A DEA-based approach for competitive environment analysis in global operations strategies

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ABSTRACT
While competitive environment analysis is critical to a global retailing operations strategy, there exist research gaps from perspectives of operational performance, retailing industrial environment, and nondiscretionary factors. Therefore, our research objective is to propose a new approach to conduct competitive environment analysis for a global operations strategy in retailing, by examining relationships between discretionary inputs of the supply chain, nondiscretionary inputs of the environment, and performance of retailing. We develop a nondiscretionary data envelopment analysis model to assess performance in retailing and integrate it with econometric analysis. Using multsource data of 124 organizations in the global retailing industry, it is interesting to find: while nondiscretionary factors significantly influence the operational performance of global retailers, firms in an environment with a higher market concentration, larger consumer spending per capita, and smaller inhabitants’ population are more likely to achieve a higher operational efficiency in retailing. Another interesting finding with practical implication is: inputs relevant to outside environment (e.g., suppliers in upstream and outlets in downstream supply chain) can influence operational efficiency more than inputs in internal supply chain (e.g., warehouses).

1. Introduction

Competitive environment analysis is important for different levels of strategy management, including corporate strategy, business strategy, global strategy (Birkinshaw et al., 1995), and functional strategies, including IT strategy and marketing strategy (Pang et al., 2014). In a global operations strategy (GOS), competitive environment analysis is critical for the decision-making of global retailing organizations (see its position in the strategy structure in (Ward and Duray, 2000; Gong, 2013)). Previous competitive environment analysis has applied a number of research methods, including qualitative analysis and quantitative methods, to address the influence of environmental factors on an operations strategy. Some influential methods such as partial least squares (PLS) models (Birkinshaw et al., 1995), spatial lag models (Geys, 2006), taxonomy, and configurations (Morrison and Roth, 1992) were applied in building theories, analyzing the operational structure, and investigating the environmental determinants for GOS. We summarize previous research in competitive environment analysis of GOS (see Table EC.1 of Appendix) and find there exist the following three research gaps in competitive environment analysis of a retailing global operations strategy.

1.1. Research gap from perspective of operational performance

The strategy management literature examines a diverse array of objectives and actions regarding the achievement of competitive advantages (Dyer, 1996; Hillman and Keim, 2001; Douglas and Judge, 2001). While current literature relevant to competitive environment analysis has considered measures like sales, market value, returns on investments (ROIs) (see Table EC.1) in other industries, these research objectives may not fully address the challenges in competitive environment analysis of the retailing industry, and new guidelines for performance measure selection relating to retailing operations are needed (Dess and Robinson, 1984; Waddock and Graves, 1997; Godfrey et al., 2009; Combs et al., 2005). An important operational performance is operational efficiency, considering industrial characteristics of low profit ratio in the retailing industry. For example, even for the largest retailer Walmart, its profit ratio (group net profit/net sales) is only 3.4% (based on data in Planet Retail, see https://www.planetretailnetgroup.com). Low profit ratio may imply low output-to-
input ratio. Therefore, an optimal output-to-input ratio is an interesting measure for retailing practitioners.

Operational efficiency in this paper refers to a well-built definition in the literature of data envelopment analysis (DEA) (Farrell, 1957; Zhu, 2014). Generally, a decision-making unit (DMU) is regarded as the entity, which is a firm in this paper, that has multiple performance measures (classified as DEA inputs and outputs) and its performance is to be evaluated based upon the selected measures. In DEA, a group of DMUs is used to evaluate each other with each DMU having a certain degree of managerial freedom in decision-making. Fare et al. (1985) proposed to measure efficiency as the distance between an observation and an estimated ideal referred to as an efficient frontier. The efficient frontier guarantees at least the outputs of firms in all components while reducing the inputs proportionally to a value as small as possible. Although previous studies in DEA have focused on the production efficiency, DEA is more than an efficiency measure under the notion of a conventional production process (Cook et al., 2014; Liu et al., 2013). DEA can be a type of “balanced benchmarking” (Sherman and Zhu, 2013) that examines performance in operational processes and helps organizations to test their assumptions about performance, productivity, and efficiency in operation decisions. Thus, understanding the impact of the environment on retailing GOS requires an appropriate definition of the concept of operational efficiency.

We therefore identify the following research gap: operational efficiency, a critical indicator measured with output-to-input ratio, has not been fully studied integrated with competitive environment analysis for global retailing with industrial characteristics of low profit ratio.

1.2. Research gap from perspective of retailing industrial environment

Today’s retailing organizations are adopting different GOSs to improve operational performance considering industrial environments (Nair, 2005). In different industrial environments, retailing firms utilize various facilities such as warehouses, outlets, and the supplier resources to improve operational efficiency and increase the productivity of operational systems (Newman and Cullen, 2002). Taking advantage of the industrial environment as an opportunity for development, retailers build a global operations strategy with alignment to the industrial environment, make use of local environmental factors, and achieve competitive advantages. Evaluating efficiency without considering the environmental impacts of different regions may not accurately reflect the relative performance of firms in retailing. Therefore, while there are a number of studies assessing the performance of an operations strategy, we will further consider environmental factors in the assessment of retailing GOS (Newman and Cullen, 2002).

Current environment-relevant measures and constructs (Ward and Duray, 2000) are not regular measures used in retailing practices and cannot catch practical features in the retailing industry, which creates difficulty in the understanding of retailing practitioners and the implementation of a retailing operations strategy. We resort to PlanetRetail, a major database used by retailing practices and retailing practitioners, and an estimated ideal referred to as an efficient frontier. The efficient frontier guarantees at least the outputs of firms in all components while reducing the inputs proportionally to a value as small as possible. Although previous studies in DEA have focused on the production efficiency, DEA is more than an efficiency measure under the notion of a conventional production process (Cook et al., 2014; Liu et al., 2013). DEA can be a type of “balanced benchmarking” (Sherman and Zhu, 2013) that examines performance in operational processes and helps organizations to test their assumptions about performance, productivity, and efficiency in operation decisions. Thus, understanding the impact of the environment on retailing GOS requires an appropriate definition of the concept of operational efficiency.

