Journal of Retailing and Consumer Services 25 (2015) 96–105

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

An empirical examination of performance in the clothing retailing industry: A case study

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ARTICLE INFO

Article history:
Received 20 August 2014
Received in revised form
9 April 2015
Accepted 9 April 2015

Keywords:
Clothing retail stores
Technical efficiency
DEA
Quantile regression

ABSTRACT

This article estimates the efficiency of the 40 retail stores of a prestigious clothing company that operates in the Portuguese fast-fashion retailing market. The study compares the performance among the stores and provides insights into ways of improving performance in the retail clothing industry. A two-stage approach is used in this article. In a first stage, Data Envelopment Analysis (DEA) techniques are used to evaluate the performance of each store and to rank the stores. The input-oriented model was used to assess the summer and winter collections between 2010 and 2013. The results show that the total technical efficiency of the company decreases over time. Except for the year 2013, over 90% of the stores show increasing returns to scale during 88% of the period analyzed. The company faces a clear problem of productivity in its retailing operations. This deficiency seems to be intrinsic to the firm as it involves more than 60% of the stores. In a second stage, a quantile regression technique was used. This showed primarily that for the lowest quantiles of the efficiency score conditional distribution the coefficients on experience are very low, even close to zero, which suggests that the efforts taken by the stores in terms of experience are barely recognized by consumers in this fast-fashion retailing chain.

1. Introduction

The evolution of the clothing market broadly revolves around three fundamental axes. The first of these axes is price control, which is generally dominated by large retailers; the second is brand control, which is concentrated in the hands of major companies and/or specialized retailers; and lastly, there is a fashion sensitive segment, whose production is concentrated in areas close to the consumer markets. However, retailers have become increasingly important in the distribution of specific market segments, particularly at the low and medium end.

One of the important aspects in the specialized retailing business is the influence of the phenomenon called fast-fashion, based on short product life cycles, but with a more complete and efficient supply chain based on faster in-store stock turnover.

Given the characteristics and the aspects described associated with the specialized clothing retailing industry, and the need of analyzing and evaluating the efficiency vs the productivity, a gap found in the literature, this article seeks to fill in this gap by applying a pioneer empirical study in this specific sector.

The instability of consumers' preferences and in their consumption decisions toward fast-fashion products provoke a simultaneous increase of the heterogeneity of production, marketing and supply management activities in the clothing industry. The aggregation of those operations makes it possible to provide the market with fast responses to the new clothing consumption tendencies. Accordingly, all the information disseminated throughout the market requires a specific orientation to the retailing industry. This orientation will be better achieved the more vertical the company structure is.

The main objective of this research refers to the performance evaluation of a 40 clothing store chain of a highly notorious clothing brand in Portugal. This will be achieved by maximizing an input-oriented objective function, characterizing the type of return to scale of the stores, and identifying the stores whose scales should be increased or decreased. Data from the winter and summer collections of 2010–2013 were used to analyze the performance of the stores. This timeframe represents a particular period of a high degree of recession in the purchasing power of the majority of the Portugal's middle class (the main target of this group of stores), because of the imposition of the restrictive governmental measures that effected family budgets.

The fast-fashion paradigm is intimately associated to the level of stock turnover, whereby a careful supply chain management has

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http://dx.doi.org/10.1016/j.jretconser.2015.04.002
0969-6989/

profound effects on the profit chain management in this type of retail stores. The novelty of this study in relation to the reviewed literature is related with the inclusion of an input (the average time to restock the product) in the maximization problem of each store's business volume.

Since its creation in 1960s, this clothing brand has been streamlining the ready-to-wear Portuguese market, namely by launching innovative concepts. Parallel to the exploration of new market segments, this prestigious clothing brand's retail chain has been renovating its store chain: new spaces, innovative architectural projects and significant expansions of the store area. This Portuguese ready-to-wear chain has the experience and capacity to communicate directly to the feminine target, using its 40 own stores, spread across the country. The company has deployed a fast response strategy that has made it possible to shorten the response time between the store request and the distribution dispatch. This allows the company to respond rapidly to their clients and to the tendencies of the market. This way, the company has the flexibility needed to react to the changes of the specialized clothing market, making it possible to adjust its orders to the orders of the store chain and respond to new styles and the market needs during the season and/or collection.

The literature studying the measurement of efficiency or productivity in the retail industry has been controversial because of the difficulty in identifying the optimal level of retail services. As a non-parametric method, Data Envelopment Analysis (DEA) analysis has been extensively used in the empirical literature on operations management performance evaluation, as well as providing a means to identify and evaluate the level of productivity in retail stores. Additionally, in our study we look at the efficiency drivers in a two-stage process, considering also that this research focuses directly on the causes of technical efficiency. So, during the first phase of the empirical study we will use the solutions of the linear programming problem in order to identify efficiency scores. The second phase then 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.

Based on the evidence which we have for the clothing industry, and in particular for the chain of 40 stores from the company under study, the following topics are to be addressed:

(1) The process of analyzing efficiency for a company composed of 40 different clothing stores.
(2) The analysis of each store's ranking given the efficiency level estimated by the non-parametric DEA model. As a result, benchmarking polices will then be defined.
(3) The analysis of other determinants that can influence efficiency levels achieved during the first phase through a quantile regression.

The motivation for this work stems from three interrelated questions facing clothing retail chains: first, what factors lead to changes in the levels of profit and turnover in clothing retail chains (outputs), especially in the recent years of international crisis, namely between 2010 and 2014? The answer to this question will be found by looking at business volumes based on the sales of winter and summer collections, which may explain the different performances.

Given the uncertainty of demand for clothing and its consequences for operations management in the specialized retail clothing industry, this study seeks to respond to the lack of information and research on the subject. On the other hand, because fast-fashion retailers (as represented by the case study used here) impose the “rules of the game” in many clothing markets, it is possible that the factors identified in the second step of this study (the inducers of performance differentiation) can be considered critical success factors enabling larger competitive gains and more added value throughout the whole specialized retail chain. As such, we consider that this study is an important asset for the evaluation of future operational management policies in this sector.

Analyzing and evaluating the causes of efficiency in the clothing retail chain with a case study makes it possible to address the second question: what are the internal organizational procedures in terms of both operational management resources and human resources, since it is not clear in the literature what the determinants of efficiency are in service organizations? Moreover, the last decade witnessed major changes in the location strategies of clothing stores, namely with stores moving from classy traditional urban streets to shopping centers. As such, we may wish to question this logic with a third question: is location a key determinant of efficiency? Given the importance of geographical location as a relevant strategic option, a comparative analysis of the efficiency of Portuguese clothing retail stores is implemented comparing stores located in shopping centers with traditional urban street stores.

The answers to each of these questions can be obtained by identifying the store efficiency rankings, whose scores can be used in the analysis and evaluation of the firm’s own in-house efficiency, or efficiency *vis-à-vis* other stores of competing retailers, either located in the same shopping center or in the same traditional urban sites.

