu, 2004). A unit is considered efficient if there is no other (or combination of them) that generates the same number of products with fewer resources, or conversely that generates more products with the same use of resources.

Thanassoulis (2001) explain that in DEA the resources are typically referred to as "inputs" and the outcomes as "outputs". The identification of the inputs and the outputs in an assessment of DMUs is as difficult as it is crucial. The inputs should capture all resources which impact the outputs. The inputs should reflect the resources that affect the outputs, and the outputs should capture the relevant outcomes on which we wish to evaluate the DMU. Further, any environmental factors which impact the transformation of resources into outcomes should also be reflected in the inputs or the outputs depending on the direction of that impact (Horta e Costa, 2011).

In the traditional approach, DEA uses two main models: the original formulation, known as the Charnes, Cooper and Rhodes (CCR), that assumes constant returns to scale (CRS) (Charnes et al., 1978) and another, known as the Banker, Charnes and Cooper model (BCC) that assumes variable returns to scale (VRS). This model is known in the literature as the BCC model and accommodates the situations where there is a relation between the scale and the efficiency of operations (Banker et al., 1984). Both models generate a piecewise-linear envelopment surface and are either input or output-oriented, depending on whether the objective is to minimize inputs or maximize output, with output production or input consumption, respectively, kept constant. Both orientations yield identical envelopment (convex) surfaces but differ in the way inefficient DMUs are projected into the efficient frontier.

DEA has become an increasingly popular tool for evaluating corporate efficiency, and has been applied in education (schools, universities), banking industry (banks, branches), health care (hospitals, doctors), courts, manufacturing, fast food restaurants, retail stores, information and communication technologies, benchmarking, management evaluation, and so on. Charnes et al. (1994) have compiled an extensive discussion of efficiency models across a variety of industries. Extensive reviews of DEA can be found in Norman and Stoker (1990), Boussofiane et al. (1991)., and Charnes et al. (1994).

As stated by Yu and Ramanathan (2009) DEA presents many advantages to evaluate performance. DEA enables the estimation of an overall performance score for each unit (firm; shop; store based on multiple inputs (e.g., costs) and multiple outputs (e.g., revenues). In addition, DEA derives the weights for the different inputs and outputs directly from the data, eliminating the subjectivity on their selection. The weights are estimated recurring to optimization which attributes to each unit (firms; shop, store) the best possible score. Other major advantage of DEA is that it specifies improvement targets for the inefficient units to behave efficiently. This information is derived based on a comparison with the other units in the sample.

In the second-stage, the DEA efficiency scores regarding the first-stage are used to test important hypotheses on the impact of environmental variables. Although the results of DEA could reveal that the primary cause of efficiency is the scale economies, it does not identify the other more driving factors influencing efficiency (Barros, 2006).

One of the motivations of pursuing a study that is focused on the retail market, more precisely the Fashion and Accessories sector, relies on the fact that the author's actual professional activity is associated to the real estate market. During the professional activity, the author could observe the challenges and the difficulties that retailers must face while developing their activity in commercial locations as Shopping's and other specialize retail locations. Considering this, it seemed an opportunity to conduct a study that relies on an efficiency analysis of a company with these characteristics. To our knowledge, so far, there have not been studies of this kind applied to this sector.

Whilst there is extensive literature on DEA and related methodologies applied to a diverse range of economic fields, the relative scarcity of texts dealing with this issue in relation to retailing specially focused in the textile sector clearly shows that this is a relatively under-researched topic. Considering the literature review, two studies that focus on the fashion retail market were found (Xavier et. al., 2015a and Moreno and Carrasco, 2016). Despite similar characteristics, such as both companies are also mainly located in Shopping Centers, both studies focus on manufacturers companies in fast-fashion segment. Therefore, this study attempts to fill this gap found in the literature by focusing the analysis on a distribution company in the Brand Equity segment.

In this study, we examine the relative performance efficiency of a Portuguese retail chain of Fashion & Accessories whose stores are mainly located in Shopping centers. The study considers 185 observations over the period of 2009 and 2015. The research questions are presented as follows:

(1) The process of analyzing efficiency for a company composed by stores of three different international brands

(2) The analysis of the efficiency levels estimated by the non-parametric DEA model for each store, year, brand and location.

(a) to evaluate the effect of a strategic variable to the company (variable rents), the analysis is conducted with two different models with two different set of inputs. The objective is to analyze the impact of this variable on efficiency.

(b) to evaluate the effect scale by performing the analysis under constant return to scale (CRS) and variable return to scale (VRS) assumptions.

(3) Benchmarking polices will then be defined to improve the efficiency levels, including the definition of targets.

(4) The analysis of other determinants that can influence efficiency levels through a quantile linear regression.

This thesis is structured as follows:

i. Chapter 2 is the Literature review and has three sections: section 1 reviews the literature on DEA methodology for the retail sector, section 2 reviews the literature on inputs and outputs selection and section 3 reviews the literature on the determinants of efficiency.

ii. Chapter 3 is the Empirical setting and data and has two sections: section 1 is the Empirical setting and aims to provide a contextualization of the company under study and in section 2 we present the data used in the analysis.

iii. Chapter 4 refers to the Efficiency analysis and has four sections: section 1 presents the DEA methodology, section 2 the selection of variables, section 3 the results of the efficiency analysis and section 4 the main conclusions.

iv. Chapter 5 refers to the advanced DEA model, the Quantile regression estimation and has three sections: section 1 presents the quantile regression methodology, section 2 the variables, section 3 the results and section 4 the main conclusions.

v. Chapter 6 presents the conclusions and limitations of this study.

2. Literature Review

In this chapter, we review the literature that constitutes the background for our study. As mentioned earlier, the Data Envelopment Analysis (DEA) has become a solid tool to analyze efficiency, and it has been applied to several sectors. This chapter aims to provide a review on studies of efficiency using DEA applied to the retail sector and is divided in 3 sections: a literature review on the applications of DEA in the retail sector, the selection of inputs and outputs and the determinants of efficiency.

2.1. Efficiency analysis in the retail sector: applications of the DEA

The assessment of relative performance has been an issue of importance in the retail industry for decades. In Table I there is a resume of the studies found in literature concerning analysis of efficiency using DEA applied to the retail sector. It is possible to verify that several studies have applied DEA and related methodologies to analyze retail outlets.

The DEA is used to address a series of issues concerning the measurement of corporate performance, which includes an assessment of sales' efficiency, the effects of economies of scale, benchmarking of a firm's performance and the association between industry groups and performance (Athanassopoulos and Ballantine, 1995). These authors offer the first application of DEA methodology using financial ratios. They proposed the use of alternative methodologies for assessing corporate performance. It is argued that the use of ratio analysis is insufficient for assessing performance, and that more advanced tools like DEA should be used to complement ratio analysis. The paper uses data drawn from the grocery industry in the UK.

Table I. Literature review in retail efficiency using DEA

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Athanassopoulos and Ballantine (1995)	This paper considers the use of alternative methodologies for assessing corporate performance of industrial sectors within the economy. It is argued that the use of ratio analysis in itself is insufficient for assessing performance, and that more advanced tools like DEA should be used to complement ratio analysis.	DEA	Supermarkets UK 31 stores 31 DMUS	Capital employed, value of fixed assets, number of employees, number of outlets, Sales Floor area, Total Sales	Evaluated the efficiency of several supermarkets (different chains). These authors are the first application of DEA methodology using finantial ratios.
Donthu and Yoo (1998)	The purpose of this study is to suggest and illustrate Data Envelopment Analysis (DEA), to assess retail productivity. While still remaining in the output-to-input ratio measurement domain of retail productivity, DEA can measure retail productivity at the retail firm or store level using multiple inputs and outputs (both controllable and uncontrollable) simultaneously and provide a single relative (to best) productivity index.	DEA	Data from a major metropolitan city with 24 outlets of a Fast-Food resturant chain (USA). The data was pooled (72 obervations) to compare and track efficency over time (3 years).	Store size, location, store manager experience, promotion expenses Sales, customer satisfaction	This paper conceptualizes the retail productivity as the relative performance efficiency of a retail store characterized by multiple inputs and outputs and presents an operations research-based methodology called Data Envelopment Analysis (DEA) that seems to address most of the concerns with current retail productivity measurement.
Yu and Ramanathan (2008)	To assess performance of 41 retail companies (several sectors) working in UK between 2000-2005 using 3 methodologies. The data used in this study was collected by FAME database.	DEA (CCR and BCC) Output-oriented Malmquist Tobit Model	Retail firms from UK 41 retail companies between 200-2005 41 DMUS	Total assets, shareholders funds, number of employees Turnover (value), profit before taxation	The general conclusion is that the average efficiency of retail companies in the UK was less than 75 percent over the time. Benchmarks are provided for improving the operations of poorly performing retailers. The results have shown that about 50 percent (22 out of 41) of retail companies have expressed progress in terms of MPI during 2000 and 2005, The determinants of economic efficiency are legal form, ownership of company and retail characteristic.
Yu and Ramanathan (2009)	To assess operational efficiency of retail firms between 2000-2003 are examined using 3 related methodologies: DEA (results will highlight efficiency differences at a firm level - efficiency measurement) , MPI (dynamic approach) and a bootsstrapped Tobit regression model (will highlight drivers of efficiency). Data was obtained from China Market Statistic Yearbook.	DEA (CCR and BCC) Output-oriented Malmquist Bootstrapped Tobit model	Retail firms from China 61 retailers for the years 2000-2003 61 DMUS	Total selling floor space and number of employees Sales and Profits before taxation	The general conclusion is that the average efficiency of retail firms in China was less than 45 percent in 2002 and 37 percent in 2003. The MPI results have shown that about 37.3 percent of retail firms have expressed progress. Finally, the analysis has verified that retail characteristic is the potential driving force that might influence retail efficiency.
Perrigot and Barros (2008)	Analyses the technical efficiency for the years 2000–2004, by a two-step procedure. In the first step, our DEA models are used to identify the efficiency scores. In the second step, a Tobit model is bootstrapped in order to identify the drivers of efficiency. The use of several models enables a cross-validation of the results.	DEA: CRS, VRS, cross-efficiency and super-efficiency Output-oriented Bootstrapped Tobit model	French generalist retailers 11 retailers for 2 yeras 55 DMUS: 5 years x 11 units	Labor (number of employees), capital(value), total cost Turnover (value), profits	The results indicate that the French retailers are relatively efficient. The efficient companies in the French market are identified. These units should serve as peers for the inefficient companies, which must benchmark their activity with the peers. Scale is a major issue in performance, with units displaying decreasing returns to scale, like Mergers acquisitions, which means that is still room for M&A in french market.

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Malhotra et al. (2010)	Illustrate the use of DEA to analyze the financial performance of the seven largest retailers in the U.S. To study the performance of retail industry, 7 financial ratios that have been computed on the basis of information contained in the income statement and balance sheet.	DEA (CCR and BCC) Input-oriented	The 7 largest retailers in USA. 7 DMUS	Average collection period, debt /equity ratio Operating profit margin, quick ratio, return on assets, asset turnover, and inventory turnover	The DEA model compares a firm with the pool of efficient companies by creating an efficiency frontier of good firms. Companies lying beyond this boundary can improve one of the input values without worsening the others. Illustrates the areas in which inefficient companies are lacking behind efficient firms. Provides an insight into the benefits of DEA methodology in analyzing financial statements of firms.
Moreno and Sanz Triguero (2011)	Two methodologies are used to measure productivity and efficiency for the years 1997-2007, obtained from the SABI database. The results obtained from both methodologies can contribute to opening up a new field of analysis since the results may be compared by means of the methodologies proposed as well as those which already exist in the literature	Stochastic DEA Input-Oriented Bootstrap Malmquist	12 sectors in Spanish retail trade for the years 1997-2007 12 DMUS	Fixed assets, intermediate consumption, personnel costs Sales	The results found high levels of inefficiency in most of the sectors analyzed over the period of analysis. The evolution of the efficiency of firms belonging to this sector decreases over the period of analysis. Analyzing the relationship between firms and size, the results obtained in this work shows that the firm's size have a positive influence on efficiency that suggest that the management may have incentives to grow in order to improve their efficiency levels.
Gandhi and Shankar (2014)	Analyze the performance of indian retailers in recent past and derive meaningful insight for practicing managers in this area. 3 different methodologies are used. The data was gattered by CMIE database, and includes 18 companies observed between 2008-2010.	DEA (CCR and BCC) Input-Oriented Malmquist Tobit Regression	18 Indian Retailers between the years 2008-2010 18 DMUS analyzed by year	Cost of sales, wages and benefits, other expenses, occupancy expense Sales, Profit	DEA analysis show that 5 retail firms out of selected 18 are found efficient under CRS and 7 under VRS. MPI results indicate that 61% of the firms have progressed during the time under consideration. The Bootstrapped Tobit Regression shows that the environmental variables that be considered as the driving forces influencing efficiency are number of retail outlets and Mergers and Acquisitions.
Gandhi and Shankar (2016)	Benchmarking indian retailers using 2 methodologies. Objective: how a retailer can benchmark its performance at a company, global, store and merchandise category level. The model in this paper uses data form published annual resports from CRISIL database.	DEA (CCR and BCC) Input-Oriented SRM (Strategic resource management)	11 indian generalized retailers. 11 DMUS	Number Employees, Square Foot Area, Inventories Sales	The examples considered in the paper can be used by retailers to plan and benchmark their performance.
Thomas et al. (1998)	Developed managerial process for assessing the efficiency ofr a multi-store, multi-market retailer. This study describes an evaluation process, based on DEA., to assess the efficiency of individual stores within a chain. DEA is particularly appropriate for this evaluation because it integrates a variety of performance metrics and provides a structured methodology for evaluating the retail store performance .	DEA (CCR) Input and Output oriented Non- discretionary inputs were modeled using the formulations of Banker and Morey (1986).	552 individual stores of a multi-market retailer from USA. 552 DMUS	Employees, expenses, location-related costs, internal processes Sales revenue, profit	Incorporating assurance regions into a DEA model allowed for a more complete specification of inputs and outcomes than usually found in DEA applications. This procedure permitted the researchers to capture top management's strategic thinking. Practical usefulness of the process' results is illustrated with respect to two management issues: evaluating store managers and identifying critical success factors CSFs.

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Mateo et al. (2006)	Propose a range of dynamic DEA models which allow information on costs of adjustment to be incorporated into the DEA framework. The new models are illustrated using data relating to a chain of department stores in Chile. Quantity and price data were extracted from the accounting information for the years 2000 and 2001.	DEA (New dynamic DEA modes)	35 retail department stores in Chile for the years 2000 and 2001. 35 DMUS	Salesperson labour, cashier labour, sales and administrative expenses, marketing expenses., store floor surface Gross sales	The empirical results illustrate the wealth of information that can be derived from these models, and clearly show that static models overstate potential cost savings when adjustment costs are non-zero.Overall, findings shows that these methods have the potential to provide valuable information to the managers of this business.
Dasgupta et al. (1999)	Investigate the impact of information technology in both manufacturing and service industries. This research methodology utilizes a combination of various data envelopment analysis models and non-parametric statistical techniques in testing for the influence of information technology investment on firm productivity. Data: sample of the largest companies in terms of information systems budgets, as reported in the Information Week 500.	DEA	Sample of 85 manufacturing and 77 service firms	Information technology budget, information technology employee Net income	This study demonstrated using a relatively simple set of DEA models that productivity in the service and manufacturing sectors seem to lag as increased investment occurs. This research reconfirms the "productivity paradox" theory, which stated that information technology has negligible or even a negative effect on firm performance. This work adds the relationship between productivity and investment.
Mostafa (2010)	Measure the relative efficiency using cross-sectional data for the year 2007. DEA approach to measure the relative efficiency of 45 retailers in the USA. Specialty retail and food consumer - data Cross-section obtained from magazine Fortune (list of 500 corporations in USA)	DEA (CCR and BCC)	US specialty retailers and food consumer stores for the year 2007. 45 DMUS	Number of full time employees, asset Revenues, market value, earning per share	The results indicate that the performance of several retailers is sub-optimal, suggesting the potential for significant improvements over both profitability and marketability dimensions. From a policy perspective, this paper highlights the economic importance of encouraging increased efficiency throughout the retailing sector in the USA
Kwok Hung Lau (2013)	Feasibility of DEA to mesure efficiency and rationalize a distribution network as an alternative approach of the Tradicional Optimising Method. The data used is from a major retailer in Australia This is an analysis of performance of individual stores in the same chain.	DEA (compares this technique with Traditional optimizing method)	400 stores of parts for repair machines) in Australia. 6 stores were analyzed. 6 DMUS	Total annual transportation cost Total revenue	Findings show that despite the different designs of the two approaches, both methods give a similar outcome leading to the identical conclusion that the network under investigation can be rationalised through merging the less efficient stores with the more efficient ones. This study has expanded the current research on retail network analysis by employing DEA as a flexible user-friendly analytical tool and corroborating the outcome with the traditional optimisation method.
Barth (2007)	The purpose of this paper is to show that new-style retail wine stores with features such as tasting rooms, lecture theatres and demonstration kitchens used to educate and engage customers have better retail efficiency than old-style stores.	DEA (CRS model to paired sample of old/new style facilities)	10 wine stores from Canada. 10 DMUS	Labor hours, Liters of inventory depletion Sales	The results of the study reflected that the new-style stores had higher retail efficiency than the old style stores and reducing the input in the older stores does not increase the retail efficiency of these stores. Although the study shows that the retail efficiency is increased with the new store features, the contribution of each feature towards the overall improvement in retail performance is unknown.

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Kamakura et al. (1996)	Given the lack of information on customers and transactions, this study proposes a cluster-wise regression procedure as a method of controlling the impact of unmeasured customer characteristics on efficiency. This approach is applied on the evaluation of multiple branches and compare the efficiency measures, using the Bank's central managers classification of markets as a benchmark.	Translog Cost Function	188 branches of a Bank in Latin America (evaluation of individual store productivity within a large, multi-store multi-market chain operation). 188 DMUS	Total operational costs, wage rate and man-hours of labor in each branch. Volume of cash deposits, volume of other deposits, volume of funds "in transit" in the branch, volume of service fees	The authors found that this method eliminated efficiency differences between the groups defined by the managers, while alternative procedures did not, and that this procedure provided a clustering of the banks which was related to that provided by the managers
Joo et al. (2009)	Measure and benchmark the retail operations of selected coffee stores owned by a specialty coffee company. Data envelopment analysis is used for benchmarking the performance of eight coffee stores for the period of two years using internal annual reports.	DEA (CCR and BCC) Input-Oriented	8 Coffee Stores in USA. 16 DMUS (8 stores for two years)	Model 1: cost of sales, wages and benefits, other expenses and occupancy expenses Model 2: cost of sales, wages, and other expenses Model 1: Sales (includes restaurant and retail sales) Model 2: sales-restaurant and sales-retail	Major findings are that the inefficient stores need to improve occupancy related expenses and revenues from non-coffee items. In addition, the coffee stores locate in an affluent residential area outperform the stores in the business district. This approach is useful for measuring the performance of coffee retail stores and provides managerial insights into the company.
Joo et al. (2011)	The paper seeks to suggest a novel framework based on return on assets (ROA), which is popular and user-friendly to managers, and demonstrate it by use of an example. The paper demonstrates the selection of variables using the elements of ROA and applies DEA for measuring and benchmarking the comparative efficiency of companies in the same industry.	DEA (CCR and BCC)	14 Retail firms from the USA. 14 DMUs	Full-time employees, part-time employees, cost of labor, absenteeism, area of outlets, number of points of sale (POS), Age of the outlet, Inventory and Other costs Sales, operational results	The framework demonstrated with an example a practical approach for benchmarking with limited data. Contributions of the study are twofold: first, suggest a framework for selecting variables for DEA studies using ROA; second, demonstrate the applicability of the framework using a real world example.
Barros and Alves (2003)	Efficiency is a main issue in retailing because its a component of total productiviy. this study performs an Intra-chain comparative efficiency in retailing. Introduction of uncontrolable inputs (introducing heterogeneity into the analysis), and analysis of the outlets without uncontrollable inputs. To estimate the production frontier, it was use cross-section data for the year 2000.	DEA (CCR and BBC) Output-Oriented	One of the leading multi-market hypermarket and supermarket chain groups, on 47 of its retail outlets from Portugal. 47 DMUS	Full-time employees, part-time employees, cost of labor, absenteeism, area of outlets, number of points of sale (POS), Age of the outlet, Inventory and Other costs Sales, operational results	This article has proposed a simple framework for the evaluation of retail outlets and the rationalisation of their operational activities.The general conclusion is that the majority of the outlets are efficient, although this leaves a proportion of the outlets analysed that are not inefficient. The findings suggest that scale economies are determinant factors of efficiency in this sector.

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Keh and Chu (2003)	The purpose is to study productivity at the retail (or "firm") level. The authors in this study addressed the two issues of retail productivity: construct and measurement. Data panel was collected from a chain for the years 1988 through 1997. Performance of individual stores in the same chain.	DEA Empyrical analysis using DEA (calculate individual input and output weights wich deliver the optimal RTE for each DMU.	13 grocery stores based in USA. 130 DMUS (10 years x 13 stores)	Labor (2 categories of employees): floor staff and management wages and benefits Capital (4 categories): occupancy, utilities; maintenance and general expenses Measuring Output - 5 categories of distribution services: accessibility; assortment; assurance of product delivery; availability of information and ambience. Final output: sales revenue	While there is considerable agreement in the literature that retail output consists of distribution services, there has been little empirical research that uses the distribution services argument at the firm level. As the level of analysis of the research is at the micro (firm) level, the findings should prove useful to managers. Essentially, the research aims at extending the theoretical and empirical understanding of productivity in retailing, as well as to be of use to managers.
Goic et al. (2013)	Model to evaluate relative category performance in a retail store considering they might have different business objectives (approach is based on DEA). Ilustration on how to use the approach by applying it to the evaluation of several categories in a South American Supermarket.	DEA Model assumes homogeneity - weight resctrictions are incorporated in the model to find the expected output for each unit.	40 categories from the grocery sections of a store in a South American Supermarket (Chile) 40 DMUs (also analyzes the SKUs (Sub-units of the categories)	Space, Promotional Effort, Feature, Number of SKU (stock-keeping units) Sales, Penetration, Margin, Share, Perceived variety	The methodology implemented in this study can help store managers not only to identify sources of inefficiencies in terms of resource allocations, but also relieves them to assign a rigid definition of category roles. Results show that the proposed methodology has a significant discriminatory power to detect categories that are inefficiently managed.
Sellers - Rubio and Mas-Ruiz (2006)	Estimate the economic efficiency of supermarket chains in the Spanish retailing industry. The methodology applied is based on the non-parametric technique of data envelopment analysis. The empirical application is carried out between 1995 and 2001.	DEA (CCR and BCC) Output-oriented	100 supermarket chains from Spain between 1995 and 2001. 100 DMUS	Employees, Outlets, Capital Sales, profit	The empirical application shows the existence of high levels of inefficiency. The analysis of the efficiency of intermediaries favours the management of goods and services producers as it allows them to identify intermediaries or retailers that efficiently use their resources to bring their products to the market. In this sense, efficiency becomes an orientation criterion for the choice of vertical relationships in the distribution channel.
De Jorge Moreno (2008)	This study aims to present an approach for analyzing hypermarkets efficiency in Spanish retailing. In particular, the influence of the Retail Trade Act of 1996, by means of which the Spanish state transferred authority to concede licenses for opening commercial establishments to the regions, is to be studied. The analysis is based on a DEA model that allows the evaluation of categorical variables in DEA in cross-section data.	DEA (CCR and BBC) Input-oriented	234 Hypermarkets from Spain 234 DMUS	Employees, square meters Sales	The findings suggest the existence of three different production frontiers in relation to the markets' regulation process where the hypermarkets operate; high, medium and low regulation. In the second place, the effect of the regulatory restrictions carried out by the autonomous communities is corrected. This correction (once managerial inefficiencies have been eliminated) allows the hypermarkets operative in areas with low restrictions to be more efficient than those located in areas of greater regulation.

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Vaz et al. (2010)	Describes a method for the assessment of retail store performance based on DEA. The assessment considers the stores as complex organizations that agregatte several sub-units (sections) with management autonomy. The performance assessment of the sections envolves a comparison among similar sections in different stores, and evaluates efficiency spread. (Store performance at section and store level).	DEA Network analysis: allows the rellocation of a DMU (store) among the sub-DMUs (sections)	70 Hypermarkets and Supermarkets from Portugal. Performance of individual stores in the same chain. 70 DMUS	Area in square meter, stock, number of references, products spoiled Sales	This paper proposed In terms of developments of the DEA technique, a new method to assess complex DMUs which are composed by several sub-DMUs. In terms of results, the first stage analysis at the section level revealed some disparity in the performance levels between sections located in different stores. The results showed that there are only 7 stores with all sections operating at the best performance levels. In addition, the average performance of sections located in hypermarkets was higher than in sections of supermarkets.
Camanho et al. (2009)	Develops a method based on DEA for efficiency assessments taking into account the effect of non-discretionary factors. The objective of this paper is to evaluate the efficiency of stores in generating sales, taking into account the resources available (both discretionary and ND) and the external ND factors that characterize the store catchment area.	DEA Enhanced DEA model that accommodates non-discretionary inputs and outputs and treats them differently depending on their classification as internal or external to the production process	70 stores - 14 Hypermarkets and 56 Supermarkets from a chain operating in Portugal. 70 DMUS	Discrecionary Inputs: Stock, Operational Costs, Staff Costs (wages), Products Spoiled ND Internal Inputs: Floor Area External ND Inputs: Population, Competition Sales	In terms of the results of the retail stores' assessment, the analysis identified 36 inefficient stores when the effect of both internal and external ND conditions is taken into account. The authors found that the inefficiency estimates were quite sensible to the exclusion of the external ND factors from the assessment, so the use of the model developed in this paper was essential for obtaining unbiased efficiency estimates. However, for the stores analyzed, the impact of considering the floor space as an internal ND variable or as a discretionary factor was not very significant.
Barros (2006)	Analyse a representative sample of hypermarkets and supermarkets working in the Portuguese market, using a benchmark procedure to compare companies that compete in the same market and thereby deriving managerial and policy implications.Two-stage procedure to benchmark the companies was adopted. In the first stage DEA is used and in the second stage a Tobit model is employed to estimate the efficient drivers.	DEA (CCR and BCC) Output-oriented Tobit Regression	22 Supermarkets and hypermarkts from a chain operating in Portugal. Panel data from the years: 1998-2003 132 DMUS = 6 years x 22 units	Labor (Number of labourers), Capital (value of assets) Sales, operating results, value added	First, the efficiency of hypermarket and supermarket retail companies is high compared with that to be found in other sectors. Second, larger retail groups are, on average, more efficient than the smaller retailers, and third, that national retailers are on average more efficient than regional retailers. Third, scale plays an important role in this market. The efficiency drivers are market share, number of outlets and location. Finally, regulation has a negative effect on efficiency.
Sellers - Rubio and Mas-Ruiz (2007)	This paper seeks to estimate total productivity change in retailing firms and to decompose it into efficiency change and technical change (TC), i.e. the consequence of innovation and adoption of new technologies. This paper adopts a dynamic approach using the Malmquist productivity index between 1995 and 2003.	Malmquist	96 supermarket chains operating in Spain between 1995 and 2003 96 DMUS	Number of employees, number of outlets, capital factor Sales Revenue, Operational results	The results show a slight increase in average annual productivity among the firms analysed.It is shown that the main component of productivity change is TC. This result means that new ICTs have the capacity to alter the productive structures of retail firms, favouring their productivity. The results obtained show that the average efficiency of the analysed companies between 1995 and 2003 is 0.69, which reflects a high degree of inefficiency in the supermarket sub-sector.
Kapelko and Rialp-Criado (2009)	Compares the levels of efficiency of Polish and Spanish textile and clothing firms. The analyses were based on firm-level accounting data for the time period 1998-2001. Two steps methodology: comparison between the labour productivity and efficiency results for textile and clothing firms operating in Poland	DEA (CCR and BCC) Input-oriented	17 – Manufacture of textiles and textile products; 182 – Manufacture of other clothing and accessories. Pooled data: 436 Polish and 565 Spanish observations between 1998 and 2001	Fixed assets, Costs of goods sold and Number of full-time employees Revenues	For the period analysed, there is no statistically significant differences between the efficiency of Polish and Spanish textile/clothing firms. The general result of this study shows that firms in both countries are, on average, relatively highly efficient in their production processes. The efficiency score reaches a level of 86%.

Author	Main purpose	Methodology	Data / Market / DMUS	Inputs / Outputs	Main results / Discussion
Kapelko and Lansink (2014)	Examines the relation between intangible assets and technical efficiency of textile and clothing firms. A double bootstrap Data Envelopment Analysis approach was used to easure and explain technical efficiency. The empirical application used a data-set of the textile and clothing industry over the period 1995–2004 with a worldwide coverage.	DEA (CCR and BCC) Input-oriented Bootstrap-truncated regression	The firms in the sample are textile and clothing producers that are listed in the stock exchange between 1994 and 2004 Pooled data: 5477 DMUS	Goods sold, Tangible fixed assets, and Number of employees Revenues (sales and other operating revenues)	The results show that intangible assets had a positive relation with technical efficiency of the textile and clothing firms. Debt and membership of EU had a negative relation, whereas size, membership of NAFTA, and GDP per capita were positively related with technical efficiency.
Xavier el al. (2015 a)	Estimates the efficiency of 40 retail stores of a prestigious clothing fast fashion company. Two stage approach. The study compares the performance among the stores and provides insights into ways of improving performance. The input-oriented model was used to assess the summer and winter collections between 2010 and 2013 (data from different collections).	DEA (CCR and BCC) Input-oriented Quantile Regression	40 retail stores of a Fast Fashion company from Portugal between 2010 and 2013 40 DMUS	Rent Costs, Total salaries and wages, investments in assets Sales, EBITA	The results show that the total technical efficiency of the company decreases over time. This study identify a set of stores whose performance serves as an operational management benchmark for the less efficient stores. Differentiating factors identified in this empirical study (employees average level of education and number of workers), that differentiate operational efficiency and location of the retail store, can be pinpointed as critical success factors and key enhancers of competitiveness and value creation.
Xavier el al. (2015 b)	Analyze and evaluate the resource efficiency of 26 retail store chain of a prestigious women's clothing retail. To evaluate the efficiency, convergence , efficiency, technical (CRS) and pure technical (VRS) analysis are carried out based on data from 2010-2013. Static and Dynamic analysis. Static: cross-section efficiency - reflecting the seasonality of the clothing collections trough different seasons.	DEA (CCR and BCC) Input-oriented Convergence Analysis	26 retail store chain between 2010-2013 26 DMUS	Size of shops (size effect), personnel related costs, rent expenses, accomplished investments Sales, EBITA	Under the DEA methodology analysis it is possible to witness that the total technical efficiency of the stores diminished in most of the analysed time periods. There are no short-term scale problems (SE<PTE) in the operations of the majority of the stores analysed. However, in the long term, scale problems prevail in most of the quarterly sub periods considered, as the scale efficiency is lower than the pure technical efficiency. The firm must seriously ponder what strategy to follow: either prioritizing the reduction of scale of operations; or increasing the stores productivity, reducing the operational size.
Moreno and Carrasco (2016)	This study apllies the DEA method to analyze the efficiency of the Inditex Firm. This study adopts a mixed methods research, i.e., the combined use of quantitative and qualitative methods. Two-stage analysis: 1st the company inditex is analyzed in its competitive environment; 2nd individualized analysis of the Inditex group in the period 1990-2013, where the efficiency of the firm and the explanatory factors are analyzed.	DEA (CCR and BCC) Output-oriented Tobit regression	Analysis of competitive environment of Inditex firm (Spain) between 1990 and 2013. 24 DMUS	Capital, Intermediate consumption and labour costs Sales	The individual company analysis reveals that the average efficiency level by years for the period 1990-2013, is relatively high 88.8 percent. The years in which Inditex operates with the optimal scale has been five. The latter year 2013 has been the major reference for the rest of those who have not been part of the frontier. The determinants of efficiency have been: the resources of the company in terms of assets, degree of internationalization. Finally, the effect of liberalization of textile trade in 2005 had no influence on the efficiency levels.
Banker et al. (2009)	Based on a two-stage analysis of a panel of data on 12 outlets of a high-end retailer for 24 months, the research lies on how the level of supervisory monitoring affects retail sales productivity based on a two stage method.	DEA (CCR and BCC) Output-oriented Regression Model	12 outlets of a high-end retailer for 24 months. Each individual store month in the sample represents a DMU: 288 DMUs	Total selling hours, store size, average inventory, support activities Store sales (deflated)	Results show that supervisory monitoring has a negative impact on retail sales productivity.

Literature reports DEA applications to evaluate the performance of decision making units in many industries such as Generalist and Multi-sector Retail Firms (Yu and Ramanathan, 2008; Perrigot and Barros, 2008; Malhotra et al, 2010; Moreno and Sanz Triguero, 2011; Gandhi and Shankar, 2014), Multi-store and Multi-market retail chain (Thomas et al., 1998), Retail Department Stores (Mateo et al., 2006), Manufacturing and Service firms (Dasgupta et al., 1999), Machine Parts (Kwok Hung Lau, 2013), Wine Stores (Barth, 2007), Bank Branches (Kamakura et al., 1996), Coffee Stores (Joo et al., 2009) for measurement of efficiency across DMUs and benchmarking DEA.

