Available online at
http://www.anpad.org.br/bar

BAR, Rio de Janeiro, v. 9, n. 1, art. 4,
pp. 66-87, Jan./Mar. 2012

Determinants of Scale Efficiency in the Brazilian Third-Party Logistics Industry from 2001 to 2009

Peter F. Wanke *
E-mail address: peter@coppead.ufrj.br
Universidade Federal do Rio de Janeiro - UFRJ
Rio de Janeiro, RJ, Brazil.

* Corresponding author: Peter F. Wanke
Rua Paschoal Lemme, 355. Cidade Universitária, Rio de Janeiro, RJ, 21949-900, Brazil.

Abstract

This article investigates the Brazilian third-party logistics (3PL) sector which, increasingly competitive, offers clients a wide variety of services/information technologies in the quest to bolster efficiency. The main research objective is to determine which variables significantly impact 3PLs scale efficiency by applying two-stage DEA (Data Envelopment Analysis). Based on an unbalanced panel model, data from the annual study published by *Revista Tecnologística* (years 2001–2009) were analyzed. Results corroborate evidence in the literature that coordination mechanisms in the supply chain, supported by the availability of real time information and inventory synchronization, favor a more rational allocation of resources (inputs) to client demands (outputs).

Key words: DEA; third-party logistics; scale efficiency; Brazil.

Introduction

In Brazil, the third-party logistics industry began to gain strength with the *Plano Real* economic plan and ensuing economic stability (Fleury & Ribeiro, 2003). Currently, two-thirds of logistics-related expenditure in Brazilian firms is earmarked for logistics service providers, a fact which underscores the importance of outsourcing for the country (Centro de Estudos em Logística [CEL], 2009). As such, 3PLs must continually be on the lookout for new ways to stay competitive, with efficiency evaluation techniques serving a fundamental role in this quest.

Specifically, the Data Envelopment Analysis (DEA) technique, developed over 30 years ago (Cook & Seiford, 2009), is considered to be a powerful tool for measuring efficiency. This is primarily due to its capacity to simultaneously process multiple inputs and outputs, thereby aiding managers in decision-making. In conjunction with multivariate data analysis techniques, DEA enables the impact of contextual variables on efficiency levels to be measured (Cooper, Seiford, & Tone, 2007). Despite its major shortcomings, the non-parametric DEA frontier model remains widely used in transportation/logistics efficiency research in general, probably because it has been successfully applied to a wide number of different planning situations (see for example, Hamdan & Rogers, 2007; Lin & Tseng, 2007; Min & Joo, 2009; Panayides, Maxoulis, Wang, & Ng, 2009; Ross & Droge, 2004; Zhou, Min, Xu, & Cao, 2008).

It is worth noting that, while most multivariate data analysis methods - such as ordinary least squares regressions - are oriented towards central tendency estimates, DEA is directed towards optimal estimates for each individual observation represented in a dataset. More precisely, the performance of these observations is evaluated relative to the frontiers formed by the performance that data shows is possible to attain (Cooper *et al.*, 2007). By contrast, DEA is individually, rather than averages, oriented and deals with frontiers rather than central tendencies.

This article focuses on the Brazilian 3PL sector, with the objective of identifying the chief determinants of scale efficiency. To this end, a review of the literature was carried out, both to characterize the sector, and to justify the two-stage model adopted. More precisely, estimation of the DEA efficiency was followed by Tobit regression analysis using unbalanced panel data, thus allowing the estimation of the effect contextual variables have on sector scale efficiency. The results provided support for the positive impact of coordination processes, based on the use of information technologies and inventory synchronization mechanisms – such as just in time and milk run - on logistics performance.

The remainder of the article is comprised of five sections. Next section discusses the role of 3PLs in supply chains, the main services provided and the information technologies available to be adopted. Also presented are the scant previous studies that applied DEA to the 3PL sector in other countries. The section entitled Two-Stage DEA Modeling provides a more detailed presentation of the two-stage DEA model as well as justification for the choice of scale efficiency as a way to evaluate the impact of coordination processes on logistics performance. Then the data are analyzed and the results discussed. Last section presents the paper's conclusions.

Literature Review

As a consequence of the increasing popularity of logistics outsourcing in business and the concomitant growth in services supplied by service providers, large numbers of papers and research studies have been carried out and published in recent years in an attempt to better understand aspects related to 3PLs. Such aspects include, for example, the definition of 3PLs, the reasons for outsourcing, and the scope of the activities 3PLs provide (Zhou *et al.*, 2008).

In general terms, a 3PL is “an integrated logistics services provider that is prepared to satisfy all or almost all of a client's logistics needs in a customized way” (Fleury, 2000, p. 134). Reasons for the wave of logistics services outsourcing and the hiring of 3PLs include cost reduction, improvement of service levels, increased operational flexibility, and the enhanced ability to focus on core business (Wilding & Juriado, 2004). Based on the variety of reasons for outsourcing parts of logistics operations, the emergence of 3PLs capable of performing a range of tasks with different levels of specialization is a natural consequence (Figueiredo & Mora, 2009).

In a survey of large manufacturing firm users of 3PL services conducted in Brazil, Wanke, Arkader and Hijjar (2007) identified a strong association between the production process structure of these firms on one hand, and on the other, the type of services / technological underpinnings offered by the 3PLs. More specifically, it was evident that firms in the automotive, electric appliances, and aerospace sector tend to hire integrated 3PLs, i.e., that handle transport, storage, and inventory concurrently, and that depend heavily on information technologies. In contrast, foodstuffs, beverages, and fuels firms, for example, tend to hire 3PLs with less of a technology-intense approach – firms more geared towards providing basic transportation services.

The deployment of complex information technologies is ever more commonplace in 3PLs that coordinate a wide range of activities for their clients. In these cases the transmission of the “right information to the right person at the right time so it can be used in real time” is one of challenges of providing logistics services (Youngberg, Olsen, & Hauser, 2009). In particular, Enterprise Resource Planning (ERP) systems standardize and integrate order-related information, rendering it more reliable for the 3PL’s planning of transportation and warehousing resources relative to client inventories, and, thus, making improved operational performance possible (Chou & Chang, 2008). 3PLs have also garnered prominence in the market due to their mastery of sophisticated IT, for example, by making a variety of information, available over the Internet, including tracking of goods (Lieb & Lieb, 2008). In sum, clients consider technological prowess as a basic item expected of 3PLs (Lieb, 2005).

The recognition of the importance of coordination processes on transportation and warehousing, key supply chain functions performed by 3PLs, is by no means new (Ng, Ferrin, & Pearson, 1997). The novelty, however, is the appearance of IT applications that have transformed the operational mode of these activities and leveraged supply chain performance (Mason, Ribera, Farris, & Kirk, 2003; Stefansson & Lumsden, 2009). Transportation and warehousing management systems, for example, are key-technologies used to manage the physical flow of merchandise along the supply chain. Integrated systems (including transportation management systems, warehousing management systems and global inventory visibility via Internet) may potentially drive down costs and improve client services through a better matching of resources with demands, thus reducing shipping/receiving lead times, yielding more accurate shipping and reducing variability in response times (Mason *et al*., 2003).