Given the importance of studying these drivers that are responsible for differentiating and creating heterogeneity among the efficiency rankings of the 40 stores in the study, we propose a second phase for the empirical study which focuses on the drivers of the internal marketing, namely at the level of human resources management and with particular application to clothing retailing. As such, the information coming from the workers is also crucial for the internal operations management of an organization as it helps in taking more effective decisions (Panigyrakis and Theodoridis, 2009). The increasing recognition of the importance of workers to the organization led to the adoption of the concept of internal marketing (Roberts-Lombard, 2010), which is based on the premise that satisfying the needs of the workers is a means towards satisfying the needs of the customers (Panigyrakis and Theodoridis, 2009). The idea here is that the levels of effectiveness and motivation of among the workers will increase, which will be reflected in increased productivity and product quality, helping fulfill the customers' expectations and ensuring their satisfaction (Herington et al., 2009). On the other hand, we also consider demand-side drivers, namely regarding economic and demographic conditions which can themselves underlie the drivers which explain the differing levels of performance and/or productivity in the clothing stores.

The article is composed of five sections. Following from this introduction, Section 2 presents a literature review. The methodology used in this article is presented in Section 3. The results and the discussion are presented in Section 4. Finally, the main conclusions are presented in Section 5.

2. Review of the literature

Measuring performance or efficiency of a decision making unit (DMU) is not an easy task. One of the methodologies that have normally been used to measure DMU efficiency *vis-à-vis* a best-practice standard is the non-parametric linear programming approach, known as DEA. It measures economic efficiency, i.e. choosing optimal levels of inputs or outputs based on certain restrictions.

Data Envelopment Analysis (DEA), as a non-parametric linear programming technique was originally proposed by Charnes et al. (1978, 1981). It can be used to rank the relative performance of DMUs operating under similar conditions, namely when DMUs use different inputs to produce different outputs. DEA arrives at an efficient score for each DMU (Cooper et al., 2007).

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) 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 maximize input contraction or output expansion, with output production or input consumption, respectively, kept constant. Both orientations yield identical envelopment (convex) surfaces but differ in the manner in which inefficient DMUs are projected onto the efficient frontier. Since then, the DEA method has been widely used in many areas, as for example in banking (Avkiran, 2011; Siriopoulos and Tziogkidis, 2010), in the electrical industry (Amado et al., 2013; Santos et al., 2011), in strategy (Demirbag et al., 2010; Amado et al., 2012) and in project evaluation (Asosheh et al., 2010).

Avkiran (2011) analyzes to what extent bank DEA super-efficiency estimates are associated with key financial ratios. After analyzing nine DEA formulations and two profitability models, DEA is proven to be useful in identifying benchmarks for ratio analysis based on actual observed data collected from peers. Siriopoulos and Tziogkidis (2010) were the first to analyze the performance behavior of Greek commercial banks within the scope of change management theory using the DEA technique, namely the reaction of banks after significant events such as mergers and acquisitions, privatizations and the crisis of the Athens Stock Exchange in 1999.

Amado et al. (2013) and Santos et al. (2011) applied DEA techniques in electricity distribution utilities. Amado et al. (2013) analyzed whether differences in efficiency where attributed to a managerial program or to its control group program. They complemented the analysis applying the Malmquist Productivity Index to study the impact of the introduction of a new technology on a group of units. They concluded that DEA techniques can be successfully implemented in the improvement of process interventions in medium-voltage power lines. Santos et al. (2011) also applied DEA techniques and the Malmquist Index to evaluate the cost-efficiency of electricity distribution companies. They recommend implementing a dynamic analysis to complement the modeling of efficiency scores that result from DEA techniques.

Asosheh et al. (2010) and Amado et al. (2012) combine Balanced Scorecard (BSC) models and DEA techniques. Asosheh et al. (2010) evaluate and rank information technology projects, using a readapted DEA technique that runs both on cardinal and ordinal data. Amado et al. (2012) conclude that it is possible to promote a continuous learning process and to bring about improvements in organizational performance when applying the DEA technique with BSC models encapsulating four perspectives of performance (financial, customers, internal processes, learning and growth). They applied the DEA techniques in a multinational company that operates in two different business areas.

Demirbag et al. (2010), using the DEA technique, compare the relative efficiency of the strategic decision making (SDM) processes between British and Turkish firms. They concluded that there is a huge difference between both types of firms in terms of their SDM efficiency: whilst British firms place more emphasis on organizational structure, Turkish firms tend to concentrate on managing environmental turbulence to enhance their SDM efficiency.

Chang (2011) uses DEA to evaluate the relative managerial efficiency of technology development programs in Taiwan. Human resources and expenditures are used as inputs and patents and technology outcomes as outputs. Some differences across industries are found through the 1999–2003 period and potential improvements for inefficient industries are provided.

Beriha et al. (2011) applied the constant returns to scale DEA model to calculate the security level performance of Indian manufacturing units. The results show that there are seven inefficient units and thirty efficient units. Moreover, a benchmarking process was implemented in inefficient units in order to increase their efficiencies according to the best practices of efficient units.

Lee and Pai (2011) used a DEA model to evaluate the introduction of new technologies in the top 10 electronics manufacturers in Taiwan, Korea and Japan. The results clearly indicate that there are huge differences among firms.

Memon and Tahir (2012) applied both constant and variable returns to scale non-parametric DEA models to assess the technical efficiency and scale efficiency in 49 manufacturing companies in Pakistan. After decomposing total efficiency into pure technical efficiency and scale efficiency it was found that the pure technical efficiency rather than scale efficiency is the source of inefficiency. Moreover, the results reveal that most companies operate within increasing returns to scale.

In the retailing industry, studies where the performance evaluation methodology is defined based on contributions of the literature are the ones that predominate. While Goldman (1992) analyzed productivity from a static perspective, most of the studies follow a dynamic one (e.g. Ratchford and Brown, 1985; Ratchford and Stoops, 1988). One of the inconveniences of this dynamic perspective is the difficulty in interpreting results, i.e., properly separating productivity factors from technologically-based factors. In such cases it is mandatory to isolate those different factors.

Several studies have analyzed the productivity of distribution activities based on labor factor as a variable (Ingene, 1982, 1984), which might be misleading as not all the employees are allocated to sales-related activities. On the other hand the analysis of ratios has been extensively used (Ratchford and Brown, 1985; Goldman, 1992; Donthu and Yoo, 1998). One major limitation of this type of studies is that the existence of economies of scale are not disclosed. This have been resolved using regression analysis after estimating productivity (Ratchford and Stoops, 1988; Nooteboom, 1982, 1983; Lusch and Moon, 1984; Van Dalen et al., 1990).

Keh and Chu (2003) evaluated the efficiency of 13 supermarkets during 10 years using a three staged model, including only controllable factors. During the first stage, the inputs labor (staff costs) and capital (operational expenses, general expenses, maintenance costs and rent) where related to a group of intermediate outputs (distribution services). The second stage related the distribution services with the final output (sales). In the third stage they analyzed the direct relation between the inputs and the final output. Most of the stores showed increasing returns to scale.