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1.3. Research gap from perspective of nondiscretionary factors

We compare studies of competitive environment analysis (some of them are listed in Appendix EC.1) and find that the most competitive environment analyses in an operations strategy use environmental factors as control variables, moderate variables, or elements in configurations (Pang et al., 2014; Birkinshaw et al., 1995; Geys, 2006; Grossman et al., 1999; Morrison and Roth, 1992). We would like to introduce a new analytical perspective of nondiscretionary factors. “Nondiscretionary,” which describes the external constraints from the environment in this research, is defined as environmental factors in which the DMU in an organization may not have the ability to decide or adjust according to its own discretion or judgment. The nondiscretionary factor is a concept rooted in economics and widely used in the field of DEA, productivity analysis, and performance evaluation (Cooper et al., 2011; Gorman and Ruggiero, 2008; Pendharkar, 2013). To conduct a competitive environment analysis, we use nondiscretionary models to deal with these environmental factors in the operational process of retailing firms. The “nondiscretionary” inputs such as inhabitants’ population, market concentration, and total consumer spending per capita in different regions, which are not subject to management control in retailing, can influence the business performance of retailers. Even though nondiscretionary, it is important to take account of such inputs in a manner that is reflected in the measures of operational efficiency. Only in two special environments, including markets with high monopoly and economies where a state-owned company or a large organization can influence some environmental factors such as consumer price, may environmental factors be discretionary. However, the retailing industry is not in these special cases, and environmental factors are nondiscretionary. Thus, we consider a retailing industry where environmental factors can be nondiscretionary in a market with full competition. For example, the market share of total grocery spending is just 2.54% from top 5 grocery retailers (China Resources Enterprise, Auchan, Walmart, Lianhua, Carrefour) in China and just 22.40% from top 5 grocery retailers (Walmart, Kroger, Walgreens, CVS, Costco) in the USA (Country reports, PlanetRetail, 2013). It is difficult even for the largest retailer CRE (with 0.73% market share) in China and Walmart (with 9.58% market share) in the USA to significantly influence environmental factors.

Nondiscretionary analysis in the DEA model can be an appropriate tool and enable an accurate understanding of firm performance. Nondiscretionary analysis, as an appropriate business measurement tool, is a new method for environment analysis in a GOS study. Compared with the traditional PESTLE (political, economic, social, technological, legal, and environmental) analysis, nondiscretionary analysis provides an accurate quantitative framework of competitive environmental factors used in the environmental components of GOS. We therefore identify the following research gap: the perspective of nondiscretionary factors has not been applied in the competitive environment analysis of a global retailing operations strategy.

1.4. Research question

Considering the three research gaps, our research question therefore is, “Can we find an accurate quantitative approach to conduct a competitive environment analysis for a global operations strategy considering multiple inputs, multiple outputs, and optimal operational efficiency in the retailing industry?”

To answer this research question and understand the competitive environment in retailing clearly, it is important to build an accurate framework to measure the efficiency of supply chains in different environments when considering the multiple inputs from both internal operations and external environments in retailers. DEA, particularly suited to conceptualize and measure firm-specific capabilities (Dutta et al., 2005; Zhu, 2014), can be used by researchers to conduct environment analysis in GOS, although DEA methods are never used in a competitive analysis of GOS as far as we know.

Using data from 124 organizations in the retailing industry, we develop a nondiscretionary operational evaluation framework in retailing, integrating DEA and econometric methods in efficiency measuring, to study the relationships between facility inputs of the supply chain, environmental inputs of environment analysis, and business performance in retailing. We consider the direct impact of facility and environmental inputs on business performance and build a
nondiscretionary DEA model to assess how facility and environmental inputs can influence business performance. We adopt a multinomial logit (MNL) to conduct an empirical analysis in values of operational efficiencies provided by DEA and use hierarchical regression analysis to test the results correlated with the DEA model. Our nondiscretionary DEA model, which is a nonparametric approach, provides a new perspective to understanding the performance of retailing using supply chain facilities in different competitive environments and test the influence of competitive environmental factors on supply chain efficiency. Our model captures the relationship of facility inputs and the productivity of different DMUs based on multiple input-output data, considering nondiscretionary environmental inputs.

2. Literature review and research background

2.1. Competitive environmental analysis

Competitive environmental analysis is an integral part of systematic strategic planning (Ginter and Duncan, 1990). One of the major implications of the enacted environment concept for the strategic management theory is the prescription that organizations should adapt to their environments (Smirich and Stubbart, 1985). The relationship between strategy making and environment, besides the relationships between strategy and structure, and between environment and structure, tends to be stronger in successful firms than in unsuccessful firms (Miller and Friesen, 1983; Lumpkin and Dess, 2001). Increases in environmental dynamism, hostility, and heterogeneity have influence on specific changes in the amount of analysis and innovation which characterizes strategy-making activities (Miller and Friesen, 1983).

We summarize relevant theories in previous research (see Table EC.1 in Appendix EC.1) and find that previous competitive environment analysis is based on the following influential theories (1) strategic fit, which includes static strategic fit and dynamic strategic fit (Zajac et al., 2000); (2) contingency theory, which is widely applied in environment analysis at different levels (Van de Ven et al., 2013; Liao and Tsai, 2015); (3) institutionalization theory, in which researchers view organizations as social phenomena with appropriate behavior patterns and activities for their environment (Meyer and Rowan, 1977); (4) industry organization economics; (5) ecological theory, in which competitive environment analysis can be conducted with social ecology and even population ecology to deal with complex collective strategies of businesses (Astley and Fombrun, 1983); (6) resource dependence theory, which examines the resource dependence role of environmental factors and posits that a firm can leverage the performance impact of an existing environment through resource integration and complementarity (Song et al., 2005; Hillman et al., 2000). For environmental factors relevant to industries, researchers use these influential theories, independently or combined with other theories in environment analysis. For example, Birknshaw et al. (1995) use the structural forces perspective and the competitive action perspective, with roots in industry organization economics and contingency theory, to study global strategies in different industry contexts.

Prior research found that the roles and functions of environmental factors can work as moderating effect factors or control variables. The competitive environment could moderate the relationship between market orientation and performance (Slater and Narver, 1994). Some research found evidence that environmental factors such as share of rural population and a politically divided government have a moderating effect on the relationship between information technology and administrative efficiency, and some environmental factors that were usually treated as control variables in their research, such as population, household income, and GDP, also have an influence on operational efficiency (Pang et al., 2014). Environmental factors seem to lead to a complex nonlinear relationship (e.g., complementarity effect) between decisions or strategies with respect to investment or resource inputs (Golovko and Valentini, 2011; Russo and Fouts, 1997).