Yu and Ramanathan (2008) assessed performance of 41 retail companies (several sectors) working in UK between the years 2000 and 2005 using three methodologies: DEA, Malmquist and Bootstrapped Tobit Regression. The study shows that ten retail companies are considered efficient under the constant returns to scale (CRS) assumption and another sixteen are considered efficient under the variable returns to scale (VRS) assumption in 2005. MPI results show that 50 percent of retail companies have registered progress in terms of MPI during this period. Three environmental variables, namely, type of ownership, legal form and retail characteristic, have been found to play significant roles influencing retail efficiency using Bootstrapped Tobit Regression.

Perrigot and Barros (2008) employed DEA and a Bootstrapped Tobit Regression model for 11 generalized French retailers during the period 2000-2004. The average efficiency scores for these French retailers over five years are 0.987 as per CCR model and 0.993 as per BCC model, signifying high level of efficiency.

Gandhi and Shankar (2014) analyze the performance of 18 Indian retailers and derive meaningful insight for practicing managers in this area. As in Yu and Ramanathan (2008) DEA, Malmquist and Bootstrapped Tobit Regression are used to compute relative efficiency of retail outlets. Gandhi and Shankar (2016) also applied SRM (strategic resource management) and DEA to 11 Indian generalized retailers with the objective of benchmarking a retailer performance at a company, global, store and merchandise category level. The examples considered in the study can be used by retailers to plan and benchmark their performance.

To measure the efficiency and productivity of the Spanish retail firms, Moreno and Sanz Triguero (2011) applied Stochastic DEA (order-m) which is based on the concept of expected minimum input function and Bootstrapping Malmquist Index to measure productivity and efficiency in 12 sectors. The main contribution of this paper is to provide an efficiency analysis using a non-parametric approach with a robust estimator that has been suggested recently by Cazals et al. (2002). In addition, productivity growth is analyzed using bootstrapping Malmquist indices.

Malhotra et al. (2010) illustrate the use of data envelopment analysis (DEA) to analyze the financial performance of the seven largest retailers in the U.S. (Wal-Mart, Target, Costco, Macys, Sears, J.C. Penney, and BJ Wholesale) by benchmarking a set of financial ratios of a firm against its peers.

While there are studies on performance assessment in distinct sectors of retail outlets using DEA, the emphasis seems to have been placed on supermarket chains. The following studies applied DEA Methodology. Barros and Alves (2003) proposed a simple framework for the evaluation of retail outlets and the rationalization of their operational activities. Cross-section data for the year 2000, obtained from one of the leading multi-market hypermarket and supermarket chain groups, on 47 of its retail outlets was used. The model is output oriented and used VRS hypothesis because scale size is controllable by the retail chain's central management. CRS index is also considered for combination of pure technical and scale efficiencies. The findings suggest that scale economies are determinant factors of efficiency in this sector. Ket and Chu (2003) addressed the two issues of retail productivity: construct and measurement from a chain of grocery stores based in USA - annual observations of 13 stores for the years 1988 through 1997; Goic el al. (2013) created a model to evaluate relative category performance of several categories in a South American Supermarket (40 categories from the grocery sections of a store); Sellers-Rubio and Mas-Ruiz (2006) used a sample of 100 supermarket chains to study the economic efficiency of supermarket chains in the Spanish retailing industry between 1995 and 2001 and found high levels of economic inefficiency in the Spanish retailing sector; Moreno (2008) present an approach for analyzing hypermarkets efficiency in Spanish retailing. The influence of the Retail Trade Act of 1996, by means of which the Spanish state transferred authority to concede licenses for opening commercial establishments to the regions, is to be studied.

Vaz et al. (2010) described a method for the assessment of retail store performance at section and store level based on DEA. Using DEA, the assessment considers the stores as complex organizations that aggregate several sub-units - sections with management autonomy. The performance assessment of the sections involves a comparison among similar sections in different stores, and evaluates efficiency spread. This analysis considers the interdependencies of the sections composing a store, as they share limited resources such as the floor area. This is achieved using a Network DEA model, which determines the maximum store sales allowing for reallocations of area among the sections within a store. The method developed is illustrated using a case study consisting of a Portuguese chain of supermarkets. The performance of the retail stores can also be influenced by environmental factors, such as low population density or high competition, or by endogenous factors such as the size and the format of the store (hypermarkets or supermarkets). Camanho et al. (2009) developed an enhanced DEA model that accommodates non-discretionary (ND) inputs and outputs and treats them differently depending on their classification as internal or external to the production process. Data used from 70 stores (14 Hypermarkets and 56 Supermarkets) of a Portuguese chain. Discretionary Inputs: Stock, Operational Costs, Staff Costs (wages), Products Spoiled; ND Internal Inputs: Floor Area; External ND Inputs: Population, Competition. The objective is to evaluate the efficiency of stores in generating sales, considering the resources available (both discretionary and non-discretionary) and the external ND factors that characterize the store catchment area. Results show that the inefficiency estimates were quite sensible to the exclusion of the external ND factors from the assessment, so the use of the model developed in this paper was essential for obtaining unbiased efficiency estimates. However, for the stores analyzed, the impact of considering the floor space as an internal ND variable or as a discretionary factor was not very significant.

Still concerning the grocery sector, DEA and related methodologies were applied by several authors. Barros (2005) analyzed a sample of 22 hypermarkets and supermarkets in Portugal. The author found that the efficiency level of hypermarket and supermarket chains is comparable to other industrial sectors in Portugal. Using the same sample as the previous study, Barros (2006) adopted a two-stage procedure to benchmark the companies. In the first stage DEA is used and in the second stage a Tobit model is employed to estimate the efficient drivers. The conclusion from the research is that large retail groups are on average more efficient as compared to smaller retailers. This study also reveals that national retailers are on average more efficient than regional retailers. The efficiency drivers are market share, number of outlets and location. Finally, scale plays an important role in this market while regulation has a negative effect on efficiency.

Barros and Alves (2004), Sellers-Rubio and Mas-Ruiz (2007) developed a model based on a dynamic approach using the related methodology of DEA, the Malmquist Index. In their model, Barros and Alves (2004) analyzed the intra-chain comparative efficiency of a major Portuguese retail company, assessing the efficiency of a sample of individual stores. Total productivity change is estimated and decomposed into technically efficient change and technological change. The benchmarking procedure implemented is internal (stores in the chain are compared against each other). The aim of this procedure is to seek out those best practices that will lead to improved performance throughout the whole chain. Sellers-Rubio and Mas-Ruiz (2007) also examine the patterns of change in efficiency for a sample of 96 supermarket chains operating in Spain between 1995 and 2003. The results obtained show that the average efficiency of the analyzed companies between 1995 and 2003 is 0.69, which reflects a high degree of inefficiency in the supermarket sub-sector. This value implies that, on average, the sample companies could have achieved the same levels of outputs with 31% lower inputs. Regarding the components of this inefficiency, they reach average levels of 0.795 for technical efficiency (TE) and 0.868 for scale efficiency (SE). This means that the most of the deviation from the efficiency frontier is due to poor use of inputs (TE) and, to a lesser extent, to firms not operating at optimum size (SE).

However, in recent studies there is an application of the DEA methodology on retail industry efficiency in the textile sector such as Kapelko and Rialp-Criado (2009), Kapelko and Lansink (2014), Xavier et al. (2015 a, 2015 b) and Moreno and Carrasco (2016). Kapelko and Rialp-Criado (2009) compares the levels of efficiency of Polish and Spanish textile and clothing firms and Kapelko and Lansink (2014) examines the relation between intangible assets and technical efficiency of textile and clothing firms with a worldwide coverage. The other authors focused their analysis on companies of the Fast Fashion market segment. Xavier et al. (2015a) estimated the efficiency of 40 retail stores of a prestigious clothing fast fashion company in a two-stage approach: DEA and Quantile Regression Technique. The input-oriented model was used to assess the summer and winter collections between 2010 and 2013 (data from different collections). On the first phase of the empirical study, the solutions of the linear programming problem are used to identify efficiency scores; the second phase proceeds with the estimation of a quantile regression to assess the impact of other determinants that can influence efficiency levels achieved during the first phase. The study compares the performance among the stores and provides insights into ways of improving performance. Xavier et al. (2015b) developed a different study based on the resource efficiency analysis of 26 retail store chain of a prestigious women's clothing retail using a convergence analysis and DEA. To evaluate the efficiency, convergence efficiency, technical (CRS) and pure technical (VRS) analysis are carried out based on data from 2010-2013. Main results show that the total technical efficiency of the stores diminished in most of the analyzed time periods and that there are no short-term scale problems in the operations of the majority of the stores analyzed. However, in the long term, scale problems prevail in most of the quarterly sub periods considered, as the scale efficiency is lower than the pure technical efficiency. Benchmarking policies propose two strategies: either prioritizing the reduction of scale of operations or increasing the stores productivity, reducing the operational size. Moreno and Carrasco (2016) applied the DEA method to analyze the efficiency of Inditex Firm. This study adopts a mixed methods research, i.e., the combined use of quantitative and qualitative methods. Two-stage analysis: 1st the company Inditex is analyzed in its competitive environment; 2nd individualized analysis of the Inditex group in the period 1990-2013, where the efficiency of the firm and the explanatory factors are analyzed using DEA methodology. The individual company analysis reveals that the average efficiency level by years for the period 1990-2013, is relatively high (88.8 percent); Inditex operated at optimal scale for five years; the resources of the company in terms of assets and degree of internationalization (that is positively related to efficiency) are the determinants of efficiency. As the company increases its expansion, experience and skills, the efficiency also increases.

Considering the market segment Brand Equity, there are no studies in the literature focusing on companies of the Fashion apparel. However, one study was found concerning a High-end retailer positioned at the high end of the spectrum for department stores (offers service that is perceived by its customers to be superior and unique relative to service provided by its competitors). Based on a two-stage analysis of a panel of data on 12 outlets of a high-end retailer for 24 months, Banker et al. (2009) evaluated how the level of supervisory monitoring affects retail sales productivity. First, using DEA and then regressing the logarithm of DEA productivity scores on contextual variables to consistently estimate the impact of the contextual factors on productivity. Results show that supervisory monitoring has a negative impact on retail sales productivity.

2.2. Inputs and Outputs selection for efficiency analysis

Inputs are defined as the resources available for a decision-making unit for maximization of its performance. Outputs are results that have been defined by store managers as desirable. They include not only direct economic results but others that may be related to the store market positioning.

The most important consideration in any DEA application is the selection of the input and output variables. Management must be very careful in this process and make sure that these variables represent their overall goals and policy. The choice of the input and output variables is critical to the successful application of this technique.

According to Donthu and Yoo (1998), the factors that have a direct cost to the firm and tend to vary are a good choice for input variables. For example, if rent is a major cost to the firm that varies from store to store, then it should be included as an input variable. The choice of the output variables often reflects the goals or objectives of the company. For example, if customer satisfaction is an objective of the firm, it would make sense to include customer satisfaction as an output variable. Also, considerable effort should be used in determining which stores to include in the analyses.

Most of the previous studies found in the literature have proposed measures of output in monetary units, such as sales and profit (Thomas et al., 1998; Sellers - Rubio and Mas-Ruiz, 2006; Yu and Ramanathan, 2009; Gandhi and Shankar, 2014), revenue (Thomas et al., 1998; Mostafa, 2010; Joo et al., 2011; Kwok Hung Lau, 2013), turnover (Perrigot and Barros, 2008; Yu and Ramanathan, 2008; Malhotra et al., 2010) and net income (Dasgupta et al., 1999). However, measures of output in non-monetary units also have been proposed, such as customer store satisfaction and service quality (Keh and Chu, 2003).

The literature on productivity assessment in the retail sector generally differentiates two different kinds of inputs, controllable and non-controllable, depending on whether they are or not controllable by the firms. Often, uncontrollable input factors are ignored in the assessment of retail productivity.

Since controllable inputs can be controlled by firms to gain competitive advantage, it is a common practice to use them as part of efficiency assessment. Examples of controllable inputs used in the literature include managerial and personnel factors such as number of employees

(Thomas et al., 1998; Barros and Alves, 2004; Sellers-Rubio and Mas-Ruiz, 2006; De Jorge Moreno, 2008; Perrigot and Barros, 2008; Yu and Ramanathan, 2008, 2009; Mostafa, 2010; Gandhi and Shankar, 2016), area in square meter (Mateo et al., 2006; De Jorge Moreno, 2008; Vaz et al., 2010; Gandhi and Shankar, 2016), store size (Donthu an Yoo, 1998; Banker et. al., 2009 and Xavier at al., 2015b); assets (Barros, 2006; Yu and Ramanathan, 2008; Joo et al., 2011; Moreno and Sanz-Triguero, 2011; Xavier at al., 2015a), stock (Barros and Alves, 2004; Camanho et al., 2009; Vaz et al., 2010) and number of outlets (supermarkets) (Athanassopoulos and Ballantine, 1995; Sellers-Rubio and Mas-Ruiz, 2006, 2007).

The inputs and outputs that have been selected in previous studies are resumed in Table I above.

In contrast, non-controllable inputs are generally considered as environmental variables since they could influence the efficiency of firms but are not directly controllable by the firms.

This study relies on these studies to define the input and output variables. Details are discussed on section *3.2. Data*.

2.3. Determinants of efficiency

The DEA method provides a score for each unit under analysis, but it does not identify the factors influencing efficiency.

Environmental or non-controllable variables are not the conventional inputs and outputs in the DEA model and are assumed as not being under the control of business management (Boame, 2004; Casu and Molyneux, 2000). Examples of environmental variables considered in the literature include ownership (Barros, 2006; Yu and Ramanathan, 2008, 2009; Gandhi and Shankar, 2014), internationalization (Perrigot and Barros, 2008; Moreno and Carrasco, 2016), competition (Banker et al., 2009; Camanho et al., 2009), population density (Banker et al., 2009; Camanho et al., 2009; Xavier el al., 2015 a), location (Thomas et al., 1998; Barros, 2006; Yu and Ramanathan, 2008, 2009; Banker et al., 2009), among others. Normally, non-controllable inputs are ignored in the estimation of retail productivity (Donthu and Yoo, 1998).

Details about methodologies, variables and efficiency drivers found in the literature can be consulted in Table II.

Table II. Literature review of efficiency drivers in retail

Studies	Methodology	Variables	Efficiency drivers
Barros (2006)	Tobit Regression	Share, outlets, ownership, regulation, location	Efficient drivers: Market share, number of outlets, national ownership, Location (market coverage). Regulation is detrimental to the efficiency of retailers
Yu and Ramanathan (2008)	Tobit Regression	Head office location; types of ownership; years of incorporation; legal form; retail characteristic	Legal form, ownership of company and retail characteristic are the possible driving forces influencing efficiency.
Gandhi and Shankar (2014)	Tobit Regression	Number of outlets, Ownership, Age since incorporation, Mergers and Acquisition	Number of retail outlets and mergers and acquisitions can be considered the driving forces influencing efficiency of retailers in India.
Perrigot and Barros (2008)	Tobit Regression Bootstrap	Trend; square trend; quoted; mergers and acquisitions; group; international	Efficient drivers: quoted, mergers and acquisitions, group and international
Yu and Ramanathan (2009)	Bootstrapped Tobit model	Head office location, firm nationality, years of incorporation, ownership type and retail characteristic	Retail characteristic is the potential driving force (department stores seemed to be more efficient than the retailers in other retail subsectors in China). Other factors, such as head office location, firm nationality, years of incorporation, and ownership types are not the efficiency drivers.
Moreno and Carrasco (2016)	Tobit regression (with and without bootstrap)	Assets, level of internationalization through expansion into new markets, impact of the liberalization of textile trade in 2005.	The determinants of efficiency are: the resources of the company in terms of assets and degree of internationalization of the firm, is positively related to efficiency. The effect of liberalization of textile trade in 2005 had no influence on the efficiency levels.
Banker et al. (2009)	Regression Model	RURAL - location of the stores; INCOME - medium household income; AGE - medium age of the area population; COLLEGE - percentage of people with college education; POPUL - the population size in the geographical area; COMPET - number and quality of competitors; MONITOR - supervisory monitoring; SINDEX - economy and industry wide effects; SEASON - to control the seasonal nature of the retail business	The coefficients of all the controll variables except INCOME are statistically significant. After controlling for economy-wide effects, results show that MONITOR (supervisory monitoring) has a negative impact on retail sales productivity in high-end stores.
Xavier el al. (2015 a)	Quantile Regression Technique	Number of workers; purchasing power per capita; employees average level of education; number of years of experience; Population density; shopping or traditional urban store.	The determinants are: Shopping location store, level of staff education. Following this results, some practices were implemented: emphasis on training and career development, selection and training of employees and the creation of a more structured career path to ensure employees key skills.
Thomas et al. (1998)	DEA	Employees, expenses, location-related costs, internal processes	Critical success factors CSFs. are those tasks that should receive priority attention because they significantly drive business performance. Multivariate analysis of variance (MANOVA) to identify CSFs: easing agreements, store location, and human resource management.
De Jorge Moreno (2008)	DEA (CCR and VRS models)	Evaluates the impact of an environment variable in efficiency - the influence of the Retail Trade Act of 1996 (Spanish state transferred authority to concede licenses for openning commercial establishments to the regions)	Conclusions shows that hypermarkets operating in areas with low restrictions to be more efficient than those that are located in areas of greater regulation.
Camanho et al. (2009)	DEA	Discrecionary Inputs: Stock, Operational Costs, Staff Costs (wages), Products Spoiled ND Internal Inputs: Floor Area External ND Inputs: Population, Competition	The internal and external ND factors are included in the DEA model. The model defines the efficient frontier based exclusively on the Discretionary variables and internal ND factors. Results show that inefficiency estimates were quite sensible to the exclusion of the external ND factors from the assessment,The impact of considering the floor space as an internal ND variable or as a discretionary factor was not very significant.

Perrigot and Barros (2008) and Moreno and Carrasco (2016) obtained a positive relationship between efficiency and internationalization, which means that the opening to new markets explains greater efficiency of the companies analyzed.

As viewed in the last section, some authors chose area in square meter, number of outlets and assets as controllable inputs in the DEA models. However, other authors didn't consider these variables as controllable inputs and treat them differently. Camanho et al., 2009 considered area in square meter as an internal Non-discretionary variable, and included it as a ND input in the construction of the DEA model. The authors considered that this input was not under the control of managers. Barros (2006) analyzed the input variable number of outlets as an environmental variable and pursued a Tobit Regression model to evaluate this variable as an efficiency determinant. Moreno and Carrasco (2016) also have used a Tobit Regression model (with and without bootstrap) and have analyzed if the variable assets were an efficiency driver.

As stated by Yu and Ramanthan (2009), a bootstrapped Tobit regression allows investigating other efficiency drivers beyond the scale economies. Main conclusions refer to retail characteristic as the potential driving force of retailers in China.

Other authors have used different methodologies to analyze the impact of environmental variables on efficiency. Banker et al. (2009) first estimated the scores of DEA and then employed a regression of DEA productivity scores on contextual variables to consistently estimate the impact of the contextual factors on productivity. A quantile regression technique was used by Xavier el al. (2015 a) to evaluate which variables were the efficiency drivers that can influence the efficiency levels achieved in the first stage using DEA.

Camanho et al. (2009) proposed an enhanced DEA model that accommodates external variables as non-discretionary inputs (ND). The authors considered that the inclusion of the external factors in the model lead to unbiased efficiency estimates. The external ND Inputs used in the model were the factors that characterized the store catchment area (population and competition). In terms of the results of the retail stores' assessment, the analysis identified 36 inefficient stores when the effect of both internal and external ND conditions is considered.

Thomas et al. (1998) developed an analysis based on a DEA model that allows the evaluation of categorical variables in DEA in cross-section data. The objective was to study the influence of the Retail Trade Act of 1996, by means of which the Spanish state transferred authority to concede licenses for opening commercial establishments to the regions.

3. Empirical setting and data

The first section of this chapter aim to provide a contextualization about the retail market, the clothing and accessories sector and the description of the network distribution channel, which includes Shopping Centers, Traditional urban stores and Outlet Shopping centers, since the company under study it's included in the retail market in the clothing and accessories sector and is mainly located in distribution channels such as referred above. Last section provides an overview of the company description and the data used for the evaluation of efficiency and their determinants by applying the techniques Data Envelopment Analysis (DEA) and Quantile regression described in the following chapters 4 and 5.

3.1. Empirical setting

Is important to have present the historical evolution of the distribution concept to understand the retail trade. We present a resume of the evolution of the distribution concept taking in consideration the study developed by the Textile and Clothing Association of Portugal (ATP, 2011),

In the 60's the concept of physic distribution that is imported from USA is assumed as a specialized management area. Producers recognize gradually the benefits of distribution as a business area under development that ensures the flow of products to sales public channels.

The 80's brought the distribution professionalization, which is a consequence of the retail channels expansion and was based on the following: purchase planning and reduction of operating costs, structures centralized for optimizing stocks, information control on sales and margins and integration of Logistics processes to reduce transportation costs. Concerning the clothing sector, in the 80's there is a transition from a "product market" for a "brand market" where brands are specialized in the individual.

In the 90's, new deals concerning the international commerce, globalization and internationalization of distribution led to a closer relationship between production and distribution companies.

The 90's are also characterized by having two business cultures: independent commerce and organized distribution networks. The independent group is composed by small and medium companies that control completely their business areas. Usually they have one or a few points of sale and don't have the possibility of scale economies. The principal representative of this group is the multi-brand retail.

The group organized distribution networks are composed by mono-brand retail chains. These companies unleashed a profound change in the clothing sector and in the way of exploring the commercial space. Size, location and ways of communicating the brand become important factors on points of sale. Usually, multiple stores and scale economies are a possibility for this group (Cantista et al., 2011).

The independent multi-brand small and medium sized retail dominated the Portuguese market until the 90s. Retailers positioned in the premium segment market, commercialize fundamentally international fashion brands. They developed at a time when there was no degree of segmentation and when Lisbon didn't have a critical mass of consumers to receive high mono-brand spaces. The social and economic development and the extension of fashion brands segmentation changed this paradigm, leading to the opening of own spaces or corners in department stores (such as El Corte Ingles). The shock of competitiveness caused by the internationalization of the Portuguese market set a crisis in multi-brand retail.

The commercial margins of mono-brand stores are substantially higher that the ones at disposal of the multi-brand retailers. A lower profitability combined with a decline in sales, not only contributes to the weakness of the channel, but also decreases the possibility of implementing price strategies, due to a lower margin. The crisis of many brands is directly related to the dramatic loss of the channel market share in recent years that undercapitalized even the most efficient retailers (ATP, 2011).

In the 2000s, distribution became a decisive factor for most businesses, absorbing human and financial resources, using advanced techniques to boost sales and launch new brands and new products. On the other hand, it began to absorb more value over the sales margins because of the integration of logistic functions and the providing of structures and adequate means to reach markets.

Between 2010 and 2014, retail market was very affected by the effect of the financial and economic crisis of Portugal. The Portuguese economy was under external support since May

2011, through the Economic and Financial Adjustment Program concluded between the political leaders of the government and the largest opposition party, and the three organizations which agreed to grant financial assistance to our country, the International Monetary Fund (FMI), the Central European Bank (CEB) and the European Commission (EC), a group commonly referred to as the “Troika”. Portugal has experienced a situation of economic and social crisis during this external intervention, with a substantial increase in taxation, particularly direct taxation, in the effort to undertake the budgetary consolidation agreed with the troika (Cushman & Wakefield, 2014)

The “National Accounts” illustrate the worsening economic situation that Portuguese economy has faced. Table III shows the economic indicators in Portugal for the period between 2011 and 2014. The worst scenario is presented in 2012, were GDP growth, consumer spending and investment decreases at the highest rates for that period. These market conditions impact negatively the sales for retailers (Jones Lang LaSalle, 2015).

Table III – Economic indicators between 2011 and 2014

Economic indicators	**2011**	**2012**	**2013**	**2014**
GDP Growth	-1,3	-4,0	-1,1	0,9
Consumer spending	-3,3	-5,5	-1,2	2,2
Investment	-10,5	-16,6	-5,1	2,8
Unemployment rate (%)	12,7	15,8	16,4	14,1
Inflation	3,7	2,8	0,3	-0,3

Source: Oxford Economics Ltd. and Consensus Economics Inc.

As stated in the publication Statistics Portugal (INE – National Statistical Institute), that disseminates the main statistical findings that allow the characterization of the Portuguese Distributive Trade Sector, the retail market represents 61,2% of the companies, 36,6% of business volume and 57,1% of people at service. Taking in consideration the INE publication in 2014, Statistics of Commerce, clothing is the second most representative sector (23,8%) in retail and the food sector, the most representative (33,2%) (INE, 2014).

In what concerns the statistics divided by “Commercial Units of Relevant Size” (UCDR - *Unidades Comerciais de Dimensão Relevante*), in 2014 the number was set at 3 204 establishments, mainly dedicated to food retail or food predominant (50.8%) and the rest to non-food retail. In non-food retail establishments, the sector with most significant sales was clothing and accessories (27.1%) (INE, 2014).

3.1.1. The clothing and accessories sector

Fashion is defined as an expression that is widely accepted by a group of people over time and has been characterized by several marketing factors such as low predictability, high impulse purchase, shorter life cycle, and high volatility of market demand (Fernie and Sparks 1998).

Fashion is a global phenomenon with an important impact in the economic, social and individual level.

Until the mid-1980s, success in the fashion industry was based on low cost mass production of standardized styles that did not change frequently due to the design restrictions of the factories. Apparently, consumers during that time were less sensitive towards style and fashion, and preferred basic apparel.

Towards the late 1980s, the fashion apparel industry was dominated by several large retailers which increased the competition levels in the market (Barnes and LeaGreenwood 2006). To survive the competition, other fashion apparel retailers switched from product-driven to buyer-driven chains, developed alliances with suppliers in different markets, and promoted their distinctive brands (Tyler, Heeley, and Bhamra 2006). This resulted in an increase of profits from unique combinations of high-value research, design, sales and marketing that would allow them and the manufacturers to act strategically by linking with overseas factories (Gereffi 1999). Tyler, Heeley, and Bhamra (2006) illustrated that the fashion apparel industry developed an infrastructure around the late 1980s with an emphasis on promoting responsiveness (quick response) through reduced lead times, along with maintaining low costs. Hereafter, the phenomena of sourcing manufacturing and processes in fashion apparel industry to offshore places with low labour costs became a trend, thereby resulting in a substantial cost advantage.

The 90's, driven by the ideas of marketing gurus like Kotler, can be considered the decade of segmentation. In clothing and accessories sector, segmentation becomes increasingly sophisticated and extensive, favored by the trade liberalization from the implementation of

WTO (World Trade Organization) guidelines. For brands this liberalization meant the transition to integrated proposals involving collections, commercialization space, image and communication. The statement of lifestyles, transmitted through branding strategies, gained much more importance than the product itself.

The importance of brand identity started as a prerogative to the selective segments, but was extended to almost all sectors. The trade liberalization opened doors for multiple cheaper supply options (outsourcing), bringing the possibility of expanding the range of products offered to consumers. Therefore, higher productivity and profitability acquired by retail activities in relation to the productive activities encouraged industrial companies to devote themselves exclusively to retail (process developed in northern Europe since the 80s). The purpose of retail brands focused on expanding the range and brand portfolio (ATP, 2011).

This prerogative led to the arise of a new concept in the fashion apparel industry, Brand equity. According to Aaker (1991) is defined as a set of brand assets and liabilities linked to a brand, its name and symbol that add to or subtract from the value provided by a product or service to a firm and/or to that firm's consumers. Blackston, (1995) suggests that the strong brand equity provides a series of benefits to a service firm, such as greater customer loyalty and higher resiliency to endure crisis situations, higher profit margins, more favorable customer response to price change, and licensing and brand extension opportunities.

Muller (1998) suggests that brand equity can maintain the differences, lowers operation risk, limits new-product introduction cost, and result in the improved business performance. Highly brand equity positive affects future profits and long-term cash flow, a consumer's willingness to pay premium prices and marketing success. The higher-level brand equity increases consumer satisfaction, repurchasing intent, and degree of loyalty.

The measurable brand value serves as one of a company’s most powerful resources: it creates potential cash flow while indicating how consumers perceive, form attitudes and behave toward that company. Brand equity is an important concept in measuring corporate performances, more than just an intangible corporate asset. It is therefore imperative that a company seeks sustained operations focus on tangible factors such sales results and market share.

3.1.2. Shopping Centers

Over the past decade the "New Distribution" based in Shopping Centres, Supermarkets and other Great surfaces emerged with new concepts and distribution practices, innovative rules for using stores space and provision of management services for optimizing real resources and logistics and create proper conditions to facilitate consumer access. The spaces managed by the "New Distribution" have been on significant demand by clothing retail companies and by consumers in general. They have contributed to diversify supply, create new patterns of consumption and generate new skills to operate efficiently both in the market of vendors and customers (ATP, 2011).

The retail sector has been the protagonist of the real estate market in Portugal since the 1990s. The emergence of the first large shopping centers in the country revealed a huge appetite for consumers and retailers for this format, largely because street commerce did not evolve in Portugal as in other European capitals.

The shopping centers have acquired considerable weight in the distribution of products in general, especially for textile and clothing items. The mono-brand stores of medium and medium-high segmentation found in shopping centers the ideal habitat to develop concepts that were out of reach of multi-brand stores, such as the high pace of product renewal.

According to a market study developed by the company Cushman and Wakefield in 2015, the geographical dispersion of spaces in different dimensions now covers the whole country. The offer of commercial spaces in Portugal registered very high growth rates until 2009, when the market began to reach maturity and show a slowing in the pace of supply growth.

Shopping centers are the first choice for Portuguese consumers, and dominate the real estate market with an offer of 2,8 million square meters, which represents 80% of the global offer.

According to the Portuguese Association of Shopping Centers (APCC), at present shopping centers are creators of 100,000 direct jobs and 200,000 indirect jobs.

However, the high volume of commercial supply and the contraction in consumption in recent years have led to a substantial difference in the performance of prime and secondary units, which is expected to remain in the medium term. The Colombo, Vasco da Gama and

CascaiShopping centers in the Lisbon Region and NorteShopping in Oporto, all belonging to the Sonae Group are the major sector references. Colombo and Amoreiras centers are the references in what concerns the demand of tourists.

3.1.3. Street commerce

The traditional (or street) commerce activity in Portugal has been decreasing and losing weight in distribution, as stated by the Associations of the sector. The evolution observed in recent years is characterized by the deactivation of the number of stores and the reduction in turnover. The reasons given for the situation are as follows: competition from Shopping Centers, the lack of modernization and spaces attractiveness, lack of management dynamic, loss of purchasing power and financial difficulties. Also, the increasing competition from international brands intensified the difficulties of the Portuguese traditional commerce.

However, street commerce in the main arteries of the biggest cities evolved to a premium and luxury concept offering high segment and mono-brand stores. This new trend has seen the emergence of neighborhood and proximity concepts, making street shopping the "star" of the retail market over the last three years.

The high growth of tourism has been the main generator of the great dynamism that takes place in the street commerce of the consolidated zones of Lisbon and Porto. Retailers (national and international) positioned in the high segment look for street stores that allow greater proximity to foreigner consumers. Also, changes to the lease law that regulates this type of commerce (in vigor since 2012), have played a very important role in this market.

3.1.4. Outlets

The origin of Outlets is linked to the need of disposal of products with reduced rotation and that were not sold in retail. This is a new concept of Distribution that has evolved to such an extent that today it represents an important source of business for brands and registers very significant annual growth rates.

From the 90s onwards the Outlets evolved to high levels of professionalism and service specialization. They were implemented in large urban centers in buildings designed to associate commerce and leisure (restaurants, amusement games, etc.) in order to capture customer loyalty.

At present, outlets that represent 3% of the global offer at real estate market, ended up benefiting from the crisis, given its concept associated with sales with heavily discounted prices. In recent years, in the metropolitan areas of Lisbon and Porto, there has been significant investments in Outlets. Freeport, in the Lisbon Region, and Vila do Conde The Style Outlet, in the Porto Region, are the main outlets in the country.

3.2. Data

All the data required for this study was obtained from a Portuguese company that represents several international brands in the Portuguese retail market, in the clothing and accessories sector. For confidentiality reasons, the name of the firm cannot be disclosed.

The company under study represents and distributes brands of the premium and luxury segment and in the last decade has intensely followed the evolution and transformation of the Portuguese market in the field of distribution strategies. The trade space "mono-brand" increased to the point that now it occupies most of the surface of the modern shopping centers. The company had this market phenomenon in consideration and in the last decade has well developed a strong presence in the single-brand market, by developing a chain of mono-brand stores linked to prestigious names in international fashion.

All the stores are located in urban areas across Portugal, and most of the stores (90%) are located in Portuguese shopping centers (80% in traditional Shoppings and 10% in Outlet Shoppings), while the other stores (10%) are located in the most prestigious streets that concentrate the premium and luxury brands in Portugal.

For the analysis, 3 different brands, that will be referred as Brand 1, Brand 2 and Brand 3, were considered. Brand 1 is an American manufacturer with a focus on footwear. This brand sells apparel such as clothes, watches, glasses, sunglasses and leather goods. Brand 2 is also an American clothing brand. In addition to clothing for both men and women, Brand 2 markets other fashion accessories such as watches, jewelry, perfumes, and shoes. These brands are in the premium market segment. Brand 3 is an Italian luxury brand that features Italian-designed products that range from handbags and shoes to accessories.

All the stores that belong to this company are rented and have a Leasing agreement with the Shopping Centers, Outlets Shopping Centers and the urban stores owners.

The data available for each store of the company was analyzed for each year, between 2009 and 2015. DEA requires that data set to be non-negative for the outputs and strictly positive for the inputs (Sarkis and Weinrach, 2001). There is no DEA model to date that can be used with negative data directly without any need to transform it (Portela et al., 2004). Hereafter, several retail stores that reported negative results were not included in this study. Also, the company has been growing its portfolio over the years, which implies that the number of DMUs analyzed were different for each year. The firm represents other several international brands, but they are relatively new in the portfolio, which means that the data available didn't provide significant information to perform an analysis that offers internal benchmarking with the best performers, as is the objective of this study. Hence, it was considered three different international brands positioned in the premium market segment.