Certification processes, such as those developed by the International Organization for Standardization (ISO), are another valued aspect of the 3PL industry. By means of structuring and implementation of standardized procedures, certification tends to be associated with improved service levels. For example, it has been empirically shown that ISO 9000 compliance improves the performance of logistical operations, providing positive results soon after adoption. Better performance translates into shorter lead times for products, and shorter turnover for cash circulating between suppliers, clients and service providers (Lo, Yeung, & Cheng, 2009).

According to Zhou, Min, Xu and Cao (2008), despite the numerous studies on the 3PL sector that had been completed by that time, only two attempted to evaluate the performance of the industry using DEA. This shortcoming clearly suggests a void to be filled. It must be noted, however, that DEA has already been satisfactorily employed in other segments that deal directly with logistics, such as the airline industry, (Schefczyk, 1993), airports (Pacheco & Fernandes, 2003), road passenger transport (Odeck & Alkadi, 2001), container terminals (Cullinane, Song, & Wang, 2005; Min & Park, 2005; Turner, Windle, & Dressner, 2004; Wang, Song, & Cullinane, 2002), ports in general (Panayides *et al.*, 2009) and large petroleum distribution networks (Ross & Droge, 2004).

As mentioned, studies that discuss the application of DEA, specifically in the 3PL sector, are scarce and relatively recent. Min and Joo (2006), for example, applied the technique to a group of six leading US-based 3PLs. The authors developed a benchmark as a way to identify the 3PLs developing best practices and to allow other 3PLs to emulate them. According to the authors, the DEA technique helps guide financial investments as well as assesses the impacts of investments on firm performance. The results indicated that US 3PLs, which rank among the 25 largest in 2000, could not be considered efficient during any part of the period investigated (1999-2002). It was also noted that the fall in the growth rate of US manufacturing in 2001 correlated with a decline in the operational performance of the 3PLs studied.

Hamdan and Rogers (2007) applied the DEA technique to 3PL warehousing operations. Nineteen warehouses belonging to a US 3PL were studied. The study reflects the importance of warehousing processes for the sector. For purposes of modeling, inputs were chosen that represented work, space, technology and equipment, and outputs that represented quantity produced, order fulfillment and use of space. The analyses were validated by the 3PL: four of the six warehouses classified as efficient ranked among the firm's highest performers.

Zhou *et al*. (2008) subsequently applied the DEA technique to the 3PL sector in China. Their intention, beyond establishing a benchmark for the sector, was to identify factors that could affect the performance of the 3PLs. To do so, after having measured the operational performance of the group under study, DEA scores were regressed against four potential impacting factors. Among the main conclusions was the fact that company size does not necessarily impact 3PL efficiency in a positive way, as would be expected. It was also discovered that accumulated sales revenues enabled a better use of 3PL resources, and that investments in staff team training, as well as being good for personnel retention, positively influenced 3PL performance.

In general, the greatest challenge to studies that apply DEA to logistics firms is the identification of environmental factors or contextual variables that significantly affect efficiency (Zhou *et al.*, 2008). In this study, our interest in scale efficiency is not merely to determine whether a particular 3PL is operating at – or close to – its optimum level, given the set of inputs used and the level of outputs generated: it is also to determine the objective conditions under which this can take place, analogous to the study by Ross and Droge (2004). In other words, scale efficiency can be used to determine how close each 3PL of the sample is to its corresponding most productive scale size and to what extent such distance is a consequence of coordination processes in the supply chain: management of information flows, inventory synchronization mechanisms, and scaling of resources (Wanke, 2003).

In large-scale distribution systems (the typical situation of a 3PL), different coordination processes frequently lead to different patterns of resource allocation among activities, potentially making adjustments of the scale to the operation more flexible (Ross & Droge, 2004). In this case, the results of scale efficiency may indicate opportunities for downsizing (decreasing returns to scale) or consolidation of operations (increasing returns to scale). For example, depending on alternative uses for information technologies (ITs) and mechanisms to synchronize and move the inventories by 3PLs, there may be situations in which the warehouse experiences decreasing (increasing) returns to scale due to its very large (small) size compared to inventory levels, movement of cargoes, and orders that have been allocated (Ross & Droge, 2004).

The basic idea is, therefore, to verify the role of these coordination processes when computing the scale efficiency of the 3PL, assessing whether, in fact, the 3PL engenders a more rational allocation of resources (inputs) to the demand (outputs) and, consequently, an operation close to the most productive scale size, with real time information availability as a cornerstone.

So, in this research, the Brazilian 3PL sector was analyzed for the period 2001–2009 using a two-stage DEA model. The model involved first calculating efficiency scores, followed by an analysis of unbalanced panel data using a Tobit regression model. The modeling is presented next.

Two-Stage DEA Modeling

DEA is a non-parametric method, first introduced by Charnes, Cooper and Rhodes (1978). Although published over 30 years ago, the technique continues to receive widespread attention in academia (Cook & Seiford, 2009). Based on linear programming, DEA is used to compute the relative efficiency of a group of decision-making units (DMU), based on several measures for inputs and outputs. For a given set of DMUs, inputs and outputs, the DEA computes for each DMU an efficiency score obtained from the ratio of weighted outputs to weighted inputs. There are several technical variations, differing, for example, with respect to economies of scale and the way in which the distance between inefficient DMUs and the frontier is calculated (Zhu, 2003).

Assuming there are $s = 1..S$ production units, with $x_s^T = (x_{s1},..,x_{sm})$ inputs and $y_s^T = (y_{s1},..,y_{sn})$ outputs. Vector-columns x_s and y_s form the *s*-th column of matrices *X* and *Y*. In addition, let us assume $\lambda^T = (\lambda_1,..,\lambda_s)$ is a non-negative vector and $e^T = (1,..,1) \in R^S$ is a vector of unit values. Models DEA-CCR (Charnes, Cooper, & Rhodes, 1978) and DEA-BCC (Banker, Charnes, & Cooper, 1984) are shown in equations (1) and (2) and illustrated in Figure 1:

DEA-CCR (1)
Input-oriented

$$\min_{\theta,\lambda} \theta$$
$$\text{s.t. } \theta x_s - X\lambda \geq 0$$
$$Y\lambda \geq y_s$$
$$\lambda \geq 0$$

DEA-BCC (2)
Input-oriented

$$\min_{\theta,\lambda} \theta$$
$$\text{s.t. } \theta x_s - X\lambda \geq 0$$
$$Y\lambda \geq y_s$$
$$e\lambda = 1$$