In retailing practice, it is important to realize that industrial environmental factors have influence on firms’ business performance. Different types of competition and the resulting equilibrium behavior may arise, depending on the environment through which the firms select their strategies (Allon and Federgruen, 2007). Inconsistency in industrial environments will make operational glitch, resulting in production or shipment delays, associated with negative operational performance and an abnormal decrease in shareholder value. Firms making operational decisions that are consistent with an empirical benchmark derived from environmental and strategic factors are less likely to go bankrupt than those making inconsistent choices (Randall et al., 2006). Environmental constraints, such as performance-based contracting or output values of the product or service generated by the market, are reshaping the operation strategies in retailing industries (Kim et al., 2007).

2.2. Data envelopment analysis

DEA is an important nonparametric method in production and operations management. As an optimization method, DEA allows the measurement of the relative performance of production units in general multi-input, multi-output situations and has been widely used to assess operational performance in different industries, such as airlines (Zhu, 2011), banks (Cook et al., 2004; Sherman and Zhu, 2006), hospitals (Du et al., 2014), retailing (Lau, 2013), information technology (Chen and Zhu, 2004; Chen et al., 2006), manufacturing industry (Park et al., 2014), warehousing (Korpela et al., 2007) and sustainable product design (Chen et al., 2012). Attention has been devoted to DEA methods for aggregating empirical data in environmental analysis. Researches further deepened the application of DEA methodology for credit rating and scoring (Bruni et al., 2014; Iazzolino et al., 2013), benchmarking sustainable development Bruni et al. (2011). A review of the various basic DEA models and their extensions can be found in Adler and Golany (2001), Chen et al. (2015), and Zhu (2003).

While some classical DEA models make the implicit assumption that all inputs and outputs are “discretionary variables,” which can be varied at the discretion of managers, the nondiscretionary DEA models attempt to address the issue of inputs from external environments. These inputs called “nondiscretionary variables” (Cooper et al., 2006), such as economic and environmental factors, are those that firms may not have the ability to decide or adjust according to their own discretion or judgment. Even though nondiscretionary, it is important to take account of such inputs from the industrial environment when we evaluate operational efficiency in retailing.

2.3. Operational performance

There is considerable interest in the operations management community in evaluating retailing performance and assessing the impact of operational improvements on operational and financial performance. The main measures for the performance of a retailer or for comparing productivity across retailers are ratios such as inventory turnover, receivable turnover, total or current assets turnover, gross margin, and long-term stock returns. These indicators may have limitations, such as overrating variables at an aggregate level and cannot truly reflect the performance level. For example, the annual inventory turnover of US retailers varies widely—not only across firms, but also within firms from one year to another. If a firm realizes an increase in inventory turnover with a concurrent decrease in gross margin, it does not necessarily indicate an improvement in its capability to manage inventory (Gaur et al., 2005).

Rarely, however, these avenues of research have explicitly considered the relationship between competitive environment and GOS with an objective of operational efficiencies in retailing. Competitive environmental analysis has now become important for firms in supply chains as they face intense pressure from diverse stakeholder groups,
including end consumers, industrial customers, suppliers, and financial institutions (Hendricks and Singhal, 2005). The differences between regions implicate the diverse markets, variety of operation management, and diversified business models, thus perhaps resulting in the different operational efficiencies of firms in retailing. Besides, regional differences with variety in policies, culture, public welfare, and legislation affect the decision-making units of GOS. Multinational companies face an imperative for consistency within the organization, and they are also pulled to achieve isomorphism with the local environments (Rosenzweig and Singh, 1991). Considering the differences in economic, demographic, and political environments, some retailing organizations may tend to be localized for variety-related operational efficiency. Other multinational companies may standardize GOS in different environments for scale-related operational efficiency, which may reduce organizations’ ability to exploit cross-country differences (Christmann, 2004). Retailers in a competitive, globally integrated environment face a “liability of foreignness” (Zaheer, 1995), and they have to make the choices of either importing home-country organizational capabilities or copying the practices of successful local firms, which can help them overcome this liability when they make decisions relevant to operational efficiencies. The institutional profile of the host country and the relational context in a multinational corporation influence the adoption of a practice and the decision-making of a strategy (Kostova and Roth, 2002). A competitive environment in different regions affects the operational efficiency of retailers, and the region-relevant benefits are long term (Slater and Narver, 1994). As retailers attempt to move toward sustainable competitiveness, managers must extend their efforts to adapt and then utilize the environmental differences across their operational process to improve their operational efficiency. While “companies can vary enormously in their operating efficiency,” the related competitive advantages will be influenced by the external environment in different regions (Greenwald and Kahn, 2005) (Page 4).

2.4. Nondiscretionary factor analysis

In retailing, inputs from suppliers and upstream firms, or from external environment which are out of management control may also need to be considered. The technique for efficiency measurement known as nondiscretionary DEA has been extended to allow nondiscretionary inputs, especially environmental factors, to affect the decision making. As one of the most important methods exist for measuring efficiency while controlling for both discretionary and nondiscretionary factors of production (Cooper et al., 2006), nondiscretionary DEA models have been used in both academic and practical studies. Charner et al. (1985) first consider weather (measured in numbers of “flyable” days) as an input since the number of “sorties” (successfully completed missions) and “aborts” (non-completed mission) treated as outputs in evaluating performances of different bases for the Fighter Command of US Air Forces. The previous researches also consider exogenously inputs as “nondiscretionary” in their DEA models, pay attention to the uncontrollable data in a particular industry (or in a specific group of firms), and estimate the productivity of different production processes (Ouellele and Vierstraete, 2004). Compared with previous theories, new framework based on nondiscretionary DEA considering multiple data can explain the non-linear relationship between facility inputs and operational efficiency. In this research, nondiscretionary analysis integrating DEA can be a useful strategic tool for understanding growth or decline, business position, potentials, and development direction of operation efficiency for GOS study.

Nondiscretionary analysis is widely used for efficiency measurement in the development of DEA (Cooper et al., 2006), which illustrates the impact of exogenously determined inputs from environment on operational efficiency. These nondiscretionary inputs from the DEA literature include age of store, local unemployment rates (Brockett et al., 2004), traffic intensity (Cook et al., 1990), weather parameters and number of competitors in supply chain (Cooper et al., 2011). These findings suggest that the operational efficiency considerably varies in different DEA application environments, some of which can be ascribed to a large extent of differences in the socio-economic backgrounds.