Taking this in consideration, the data was pooled to create 185 observations. Table IV. shows the distribution of the stores for each brand by year.

Table IV. Number of stores for each brand by year

Year	Brand 1	Brand 2	Brand 3	Number of Stores
2015	16	13	6	35
2014	16	12	6	34
2013	16	12	6	34
2012	13	9	4	26
2011	13	3	4	20
2010	13	2	4	19
2009	11	2	4	17
185 DMUS				

Source: Own elaboration

In such examination, the store efficiency may be directly compared and tracked over time. However, in this analysis the benchmark is not the best performer in any given year (Donthu and

Yoo, 1998). In the literature some studies were applied using pooled data: Barros (2006) – 22 Portuguese supermarkets for the years 1998-2003 (6 years x 22 units = 132 observations), Perrigot and Barros (2008) – 11 French generalist retailers for the years 2000-2004 (5 years x 11 units = 55 observations), Banker et al. (2009) - 12 outlets of a high-end retailer for 24 months (each individual store month in the sample represents a DMU = 288 DMUS), Joo et al. (2009) - 8 coffee stores for two years owned by a specialty coffee company (2 x 8 = 16 observations) and Yu and Ramanathan (2009) - 61 Chinese retailers for the years 2000-2003 (2 years x 61 units = 122 observations).

4. Efficiency analysis

This chapter is focused upon the DEA analysis. First, we explain the method in detail, then the options taken in terms of inputs and outputs, then the results are presented and discussed. The last section presents a summary of the main results of the efficiency analysis, including benchmarking and the calculation of targets.

4.1. DEA methodology

Data Envelopment Analysis is a body of concepts and methodologies that have been incorporated in a collection of models with accompanying interpretive possibilities (Charnes et al., 1994).The seminal work of Cobb and Douglas (1928) related to the estimation of an average production function, contributed considerably to the development of this field in economics.

One of his articles, which represents the inception of DEA, Farrell (1957) was motivated by the need for developing better methods and models for evaluating productivity. The author proposed to estimate an empirical frontier against which actual efficiency could be compared. In particular, the author suggested changing the focus from absolute to relative efficiency by promoting the comparison of a unit to the best actually achieved by peers performing a similar function. After the seminal work of Farrel (1957), efficiency measurement methods evolved, leading to models for measuring the efficiency of a DMU *relative* to similar DMUs in order to estimate a 'best practice' frontier. The initial DEA model, as originally presented in Charnes, Cooper, and Rhodes (CCR) (1978), was based on the earlier work of Farrell (1957).

To allow for applications to a wide variety of activities, the term Decision Making Unit (=DMU) is used to refer to any entity that is to be evaluated in terms of its abilities to convert inputs into outputs. These evaluations can involve governmental agencies and not-for-profit organizations as well as business firms. An efficiency measure compares the ratio output over input. This notion of efficiency leads to an easy evaluation in the case of analysis involving a single input and a single output, since it reduces to a comparison of a ratio (output/input) for the unit analyzed (unit j_0), with the maximum value of this ratio observed in other units ($j = 1, \ldots, n$).

$$\boldsymbol{Efficiency} = \frac{output}{input} \tag{1}$$

However, more typically processes and organizational decision making units (DMUs) use multiple inputs (resources) to produce multiple outputs (outcomes).

- There are *n* DMUs to be evaluated. Each DMU consumes varying amounts of *m* different inputs to produce *s* different outputs. Specifically, DMU_j consumes amount x_{ij} of input *i* and produces amount y_{ij} of output *r*.

- $x_{ij} \geq 0$ and $y_{ij} \geq 0$

- Each DMU has at least one positive input and one positive output value.

- For each DMU, inputs and outputs are attached by weights (v_i) and (u_r)

As introduced by Charnes, Cooper, and Rhodes, the ratio of outputs to inputs is used to measure the relative efficiency of DMU_j, where *j* = 1, 2, …, *n*. The multiple inputs (i = 1, . . . ,m) and outputs (r = 1, . . . , s) are aggregated in a single efficiency ratio corresponding to the weighted sum of outputs divided by the weighted sum of inputs.

$$\boldsymbol{Efficiency} = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs} \tag{2}$$

Which introducing the usual notation can be written as:

$$\boldsymbol{Efficiency\ of\ unit\ j} = \frac{u_1 y_{1j} +\ u_2 y_{2j} + \cdots + u_s y_{sj}}{v_1 x_{1j} +\ v_2 x_{2j} + \cdots + v_m x_{mj}} \tag{3}$$

Where:

u_1 – the weight given to output 1

Y_{1j} – amount of output 1 from unit j

v_1 – the weight given to input 1

X_{1j} – amount of input 1 to unit j

The initial assumption is that this measure of efficiency requires a common set of weights to be applied across all units. This immediately raises the problem of how such an agreed common set of weights can be obtained. Charnes, Cooper and Rhodes recognized the difficulty in seeking a common set of weights to determine relative efficiency. They acknowledged the legitimacy of the proposal that units might value inputs and outputs differently and therefore adopt different weights, and proposed that each unit should be allowed to adopt a set of weights which shows it in the most favorable light in comparison to the other units. Under these circumstances, efficiency of a target unit j_0 can be obtained as a solution to the following problem (maximize the efficiency of unit j_0):

$$e_{j_0} = max \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} \tag{4}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad j = 1, \dots, n$$

$$v_i \geq \varepsilon, \quad i = 1,2, \dots, m$$

$$u_r \geq \varepsilon, \quad r = 1,2, \dots, s$$

Linear programming is used to determine the weight. The optimal weights may (and generally will) vary from one DMU to another DMU. Thus, the "weights" in DEA are derived from the data instead of being fixed in advance. Each DMU is assigned a best set of weights with values that may vary from one DMU to another.

This model searches for the optimal input and output weights that maximize the efficiency of DMU_{j_0} under assessment, subject to the condition that the efficiency of all units in the sample is less than or equal to 1, when evaluated with the same set of weights. The other two constraints are included to guarantee that weights are positive and higher than a very small number ε, to consider all the inputs and outputs in the efficiency assessment. Thus, the efficiency measure ($e_{j_0}^*$) of DMU_{j_0}, obtained at the optimal solution to the DEA model, is between 0 and 1. The symbol ($*$) denotes the value of a variable at the optimal solution. The efficient DMUs obtain a performance score equal to 1, and the inefficient ones obtain a score lower than 1. The efficient DMUs are considered as examples of best practices (or benchmarks), and are used to specify the efficient frontier. For the inefficient DMUs, the magnitude of their inefficiency is derived by the distance to the frontier constructed from the benchmark DMUs. This comparison with benchmarks also allows determining the input and output targets corresponding to efficient operation (Horta e Costa, 2011).

4.1.1. CCR and BCC models

As shown in Charnes et al. (1978) the fractional model above can be converted into a linear programming model through simple transformations. The linearization of (4) can lead to an input oriented DEA model or to an output oriented DEA model. Both formulations assume constant returns to scale.

Input Oriented

In this perspective, the conversion into a linear programming model can be achieved by maximizing the numerator and setting the denominator equal to 1 as a restriction of the model

$$e_{j_0} = \boldsymbol{max} \sum_{r=1}^{s} u_r y_{r\,j_0} \qquad (5)$$

subject to:

$$\sum_{i=1}^{m} v_i x_{ij\,0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$v_i \geq \varepsilon, \quad i = 1,2,\dots,m$$

$$u_r \geq \varepsilon, \quad r = 1,2,\dots,s$$

The relative efficiency score for DMU_{j_0} is given by $e_{j_0}^*$ which reflects the proportion by which all inputs observed can be proportionally reduced without reducing any outputs levels.

Output Oriented

For the output oriented perspective, the linearization is done by minimizing the denominator and setting the numerator equal to 1 as a restriction of the model

$$h_{j_0} = \boldsymbol{max} \sum_{i=1}^{m} v_i x_{ij\,0} \qquad (6)$$

subject to:

$$\sum_{r=1}^{s} u_r y_{r\,j_0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$v_i \geq \varepsilon, \quad i = 1,2,\dots,m$$

$$u_r \geq \varepsilon, \quad r = 1,2,\dots,s$$

The relative efficiency score for DMU_{j_0} is given by $1/h_{j_0}^*$ where $h_{j_0}^*$ corresponds to the proportion by which all outputs observed can be expanded proportionally without requiring an increase to input level.

In the case of constant returns to scale, the efficiency scores provided by the two models coincide: $e_{j_0}^* = {}^{1}/_{h_{j_0}^*}$

These models are known as “weight formulations” of the DEA model. The variables are v_i and u_r, that represent the weights associated to the inputs and outputs, respectively. At the optimal solution, the input and output weights can be used to indicate the relative importance of the inputs and outputs in determining the efficiency level of the DMU. However, these weights depend on the units of measurement of each, therefor “virtual inputs” and “virtual” outputs are used instead (“virtual” are normalized weights that do not depend on the scale of the variables, adding up to one for efficient DMUs in terms of inputs and outputs).

The duality of linear programming, that is referred as “envelopment formulation” of the DEA models, states that the objective function value of the weight and envelopment problems is equal, corresponding to the efficiency score. In DEA assessment, the weights form provides information on the relative importance (weights) of the input and output variables, whereas the envelopment form provides information on peers and targets. Using the duality of the linear programming, equivalent forms can derive from the models (5) and (6) above.

$e_{j_0} = \min \theta_0 - \epsilon\ (\sum_{i=1}^{m} s_i + \sum_{r=1}^{s} s_r\ )$

subject to: (7)

$\theta_0\ x_{ij_0} - \sum_{j=1}^{n} \lambda_j\ x_{ij} - s_i = 0,$

$i = 1, \dots, m$

$y_{rj_0} = \sum_{j=1}^{n} \lambda_j\ y_{rj} - s_r = 0,$

$r = 1, \dots, s$

$\lambda_j, s_i, s_r\ \geq, \forall_{j,i,r}$

$h_{j_0} = \max \delta_0 + \epsilon\ (\sum_{i=1}^{m} s_i + \sum_{r=1}^{s} s_r\ )$

subject to: (8)

$\delta_0\ y_{rj_0} - \sum_{j=1}^{n} \lambda_j\ y_{rj} + s_r = 0,$

$r = 1, \dots, s$

$x_{ij_0} = \sum_{j=1}^{n} \lambda_j\ x_{ij} + s_i = 0,$

$i = 1, \dots, m$

$\lambda_j, s_i, s_r\ \geq, \forall_{j,i,r}$

These models seek to identify a comparator, i.e., a composite DMU corresponding to a linear combination of efficient DMUs ($\sum_{j=1}^{n} \lambda_j^*\ x_{ij}\ , \sum_{j=1}^{n} \lambda_j^*\ y_{rj}$), with $i = 1, \dots, m$ and $r = 1, \dots, s$ that dominates DMU_{j_0} in all input and output dimensions. It is possible to obtain a set of targets so that inefficient DMUS can become efficient. The targets correspond to a linear combination of the values observed in the peers.

For example, the targets for input variables (${x_{i j_0}}^{IT}$) in input-oriented models will comprise the reduction of the input variables by the efficiency score of the DMU minus the slack value. The targets for output variables (${y_{r j_0}}^{IT}$) will comprise the augmentation of the output variables by adding the slack value. The levels of efficient targets for inputs and outputs can be calculated as follows:

$$\begin{aligned} {x_{i j_0}}^{IT} &= {\theta_0}^* x_{i j_0} - {s_i}^* = \sum_{j=1}^{n} \lambda_j^* \, x_{ij} \qquad i = 1, \ldots, m \\ {y_{r j_0}}^{IT} &= y_{r j_0} + {s_r}^* = \sum_{j=1}^{n} \lambda_j^* \, y_{rj} \qquad r = 1, \ldots, s \end{aligned} \tag{9}$$

Additional information obtained from these models relates to the slack variables, s_i and s_r. These indicate the extent to which individual inputs or outputs could be improved beyond the radial expansion corresponding to the efficiency score. Some boundary points may be “weakly efficient” because we have non-zero slacks. In the operations research, the presence of non-zero slacks is referred to as “weak efficiency”.

DMU_{j_0} is efficient if and only if $\theta^* = 1$ or $\delta^* = 1$ (radial efficiency score equals 1 in input oriented and output oriented model, respectively) and ${s_i}^* = {s_r}^* = 0$ for all i and r. (Koopmans’s, 1951).

DMU_{j_0} is weakly efficient if $\theta^* = 1$ or $\delta^* = 1$ and ${s_i}^* \neq 0 \; and \; (or) \; {s_r}^* \neq 0$ for all i and r. (Farrel’s, 1957). In Farrell’s sense a DMU_{j_0} is efficient if it has a radial efficiency score equals 1.

Table V. CCR DEA Models

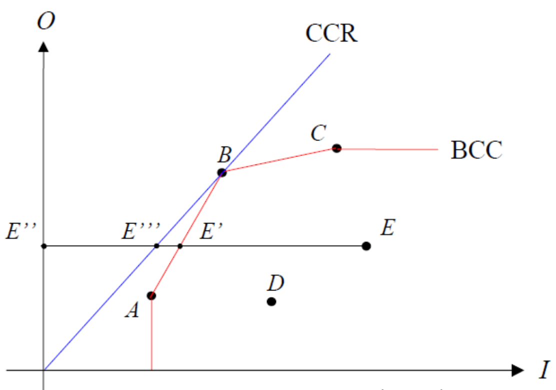
Input Oriented	
Multiplier model	Envelopment model
$\boldsymbol{max}\ \sum_{r=1}^{s} u_r y_{r\,j_0}$	$\min \theta_0 - \epsilon\ (\sum_{i=1}^{m} s_i + \sum_{r=1}^{s} s_r\ )$
subject to:	subject to:
$\sum_{i=1}^{m} v_i x_{ij_0} = 1$	$\theta_0\ x_{ij_0} - \sum_{j=1}^{n} \lambda_j\ x_{ij} - s_i = 0,$
$\sum_{r=1}^{s} u_r y_{rj}$ – $\sum_{i=1}^{m} v_i x_{ij}\ \leq 0$	$i = 1, \dots, m$
$v_i \geq \varepsilon, \quad i = 1,2, \dots, m$	$y_{rj_0} = \sum_{j=1}^{n} \lambda_j\ y_{rj} - s_r = 0,$
$u_r \geq \varepsilon, \quad r = 1,2, \dots, s$	$r = 1, \dots, s$
	$\lambda_j, s_i, s_r\ \ \geq, \forall_{j,i,r}$

These are known as CCR (Charnes, Cooper, Rhodes, 1978) models. If the constraint $\sum_{j=1}^{n} \lambda_j = 1$ is adjoined, they are known as BCC (Banker, Charnes, Cooper, 1984) models. This added constraint introduces an additional variable into the (dual) multiplier problems, and make it possible to effect returns-to-scale evaluations (increasing, constant and decreasing). So, the BBC model is also referred to as the VRS (Variable Returns to Scale) model and distinguished form the CCR model which is referred to as the CRS (Constant Returns to Scale) model.

In the traditional approach, DEA uses two main models: the original formulation, known as the Charnes, Cooper and Rhodes (CCR), that assumes constant returns to scale (CRS) (Charnes et al., 1978) and another, known as the Banker, Charnes and Cooper model (BCC) that assumes variable returns to scale (VRS). This model is known in the literature as the BCC model and accommodates the situations where there is a relation between the scale and the efficiency of operations. Banker et al. (1984) extended the original DEA models of Charnes et al. (1978) to enable the estimation of efficiency under VRS. Under CRS assumption the efficiency obtained is called Technical Efficiency (TE) and under VRS is called Pure Technical Efficiency (PTE).

The differences between an assessment under CCR (CRS) and under BCC (VRS) with input orientation are illustrated in Fig. 1.

Fig. 1. CCR and BCC frontiers



Source: Soares de Mello et al. (2001)

Under the CRS assumption, DMU B can be extrapolated to points on the CCR frontier, such that the change in the input level causes an equally proportional change to the output level. If the scale extrapolation assumption used in the construction of the CRS frontier is not allowed, the frontier must be based on the observed performance of the DMUs given their scale of operation. Under the VRS assumption, the efficient frontier in Figure 1 is redefined as the segments between A, B, and C.

- For the CCRS (CRS) the efficiency of DMU E is given by: $\frac{\overline{E''E'''}}{\overline{E''E}}$

- For the BCC (VRS) the efficiency of DMU E is given by: $\frac{\overline{E''E'}}{\overline{E''E}}$

Finally, it is important to distinguish between two concepts of efficiency proposed by Farrell (1957) and Koopmans (1951) as they differ for any DMU on an expansion of the frontier parallel to the axes. According to Farrell's efficiency notion, a DMU is technically efficient if it is not possible to increase the outputs (or decrease the inputs) proportionally without increasing at least one input (or decreasing at least one output). According to Koopmans's efficiency notion, a DMU is technically efficient if an increase in any output (or a decrease in any input) requires a decrease in at least another output (or an increase in at least another input) (Horta e Costa, 2011).

4.2. Selection of variables

As referred above, the DEA model requires the identification of inputs and outputs. Based on the literature review, on the data available and on the main characteristics of retail stores, the inputs and outputs variables have been selected.

Three inputs: costs with personnel following Thomas et al. (1998), Barros and Alves (2004), Camanho et al. (2009), Moreno and Sanz-Triguero (2011), Gandhi and Shankar (2014), Xavier et al. (2015a, 2015b) cost of goods following Joo et al. (2011) and Gandhi and Shankar (2014) and rents following Joo et al. (2009) and Xavier et al. (2015a, 2015b).

The choice of the DEA model is also an important consideration. We should select the appropriate DEA model with options such as input maximizing or output minimizing, and constant or variable returns to scale. The model used is input-oriented (proportion by which all inputs observed can be proportionally reduced without reducing any outputs levels) considering constant returns to scale (CCR model) and variable returns to scale (BCC model). The input-oriented model is considered more appropriate, mainly because the company managers have relatively less control over the outputs. CRS and VRS index are considered for combination of technical and scale efficiencies.

The two outputs are Sales and Earnings before taxes and amortization (EBITA) following Barros and Alves (2003, 2004), Sellers-Rubio and Mas-Ruiz (2007) and Xavier et al. (2015a, 2015b).

Table VI. Literature inputs and outputs selection

Input variables	Literature
cost of goods	Joo et al. (2011), Gandhi and Shankar (2014)
cost with personnel	Thomas et al. (1998), Barros and Alves (2004), Camanho et al. (2009), Moreno and Sanz-Triguero (2011), Gandhi and Shankar (2014), Xavier et al. (2015a, 2015b)
Rents	Joo et al. (2009); Xavier et al. (2015a, 2015b)

Output variables	Literature
Sales	Athanassopoulos and Ballantine (1995), Donthu and Yoo (1998), Thomas et al. (1998), Keh and Chu (2003), Barros and Alves (2003, 2004), Barros (2006), Mateo et al. (2006), Barth (2007), Sellers - Rubio and Mas-Ruiz (2006, 2007), De Jorge Moreno (2008), Banker et al. (2009), Camanho et al. (2009), Joo et al. (2009), Yu and Ramanathan (2009), Vaz et al. (2010), Moreno and Sanz Triguero (2011), Goic et al. (2013), Gandhi and Shankar (2014, 2016), Xavier el al. (2015a, 2015b), Moreno and Carrasco (2016)
EBITA	Barros and Alves (2003, 2004), Sellers - Rubio and Mas-Ruiz (2007), Xavier et al. (2015a, 2015b)

As mentioned in the literature, there are two kinds of inputs, controllable and non-controllable, according to whether they are or not controllable by the firms. Two controllable inputs are used: costs with personnel and costs of goods. While, Xavier et al. (2015a, 2015b) didn't make the distinction between controllable and uncontrollable inputs concerning the variable rent costs, Joo et al. (2009) treated this variable as an uncontrollable input, and implemented two analysis with two set of different variables. The difference between the two models is the addition of the variable occupancy expenses which includes rent costs as an uncontrollable variable.

In this study, models with different set of variables are also implemented. Two different models are considered to analyze the efficiency of the stores:

1st model: Cost with personnel and Cost of goods

2nd Model: Cost with personnel, Cost of goods and Rent Costs

The first model excludes the variable Rents because this is a strategic variable on which managers can make premeditated decisions concerning for example closing the store, location changing or even renegotiating the leasing agreements with owners. Considering this, it seemed appropriate to implement a comparative analysis between the effects of this variable in efficiency.

The DEA results have been calculated by using the software Efficiency Measurement System (EMS). Efficiency Measurement System (EMS) is a software for Windows 9x/NT which computes Data Envelopment Analysis (DEA) efficiency measures. EMS uses the LP Solver DLL BPMPD 2.11 by Csaba Mészáros for the computation of the scores (Sources: http://www.netlib.org).

The descriptive statistics of variables used for the estimations are presented in Table VII.

Table VII. Descriptive statistics of Data

Year	Number of observations	Cost with personnel	Cost of goods	Rents	Sales	EBITA
2015	35	115.325,89	265.092,07	79.841,91	788.271,19	89.867,11
2014	34	111.361,25	236.763,08	75.002,50	758.406,09	81.956,41
2013	34	96.528,83	226.468,93	72.484,75	681.782,18	71.682,06
2012	26	84.822,73	220.599,79	82.366,42	631.050,79	83.232,71
2011	20	95.505,24	162.632,44	71.182,18	755.729,55	95.372,63
2010	19	97.922,97	250.506,20	65.631,00	841.663,33	121.317,36
2009	17	84.048,64	182.696,39	66.594,91	741.926,98	72.346,38
	Mean	88.601,32	178.949,09	65.577,95	637.410,82	70.200,87
	Standard Deviation	45.881,72	138.218,88	46.729,85	386.370,38	77.134,27

Source: Own elaboration

4.3. Results

In this section the results of the DEA methodology performed on the 185 DMUS for both models composed by 2 and 3 inputs respectively and under both assumptions, CRS and VRS are presented and discussed. The results are presented by a different set of analyses: store, brand, year, type of commercial location, region and by shopping. Finally, we identify the DMUS whose performance serves as an operational management benchmark to the less efficient ones.

All Tables and Figures presented in this section were elaborated taking into consideration the efficient scores and the Benchmarks obtained from DEA methodology for each model under CRS and VRS assumption. Those results are presented in Annex I.

The descriptive statistics of the DEA scores for all models are presented in Table VIII.

Table VIII. Descriptive statistics of the DEA scores for each model

Model		Minimum	Maximum	Average	SD
1st model	CRS (2 Input)	0,2875	1	0,5936	0,1446
	VRS (2 Input)	0,3335	1	0,6769	0,1498
2nd model	CRS (3 Input)	0,2875	1	0,7266	0,1476
	VRS (3 Input)	0,3775	1	0,7494	0,1534

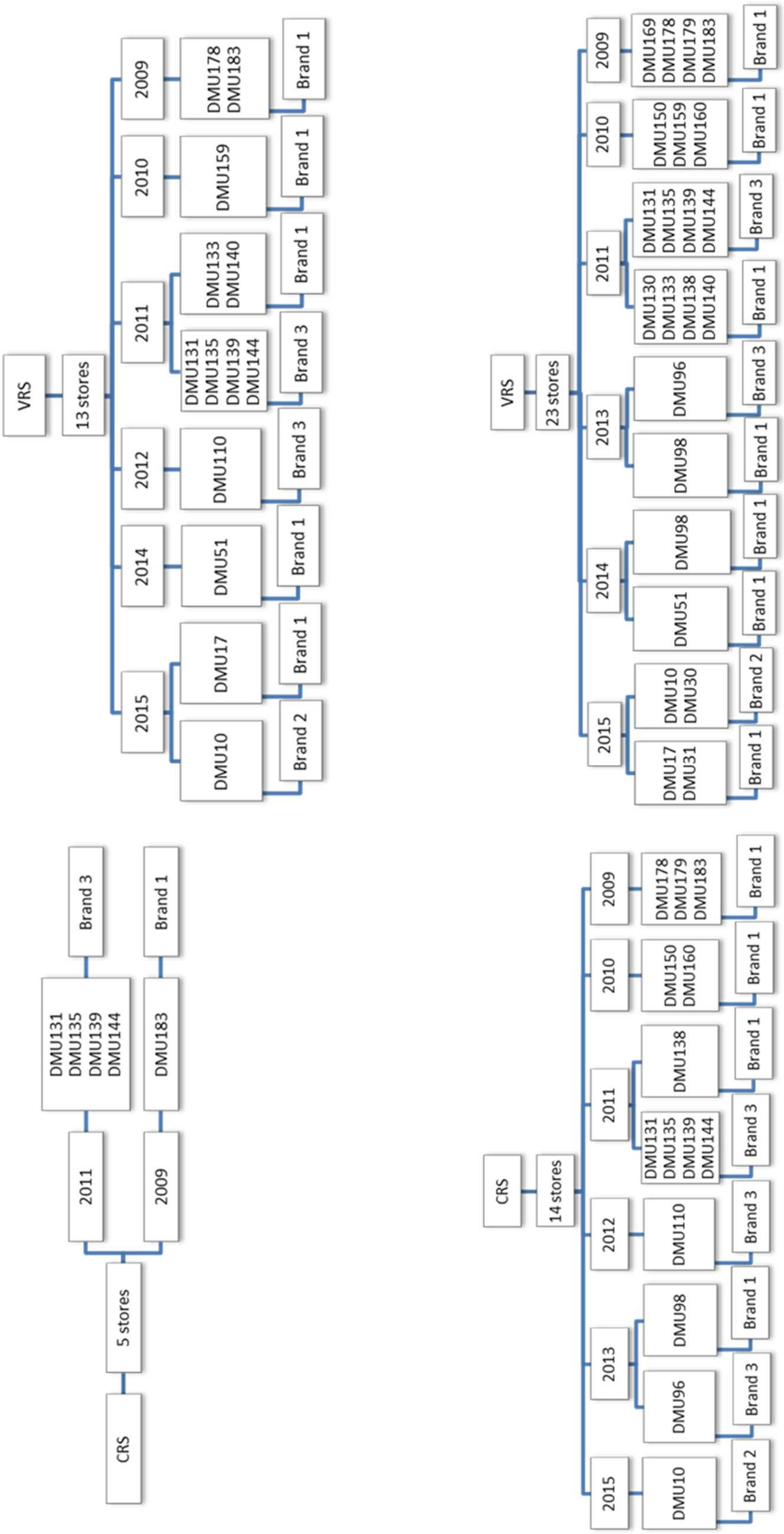
Source: Own elaboration

1st model: to determine the efficient stores under CRS and VRS assumption two inputs are used: costs with personnel and costs of goods. In the 1st model 5 stores are considered efficient under CRS and 13 stores under VRS assumption.

2nd model: also, using both CRS and VRS, the variable rent is included in the model as an input. With the addition of this variable, the number of efficient stores increases under CRS and VRS assumption. Once again, and as in the previous model, the number of efficient DMUS is superior under variable returns to scale. 14 stores are considered efficient under CRS analysis, and 23 stores under VRS analysis. The inclusion of the variable Rent as an input leads to a higher number of efficient units relatively to the previous model.

In the schemes bellow the efficient DMUS are identified and presented for each model, assumption (CRS and VRS), year and brand.

Fig. 2 – Efficient DMUS for each brand by year for both models (CRS and VRS)



a) Analysis by store and brand

This part presents the results for each store and brand for all the years over the period under analysis. To perform a better comparative analysis, we only consider to present the stores that have more than one DMU. The results for all stores and brands for each model under both assumptions can be consulted in Annex II.

Table IX. shows the efficient scores and average efficiency between 2009 and 2015 for the three most and less efficient stores of all the brands for the 1st model under CRS assumption.

Table IX. Efficiency scores by store and brand – 1st model (CRS)

1st model (2 Input)		2009 CRS	2010 CRS	2011 CRS	2012 CRS	2013 CRS	2014 CRS	2015 CRS	Average
Brand 1	Store 7	81,67%	72,69%	85,46%	66,16%	61,04%	62,49%	57,72%	69,60%
	Store 10				62,30%	59,11%	60,80%	56,33%	59,64%
	Store 11		61,21%			54,22%	57,24%	51,88%	56,14%
	Store 14					66,83%	57,75%	54,45%	59,68%
	Store 15	100,00%	66,51%	78,59%	65,26%	56,94%	59,17%	54,62%	68,73%
	Store 16	78,32%	71,66%	83,30%	64,51%	59,34%	59,04%	55,23%	67,34%
Average Brand 1		77,31%	67,89%	80,30%	62,26%	58,10%	58,65%	54,43%	
Standard Deviation		0,0840	0,0306	0,0229	0,0254	0,0293	0,0206	0,0206	
Brand 2	Store 18				30,63%	42,61%	46,66%	46,03%	41,48%
	Store 19	36,20%	30,30%	50,60%	31,68%	43,08%	47,65%	46,83%	40,91%
	Store 22					42,83%	46,69%	46,89%	45,47%
	Store 23				30,74%	42,86%	46,36%	46,37%	41,58%
	Store 26					43,92%	48,23%	47,55%	46,57%
	Store 28					44,50%	49,68%	48,20%	47,46%
Average Brand 2		36,42%	30,52%	51,64%	31,21%	43,44%	48,05%	47,56%	
Standard Deviation		0,0030	0,0030	0,0107	0,0143	0,0059	0,0105	0,0186	
Brand 3	Store 31	57,32%	67,71%	100,00%	82,08%	66,78%	64,03%	62,90%	71,55%
	Store 32	56,05%	68,90%	100,00%	92,61%	69,12%	65,80%	64,19%	73,81%
	Store 33					62,53%	60,81%	59,38%	60,91%
	Store 34	55,55%	65,19%	100,00%	83,40%	66,81%	63,05%	61,49%	70,78%
	Store 35	54,96%	64,56%	100,00%	82,08%	64,39%	62,29%	60,62%	69,84%
	Store 37						63,19%	61,57%	62,38%
Average Brand 3		55,97%	66,59%	100,00%	85,04%	65,26%	63,20%	61,69%	
Standard Deviation		0,0100	0,0206	0,0000	0,0508	0,0279	0,0167	0,0169	

Source: Own elaboration

As described in section *3.2 Data*, Brand 1 has a higher number of stores in 2015 (16 stores) following by Brand 2 (13 stores) and by last Brand 3 (6 stores). In what concerns the opening of new stores, in the period, Brand 2 has the highest variance with six openings between 2011 and

2012 and three openings between 2012 and 2013. Brand 1 opened 2 stores in 2013 and Brand 3 opened 2 stores also in 2013.

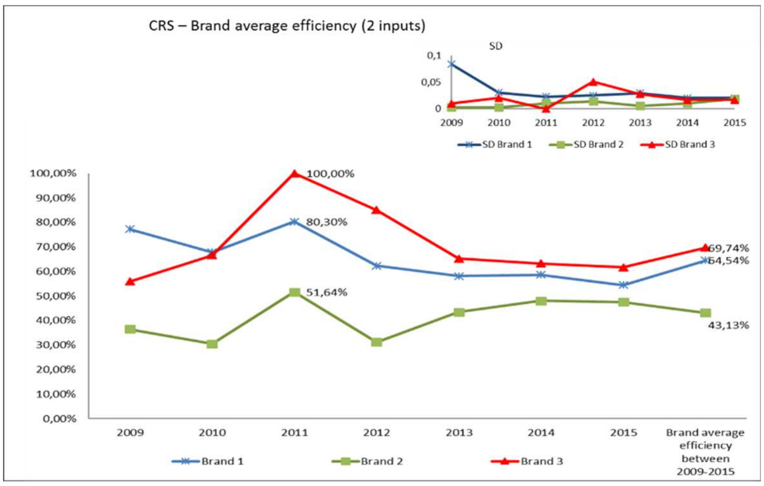
On average for Brand 1, Store 7 is the most efficient store presenting high levels of efficiency in 2009 and 2010. On average, Store 15 is the second most efficient store and is 100 per cent efficient in 2009. The less efficient store is Store 11 and presents the smallest efficient score for Brand 1 in 2015. The other less efficient stores are Store 10 and Store 14 and have similar levels of efficiency. We highlight the fact that the years of 2009, 2010 and 2011 have the highest efficient scores and that the less efficient stores for Brand 1 don't have observations for those years.

For Brand 2 all the stores present low levels of efficiency and on average store 19 is the less efficient store and Store 28 the most efficient. The highest average efficiency for this Brand is given in 2011. Brand 2 became more representative after 2012 which means that the increasing of the number of stores affects positively efficiency, since on average, levels of efficiency seems to increase over time.

For Brand 3, the most efficient store on average is Store 32 and Store 33 the less efficient. All the stores that were opened in 2011 were 100 per cent efficient. The Stores for the years of 2010, 2011 and 2012 have the highest efficient scores and the year of 2009 has the lowest scores.

The Fig. 3 shows the evolution of the efficiency and the standard deviation for all the brands over the years.

Fig. 3. Brand average efficiency and standard deviation – 1st model (CRS)



Over time, the average efficiencies tend to approach each other, with decreasing scores for Brand 1 and Brand 3 and increasing scores for Brand 2, mainly after 2012. The higher average efficiencies are given in 2011 for all brands.

The average efficiency between the period of analysis, 2009-2015 is also presented in Fig. 3. Those values show that Brand 1 and Brand 3 have a similar performance on average over the years and that Brand 2 is highly inefficient, presenting the lower scores for all the years.

For the 1st model under VRS assumption Table X. shows the three most and less efficient stores and the stores that were 100 per cent efficient in any given year.