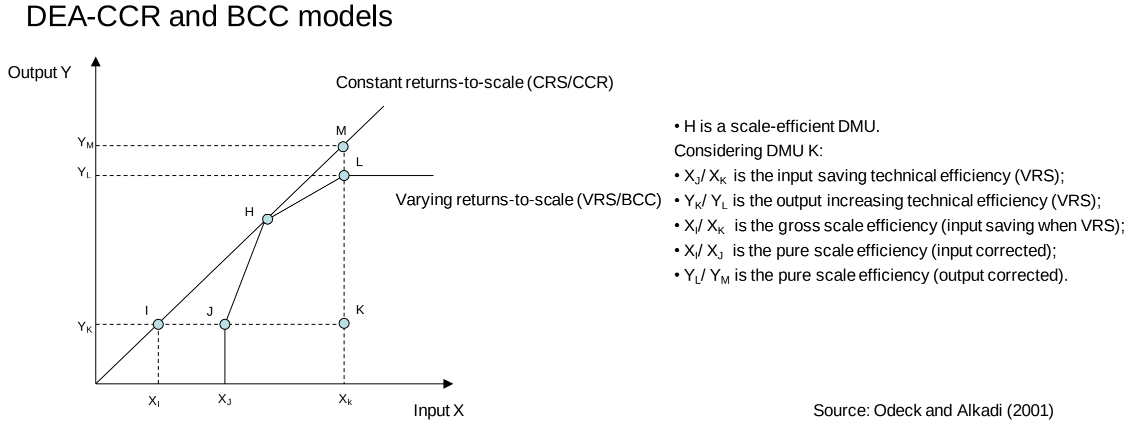

Figure 1. Efficiency measurement - DEA-CCR and BCC.

One advantage of DEA models is that the relative weights of variables need not be known *a priori*. Their efficient frontier envelops the limit of a convex polytope created from the space of inputs/outputs, where each vertex is an **efficient DMU** (Dulá & Helgason, 1996). Besides estimating efficiency scores, DEA also provides other information relevant to the inefficient DMUs. DEA identifies the efficient facet being used for comparison, the combination of the inputs that are being inefficiently used, and the deviation of specific outputs from the efficient level. It should be noted that efficient DMUs tend not to present any slack, such information being available only to inefficient DMUs (Green, Doyle, & Cook, 1996; Lin & Tseng, 2007).

The scale inefficiency is due to the increase or decrease of returns to scale, which can be computed by inspecting the sum of the weights under the CCR model specification. If the sum is equal to one, the law of constant returns to scale prevails; however, if the sum is less than one or more than one, increasing returns to scale and decreasing returns to scale prevail, respectively, assuming an input-oriented model. Also according to Cooper, Seiford and Tone (2007), in order to identify the degree to which the inefficiency of a DMU is due to inefficient operations or to its scale efficiency, scale efficiency is computed using the ratio $SE = \theta_{CCR} / \theta_{BCC}$, where θ_{CCR} and θ_{BCC} denote, respectively, the CCR and BCC efficiency scores for a given DMU . It is important to point out that the maximum value of *SE* is 1, indicating that the DMU is operating at the most productive scale size.

The approaches to the statistical treatment of the variations in the scores produced using DEA have evolved over the course of the years; see, for example Banker (1993) and Simar and Wilson (2007). As a depiction of this evolution, Cooper *et al.* (2007) point to the growing number of studies that combine the results of DEA, in a first stage, with those of multivariate data analysis, such as regression analysis and stochastic frontier analysis (SFA), in a second stage. According to Fried, Lovell, Schmidt and Yaisawarng (2002), such two-stage DEA approaches are the fruit of recognition on the part of researchers that environmental factors or contextual variables can significantly influence efficiency scores. For example, according to those authors, managerial competence (or incompetence) is insufficient to explain individual variations in efficiency, given that environmental factors, contextual variables, or even statistical noise could exercise some influence over measured performance. The adequate control for these impacts might suggest possible paths for a DMU to become more efficient (see, for example, Souza, Gomes, Magalhães, & Ávila, 2007).

In this article, the multivariate analysis in the second stage makes use of Tobit regression applied to an unbalanced panel of data relative to the Brazilian 3PL industry, for the period 2001–2009. According to Turner, Windle and Dressner (2004), because the dependent variable (scale efficiency) is continuous, but truncated at 1, the ordinary least squares approach is inappropriate, since it could produce inconsistent estimators. Along general lines, the base case model for Tobit regression is similar to that for ordinary least squares; however, the former assumes a truncated normal distribution in lieu of a normal distribution and employs maximum likelihood estimation (Greene, 2007). Banker (1993), nevertheless, also opens up the possibility of using other adequate distributions to the Tobit regression, such as the exponential distribution and the half-normal distribution.

In fact, DEA-based procedures using Tobit regression in the second stage perform as well as the best of the parametric methods in the estimation of the impact contextual variables have on productivity (Banker & Natarajan, 2008). Finally, it should be noted that the use of non-parametric tests, such as those presented in Banker and Natarajan (2004) and Gomes, Soares-de-Melo, Angulo-Meza and Mangabeira (2009), constitute an alternative used just as commonly as Tobit regressions in similar situations.

Differently from other non-parametric methods, Tobit regression can be easily applied to (un)balanced panel data (Greene, 2007). Generally speaking, panel data models allow the examination of fixed or random effects of a specific firm or of time periods on efficiency scores (Park, 2005). Fixed effects are tested by the (incremental) F test, while random effects are examined by the Lagrange Multiplier (LM) test (Breusch & Pagan, 1980). If data are severely unbalanced, a random effects model is preferable due to the lack of discerning of fixed effects on how group and time affect the intercept (Park, 2005).

For random effects models — according to Greene (2007), the model most frequently used —, the basic assumptions are: the random effect u_i is the same for all periods and should not be correlated with other regressors; the angular coefficients are the same for all groups and periods; and ε_{it} , the stochastic component of the model, does not correlate across periods.

Analysis of Data and Discussion of Results

Taking the preceding discussion as a starting point, this study intends to determine the main factors that affect scale efficiency in the Brazilian 3PL industry. The data used was collected from the special edition dedicated to the 3PL sector in Revista Tecnologística (2001–2009), published each year in June or July. In addition, it should be noted that the original datasets were cleaned up, rejecting the independent variables that were not collected for all of the individuals listed in the panel, in order to render the information sufficiently homogeneous for the analysis.

Conducting a secondary analysis of existing data saved the time and resources needed to collect primary data. However, the benefits of saving time and effort must be weighted against the limitations due to the level of data and the lack of specificity of the data for the secondary project (Shepard *et al.*, 1999). All the data collected from Revista Tecnologística are objective measures based on explicit criteria, represented by metric (inputs and outputs) and nominal scales (most of the contextual variables, with the exception of age). As single-item indicators of objective measures, data can be valid and reliable indicators of the variables under consideration (Youngblut & Casper, 1993).

Although the data set provided by Revista Tecnologística might not have been collected in the context of a theoretical model, a theoretical model can still be identified and applied to the research process and data that are theoretically consistent can be identified (Moriarty *et al.*, 1999; Zill & Daly, 1993). The importance of this step in secondary analysis cannot be underestimated (Shepard *et al.*, 1999). As with any quantitative method of research, selection of the variables to be studied must first involve combing through the model to identify critical concepts. The theoretical concepts are then matched with appropriate variables form the data set.