3. Measures, models, and methodologies

3.1. Inputs and outputs of DMU

In the operational decisions process in retailing, we consider three discretionary inputs $X_P$: the number of outlets which is critical to downstream supply chain operations (Hollander, 1960; Chopra and Meindl, 2012), the number of warehouses which is critical to internal supply chain operations (Beamon, 1998; Gong and de Koster, 2011), and the number of suppliers which is important to upstream supply chain operations (Pedrick et al., 2008; Chopra and Meindl, 2012). By optimizing the number of suppliers, outlets, and warehouses in a region, the supply chain in retailing can improve operational performance (Guo and Ganeshan, 1995; Berger et al., 2004; Pedrick et al., 2008). (1) An outlet, a term used in retailing industry, refers to different types of stores, including cash & carries, warehouse clubs, catering, convenience & forecast stores, department & variety stores, discount stores, drug-stores, pharmacies, perfumeries, hypermarkets, supermarkets, supermarkets, and neighbourhood stores (see definition by (PlanetRetail, 2017)). Outlets in the supply chain, serving a small region, are close to the local market and help retailers deliver products and services to customers quickly. With more outlets in a region, while the cost is higher, retailers invest more in supply chain agility to achieve business success by responding to customers’ needs. The number of outlets has been regarded as an important factor to improve the performance of retailers in literature of marketing and retailing (Hollander, 1960; Gripsrud and Gronhaug, 1985). (2) Warehouses, both owned and leased, hold the inventory for a region and maximize the utilization of space, workers, and equipment, and thereby a critical factor to improve operational performance (Van den Berg and Zijm, 1999). The number of warehouses, including distribution centers, have been regarded as one of the most important factors or decision variables in distribution network design and retailing operational systems (Amiri, 2006). (3) Besides the facility inputs, more suppliers show retailers invest more in their relationship with their upstream partners. In literature of supply chain and retailing (Beamon, 1998; Ghodsypour and O’Brien, 2001), the number of suppliers is an important factor to improve operational performance (Berger et al., 2004; Guo and Ganeshan, 1995; Bakos and Brynolfsson, 1993).

The structure of a retailing system is dependent upon selected characteristics of the country served (Arndt, 1972), and operation strategies in retailing industries are affected by the industrial environment where these firms are located. To describe industrial characteristics, we use three important competitive environmental factors and nondiscretionary inputs, inhabitants’ population, market concentration, and consumer spending per capita, from the database PlanetRetail which is the world’s provider of global retail intelligence (PlanetRetail, 2013). (1) Inhabitants’ population is one of the most important factors of a consumer market (Arndt, 1972). Efficiency of multinational corporations has been shown to be relevant with population and size of market (Hymer, 1970). As one of the urban elements that draws individuals to the local market, a region’s livability has a direct effect on business activities in retailing (Rotem-Mindali, 2012). Inhabitants’ population is relevant to potential revenue for retailers, which implies that a retail operations strategy in locations with huge inhabitants will influence business performance considering economics of scale. However, its influence on operational efficiency is still unclear yet since it is possible to easily implement an operations strategy with smaller population. (2) Market concentration that weighs the competitive nature of retailing, is a basic factor for determining market structure. PlanetRetail uses the market share of top 5 retailers to measure market
concentration (PlanetRetail, 2017). Efficiency of multinational corporations is relevant with market structure (Hymer, 1979). Because of the relative independence of regional markets, retailers have to face all kinds of market concentration in different markets when they draw up their global operations strategies. (Cotterill, 1986) shows the "profits of leading firms in concentrated markets may be due to market share related cost efficiencies or market power" in retailing industry (Page 379). However, it is still unclear how market concentration, monopolized or competitive industrial environments, will influence the retailing format and operations strategy of retailers, and further business performance. (3) Another important indicator evaluating the industrial environment and affecting business performance in retailing is consumer spending per capita (Fox et al., 2004; Fornell et al., 2010; Rucker et al., 2011). PlanetRetail (2017) measures it as follows: total annual private household spending (including VAT or sales tax), including expenditure on total grocery and non-grocery product categories, and spend in non-profit organisations such as charity shops per capita. Consumer spending shows the attitudes of consumers and retailers toward the economy and the health of local markets. If these attitudes toward the industrial environment are negative, consumers will be reluctant to spend (Rucker et al., 2011; Fornell et al., 2010). Consumer spending per capita is a powerful predictor of environmental factors and has influence on business performance in retailing (Fox et al., 2004).

Output Y, which describes the business performance of retailers, contains three variables: sales, market shares, and ROI measured by (PlanetRetail, 2017). (1) PlanetRetail (2017) measures sales as follows: nationwide total sales from all retail outlets and B2C ecommerce, including warehouse clubs. It excludes wholesale operations and all non-retail business such as restaurants, financial services and travel services. This data includes VAT. (2) PlanetRetail (2017) measures market shares as follows: total sales (including grocery and non-grocery) from a company’s retail outlets (excluding wholesale and all non-retail operations) as a percentage of nationwide sales of all retail outlets and B2C ecommerce, excluding wholesale channels such as cash & carry and delivered wholesale. (3) ROI measures the amount of return on an investment relative to the cost of investment. To calculate ROI, the return of an investment is divided by the cost of the investment, and the result is expressed as a ratio. ROI as a measure have been applied in competitive environment analysis (Birkinshaw et al., 1995; Morrison and Roth, 1992), and is an important measure for business performance of retailers since it can be easily compared with returns from other investments (Burt, 1978). Table 1 shows the data description of these inputs and outputs.

3.2. Nondiscretionary DEA model

We then use DEA models to evaluate the operational efficiencies of retailers with the nondiscretionary inputs. The conventional DEA considers a set of DMUs indexed by K. For all k ∈ K, DMUk uses inputs $X_k = \{x_{0k}^1, x_{0k}^2, \ldots, x_{0k}^m\}$ to obtain the output $Y_k = \{y_{1k}, y_{2k}, \ldots, y_{nk}\}$, where I and J are the index sets for inputs and outputs. $R^n$ represents the n-dimensional positive real space. All inputs used are assumed to have a contingent corresponsence to outputs, meaning that inputs contribute only to the outputs in the same time and vice versa.

In our DEA model for operational efficiency in the retailing supply chain, we consider two types of inputs: the discretionary inputs $X_0$, which can be varied at the discretion of DMUs, and the nondiscretionary inputs $X_{ND}$ from policy constraints and industrial environments in different regions, which are not subject to management control in the supply chain. Even though some inputs are nondiscretionary, it is important to take account of such inputs in a manner that is reflected in the measures of efficiency used (Cooper et al., 2006).