Table X. Efficiency scores by store and brand – 1st model (VRS)

1st model (2 Input)		2009 VRS	2010 VRS	2011 VRS	2012 VRS	2013 VRS	2014 VRS	2015 VRS	Average
Brand 1	Store 1	89,24%	92,90%	93,69%	72,33%	67,93%	67,05%	60,41%	77,65%
	Store 2			100,00%	70,59%	67,90%	67,95%	58,20%	72,93%
	Store 3	70,60%	70,71%	79,03%	59,52%	59,30%	60,58%	54,87%	64,94%
	Store 7	100,00%	100,00%	100,00%	79,93%	78,31%	100,00%	100,00%	94,03%
	Store 11		61,35%			54,61%	59,07%	53,95%	57,25%
	Store 15	100,00%	72,22%	85,67%	76,01%	65,04%	67,26%	63,50%	75,67%
	Store 16	92,19%	93,26%	94,56%	74,47%	69,34%	66,08%	65,05%	79,28%
	Store 17		64,34%	83,05%	61,71%	55,93%	58,83%	53,00%	62,81%
Average Brand 1		85,21%	78,69%	88,53%	68,36%	65,66%	66,15%	62,84%	
Standard Deviation		0,1050	0,1206	0,0743	0,0624	0,0930	0,0973	0,1093	
Brand 2	Store 18				33,35%	47,16%	49,83%	49,94%	45,07%
	Store 21				36,81%	55,04%	77,83%	100,00%	67,42%
	Store 22					47,18%	49,06%	52,78%	49,67%
	Store 23				42,74%	50,39%	51,44%	53,56%	49,53%
	Store 29				86,28%	55,74%	59,79%	64,04%	66,46%
	Store 30	36,86%	68,27%	64,62%	69,49%	54,12%	57,57%	57,10%	58,29%
Average Brand 2		38,15%	63,47%	61,01%	51,22%	51,30%	57,14%	59,26%	
Standard Deviation		0,0182	0,0679	0,0351	0,1712	0,0340	0,0748	0,1289	
Brand 3	Store 31	66,98%	72,44%	100,00%	82,57%	70,68%	67,21%	65,59%	75,07%
	Store 32	60,81%	74,37%	100,00%	100,00%	76,41%	70,80%	68,31%	78,67%
	Store 33					64,17%	61,98%	61,35%	62,50%
	Store 34	62,65%	67,85%	100,00%	85,15%	71,66%	65,77%	62,16%	73,61%
	Store 35	60,30%	65,77%	100,00%	82,69%	65,34%	63,65%	60,95%	71,24%
	Store 37						68,68%	62,29%	65,49%
Average Brand 3		62,69%	70,11%	100,00%	87,60%	71,68%	66,35%	63,44%	
Standard Deviation		0,0304	0,0398	0,0000	0,0835	0,0668	0,0325	0,0289	

Source: Own elaboration

As we may observe, for Brand 1, Store 7 is on average the most efficient store and hits the maximum score in all the years of analysis, except for the years 2012 and 2013 when efficiency dropped for levels of 79%. Store 7 is highly efficient with an average level of efficiency of 94,03%. The second store with highest efficiency on average is Store 16 and the third one is Store 1. Despite high levels of efficiency in the years of 2009 and 2010, any of these stores were 100 per cent efficient in any given year. Store 2 and Store 15 are 100 per cent efficient in 2011 and 2009, respectively, but have on average lower levels of efficiency than the Store 16 and Store 1. Store 11 remains as the less efficient store while Store 17 and Store 3 are the other two less efficient stores under this assumption.

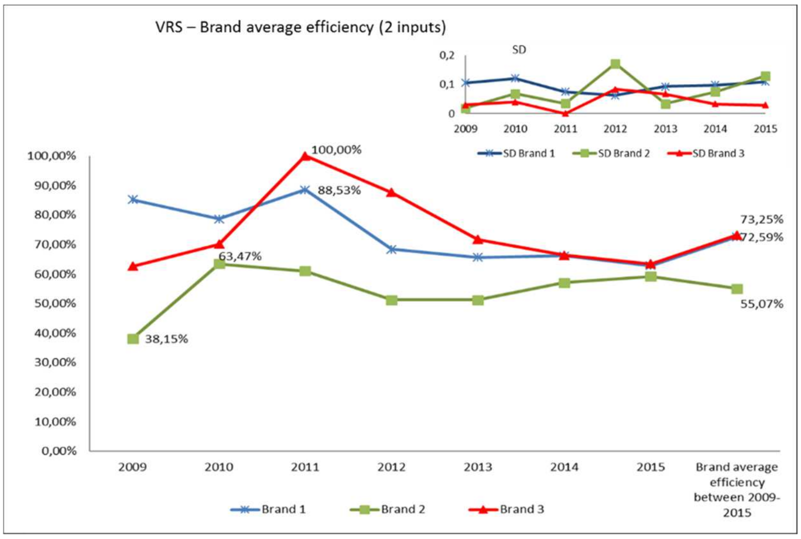
Under VRS and for Brand 2, the efficiencies increase when comparing to the CRS assumption and on average the most efficient store is Store 21 that is 100 per cent efficient in 2015. The most efficient stores and the average efficiencies in this assumption don’t follow the tendency of the previous assumption (Store 21 was not even listed as one of the three most efficient stores in CRS). It also should be noted that in variable return to scale the lowest average efficiency, given by Store 18, is equivalent to the highest levels of efficiency for Brand 2 in CRS. The less efficient stores in this assumption are consistent with the previous one.

Brand 3 follows the tendency presented in the preceding assumption (CRS): the most efficient stores on average are Store 32, followed by Store 31 and then Store 34, the less efficient stores are Store 33, followed by Store 37 and then Store 35 and all the stores in 2011 are 100 per cent efficient. However, in VRS assumption, Store 32 is also 100 per cent efficient for the year of 2012, which differs from the previous assumption. Despite that the efficiency for this Brand is higher under this assumption, the difference in levels of efficiency relatively to CRS assumption is not very significant.

In Fig. 4 we present the evolution of each brand over the years and the brand average efficiency for the all period. Brand 2 has the higher score in 2010, while Brand 1 and Brand 3 have the highest scores levels in 2011. For Brand 1 and Brand 3, the highest levels of efficiency are given by the years that precedes 2011, while for Brand 2 are the years that follows 2011.

In Fig. 4 it can be perceived that the efficiency between brands tends to approach mainly after 2012, specially for Brand 1 and Brand 3. Although Brand 2 has higher efficient scores under this assumption, it remains considerably inefficient when comparing to Brand 1 and Brand 3.

Fig. 4. Brand average efficiency and standard deviation – 1st model (VRS)



In the 2nd model, it can be analyzed how each store and each brand are affected by the inclusion of the variable rent. In Table XI., the three most and less efficient stores and the stores that were 100 per cent efficient in any given year under CRS assumption are presented.

With the inclusion of the variable rent in the model, under CRS assumption, the levels of efficiency on average increase. However, in what concerns the number of DMUS that were 100 per cent efficient, the results remain consistent with the previous model under VRS. The difference between the number of efficient DMUS given in this model (14DMUS) with the previous one (13 DMUS) relates to a Store that was open for just a year, which implies that it only represents one DMU in the model.

For Brand 1, under CRS assumption the most efficient store on average is Store 15 while Store 7 is the second more efficient. Store 11 and Store 17, as in the 1st model under VRS assumption, remains as the less efficient stores.

While in the 1st model under VRS assumption the number of DMUS that were 100 per cent efficient mainly belong to Store 7 (was 100 per cent efficient in 5 of the 7 years analyzed), in this model, the DMUS that are 100 per cent efficient belong to several stores, as presented in Table XI. Brand 1 has the highest average score in 2009 and decreasing average scores over time.

Table XI. Efficiency scores by store and brand – 2nd model (CRS)

2nd model (3 Input)		2009 CRS	2010 CRS	2011 CRS	2012 CRS	2013 CRS	2014 CRS	2015 CRS	Average
Brand 1	Store 1	93,56%	100,00%	91,56%	76,41%	74,61%	70,54%	63,98%	81,52%
	Store 4	72,22%	70,80%	78,59%	66,26%	61,68%	60,12%	57,07%	66,68%
	Store 6	95,95%	99,92%	100,00%	81,50%	77,51%	78,80%	74,66%	86,91%
	Store 7	100,00%	97,38%	93,29%	79,83%	78,98%	79,27%	80,30%	87,01%
	Store 8	100,00%	100,00%	98,14%	77,45%	74,30%	77,89%	77,93%	86,53%
	Store 11		63,63%			57,74%	61,89%	56,93%	60,05%
	Store 14					100,00%	76,20%	80,29%	85,50%
	Store 15	100,00%	79,87%	91,83%	89,37%	80,48%	81,91%	88,54%	87,43%
	Store 17		70,55%	78,59%	62,63%	61,71%	61,00%	58,35%	65,47%
Average Brand 1		90,25%	85,25%	88,02%	72,74%	72,14%	70,52%	68,95%	
Standard Deviation		0,0904	0,1236	0,0777	0,0829	0,1016	0,0760	0,1095	
Brand 2	Store 18				41,83%	52,18%	53,08%	53,80%	50,22%
	Store 19	56,69%	83,97%	73,82%	71,48%	67,59%	71,01%	72,12%	70,95%
	Store 21				53,45%	61,25%	66,89%	100,00%	70,40%
	Store 23				41,66%	49,14%	49,34%	51,06%	47,80%
	Store 25				28,75%	55,42%	56,74%	58,31%	49,81%
	Store 28					69,52%	71,31%	70,86%	70,56%
	Store 29				83,77%	71,22%	75,13%	88,41%	79,63%
Average Brand 2		47,11%	74,49%	68,13%	52,08%	58,77%	61,95%	66,00%	
Standard Deviation		0,1356	0,1341	0,0631	0,1842	0,0736	0,0792	0,1469	
Brand 3	Store 31	81,67%	78,87%	100,00%	88,64%	76,08%	73,76%	72,48%	81,64%
	Store 32	73,07%	84,08%	100,00%	100,00%	86,72%	79,16%	77,25%	85,75%
	Store 33					62,66%	61,60%	59,38%	61,21%
	Store 34	68,52%	70,63%	100,00%	87,00%	73,80%	68,79%	65,06%	76,26%
	Store 35	62,97%	67,42%	100,00%	82,08%	66,60%	65,21%	61,97%	72,32%
	Store 36					100,00%			100,00%
	Store 37						74,10%	72,49%	73,30%
Average Brand 3		71,56%	75,25%	100,00%	89,43%	77,64%	70,44%	68,11%	
Standard Deviation		0,0791	0,0761	0,0000	0,0758	0,1375	0,0646	0,0700	

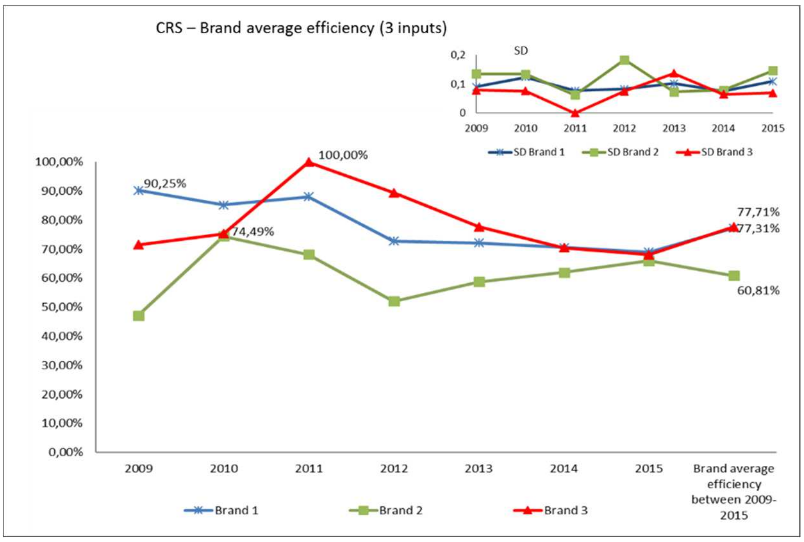
Source: Own elaboration

For Brand 2, on average the most efficient store is Store 29 followed by Store 19 and then Store 28. Despite that Store 21 is 100 per cent efficient in 2015 when considering values of the average efficiency over the years, this store is ranked as the 4th most efficient. We also highlight the fact that for the 1st model under CRS assumption, Store 18 has the lowest average score and Store 28 has the highest average score. This means that the variable rent has a great influence in efficiency of Store 2. In what concerns the less efficient stores, Store 23 is the less efficient store in this model and Store 18 the second less efficient which follows the pattern of the previous model under both assumptions since these stores were also ranked as one of the three less efficient stores.

For Brand 3 and with the inclusion of the variable rent, efficiencies increase for all stores. However, the ranking of the most and less efficient scores follows the same pattern as the previous model in both assumptions: Store 32 is the most efficient, followed by Store 31 and then Store 34, the less efficient stores are Store 33, Store 35 and Store 37 and all the stores of Brand 3 were 100 per cent efficient in 2011. As mentioned above, Store 36 just has one DMU in the model, which means that doesn't give us enough information to perform a comparative analysis with the other stores in the model.

Fig. 5 shows the evolution of each brand over the years and the brand average efficiency for the all period for the 1st model under CRS assumption.

Fig. 5. Brand average efficiency and standard deviation – 2nd model (CRS)



As in the previous analysis Brand 1 and Brand 3 have very similar average scores between 2009 and 2015 and decreasing efficiency after 2011. Brand 1 has the highest average technical efficiency in 2009, Brand 2 in 2010 and Brand 3 remains 100 per cent efficient in 2011. In 2015, Brand 1 presents a better performance that Brand 3, which varies from the previous results, where Brand 3 had a better performance than Brand 1 for all the years after 2011.

Over time, the average efficiencies of all brands tend to approach to each other. With the variable rent in the model, the efficiency levels for all brands increase, specially for Brand 2, where the average efficiency for the period between 2009 and 2015 is 29 per cent higher that in the 1st model (without the variable rent) in CRS assumption.

For the 2nd model with the inclusion of the variable rent and under VRS assumption, the results of the three most and less efficient stores and the stores that were 100 per cent efficient in any given year are presented in Table XII. In variable return to scale, efficiencies increase relatively to the previous assumption (CRS). However, the impact of scale on the efficiency is not proportional for all brands and stores.

Table XII. Efficiency scores by store and brand – 2nd model (VRS)

2nd model (3 Input)		2009	2010	2011	2012	2013	2014	2015	Average
		CRS	CRS	CRS	CRS	CRS	CRS	CRS	
Brand 1	Store 1	100,00%	100,00%	100,00%	78,79%	75,68%	73,04%	64,91%	84,63%
	Store 4	73,19%	71,22%	79,17%	66,67%	62,07%	60,13%	57,24%	67,10%
	Store 6	96,03%	99,98%	100,00%	81,50%	77,65%	79,16%	75,08%	87,06%
	Store 7	100,00%	100,00%	100,00%	80,93%	82,56%	100,00%	100,00%	94,78%
	Store 8	100,00%	100,00%	99,17%	77,92%	74,31%	78,17%	78,03%	86,80%
	Store 11		63,68%			58,52%	62,17%	57,25%	60,41%
	Store 14					100,00%	79,67%	88,92%	89,53%
	Store 15	100,00%	80,12%	96,97%	89,91%	96,47%	94,95%	100,00%	94,06%
	Store 17		72,11%	83,79%	64,88%	63,62%	63,43%	60,46%	68,05%
Average Brand 1		90,25%	85,25%	88,02%	72,74%	72,14%	70,52%	68,95%	
Standard Deviation		0,0904	0,1236	0,0777	0,0829	0,1016	0,0760	0,1095	
Brand 2	Store 18				42,45%	52,31%	53,17%	54,03%	50,49%
	Store 19	59,08%	85,78%	73,89%	71,56%	67,70%	74,19%	72,80%	72,14%
	Store 21				58,69%	65,64%	81,23%	100,00%	76,39%
	Store 23				42,82%	50,39%	51,44%	53,56%	49,55%
	Store 25				40,62%	55,81%	57,35%	58,33%	53,03%
	Store 28					70,56%	72,28%	78,90%	73,91%
	Store 29				91,78%	75,95%	81,19%	100,00%	87,23%
Average Brand 2		47,11%	74,49%	68,13%	52,08%	58,77%	61,95%	66,00%	
Standard Deviation		0,1356	0,1341	0,0631	0,1842	0,0736	0,0792	0,1469	
Brand 3	Store 31	82,63%	78,89%	100,00%	88,65%	76,31%	74,03%	72,77%	81,90%
	Store 32	73,15%	84,13%	100,00%	100,00%	86,77%	79,57%	77,61%	85,89%
	Store 33					64,40%	62,50%	61,63%	62,84%
	Store 34	68,55%	70,75%	100,00%	87,97%	74,19%	69,32%	65,58%	76,62%
	Store 35	63,03%	67,55%	100,00%	82,77%	66,70%	65,30%	62,41%	72,54%
	Store 36					100,00%			100,00%
	Store 37						79,10%	74,20%	76,65%
Average Brand 3		71,56%	75,25%	100,00%	89,43%	77,64%	70,44%	68,11%	
Standard Deviation		0,0791	0,0761	0,0000	0,0758	0,1375	0,0646	0,0700	

Source: Own elaboration

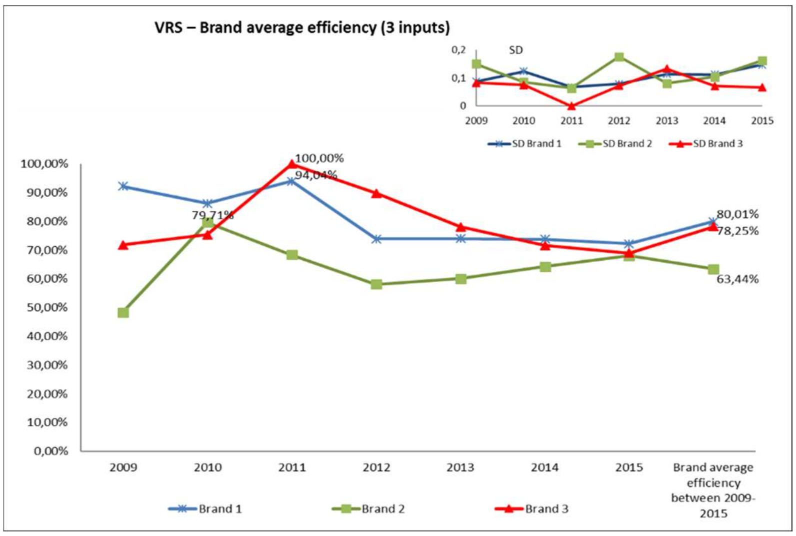
Despite some variations in the ranking of the stores, for Brand 1, the highest scores are given by the same stores as in the previous assumption. Comparing to the 1st model, under VRS assumption Store 7 was also 100 per cent efficient in five of the seven analyzed years. For Store 7, scale has an important impact on efficiency. The third most efficient store is Store 14 which was one of the three less efficient stores in the 1st model under CRS assumption. Efficiency of Store 14 is highly affected by scale and by the variable rent. Store 11 remains as the less efficient store for both models and assumptions. The other two less efficient stores also remain the same as the previous assumption.

For Brand 2, and Despite some variations of the ranking of the stores, the results obtained are consistent with previous assumption. Store 21 is 100 per cent efficient in 2015 and the highest score on average is given by Store 29.

Under VRS assumption, the efficiencies of Brand 1 and Brand 2 stores are relatively higher than in CRS assumption. For Brand 3 efficiency increases at very low levels which means that for this Brand in this model, scale does not have a significant influence on efficiency. Regarding the stores ranking of the highest and the lowest efficient scores, Brand 3 follows the same pattern as the previous model in both assumptions.

The Fig. 6 shows the evolution of the efficiency and the standard deviation for all the brands over the years.

Fig. 6. Brand average efficiency and standard deviation – 2nd model (VRS)



Under variable return to scale the trend of having a similar average score levels of efficiency between 2009 and 2015 for Brand 1 and Brand 3 and decreasing scores after 2011 persists (which indicates a consistently behavior of Brand 1 and Brand 3 in all models). Besides Brand 2 is the most inefficient brand, comparing to the previous models, is perceived that the impact of introducing the variable rent in the model and the effect scale is higher for Brand 2.

Brand 1 increased the number of stores in 2010 (eleven to thirteen) and in 2013 (thirteen to sixteen). Brand 3 had two openings in 2013, but the variance among the number of stores over the years is very low. Brand 2 is the brand that had more openings over the years. Between 2011 and 2013, this Brand opened 10 stores. For Brand 1 and Brand 3 the years that follow the openings presented decreasing average efficiencies while Brand 2 has increasing average efficiencies after the openings.

b) Analysis by year

As resumed in Table XIII., the efficiencies and standard deviation are given for each year and for each model. Over time and for all the models, the efficiency on average tends to decrease principally after 2011, where levels of efficiency drop in about 25%. The accentuated reduction of efficiency that occurred after 2011 also can be explained by exogenous factors that are affecting outputs. Market conditions can impact efficiency and one of the examples of that is the austerity plan that was implemented in Portugal in 2011, as described in chapter 3 – Empirical Setting. 2011 is also the year with higher average efficiency for all the models. The standard deviation average over the years indicates a small and similar dispersion of the values which means that dispersion tends to be close to the median (the expected value).

Table XIII. Efficiency average by year

Efficiency average for each year	CRS (2 input)		VRS (2 input)		CRS (3 input)		VRS (3 input)	
	Average	SD	Average	SD	Average	SD	Average	SD
2009	67,48%	0,1626	74,37%	0,1870	80,77%	0,1729	82,30%	0,1774
2010	63,68%	0,1208	75,28%	0,1149	82,01%	0,1206	83,26%	0,1177
2011	79,94%	0,1465	86,69%	0,1341	87,43%	0,1160	91,39%	0,1171
2012	55,02%	0,1956	65,38%	0,1663	68,15%	0,1802	70,90%	0,1601
2013	54,19%	0,0877	61,65%	0,1072	68,40%	0,1224	69,82%	0,1280
2014	55,71%	0,0620	63,00%	0,0909	67,48%	0,0841	70,09%	0,1098
2015	53,13%	0,0539	61,61%	0,1077	67,71%	0,1176	70,13%	0,1416
Average between 2009-2015	59,36%	0,1446	67,69%	0,1498	72,66%	0,1476	74,94%	0,1534

Source: Own elaboration

c) Analysis by region:

The DMUS under analysis are in different regions in Portugal. The analysis by region (NUTS III) will allow capturing the differences of efficiency in the location of the stores. NUTS is the acronym of "Nomenclature of Territorial Units for Statistics", a hierarchical division system of the Portuguese territory into regions. NUTS III (third sub-level) is composed by 25 regions. For this analysis 8 regions were considered (the other regions were not included because the company doesn’t have any stores in that regions).

Regions: 1- Norte – Alto Minho, 2 – Área metropolitana do Porto, 3 – Centro – Região de Aveiro, 4 – Centro – Região de Coimbra, 5 – Centro- Viseu Dão Lafões, 6 – Área metropolitana de Lisboa, 7 – Região do Algarve and 8 – Região da Madeira.

Table XIV. Average efficiency by region (NUTS III)

Efficiency average by location (NUTS III)	CRS (2 input)	VRS (2 input)	CRS (3 input)	VRS (3 input)
	Average	Average	Average	Average
Norte - Alto Minho	44,44%	59,81%	65,23%	69,09%
Área Metropolitana do Porto	60,20%	67,78%	72,28%	75,49%
Centro - Região de Aveiro	63,14%	64,94%	75,11%	75,77%
Centro - Região de Coimbra	66,43%	73,19%	86,91%	87,06%
Centro - Viseu Dão Lafões	60,30%	62,81%	65,47%	68,05%
Área Metropolitana de Lisboa	58,92%	68,38%	71,41%	73,80%
Região do Algarve	60,17%	67,31%	78,93%	79,42%
Região da Madeira	64,79%	67,10%	79,09%	80,30%

Source: Own elaboration

It's important to highlight the differences between the number of stores that are part of each region. The stores are mainly located in Lisbon region following by Porto region. The regions as Alto Minho and Algarve are mainly composed by a fewer number of stores, and some regions as Aveiro, Coimbra, Viseu and Madeira just have one store that belongs to Brand 1.

For all the models, Porto region has a better average performance than Lisbon region. Alto Minho is the region with lower levels of efficiency. For all these regions, the inclusion of the variable rent and the effect scale has a great influence on levels of efficiency.

In the 2nd stage of this analysis, other external factors as purchasing power index by region will be analyzed to verify how this factor can affect efficiency in each region.

d) Analysis by type of commercial retail location

The number of stores that are located in Shopping Centers represents 80% of the sample, 28 stores (147 DMUS) and the number of stores located in Urban Streets and Outlets represents 10% each one, i.e, 4 stores (19 DMUS) for Urban Streets and 5 stores (19 DMUS) for Outlets.

Table XV. Average efficiency by commercial location

Efficiency average by type of commercial location	CRS (2 input) Average	VRS (2 input) Average	CRS (3 input) Average	VRS (3 input) Average
Shopping	59,20%	67,22%	71,43%	73,38%
Street	61,97%	69,95%	73,50%	75,08%
Outlet	58,04%	69,12%	81,33%	86,89%

Source: Own elaboration

For the 1st model under CRS assumption, the stores located in urban street areas have on average a higher performance. However, the levels of efficiencies are very close to each other. This tendency is maintained when analyzed under VRS assumption. However, in 2nd model, with the inclusion of the variable rent and under VRS assumption, levels of efficiency for Outlets on average increase.

Considering that 28 stores are located in shopping centers, below we present the analysis by Shopping in each region NUTS III. We pretend to verify how the location of Shopping Centers is affecting efficiency. We will perform the comparison between regions that have more than one shopping (Porto, Lisbon and Algarve regions). For the 1st model under CRS analysis Shopping S5 from Coimbra region presents on average the best performance and Shopping S1 from the Alto Minho region the lower performance. Under VRS analysis Shopping S12 from Lisbon region has the higher efficiency on average however this value is not very significant since it has just one DMU in the model. Taking this in consideration Shopping S14 from the Algarve region has the best performance. In this model the lower levels of efficiency are also given by Shopping S1 from Alto Minho region.

Table XVI. Average efficiency by region (NUTS III) and by Shopping – 1st model

NUTS III	Eficciency average (CRS 2 Input)	Eficciency average (VRS 2 Input)	Sub units Shopping	Eficciency average (CRS 2 Input)	Eficciency average (VRS 2 Input)	Number of stores	Number of DMUS
Alto Minho	45,47%	49,67%	S1	45,47%	49,67%	1	3
Área metropolitana do Porto	60,25%	65,80%	S2	56,14%	57,25%	1	4
			S3	61,12%	67,61%	3	19
Região de Aveiro	63,14%	64,94%	S4	63,14%	64,94%	1	7
Região de Coimbra	66,43%	73,19%	S5	66,43%	73,19%	1	7
Viseu Dão Lafões	60,30%	62,81%	S6	60,30%	62,81%	1	6
Área metropolitana de Lisboa	57,86%	68,25%	S7	57,38%	65,80%	2	11
			S8	58,03%	66,07%	3	19
			S9	57,48%	65,22%	3	14
			S10	60,05%	72,46%	4	22
			S11	59,30%	65,68%	1	1
			S12	61,93%	81,82%	1	1
			S13	54,57%	68,78%	2	14
Região do Algarve	60,17%	67,31%	S14	66,31%	77,48%	1	7
			S15	54,03%	61,13%	2	7
Região da Madeira	64,79%	67,10%	S16	64,79%	67,10%	1	5
Eficciency average Shoppings				59,20%	67,22%	**28**	**147**

Source: Own elaboration

When the variable rent is included in the model, under CRS and VRS analysis the Shopping S12 form Lisbon region presents an efficiency of 100 per cent. However this shopping just has a DMU in the model, which means that for that year, that store was 100 per cent efficient when comparing to the other stores. Following this Shopping S5 from Coimbra region has the highest levels of average efficiency for both CRS and VRS and Shopping S1 from Alto Minho region the lowest levels. Shopping S14 from the Algarve region presents high scores of efficiency in all the models and Shopping S2 from Porto region the lowest scores on average after Alto Minho region.

Table XVII. Average efficiency by region (NUTS III) and by Shopping – 2nd model

NUTS III	Eficciency average (CRS 3 Input)	Eficciency average (VRS 3 Input)	Sub units	Eficciency average (CRS 3 Input)	Eficciency average (VRS 3 Input)	Number of stores	Number of DMUS
Alto Minho	58,34%	59,35%	S1	58,34%	59,35%	1	3
Área metropolitana do Porto	66,30%	67,70%	S2	60,05%	60,41%	1	4
			S3	67,62%	69,23%	3	19
Região de Aveiro	75,11%	75,77%	S4	75,11%	75,77%	1	7
Região de Coimbra	86,91%	87,06%	S5	86,91%	87,06%	1	7
Viseu Dão Lafões	65,47%	68,05%	S6	65,47%	68,05%	1	6
Área metropolitana de Lisboa	70,40%	73,05%	S7	70,14%	72,22%	2	11
			S8	75,27%	76,95%	3	19
			S9	62,73%	65,71%	3	14
			S10	70,31%	74,13%	4	22
			S11	66,25%	66,59%	1	1
			S12	100,00%	100,00%	1	1
			S13	69,95%	72,58%	2	14
Região do Algarve	78,93%	79,42%	S14	86,53%	86,80%	1	7
			S15	71,33%	72,03%	2	7
Região da Madeira	79,09%	80,30%	S16	79,09%	80,30%	1	5
Eficciency average Shoppings				71,43%	73,38%	**28**	**147**

Source: Own elaboration

e) Benchmarks

Considering the results above, and the influence of the variable rent in the efficiency, the benchmarks and targets are calculated taking into consideration the efficient scores and slacks obtained from the 2nd model with 3 inputs. Slacks represent the leftover portions of inefficiencies. After reductions in inputs, if a DMU cannot reach the efficiency frontier (to its efficient target), slacks are needed to push the DMU to the frontier (target). The "benchmarks" were created through the EMS software for DEA and indicate for inefficient DMUS their reference and the corresponding intensities (λ_j) in brackets and for efficient DMUS the number of inefficient DMUs which have chosen the DMU as Benchmark.

As an example, Table XVIII. shows the references and slacks for some inefficient stores with different levels of scores of each brand for the year of 2015 under CRS assumption. In Annex III the results for all DMUS and under both assumptions are presented. These results show that for CRS and VRS assumptions, although DMU131 is 100 per cent efficient it has non-zero slacks. As explained in Chapter 4, section 4.1. DEA methodology, and taking into consideration the definition of efficiency of Koopmans (1951) the presence of non-zero slacks is referred to as "weak efficiency". The others DMUS that are 100 per cent efficient have zero slacks.

Table XVIII. Benchmarks and slacks by store and brand (CRS)

2nd model (CRS)		DMU	Score	Benchmarks	Slacks: Costs with personnel	Slacks: Costs of Goods	Slacks: Rents
Brand 1	Store 2	DMU5	61,78%	10 (0,3939) 110 (1,0460) 179 (0,0642)	0	0	0
	Store 7	DMU17	80,30%	98 (1,3015) 110 (0,6439) 150 (0,7493)	0	0	0
	Store 10	DMU22	87,46%	150 (0,1380) 160 (0,9257)	0	8358,02	0
	Store 11	DMU23	56,93%	110 (0,6812) 139 (0,1988) 183 (0,0059)	0	0	0
	Store 15	DMU31	88,54%	96 (0,9668) 160 (1,2221)	15776,32	34313,02	0
Brand 2	Store 20	DMU8	47,87%	110 (0,39) 139 (0,35) 183 (0,95)	0	0	0
	Store 21	DMU10	100,00%	61			
	Store 22	DMU11	66,11%	10 (1,72) 179 (0,52)	0	3017,16	0
Brand 3	Store 33	DMU12	59,38%	131 (0,0403) 135 (0,0047) 139 (0,6275) 144 (0,0109)	1443,15	0	1889,61
	Store 34	DMU16	65,06%	110 (0,3721) 135 (0,0334) 139 (0,4430)	0	0	0

Source: Own elaboration

The efficient stores in any given year may consider themselves to be their own "benchmarks." However, for inefficient stores, their benchmarks are one or many of the efficient stores for any given year. Table XIX. shows the list of the 100 per cent efficient DMUS for CRS assumption and the corresponding store, brand and year of the observation. It also indicates the number of inefficient DMUs which have chosen that DMU as Benchmark.

Table XIX. List of benchmarks by brand, store year and DMU (CRS)

Benchmarks CRS assumption									
Brand 1	Store 14	DMU98	2013	4	Brand 3	Store 36	DMU96	2013	15
	Store 6	DMU138	2011	32		Store 32	DMU110	2012	125
	Store 1	DMU150	2010	6		Store 31	DMU131	2011	4
	Store 8	DMU160	2010	14		Store 32	DMU135	2011	32
	Store 7	DMU178	2009	40		Store 34	DMU139	2011	53
	Store 8	DMU179	2009	56		Store 35	DMU144	2011	5
	Store 15	DMU183	2009	59					
Brand 2	Store 21	DMU10	2015	61					

Source: Own elaboration

For example, the benchmark for the less efficient unit of Brand 1, the DMU23 (which corresponds to Store 11 of Brand 1 in 2015) are three different stores from different years: DMU110 (Store 32 of Brand 3 in 2011), DMU139 (Store 34 of Brand 3 in 2011) and DMU183 (Store 15 of Brand 1 in 2009). This means that DMU11 must use a combination from these three DMUs to become efficient. To calculate how much the combination of the three benchmarks

DMUS the λ (lambda) weights obtained from the dual version of the linear program is solved to estimate these values. For example, DMU11 will attempt to become like DMU110 (λ = 0,6812) more than DMU139 (λ = 0,1988) and DMU183 (λ = 0,0059) as observed from respective λ weights.