Barros and Alves (2004) used the DEA technique to estimate the Malmquist index in order to evaluate the productivity evolution in time, disaggregating it into the following components: pure technical efficiency change; scale efficiency change; and technology change. This study evaluated a chain of 47 supermarkets of a Portuguese company between 1999 and 2000. According to them, the company's retail activity is market oriented, making their outputs orientation a natural choice according to their position in the competitive market. Korhonen and Syrjänen (2004) evaluated the performance of a chain of 25 supermarkets in Finland. The inputs where labor (number of hours worked) and the total area of the supermarket. The outputs included the sales volume and profit. The emphasis of this study was in defining models to reallocate all the resources among the supermarkets, assuming that the total amount of inputs can increase until the maximum of its limit.

Wu et al. (2006) used a CCR DEA model to examine the performance of the retailing industry in Taiwan between 1998 and 2002. They found that nearly three quarters of the companies analyzed were inefficient during the five-year time span. Moreover, there were only six consistently efficient companies throughout the period under analysis.

Sellers-Rubio and Mas-Ruiz (2007) used the Malquist index to evaluate the intertemporal performance change of 96 stores in a chain of supermarkets in Spain between 1995 and 2003. Perrigot and Barros (2008) analyzed the technical efficiency in the retailing industry in France using the DEA evaluation. In the first stage four models of DEA were used to identify the efficiency indicators. In a second stage, using a Tobit regression, they identified the main drivers of the retail chain efficiency.

The DEA literature concerning efficiency or performance evaluation in the textile industry is even more scarce in the retail industry. However, in the textile industry it is possible to highlight mainly cross-sectoral studies (Thomas et al., 1998; Dubelaar et al., 2002; Moreno, 2008; Mostafa, 2009, 2010a, 2010b).

While Dubelaar et al. (2002) applied a structural equation modeling methodology in the analysis of 800 pharmacy stores in Australia and New Zealand. Moreno (2008) used the input-oriented DEA technique to evaluate the efficiency of 234 Spanish Hypermarket stores of four different chains. Mostafa (2009, 2010a, 2010b) used the output-oriented DEA method to study US generalist retailers. Finally, Thomas et al. (1998) analyzed 520 outlets in the US multi-retailer chain using an output-oriented DEA methodology to study 520 outlets in the US multi-retailer chain. They complemented the analysis with a MANOVA.

3. Data and methodology

3.1. DEA and the description of variables

As the main objective of the mass-market clothing retailers is to maximize sales volume, the objective function involves certain restrictions in terms of the cost function. As such, some precautions associated with the optimization model should be taken in order to maximize results, given the resources available in the organization. The most consensual model in the literature that has been applied to the retail sector is DEA.

Data Envelopment Analysis is a methodology traditionally used for efficiency analysis using linear programming to determine a production frontier. Its main purpose is to empirically measure and compare a number of DMUs performing similar activities, differentiating the input demanded quantities and the output produced quantities. Three steps are required when implementing the DEA techniques: the definition and selection of DMUs; the selection of (inputs and outputs) variables; the selection and application of the model (type of returns to scale, orientation, advanced models) (Cooper et al., 2000, 2004.).

The DEA approach can be divided into two steps: the determination of efficiency measures and projection onto the efficient frontier. The evaluation of the results of these two steps can be extremely useful in determining actions that improve performance in the specialized clothing retail sector. In this study the DMUs are the clothing stores that compose the firm's retail chain. The different levels of relative performance will be assessed in terms of quantities sold and their consumption (measured by the input resources) which allows the direct comparison among the sample's DMUs. For a given consumption level, any DMU selling lower quantities of clothing than any other store will be referred to as inefficient. Similarly, any DMU generating an identical levels of sales volume and consuming more resources than any other store will also be considered inefficient.

In the DEA methodology each DMU is assigned a score representing its relative performance. Usually, scores range between 0 and 1 or between 0% and 100%; efficient units are those whose score is equal to 1% or 100%. The DEA model allows the identification, for each DMU, of the levels of inputs and outputs that would categorize units as efficient. Another interesting feature of the model is its capacity to discern optimal levels of output in the clothing sector, optimal levels or targets, which may serve as benchmarking tool to improve inefficient DMUs towards the efficient frontier.

It is widely acknowledge, in the literature of both retail efficiency and productivity (Sellers-Rubio and Mas-Ruiz, 2006; Perrigot and Barros, 2008; Mostafa, 2010a, 2010b) that the choice of output and inputs measures is controversial. Monetary measures of outputs have received considerable attention and application, specifically profit and revenues as well as the retailer's market value. In addition, others authors (Kamakura et al., 1996; Donthu and Yoo, 1998; Dubelaar et al., 2002; Athanassopoulos, 2003; De Jorge 2008; 2010; Perrigot and Barros, 2008; Sellers-Rubio and Mas-Ruiz, 2009) suggest sales as output variable, while Sellers-Rubio and Mas-Ruiz (2007) select EBITA and Net income measures of both retail efficiency and productivity.

In contrast with the selection of adequate output measures, the difficulty in the selecting satisfactory input measures is associated with technical and operative issues, but not with conceptual problems. In order to maximize the outputs, some authors included controllable factors in linear programming, such as physical or monetary variables. Among physical variables, Reardon et al. (1996) selected the number of full-time equivalent employees, Kamakura et al. (1996) selected the number of man-hours allocated, Dubelaar et al. (2002) selected the number of employees, De Jorge (2006, 2010), Barros (2006) and Perrigot and Barros (2008) selected full-time or part-time employees. Among others Reardon et al. (1996), Thomas et al. (1998), Mostafa (2009, 2010a, 2010b) and De Jorge (2010) selected payroll as input monetary variable.

The capital invested (physical and monetary variable) is other input used in the literature of both retail efficiency and productivity. For instance, some authors (Kamakura et al. 1996; Dubelaar et al., 2002; De Jorge, 2008) selected the selling space as physical variable. The following variables have been used as monetary variables: investments on assets (Dubelaar et al., 2002; Sellers-Rubio and Mas-Ruiz, 2007); assets value (De Jorge, 2010; Perrigot and Barros, 2008; Sellers-Rubio and Mas-Ruiz, 2006; Barros, 2006; Dubelaar et al. 2002); rent costs (Reardon et al., 1996; Thomas et al., 1998); and inventory (De Jorge, 2010).

In order to analyze the efficiency of the firm's 40 clothing stores we will calculate and analyze the technical efficiency measurements for each decision making unit. Data from two different clothing collections are going to be analyzed – a winter and a summer collection – for the period between 2010 and 2013. We are going to consider input-oriented models, considering both constant and variable returns to scale. The input-oriented model is considered more appropriate, mainly because the store managers have relatively less control over the outputs. Three inputs are going to be used: the rent costs, following Reardon et al. (1996) and Thomas et al. (1998); total salaries and wages, following Thomas et al. (1998), Mostafa (2009; 2010a; 2010b), and De Jorge (2010); and investments in assets, following Dubelaar et al. (2002) and Sellers-Rubio and Mas-Ruiz (2007). Sales volume and earnings before income taxes and amortization (EBITA) are the outputs, following Barros and Alves (2004) and Sellers-Rubio and Mas-Ruiz (2007).