Nondiscretionary DEA model, which is a modification of the CCR model using nondiscretionary variables, measures the efficiency of each firm in the sample—that is, it seeks to find the factor, $\delta_k$, by which the k-th firm can shrink its discretionary input vectors. For example, an efficiency score $\delta_k$ indicates that the DMUk could reduce the investment levels by $1 - \delta_k$ compared with the original inputs and can still achieve the same level of outputs. If $\delta_k$ is appropriate, DMUk can get an efficient point, which has a discretionary input mix and output mix by only inputting $\delta_k x_{pk} - x_{pk} x_k x_k x_k$ refers to the sets of “discretionary” inputs.

However, the projection of an inefficient DMU onto the efficient frontier is usually far from the values of DMUk in the sense that the input mix and the output mix of the project point are very different from those values of DMUk in most classical DEA methods. Hence, we extend a DEA model to achieve the opposite approach and project DMUk onto an efficient point as near as possible to itself. By finding the optimal inputs with a real variable $\theta$ and a nonnegative vector $\lambda = (\lambda_1, \ldots, \lambda_m)^T$ of variables, the input-oriented performance efficiency of DMUk can be measured by our mathematical formulation of the nondiscretionary DEA model below:

\[
\begin{align*}
\min \quad & \delta_k - \theta \left( \sum_{i=0}^{m} s_{i}^+ + \sum_{j=1}^{n} s_{j}^- \right) \\
\text{subject to:} \quad & \delta_k x_{pk} = \sum_{k=1}^{K} x_{pk} \lambda_k + s_{p}^- \quad \text{(pD)} \\
& x_{lk} = \sum_{l=1}^{L} x_{lk} \lambda_k + s_{l}^- \quad \text{(qND)} \\
& y_{jk} = \sum_{j=1}^{J} y_{jk} \lambda_k - s_{j}^+ \quad \text{\quad (j = 1, ..., J)} \\
& \lambda_k, s_{p}^-, s_{l}^-, s_{j}^+ \geq 0, \quad \text{\quad (V k, i, j)}
\end{align*}
\]

where $\delta_k, x_{pk}, y_{jk}, \lambda_k, s_{p}^-, s_{l}^-, s_{j}^+$ are the input-oriented efficiency measurement for DMUk. [\lambda_k], as the weight assigned to inputs and outputs, are the

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outlets</td>
<td>1905.68</td>
<td>3259.03</td>
<td>1</td>
<td>596</td>
<td>17948</td>
<td>(Chopra and Meindl, 2012; Gong and de Koster, 2011)</td>
</tr>
<tr>
<td>Warehouses</td>
<td>17.21</td>
<td>32.11</td>
<td>1</td>
<td>8</td>
<td>272</td>
<td>(Rucker et al., 2011)</td>
</tr>
<tr>
<td>Suppliers</td>
<td>7630.39</td>
<td>14022.95</td>
<td>8</td>
<td>3000</td>
<td>101350</td>
<td>(Fornell et al., 2010)</td>
</tr>
<tr>
<td>Inhabitants (million)</td>
<td>367.27</td>
<td>512.03</td>
<td>4.55</td>
<td>91.59</td>
<td>1374.31</td>
<td>(Birkinshaw et al., 1995; Morrison and Roth, 1992)</td>
</tr>
<tr>
<td>Market concentration</td>
<td>25.94</td>
<td>20.89</td>
<td>0.73</td>
<td>22.25</td>
<td>68.5</td>
<td></td>
</tr>
<tr>
<td>Consumer spending</td>
<td>14238.39</td>
<td>9179.02</td>
<td>463</td>
<td>13901</td>
<td>35620</td>
<td></td>
</tr>
<tr>
<td>Market share (%)</td>
<td>5.74</td>
<td>6.96</td>
<td>0.005</td>
<td>3.4</td>
<td>31.26</td>
<td></td>
</tr>
<tr>
<td>Total sales (million)</td>
<td>196798.53</td>
<td>197172.53</td>
<td>2</td>
<td>28200</td>
<td>693000</td>
<td></td>
</tr>
<tr>
<td>ROI (%)</td>
<td>7.32</td>
<td>4.11</td>
<td>0.31</td>
<td>8.41</td>
<td>17.4</td>
<td></td>
</tr>
</tbody>
</table>

Note: data are from 124 firms in retailing.
multiplier vectors for the firm \( k \), \( x_k \) is the input excesses slack vectors, and \( s_k^j \) is the output shortfalls slack vectors. \( \delta > 0 \) is smaller than any positive real number as a non-Archimedean infinitesimal. \( X \) is the \( I \times K \) matrix of observed input quantities, \( Y \) is the \( J \times K \) matrix of observed output quantities, and the vectors \( x_k \) and \( y_k \) contain the observed input and output quantities of firm \( k \), respectively. A similar procedure is proposed in Coelli et al. (2005). Constraints (1), (2), and (3) guarantee at least the output level \( y_k \) of DMU\(_k\) in all components while reducing the input vector \( x_k \) to a value as small as possible. Constraint (4) ensures \( \lambda_k \epsilon \lambda_k \) as a semipositive vector in \( 9^p \).

The symbols \( pD \) and \( qND \) in Constraints (1) and (2) refer to the sets of “discretionary” and “non-discretionary” inputs. The variable \( \theta_k \) is not applied to the inputs \( qND \) because these values are exogenously fixed, and it is therefore impossible to vary them at the discretion of DMU\(_k\). Therefore, this is recognized by entering all \( x_{qk} \), \( qND \) at their fixed value, \( s_j \) in Constraint (1) denotes the relative deviation ratio from the observed \( x_{qk} \) in the “Discretionary” inputs set, and \( s_j \) in Constraint (2) denotes the relative deviation ratio from the observed \( x_{qk} \) in the “Non-Discretionary” inputs set. Finally, we minimize \( \theta - \delta \sum_{k \in D} s^j + \sum_{m \in D} \gamma^m j^j \) in the objective function to measure the operational efficiencies of retailers.

In this model, only the efficiency measurement \( \theta_k \) and the multiplier vector \( \lambda_k \) are decision variables. We further determine the optimal input vector \( \theta_k x_{qk} \) while seeking the efficiency measurement \( \theta_k \), which the firm can use to determine the given output vector \( y_k \), given the technology defined by the DEA frontier. We calculate the efficiency score of the \( k \)-th firm as the ratio of the optimal inputs to the observed inputs. In particular, if \( \theta_k = 1 \), then \( \theta_k x_{qk} = x_{qk} \), which means that the current discretionary input \( x_{qk} \) has reached optimality, and efficiency of the firm achieves optimal value in a competitive environment.