For the VRS assumption, and as an example Table XX. shows the references and slacks for some inefficient stores of each brand for the year of 2015.

Table XX. Benchmarks and slacks by store and brand (VRS)

2nd model (VRS)		DMU	Score	Benchmarks	Slacks: Costs with personnel	Slacks: Costs of Goods	Slacks: Rents
Brand 1	Store 2	DMU5	62,27%	110 (0,7888) 140 (0,0255) 178 (0,0257) 179 (0,1601)	0	0	0
	Store 7	DMU17	100,00%	0			
	Store 10	DMU22	89,61%	150 (0,2104) 160 (0,7896)	4875,46	17791,36	0
	Store 11	DMU23	57,25%	10 (0,1258) 110 (0,6438) 135 (0,0211) 139 (0,2093)	0	0	0
	Store 15	DMU31	100,00%	3			
Brand 2	Store 3	DMU8	50,03%	139 (0,4243) 178 (0,1427) 183 (0,4330)	0	0	12931,69
	Store 4	DMU10	100,00%	95			
	Store 5	DMU11	66,66%	10 (0,4884) 150 (0,1066) 179 (0,4050)	0	8447,54	0
	Store 12	DMU30	100,00%	11			
Brand 3	Store 3	DMU12	61,63%	135 (0,4754) 139 (0,0840) 144 (0,1581) 183 (0,2825)	0	0	0
	Store 4	DMU16	65,58%	10 (0,1588) 110 (0,3229) 135 (0,0703) 139 (0,4479)	0	0	0

Source: Own elaboration

Under VRS assumption the number of benchmarks increase relatively to CRS assumption, since the number of efficient DMUS is higher in this assumption. Table XXI. shows the list of the 100 per cent efficient DMUS for VRS assumption and the corresponding store, brand and year of the observation. It also indicates the number of inefficient DMUs which have chosen that DMU as Benchmark.

Table XXI. List of benchmarks by brand, store, year (VRS)

Benchmarks VRS assumption

Brand 1	Store 7	2015	DMU17	0	Brand 2	Store 19	2015	DMU10	95
	Store 15	2015	DMU31	3		Store 29	2015	DMU30	11
	Store 7	2014	DMU51	0					
	Store 14	2013	DMU98	3	Brand 3	Store 36	2013	DMU96	19
	Store 1	2011	DMU130	2		Store 32	2012	DMU110	93
	Store 2	2011	DMU133	4		Store 31	2011	DMU131	
	Store 6	2011	DMU138	34		Store 32	2011	DMU135	37
	Store 7	2011	DMU140	32		Store 34	2011	DMU139	48
	Store 1	2010	DMU150	36		Store 35	2011	DMU144	3
	Store 7	2010	DMU159	7					
	Store 8	2010	DMU160	17					
	Store 1	2009	DMU169	5					
	Store 7	2009	DMU178	72					
	Store 8	2009	DMU179	63					
	Store 15	2009	DMU183	39					

Source: Own elaboration

As mentioned above, DMU131 (which corresponds to Store 31 of Brand 3 in 2011) has non-zero slacks, which means that this DMU is weakly efficient and because of that is not consider as a benchmark for inefficient units.

As we may observe in Table XXI., in this assumption, the benchmark for the less efficient unit of Brand 1 in 2015, Store 11, is given by four different DMUS that belong to different stores in different years. In opposite to previous assumption, DMU17 and DMU31, which corresponds to Store 7 and Store 15 of Brand 1 in 2015, respectively, are 100 per cent efficient in VRS assumption. This means that they serve as a reference to inefficient units. However, we highlight the fact that DMU17 and DMU51, which corresponds to Store 7 in 2015 and 2014, respectively, have not been chosen as a Benchmark to the inefficient DMUS.

Since the orientation used in the model was input orientation, targets are calculated taking into the consideration the levels of the input reduction to become the unit efficient, maintaining outputs constant. To calculate the inputs targets we used the formulation (9) on presented in Chapter 4, Section 4.1. DEA methodology. For confidentiality reasons, the targets results are presented in percentage (level of reduction). As an example, in Table XXII. we present the targets calculated for the inefficient DMUS presented in Table XX. under VRS assumption. The targets for all DMUS and under both assumptions are presented in Annex III.

Table XXII. Targets of input reduction under VRS assumption

2nd model		**DMU**	**Score**	**Targets (VRS)**		
				Costs with personnel	**Costs of Goods**	**Rents**
Brand 1	Store 2	DMU5	62,27%	-37,73%	-37,73%	-37,73%
	Store 10	DMU22	89,61%	-6,33%	-4,38%	-10,39%
	Store 11	DMU23	57,25%	-42,75%	-42,75%	-42,75%
Brand 2	Store 20	DMU8	50,03%	-49,97%	-49,97%	-41,88%
	Store 22	DMU11	66,66%	-33,34%	-29,04%	-33,34%
Brand 3	Store 33	DMU12	61,63%	-38,37%	-38,37%	-38,37%
	Store 34	DMU16	65,58%	-34,42%	-34,42%	-34,42%

Source: Own elaboration

In Table XXII. an example of the target input levels for inefficient stores of each brand are prescribed. These targets are the results of the input value multiplication with an optimal efficiency score, and then slack amounts are subtracted from this amount.

These input reductions are called total inefficiencies which comprise not only the amount of proportional reductions, but also an amount called "Slack" for those stores that cannot reach their efficiency targets (at frontier) despite the proportional reductions.

4.4. Main conclusions

In previous section, we performed an analysis using DEA methodology in two models with different set of inputs, to study the impact of the variable rent in efficiency. As mentioned, since the company under analysis does not own the stores that are part of their commercial activity, it is important to evaluate the impact that this input has on efficiency. Being the analysis pursued with two different models we could identify how this variable affects stores of each brand over the years by comparing the two different models (with and without the input rent). Both assumptions, CRS and VRS, were also taken into consideration to verify the impact of scale on efficiency. Various analysis: Store and Brand analysis, Year, Region and Commercial type of location analysis. Following these analyzes, and because it was demonstrated that the variable rent has a great impact on efficiency, we identified the benchmarks and calculated the targets for the 2nd model under both assumptions.

In resume, the results for the 1st model under CRS and VRS assumption are given by:

CRS assumption:

- 5 stores are 100 per cent efficient for the years of 2009 (1 store) and 2011 (4 stores)
- Store 15 of Brand 1 is 100 per cent efficient in 2015 and all the stores (4 stores) of Brand 3 were 100 per cent efficient in 2011
- In average for the all period considered, efficiency is higher for Brand 3, then Brand 1 and finally Brand2. Brand 2 is highly inefficient.
- High levels of efficiency on average are given in 2011 for all the brands.

VRS assumption:

- 13 stores are 100 per cent efficient for all the years except for 2013.
- For Brand 1, Store 2 is 100 per cent efficient in 2015, Store 7 is 100 per cent in all the years except for 2012 and 2013 and Store 15 is 100 per cent efficient in 2009. Brand 2 has higher levels of efficiency and has one store that is 100 per cent efficient in 2015. All the stores of Brand 3 (4 Stores) were 100 per cent efficient in 2011 and Store 19 is also 100 per cent efficient in 2012.
- In average for the all period considered, efficiency is higher for Brand 3, then Brand 1 and finally Brand 2. Despite higher levels of efficiency, Brand remains considerably inefficient when comparing to Brand 1 and Brand 3.
- High levels of efficiency are given in 2011 for Brand 1 and Brand 3 and in 2010 for Brand 2.

The efficiencies under variable return to scale increase relatively to constant return to scale, mainly for Brand 1 and Brand 2 and the stores behavior of these brands under this assumption substantially varies. However, for Brand 3, the pattern verified under CRS assumption remains under VRS assumption. For the 1st model, we can conclude that Brand 3 is the most efficient brand on average for the all period and the one that is less affected by scale. The effect of scale is higher for Brand 2.

In resume, the results for the 1st model under CRS and VRS assumption are given by:

CRS assumption:

- 14 stores are 100 per cent efficient for the years of 2009, 2010, 2011, 2013 and 2015.
- Brand 1 has more stores that are 100 per cent efficient that in last model under VRS. For Brand 2 and Brand 3 the stores that were 100 per cent efficient remains the same as in the previous model under VRS.
- Brand 1 has a better performance in 2009, Brand 2 in 2010 and Brand 3 in 2011.
- In average for the all period considered, efficiency is higher for Brand 3, then Brand 1 and finally Brand2. Brand 2 is highly inefficient.

- In average for the all period considered, efficiency is higher for Brand 3, then Brand 1 and finally Brand 2. However, levels of average efficiency of Brand 1 and Brand 3 are very similar.

VRS assumption:

- 23 stores are 100 per cent efficient for all the years.
- For Brand 1, the number of stores that are 100 per cent efficient remains the same as in the previous assumption, however those same stores are 100 per cent efficient for more observations (years). Brand 2 has 2 stores that are 100 per cent efficient for the year of 2015 and for Brand 3 the stores that were 100 per cent efficient remains the same as in the previous model under VRS.
- Brand 1 and Brand 3 have a better performance in 2011 and Brand 2 in 2010.
- In average for the all period considered, and in opposite to the previous results, Brand 1 has a better average performance than Brand 3 after 2014 and in average for all the period under analysis (2009 – 2015).

In what concerns the behavior of each brand over time, we highlight that for both models and under both assumptions, the average efficiency for the all period under analysis of Brand 1 and Brand 3 is very similar and efficiencies levels tend to approach mainly after 2012. Brand 1 and Brand 3 have decreasing levels of efficiency after 2011 while Brand 2 presents increasing levels of efficiency after that year. Despite higher levels of efficiency when the variable rent is included in the model and under VRS assumption, Brand 2 remains the most inefficient brand for all the models. While the variable rent affected efficiency for all brands, scale has a higher effect on Brand 2. We also highlight that the number of store openings during the period under analysis is higher for this brand. For Brand 1, scale has a higher effect in some stores rather than others (for example: Store 7) and for Brand 3, for the 2nd model the effect scale is almost null.

The most efficient years are 2009, 2010 and 2011. After that year, the efficiency levels on average tend to decrease. However, for the year of 2015 levels of efficiency for the 2nd model under VRS assumption are relatively high (70,13%). Highest levels of efficiency are given in 2011.

Considering the stores efficiency by region and since the number of stores that are in Lisbon and Porto are more representative, we compare efficiency for these two regions and verify that for both models and under both assumptions, Porto region has a better performance than Lisbon region.

For the analysis by type of commercial location we conclude that the variable rent has a great impact on Outlets levels of efficiency. This can be explained by the fact that in some Outlets the rent negotiated in the Leasing agreements is a percentage of Sales, which means that managers have more control over this input when outputs (Sales) decrease because the input rents are reduced in proportion.

Finally, we identified the benchmarks and calculated the targets for the 2nd model under both assumptions. This managerial information is very important to drive company strategy, since the aspects that need more attention can be identified. The analysis performed shows the peers of the inefficient stores and how companies can improve their activity by defining the targets of input reductions maintaining outputs constant (input-orientation).

5. Analysis of the Quantile Regression Estimates

In this chapter, we estimate the DEA scores under CRS and VRS assumption of the 2nd model through a Quantile Regression to determine the external factors that influence efficiency. The first section explains the methodology used, the second one presents the variables selected, in the third section results are presented and discussed and last section resumes the main conclusions of this analysis.

5.1. Quantile Regression

Quantile regression as introduced in Koenker and Bassett (1978) may be viewed as a natural extension of classical least squares estimation of conditional mean models to the estimation of an ensemble of models for conditional quantile functions. The central special case is the median regression estimator that minimizes a sum of absolute errors. The remaining conditional quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors. Taken together the ensemble of estimated conditional quantile functions offers a much more complete view of the effect of covariates on the location, scale and shape of the distribution of the response variable.

Quantile regression is as an estimation technique that has become widely used in the economics literature as large micro data sets have become available. The methodology and equations for running quantile regression are set out in Koenker (2005). For a general discussion of quantile regression see Koenker and Hallock (2001).

In ordinary least-squares regression models (OLS) the relationship between one or more covariates X and the *conditional mean* of the response variable Y given $X = x$. Quantile regression extends the regression model to *conditional quantiles* of the response variable. This technique is particularly useful when the rate of change in the conditional quantile, expressed by the regression coefficients, depends on the quantile.

Least square regression assumes that the covariates affect only the location of the conditional distribution of the response, and not its scale or any other aspect of its distributional shape. The main advantage of quantile regression over least squares regression is its flexibility for modeling data with heterogeneous conditional distributors (Koenker and Hallock, 2001). Quantile regression provides a complete picture of the covariate effect when a set of percentiles is modeled, and it makes no distributional assumption about the error term in the model.

Limitations concerning regressions are also pointed for some authors related to the Tobit regression model. According to Zelenyuk and Zheka (2006) and Simar and Wilson (2007) the use of a Tobit estimator is inadequate to estimate the efficient determinants because it fails to address the dependency problem of the DEA efficiency scores. The application of the quantile regression provides the capability of describing the relationship at different points in the conditional distribution of the response variable Y.

Quantile regression generalizes the concept of a univariate quantile to a conditional quantile given one or more covariates. For a random variable Y with probability distribution function:

$F(y) = Prob\ (Y \leq y)$

The q^{th} quantile of Y^* is defined as the inverse function:

$Q(q) = inf\ \{y :\ F(y) \geq q\ \}$ where $0 < q < 1$ and the median is $Q\left(\frac{1}{2}\right)$

For a random sample $\{y_1\ , \dots , y_n\ \}$ of Y the sample median is the minimizer of the sum of the absolute deviations. Likewise, the general q^{th} sample quantile $Q(q)$ may be formulated as the solution of the optimization problem:

$\underset{\xi\ \in R}{min}\ \sum_{i=1}^{n} \rho_q\ (y_i - \ \xi)$ where $\rho_q\ (z) = q\ |z|\ if\ z \geq 0\ or\ \rho_q\ (z) = q - 1\ if\ z < 0$ and ξ is the model prediction error.

The quantile regression may be described as function by:

$Q_q\left({}^{y}/_{x}\ \right) = x\beta^q,\ \ q\ \in\ [0,1]$ where $Q(q)$ respects to the quantile q

The quantile regression estimator for quantile q minimizes the objective function:

$$\sum_{y_i\ \geq x_i\beta^q} q\ |y_i -\ x_i\beta^q| + \sum_{y_i\ \geq x_i\beta^q} (1 - q)\ |y_i -\ x_i\beta^q|$$

This non-differentiable function is minimized via the simplex method which guarantees to yield a solution in a finite number of interactions.

The model for linear quantile regression is: $y = A'\beta^q +\ \xi$

$A = (x_{1,\ldots,}x_n)$ is the matrix consisting of n observed vectors of X and $y = (y_{1,\ldots,}y_n)$ the n observed responses, $\beta^q = (\beta_{1,\ldots,}\, \beta_p)$ is the unknown p-dimensional vector of parameters and $\xi = (\xi_{1,\ldots,}\, \xi_n)$ is the n-dimensional vector of unknown errors.

Also, quantile regression is more robust to non-normal errors and outliers when compared to ordinary linear regressions.

5.2. Variables

Taking in consideration the literature review described in section 2.3. Determinants of Efficiency, the characteristics and the data available of the company under study, the external variables are selected:

- SArea - to evaluate the size effect, the area of the stores in square meters is included. Consumers associate premium brands with store size. Considering that the company under study belongs to the brand equity market, it's important to analyze how this factor is influencing efficiency.

- SBrand – represents the brands of the stores analyzed. The DMUS are composed by 3 different brands, each one with its own characteristics. These characteristics may influence efficiency and including this variable will allow to estimate the impact of the average differential of efficiency (higher or lower levels) caused by the variation of a brand against the others.

- SLoc – represents the location of the stores by type of commercial retail locations – Shopping Center, urban store or Outlet Shopping Center. With this variable, it's possible to analyze the store location factors that can explain efficiency.

- SAge – represents the store age, i.e., the number of years since the store opening. The company portfolio has been growing and with that, the number of stores also has been increasing over the years. The inclusion of this variable will allow evaluating if older stores have a better performance then new stores or vice-versa. Also, the experience acquired over the years can influence the strategic decisions of managers that can help improve efficiency.

- PPPI – represents the purchasing power parity index per capita. This variable is specified by region NUTS III. NUTS is the acronym of "Nomenclature of Territorial Units for Statistics", a hierarchical division system of the Portuguese territory into regions. NUTS III (third sub-level) is composed by 25 regions. For this analysis 8 regions were considered (the other regions were not included because the company doesn't have any stores in that region). Regions: 1- Norte – Alto Minho, 2 – Área metropolitana do Porto, 3 – Centro – Região de Aveiro, 4 – Centro – Região de Coimbra, 5 – Centro- Viseu Dão Lafões, 6 – Área metropolitana de Lisboa, 7 – Região do Algarve and 8 – Região da Madeira. The a priori assumptions consider that retail sales productivity is likely to be higher for stores located in those regions where the costumers have higher purchasing power parity. The inclusion of this external variable will verify the accuracy of this assumption.

- SReg- to capture the differences in the location of the stores, this variable is included and represents the location of the stores by region. Considering that the stores of the company under analysis are mainly located in Lisbon and Porto regions, and the other stores are scattered throughout the country, we perform the analysis between three regions: Lisbon, Porto and other regions.

Considering the expose and according to the theoretical background of the linear quantile regression and the literature, the estimation of the following regression, using the 2nd model under CRS and VRS assumptions, is proposed:

$$y_i = \beta_0 + \beta_1 X_1 + \beta_1 X_2 + \beta_2 X_3 + \beta_3 D_1 + \beta_4 D_2 + \beta_5 D_3 + \beta_6 M_1 + \beta_7 M_2 + \beta_8 M_3 + \beta_9 R_1 + \beta_{10} R_2 + \beta_{11} R_3 + \xi_i$$

Where:

Y_i is the DEA score (dependent variable)

X_1 is Store Area (SArea)

X_2 is the purchasing power parity index (PPPI)

X_3 is the Store Age (SAge)

D_1, D_2 and D_3 are dummy variables and represent the commercial retail location of stores (Shopping, Outlet, Urban Store)

- D_1 is 1 if the store is located in Shopping and is 0 if not
- D_2 is 1 if the store is located in an Outlet and is 0 if not
- D_3 is 1 if the store is located in a Urban street and is 0 if not D_1, D_2 and D_3 are dummy variables and represent the commercial retail location of stores (Shopping, Outlet, Urban Store)

M_1, M_2 and M_3 are dummy variables and represent the brands

- M_1 is 1 for Brand 1 and is 0 if not
- M_2 is 1 for Brand 2 and is 0 if not
- M_3 is 1 for Brand 3 and is 0 if not

R_1, R_2 and R_3 are dummy variables and represent the regions

- R_1 is 1 if the store is located in Lisbon and is 0 if not
- R_2 is 1 if the store is located in Porto and is 0 if not
- R_3 is 1 if the store is located in other regions and is 0 if not

5.3. Results

In this section, to determine the factors that influence efficiency we analyze the Quantile Regression model by estimating the DEA scores (CRS and VRS) using the 2nd model with 3 inputs. For the estimates 96 observations that corresponds to 32 stores that were efficiency analyzed for the years 2015, 2014 and 2013 were used.

The estimation was performed using the software STATA. In the estimation regression process the program omitted the variables M3 and R1 because they reveal collinearity with the other variables. The variables included in the estimation are: X_1 – Area of the stores, X_2 – PPPI (Purchasing power parity index), X_3 – Store age, M_1 – Brand 1, M_2 – Brand 2, M_3 – Brand 3, D_1 – Shoppings, D_2 – Outlets, D_3 - Urban Stores, R_2 – Porto region, R_3 – Other regions

For the 2nd model under CRS assumption, the estimation results of Table XXIII. shows that in OLS Robust regression most of the variables analyzed, at different levels of significance, influence positively efficiency, as is the case of variable X_2 (PPPI) and the dummy variables D_2 (Outlets), M_1 (Brand 1), M_2 (Brand 2) and R_3 (Other regions) and other influence negatively efficiency, as is the case of variables X_1 (Area of the stores), X_3 (Store age) and the dummy variable D_1 (Shoppings). Variable D_3 (Urban Stores) and R_2 (Porto region) has no statistic significance.

Table XXIII. Results of OLS and Quantile Regression estimates – 2nd model (CRS)

Independent variables	OLS.Robust	Quantile Regression - 2nd model (CRS)					
		Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
X1	**-.0004944*****	**-.0002781***	-.0002419	**-.0007537*****	-.0002031	-.0007311	-.0010022
X2	**.3058447*****	.3450775	.6047234	.2092186	. .1320965	.0428005	. .3000071
X3	**-.004667*****	.0006678	-.0015402	**-.005028*****	-.004327	-.0057251	**-.01716****
D1	**-.0612344*****	-.012003	-.02843	**-.1002918*****	-.0595411	**-.1263455****	**-.1337406***
D2	**.1390363***	**.2071355***	**.1831965****	**.111547*****	.1206948	**.1552503*****	.0454577
D3	-.0454131	-.0311678	-.0430197	-.0026743	.2927463	.2169862	.258656
M1	**.1082394***	-.0073625	-.0067494	.0271074	. -.0025678	.0648311	.1231373
M2	**.1113297***	**-.077329****	**-.0886676****	. -.0806958	. -.1183403	-.0167043	-.013421
R2	-.0470175	-.0691115	-.1245328	-.0305628	.0269483	.0613957	-.0598222
R3	**.0841206****	.085326	**.1395347*****	. .06336	**.1146139***	.0499704	-.0255277
Constant	**.387177****	.2701333	.0470918	**.6490594***	**.6560752***	**.8520418****	**.7723362****
Observations	96	96	96	96	96	96	96
Pseudo R2		0.4125	0.3179	0.3547	0.3542	0.4316	0.5149

Note: Dependent variable: Scores of efficiency (based on the DEA model). p-values in parenthesis; *, **, *** means significant at 1%, 5% and 10%, respectively

Source: Own elaboration

In turn, the quantile regression estimation allows us to analyze the differential impact of variables for the different quantiles considered (10th quantile – Q (0.10), 25th quantile – Q (0.25), 50th quantile – Q (0.50), 75th quantile – Q (0.75), 90th quantile – Q (0.90) and 95th quantile – Q (0.95)). Variable X_1 (Area of the stores) influences negatively the efficiency scores at levels of significance of 1% and 10% for the 10th and 50th quantiles. This means that the impact of this variable in stores whose scores belong to the lowest quantile are negatively affected by Store area. Variable X_3 (Store age) also has a negative impact on efficiency scores but only for the 50th quantile (with 10% of significance) and the 95th quantile (with 5% of significance). Despite in OLS

Robust regression estimation variable X_2 (PPPI) has statistical significance at a level of 10%, it does not have any influence on efficiency scores for the quantiles analyzed.

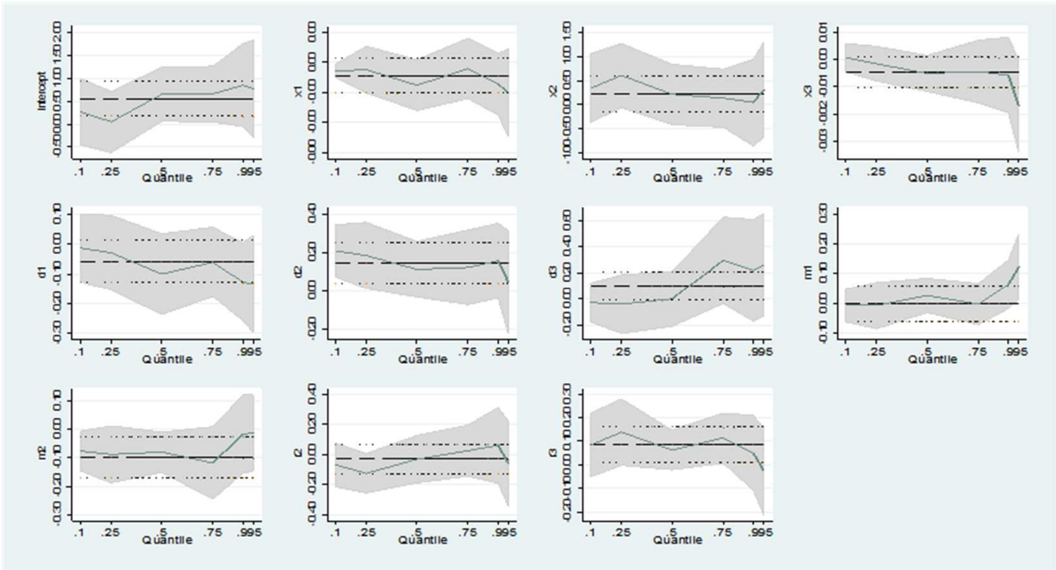
In what concerns the induced effects of the differentials of the dummy variables in efficiency scores under CRS assumption, there is a negative differential impact of variable D_1 (Shoppings) relatively to variable D_3 (Urban Stores) at the 50th quantile (with 10% of significance), at the 90th quantile (with 5% of significance) and at the 95th quantile (with 1% of significance). This means that when comparing the variable D_1 (Shoppings) with the variable D_3 (Urban Stores), that the first has a negative impact on efficiency scores mainly for the stores whose scores are in the highest quantile.

For the dummy variable D_2 (Outlets) relatively to variable D_3 (Urban Stores) there is a positive impact of D_2 (Outlets) in efficiency scores for the 10th quantile, with 1% of significance, for the 25th quantile, with 5% of significance and for the 50th and 90th quantiles, with 10% of significance.

At the lowest quantiles (10th and 25th) it is noted that the variable M_2 (Brand 2) has a negative impact on efficiency scores, with a level of 5 % of statistical significance. At the 25th and 75th quantiles there is a positive effect on the differential efficiency scores by variable R_3 (Other regions) with 10% and 1% level of significance, respectively. It is estimated that for the stores that belong to Brand 2 relatively to the ones that belong to Brand 3, that there is a negative impact on the differential efficiency average scores and that there is a positive impact on the differential efficiency scores when comparing the stores of R_3 (Other regions) to the stores of R_1 (Lisbon region).

According to Baum (2013), Fig. 7 illustrates how the effects of each variable may vary over different quantiles and how the magnitude of those effects on the different quantiles would differ considerable from the OLS estimations, in terms of the confidence interval around each coefficient included in the estimation.

Fig. 7. Results of OLS and Quantile Regression estimates – 2nd model (CRS)



The results of Fig. 7 show that for the 50th, 75th and 90th quantiles, the coefficients on X_2 (PPPI) and X_3 (Store age) are very low, close to zero. This suggests that the Purchasing Power Parity and the Store Age does not influence the conditional scores of efficiencies distribution for those quantiles. However, as we move up over the conditional distribution, the coefficient rises significantly specially at the extreme upper quantile (95th).

For the 2nd model under VRS assumption, Table XXIV. show the results of the OLS Robust regression and quantile regression estimation. The estimation results of the OLS Robust show that, at different levels of significance, a several number of variables are statistical significant. Specifically, the dummy variables D_2 (Outlets), M_1 (Brand 1), M_2 (Brand 2) and R_3 (Other regions) have a positive impact in the average differential of efficiency scores, with 1% of significance while variables as X_2 (PPPI), D_1 (Shoppings) and R_2 (Porto region) have a negative impact in the average differential of efficiency scores at levels of significance of 10%, 5% and 1%, respectively.

In what concerns the quantile regression results, the estimated coefficients associated with variables X_2 (PPPI) and X_3 (Store age) does not have statistical significance in any of the quantiles. However, the coefficient of variable X_1 (Area of the stores) presents statistical significance for the 90th and 95th quantiles.

Table XXIV. Results of OLS and Quantile Regression estimates – 2nd model (VRS)

Independent variables	OLS.Robust	Quantile Regression - 2nd model (CRS)					
		Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
X1	-.0002746	-.0001211	-.0005165	-.0006498	-.0004621	**-.0027558****	**-.0023549*****
X2	**.339079*****	.3992282	.3415856	.0831356	-.0085681	-.0305303	-.0124215
X3	-.0033619	. -.00435	-.0024417	-.0040966	-.002945	-.0058313	-.0023725
D1	**-.1044033***	-.0623908	-.0337254	**-.1272628*****	**-.1345013****	**-.1347618***	**-.1291318***
D2	**.1299636***	.1413261	**.2201032 *****	.1417599	**.1833962*****	**.2251887****	**.2287019****
D3	-.0750575	-.0202	-.0264583	-.0114068	.1935899	.1935313	. .1900725
M1	**.0815498***	-.0451385	.0044541	.0464376	.0315566	**.3406653***	**.3336311***
M2	**0965916***	**-.1190203***	-.047211	-.0603214	-.0571047	**.2579****	**.2362749****
R2	**-.0865615****	-.0914912	-.1003472	-.0055439	.0355563	.0055954	.0121383
R3	**.1045571***	**.1350534****	.0933712	.0814396	**.0956285*****	-.0624562	-.0436782
Constant	**.3980688****	.3235574	.3773179	**.7770006****	**. .8579122***	**1.072677****	**.9877383****
Observations	96	96	96	96	96	96	96
Pseudo R2		0.3780	0.3338	0.3798	0.3658	0.4309	0.4796

Note: Dependent variable: Scores of efficiency (based on the DEA model). p-values in parenthesis; *, **, *** means significant at 1%, 5% and 10%, respectively

Source: Own elaboration

It is noted, for the set of stores under analysis, that the average differential on efficiency scores (with 1% of significance), of variable D_1 (Shoppings) relatively to the variable D_2 (Outlets) and variable D_3 (Urban Stores) at the 50th, 75th, 90th and 95th quantiles, impact negatively the average efficiency score in 0.127, 0.1345, 0.1347 and 0.129 percentage points, respectively.

For the variable M_1 (Brand 1) relatively to M_3 (Brand 3) at the 90th and 95th quantiles and with a level of significance of 1%, variable M_1 (Brand 1) impacts negatively in 0.340 and 0.333 percentage points the differential efficiency scores. At the lowest quantile (10th) M_1 (Brand 1) relatively to M_3 (Brand 3) also impacts negatively the differential efficiency scores, with a level of significance of 1 %. However, for the highest quantiles (90th and 95th) the variable M_2 (Brand 2) relatively to variable M_3 (Brand 3) has a positive impact on average efficiency scores of 0.257 and 0.235 percentage points, with a level of significance of 5%.

Finally, the coefficient associated with the dummy variable R_3 (Other regions) relatively to the variable R_1 (Lisbon region) for the 75th percentile has a positive impact on the differential average efficiency score in 0.095 percentage points, with a level of 10% of significance. R_2 (Porto region) does not have statistical significance in any of the quantiles estimated.

Fig. 8. Results of OLS and Quantile Regression estimates – 2nd model (VRS)

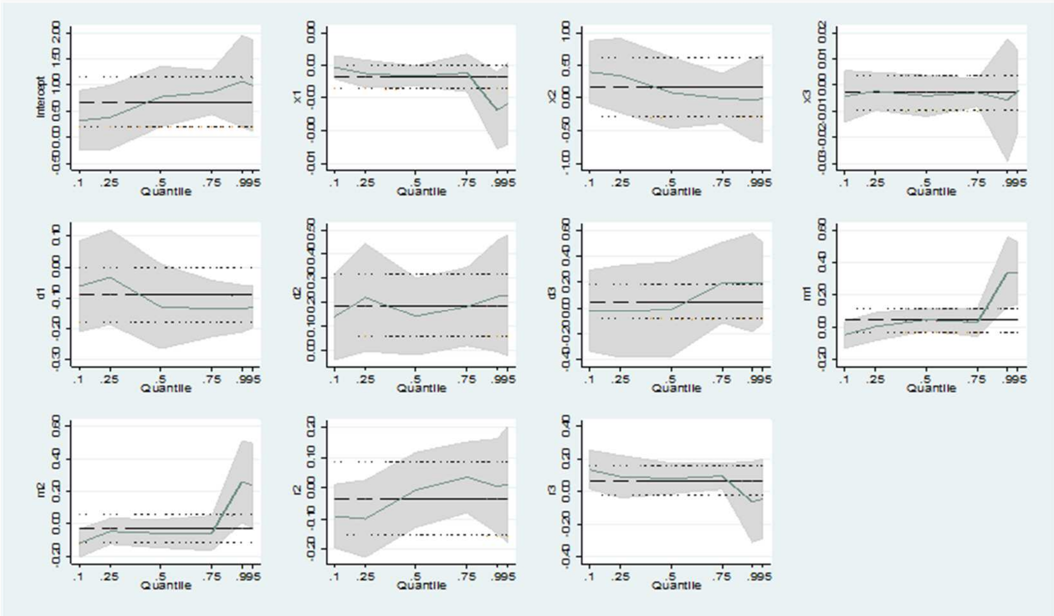


Fig. 8 shows that for the 50th and 75th quantiles, the coefficients of the variable X_1 (Area of the stores) and for the 10th, 25th, 50th and 75th quantiles, the coefficients for the variable X_3 (Store age) are very low, close to zero. However, as we move up over the conditional distribution, the coefficient rises significantly specially at the extreme upper quantiles (90th and 95th).