3.2. Technical efficiency

In the retail industry, measuring the performance or efficiency of a production or decision making unit can be a complicated proposition. Over the past thirty years, two classes of frontier methodologies have been developed to measure DMU efficiency relative to an empirically defined best-practice standard: the non-parametric linear programming approach, namely DEA, and the parametric econometric approach, namely Stochastic Frontier Analysis. These approaches differ in their assumptions of the shape of the efficient frontier, the treatment of random error, and the distributional assumptions regarding inefficiency and random error. Specifically, nonparametric approaches measure *technical efficiency*, focusing on levels of input relative to levels of output. For a DMU to be technically efficient, it must either minimize its inputs for given outputs and/or maximize its outputs for given inputs.

According to Perrigot and Barros (2008), technical efficiency refers to the ability of a company to maximize outputs from a given set of inputs. However, allocative efficiency refers to the ability of a company to use both inputs and outputs in optimal proportion, given their respective price levels. The combination of the two measures can provide an overall measurement of the total economic efficiency.

In an initial phase the efficiency evaluation will be calculated, using the DEA, a linear programming technique that converts multiple inputs and outputs into a single relative efficiency measurement for each DMU. The identification of one reference frontier makes it possible to compare the position of different DMUs. This non-parametric technique was initially proposed by Charnes et al. (1978), with a definition of technical efficiency with constant returns to scale (CRS) with the maximization of the efficiency objective function, ignoring the dimension of the DMUs. This index is known as technical efficiency (TE) and can be expressed by the following expression:

$$\mathrm{TE}_k = \frac{v_1 y_{1k} + v_2 y_{2k} + v_3 y_{3k} + \ldots + v_m y_{mk}}{\varpi_1 x_{1k} + \varpi_2 x_{2k} + \varpi_3 x_{3k} + \ldots + \varpi_n x_{3nk}} = \frac{\sum_{p=1}^{k} v_p y_{pk}}{\sum_{q=1}^{k} \varpi_q y_{qk}} \tag{1}$$

where TE_k is the technical efficiency score given to the unit k; $x$and y represent inputs and outputs, ν and ϖ are the weight of the inputs and outputs, respectively; p is the number of inputs (p= 1; 2; …; m), q is the number of outputs (q=1; 2; …; n), and k represents the kth DMU (k=1; 2; …; j). The Eq. (1) can be expressed as a linear programming problem as expressed below:

$$\max\ \theta = \sum_{p=1}^{k} v_p y_{pk}$$

subject to the following set of restrictions:

$$\begin{cases} (i)\ \sum_{q=1}^{k} \varpi_q y_{qk} x_n = 1,\ i = 1, 2, 3, \ldots, k \\ (ii)\ \sum_{p=1}^{k} v_p y_{pk} - \sum_{q=1}^{k} \varpi_q y_{qk} x_n \le 0 \\ (iii) v_p \ge 0,\ p = 1, 2, 3, \ldots, m \\ (iv) \varpi_q \ge 0,\ q = 1, 2, 3, \ldots, n \end{cases}$$

where θ is the technical efficiency parameter. The score of efficiency in DEA is given by a specific value of v, assuming values between 0 and 1, where 1 indicates a DMU that shows a better performance localized at the frontier of production and not revealing any potential reduction. Whatever value of v lower than 1 indicates that the DMU is using inputs inefficiently. The objective function of the model maximizes the ratio between the weighted outputs by the weighted inputs for the DMU under analysis subject to the condition that there are similar relations for all the DMUs presenting values of efficiency lower, or equal to 1. The best value for the objective function of the model is the efficiency score attributed to a certain kth DMU. If the efficiency score is equal to 1, at a kth DMU, this decision making unit satisfies the needed condition to be considered efficient, otherwise it would be considered inefficient. The optimization is performed once for each DMU in the sample with the objective of reducing all inputs equiproportionally, i.e., optimality is achieved by minimizing inputs by a factor of q. Consequently, CCR models are *radial* models as their goal is to adjust inputs or outputs (in the case of output orientation) radially from the origin. However, further input decreases or output increases may still be possible after radial optimization has been achieved.

Frequently, the technical efficiency reflects the success of a DMU in producing at its maximum output using a specific group of inputs, which, in a certain context, means the inputs are then exogenous and the outputs are endogenous. The efficiency model with constant returns to scale is probably the most used and the most known within the DEA models.

Subsequently, Banker et al. (1984) formulate the problem of optimizing under variable returns scale (VRS), where the efficiency of a DMU depends on the size of the companies, and where the effect of increasing resources will be different across the DMUs. This relationship is known as the pure technical efficiency and it is a measurement of the transformation process of resources into outputs.

The BCC model can be described by a dual problem of linear programming, expressed by the following objective function:

$$\max\ Z = v y_i - \nu_i$$

subject to the following set of restrictions:

$$\begin{cases} (i) \varpi x_i = 1, \\ (ii) - \varpi Y + \nu X - \nu_0 \varepsilon \le 0 \\ (iii) \varpi \ge 0,\ \nu \ge 0 \wedge \nu_0 \end{cases}$$

where ν_0 is unrestricted in sign, where z and ν_0 are scalar, ϖ and ν are outputs and matrices of the weight of inputs, and Y and X are the correspondent outputs and matrices of inputs, respectively. y_i and x refer to inputs and outputs of a DMU. The main advantages of the BCC model is that the units with scale inefficiency are only compared with efficient units with a similar dimension.

3.3. Regression analysis of efficiency determinants

The non-parametric frontier model is adequate for estimating technical efficiency scores in 40 fast-fashion retail outlets. We expect a statistically significant association between the shop's management capability and its technical efficiency scores for the overall management capability score and for two important economic and demographic effects. More specifically, in this second approach we discuss quantile regression techniques as a robust and easily implemented complementary technique. In keeping with the retailing literature, we proposed to estimate the following linear regression model:

$$\theta_{it} = \alpha_{1t} + \beta_{1i}\mathrm{NWork}_{it} + \beta_{2i}\mathrm{NYExp}_{it} + \beta_{3i}\mathrm{IpcPC}_{jt} + \beta_{4i}\mathrm{DPop}_{jt} + \beta_{5i}\mathrm{EEsc}_{it} + \beta_{6i}\mathrm{DLoc}_{it} + \mu_{it}$$

where θ_{it} is the dependent variable (i.e., the technical efficiency score for store i at the municipality j at time t). IpcPC_{jt} represents the purchasing parity index per capita at the municipality j, and DPop_{jt} is the population density, measured by the number of inhabitants per km^2 at the municipality j. We used the following control variables: NWork_{it} records the number of employees in store i, NYExp_{it} records the number of years of experience of the head of store i, $\mathrm{EEsc}_{i,t}$ expresses the average level of education of the staff of store i and DLoc_{it} is a binary dummy variable that takes the value 1 if the store is localized in a shopping mall and 0 if the store is localized in a in classy traditional urban street.