The model (ND) can be applied in operational decision-making. When firms consider the direct influence between inputs and outputs of a global operations strategy, the model (ND) is suitable for the DMU\(_k\) that has a decision-making process considering global competitive environmental factors.

The advantages of DEA models are in performance evaluation and efficiency measurement. We integrate them with quantitative methods to further explain the results of nondiscretionary DEA models or provide new findings for the research question. First, we use MNL to test the relationship between the environmental factors and the efficiency values calculated by the DEA model. Then we use a hierarchical regression model to verify the findings provided by DEA methods.

3.3. Multinomial logit regression analysis

For further research on the influence of environmental factors on retailers’ operational efficiency, we use MNL to test the relationship between environmental inputs and efficiency calculated by a nondiscretionary DEA model. All the models make the independence of irrelevant alternatives assume that categories of inputs are independent. We consider efficient performance (\( \theta_k = 1 \)) and inefficient performance (\( \theta_k \neq 1 \)) as binary variables, respectively, representing the decisions of DMU\(_k\) to secure a full or insufficient efficient performance. In this model, we identify “performance” as a value equal to one for those efficient DMUs (whose \( \theta_k = 1 \)) and zero otherwise (whose \( \theta_k \neq 1 \)). We use this “performance” measure as a dependent variable in the MNL, which provides an estimation of the likelihood that a given DMU\(_k\) would secure the optimal efficiency. We use three environmental inputs as explanatory variables that produce an effect on the likelihood of firms being “efficiency” or “inefficiency.” This model allows us to analyze the aggregate effectiveness of the environmental inputs in the multinomial logistic regression.

The “performance” in the MNL is specified as

\[
\text{Prob}(\text{performance}_k 
eq 1) = \frac{e^{\beta_0 + \beta^T y_k}}{1 + e^{\beta_0 + \beta^T y_k}}
\]

\[
\text{Prob}(\text{performance}_k = 1) = \frac{e^{\beta_0 + \beta^T y_k}}{1 + e^{\beta_0 + \beta^T y_k}}
\]

(M)

where \( X_k = (1, x_{1k}, x_{2k}, x_{3k}) \) is the set of exogenous independent variables and \( \beta = (\beta_1, \beta_2, \beta_3) \) is a vector set of weights corresponding to “performance.” Standardizing the model (M), we find

\[
\beta^0 = \frac{\delta \log \left( \frac{\text{Prob}(\text{performance}_k = 1)}{\text{Prob}(\text{performance}_k = 0)} \right)}{\delta X_k}
\]

which means that vector \( \beta \) demonstrates and explains the probability of efficient and inefficient performance. If \( \beta^0 \) is significantly negative, the change of the relevant inputs will make the DMUs have higher probability to ensure performance\(_k \neq 1 \) than performance\(_k = 1 \), which means that the probability of being optimally efficient increases, while the probability of being inefficient decreases. Thus, in this research we use \( \beta \) as measurable indicators to explain the impact of environmental factors on organizational efficiency combined with a DEA model and verify the results provided by DEA methods.

3.4. Hierarchical regression analysis

To further explore the data and verify the results provided by the DEA model, we also conduct an empirical analysis integrating DEA with hierarchical regression methods. In this hierarchical regression model, we first use hierarchical regression to test the relationship between inputs (both nondiscretionary and discretionary inputs) and operational efficiency provided by the DEA model. To further analyze the influence of a competitive environment and test our results provided by the DEA model, we consider the influence of all the inputs with different competitive environments on each output.

In our hierarchical regression model, we use a linear predictor function \( f(x, \epsilon) \) to predict the probability that observation \( k \) has outcome \( y_k \) in the following form:

\[
\log y_k = \log f(x_k) + \gamma_k = \beta_0 + \sum_{j=1}^{4} \beta_j \log x_{ak} + \eta_k + \gamma_k
\]

\[
\eta_k = \varphi_0 + \sum_{j=1}^{3} \varphi_j \log x_{3k} + \omega_k
\]

(H)

where \( x_{ak} = x_{ak}, x_{ak} \) represents all the six independent variables, including three discretionary inputs (number of outlets, warehouses, and suppliers) as inputs \( x_{ak} \), \( x_{1k}, x_{2k}, x_{3k} \) and three nondiscretionary inputs (inhabitants’ population, market concentration, and consumer spending per capita) as \( x_{ak} \), \( b_{1k}, b_{2k}, b_{3k} \). To explore the results provided by the DEA model and test the consistency of these regression results from efficiency \( \epsilon_k \) and those from outputs \( y_k \), \( y_k, j, k \{1,2,3,4\} \) represents four different dependent variables: efficiency \( \epsilon_k \), sales, market shares, and ROI of DMU\(_k\). The function \( f(x) \) transforms input factors \( x_{ak} \) into these different dependent variables \( y_{ak} \), \( j, k \{1,2,3,4\} \) without any loss of measure errors and residuals. \( \eta_k \) represents the random error assumed to follow normal distribution \( N(0, \sigma^2) \). \( \eta_{ak} \) represents the stochastic environmental factors assumed to follow half-normal distribution \( \text{N}(0, \sigma^2) \) (Kumbhakar and Lovell, 2003; Coelli et al., 2005), \( x_{ak} \), as explanatory variables for the influence of a stochastic environment, demonstrates and explains these \( \eta_{ak} \), \( \beta_0 = (\beta_1, \beta_2, \beta_3) \), as measurable indicators, explain the impact of discretionary inputs on different dependent variables \( y_{ak} \), while \( \varphi_0 = (\varphi_1, \varphi_2, \varphi_3) \) explain the impact of nondiscretionary inputs. To further analyze the influence of a competitive environment on organizational efficiency and compare it with the impact of environmental factors on outputs, we first test the influence of all the discretionary inputs \( x_{ak} \) and nondiscretionary inputs \( x_{ak} \) on efficiency \( \epsilon_k \) provided by the DEA model. Then we can compare the indicators \( \beta_0 \) and \( \varphi_0 \) with those on three different outputs to verify the hierarchical regression results provided by DEA methods.