5.4. Main conclusions

In previous section, we evaluated the impact on efficiency performing an advance model of DEA methodology, a Linear Quantile regression, to estimate the other efficiency determinants, factors that are considered external to the operational management and that are affecting efficiency. Considering the OLS Robust regression estimation and the panel data for the years of 2013-2015 (32 Stores – 96 observations), bellow we resume the results for OLS Regression:

- X_1 (Area of the stores) – impacts negatively the efficiency scores
    - CRS – 10% of significance
    - VRS – no significance

- X_2 (PPPI) – impacts positively the efficiency scores
    - CRS and VRS – 10% of significance

- X_3 (Store age) – impacts negatively the efficiency scores
    - CRS – 10% of significance
    - VRS – no significance

For the dummy variables, we present a resume of the average differential impact on variables for OLS Robust:

- D_1 (Shoppings) relatively to the dummy variables D_2 (Outlets) and D_3 (Urban Stores) – impacts negatively the efficiency scores
    - CRS – 10% of significance
    - VRS – 1% of significance

- D_2 (Outlets) relatively to the dummy variables D_2 (Outlets) and D_3 (Urban Stores) – impacts positively the efficiency scores
    - CRS and VRS – 1% of significance

- D_3 (Urban Stores) relatively to the dummy variables D_2 (Outlets) and D_1 (Shoppings) – no significance

- M_1 (Brand 1) relatively to the dummy variable M_3 (Brand 3) – impacts positively the efficiency scores
    - CRS and VRS – 1% of significance

- M_2 (Brand 2) relatively to the dummy variable M_3 (Brand 3) – impacts positively the differential efficiency scores
    - CRS and VRS – 1% of significance

- R_2 (Porto Region) relatively to the dummy variable R_1 (Lisbon Region) – impacts negatively the efficiency scores
    - CRS – no significance
    - VRS – 5% of significance

- R_3 (Other Regions) relatively to the dummy variable R_1 (Lisbon Region) – impacts positively the efficiency scores
  - CRS – 5% of significance
  - VRS – 1% of significance

When the results are stratified by quantiles, the impact of each external variable under CRS and VRS is resumed bellow:

- X_1 (Area of the stores) – impacts negatively the efficiency scores
  - CRS – 10^{th} quantile (1% of significance) and 50^{th} quantile (5% of significance)
  - VRS – 90^{th} quantile (5% of significance) and 95^{th} quantile (10% of significance)

- X_2 (PPPI) – no statistical significance for both assumptions except for OLS Robust

- X_3 (Store age) – impacts negatively the efficiency scores
  - CRS – 50^{th} quantile (10% of significance) and 95^{th} quantile (5% of significance)
  - VRS – no significance

For the dummy variables, we present a resume of the average differential impact on variables:

- D_1 (Shoppings) relatively to the dummy variables D_2 (Outlets) and D_3 (Urban Stores) – impacts negatively the efficiency scores
  - CRS – 50^{th} quantile (10% of significance), 90^{th} quantile (5% of significance) and 95^{th} quantile (1% of significance)
  - VRS – 50^{th} quantile (10% of significance), 75^{th} quantile (5% of significance) and 90^{th} and 95^{th} (1% of significance)

- D_2 (Outlets) relatively to the dummy variables D_2 (Outlets) and D_3 (Urban Stores) – impacts negatively the efficiency scores
  - CRS – 10^{th} quantile (1% of significance), 25^{th} quantile (5% of significance) and 50^{th} and 90^{th} quantile (10% of significance)
  - VRS – 25^{th} and 50^{th} quantile (10% of significance) and 90^{th} and 95^{th} quantile (5% of significance)

- D_3 (Urban Stores) relatively to the dummy variables D_2 (Outlets) and D_1 (Shoppings) – no significance

- M_1 (Brand 1) relatively to the dummy variable M_3 (Brand 3) – impacts positively the efficiency scores
    - CRS – no significance
    - VRS – 90^{th} and 95^{th} quantile (1% of significance)

- M_2 (Brand 2) relatively to the dummy variable M_3 (Brand 3) – impacts positively and negatively the differential efficiency scores
    - CRS – impacts negatively the lowest quantiles – 10^{th} and 25^{th} quantiles (5% of significance)
    - VRS – impacts negatively the lowest quantile – 10^{th} quantile (1% of significance) and positively the highest quantiles – 90^{th} and 95^{th} quantiles (5% of significance)

- R_2 (Porto Region) relatively to the dummy variable R_1 (Lisbon Region) – no significance under both assumptions

- R_3 (Other Regions) relatively to the dummy variable R_1 (Lisbon Region) – impacts positively the efficiency scores
    - CRS – 25^{th} quantile (10% of significance) and 75^{th} quantile (1% of significance)
    - VRS – 10^{th} quantile (5% of significance) and 75^{th} quantile (10% of significance)

As stated above, the OLS Robust estimation provides different results under the different assumptions and when comparing to the analysis stratified by different quantiles. For example, variables X_1 (Area of the stores) and X_3 (Store age) are significant under CRS assumption but have no statistical significance under VRS assumption; the variable X_2 (PPPI) is significant for the OLS Robust estimation, under both assumptions but has no significance for any of the quantiles analyzed.

Taking this into consideration, we can conclude that variable X_1 (Area of the stores) has a negative impact on the efficiency scores with a higher significance in the lowest quantiles under CRS assumption and in the highest quantiles for VRS assumption; X_2 (PPPI) has no significance for the quantiles and stores analyzed, which means that does not affect the operational management efficiency and X_3 (Store age) impacts negatively the efficiency scores under CRS assumption while for VRS assumption it has no significance.

For the analysis of the variables commercial location and when comparing the average impact on the differential efficiency scores, it should be emphasized that the variable D_3 (Urban Stores) has no statistical significance for both estimations (OLS Robust and Quantile regression) and in any of the assumptions (CRS and VRS). In what concerns the variables D_1 (Shoppings) and D_2 (Outlets), the results are similar for both estimations and under both assumptions. However, while variable D_2 (Outlets) affects positively the efficiency scores, the variable D_1 (Shoppings) affects these scores negatively (the biggest impact is verified in the highest quantiles).

Concerning the influence of brands in efficiency, we can conclude that M_1 (Brand 1) affects positively efficiency, for OLS Robust estimation under both assumptions. When stratified by quantiles, the variable M_1 (Brand 1) has no significance under CRS assumption, while in VRS assumption is significant for the highest quantiles (90^{th} and 95^{th}). The variable M_2 (Brand 2) also impacts positively efficiency and this results are verified for both estimations and assumptions. However, the quantile estimation reveals that under VRS assumption, the stores whose efficiency scores belong to the lowest quantile (10^{th}) are negatively affected by the variable M_2 (Brand 2), while for the highest quantiles (90^{th} and 95^{th}) the variable M_2 (Brand 2) has a positive impact on efficiency scores.

For the regions considered, the variable R_2 (Porto region) has no significance for all the estimations, excepting for the OLS Robust under VRS assumption. However, for the stores of region R_3 (Other regions) and relatively to R_1 (Lisbon region), there is a positive impact of this variable on efficiency scores.

it allows us to analyze the impact on the stores with different efficiency scores and that are set in the different quantiles.

6. Conclusions and limitations

This study has proposed a simple framework for the evaluation of retail outlets and the rationalization of their operational activities. The analysis is based on a DEA model that allows the incorporation of multiple inputs and outputs in determining the relative efficiencies. Benchmarks are provided for improving the operations of poorly performing stores.

For the analysis, data was pooled between 2009 and 2015 to create 185 DMUS. The DMUS are the stores that are composed by three different brands of Fashion and Accessories sector. The company under analysis belongs to the Brand Equity segment, which means that their products are in premium segment. To determine efficiency of the stores that are part of the company, a two-stage approach is used: first we estimate the DEA scores using two different models with two different set of inputs and in second stage a Linear Quantile regression estimation is performed to determine the efficiency drivers. As reviewed in the literature, some authors also used a two-stage approach using both assumptions (CRS and VRS) (Perrigot and Barros, 2008; Yu and Ramanathan, 2008, 2009; Banker et al., 2009; Xavier et al., 2015a; Moreno and Carrasco, 2016).

To determine the DEA scores, CRS and VRS assumption are used to compare how scale effects efficiency. The use of two different models with two set of inputs allowed us to analyze the impact of the input rent in efficiency under both assumptions, as this variable is strategic to the stores of the company under analysis (Leasing Agreements). Joo et al. (2009) also implemented a study with two different models. However, the two models were based on a different set of inputs and outputs, instead of analyzing the impact of an input when considered in the DEA model.

Results show that the levels of efficiency increased with variable returns to scale and when the variable rent was included in the model. The VRS assumption with the variable rent presents 23 stores 100 per cent efficient while the model VRS without this variable only has 13 stores 100 per cent efficient. The CRS model without the variable rent presented only 5 stores 100 per cent efficient. The fact that efficiency increases when an input is included in the model means that there is a good resource management considering the given outputs. Scale is also very important for highest levels of efficiency, since that on average all the efficiencies increase when we assume VRS. While the impact of the variable rent in the model affected efficiency for all brands, scale has different levels of impact considering the stores and the brands. Brand 2 is highly affected by scale while for Brand 3, scale has an almost null effect for the 2nd model. For Brand 1 scale has a more impact in some set of stores than others.

2011 is in general and for all the models the most efficient year and after that year a decreasing tendency is verified for Brand 1 and Brand 3, while Brand 2 presents over time on average a growth in the efficiency levels. Brand 1 and Brand 3 are the brands with better performance and on average presents similar levels of efficiency for all the models. For Brand 1 and Brand 3 the years that follow the openings presented decreasing average efficiencies while Brand 2 has increasing average efficiencies after the openings. Benchmarking and the identification of targets considering the different brands are presented. Targets are calculated for the 2nd model under both assumptions. Benchmarking efficiency is very handy for managers, who can use it to compare their performance with the best-in-class and accordingly make the required changes for improvement (Ghandi and Shakar, 2014). The identification of the inefficient stores and the calculation of targets used in this study can help the company under analysis to perform the adjustments necessary in inputs maintaining outputs constant, to increase efficiency.

For the 2nd stage of the study we performed a quantile regression estimation on DEA scores of the 2nd model under both assumptions to determine which are the external factors that impacts efficiency. As stated by (Xavier at al. 2015a), this technique adds a new dimension to the empirical literature by analyzing the retail sector, and suggests that the coefficients can be interpreted as the partial derivative of the conditional quantile of the efficiency score (dependent variable). Results of second stage shows that independently of the model estimated there is persistency in the differentiation concerning the variables brand and store commercial location. This means that these are important determinants to explain the average differential of the efficiency scores. Opposing to a priori assumptions, Purchase Power Parity Index does not have a significant impact on efficiency. The results acknowledged by Xavier at al. (2015a) also indicates the commercial retail location as a critical success factor of efficiency.

As to our knowledge, this study seems to be the first applying an efficiency analysis with a two-stage approach to a retail distribution Portuguese company that distributes International premium brands on the Fashion and Accessories sector. The novelty of this study is the possibility to perform a different set of analysis considering the different brands and the whole set of stores and to evaluate the impact of an input that is considered strategic by the company manager. The analysis of the effect scale by performing a two-different set of models also leads to conclusions that only are possible to obtain by comparing the different set of models under both assumptions. Considering that all the stores of the company have Leasing Agreements, results of this study also provide the possibility to the company manager of making strategic decisions concerning the less efficient stores (for example, don't renovate the leasing agreement and close the store).

The advantage of using this methodology is that DEA only requires a relatively small amount of aggregate data to operate. Apart from being less data demanding, the methodology is also simpler in problem formulation than the full-fledged linear programming approach. The analysis is relatively easy to implement and the outcome is straight forward to understand. Not only that DEA compares directly the efficiency of stores against that of the best performer in the group, it also shows the areas for improvement for the less efficient stores. This is ideal for managers to monitor store performance through benchmarking as well as to enforce continuous improvement (Donthu and Yoo, 1998).

Nevertheless, it as to be noted that DEA is not designed to find an optimal solution. It only compares among DMUs to identify the most and the less efficient ones in a group in a relative manner given the set of inputs and outputs. (Kwok Hung Lau, 2013). Considering the analysis performed, we cannot assume that the stores that were considered 100 per cent efficient are performing at an optimal solution. This analysis only gives us the best performers in the set of stores analyzed.

The major limitation of this study is the variance among the number of stores over the period under analysis. For the most recent stores and because the number of observations is smaller, results may be affected.

As the selection of input and output variables is crucial in DEA, the involvement of the company manager in the selection of inputs and outputs can be incorporated in the DEA analysis using weight restrictions (Ket and Chu, 2003; Goic et al., 2013) and the identification of controllable and uncontrollable factors. (Thomas et al., 1998; Camanho et al., 2009). Future research regarding the use of weight restrictions taking into consideration the company manager involvement on weights assignment can provide a better definition of the store's peers and targets.

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8. Annexes

Annex I. DEA Scores for the 1st model and 2nd model under CRS under CRS e VRS assumption

DMUS	Ano	1st model - 2 Inputs		2nd model - 3 Inputs	
		Score (CRS)	Score (VRS)	Score (CRS)	Score (VRS)
DMU1	2015	46,03%	49,94%	53,80%	54,03%
DMU2	2015	53,96%	60,41%	63,98%	64,91%
DMU3	2015	62,90%	65,59%	72,48%	72,77%
DMU4	2015	46,83%	54,17%	72,12%	72,80%
DMU5	2015	53,29%	58,20%	61,78%	62,27%
DMU6	2015	52,74%	54,87%	64,18%	65,03%
DMU7	2015	64,19%	68,31%	77,25%	77,61%
DMU8	2015	45,50%	50,03%	47,87%	50,03%
DMU9	2015	52,23%	55,31%	57,07%	57,24%
DMU10	2015	53,10%	100,00%	100,00%	100,00%
DMU11	2015	46,89%	52,78%	66,11%	66,66%
DMU12	2015	59,38%	61,35%	59,38%	61,63%
DMU13	2015	46,37%	53,56%	51,06%	53,56%
DMU14	2015	53,12%	59,84%	58,73%	61,00%
DMU15	2015	54,89%	60,87%	74,66%	75,08%
DMU16	2015	61,49%	62,16%	65,06%	65,58%
DMU17	2015	57,72%	100,00%	80,30%	100,00%
DMU18	2015	47,49%	57,19%	61,18%	61,32%
DMU19	2015	47,35%	57,39%	58,31%	58,33%
DMU20	2015	55,53%	63,84%	77,93%	78,03%
DMU21	2015	47,55%	56,61%	68,34%	69,51%
DMU22	2015	56,33%	69,59%	87,46%	89,61%
DMU23	2015	51,88%	53,95%	56,93%	57,25%
DMU24	2015	59,30%	65,68%	66,25%	66,59%
DMU25	2015	60,62%	60,95%	61,97%	62,41%
DMU26	2015	46,99%	55,66%	57,64%	57,65%
DMU27	2015	53,47%	59,25%	59,41%	60,50%
DMU28	2015	48,20%	61,87%	70,86%	78,90%
DMU29	2015	54,45%	62,12%	80,29%	88,92%
DMU30	2015	48,52%	64,04%	88,41%	100,00%
DMU31	2015	54,62%	63,50%	88,54%	100,00%
DMU32	2015	61,57%	62,29%	72,49%	74,20%
DMU33	2015	47,48%	57,10%	62,33%	62,54%
DMU34	2015	55,23%	65,05%	67,33%	68,29%
DMU35	2015	52,19%	53,00%	58,35%	60,46%
DMU36	2014	46,66%	49,83%	53,08%	53,17%
DMU37	2014	59,59%	67,05%	70,54%	73,04%
DMU38	2014	64,03%	67,21%	73,76%	74,03%
DMU39	2014	47,65%	54,01%	71,01%	74,19%
DMU40	2014	60,34%	67,95%	73,11%	73,29%
DMU41	2014	58,20%	60,58%	70,02%	70,77%
DMU42	2014	65,80%	70,80%	79,16%	79,57%
DMU43	2014	56,79%	58,57%	60,12%	60,13%
DMU44	2014	48,64%	77,83%	66,89%	81,23%
DMU45	2014	46,69%	49,06%	58,52%	59,00%
DMU46	2014	46,36%	51,44%	49,34%	51,44%
DMU47	2014	60,81%	61,98%	61,60%	62,50%
DMU48	2014	58,86%	66,65%	64,74%	67,46%
DMU49	2014	60,09%	65,97%	78,80%	79,16%
DMU50	2014	63,05%	65,77%	68,79%	69,32%
DMU51	2014	62,49%	100,00%	79,27%	100,00%
DMU52	2014	48,26%	56,39%	57,64%	57,67%
DMU53	2014	48,34%	57,29%	56,74%	57,35%
DMU54	2014	60,09%	66,16%	77,89%	78,17%
DMU55	2014	54,11%	58,89%	64,38%	66,82%
DMU56	2014	48,23%	55,44%	64,31%	64,46%

DMUS	Ano	1st model - 2 Inputs		2nd model - 3 Inputs	
		Score (CRS)	Score (VRS)	Score (CRS)	Score (VRS)
DMU57	2014	60,80%	68,82%	79,34%	79,36%
DMU58	2014	57,24%	59,07%	61,89%	62,17%
DMU59	2014	48,09%	56,15%	57,41%	57,42%
DMU60	2014	62,29%	63,65%	65,21%	65,30%
DMU61	2014	58,14%	63,25%	63,08%	64,49%
DMU62	2014	49,68%	60,88%	71,31%	72,28%
DMU63	2014	57,75%	63,20%	76,20%	79,67%
DMU64	2014	49,39%	59,79%	75,13%	81,19%
DMU65	2014	59,17%	67,26%	81,91%	94,95%
DMU66	2014	63,19%	68,68%	74,10%	79,10%
DMU67	2014	48,59%	57,57%	61,98%	62,10%
DMU68	2014	59,04%	66,08%	66,07%	68,73%
DMU69	2014	55,77%	58,83%	61,00%	63,43%
DMU70	2013	42,61%	47,16%	52,18%	52,31%
DMU71	2013	58,65%	67,93%	74,61%	75,68%
DMU72	2013	66,78%	70,68%	76,08%	76,31%
DMU73	2013	43,08%	50,15%	67,59%	67,70%
DMU74	2013	59,07%	67,90%	74,74%	74,85%
DMU75	2013	56,62%	59,30%	68,22%	69,10%
DMU76	2013	69,12%	76,41%	86,72%	86,77%
DMU77	2013	56,47%	60,36%	61,68%	62,07%
DMU78	2013	42,82%	55,04%	61,25%	65,64%
DMU79	2013	42,83%	47,18%	50,40%	52,38%
DMU80	2013	42,86%	50,39%	49,14%	50,39%
DMU81	2013	62,53%	64,17%	62,66%	64,40%
DMU82	2013	57,96%	67,12%	66,34%	68,57%
DMU83	2013	58,41%	64,81%	77,51%	77,65%
DMU84	2013	66,81%	71,66%	73,80%	74,19%
DMU85	2013	61,04%	78,31%	78,98%	82,56%
DMU86	2013	43,61%	52,40%	55,18%	55,40%
DMU87	2013	43,76%	54,98%	55,42%	55,81%
DMU88	2013	57,89%	63,56%	74,30%	74,31%
DMU89	2013	55,21%	55,36%	67,54%	69,44%
DMU90	2013	43,92%	48,53%	55,87%	55,97%
DMU91	2013	59,11%	66,55%	76,12%	76,23%
DMU92	2013	54,22%	54,61%	57,74%	58,52%
DMU93	2013	43,64%	53,33%	57,50%	58,03%
DMU94	2013	64,39%	65,34%	66,60%	66,70%
DMU95	2013	56,56%	62,23%	62,17%	63,33%
DMU96	2013	61,93%	81,82%	100,00%	100,00%
DMU97	2013	44,50%	46,52%	69,52%	70,56%
DMU98	2013	66,83%	92,13%	100,00%	100,00%
DMU99	2013	43,94%	55,74%	71,22%	75,95%
DMU100	2013	56,94%	65,04%	80,48%	96,47%
DMU101	2013	43,76%	54,12%	60,01%	60,86%
DMU102	2013	59,34%	69,34%	72,17%	72,20%
DMU103	2013	55,20%	55,93%	61,71%	63,62%
DMU104	2012	30,63%	33,35%	41,83%	42,45%
DMU105	2012	63,48%	72,33%	76,41%	78,79%
DMU106	2012	82,08%	82,57%	88,64%	88,65%
DMU107	2012	31,68%	51,10%	71,48%	71,56%
DMU108	2012	63,75%	70,59%	73,39%	73,40%
DMU109	2012	59,26%	59,52%	69,10%	70,38%
DMU110	2012	92,61%	100,00%	100,00%	100,00%
DMU111	2012	61,46%	65,24%	66,26%	66,67%
DMU112	2012	30,12%	36,81%	53,45%	58,69%
DMU113	2012	30,74%	42,74%	41,66%	42,82%
DMU114	2012	60,84%	67,46%	64,99%	67,46%
DMU115	2012	63,72%	69,87%	81,50%	81,50%
DMU116	2012	83,40%	85,15%	87,00%	87,97%
DMU117	2012	66,16%	79,93%	79,83%	80,93%
DMU118	2012	30,83%	44,41%	30,83%	44,41%
DMU119	2012	28,75%	40,62%	28,75%	40,62%
DMU120	2012	62,54%	67,43%	77,45%	77,92%

DMUS	Ano	1st model - 2 Inputs		2nd model - 3 Inputs	
		Score (CRS)	Score (VRS)	Score (CRS)	Score (VRS)
DMU121	2012	62,30%	62,39%	67,89%	69,10%
DMU122	2012	31,93%	56,16%	53,91%	58,61%
DMU123	2012	82,08%	82,69%	82,08%	82,77%
DMU124	2012	58,69%	61,67%	61,13%	62,93%
DMU125	2012	33,61%	86,28%	83,77%	91,78%
DMU126	2012	65,26%	76,01%	89,37%	89,91%
DMU127	2012	32,62%	69,49%	63,00%	72,28%
DMU128	2012	64,51%	74,47%	75,64%	76,94%
DMU129	2012	57,45%	61,71%	62,63%	64,88%
DMU130	2011	81,62%	93,69%	91,56%	100,00%
DMU131	2011	100,00%	100,00%	100,00%	100,00%
DMU132	2011	50,60%	57,60%	73,82%	73,89%
DMU133	2011	78,99%	100,00%	78,99%	100,00%
DMU134	2011	78,59%	79,03%	89,27%	89,35%
DMU135	2011	100,00%	100,00%	100,00%	100,00%
DMU136	2011	78,59%	78,95%	78,59%	79,17%
DMU137	2011	79,45%	93,95%	81,56%	93,95%
DMU138	2011	82,54%	87,42%	100,00%	100,00%
DMU139	2011	100,00%	100,00%	100,00%	100,00%
DMU140	2011	85,46%	100,00%	93,29%	100,00%
DMU141	2011	80,94%	84,44%	98,14%	99,17%
DMU142	2011	78,59%	80,35%	93,28%	93,53%
DMU143	2011	51,60%	60,80%	61,35%	61,44%
DMU144	2011	100,00%	100,00%	100,00%	100,00%
DMU145	2011	78,59%	89,72%	78,67%	89,72%
DMU146	2011	78,59%	85,67%	91,83%	96,97%
DMU147	2011	52,73%	64,62%	69,22%	69,86%
DMU148	2011	83,30%	94,56%	90,46%	96,92%
DMU149	2011	78,59%	83,05%	78,59%	83,79%
DMU150	2010	71,48%	92,90%	100,00%	100,00%
DMU151	2010	67,71%	72,44%	78,87%	78,89%
DMU152	2010	30,30%	58,67%	83,97%	85,78%
DMU153	2010	66,58%	70,71%	81,01%	81,66%
DMU154	2010	68,90%	74,37%	84,08%	84,13%
DMU155	2010	65,38%	69,53%	70,80%	71,22%
DMU156	2010	69,92%	85,35%	83,81%	86,66%
DMU157	2010	69,80%	81,31%	99,92%	99,98%
DMU158	2010	65,19%	67,85%	70,63%	70,75%
DMU159	2010	72,69%	100,00%	97,38%	100,00%
DMU160	2010	69,94%	82,27%	100,00%	100,00%
DMU161	2010	65,59%	68,29%	84,61%	84,94%
DMU162	2010	61,21%	61,35%	63,63%	63,68%
DMU163	2010	64,56%	65,77%	67,42%	67,55%
DMU164	2010	69,17%	81,46%	82,18%	84,52%
DMU165	2010	66,51%	72,22%	79,87%	80,12%
DMU166	2010	30,73%	68,27%	65,00%	73,64%
DMU167	2010	71,66%	93,26%	94,46%	96,30%
DMU168	2010	62,61%	64,34%	70,55%	72,11%
DMU169	2009	76,52%	89,24%	93,56%	100,00%
DMU170	2009	57,32%	66,98%	81,67%	82,63%
DMU171	2009	36,20%	39,43%	56,69%	59,08%
DMU172	2009	69,99%	70,60%	83,97%	84,07%
DMU173	2009	56,05%	60,81%	73,07%	73,15%
DMU174	2009	69,58%	70,63%	72,22%	73,19%
DMU175	2009	75,51%	87,08%	83,25%	88,11%
DMU176	2009	75,57%	82,10%	95,95%	96,03%
DMU177	2009	55,55%	62,65%	68,52%	68,55%
DMU178	2009	81,67%	100,00%	100,00%	100,00%
DMU179	2009	77,24%	86,69%	100,00%	100,00%
DMU180	2009	70,47%	72,63%	85,64%	86,77%
DMU181	2009	54,96%	60,30%	62,97%	63,03%
DMU182	2009	75,52%	86,14%	84,01%	89,02%
DMU183	2009	100,00%	100,00%	100,00%	100,00%
DMU184	2009	36,63%	36,86%	37,52%	37,75%
DMU185	2009	78,32%	92,19%	94,10%	97,76%

Annex II. Efficient stores for the 1st and 2nd model under CRS and VRS assumption

1st model (2 Input)		2009 CRS	2010 CRS	2011 CRS	2012 CRS	2013 CRS	2014 CRS	2015 CRS	Average
Brand 1	Store 1	76,52%	71,48%	81,62%	63,48%	58,65%	59,59%	53,96%	66,47%
	Store 2			78,99%	63,75%	59,07%	60,34%	53,29%	63,09%
	Store 3	69,99%	66,58%	78,59%	59,26%	56,62%	58,20%	52,74%	63,14%
	Store 4	69,58%	65,38%	78,59%	61,46%	56,47%	56,79%	52,23%	62,93%
	Store 5	75,51%	69,92%	79,45%	60,84%	57,96%	58,86%	53,12%	65,09%
	Store 6	75,57%	69,80%	82,54%	63,72%	58,41%	60,09%	54,89%	66,43%
	Store 7	81,67%	72,69%	85,46%	66,16%	61,04%	62,49%	57,72%	69,60%
	Store 8	77,24%	69,94%	80,94%	62,54%	57,89%	60,09%	55,53%	66,31%
	Store 9	70,47%	65,59%	78,59%		55,21%	54,11%		64,79%
	Store 10				62,30%	59,11%	60,80%	56,33%	59,64%
	Store 11		61,21%			54,22%	57,24%	51,88%	56,14%
	Store 12							59,30%	59,30%
	Store 13	75,52%	69,17%	78,59%	58,69%	56,56%	58,14%	53,47%	64,31%
	Store 14					66,83%	57,75%	54,45%	59,68%
	Store 15	100,00%	66,51%	78,59%	65,26%	56,94%	59,17%	54,62%	68,73%
	Store 16	78,32%	71,66%	83,30%	64,51%	59,34%	59,04%	55,23%	67,34%
	Store 17		62,61%	78,59%	57,45%	55,20%	55,77%	52,19%	60,30%
Average Brand 1		77,31%	67,89%	80,30%	62,26%	58,10%	58,65%	54,43%	
Standard Deviation		0,0840	0,0355	0,0229	0,0263	0,0293	0,0206	0,0206	
Brand 2	Store 18				30,63%	42,61%	46,66%	46,03%	41,48%
	Store 19	36,20%	30,30%	50,60%	31,68%	43,08%	47,65%	46,83%	40,91%
	Store 10							45,50%	45,50%
	Store 21				30,12%	42,82%	48,64%	53,10%	43,67%
	Store 22					42,83%	46,69%	46,89%	45,47%
	Store 23				30,74%	42,86%	46,36%	46,37%	41,58%
	Store 24				30,83%	43,61%	48,26%	47,49%	42,55%
	Store 25				28,75%	43,76%	48,34%	47,35%	42,05%
	Store 26					43,92%	48,23%	47,55%	46,57%
	Store 27			51,60%	31,93%	43,64%	48,09%	46,99%	44,45%
	Store 28					44,50%	49,68%	48,20%	47,46%
	Store 29				33,61%	43,94%	49,39%	48,52%	43,87%
	Store 30	36,63%	30,73%	52,73%	32,62%	43,76%	48,59%	47,48%	41,79%
Average Brand 2		36,42%	30,52%	51,64%	31,21%	43,44%	48,05%	47,56%	
Standard Deviation		0,0030	0,0030	0,0107	0,0143	0,0059	0,0105	0,0186	
Brand 3	Store 31	57,32%	67,71%	100,00%	82,08%	66,78%	64,03%	62,90%	71,55%
	Store 32	56,05%	68,90%	100,00%	92,61%	69,12%	65,80%	64,19%	73,81%
	Store 33					62,53%	60,81%	59,38%	60,91%
	Store 34	55,55%	65,19%	100,00%	83,40%	66,81%	63,05%	61,49%	70,78%
	Store 35	54,96%	64,56%	100,00%	82,08%	64,39%	62,29%	60,62%	69,84%
	Store 36					61,93%			61,93%
	Store 37						63,19%	61,57%	62,38%
Average Brand 3		55,97%	66,59%	100,00%	85,04%	65,26%	63,20%	61,69%	
Standard Deviation		0,0100	0,0206	0,0000	0,0508	0,0279	0,0167	0,0169	

Source: Own elaboration

1st model (2 Input)		2009 VRS	2010 VRS	2011 VRS	2012 VRS	2013 VRS	2014 VRS	2015 VRS	Average
Brand 1	Store 1	89,24%	92,90%	93,69%	72,33%	67,93%	67,05%	60,41%	77,65%
	Store 2			100,00%	70,59%	67,90%	67,95%	58,20%	72,93%
	Store 3	70,60%	70,71%	79,03%	59,52%	59,30%	60,58%	54,87%	64,94%
	Store 4	70,63%	69,53%	78,95%	65,24%	60,36%	58,57%	55,31%	65,51%
	Store 5	87,08%	85,35%	93,95%	67,46%	67,12%	66,65%	59,84%	75,35%
	Store 6	82,10%	81,31%	87,42%	69,87%	64,81%	65,97%	60,87%	73,19%
	Store 7	100,00%	100,00%	100,00%	79,93%	78,31%	100,00%	100,00%	94,03%
	Store 8	86,69%	82,27%	84,44%	67,43%	63,56%	66,16%	63,84%	73,48%
	Store 9	72,63%	68,29%	80,35%		55,36%	58,89%		67,10%
	Store 10				62,39%	66,55%	68,82%	69,59%	66,84%
	Store 11		61,35%			54,61%	59,07%	53,95%	57,25%
	Store 12							65,68%	65,68%
	Store 13	86,14%	81,46%	89,72%	61,67%	62,23%	63,25%	59,25%	71,96%
	Store 14					92,13%	63,20%	62,12%	72,48%
	Store 15	100,00%	72,22%	85,67%	76,01%	65,04%	67,26%	63,50%	75,67%
	Store 16	92,19%	93,26%	94,56%	74,47%	69,34%	66,08%	65,05%	79,28%
	Store 17		64,34%	83,05%	61,71%	55,93%	58,83%	53,00%	62,81%
Average Brand 1		85,21%	78,69%	88,53%	68,36%	65,66%	66,15%	62,84%	
Standard Deviation		0,1050	0,1206	0,0743	0,0624	0,0930	0,0973	0,1093	
Brand 2	Store 18				33,35%	47,16%	49,83%	49,94%	45,07%
	Store 19	39,43%	58,67%	57,60%	51,10%	50,15%	54,01%	54,17%	52,16%
	Store 10							50,03%	50,03%
	Store 21				36,81%	55,04%	77,83%	100,00%	67,42%
	Store 22					47,18%	49,06%	52,78%	49,67%
	Store 23				42,74%	50,39%	51,44%	53,56%	49,53%
	Store 24				44,41%	52,40%	56,39%	57,19%	52,60%
	Store 25				40,62%	54,98%	57,29%	57,39%	52,57%
	Store 26					48,53%	55,44%	56,61%	53,53%
	Store 27			60,80%	56,16%	53,33%	56,15%	55,66%	56,42%
	Store 28					46,52%	60,88%	61,87%	56,42%
	Store 29				86,28%	55,74%	59,79%	64,04%	66,46%
	Store 30	36,86%	68,27%	64,62%	69,49%	54,12%	57,57%	57,10%	58,29%
Average Brand 2		38,15%	63,47%	61,01%	51,22%	51,30%	57,14%	59,26%	
Standard Deviation		0,0182	0,0679	0,0351	0,1712	0,0340	0,0748	0,1289	
Brand 3	Store 31	66,98%	72,44%	100,00%	82,57%	70,68%	67,21%	65,59%	75,07%
	Store 32	60,81%	74,37%	100,00%	100,00%	76,41%	70,80%	68,31%	78,67%
	Store 33					64,17%	61,98%	61,35%	62,50%
	Store 34	62,65%	67,85%	100,00%	85,15%	71,66%	65,77%	62,16%	73,61%
	Store 35	60,30%	65,77%	100,00%	82,69%	65,34%	63,65%	60,95%	71,24%
	Store 36					81,82%			81,82%
	Store 37						68,68%	62,29%	65,49%
Average Brand 3		62,69%	70,11%	100,00%	87,60%	71,68%	66,35%	63,44%	
Standard Deviation		0,0304	0,0398	0,0000	0,0835	0,0668	0,0325	0,0289	