In our case, the decision to use quantile regression *vis-à-vis* multiple regression methods is based on the following two important reasons. On the one hand, the quantile regression describes the entire conditional distribution of the dependent variable (efficiency score). As such, instead of returning the conditional mean of the dependent variable given certain values of the predictor variables, quantile regression aims to estimate the conditional quantiles of the dependent variable. On the other hand, a quantile regression avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. This quantile regression adds a new dimension to the empirical literature 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) with respect to particular regressors. More specifically, following Yasar et al. (2006), this derivative is interpreted as the marginal change in the dependent variable at the conditional quantile as a result of the marginal change in a particular regressor (independent variable) $\triangle Q\theta_{it}\,(y_{it}\,x_{it})/\triangle x$. For example, in our case, this derivative could be interpreted as the marginal change in the efficiency score at the conditional quantile as a result of the marginal change in the purchasing parity index per capita (IpcPC).

4. Results and discussion

4.1. Efficiency analysis per store

The technical efficiency scores for the winter and summer collections are presented in the Appendix. The closer the technical efficiency score is to 1 the more efficient the store, which means that the store is making the best use of resources (inputs) at both seasons (summer and winter collection) based on the sales or EBITA (outputs). Therefore we will focus on the analysis and interpretation of the results showing the modification of the ranking of stores, as well as on the trend of technical efficiency of both winter and summer collections, considering only the results of the DEA estimator.

The results in Table 1 show the behavior of the stores based on their technical efficiency. The analysis of the modifications to the stores' rankings will be carried out using this technical efficiency.

The ranking of DMU_{15} and DMU_{26} show an upward trend, both in summer and winter collections and in both periods of analysis. As such, with the summer collections DMU_{15} and DMU_{26} went up 9 and 3 positions respectively during the period 2010–2012, and 1 and 2 positions respectively during the 2012-2013 period. In the winter collections, the same DMUs went up 8 and 6 positions respectively between 2010 and 2012 and 9 and 5 positions respectively in the 2012–2013 period.

DMU_{35} and DMU_{36} are also notable performers in the rankings, rising 31 and 17 positions respectively during the 2010-2012

Table 1
Rankings of technical efficiency.

	Comparison 2013 vs 2012 summer			Comparison 2013 vs 2012 winter			Comparison 2012 vs 2010 summer			Comparison 2012 vs 2010 winter		
DMU_{7}	Went down	−19	positions	Went down	−20	positions	Same position	0	positions	Went down	−10	positions
DMU_{10}	Went up	1	position	Went up	7	positions	Same position	0	positions	Went down	−6	positions
DMU_{12}	Went down	−1	positions	Went down	−9	positions	Went down	−1	positions	Went up	2	positions
DMU_{24}	Went up	3	positions	Went up	3	positions	Went down	−2	positions	Went down	−3	positions
DMU_{29}	Went up	3	positions	Went down	−8	positions	Went down	−7	positions	Same position	0	positions
DMU_{33}	Went down	−1	positions	Went up	1	position	Went down	−16	positions	Went down	−18	positions
DMU_{22}	Went up	1	position	Went down	−2	positions	Went down	−11	positions	Went down	−16	positions
DMU_{4}	Went down	−4	positions	Went down	−6	positions	Went down	−2	positions	Went down	−2	positions
DMU_{34}	Went up	9	positions	Went up	5	positions	Went down	−11	positions	Went down	−8	positions
DMU_{28}	Same position	0	positions	Went down	−3	positions	Went up	3	positions	Went up	6	positions
DMU_{3}	Went up	4	positions	Went up	1	position	Went down	−3	positions	Went up	3	positions
DMU_{17}	Went down	−15	positions	Went up	13	positions	Went up	1	position	Went down	−9	positions
DMU_{5}	Went down	−9	positions	Went down	−3	positions	Went down	−8	positions	Went down	−8	positions
DMU_{11}	Went down	−15	positions	Went down	−7	positions	Went up	11	positions	Went up	4	positions
DMU_{18}	Went down	−2	positions	Went down	−17	positions	Went down	−8	positions	Went up	18	positions
DMU_{15}	Went up	3	positions	Went up	9	positions	Went up	1	position	Went up	8	positions
DMU_{13}	Went up	3	positions	Went down	−1	positions	Went up	12	positions	Went up	14	positions
DMU_{25}	Went up	11	positions	Went up	2	positions	Went down	−20	positions	Went down	−18	positions
DMU_{19}	Went down	−6	positions	Went up	7	positions	Went down	−10	positions	Went down	−13	positions
DMU_{26}	Went up	2	positions	Went up	5	positions	Went up	3	positions	Went up	6	positions
DMU_{32}	Went up	1	position	Went down	−5	positions	Went down	−16	positions	Went down	−13	positions
DMU_{21}	Went up	10	positions	Went down	−10	positions	Went down	−9	positions	Went up	8	positions
DMU_{39}	Went down	−10	positions	Went down	−10	positions	Went down	−4	positions	Went down	−10	positions
DMU_{16}	Went up	2	positions	Went up	13	positions	Went down	−10	positions	Went down	−16	positions
DMU_{2}	Went down	−8	positions	Went down	−2	positions	Same position	0	positions	Went down	−5	positions
DMU_{36}	Went up	3	positions	Went up	1	position	Went up	17	positions	Went up	17	positions
DMU_{9}	Same position	0	positions	Went up	6	positions	Went up	3	positions	Went down	−7	positions
DMU_{20}	Went up	14	positions	Went down	−4	positions	Went down	−8	positions	Went up	4	positions
DMU_{23}	Went up	1	position	Went up	11	positions	Went down	−6	positions	Went down	−7	positions
DMU_{8}	Went up	1	position	Went up	7	positions	Same position	0	positions	Went down	−6	positions
DMU_{1}	Went down	−3	positions	Went down	−3	positions	Went up	15	positions	Went up	5	positions
DMU_{40}	Went up	5	positions	Went up	1	position	Went up	19	positions	Went up	28	positions
DMU_{18}	Went down	−2	positions	Went down	−17	positions	Went down	−8	positions	Went up	18	positions
DMU_{31}	Went down	−3	positions	Went up	20	positions	Went up	6	positions	Went down	−1	positions
DMU_{6}	Went up	5	positions	Went up	11	positions	Went up	2	positions	Same position	0	positions
DMU_{27}	Went up	10	positions	Went down	−4	positions	Went up	10	positions	Went up	21	positions
DMU_{30}	Same position	0	positions	Same position	0	positions	Went down	−3	positions	Same position	0	positions
DMU_{14}	Same position	0	positions	Went up	3	positions	Went down	−1	positions	Same position	0	positions
DMU_{35}	Went up	4	positions	Went up	2	positions	Went up	31	positions	Went up	17	positions
DMU_{37}	Went down	−6	positions	Went down	−12	positions	Went up	8	positions	Went up	11	positions

period, and rising again 4 and 3 positions respectively from 2012 to 2013, for the summer collection. Meanwhile, for the winter collections those same DMUs both increased 17 positions during the 2010–2012 period, rising again 2 and 1 positions respectively during 2012-2013.