In order to build the DEA models, four inputs and two outputs common to all 3PLs in the study were initially selected. Following the example of previous studies (Zhou *et al.*, 2008), measurement units were chosen that would represent resources that are critical not only financially, but also for the execution of logistical services. With respect to inputs, the 3PL’s total number of staff involved in either strategic activities or operational activities is the measure used to represent labor force utilization.

Beyond that measure, selection of measures that translate how the 3PLs handle warehousing is also necessary, warehousing being the activity that grew the most over the time period (until 2008) in Brazil (Marino, 2008). According to the author, the availability of warehousing services is greater than transportation services in the 3PL sector. This being the case, the total area of owned warehouses was selected as an input for the model. It is also important to take into account those situations where the 3PL operates the warehouse, although the asset itself belongs to the client (Marino, 2008). In the latter case, that warehouse, which functions as one of the 3PL’s operational resources but not as one of its assets, is computed based on the total number of the client's warehouses, constituting the model’s last input.

On the outputs side, measures that would represent financial and operational aspects were initially selected. As such, since the 3PL’s gross revenues portray the product of service-provided sales, gross revenues were selected as an output. The firm’s total number of clients, in a similar way, reflects its operational complexity — a large client roster looks good, not only in the market, but also in terms of suggesting greater ability in the management of different logistics services needs.

Several methods have been proposed in the literature that suggest limiting the number of variables in relation to the number of DMUs (Wagner & Shimshak, 2007). Some studies have suggested that judgment should be performed by specialists in order to indicate which variables are the most relevant for the DEA model (Golany & Roll, 1989). Other studies have suggested regression analysis, in order to indicate highly correlated variables as redundant (Lewin, Morey, & Cook, 1982); or even application of DEA to smaller models, in order to rank the effect of variables on efficiency scores (Wagner & Shimshak, 2007).

So, in order to check on the possibility of reducing the number of inputs and outputs to be considered for the analysis, correlation analyses were performed. Table 1 shows the correlation coefficients between the pairs of inputs and the pair of outputs. Because the serial correlations are relatively low, we decided to keep all inputs and outputs in the analysis.

Table 1

Correlations between Inputs and Outputs

INPUTS	Number of Staff	Total Warehouse Area	Total Owned Warehouses	Total Client Warehouses
Number of Staff	1.00			
Total Warehouse Area	0.50	1.00		
Total Owned Warehouses	0.29	0.46	1.00	
Total Client Warehouses	0.48	0.38	0.26	1.00
OUTPUTS	Number of Clients	Gross Revenues		
Number of Clients	1.00			
Gross Revenues	0.11	1.00		

In the first stage, the DEA-CCR and BBC models were executed nine times using Frontier Analyst 4.0.10, i.e., once for each year for the period 2001–2009. More specifically, the unbalanced panel data pertaining to the Brazilian 3PL industry comprises 122 individuals; totaling 213 observations distributed over the course of these nine years (see Appendix).

Table 2 shows descriptive statistics of the scores computed for the CCR and BCC models and for scale efficiency for the 2001–2009 years. As expected, the CCR models returned efficiency scores that were lower than those computed for the BCC models. In other words, the CCR models identified fewer efficient 3PLs than the BCC models for each year. This result is unsurprising, given that the CCR model assumes a production technology with constant (linear) returns of scale (cf. Figure 1). The BCC model, on the other hand, assumes variable returns to scale, which more closely parallels reality since they reflect the technical efficiency of different DMUs. In addition, it can be seen that very few 3PLs operate at the most productive scale size (when *SE* is equal to 1).

Table 2

Summary of Efficiencies Calculated by Year

SCORE	YEAR	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
CCR	Average	0.19	0.57	0.43	0.62	0.53	0.45	0.44	0.53	0.28	0.40
	Minimum	0.00	0.15	0.06	0.10	0.20	0.14	0.05	0.09	0.01	0.00
	Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Standard deviation	0.28	0.33	0.34	0.31	0.30	0.33	0.36	0.33	0.34	0.35
	Coefficient of variation	1.47	0.59	0.80	0.50	0.57	0.74	0.82	0.62	1.23	0.87
	# of efficient DMUs	3	3	4	5	2	1	6	7	7	38
	% of efficient DMUs	9%	27%	17%	25%	17%	20%	20%	23%	14%	18%

Continue

Table 2 (continued)

SCORE	YEAR	2001	2002	2003	2004	2005	2006	2007	2008	2009	All
BCC	Average	0.70	0.87	0.87	0.80	0.83	0.63	0.65	0.77	0.72	0.75
	Minimum	0.17	0.37	0.47	0.25	0.25	0.31	0.06	0.24	0.11	0.06
	Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Standard deviation	0.29	0.21	0.19	0.28	0.31	0.25	0.34	0.27	0.34	0.35
	Coefficient of variation	0.42	0.24	0.22	0.35	0.37	0.39	0.52	0.35	0.48	0.46
	# of efficient DMUs	11	10	9	12	11	4	13	11	27	111
	% of efficient DMUs	33%	91%	39%	60%	92%	80%	43%	37%	55%	52%
SE	Average	0.24	0.65	0.48	0.78	0.65	0.71	0.63	0.70	0.39	0.53
	Minimum	0.01	0.21	0.06	0.27	0.24	0.26	0.17	0.09	0.02	0.01
	Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Standard deviation	0.28	0.32	0.34	0.26	0.26	0.32	0.30	0.32	0.36	0.36
	Coefficient of variation	1.13	0.49	0.70	0.33	0.39	0.46	0.48	0.46	0.92	0.67
	# of efficient DMUs	3	3	4	6	2	1	6	7	7	39
	% of efficient DMUs	9%	27%	17%	30%	17%	20%	20%	23%	14%	18%
Total DMUs		33	11	23	20	12	5	30	30	49	213
# of DMUs – CRS		11	10	9	12	11	4	13	11	7	88
# of DMUs VRS – Increasing		-	0	1	1	0	0	1	1	41	45
# of DMUs VRS – Decreasing		22	1	13	7	1	1	16	18	1	80

Note. CRS = constant returns to scale / VRS = variable return to scale

In the second stage, in order to identify the determinants of scale efficiency of 3PLs operating nationally, traditional characteristics and services commonly offered by 3PLs in Brazil were researched. Once again, datasets from *Revista Tecnologística* were used. Such characteristics/services serve as study control variables, since they comprise neither process inputs nor products, but, rather, their attributes, in a total of twenty-five contextual variables. Table 3 shows the list of binary control variables (i.e., that use a dummy scale) considered in the study. These variables are terminal, i.e., they assume the value of a unit if the observation has the mentioned characteristic and zero otherwise. It is understood that *k*-1 dummy variables are required to represent a variable with *k* categories (Levine, Stephan, Krehbiel, & Berenson, 2007). The base-category is the absence itself of this characteristic. Besides these variables, the only exception should be mentioned: age of the 3PL, measured in months (metric scale).