With six-dimensional inputs, three-dimensional outputs, and
efficiency provided by the DEA model, we can test the real data in our models to verify the impact of a competitive environment on a retailing global operations strategy.

4. Data and results

4.1. Data

We applied our nondiscretionary DEA model to a real multiple-source data set for 124 retailing DMUs. Data were collected from multiple sources, including first-hand and second-hand data. We obtained detailed information on output and input quantities from firms and were also able to obtain all the measures from managers.

The main data sources are from the second-hand data of the database “PlanetRetail”. We obtained detailed information and all the indicators on three outputs and six inputs from the database of retailers in 2016. All data were extracted from the public statements of these firms, and we cross-checked and verified them with the data from our questionnaires.

To cross-check, we also collected first-hand data with a sample size of 124 from 32 countries and regions (Canada, USA, Argentina, Brazil, Mexico, France, Germany, United Kingdom, Spain, Sweden, Italy, Netherlands, Norway, Austria, Belgium, Czech Republic, Denmark, China, Japan, South Korea, Indonesia, Malaysia, Philippines, Singapore, Thailand, Vietnam, India, Turkey, Israel, Russia, Morocco, and New Zealand). We generated the initial sample frame from a mailing list of retailing organizations in PlanetRetail.com and obtained basic information about the targeted organization. We sent e-mails to senior executives in those organizations to know whether they were interested in our study. A total of 522 organizations replied and offered their addresses. Then we mailed out the questionnaire packages. With the follow-up phone calls and second mailings, we ensured that the operations managers or the executive managers filled in the questionnaires about a global operations strategy. We finally collected a valuable data set of 124 organizations with a response rate 0.24. After obtaining the data, we compared them with the data from the database “PlanetRetail.com.” For the indicators of inputs X and outputs Y, we used Table EC.2 in Appendix to show the sample profile.

Using data from 124 retailing DMUs, we explore and explain the impact of competitive environments in retailing from the perspective of DEA. First, we apply the nondiscretionary DEA model to evaluate the efficiency of the 124 organizations. Then we combine the DEA model with the MNL to show the impact of competitive environments on organizational efficiency in retailing. To verify our empirical results from the DEA model combined with the MNL, we also use the hierarchical regression model to further analyze the impact of environmental factors on organizational efficiency and all the outputs.

4.2. DEA results and regional analysis

Using data of 124 firms, we apply our DEA model to evaluate the performance of DMUs. The results show in Table 2. θk represents the different efficiency measurements for DMUs.

One technique applicable to DEA efficiency is to proceed with the analysis in two stages. First, DEA models calculate the efficiency scores, and then the efficiency scores obtained by DEA can be regressed as a dependent variable. This approach is applied by Chortareas et al. (2013), Curi et al. (2015), Chortareas et al. (2012), Wanke et al. (2016), and Simar and Wilson 2007, among others. Although it is commonly used, there is discussion in the literature whether this characteristic makes the efficiency scores truncated or fractional (McDonald, 2009). Simar and Wilson (2007) have argued that DEA efficiency estimates lacking a sound statistical foundation are somehow censored. However, Banker and Natarajan (2008) show that the two-stage approach for DEA can yield statistically consistent coefficient estimators under certain general distributional assumptions. Johnson and Kuosmanen (2012) further show that the estimators remain statistically consistent even when the first-stage input and output variables in DEA are correlated with the second-stage variables in the regression model. Recent researches (Simar and Wilson 2007, Wanke et al. (2016), Curi et al., 2015, Chortareas et al., 2013) suggest that bootstrap appears to offer the way to approximate asymptotic distribution of the distance function estimators in multivariate settings. Therefore, we apply the bootstrap procedure based on Simar and Wilson (2007), Algorithm 1, using 2000 bootstrap replications for the confidence intervals of the estimated coefficients. See Table EC.3 in Appendix, Table EC.3 in Appendix reports the results of parameter estimates in truncated regression and their bootstrapped confidence intervals. We also present the mean and standard deviation for lower and upper bounds of the efficiency scores. We perform a multigroup comparison by region. We divide the 124 firms into four regions: 33 firms in Europe (France, Germany, United Kingdom, Spain, Sweden, Italy, Netherlands, Norway, Poland, Austria, Belgium, Czech Republic, Denmark), 37 firms in Asia (China, Japan, South Korea, Indonesia, Malaysia, Philippines, Singapore, Thailand, Vietnam, India), 26 firms in America (Canada, USA, Argentina, Brazil, Mexico), and 28 firms in other regions (Turkey, Israel, Russia, Morocco, Australia, New Zealand). The classification method is based on the Geographica (McKnight, 2004). Before analysis of variance (ANOVA) was conducted to detect regional differences, we evaluated normality and homogeneity of variance to detect if the variance within each of the regions is equal.
populations is equal (Piran et al., 2016). The Levene’s tests show that the significance levels are $p = 0.87$. No significant differences were detected. Thus, all comparison groups were not compromised by normality and homogeneity of variance. Using double-factor variance analysis, we find that the difference between the four regions is significant (see Table 3). Table 3 shows that the variances of operational efficiencies in retailing between the four groups of regions are significant ($p$-value = 0.000307).

To compare these measures visually, we use the mean plots with 95% confidence interval (CI) to show these significant differences between these four geographic regions (see Fig. 1). In Fig. 1, the ranking results of these efficiency measures in different regions are illustrated. We find that the firms from Asia obtain the lowest operational efficiencies, while those from America and Europe achieve higher efficiencies.

From Table 3 and Fig. 1, we find that regional differences with different degrees of economic development significantly affect firms’ efficiency in retailing. These analyses demonstrate that regional differences significantly influence operational efficiency in retailing organizations.

4.3. Integrating DEA and MNL analysis

To further illustrate the impact of a competitive environment on firm performance, we use the MNL model (M) to compare the effectiveness of firms in regions with different environmental factors. Table 4 presents the result for the model (M) using the binary logit specification that shows the relationship between effectiveness of retailers and inhabitants’ population, market concentration, and consumer spending per capita. As discussed earlier, this methodology allows us to compare the effectiveness of the performance. The results in Table 3 explain the probability of Performance = 1, which means that the firms achieve optimal efficiency in their industry.