Source: Own elaboration

2nd model (3 Input)		2009 CRS	2010 CRS	2011 CRS	2012 CRS	2013 CRS	2014 CRS	2015 CRS	Average
Brand 1	Store 1	93,56%	100,00%	91,56%	76,41%	74,61%	70,54%	63,98%	81,52%
	Store 2			78,99%	73,39%	74,74%	73,11%	61,78%	72,40%
	Store 3	83,97%	81,01%	89,27%	69,10%	68,22%	70,02%	64,18%	75,11%
	Store 4	72,22%	70,80%	78,59%	66,26%	61,68%	60,12%	57,07%	66,68%
	Store 5	83,25%	83,81%	81,56%	64,99%	66,34%	64,74%	58,73%	71,92%
	Store 6	95,95%	99,92%	100,00%	81,50%	77,51%	78,80%	74,66%	86,91%
	Store 7	100,00%	97,38%	93,29%	79,83%	78,98%	79,27%	80,30%	87,01%
	Store 8	100,00%	100,00%	98,14%	77,45%	74,30%	77,89%	77,93%	86,53%
	Store 9	85,64%	84,61%	93,28%		67,54%	64,38%		79,09%
	Store 10				67,89%	76,12%	79,34%	87,46%	77,70%
	Store 11		63,63%			57,74%	61,89%	56,93%	60,05%
	Store 12							66,25%	66,25%
	Store 13	84,01%	82,18%	78,67%	61,13%	62,17%	63,08%	59,41%	70,09%
	Store 14					100,00%	76,20%	80,29%	85,50%
	Store 15	100,00%	79,87%	91,83%	89,37%	80,48%	81,91%	88,54%	87,43%
	Store 16	94,10%	94,46%	90,46%	75,64%	72,17%	66,07%	67,33%	80,03%
	Store 17		70,55%	78,59%	62,63%	61,71%	61,00%	58,35%	65,47%
Average Brand 1		90,25%	85,25%	88,02%	72,74%	72,14%	70,52%	68,95%	
Standard Deviation		0,0904	0,1236	0,0777	0,0829	0,1016	0,0760	0,1095	
Brand 2	Store 18				41,83%	52,18%	53,08%	53,80%	50,22%
	Store 19	56,69%	83,97%	73,82%	71,48%	67,59%	71,01%	72,12%	70,95%
	Store 10							47,87%	47,87%
	Store 21				53,45%	61,25%	66,89%	100,00%	70,40%
	Store 22					50,40%	58,52%	66,11%	58,34%
	Store 23				41,66%	49,14%	49,34%	51,06%	47,80%
	Store 24				30,83%	55,18%	57,64%	61,18%	51,21%
	Store 25				28,75%	55,42%	56,74%	58,31%	49,81%
	Store 26					55,87%	64,31%	68,34%	62,84%
	Store 27			61,35%	53,91%	57,50%	57,41%	57,64%	57,56%
	Store 28					69,52%	71,31%	70,86%	70,56%
	Store 29				83,77%	71,22%	75,13%	88,41%	79,63%
	Store 30	37,52%	65,00%	69,22%	63,00%	60,01%	61,98%	62,33%	59,87%
Average Brand 2		47,11%	74,49%	68,13%	52,08%	58,77%	61,95%	66,00%	
Standard Deviation		0,1356	0,1341	0,0631	0,1842	0,0736	0,0792	0,1469	
Brand 3	Store 31	81,67%	78,87%	100,00%	88,64%	76,08%	73,76%	72,48%	81,64%
	Store 32	73,07%	84,08%	100,00%	100,00%	86,72%	79,16%	77,25%	85,75%
	Store 33					62,66%	61,60%	59,38%	61,21%
	Store 34	68,52%	70,63%	100,00%	87,00%	73,80%	68,79%	65,06%	76,26%
	Store 35	62,97%	67,42%	100,00%	82,08%	66,60%	65,21%	61,97%	72,32%
	Store 36					100,00%			100,00%
	Store 37						74,10%	72,49%	73,30%
Average Brand 3		71,56%	75,25%	100,00%	89,43%	77,64%	70,44%	68,11%	
Standard Deviation		0,0791	0,0761	0,0000	0,0758	0,1375	0,0646	0,0700	

Source: Own elaboration

2nd model (3 Input)		2009 VRS	2010 VRS	2011 VRS	2012 VRS	2013 VRS	2014 VRS	2015 VRS	Average
Brand 1	Store 1	100,00%	100,00%	100,00%	78,79%	75,68%	73,04%	64,91%	84,63%
	Store 2			100,00%	73,40%	74,85%	73,29%	62,27%	76,76%
	Store 3	84,07%	81,66%	89,35%	70,38%	69,10%	70,77%	65,03%	75,77%
	Store 4	73,19%	71,22%	79,17%	66,67%	62,07%	60,13%	57,24%	67,10%
	Store 5	88,11%	86,66%	93,95%	67,46%	68,57%	67,46%	61,00%	76,17%
	Store 6	96,03%	99,98%	100,00%	81,50%	77,65%	79,16%	75,08%	87,06%
	Store 7	100,00%	100,00%	100,00%	80,93%	82,56%	100,00%	100,00%	94,78%
	Store 8	100,00%	100,00%	99,17%	77,92%	74,31%	78,17%	78,03%	86,80%
	Store 9	86,77%	84,94%	93,53%		0,6944	66,82%		80,30%
	Store 10				69,10%	76,23%	79,36%	89,61%	78,58%
	Store 11		63,68%			58,52%	62,17%	57,25%	60,41%
	Store 12							66,59%	66,59%
	Store 13	89,02%	84,52%	89,72%	62,93%	63,33%	64,49%	60,50%	73,50%
	Store 14					100,00%	79,67%	88,92%	89,53%
	Store 15	100,00%	80,12%	96,97%	89,91%	96,47%	94,95%	100,00%	94,06%
	Store 16	97,76%	96,30%	96,92%	76,94%	72,20%	68,73%	68,29%	82,45%
	Store 17		72,11%	83,79%	64,88%	63,62%	63,43%	60,46%	68,05%
Average		92,27%	86,25%	94,04%	73,91%	74,04%	73,85%	72,20%	
Standard Deviation		0,0879	0,1243	0,0678	0,0787	0,1142	0,1122	0,1476	
Brand 2	Store 18				42,45%	52,31%	53,17%	54,03%	50,49%
	Store 19	59,08%	85,78%	73,89%	71,56%	67,70%	74,19%	72,80%	72,14%
	Store 10							50,03%	50,03%
	Store 21				58,69%	65,64%	81,23%	100,00%	76,39%
	Store 22					52,38%	59,00%	66,66%	59,35%
	Store 23				42,82%	50,39%	51,44%	53,56%	49,55%
	Store 24				44,41%	55,40%	57,67%	61,32%	54,70%
	Store 25				40,62%	55,81%	57,35%	58,33%	53,03%
	Store 26					55,97%	64,46%	69,51%	63,31%
	Store 27			61,44%	58,61%	58,03%	57,42%	57,65%	58,63%
	Store 28					70,56%	72,28%	78,90%	73,91%
	Store 29				91,78%	75,95%	81,19%	100,00%	87,23%
	Store 30	37,75%	73,64%	69,86%	72,28%	60,86%	62,10%	62,54%	62,72%
Average		48,42%	79,71%	68,40%	58,14%	60,08%	64,29%	68,10%	
Standard Deviation		0,1508	0,0858	0,0635	0,1764	0,0812	0,1042	0,1632	
Brand 3	Store 31	82,63%	78,89%	100,00%	88,65%	76,31%	74,03%	72,77%	81,90%
	Store 32	73,15%	84,13%	100,00%	100,00%	86,77%	79,57%	77,61%	85,89%
	Store 33					64,40%	62,50%	61,63%	62,84%
	Store 34	68,55%	70,75%	100,00%	87,97%	74,19%	69,32%	65,58%	76,62%
	Store 35	63,03%	67,55%	100,00%	82,77%	66,70%	65,30%	62,41%	72,54%
	Store 36					100,00%			100,00%
	Store 37						79,10%	74,20%	76,65%
Average		71,84%	75,33%	100,00%	89,85%	78,06%	71,64%	69,03%	
Standard Deviation		0,0830	0,0756	0,0000	0,0726	0,1335	0,0712	0,0671	

Source: Own elaboration

Annex III. Benchmarks and targets for the 2nd model under CRS and VRS assumption

CRS - Input Oriented2nd model

Ano	DMU	Input reduction Cost with staff	Input reduction Cost of goods	Input reduction Rents	Score	Benchmarks	(S) Cost with staff {I}	(S) Cost of goods {I}	(S) Rents {I}
2015	DMU1	-46,20%	-46,20%	-46,20%	53,80%	110 (0,3693) 178 (0,1228) 183 (0,1140)	0	0	0
2015	DMU2	-36,02%	-36,02%	-36,02%	63,98%	10 (1,2118) 110 (1,2421) 179 (0,0490)	0	0	0
2015	DMU3	-27,52%	-27,52%	-27,52%	72,48%	110 (0,5506) 135 (0,0837) 138 (0,2821)	0	0	0
2015	DMU4	-27,88%	-41,28%	-27,88%	72,12%	96 (0,3796) 179 (0,7853)	0	36424,8	0
2015	DMU5	-38,22%	-38,22%	-38,22%	61,78%	10 (0,3939) 110 (1,0460) 179 (0,0642)	0	0	0
2015	DMU6	-35,82%	-35,82%	-35,82%	64,18%	110 (0,2338) 138 (0,2182) 179 (0,2044)	0	0	0
2015	DMU7	-22,75%	-22,75%	-22,75%	77,25%	110 (0,3786) 138 (0,2631) 179 (0,2061)	0	0	0
2015	DMU8	-52,13%	-52,13%	-52,13%	47,87%	110 (0,3863) 139 (0,3463) 183 (0,9466)	0	0	0
2015	DMU9	-42,93%	-42,93%	-42,93%	57,07%	110 (0,7345) 139 (0,2377) 183 (0,1266)	0	0	0
2015	DMU10	0,00%	0,00%	0,00%	100,00%	61			
2015	DMU11	-33,89%	-35,43%	-33,89%	66,11%	10 (1,7173) 179 (0,5218)	0	3017,16	0
2015	DMU12	-42,55%	-40,62%	-43,14%	59,38%	131 (0,0403) 135 (0,0047) 139 (0,6275) 144 (0,0109)	1443,15	0	1889,61
2015	DMU13	-48,94%	-48,94%	-48,94%	51,06%	110 (1,0948) 139 (0,0016) 183 (1,2952)	0	0	0
2015	DMU14	-41,27%	-41,27%	-41,27%	58,73%	110 (1,4297) 139 (0,1865) 183 (0,4304)	0	0	0,01
2015	DMU15	-25,34%	-25,34%	-25,34%	74,66%	110 (0,0995) 138 (0,0441) 160 (0,4397) 179 (0,1464)	0	0	0
2015	DMU16	-34,94%	-34,94%	-34,94%	65,06%	110 (0,3721) 135 (0,0334) 139 (0,4430)	0	0	0
2015	DMU17	-19,70%	-19,70%	-19,70%	80,30%	98 (1,3015) 110 (0,6439) 150 (0,7493)	0	0	0
2015	DMU18	-38,82%	-38,82%	-38,82%	61,18%	10 (3,6951) 110 (0,7294) 178 (0,2907)	0	0	0
2015	DMU19	-41,69%	-41,69%	-41,69%	58,31%	10 (0,8092) 110 (0,2583) 178 (0,6958)	0	0	0
2015	DMU20	-22,07%	-22,07%	-22,07%	77,93%	110 (0,0719) 150 (0,0333) 160 (0,6486) 179 (0,0308)	0	0	0
2015	DMU21	-31,66%	-31,66%	-31,66%	68,34%	10 (4,6328) 110 (0,0188) 179 (0,7673)	0	0	0
2015	DMU22	-12,54%	-15,36%	-12,54%	87,46%	150 (0,1380) 160 (0,9257)	0	8358,02	0
2015	DMU23	-43,07%	-43,07%	-43,07%	56,93%	110 (0,6812) 139 (0,1988) 183 (0,0059)	0	0	0
2015	DMU24	-33,75%	-33,75%	-33,75%	66,25%	10 (0,4404) 110 (0,3503) 178 (0,0000) 183 (0,7027)	0	0	0
2015	DMU25	-38,03%	-38,03%	-38,03%	61,97%	110 (0,1424) 139 (0,6499) 183 (0,0459)	0	0	0
2015	DMU26	-42,36%	-42,36%	-42,36%	57,64%	10 (0,8898) 110 (0,4276) 178 (0,4080)	0	0	0
2015	DMU27	-40,59%	-40,59%	-40,59%	59,41%	110 (1,2056) 139 (0,0764) 183 (0,4120)	0	0	0
2015	DMU28	-29,14%	-29,14%	-29,14%	70,86%	10 (10,9633) 110 (0,1976) 179 (1,1475)	0	0,04	0
2015	DMU29	-20,45%	-20,56%	-19,71%	80,29%	96 (0,9479) 160 (0,9732)	1065,38	2639,66	0
2015	DMU30	-11,59%	-40,77%	-11,59%	88,41%	96 (1,6660) 179 (1,6718)	0	183002,66	0
2015	DMU31	-20,55%	-20,54%	-11,46%	88,54%	96 (0,9668) 160 (1,2221)	15776,32	34313,02	0
2015	DMU32	-27,51%	-27,51%	-27,51%	72,49%	110 (0,1056) 135 (0,1279) 138 (0,4047)	0	0	0
2015	DMU33	-37,67%	-37,67%	-37,67%	62,33%	10 (5,0271) 110 (0,9985) 178 (0,1482)	0	0	0
2015	DMU34	-32,67%	-32,67%	-32,67%	67,33%	10 (2,2545) 110 (1,2788) 178 (0,1116)	0	0	0
2015	DMU35	-41,65%	-41,65%	-41,65%	58,35%	110 (0,5035) 135 (0,0297) 139 (0,0257)	0	0	0
2014	DMU36	-46,92%	-46,92%	-46,92%	53,08%	110 (0,6448) 178 (0,0447) 183 (0,1402)	0	0	0
2014	DMU37	-29,46%	-29,46%	-29,46%	70,54%	10 (0,8633) 110 (1,2991) 179 (0,1750)	0	0	0
2014	DMU38	-26,24%	-26,24%	-26,24%	73,76%	110 (0,6222) 135 (0,0379) 138 (0,2631)	0	0	0
2014	DMU39	-28,99%	-38,55%	-28,99%	71,01%	96 (0,6486) 179 (0,7492)	0	25339,73	0
2014	DMU40	-26,89%	-26,89%	-26,89%	73,11%	10 (1,4948) 110 (1,0952) 179 (0,1269)	0	0	0
2014	DMU41	-29,98%	-29,98%	-29,98%	70,02%	110 (0,2775) 138 (0,2908) 179 (0,1425)	0	0	0
2014	DMU42	-20,84%	-20,84%	-20,84%	79,16%	110 (0,5244) 138 (0,0013) 179 (0,3094)	0	0	0
2014	DMU43	-39,88%	-39,88%	-39,88%	60,12%	110 (0,4267) 139 (0,4647) 183 (0,1038)	0	0	0
2014	DMU44	-33,11%	-33,11%	-33,11%	66,89%	10 (0,2851) 110 (0,0184) 179 (0,0589)	0	0	0
2014	DMU45	-41,48%	-41,48%	-41,48%	58,52%	10 (0,2543) 110 (0,2421) 179 (0,3099)	0	0	0
2014	DMU46	-50,66%	-50,66%	-50,66%	49,34%	110 (0,6716) 139 (0,4574) 183 (0,8916)	0	0	0
2014	DMU47	-38,40%	-38,40%	-38,40%	61,60%	110 (0,0774) 139 (0,6600) 183 (0,0264)	0	0	0
2014	DMU48	-35,26%	-35,26%	-35,26%	64,74%	110 (1,4344) 139 (0,2745) 183 (0,4816)	0	0	0
2014	DMU49	-21,20%	-21,20%	-21,20%	78,80%	110 (0,0867) 138 (0,1320) 160 (0,2277) 179 (0,3286)	0	0	0
2014	DMU50	-31,21%	-31,21%	-31,21%	68,79%	110 (0,6942) 135 (0,1065) 139 (0,2534)	0	0	0
2014	DMU51	-20,73%	-20,73%	-20,73%	79,27%	10 (6,6050) 110 (2,0186) 178 (0,2327)	0	0	0
2014	DMU52	-42,36%	-42,36%	-42,36%	57,64%	110 (0,5014) 178 (0,3897) 183 (0,0029)	0	0	0
2014	DMU53	-43,26%	-43,26%	-43,26%	56,74%	110 (0,8629) 178 (0,4019) 183 (0,4988)	0	0	0
2014	DMU54	-22,11%	-22,11%	-22,11%	77,89%	110 (0,1759) 138 (0,0713) 160 (0,1939) 179 (0,3761)	0	0	0
2014	DMU55	-38,51%	-35,62%	-35,62%	64,38%	135 (0,1791) 138 (0,3056)	1672,99	0	0
2014	DMU56	-35,69%	-35,69%	-35,69%	64,31%	10 (2,4827) 110 (0,3865) 179 (0,4839)	0	0	0
2014	DMU57	-20,66%	-20,66%	-20,66%	79,34%	110 (0,2747) 150 (0,1165) 160 (0,1538) 179 (0,3936)	0	0	0
2014	DMU58	-38,11%	-38,11%	-38,11%	61,89%	110 (0,5575) 139 (0,2966) 183 (0,0375)	0	0	0
2014	DMU59	-42,59%	-42,59%	-42,59%	57,41%	10 (0,2108) 110 (0,6485) 178 (0,3647)	0	0	0
2014	DMU60	-34,79%	-34,79%	-34,79%	65,21%	110 (0,3452) 139 (0,5676) 183 (0,0492)	0	0	0
2014	DMU61	-36,92%	-36,92%	-36,92%	63,08%	110 (0,9209) 139 (0,3809) 183 (0,2887)	0	0	0

Ano	DMU	Input reduction Cost with staff	Input reduction Cost of goods	Input reduction Rents	Score	Benchmarks	(S) Cost with staff {I}	(S) Cost of goods {I}	(S) Rents {I}
2014	DMU62	-28,69%	-28,69%	-28,69%	71,31%	10 (7,8252) 110 (0,3082) 179 (0,8927)	0	0	0
2014	DMU63	-23,80%	-23,80%	-23,80%	76,20%	96 (0,9025) 138 (0,4212) 179 (0,5233)	0	0	0
2014	DMU64	-24,87%	-37,82%	-24,87%	75,13%	10 (1,0549) 179 (1,4076)	0	58226,18	0
2014	DMU65	-18,09%	-18,09%	-18,09%	81,91%	96 (1,0678) 138 (0,2210) 160 (0,4786) 179 (0,4283)	0	0	0
2014	DMU66	-25,90%	-25,90%	-25,90%	74,10%	110 (0,1430) 135 (0,0356) 138 (0,2070)	0	0	0
2014	DMU67	-38,02%	-38,02%	-38,02%	61,98%	10 (4,3039) 110 (1,2785) 178 (0,0911)	0	0	0
2014	DMU68	-33,93%	-33,93%	-33,93%	66,07%	110 (1,5165) 139 (0,0332) 183 (0,2745)	0	0	0
2014	DMU69	-39,00%	-39,00%	-39,00%	61,00%	110 (0,3058) 135 (0,1522) 139 (0,0839)	0	0	0
2013	DMU70	-47,82%	-47,82%	-47,82%	52,18%	10 (0,3851) 110 (0,2016) 178 (0,1786)	0	0	0
2013	DMU71	-25,39%	-25,39%	-25,39%	74,61%	10 (2,6130) 110 (0,9620) 179 (0,4851)	0	0	0
2013	DMU72	-23,92%	-23,92%	-23,92%	76,08%	110 (0,8164) 138 (0,0977) 179 (0,0108)	0	0	0
2013	DMU73	-32,41%	-46,93%	-32,41%	67,59%	96 (0,1725) 179 (0,7455)	0	39570,5	0
2013	DMU74	-25,26%	-25,26%	-25,26%	74,74%	10 (2,7693) 110 (1,0040) 179 (0,1355)	0	0	0
2013	DMU75	-31,78%	-31,78%	-31,78%	68,22%	110 (0,3741) 138 (0,0703) 179 (0,2257)	0	0	0
2013	DMU76	-13,28%	-13,28%	-13,28%	86,72%	10 (0,7652) 110 (0,4646) 179 (0,3884)	0	0	0
2013	DMU77	-38,32%	-38,32%	-38,32%	61,68%	110 (0,7018) 139 (0,1929) 183 (0,3043)	0	0	0
2013	DMU78	-38,75%	-40,86%	-38,75%	61,25%	10 (0,4016) 179 (0,1105)	0	981,25	0
2013	DMU79	-49,60%	-49,60%	-49,60%	50,40%	110 (0,0843) 178 (0,0594) 183 (0,1088)	0	0	0
2013	DMU80	-50,86%	-50,86%	-50,86%	49,14%	110 (0,6212) 178 (0,1849) 183 (0,9528)	0	0	0
2013	DMU81	-37,34%	-37,34%	-37,34%	62,66%	110 (0,0121) 139 (0,6851) 183 (0,0630)	0	0	0
2013	DMU82	-33,66%	-33,66%	-33,66%	66,34%	110 (1,4456) 178 (0,1611) 183 (0,3634)	0	0	0
2013	DMU83	-22,49%	-22,49%	-22,49%	77,51%	110 (0,0137) 150 (0,0821) 160 (0,0730) 179 (0,4929)	0	0	0
2013	DMU84	-26,20%	-26,20%	-26,20%	73,80%	110 (0,9057) 139 (0,1582) 183 (0,1268)	0	0	0
2013	DMU85	-21,02%	-21,02%	-21,02%	78,98%	10 (6,3132) 110 (1,2128) 178 (0,3994) 183 (0,1065)	0	0	0
2013	DMU86	-44,82%	-44,82%	-44,82%	55,18%	10 (1,1437) 178 (0,4639) 183 (0,0031)	0	0	0
2013	DMU87	-44,58%	-44,58%	-44,58%	55,42%	10 (1,8145) 178 (0,6534) 183 (0,1442)	0	0	0
2013	DMU88	-25,70%	-25,70%	-25,70%	74,30%	10 (0,4308) 110 (0,1848) 179 (0,5484)	0	0	0
2013	DMU89	-32,46%	-32,46%	-32,46%	67,54%	110 (0,0314) 138 (0,4119) 179 (0,0860)	0	0	0
2013	DMU90	-44,13%	-44,13%	-44,13%	55,87%	10 (0,6087) 178 (0,1826) 183 (0,0669)	0	0	0
2013	DMU91	-23,88%	-23,88%	-23,88%	76,12%	10 (1,9306) 110 (0,5704) 179 (0,2362)	0	0	0
2013	DMU92	-42,26%	-42,26%	-42,26%	57,74%	110 (0,3967) 139 (0,3690) 183 (0,0025)	0	0	0
2013	DMU93	-42,50%	-42,50%	-42,50%	57,50%	10 (4,1374) 110 (0,5092) 178 (0,3149)	0	0	0
2013	DMU94	-33,40%	-33,40%	-33,40%	66,60%	110 (0,2316) 139 (0,5824) 183 (0,1490)	0	0	0
2013	DMU95	-37,83%	-37,83%	-37,83%	62,17%	110 (1,0738) 139 (0,2079) 183 (0,3923)	0	0	0
2013	DMU96	0,00%	0,00%	0,00%	100,00%	15			
2013	DMU97	-30,48%	-34,10%	-30,48%	69,52%	10 (1,8475) 179 (0,1932)	0	3747,16	0
2013	DMU98	0,00%	0,00%	0,00%	100,00%	4			
2013	DMU99	-28,78%	-45,44%	-28,78%	71,22%	10 (1,1562) 179 (1,3185)	0	80874,36	0
2013	DMU100	-19,52%	-21,33%	-19,52%	80,48%	96 (1,4343) 160 (0,2982) 179 (0,7777)	0	6029,42	0
2013	DMU101	-39,99%	-39,99%	-39,99%	60,01%	10 (6,9077) 110 (0,9590) 178 (0,0966)	0	0	0
2013	DMU102	-27,83%	-27,83%	-27,83%	72,17%	10 (1,4355) 110 (0,9018) 178 (0,2509)	0	0	0
2013	DMU103	-38,29%	-38,29%	-38,29%	61,71%	110 (0,5090) 135 (0,0735) 139 (0,0155)	0	0	0
2012	DMU104	-58,17%	-58,17%	-58,17%	41,83%	10 (1,4009) 178 (0,0994) 183 (0,2074)	0	0,01	0
2012	DMU105	-23,59%	-23,59%	-23,59%	76,41%	10 (1,4950) 110 (1,3485) 179 (0,1940)	0	0	0
2012	DMU106	-11,36%	-11,36%	-11,36%	88,64%	110 (0,3374) 135 (0,5676) 139 (0,0943)	0	0	0
2012	DMU107	-28,52%	-60,11%	-28,52%	71,48%	10 (0,5858) 160 (0,5191) 179 (0,2127)	0	128365,33	0
2012	DMU108	-26,61%	-26,61%	-26,61%	73,39%	110 (0,7700) 178 (0,1061) 183 (0,1091)	0	0	0
2012	DMU109	-30,90%	-30,90%	-30,90%	69,10%	110 (0,1850) 135 (0,1559) 138 (0,3552)	0	0	0
2012	DMU110	0,00%	0,00%	0,00%	100,00%	125			
2012	DMU111	-33,74%	-33,74%	-33,74%	66,26%	110 (0,6191) 139 (0,3223) 183 (0,2664)	0	0	0
2012	DMU112	-46,55%	-64,49%	-46,55%	53,45%	96 (0,0014) 179 (0,1344)	0	12616,98	0
2012	DMU113	-58,34%	-58,34%	-58,34%	41,66%	10 (3,4808) 178 (0,2461) 183 (0,6704)	0	0	0
2012	DMU114	-35,01%	-35,01%	-35,01%	64,99%	110 (0,8937) 139 (0,6768) 183 (0,3449)	0	0	0
2012	DMU115	-18,50%	-18,50%	-18,50%	81,50%	10 (0,4262) 110 (0,2081) 179 (0,5282)	0	0	0
2012	DMU116	-13,00%	-13,00%	-13,00%	87,00%	110 (0,2939) 135 (0,1332) 139 (0,6524)	0	0	0
2012	DMU117	-20,17%	-20,17%	-20,17%	79,83%	10 (0,0561) 110 (0,5112) 178 (0,7389)	0	0	0
2012	DMU118	-69,17%	-69,17%	-85,96%	30,83%	139 (0,0561) 183 (0,3551)	0	0	22425,49
2012	DMU119	-71,25%	-71,25%	-91,01%	28,75%	139 (0,0958) 183 (0,2765)	0	0	39369,73
2012	DMU120	-22,55%	-22,55%	-22,55%	77,45%	110 (0,2544) 138 (0,1359) 179 (0,4124)	0	0	0
2012	DMU121	-32,11%	-32,11%	-32,11%	67,89%	110 (0,3987) 139 (0,1187) 183 (0,2004)	0	0	0
2012	DMU122	-46,09%	-46,09%	-46,09%	53,91%	10 (13,2192) 178 (0,1136) 183 (0,3345)	0	0,03	0

Ano	DMU	Input reduction Cost with staff	Input reduction Cost of goods	Input reduction Rents	Score	Benchmarks	(S) Cost with staff {I}	(S) Cost of goods {I}	(S) Rents {I}
2012	DMU123	-24,42%	-17,92%	-45,11%	82,08%	131 (0,5579) 135 (0,1096) 139 (0,1031) 144 (0,1152)	5449,22	0	21089,03
2012	DMU124	-38,87%	-38,87%	-38,87%	61,13%	110 (0,4010) 135 (0,0249) 139 (0,8212)	0	0	0
2012	DMU125	-16,23%	-43,43%	-16,23%	83,77%	10 (8,0924) 98 (0,6528)	0	99442,44	0
2012	DMU126	-10,63%	-10,63%	-10,63%	89,37%	10 (1,1740) 150 (0,1250) 160 (0,2006) 179 (0,6955)	0	0	0
2012	DMU127	-37,00%	-39,50%	-37,00%	63,00%	10 (20,9354) 183 (0,1720)	0	15386,45	0
2012	DMU128	-24,36%	-24,36%	-24,36%	75,64%	110 (0,9197) 178 (0,2907) 183 (0,0321)	0	0	0
2012	DMU129	-37,37%	-37,37%	-37,37%	62,63%	110 (0,2354) 135 (0,2727) 139 (0,0652)	0	0	0
2011	DMU130	-8,44%	-8,44%	-8,44%	91,56%	110 (1,2127) 135 (0,5954) 138 (0,1563)	0	0	0
2011	DMU131	-14,03%	0,00%	-3,26%	100,00%	4	10797,11	0	1368,97
2011	DMU132	-26,18%	-35,76%	-26,18%	73,82%	96 (0,2983) 179 (0,7813)	0	23267,54	0
2011	DMU133	-21,01%	-21,01%	-72,34%	78,99%	139 (0,2703) 183 (0,0154)	0	0	33106,14
2011	DMU134	-15,96%	-10,73%	-10,73%	89,27%	135 (0,5032) 138 (0,3674)	3828,6	0	0
2011	DMU135	0,00%	0,00%	0,00%	100,00%	32			
2011	DMU136	-24,07%	-21,41%	-22,00%	78,59%	131 (0,0823) 135 (0,0626) 139 (0,8762) 144 (0,0119)	2297,08	0	467,03
2011	DMU137	-18,44%	-18,44%	-18,44%	81,56%	110 (0,3351) 135 (0,1339) 139 (1,4670)	0	0	0
2011	DMU138	0,00%	0,00%	0,00%	100,00%	32			
2011	DMU139	0,00%	0,00%	0,00%	100,00%	53			
2011	DMU140	-6,71%	-6,71%	-6,71%	93,29%	110 (2,3095) 139 (0,5662) 183 (0,6620)	0	0	0
2011	DMU141	-5,00%	-1,86%	-1,86%	98,14%	135 (0,1203) 138 (0,9258)	2658,87	0	0
2011	DMU142	-25,45%	-6,72%	-6,72%	93,28%	135 (0,2620) 138 (0,4196)	12547,72	0	0
2011	DMU143	-38,65%	-38,65%	-38,65%	61,35%	110 (0,3643) 178 (0,3570) 183 (0,3518)	0	0,01	0
2011	DMU144	0,00%	0,00%	0,00%	100,00%	5			
2011	DMU145	-21,33%	-21,33%	-21,33%	78,67%	110 (0,0069) 135 (0,6598) 139 (0,9614)	0	0	0
2011	DMU146	-11,58%	-8,17%	-8,17%	91,83%	135 (0,5771) 138 (0,6851)	3520,63	0	0
2011	DMU147	-30,78%	-30,78%	-30,78%	69,22%	10 (3,7320) 110 (0,4035) 178 (0,3546)	0	0	0
2011	DMU148	-9,54%	-9,54%	-9,54%	90,46%	110 (1,3684) 139 (0,6228) 183 (0,0526)	0	0	0
2011	DMU149	-22,84%	-21,41%	-21,95%	78,59%	131 (0,1426) 135 (0,4510) 139 (0,0545) 144 (0,0222)	835,32	0	186,01
2010	DMU150	0,00%	0,00%	0,00%	100,00%	6			
2010	DMU151	-21,13%	-21,13%	-21,13%	78,87%	10 (0,5295) 110 (0,8024) 178 (0,0074)	0	0	0
2010	DMU152	-16,03%	-66,56%	-16,03%	83,97%	96 (0,4257) 179 (0,8497)	0	261999,37	0
2010	DMU153	-18,99%	-18,99%	-18,99%	81,01%	110 (0,3186) 138 (0,1727) 179 (0,2706)	0	0	0
2010	DMU154	-15,92%	-15,92%	-15,92%	84,08%	10 (1,0695) 110 (0,6480) 179 (0,0523)	0	0	0
2010	DMU155	-29,20%	-29,20%	-29,20%	70,80%	110 (0,7194) 139 (0,3390) 183 (0,1594)	0	0	0
2010	DMU156	-16,19%	-16,19%	-16,19%	83,81%	10 (0,9053) 110 (1,0838) 178 (0,4268) 183 (0,0558)	0	0	0
2010	DMU157	-0,08%	-0,08%	-0,08%	99,92%	96 (0,0647) 138 (0,0030) 160 (0,9127) 179 (0,0006)	0,01	0	0
2010	DMU158	-29,37%	-29,37%	-29,37%	70,63%	110 (0,6094) 139 (0,2972) 183 (0,0531)	0	0	0
2010	DMU159	-2,62%	-2,62%	-2,62%	97,38%	10 (4,9977) 98 (1,5736) 110 (1,7200) 183 (0,1317)	0	0	0
2010	DMU160	0,00%	0,00%	0,00%	100,00%	14			
2010	DMU161	-15,39%	-15,39%	-15,39%	84,61%	96 (0,3105) 138 (0,3143) 179 (0,2854)	0	0	0
2010	DMU162	-36,37%	-36,37%	-36,37%	63,63%	110 (0,1642) 135 (0,5813) 139 (0,2395)	0	0	0
2010	DMU163	-32,58%	-32,58%	-32,58%	67,42%	110 (0,2868) 139 (0,4845) 183 (0,1832)	0	0	0
2010	DMU164	-17,82%	-17,82%	-17,82%	82,18%	10 (0,8086) 110 (1,1676) 178 (0,2666)	0	0	0
2010	DMU165	-20,13%	-20,13%	-20,13%	79,87%	110 (0,5467) 138 (0,1867) 179 (0,2886)	0	0	0
2010	DMU166	-35,00%	-43,11%	-35,00%	65,00%	10 (22,3774) 183 (0,0066)	0	55962,06	0
2010	DMU167	-5,54%	-5,54%	-5,54%	94,46%	10 (6,5026) 98 (0,2156) 110 (1,5906) 183 (0,1044)	0	0	0
2010	DMU168	-29,45%	-29,45%	-29,45%	70,55%	110 (0,2935) 135 (0,2684) 138 (0,1132)	0	0	0
2009	DMU169	-6,44%	-6,44%	-6,44%	93,56%	10 (0,0978) 110 (1,0456) 179 (0,9390)	0	0	0
2009	DMU170	-18,33%	-18,33%	-18,33%	81,67%	10 (4,0612) 110 (0,3620) 179 (0,2016)	0	0	0
2009	DMU171	-43,31%	-43,31%	-43,31%	56,69%	10 (2,8769) 110 (0,0551) 178 (0,0475)	0	0	0
2009	DMU172	-20,21%	-16,03%	-16,03%	83,97%	135 (0,2448) 138 (0,5661)	3161,35	0	0
2009	DMU173	-26,93%	-26,93%	-26,93%	73,07%	10 (1,8206) 110 (0,4429) 178 (0,0170)	0	0	0
2009	DMU174	-27,78%	-27,78%	-27,78%	72,22%	110 (0,1836) 135 (0,3417) 139 (0,5677)	0	0	0
2009	DMU175	-16,75%	-16,75%	-16,75%	83,25%	110 (1,8270) 139 (0,3204) 183 (0,4722)	0	0	0
2009	DMU176	-4,05%	-4,05%	-4,05%	95,95%	96 (0,0831) 138 (0,3785) 179 (0,5113)	0	0	0
2009	DMU177	-31,48%	-31,48%	-31,48%	68,52%	10 (0,9901) 110 (0,4311) 178 (0,1494)	0	0	0
2009	DMU178	0,00%	0,00%	0,00%	100,00%	40			
2009	DMU179	0,00%	0,00%	0,00%	100,00%	56			
2009	DMU180	-19,44%	-14,36%	-14,36%	85,64%	135 (0,1207) 138 (0,4914)	2926,67	0	0
2009	DMU181	-37,03%	-37,03%	-37,03%	62,97%	110 (0,4782) 178 (0,0867) 183 (0,3440)	0	0	0
2009	DMU182	-15,99%	-15,99%	-15,99%	84,01%	110 (1,7654) 139 (0,1557) 183 (0,2801)	0	0	0
2009	DMU183	0,00%	0,00%	0,00%	100,00%	59			
2009	DMU184	-62,48%	-62,48%	-62,48%	37,52%	110 (0,0567) 139 (0,0628) 183 (0,8262)	0	0	0
2009	DMU185	-5,90%	-5,90%	-5,90%	94,10%	10 (2,2774) 110 (1,7329) 178 (0,1340)	0	0	0