Table 3

Categorical Variables Used in this Study

ISO Certification	Internet Queries	Stock Control	Project Development	Distribution
Packaging	ERP	Foreign Offices	Intermodal Management	Customs Clearance
JIT – Just in time	Reverse Logistics	Milk Run	Kit Assembly	Door to door
Local Operation	Regional Operation	Tracking - Own Radio	Tracking - Outsourced Radio	Tracking - Outsourced Satellite
Tracking - Own Satellite	Routing – Own	Inspections Support	Transfers	WMS

Note. (1 = characteristic present; 0 = characteristic not present).

Given the large number of potential contextual variables to be considered, data reduction techniques assume particular relevance here. Several authors have used some of these techniques together with DEA. Adler and Golany (2001) and Adler and Berechman (2001), for instance, employed principal component analysis. The use of factor analysis was proposed by Vargas and Bricker (2000) and implemented in Jenkins and Anderson (2003) and Nadimi and Jolai (2008). Specifically, factor analysis is an appropriate procedure for data reduction based on observed variables and on existing theoretical constructs (Hair, Anderson, Tatham, & Black, 2005).

In order to make the concept of coordination processes and information technologies operational, a factor analysis with Varimax standardized rotation was conducted – with the use of SPSS 15.0 package - in order to reduce these 25 categorical variables into a smaller number of dimensions. Specifically, factor analysis is an appropriate procedure for data reduction based on observed variables and on existing theoretical constructs (Hair *et al.*, 2005). Table 4 presents the six factors related to coordination processes and information technologies – the theoretical constructs of this research - , obtained from the variables presented in Table 3.

Table 4

Rotated Component Matrix - Coordination Processes and Information Technologies

FACTOR 1 - Stock and warehousing related ITs and services	Stock control	0.75	0.08	(0.04)	(0.24)	0.09	(0.09)
	Packaging	0.74	(0.17)	(0.08)	0.23	(0.13)	(0.04)
	Kit assembly	0.83	(0.07)	(0.05)	0.14	(0.17)	0.10
	Inspections support	0.67	(0.18)	0.17	0.18	0.07	0.25
	WMS	0.55	0.14	0.10	(0.03)	0.28	(0.31)
FACTOR 2 -Owned tracking and routing ITs	Routing – Own	0.05	0.81	0.13	0.11	0.07	0.10
	Tracking – Own satellite	(0.12)	0.85	0.09	0.07	0.03	(0.03)
	Tracking – Own radio	(0.11)	0.75	0.16	0.12	(0.05)	0.21
FACTOR 3 - Classical transportation related services	Distribution	0.07	0.09	0.73	0.02	0.02	(0.16)
	Door to door	(0.07)	0.15	0.72	0.15	0.01	(0.03)
	Transfers	(0.07)	0.09	0.73	0.21	0.00	(0.02)
	Reverse logistics	0.06	0.10	0.55	0.04	0.07	0.08
FACTOR 4 - Express logistics related ITs and services	Tracking – Outsourced satellite	0.02	0.28	0.14	0.55	(0.06)	(0.30)
	Tracking – Outosourced radio	(0.00)	(0.07)	0.24	0.65	(0.06)	0.10
	Just in time	0.19	0.20	(0.07)	0.63	0.05	0.22
	Milk run	0.05	0.32	0.25	0.57	0.17	0.10
	Intermodal management	0.17	(0.19)	0.31	0.57	0.18	0.10
	ERP	(0.06)	0.13	0.05	0.53	0.26	(0.21)
FACTOR 5 - Foreign Operations and ISO Certification	ISO certification	(0.04)	0.30	0.18	0.08	0.54	0.32
	Foreign offices	(0.14)	(0.10)	(0.07)	0.00	0.79	(0.05)
	Customs clearance	0.22	0.02	0.12	0.28	0.62	(0.03)
FACTOR 6 – Age	Age	0.02	0.16	(0.11)	0.14	0.17	0.56

Note. KMO = 0.685; Chi-square = 1475.703 (Sig. = 0.000); All factor loads greater than 0.50 should be interpreted.

LIMDEP 9.0 econometric software was used to carry out the Tobit regression on the unbalanced panel data, using the random effects model. The results were adjusted as a function of the heteroscedasticity generated due to the fact the groups are of differing sizes (Greene, 2007). With respect to the acceptable level of significance, the range 0.05–0.10 was established, as has been customary in exploratory research studies on logistics (Mentzer & Flint, 1997; Wanke & Hijjar, 2009). Table 5 shows the Tobit regression results for each one of these six factors.

Table 5

Results of Tobit Regression for Unbalanced Panel Data

Tobit Regression - Random Effects (*)					
Variable	**Coefficient**	**Standard Error**	**b/St.Err.**	**P[Z>z]**	**Mean of X**
FACTOR 1 - Inventory and warehousing related ITs and services	.011	.052	.215	.829	.000
FACTOR 2 -Owned tracking and routing ITs	.012	.035	.349	.727	.000
FACTOR 3 - Classical transportation related services	.003	.055	.068	.945	.000
FACTOR 4 - Express logistics related ITs and services	.139	.032	4.301	.000 (***)	.000
FACTOR 5 - Foreign Operations and Certification	-.026	.039	-.674	.500	.000
FACTOR 6 – Age	.104	.044	2.370	.0178 (***)	.000
Sigma (v)	.328	.028	11.704	.0000	
Sigma (u)	.586	.038	15.249	.0000	
Marginal Effects (**)					
Variable	**Coefficient**	**Standard Error**	**b/St.Err.**	**P[Z>z]**	**Mean of X**
FACTOR 1 - Inventory and warehousing related ITs and services	.005	.026	.215	.8299	.000
FACTOR 2 -Owned tracking and routing ITs	.006	.026	.241	.8094	.000
FACTOR 3 - Classical transportation related services	.001	.026	.073	.9421	.000
FACTOR 4 - Express logistics related ITs and services	.069	.026	2.677	.0074 (***)	.000
FACTOR 5 - Foreign Operations and Certification	-.013	.026	-.508	.6118	.000
FACTOR 6 – Age	0.052	.026	2.008	.0446 (***)	.000
Sigma(v)	.000000		(Fixed parameter)		

Note. (*) McFadden's pseudo-R^2 = .214; (*) Chi-squared = 102.672; (*) Degrees of freedom = 1; (*) Prob [Chi-squared > value] = .0000000; (*) Unbalanced panel contains 122 individuals; (**) Conditional average = .1296; (**) Scale Factor for marginal effects = .4989; (***) Significant variables.

The results presented in Table 5 confirm the impact of coordination processes on the supply chain and, in particular, the impact of ITs on increased scale efficiency for Brazilian 3PLs. The adoption of express logistics related ITs and services (FACTOR 4) merit attention: radio and satellite tracking (outsourced), ERP, just in time, milk run, and intermodal management.

Embedded within these results, it should be noted that inventory-related coordination processes, such as just in time and milk run, presented significant positive impacts on efficiency. A possible justification for this effect is the fact that inventory-related coordination processes allow for a greater integration of client product flow with the 3PL transportation and warehousing resources needed for their movement.

It should also be noted that the age (FACTOR 6) of the 3PL also has a positive effect on scale efficiency. In addition to the experience accumulated from operating for a longer time in the market, we should also take into account the fact that the relationship between the contracting company and the 3PL tends to become more focused, thereby allowing for a better tailoring of resources to client exigencies (Bhatnagar, Sohal, & Millen, 1999).