DMU_{25} and DMU_{21} stand out for their positive performance during the 2012-2013 period in relation to the 2010–2012 period in the summer collection: after going down 20 and 9 positions respectively during the 2010–2012 period, they went up 11 and 10 positions respectively in the ranking in the 2012–2013 period. DMU_{35}, DMU_{40} and DMU_{36} equally stand out because of their inability to maintain a positive performance: after having risen 31, 19 and 17 positions respectively during the 2010-2012 period they rose only 4, 5 and 3 positions respectively during the 2012-2013 period.

DMU_{16}, DMU_{17} and DMU_{23} stand out for their positive performance with the winter collection during 2012 and 2013 compared to their performance during the 2010-2012 period. Here they improved 13, 13 and 11 positions respectively in the ranking during the 2012-2013 period after having gone down 16, 9 and 7 positions between 2010 and 2012. On balance, DMU_{18} and DMU_{27} remained largely unchanged, with an increase and decrease in performance in the two periods counteracting each other. Additionally, it is worth noting the performance of DMU_{37}, DMU_{40} and DMU_{36} in the winter collection, with these three units having risen 11, 28 and 17 positions between 2010 and 2012, and then rising -12, 1, and 1 positions during the 2012-2013 period.

Some of the DMUs have gone down in the ranking. DMU_7 went down 19 positions between 2012 and 2013 with the summer collection, having maintained its position in the ranking during the 2010–2012 period; in contrast, it went down 10 positions in this first period, and continued to drop another 20 positions during 2012-2013 with the winter collection. Besides that, DMU_5 also fell in the ranking with a continuous decrease during both periods for both the winter and summer collections.

Generally speaking, different behaviors are visible when it comes to the variations of the relative positions of the DMUs when we consider (a) the summer and winter collections for the same period or (b) the intertemporal variation of just one collection.

4.2. Analysis of the quantile regression estimates

The numerical results for both the OLS and quantile regression estimation are shown in Table 2. OLS regression estimates show a positive and significant influence of IpcPC and a negative and significant influence on the technical efficiency scores in all stores. Median (50%) quantile regression results, which correspond to the minimum absolute deviation estimator, are significantly lower than the OLS estimates. The coefficient estimates of the 75% quantile are more than three times greater than those of the 25% quantile.

Fig. 1 provides a visual depiction of the quantile regression results. Using Azevedo's (2004) approach, one can view how each covariate's effects vary across quantiles, and contrast them with the OLS robust estimates. According to Powell (2014), the graphs display how the effect of each regressor vary over quantiles, and how the magnitude of the effects of the various quantiles differ considerably from the OLS coefficient, even in terms of the confidence intervals around each coefficient. Our results show that for the lowest quantiles of the efficiency score conditional distribution, the coefficients on experience are very low, even close to zero, which suggests that the efforts taken by the stores in terms of experience are barely recognized by consumers in this fast-fashion retailing chain. However, as we move up the conditional distribution, the coefficient rises significantly, especially at the extreme upper quantiles.

There are some important policy and practical implications that arise when using external factors and internal resources simultaneously to explain the differences in the technical efficiency in this clothing retail chain firm. Our results show that in this case of the retail industry, which is capital-intensive and is increasingly using the same management practices and strategies, stores operating in shopping centers appear to have superior managerial capabilities compared to stores operating in traditional urban streets. Moreover, purchasing power per capita and the number of years of experience of the head of the store seem to be of no competitive added value in terms of efficiency, which means that all stores operate under the same knowledge base.

On the one hand, some human resources management capabilities are reflected in codifiable management practices. Those

Table 2
Determinants of technical efficiency: benchmark of OLS and quantile regression estimates.

Independent variables	**OLS**	**Quantile regression**				
		Q (0.10)	**Q (0.25)**	**Q (0.50)**	**Q (0.75)**	**Q (0.90)**
Number of workers	0.037847 (0.00910)***	0.031594 (.00907)***	0.043225 (0.0142)***	0.023342 (0.01440)*	0.042141 (0.01376)***	0.034177 (0.0204)*
Number of years of experience	−0.000620 (0.00131)	0.002753 (0.00163)*	−0.000271 (0.002011)	0.000942 (0.00199)	0.000492 (0.00282)	−0.002420 (0.00218)
Purchasing power per capita Index	0.000035 (0.0036)	−2.38e-06 (0.000418)	−0.000134 (0.000593)	−0.0005206 (0.000647)	0.000723 (0.00082)	0.000503 (0.000347)
Employees average level of education	0.015405 (0.00660)**	0.009985 (0.00614)*	0.006230 (0.010253)	0.0248133 (0.010359)**	0.027106 (0.01204)**	0.030108 (0.013825)**
Population density	0.000016 (7.7e-06)**	−5.73e-06 (8.42e-06)	4.25e-06 (0.000015)	0.0000326 (0.000013)**	0.000013 (0.00001)	−4.61e-07 (6.21e-06)
Shopping or traditional urban store	−0.180988 (0.03784)***	−0.135049 (0.0567)**	−0.164031 (0.06231)***	−0.1613812 (0.05397)***	−0.221367 (0.05795)***	−0.143168 (0.06800)**
Constant	0.557731 (0.06831)***	0.369011 (0.08863)***	0.460875 (0.1175)***	0.57339 (0.10988)***	0.546269 (0.10182)***	0.68753 (0.10660)***
Observations	320	320	320	320	320	320
R^2/Pseudo R^2	0.155	0.1139	0.067	0.0946	0.1288	0.0559

Dependent variable: Technical Efficiency Scores (based on the DEA model)
Standard deviation scores are under parenthesis ()