VRS - Input Oriented2nd model

Ano	DMU	Input reduction Cost with staff	Input reduction Cost of goods	Input reduction Rents	Score	Benchmarks	(S) Cost with staff {I}	(S) Cost of goods {I}	Rents {I}
2015	DMU1	-45,97%	-45,97%	-45,97%	54,03%	10 (0,2919) 110 (0,4579) 178 (0,0805) 183 (0,1698)	0	0	0
2015	DMU2	-35,09%	-35,09%	-35,09%	64,91%	110 (0,5454) 140 (0,0555) 178 (0,0846) 179 (0,3145)	0	0	0
2015	DMU3	-27,23%	-27,23%	-27,23%	72,77%	10 (0,0874) 110 (0,5256) 135 (0,1050) 138 (0,2820)	0	0	0
2015	DMU4	-27,20%	-22,64%	-27,20%	72,80%	30 (0,0277) 96 (0,2354) 160 (0,7369)	0	12404,06	0
2015	DMU5	-37,73%	-37,73%	-37,73%	62,27%	110 (0,7888) 140 (0,0255) 178 (0,0257) 179 (0,1601)	0	0	0
2015	DMU6	-34,97%	-34,97%	-34,97%	65,03%	10 (0,3560) 110 (0,1671) 138 (0,3715) 179 (0,1054)	0	0	0
2015	DMU7	-22,39%	-22,39%	-22,39%	77,61%	10 (0,1576) 110 (0,3494) 138 (0,3309) 179 (0,1620)	0	0	0
2015	DMU8	-49,97%	-49,97%	-41,88%	50,03%	139 (0,4243) 178 (0,1427) 183 (0,4330)	0	0	12931,69
2015	DMU9	-42,76%	-42,76%	-42,76%	57,24%	110 (0,6286) 139 (0,2821) 178 (0,0255) 183 (0,0638)	0	0	0
2015	DMU10	0,00%	0,00%	0,00%	100,00%	95			
2015	DMU11	-33,34%	-29,04%	-33,34%	66,66%	10 (0,4884) 150 (0,1066) 179 (0,4050)	0	8447,54	0
2015	DMU12	-38,37%	-38,37%	-38,37%	61,63%	135 (0,4754) 139 (0,0840) 144 (0,1581) 183 (0,2825)	0	0	0
2015	DMU13	-46,44%	-46,44%	-38,57%	53,56%	139 (0,3514) 178 (0,3247) 183 (0,3239)	0	0	14696,52
2015	DMU14	-39,00%	-39,00%	-39,00%	61,00%	110 (0,4105) 139 (0,2343) 140 (0,2450) 178 (0,1103)	0	0	0
2015	DMU15	-24,92%	-24,92%	-24,92%	75,08%	10 (0,2838) 110 (0,0465) 138 (0,1422) 160 (0,4155) 179 (0,1121)	0	0	0
2015	DMU16	-34,42%	-34,42%	-34,42%	65,58%	10 (0,1588) 110 (0,3229) 135 (0,0703) 139 (0,4479)	0	0	0
2015	DMU17	0,00%	0,00%	0,00%	100,00%	0			
2015	DMU18	-38,68%	-38,68%	-38,68%	61,32%	10 (0,3226) 150 (0,2471) 178 (0,4163) 179 (0,0140)	0	0	0
2015	DMU19	-41,67%	-41,67%	-41,67%	58,33%	10 (0,1386) 110 (0,0079) 178 (0,7487) 179 (0,1049)	0	0	0
2015	DMU20	-21,97%	-21,97%	-21,97%	78,03%	10 (0,1938) 110 (0,0973) 138 (0,0071) 160 (0,6826) 179 (0,0192)	0	0	0
2015	DMU21	-30,49%	-24,97%	-30,49%	69,51%	10 (0,2670) 150 (0,3942) 179 (0,3388)	0	18241,88	0
2015	DMU22	-6,33%	-4,38%	-10,39%	89,61%	150 (0,2104) 160 (0,7896)	4875,46	17791,36	0
2015	DMU23	-42,75%	-42,75%	-42,75%	57,25%	10 (0,1258) 110 (0,6438) 135 (0,0211) 139 (0,2093)	0	0	0
2015	DMU24	-33,41%	-33,41%	-33,41%	66,59%	110 (0,2632) 150 (0,0198) 159 (0,0180) 178 (0,0070) 183 (0,6919)	0	0	0
2015	DMU25	-37,59%	-37,59%	-37,59%	62,41%	10 (0,2071) 110 (0,0761) 139 (0,7067) 183 (0,0101)	0	0	0
2015	DMU26	-42,35%	-42,35%	-42,35%	57,65%	10 (0,2525) 110 (0,1897) 178 (0,4582) 179 (0,0997)	0	0	0
2015	DMU27	-39,50%	-39,50%	-39,50%	60,50%	110 (0,4732) 139 (0,3372) 140 (0,0283) 178 (0,1612)	0	0	0
2015	DMU28	-21,10%	-19,15%	-21,10%	78,90%	30 (0,3075) 150 (0,4766) 159 (0,2158)	0	11733,81	0
2015	DMU29	-0,97%	-11,08%	-11,08%	88,92%	30 (0,1135) 31 (0,0889) 160 (0,7156) 179 (0,0820)	14541,51	0	0
2015	DMU30	0,00%	0,00%	0,00%	100,00%	11			
2015	DMU31	0,00%	0,00%	0,00%	100,00%	3			
2015	DMU32	-25,80%	-25,80%	-25,80%	74,20%	10 (0,3690) 96 (0,0110) 135 (0,2190) 138 (0,4011)	0	0	0
2015	DMU33	-37,46%	-37,46%	-37,46%	62,54%	10 (0,3267) 150 (0,3532) 178 (0,3181) 179 (0,0019)	0	0	0
2015	DMU34	-31,71%	-31,71%	-31,71%	68,29%	110 (0,4396) 140 (0,0640) 150 (0,1355) 178 (0,2018) 179 (0,1590)	0	0	0
2015	DMU35	-39,54%	-39,54%	-39,54%	60,46%	10 (0,4622) 110 (0,3699) 135 (0,1373) 139 (0,0306)	0	0	0
2014	DMU36	-46,83%	-46,83%	-46,83%	53,17%	10 (0,1260) 110 (0,6834) 178 (0,0262) 183 (0,1643)	0	0	0
2014	DMU37	-26,96%	-26,96%	-26,96%	73,04%	110 (0,2743) 140 (0,1600) 178 (0,0355) 179 (0,5301)	0	0	0
2014	DMU38	-25,97%	-25,97%	-25,97%	74,03%	10 (0,0804) 110 (0,5994) 135 (0,0573) 138 (0,2629)	0	0	0
2014	DMU39	-22,58%	-25,81%	-25,81%	74,19%	30 (0,0688) 96 (0,2674) 160 (0,6639)	3778,43	0	0
2014	DMU40	-26,71%	-26,71%	-26,71%	73,29%	110 (0,5062) 140 (0,0070) 178 (0,1162) 179 (0,3706)	0	0	0
2014	DMU41	-29,23%	-29,23%	-29,23%	70,77%	10 (0,2994) 110 (0,2217) 138 (0,4204) 179 (0,0585)	0	0	0
2014	DMU42	-20,43%	-20,43%	-20,43%	79,57%	10 (0,1707) 110 (0,4936) 138 (0,0735) 179 (0,2622)	0	0	0
2014	DMU43	-39,87%	-39,87%	-39,87%	60,13%	10 (0,0061) 110 (0,4248) 139 (0,4663) 183 (0,1028)	0	0	0
2014	DMU44	-12,81%	-18,77%	-18,77%	81,23%	10 (0,8487) 96 (0,1182) 135 (0,0330)	650,31	0	0
2014	DMU45	-41,00%	-41,00%	-41,00%	59,00%	10 (0,4554) 110 (0,2050) 138 (0,0840) 179 (0,2556)	0	0	0
2014	DMU46	-48,56%	-48,56%	-40,25%	51,44%	139 (0,6397) 178 (0,2218) 183 (0,1385)	0	0	15423,14
2014	DMU47	-37,50%	-37,50%	-37,50%	62,50%	10 (0,2387) 135 (0,0662) 139 (0,6600) 183 (0,0351)	0	0	0
2014	DMU48	-32,54%	-32,54%	-32,54%	67,46%	110 (0,2740) 139 (0,3190) 140 (0,2865) 178 (0,1205)	0	0	0
2014	DMU49	-20,84%	-20,84%	-20,84%	79,16%	10 (0,2361) 110 (0,0425) 138 (0,2145) 160 (0,2072) 179 (0,2998)	0	0	0
2014	DMU50	-30,68%	-30,68%	-30,68%	69,32%	110 (0,6274) 135 (0,1346) 139 (0,2090) 140 (0,0290)	0	0	0
2014	DMU51	0,00%	0,00%	0,00%	100,00%	0			
2014	DMU52	-42,33%	-42,33%	-42,33%	57,67%	10 (0,0787) 110 (0,5251) 178 (0,3784) 183 (0,0178)	0	0	0
2014	DMU53	-42,65%	-42,65%	-42,65%	57,35%	110 (0,0431) 139 (0,3351) 178 (0,6015) 183 (0,0202)	0	0	0
2014	DMU54	-21,83%	-21,83%	-21,83%	78,17%	10 (0,1918) 110 (0,1403) 138 (0,1381) 160 (0,1770) 179 (0,3528)	0	0	0
2014	DMU55	-33,18%	-33,18%	-33,18%	66,82%	10 (0,2695) 96 (0,2957) 135 (0,2970) 138 (0,1378)	0	0	0
2014	DMU56	-35,54%	-35,54%	-35,54%	64,46%	10 (0,3295) 150 (0,1948) 178 (0,0587) 179 (0,4170)	0	0	0
2014	DMU57	-20,64%	-20,64%	-20,64%	79,36%	10 (0,0543) 110 (0,2839) 150 (0,1060) 160 (0,1649) 179 (0,3908)	0	0	0
2014	DMU58	-37,83%	-37,83%	-37,83%	62,17%	10 (0,1387) 110 (0,5149) 139 (0,3329) 183 (0,0135)	0	0	0
2014	DMU59	-42,58%	-42,58%	-42,58%	57,42%	10 (0,0140) 110 (0,5750) 178 (0,3802) 179 (0,0308)	0	0	0
2014	DMU60	-34,70%	-34,70%	-34,70%	65,30%	10 (0,0486) 110 (0,3299) 139 (0,5807) 183 (0,0408)	0	0	0
2014	DMU61	-35,51%	-35,51%	-35,51%	64,49%	110 (0,3219) 139 (0,4944) 140 (0,0904) 178 (0,0932)	0	0	0

Ano	DMU	Input reduction Cost with staff	Input reduction Cost of goods	Input reduction Rents	Score	Benchmarks	(S) Cost with staff {I}	(S) Cost of goods {I}	Rents {I}
2014	DMU62	-27,72%	-24,27%	-27,72%	72,28%	10 (0,1106) 150 (0,8832) 179 (0,0062)	0	16300,55	0
2014	DMU63	-8,97%	-20,33%	-20,33%	79,67%	30 (0,0182) 169 (0,0182) 179 (0,9636)	15322,09	0	0
2014	DMU64	-18,81%	-18,81%	-18,81%	81,19%	30 (0,2699) 150 (0,2661) 160 (0,4130) 179 (0,0510)	0	0,01	0
2014	DMU65	3,31%	-5,05%	-5,05%	94,95%	30 (0,0415) 31 (0,3722) 169 (0,1355) 179 (0,4508)	12966,43	0	0
2014	DMU66	-20,90%	-20,90%	-20,90%	79,10%	10 (0,5947) 96 (0,0539) 135 (0,1783) 138 (0,1732)	0	0	0
2014	DMU67	-37,90%	-37,90%	-37,90%	62,10%	10 (0,1412) 150 (0,1286) 178 (0,3458) 179 (0,3844)	0	0	0
2014	DMU68	-31,27%	-31,27%	-31,27%	68,73%	110 (0,6606) 140 (0,2465) 178 (0,0471) 179 (0,0458)	0	0	0
2014	DMU69	-36,57%	-36,57%	-36,57%	63,43%	10 (0,4794) 110 (0,1605) 135 (0,2688) 139 (0,0913)	0	0	0
2013	DMU70	-47,69%	-47,69%	-47,69%	52,31%	10 (0,5597) 110 (0,2538) 178 (0,1536) 183 (0,0329)	0	0	0
2013	DMU71	-24,32%	-24,32%	-24,32%	75,68%	140 (0,0508) 150 (0,1331) 169 (0,0358) 178 (0,1212) 179 (0,6592)	0	0	0
2013	DMU72	-23,69%	-23,69%	-23,69%	76,31%	10 (0,0780) 110 (0,7989) 135 (0,0096) 138 (0,1135)	0	0	0
2013	DMU73	-32,30%	-17,89%	-32,30%	67,70%	10 (0,0692) 96 (0,1926) 179 (0,7382)	0	39277,41	0
2013	DMU74	-25,15%	-25,15%	-25,15%	74,85%	10 (0,1860) 110 (0,1735) 150 (0,0624) 178 (0,1678) 179 (0,4103)	0	0	0
2013	DMU75	-30,90%	-30,90%	-30,90%	69,10%	10 (0,3417) 110 (0,3118) 138 (0,2155) 179 (0,1309)	0	0	0
2013	DMU76	-13,23%	-13,23%	-13,23%	86,77%	10 (0,2099) 110 (0,3159) 150 (0,0272) 178 (0,0282) 179 (0,4188)	0	0	0
2013	DMU77	-37,93%	-37,93%	-37,93%	62,07%	110 (0,4875) 139 (0,2825) 178 (0,0515) 183 (0,1785)	0	0	0
2013	DMU78	-34,36%	-34,36%	-34,36%	65,64%	10 (0,8100) 96 (0,1183) 138 (0,0254) 179 (0,0462)	0	0	0
2013	DMU79	-47,62%	-47,62%	-47,62%	52,38%	10 (0,6512) 110 (0,1380) 139 (0,0581) 183 (0,1527)	0	0	0
2013	DMU80	-49,61%	-49,61%	-45,84%	50,39%	139 (0,2029) 178 (0,3654) 183 (0,4317)	0	0	6993,99
2013	DMU81	-35,60%	-35,60%	-35,60%	64,40%	10 (0,0255) 135 (0,2913) 139 (0,4031) 183 (0,2802)	0	0	0
2013	DMU82	-31,43%	-31,43%	-31,43%	68,57%	110 (0,4803) 140 (0,2525) 178 (0,2469) 179 (0,0204)	0	0	0
2013	DMU83	-22,35%	-22,35%	-22,35%	77,65%	10 (0,2991) 110 (0,0646) 150 (0,0243) 160 (0,1348) 179 (0,4771)	0	0	0
2013	DMU84	-25,81%	-25,81%	-25,81%	74,19%	110 (0,7018) 139 (0,2434) 178 (0,0492) 183 (0,0056)	0	0	0
2013	DMU85	-17,44%	-17,44%	-17,44%	82,56%	140 (0,0653) 150 (0,2278) 159 (0,6153) 178 (0,0915)	0	0	0
2013	DMU86	-44,60%	-43,12%	-44,60%	55,40%	10 (0,5187) 150 (0,0023) 178 (0,4790)	0	5265,4	0
2013	DMU87	-44,19%	-41,45%	-44,19%	55,81%	10 (0,1750) 178 (0,6987) 183 (0,1262)	0	14014,14	0
2013	DMU88	-25,69%	-25,69%	-25,69%	74,31%	10 (0,2852) 110 (0,1378) 150 (0,0035) 178 (0,0095) 179 (0,5640)	0	0	0
2013	DMU89	-30,56%	-30,56%	-30,56%	69,44%	10 (0,4032) 96 (0,0966) 135 (0,0183) 138 (0,4820)	0	0	0
2013	DMU90	-44,03%	-44,03%	-44,03%	55,97%	10 (0,7143) 110 (0,0312) 178 (0,1676) 183 (0,0869)	0	0	0
2013	DMU91	-23,77%	-23,77%	-23,77%	76,23%	10 (0,3744) 110 (0,1342) 150 (0,0675) 178 (0,0841) 179 (0,3398)	0	0	0
2013	DMU92	-41,48%	-41,48%	-41,48%	58,52%	10 (0,2457) 110 (0,3214) 135 (0,0532) 139 (0,3797)	0	0	0
2013	DMU93	-41,97%	-39,34%	-41,97%	58,03%	10 (0,3796) 150 (0,1906) 178 (0,4298)	0	11350,82	0
2013	DMU94	-33,30%	-33,30%	-33,30%	66,70%	10 (0,0472) 110 (0,2166) 139 (0,5952) 183 (0,1410)	0	0	0
2013	DMU95	-36,67%	-36,67%	-36,67%	63,33%	110 (0,3641) 139 (0,4490) 140 (0,0359) 178 (0,1510)	0	0	0
2013	DMU96	0,00%	0,00%	0,00%	100,00%	19			
2013	DMU97	-29,44%	-21,32%	-29,44%	70,56%	10 (0,8163) 150 (0,0908) 179 (0,0929)	0	8405,84	0
2013	DMU98	0,00%	0,00%	0,00%	100,00%	3			
2013	DMU99	-24,05%	-16,85%	-24,05%	75,95%	30 (0,1991) 150 (0,2399) 160 (0,5610)	0	34948,95	0
2013	DMU100	12,40%	-3,53%	-3,53%	96,47%	30 (0,2333) 31 (0,1018) 169 (0,1007) 179 (0,5642)	26431,09	0	0
2013	DMU101	-39,14%	-35,23%	-39,14%	60,86%	10 (0,3421) 150 (0,3575) 178 (0,3004)	0	17173,21	0
2013	DMU102	-27,80%	-27,80%	-27,80%	72,20%	10 (0,0401) 110 (0,3809) 178 (0,3607) 179 (0,2183)	0	0	0
2013	DMU103	-36,38%	-36,38%	-36,38%	63,62%	10 (0,4210) 110 (0,3865) 135 (0,1729) 139 (0,0195)	0	0	0
2012	DMU104	-57,55%	-53,67%	-57,55%	42,45%	10 (0,6790) 178 (0,1192) 183 (0,2019)	0	6299,05	0
2012	DMU105	-21,21%	-21,21%	-21,21%	78,79%	110 (0,1246) 140 (0,1499) 178 (0,0886) 179 (0,6369)	0	0	0
2012	DMU106	-11,35%	-11,35%	-11,35%	88,65%	10 (0,0007) 110 (0,3372) 135 (0,5677) 139 (0,0943)	0	0	0
2012	DMU107	-28,44%	3,73%	-28,44%	71,56%	10 (0,2689) 150 (0,0260) 160 (0,4875) 179 (0,2177)	0	130733,2	0
2012	DMU108	-26,60%	-26,60%	-26,60%	73,40%	10 (0,0110) 110 (0,7734) 178 (0,1045) 183 (0,1112)	0	0	0
2012	DMU109	-29,62%	-29,62%	-29,62%	70,38%	10 (0,3181) 110 (0,0896) 135 (0,2350) 138 (0,3573)	0	0	0
2012	DMU110	0,00%	0,00%	0,00%	100,00%	93			
2012	DMU111	-33,33%	-33,33%	-33,33%	66,67%	110 (0,3948) 139 (0,4165) 178 (0,0538) 183 (0,1349)	0	0	0
2012	DMU112	-41,31%	-26,98%	-41,31%	58,69%	10 (0,7318) 96 (0,2111) 179 (0,0571)	0	10081,45	0
2012	DMU113	-57,18%	-49,89%	-57,18%	42,82%	10 (0,0110) 178 (0,3410) 183 (0,6480)	0	30251,25	0
2012	DMU114	-32,54%	-32,54%	-32,54%	67,46%	110 (0,0008) 139 (0,6772) 140 (0,2488) 178 (0,0732)	0	0	0,01
2012	DMU115	-18,50%	-18,50%	-18,50%	81,50%	10 (0,2834) 110 (0,1548) 178 (0,0112) 179 (0,5506)	0	0	0
2012	DMU116	-12,03%	-12,03%	-12,03%	87,97%	110 (0,1911) 135 (0,1747) 139 (0,5915) 140 (0,0426)	0	0	0
2012	DMU117	-19,07%	-19,07%	-19,07%	80,93%	110 (0,0221) 140 (0,1031) 178 (0,7311) 179 (0,1436)	0	0	0
2012	DMU118	-55,59%	-55,59%	-25,76%	44,41%	10 (0,6741) 133 (0,1544) 183 (0,1716)	0	0	39844,56
2012	DMU119	-59,38%	-59,38%	-32,23%	40,62%	10 (0,5814) 133 (0,3249) 183 (0,0937)	0	0	54097,57
2012	DMU120	-22,08%	-22,08%	-22,08%	77,92%	10 (0,2047) 110 (0,2158) 138 (0,2232) 179 (0,3563)	0	0	0
2012	DMU121	-30,90%	-30,90%	-30,90%	69,10%	10 (0,3578) 110 (0,2895) 139 (0,2110) 183 (0,1417)	0	0	0
2012	DMU122	-41,39%	-19,26%	-41,39%	58,61%	10 (0,2673) 98 (0,1263) 178 (0,4500) 183 (0,1565)	0	116596,6	0

Ano	DMU	Input reduction Cost with staff	Input reduction Cost of goods	Input reduction Rents	Score	Benchmarks	(S) Cost with staff {I}	(S) Cost of goods {I}	Rents {I}
2012	DMU123	-3,66%	-17,23%	-17,23%	82,77%	133 (0,0888) 135 (0,2562) 144 (0,6550)	11383,62	0	0,28
2012	DMU124	-37,07%	-37,07%	-37,07%	62,93%	110 (0,0840) 135 (0,1498) 139 (0,6341) 140 (0,1321)	0	0	0
2012	DMU125	-8,22%	39,93%	-8,22%	91,78%	98 (0,8159) 150 (0,0458) 159 (0,1308) 178 (0,0076)	0	175997,8	0
2012	DMU126	-10,09%	-10,09%	-10,09%	89,91%	30 (0,0003) 150 (0,2349) 160 (0,3997) 179 (0,3651)	0	0,14	0
2012	DMU127	-27,72%	5,03%	-27,72%	72,28%	98 (0,5129) 150 (0,1137) 159 (0,1255) 178 (0,2478)	0	201238,6	0
2012	DMU128	-23,06%	-23,06%	-23,06%	76,94%	110 (0,5293) 140 (0,0910) 178 (0,2877) 179 (0,0920)	0	0	0
2012	DMU129	-35,12%	-35,12%	-35,12%	64,88%	10 (0,4459) 110 (0,0974) 135 (0,3853) 139 (0,0714)	0	0	0
2011	DMU130	0,00%	0,00%	0,00%	100,00%	2			
2011	DMU131	16,45%	0,00%	0,63%	100,00%	135 (0,7779) 139 (0,2082) 144 (0,0139)	12657,02	0	266,35
2011	DMU132	-26,11%	-22,76%	-26,11%	73,89%	96 (0,2208) 160 (0,5999) 179 (0,1793)	0	8123,6	0
2011	DMU133	0,00%	0,00%	0,00%	100,00%	4			
2011	DMU134	-7,67%	-10,65%	-10,65%	89,35%	96 (0,1476) 135 (0,5536) 138 (0,2988)	2181,4	0	0
2011	DMU135	0,00%	0,00%	0,00%	100,00%	37			
2011	DMU136	-15,05%	-20,83%	-20,83%	79,17%	135 (0,0441) 139 (0,9468) 140 (0,0091)	4991,64	0	0
2011	DMU137	7,50%	-6,05%	8,39%	93,95%	139 (0,5402) 140 (0,4598)	19808,47	0	19504,55
2011	DMU138	0,00%	0,00%	0,00%	100,00%	34			
2011	DMU139	0,00%	0,00%	0,00%	100,00%	48			
2011	DMU140	0,00%	0,00%	0,00%	100,00%	32			
2011	DMU141	3,67%	-0,83%	-0,83%	99,17%	130 (0,0452) 135 (0,0537) 138 (0,9010)	3810,5	0	0
2011	DMU142	6,24%	-6,47%	-6,47%	93,53%	96 (0,3632) 135 (0,3857) 138 (0,2511)	8519,13	0	0
2011	DMU143	-38,56%	-38,56%	-38,56%	61,44%	110 (0,2857) 139 (0,0320) 178 (0,3761) 183 (0,3061)	0	0	0
2011	DMU144	0,00%	0,00%	0,00%	100,00%	3			
2011	DMU145	7,45%	-10,28%	-3,19%	89,72%	139 (0,7337) 140 (0,2663)	23202,94	0	7627,54
2011	DMU146	6,92%	-3,03%	-3,03%	96,97%	130 (0,2636) 135 (0,2140) 138 (0,5225)	10264,54	0	0
2011	DMU147	-30,14%	-26,74%	-30,14%	69,86%	10 (0,3933) 150 (0,1534) 178 (0,4533)	0	12018,92	0
2011	DMU148	-3,08%	-3,08%	-3,08%	96,92%	110 (0,0406) 135 (0,3274) 138 (0,1197) 140 (0,5123)	0	0	0
2011	DMU149	-7,62%	-16,21%	-16,21%	83,79%	10 (0,2785) 133 (0,0915) 135 (0,6299)	5009,48	0	0
2010	DMU150	0,00%	0,00%	0,00%	100,00%	36			
2010	DMU151	-21,11%	-21,11%	-21,11%	78,89%	10 (0,2314) 110 (0,6912) 178 (0,0308) 179 (0,0466)	0	0	0
2010	DMU152	-14,22%	30,91%	-14,22%	85,78%	30 (0,0741) 96 (0,2012) 160 (0,7247)	0	233991,3	0
2010	DMU153	-18,34%	-18,34%	-18,34%	81,66%	10 (0,2467) 110 (0,2727) 138 (0,2783) 179 (0,2023)	0	0	0
2010	DMU154	-15,87%	-15,87%	-15,87%	84,13%	10 (0,3930) 110 (0,3956) 178 (0,0532) 179 (0,1582)	0	0	0
2010	DMU155	-28,78%	-28,78%	-28,78%	71,22%	110 (0,4852) 139 (0,4375) 178 (0,0562) 183 (0,0211)	0	0	0
2010	DMU156	-13,34%	-13,34%	-13,34%	86,66%	110 (0,2411) 140 (0,2109) 150 (0,1585) 159 (0,0496) 178 (0,3399)	0	0	0
2010	DMU157	0,04%	-0,02%	-0,02%	99,98%	10 (0,0179) 96 (0,0673) 138 (0,0028) 160 (0,9119)	52,05	0	0
2010	DMU158	-29,25%	-29,25%	-29,25%	70,75%	10 (0,0515) 110 (0,5936) 139 (0,3107) 183 (0,0442)	0	0	0
2010	DMU159	0,00%	0,00%	0,00%	100,00%	7			
2010	DMU160	0,00%	0,00%	0,00%	100,00%	17			
2010	DMU161	-15,06%	-15,06%	-15,06%	84,94%	10 (0,0708) 96 (0,3359) 138 (0,3258) 179 (0,2675)	0	0	0
2010	DMU162	-36,32%	-36,32%	-36,32%	63,68%	10 (0,0157) 110 (0,1592) 135 (0,5853) 139 (0,2398)	0	0	0
2010	DMU163	-32,45%	-32,45%	-32,45%	67,55%	10 (0,0580) 110 (0,2685) 139 (0,5000) 183 (0,1735)	0	0	0
2010	DMU164	-15,48%	-15,48%	-15,48%	84,52%	110 (0,3235) 140 (0,1578) 150 (0,0744) 178 (0,2629) 179 (0,1814)	0	0	0
2010	DMU165	-19,88%	-19,88%	-19,88%	80,12%	110 (0,4979) 138 (0,1968) 140 (0,0082) 179 (0,2972)	0	0	0
2010	DMU166	-26,36%	12,80%	-26,36%	73,64%	10 (0,3849) 150 (0,1523) 178 (0,4628)	0	270174,8	0
2010	DMU167	-3,70%	-3,70%	-3,70%	96,30%	110 (0,2095) 150 (0,3625) 159 (0,2951) 178 (0,0813) 183 (0,0516)	0	0	0
2010	DMU168	-27,89%	-27,89%	-27,89%	72,11%	10 (0,3388) 110 (0,1947) 135 (0,3555) 138 (0,1109)	0	0	0
2009	DMU169	0,00%	0,00%	0,00%	100,00%	5			
2009	DMU170	-17,37%	-13,96%	-17,37%	82,63%	10 (0,6375) 150 (0,3070) 178 (0,0555)	0	6205,21	0
2009	DMU171	-40,92%	-29,26%	-40,92%	59,08%	10 (0,8749) 150 (0,0319) 178 (0,0932)	0	15334,5	0
2009	DMU172	-14,93%	-15,93%	-15,93%	84,07%	96 (0,2157) 135 (0,3182) 138 (0,4660)	752,82	0	0
2009	DMU173	-26,85%	-26,85%	-26,85%	73,15%	10 (0,6956) 110 (0,0226) 178 (0,1056) 179 (0,1762)	0	0	0
2009	DMU174	-26,81%	-26,81%	-26,81%	73,19%	110 (0,0614) 135 (0,3933) 139 (0,4952) 140 (0,0501)	0	0	0
2009	DMU175	-11,89%	-11,89%	-11,89%	88,11%	110 (0,3387) 139 (0,0411) 140 (0,5864) 178 (0,0338)	0	0	0
2009	DMU176	-3,97%	-3,97%	-3,97%	96,03%	10 (0,0215) 96 (0,0906) 138 (0,3819) 179 (0,5060)	0	0	0
2009	DMU177	-31,45%	-31,45%	-31,45%	68,55%	10 (0,4888) 110 (0,2439) 178 (0,1888) 179 (0,0784)	0	0	0
2009	DMU178	0,00%	0,00%	0,00%	100,00%	72			
2009	DMU179	0,00%	0,00%	0,00%	100,00%	63			
2009	DMU180	-13,23%	-13,23%	-13,23%	86,77%	10 (0,1108) 96 (0,3229) 135 (0,2362) 138 (0,3301)	0	0	0
2009	DMU181	-36,97%	-36,97%	-36,97%	63,03%	10 (0,0674) 110 (0,4987) 178 (0,0769) 183 (0,3570)	0	0	0
2009	DMU182	-10,98%	-10,98%	-10,98%	89,02%	110 (0,3869) 138 (0,0109) 140 (0,4536) 179 (0,1486)	0	0	0
2009	DMU183	0,00%	0,00%	0,00%	100,00%	39			
2009	DMU184	-62,25%	-62,25%	-62,25%	37,75%	10 (0,0645) 110 (0,0360) 139 (0,0794) 183 (0,8201)	0	0	0
2009	DMU185	-2,24%	-2,24%	-2,24%	97,76%	140 (0,1488) 169 (0,2147) 178 (0,2911) 179 (0,3454)	0	0	0