3PL managers may use these results as guidance for future steps towards higher levels of scale efficiency. **What ITs should be developed (acquired) first?** and **what kinds of logistics services should be offered to shippers?** constitute example of questions that may direct 3PLs through a shorter path to the most productive scale size, helping them in establishing a business plan or a course of action over time.

The findings of this study may also serve as a valuable tool for shippers to benchmark their logistics services providers against each other. Even though no link among scale efficiency, costs, and service levels is claimed in the evidence presented and discussed in this paper, it serves as indication of the directions shippers should take when hiring 3PL services. The basic underlying idea is that 3PLs with higher levels of scale efficiency may simultaneously achieve lower costs and higher service levels, thus benefiting shippers in terms of competitive advantages.

Conclusions

This research differs from previous studies by analyzing the Brazilian 3PL sector between 2001 and 2009 using a two-stage DEA model. In the first stage, DEA is used to calculate efficiency scores for each 3PL firm and, in the second stage, these scores are used as the dependent variable in the corresponding Tobit regression model for unbalanced panel data. Contextual variables such as ITs adopted and services provided by the 3PLs constituted the regressors or the independent variables.

Previous attempts to apply DEA to 3PL industry indicate that the identification of contextual variables (environmental factors) that significantly affect efficiency is, in general, the most relevant methodological issue to studies that apply DEA to logistics firms. Particularly, only Zhou *et al.* (2008) managed to regress DEA scores against contextual variables. However, other DEA methodological issues - related to the sample size adequacy required in order to avoid concentration of scores in one, the proper use of Tobit regression in order to handle with truncated scores in zero and one, and the use of panel data models so as to adequately regress different efficiency scores against contextual variables - were not observed in the scant previous studies.

The results presented here provide support for the evidence in the literature that coordination mechanisms in the supply chain, including exploitation of IT and inventory synchronization mechanisms, favor a more rational allocation of 3PL resources (inputs) to client demands (outputs) and, as a corollary, favor an operation that, supported by the availability of real time information, is close to the most productive scale size.

The results also lend a contribution of a practical nature to the 3PL sector in Brazil. More precisely, the study enables managers and investors to use the results presented in Table 6 as a resource for decision-making. A range of drivers were statistically validated, revealing areas where there is space not only for more investment, but also for the development of future studies to enable a better understanding of the relationship between these drivers and sector scale efficiency.

Brazilian 3PLs are more and more geared towards an increased availability of services, with steadily falling costs, in an effort to buttress an ever-more competitive marketplace. As such, it is hoped that 3PLs often turn to ways to evaluate their performance as they expand, both quantitatively as well as qualitatively. The structure used in this article can be applied as a tool in both senses. DEA models the situation of the 3PL at the moment of application, aiding to direct resources to critical areas that significantly affect performance. The model constructed above can easily be modified to develop in parallel with a firm's structural parameters and to present up to date results.

Finally, the fact of working with secondary data instead of primary data brings certain limitations to this work, mainly with respect to the set of inputs, outputs, and contextual variables used in the analysis, which may not cover all aspects relevant to build and assess an efficiency frontier.

Received 8 April 2010; received in revised form 17 December 2010.

References

Adler, N., & Berechman, J. (2001). Measuring airport quality from the airlines' viewpoint: an application of data envelopment analysis. *Transport Policy, 8*(3), 171-181. doi: 10.1016/S0967-070X(01)00011-7

Adler, N., & Golany, B. (2001). Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. *European Journal of Operations Research, 132*(2), 260-273. doi: 10.1016/S0377-2217(00)00150-8

Banker, R. D. (1993). Maximum likelihood, consistency and DEA: a statistical foundation. *Management Science, 39*(10), 1265-1273. doi: 10.1287/mnsc.39.10.1265

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for the estimation of technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078-1092. doi: 10.1287/mnsc.30.9.1078

Banker, R. D., & Natarajan, R. (2004). Statistical tests based on DEA efficiency scores. In W. W. Cooper, L. M. Seiford, & J. Zhu (Eds.), *Handbook on data envelopment analysis* (pp. 299-321). Boston: Kluwer International Series.

Banker, R. D., & Natarajan, R. (2008) Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research, 56*(1), 48-58. doi: 10.1287/opre.1070.0460

Bhatnagar R., Sohal, A. S., & Millen, R. (1999). Third party logistics services: a Singapore perspective. *International Journal of Physical Distribution & Logistics Management, 29*(9), 569-587. doi: 10.1108/09600039910287529

Breusch, T. S., & Pagan, A. R. (1980). The lagrange multiplier test and its applications to model speficiation in econometrics. *Review of Economic Studies, 47*(1), 238-253.

Centro de Estudos em Logística. (2009). *Panorama logístico CEL/COPPEAD – terceirização logística no Brasil*. Rio de Janeiro: COPPEAD/UFRJ.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429-444. doi: 10.1016/0377-2217(78)90138-8

Chou, S., & Chang, Y. (2008). The implementation factors that influence the ERP (enterprise resource planning) benefits. *Decision Support Systems, 46*(1), 149-157. doi :10.1016/j.dss.2008.06.003

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA) – thirty years on. *European Journal of Operational Research, 192*(1), 1-17. doi: 10.1016/j.ejor.2008.01.032

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*. New York: Springer.

Cullinane, K., Song, D. W., & Wang, T. (2005). The application of mathematical programming approaches to estimating container port production efficiency. *Journal of Productivity Analysis, 24*(1), 73-92. doi: 10.1007/s11123-005-3041-9

Dulá, J. H., & Helgason, R. V. (1996). A new procedure for identifying the frame of the convex hull of a finite collection of points in multidimensional space. *European Journal of Operational Research, 92*(2), 352-367. doi: 10.1016/0377-2217(94)00366-1

Figueiredo, K. F., & Mora, D. M. (2009). A segmentação dos operadores logísticos no mercado brasileiro de acordo com suas capacitações para oferecer serviços. *RAC-Eletrônica, 3*(1), 123-141. Retrieved from http://www.anpad.org.br/periodicos/arq_pdf/a_817.pdf

Fleury, P. F. (2000) Vantagens competitivas e estratégicas do uso de operadores logísticos. In P. F. Fleury, K. F. Figueiredo, & P. F. Wanke (Eds.), *Logística empresarial: a perspectiva brasileira* (pp. 133-142). São Paulo: Atlas.

Fleury, P. F., & Ribeiro, A. F. M. (2003). A indústria de provedores de serviços logísticos no Brasil. In P. F. Fleury, K. F. Figueiredo, & P. F. Wanke (Eds.), *Logística e gerenciamento da cadeia de suprimentos: planejamento do fluxo e dos recursos* (pp. 302-312). São Paulo: Atlas.