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$

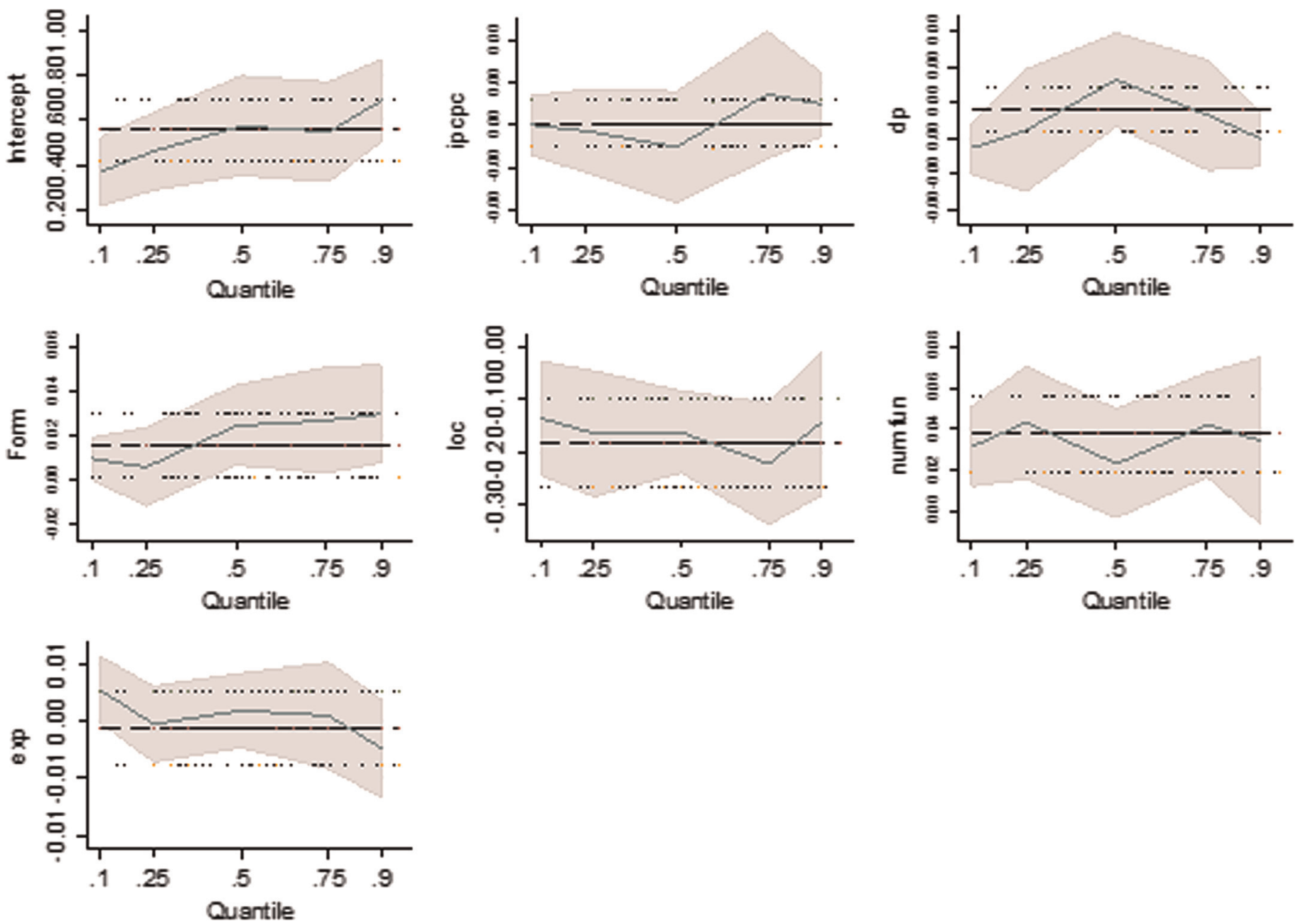

Fig. 1. Results of OLS and quantile regression.

capabilities affect stores operating in shopping centers through, among other things, demonstration or word-of-mouth diffusion, for example, 'routinely giving feedback to shop-floor staff on their performance', 'ensuring stock is on the shelves and available at the right time', 'providing incentives that motivate staff' and 'empowering shop floor staff to take responsibility and make operational decisions on retailing'. These human resources capabilities and practices may be imitated by other brands operating fashion stores in the other urban regions of the North, Center and South of Portugal by adopting the same practices. However, the quality of adoption and execution of these practices may differ in other fast-fashion stores and vary according to the skills and competences of top-level and shop-floor managers. On the other hand, most capabilities needed in retail stores in specific shopping centers and in certain traditional locations are tacit and situation specific. But there is no unified code and routine for such tacit capabilities – they are very much dependent on the experiences of managers, on the socio economic context of the consumer, and on the characteristics of the employees concerned. Similar productivity-enhancing tacit capabilities include 'controlling waste', 'solving problems quickly on the shop floor', 'working flexibly on the shop floor', and 'using shop-floor systems and processes that are clear and well-understood'. All these tacit management capabilities represent a competitive advantage for fast-fashion in this case study of the Portuguese retail chain. These capabilities are important for the productivity of retail firms.

5. Final conclusions and implications for management

From a technical standpoint, this study was primarily focused on analyzing the scores obtained from the objective function defined in the DEA model, allowing the reallocation of the total resources of the clothing retailing stores that are part of the company, assuming that the total inputs of this clothing retail chain can increase up to a maximum limit based on the analysis of the slacks. The performance of every DMU and the recommended ways to improve each of them was based on the conceptual framework. With the integration of all DMUs in the DEA approaches it is possible to identify where there is room for improving each store's managerial performance and pointing out opportunities for reciprocal learning among DMUs.

The results of this study reveal that the total technical efficiency of the 40 stores analyzed decreases across the period of analysis since the outputs of operations contracted more than the inputs originally yielded, which signals a productivity problem in the operation of stores. Except for the year 2013 over 90% of the stores show increasing returns to scale during 88% of the period analyzed. On this basis it can be argued that the productivity of the operations in the clothing stores suffers from a structural problem in more than 60% of cases.

From a different perspective, there are no problems of scale, since the levels of scale efficiencies are greater than the levels of pure efficiency. In other words, in most of the sub-periods considered (winter and summer collections) scale efficiency is larger than pure technical efficiency, which indicates a structural productivity problem in the operation of the stores. The application of DEA and its integration framework provides a set of recommendations that promote a continuous learning process and bring about improvements in the stores' performance.

In line with other studies referenced in the literature review, this study also allowed, among other objectives, to identify a set stores whose performance serves as an operational management benchmark for the less efficient stores. Moreover, several output and input-oriented models were applied to DMUs in which constant and variable returns to scale co-exist.

Following constant returns to scale, it is possible to claim that the following DMUs are benchmark stores: for the winter collection, DMU_{29} in 2010, DMU_{28} in 2011, and DMU_{35} in 2012 and 2013; for the summer collection, DMU_{29} in 2010, and DMU_{35} in 2011, 2012 and 2013. However, considering the case where stores are operating under variable returns to scale, the situation is as follows: for the winter collection, DMU_{33} in 2010 and 2011, and DMU_{35} in 2012 and 2013; for the summer collection, DMU_{33} in 2010, DMU_{36} in 2011, and DMU_{35} in 2012 and 2013.

Combining the results for the different periods (years and collections) and also for constant and variable returns to scale, DMU_{35} is singled out as the target benchmark, which in point of fact is specialized in children's clothes. The reason behind this result stems from the relatively low cost of capital invested and required *vis-à-vis* the stores that trade predominantly in women's clothes, which are more demanding in terms of capital requirements due to the location, decoration and design of the store.