Fried, H. O., Lovell, C. A. K., Schmidt, S. S., & Yaisawarng, S. (2002). Accounting for environmental effects and statistical noise in data envelopment analysis. *Journal of Productivity Analysis, 17*(1-2), 157-174. doi: 10.1023/A:1013548723393

Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega, 17*(3), 237-250. doi: 10.1016/0305-0483(89)90029-7

Gomes, E. G., Soares-de-Mello, J. C. C. B., Souza, G. S., Angulo-Meza, L., & Mangabeira, J. A. C. (2009). Efficiency and sustainability assessment for a group of farmers in the Brazilian Amazon. *Annals of Operations Research, 169*(1), 167-182. doi: 10.1007/s10479-008-0390-6

Green, R., Doyle, J., & Cook, W. D. (1996). Efficiency bounds in data envelopment analysis. *European Journal of Operational Research, 89*(3), 482-490. doi: 10.1016/0377-2217(95)00043-7

Greene, W. H. (2007). *LIMDEP version 9.0 – Econometric modeling guide*. New York: Econometric Software, Inc.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2005). *Análise multivariada de dados*. Porto Alegre: Bookman.

Hamdan, A., & Rogers, K. J. (2007). Evaluating the efficiency of 3PL logistics operations. *International Journal of Production Economics, 113*(1), 235-244. doi: 10.1016/j.ijpe.2007.05.019

Jenkins, L., & Anderson, L. (2003). A multivariate statistical approach to reducing the number of variables in data envelopment analysis. *European Journal of Operational Research, 147*(1), 51-61. doi: 10.1016/S0377-2217(02)00243-6

Levine, D. M., Stephan, D. F., Krehbiel, T. C., & Berenson, M. L. (2007). *Estatística: teoria e aplicações*. São Paulo: LTC.

Lewin, A., Morey, R., & Cook, T. (1982). Evaluating the administrative efficiency of courts. *Omega*, *10*(4), 401-411. doi: 10.1016/0305-0483(82)90019-6

Lieb, R. C. (2005). The 3PL industry: where it's been, where it's going. *Supply Chain Management Review*, *9*(6), 20-27.

Lieb, R. C., & Lieb, K. J. (2008). Why 3PLs need to build their brand? *Supply Chain Management Review*, *12*(8), 46-52.

Lin, L. C., & Tseng, C. C. (2007). Operational performance evaluation of major container ports in the Asia-Pacific region. *Maritime Policy & Management*, *34*(6), 535-551. doi: 10.1080/03088830701695248

Lo, C. K. Y., Yeung, A. C. L., & Cheng, T. C. E. (2009). ISO 9000 and supply chain efficiency: empirical evidence on inventory and account receivable days. *International Journal of Production Economics*, *118*(2), 367-374. doi: 10.1016/j.ijpe.2008.11.010

Marino, S. (2008). Mercado promissor. *Revista Tecnologística*, *19*(151), 68-73.

Mason, S. J., Ribera, P. M., Farris, J. A., & Kirk, R. G. (2003). Integrating the warehousing and transportation functions of the supply chain. *Transportation Research Part E – Logistics & Transportation Review*, *39*(2), 141-159. doi: 10.1016/S1366-5545(02)00043-1

Mentzer, J. T., & Flint, D. J., (1997). Validity in logistics research. *Journal of Business Logistics*, *18*(1), 199-216.

Min, H., & Joo, S. J. (2006). Benchmarking the operational efficiency of third party logistics providers using data envelopment analysis. *Supply Chain Management: An International Journal*, *11*(3), 259-265. doi: 10.1108/13598540610662167

Min, H., & Joo, S. J. (2009). Benchmarking third-party logistics providers using data envelopment analysis: an update. *Benchmarking: an international journal*, *16*(5), 572-587. doi: 10.1108/14635770910987814

Min, H., & Park, B.-I. (2005). Evaluating the inter-temporal efficiency trends of international container terminals using data envelopment analysis. *International Journal of Integrated Supply Management*, *1*(3), 258-277. doi: 10.1504/IJISM.2005.005950

Moriarty, H. J., Deatrick, J. A., Mahon, M. M., Feetham, S. L., Carroll, R. M., Shepard, M. P., & Orsi, A. J. (1999). Issues to consider when choosing and using large national databases for research of families. *Western Journal of Nursing Research*, *21*(2), 143-153. doi: 10.1177/01939459922043794

Nadimi, R., & Jolai, F. (2008). Joint use of factor analysis (FA) and data envelopment analysis (DEA) for ranking of data envelopment analysis. *International Journal of Mathematical, Physical and Engineering Sciences*, *2*(4), 218-222.

Ng, B., Ferrin, B. G., & Pearson, J. N. (1997). The role of purchasing/transportation in cycle time reduction. *International Journal of Operations & Production Management*, *17*(6), 574-591. doi: 10.1108/01443579710167267

Odeck, J., & Alkadi, A. (2001). Evaluating efficiency in the Norwegian bus industry using data envelopment analysis. *Transportation*, *28*(3), 211-232. doi: 10.1023/A:1010333518966

Pacheco, R. R., & Fernandes, E. (2003). Managerial efficiency of Brazilian airports. *Transportation Research Part A*, *37*(8), 667-680. doi: 10.1016/S0965-8564(03)00013-2

Panayides, P. M., Maxoulis, C. N., Wang, T. F., & Ng, K. (2009). A critical analysis of DEA applications to seaport economic efficiency measurement. *Transport Reviews, 29*(2), 183-206. doi: 10.1080/01441640802260354

Park, H. M. (2005). *Linear regression models for panel data using SAS, Stata, LIMDEP, and SPSS*. Retrieved April 15, 2005, from http://www.indiana.edu/~statmath/stat/all/panel/panel.pdf

Ross, A. D., & Droge, C. (2004). An analysis of operations efficiency in large-scale distribution systems. *Journal of Operations Management, 21*(6), 673-688. doi: 10.1016/j.jom.2003.11.003

Schefczyk, M. (1993). Operational performance of airlines: an extension of traditional measurement paradigms. *Strategic Management Journal, 14*(4), 301-317. doi: 10.1002/smj.4250140406

Shepard, M. P., Carroll, R. M., Mahon, M. M., Moriarty, H. J., Feetham, S. L., Deatrick, J. A., & Orsi, A. J. (1999). Conceptual and pragmatic considerations in conducting a secondary analysis – an example from research of families. *Western Journal of Nursing Research, 21*(2), 154-167. doi: 10.1177/01939459922043802

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semiparametric models of production processes. *Journal of Econometrics, 136*(1), 31-64. doi: 10.1016/j.jeconom.2005.07.009

Souza, G. S., Gomes, E. G., Magalhães, M. C., & Avila, A. F. D. (2007). Economic efficiency of Embrapa`s research centers and the influence of contextual variables. *Pesquisa Operacional, 27*(1), 15-26. doi: 10.1590/S0101-74382007000100002

Stefansson, G., & Lumsden, K. (2009). Performance issues of smart transportation management systems. *International Journal of Productivity and Performance Management, 58*(1), 55-70. doi: 10.1108/17410400910921083

Turner, H., Windle, R., & Dressner, M. (2004). North American containerport productivity: 1984-1997. *Transportation Research Part E, 40*(4), 339-356. doi: 10.1016/j.tre.2003.06.001

Vargas, C., & Bricker, D. (2000). Combining DEA and factor analysis to improve evaluation of academic departments given uncertainty about the output constructs [Working Paper nº 1]. *University of Iowa*, Iowa City, USA.