It is possible to conclude that, for example, stores DMU_{13} and DMU_{35} show higher levels of technical efficiency for the Winter and Summer collections; DMU_{35} consistently from 2011 to 2013, whereas DMU_{13} for the year 2012. Once all information and data mining systems are similar across the 40 retail stores, performance differences between stores will depend on unique characteristics of each store. Thus, the performance of DMU_{13} and DMU_{35} result from better utilization of human capital resources, whose evidence the regression results corroborate for most stores. Moreover, the store managers of these two DMUs have higher education degrees as academic qualifications, well above the average of the 40 retail stores. On the other hand, these two stores have, compared to the remaining stores, a higher proportion of variable remuneration in relation to staff expenses, about 61%. Thus, one can claim that what distinguishes these two stores is a very particular success in improving service quality provided to consumers thanks to the very good qualification of the employees of these two stores, located in shopping centers.

Looking at the efficiency with which different entities operate helps uncover the determinant causes of their different efficiency levels, ultimately allowing the value of the different strategies adopted to be measured. In particular, the results show a positive impact of inventory stocks and the shopping location store on technical efficiency, highlighting the importance of having more merchandise for the customers to select from. This result also reflects evidence presented in Lusch and Moon (1984). Furthermore, the level of staff education also has a positive effect on technical efficiency, and shows the importance of correct employee motivation through an appropriate wage level. In other words, human resource management policies and practices are of vital importance for management, combining wage levels and education/training levels for employees, adequate staffing of stores, fostering team work and establishing practices designed to enhance customer intimacy.

Since fast fashion retailers impose the rules of the game in the Portuguese clothing market, it is possible that in the near future the 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 across the clothing retail chain. On the other hand, it is possible to claim internal marketing orientation practices that are implemented by the most efficient stores located in shopping centers, whose determinants proved to be the main differentiating drivers, are aligned to the practices of leading competing retailers with stores in the same shopping centers.

More broadly, we believe that the evidence found in this study for the most efficient stores may reflect a number of best practices of the clothing retail sector, that differentiate the quality of service provided of fast fashion retailers with prestigious brands. In addition, there may be important contexts in terms of marketing capabilities, such as internal and customer marketing orientation, enabling store managers and personnel to create an added value customer-relationship based environment. As such, adding value to consumers through changing human resources practices can provide a competitive advantage in the retail market.

For example, with the introduction of a more flexible labor policy, namely a different working hours pattern, for 2012 and 2013, DMU_{13} and DMU_{35} benefitted in creating a more competent and better trained workforce. The labor market has given retailers a huge opportunity to employ high talented (unemployed) people, particularly qualified staff with high degree level; this is the case of these two DMUs who selected high qualified personnel with positive consequences for the two stores. Other successful

Table A1
Scores of the technical efficiency for the winter and summer collections.

DMUs	Winter collection				Summer collection			
	2010	2011	2012	2013	2010	2011	2012	2013
DMU_{1}	73.17	57.43	71.95	52.40	63.47	64.02	84.74	65.14
DMU_{2}	66.02	40.60	48.18	34.90	70.36	59.73	66.62	46.89
DMU_{3}	88.76	48.11	86.68	61.86	88.68	75.76	84.25	80.52
DMU_{4}	91.61	58.81	78.38	57.22	95.55	72.59	94.43	74.67
DMU_{5}	75.73	42.31	58.96	41.80	85.79	74.73	72.70	51.79
DMU_{6}	50.12	42.17	46.45	46.62	49.26	41.98	59.47	54.74
DMU_{7}	100.00	90.45	78.51	43.64	100.00	100.00	100.00	64.98
DMU_{8}	72.37	52.36	57.00	50.92	64.24	44.71	62.11	51.48
DMU_{9}	77.27	56.19	61.17	56.65	67.27	45.06	69.38	58.79
DMU_{10}	95.43	70.77	65.36	46.72	100.00	59.07	86.90	50.07
DMU_{11}	79.91	57.39	74.87	54.44	85.42	72.47	99.79	67.09
DMU_{12}	100.00	80.13	100.00	65.80	100.00	100.00	100.00	94.43
DMU_{13}	83.30	84.39	100.00	92.38	82.56	94.13	100.00	100.00
DMU_{14}	45.39	36.17	35.21	35.12	42.24	36.11	42.14	27.51
DMU_{15}	66.40	60.04	68.25	62.94	83.82	67.04	88.07	73.87
DMU_{16}	86.39	56.97	58.98	58.77	70.72	63.32	59.05	48.25
DMU_{17}	91.27	62.48	68.59	73.12	87.08	82.41	92.82	56.27
DMU_{18}	54.77	61.84	73.57	38.88	49.74	57.98	70.64	56.70
DMU_{19}	74.15	49.11	46.49	44.61	77.83	64.09	63.21	44.49
DMU_{20}	65.28	51.77	58.99	43.05	66.06	60.60	56.74	60.90
DMU_{21}	68.26	51.50	73.16	44.78	72.28	65.41	60.52	64.20
DMU_{22}	90.47	56.99	68.03	49.32	96.26	86.22	73.17	67.13
DMU_{23}	66.13	47.70	45.06	45.82	66.06	55.70	57.16	47.42
DMU_{24}	100.00	100.00	85.49	65.14	100.00	100.00	100.00	100.00
DMU_{25}	85.15	58.94	53.36	44.51	78.17	76.92	54.05	55.39
DMU_{26}	66.95	57.74	68.20	58.38	76.61	67.07	80.91	72.32
DMU_{27}	53.76	43.15	74.50	55.34	44.94	54.79	66.53	65.24
DMU_{28}	92.88	100.00	98.76	54.26	92.88	100.00	99.31	80.75
DMU_{29}	100.00	84.50	91.66	56.54	100.00	91.02	91.92	82.69
DMU_{30}	43.85	38.15	26.42	3.19	42.46	39.71	32.79	19.98
DMU_{31}	56.66	60.53	51.32	59.57	48.98	67.15	61.19	48.21
DMU_{32}	77.10	58.57	52.27	23.21	74.39	56.64	53.76	31.29
DMU_{33}	100.00	66.03	67.40	38.36	100.00	64.98	68.26	48.99
DMU_{34}	94.54	48.97	74.23	40.71	94.54	63.43	70.40	62.84
DMU_{35}	60.98	100.00	100.00	96.45	33.93	100.00	100.00	100.00
DMU_{36}	63.20	53.19	64.11	37.32	68.04	70.33	69.85	56.41
DMU_{37}	46.07	53.20	60.08	30.68	35.81	50.07	59.33	33.16
DMU_{38}	81.87	47.28	77.82	40.45	84.00	40.51	75.14	62.00
DMU_{39}	85.13	47.78	67.40	37.58	70.96	26.14	65.67	41.01
DMU_{40}	59.40	79.07	91.31	74.00	60.74	83.47	91.56	86.94

practices that stand out in these two stores were the introduction of flexible working arrangements with the search of new qualified talents in the labor market. This process enhances some of the previous practices in the retailing sector as it provided the possibility to shift to peak (winter or summer) sales periods part of the labor time during the low demand sales periods, i.e. to change the annually distributed labor workload. Finally, and simultaneously with what was just referred, the following practices were implemented: a greater emphasis on training and career development seeking the requalification of the workforce, the selection and training of employees with the greatest potential to increase sales, and the creation of a more structured career path to ensure employees key skills.

Appendix

See Table A1

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