Wang, T. F., Song, D. W., & Cullinane, K. (2002, June). The applicability of data envelopment analysis to efficiency measurement of container ports. *Proceedings of the IAME Panama International Steering Comitee*, Panamá.

Wagner, J. M., & Shimshak, D. G. (2007). Stepwise selection of variables in data envelopment analysis: procedures and managerial perspectives. *European Journal of Operational Research, 180*(1), 57-67. doi: 10.1016/j.ejor.2006.02.048

Wanke, P. F. (2003). Logística, gerenciamento de cadeias de suprimento e estratégia logística. In P. F. Fleury, K. F. Figueiredo, & P. F. Wanke (Eds.), *Logística e gerenciamento da cadeia de suprimentos: planejamento do fluxo e dos recursos* (pp. 27-47). São Paulo: Atlas.

Wanke, P. F., Arkader, R., & Hijjar, M. F. (2007). Logistics sophistication, manufacturing segments and the choice of logistics providers. *International Journal of Operations & Production Management, 27*(5), 542-559. doi: 10.1108/01443570710742401

Wanke, P. F., & Hijjar, M. F. (2009). Exportadores brasileiros: estudo exploratório das percepções sobre a qualidade da infraestrutura logística. *Produção, 19*(1), 143-162. doi: 10.1590/S0103-65132009000100010

Wilding, R., & Juriado, R. (2004). Customer perceptions on logistics outsourcing in the European consumer goods industry. *International Journal of Physical Distribution & Logistics Management, 34*(8), 28-48. doi: 10.1108/09600030410557767

Youngberg, E., Olsen, D., & Hauser, K. (2009). Determinants of professionally autonomous end user acceptance in an enterprise resource planning system environment. *International Journal of Information Management*, *29*(2), 138-144. doi: 10.1016/j.ijinfomgt.2008.06.001

Youngblut, J. M., & Casper, G. R. (1993). Focus on psychometrics: single-item indicators in nursing research. *Research on Nursing in Health*, *16*(6), 459-465. doi: 10.1002/nur.4770160106

Zhou, G., Min, H., Xu, C., & Cao, Z. (2008). Evaluating the comparative efficiency of Chinese third-party logistics providers using data envelopment analysis. *International Journal of Physical Distribution & Logistics Management*, *38*(4), 262-279. doi: 10.1108/09600030810875373

Zhu, J. (2003). *Quantitative models for performance evaluation and benchmarking: data envelopment analysis with spreadsheets and DEA excel solver*. New York: Springer.

Zill, N., & Daly, M. (1993). *Researching the family: a guide to survey and statistical data in US families*. Washington: U.S. Department of Health and Human Services.

APPENDIX

Table 1

Unbalanced Panel Data for the Brazilian 3PL Industry

2001	2002	2003	2004	2005	2006	2007	2008	2009
						4PL		
ABRANGE								
								ADL
			AGM	AGM		AGM		
						AGR	AGR	AGR
ÁGUIA								
AGV	AGV					AGV	AGV	AGV
ARGIMPEL								
	ARMAVALE							
						ATLAS	ATLAS	ATLAS
			BETA					
					BINOTTO	BINOTTO	BINOTTO	
								BMS
BRASEX								
		BRASILIENSE	BRASILIENSE			BRASILIENSE	BRASILIENSE	
BRAVO	BRAVO	BRAVO	BRAVO		BRAVO	BRAVO		
							BRAZILIAN	
BRILHANTE								
								BRUCAI
							BUENO	
								CAM
								CARDOSO
						CBCE		
						CELERE		
						CESA		CESA
								CEVA
COLUMBIA	COLUMBIA			COLUMBIA				COLUMBIA
			COMINT	COMINT		COMINT		
CONSEIL		CONSEIL						
			CONTINENTAL					
COOPERCARGA				COOPERCARGA				
CRAGEA			CRAGEA		CRAGEA		CRAGEA	

Continue

Table 1 (continued)

2001	2002	2003	2004	2005	2006	2007	2008	2009
							CSI	CSI
CUSTOM								
DANZAS	DANZAS							
DEICIMAR								
DELARA	DELARA					DELARA		
								DELTA
								DEX
DHL-EXCEL								
DRAGO								
							DRY PORT	
								DSR
						EBA		
EICHENBERG			EICHENBERG					
		ELBA						
ENAR	ENAR							
ESTRADA	ESTRADA	ESTRADA	ESTRADA			ESTRADA	ESTRADA	
				EUDMARCO				
								EXATA
								EXOLOGISTICA
			EXPLIMEIRA	EXPLIMEIRA				
								EXP_JUNDIAI
		FLEXIL					FLEXIL	
		FLUXO						
		GAT				GAT		
								GEFCO
							GOLDEN	
		GPT						
						GRANDEABC		
							GRANVALE	GRANVALE
			GRECCO					GRECCO
GTECH		GTECH	GTECH					GTECH
			INTERMAR	INTERMAR		INTERMAR		
INTERMOD								
								IRAPURU
		ITAMARLOG	ITAMARLOG	ITAMARLOG		ITAMARLOG		
								JADLOG

Continue

Table 1 (continued)

2001	2002	2003	2004	2005	2006	2007	2008	2009
								JULIOSIMOES
								KEEPERS
		KT&T	KT&T			KT&T	KT&T	
		KUEHNENAGEL	KUEHNENAGEL				KUEHNENAGEL	
								K-WAY
		LAMOUNIER						
LG								LG
							LIBRA	
								LIDER
								LINKERS
LOGHIS								LOGHIS
		LOGISPLANPREM						
M3								
								MCLANE
MCP			MCP	MCP		MCP	MCP	
							MERCÚRIO	
								METROPOLITAN
		MIRASSOL						
								MSLOG
NORLOG								
NSF	NSF	NSF		NSF		NSF	NSF	
		PANAZZOLO						
					PANZAN	PANZAN	PANZAN	
								PENSKE
		PETROLOG				PETROLOG		
						PROLOG		
							PRONTO	
								QUICK
								QUIMITRANS
						RAP900	RAP900	
								RAPIDAO
RODOBORGES		RODOBORGES	RODOBORGES	RODOBORGES	RODOBORGES			
							RYDER	
								SADA
								SATLOG
							STANDART	

Continue

Table 1 (continued)

2001	2002	2003	2004	2005	2006	2007	2008	2009
	STOCKTECH							
							SULISTA	
								SUPPORT
SYN		SYN				SYN		
								TA
						TAC	TAC	
TDS	TDS	TDS	TDS	TDS				
TEGMA							TEGMA	
								TGESTIONA
TNT		TNT						
								TORA
								TPC
								TRANSCASTRO
								TRANSMIRO
						ULTRACARGO	ULTRACARGO	ULTRACARGO
			UPS				UPS	
						VALE LOG-IN		
								VILLANOVA