From Table 4, we find that the environmental input variables inhabitants’ population ($Z$ value = −2.678) are negative, while market concentration ($Z$ value = 3.171) and consumer spending per capita ($Z$ value = 3.160) are positive, and all of them are significant at a level of 5%, respectively. These results show that firms located at a higher level of market concentration and total consumer spending per capita with a smaller populations are more likely to achieve top efficiency in the retailing industry. These results from Table 4 may help interpret the reasons of regional efficiency differences presented in Table 3 and Fig. 1. Firms located in the Asian market with huge populations and a relatively low average level of economic development have relatively lower efficiency, while those in America and Europe with small-scale, concentrated inhabitants and a high level of market concentration and total consumer spending per capita obtain better organizational performance.

4.4. Integrating DEA and hierarchical regression analysis

To explore the results provided by the DEA model, we present an empirical analysis integrating DEA with hierarchical regression methods. To further analyze the influence of a competitive environment on organizational efficiency and compare it with the impact of environmental factors on outputs, we consider the influence of all the inputs with different economic environments on efficiency $\theta_i$ and each output.

Table 5 presents the estimation results of Model (H), which shows the relationship between dependent variables: operational efficiency $\theta$, sales, market share, ROI, and all the independent variables: facility inputs and environmental factors. We first test the influence of all the discretionary inputs $x_{di}$ with nondiscretionary inputs $x_{di}$ on efficiency $\theta_i$ provided by the DEA model in Models 1 and 2. Then we compare these hierarchical regression results with those on sales in Models 3 and 4, sales in Models 5 and 6, and sales in Models 7 and 8.

In Table 5, we first only consider the relationship between the discretionary inputs: outlets, warehouses, suppliers, and four dependent variables in Models 1, 3, 5, and 7. Then we add the impact of environmental factors: inhabitants’ population, market concentration, and consumer spending per capita in Models 2, 4, 6, and 8 (see Table 5).

Finding 1. From Table 5, we find that all the coefficients of outlets and suppliers are positive and significant when we only consider the relationship between these inputs and operational efficiency in Model 1, or outputs in Models 3, 5, and 7. All the coefficients of warehouses are not significant in these four models, showing that outlets and suppliers may play a more important role than warehouses in improving business performance and efficiency. This is an interesting finding, which is not in existing literature: inputs relevant to outside environment (e.g., suppliers in upstream and outlets in downstream supply chain) can influence operational efficiency more than inputs in internal supply chain (e.g., warehouses).
Finding 2. However, when we add the impact of competitive environmental factors in Models 1, 3, 5, and 7, almost all the coefficients of outlets and suppliers decrease. These results show that besides these discretionary inputs, environmental factors may also play a pivotal role in operation efficiency and business performance. Specially, we find that: (i) for operational efficiency $\theta$, the coefficients of the market concentration and total consumer spending per capita are positive and highly significant, while those of the inhabitants are negative and also highly significant, suggesting that the firms located in the low inhabitants and high market concentration and total consumer spending per capita regions in general have gained better operational performance; (ii) for total banner sales and ROI, all the coefficients of industrial environmental factors are positive and highly significant, showing a positive relationship between these three environmental factors and business performance in retailing; (iii) the coefficients of inhabitants for operational efficiencies in Model 2 are negative and highly significant, while those for sales in Model 4, market share in Model 6, ROIs in model 8 are positive and also highly significant. The dissimilarity (between efficiency model and business-performance models) is reasonable that large inhabitants may bring population bonus to business performance in retailing, while retailers have to provide more products or services and invest more on facilities, which may cause disorganization and operational inefficiency.

These findings from hierarchical regression models are consistent with our results provided by the DEA method integrating the MNL method. We find that: retailing firms from higher market concentration, higher total consumer spending per capita, and smaller inhabitants are more likely to operate efficiently. This confirms the results of the DEA model in regional analysis concerning the influence of a competitive environment on operational efficiency.

5. Discussion

5.1. Implications in methodologies

We proposed an integrated nondiscretionary approach for competitive environment analysis, including six steps: factor identification, data collection, model building and nonparametric methods, model analysis, result verification and exploration with parametric methods, and result explaining. We summarize the research steps in Table 6.

“In recent years, there is an emerging trend toward employing a multi-methodological approach (MMA) to address complex and intriguing OM issues.” (Choi et al., 2016, Page 379). While many multi-method approaches refer to combining quantitative and qualitative methods, our multi-method approach essentially refers to a new multi-method approach integrating nonparametric and parametric methods for a global operations strategy. The motivation to apply a multi-method approach is from considering both the advantages and disadvantages of DEA methods. DEA methods have advantages in performance evaluation and efficiency measurement, and its disadvantages are in further mechanism discovery and explanation. We therefore first apply a nondiscretionary DEA method to provide a rigorous efficiency measurement for competitive environment analysis and then integrate it with quantitative methods to explain the results of nondiscretionary

### Table 5

Parameter estimates of the hierarchical regression model (H).

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>$\theta$</th>
<th>Sales</th>
<th>Market share</th>
<th>ROI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Outlets</td>
<td>0.43(2.30)</td>
<td>0.34(2.16)</td>
<td>0.43(3.08)</td>
<td>0.32(2.09)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.46)</td>
<td>(1.09)</td>
<td>(0.58)</td>
</tr>
<tr>
<td>Warehouses</td>
<td>0.18</td>
<td>0.10</td>
<td>0.17</td>
<td>0.15</td>
</tr>
<tr>
<td>Suppliers</td>
<td>0.34(2.39)</td>
<td>0.32(2.26)</td>
<td>0.36(2.76)</td>
<td>0.30(2.06)</td>
</tr>
<tr>
<td>Inhabitants’ population</td>
<td>0.17(−2.24)</td>
<td>0.22(2.35)</td>
<td>0.22(2.29)</td>
<td>0.24(2.36)</td>
</tr>
<tr>
<td>Market concentration</td>
<td>0.24(9.90)</td>
<td>0.28(14.7)</td>
<td>0.24(6.30)</td>
<td>0.25(12.6)</td>
</tr>
<tr>
<td>Consumer spending</td>
<td>0.25(9.37)</td>
<td>0.28(10.2)</td>
<td>0.19</td>
<td>0.31(10.3)</td>
</tr>
</tbody>
</table>

Residual standard error 0.67 0.34 4.04 1.58 7.84 6.39 4.18 1.77
Adjusted R-squared 0.32 0.70 0.27 0.60 0.19 0.46 0.36 0.58
F-statistic 22.5*** 96.4*** 12.8*** 45.6*** 10.4*** 18.5*** 24.3*** 42.3***

Note: *p < 0.1, **p < 0.01, ***p < 0.01, Significance from zero at the 10%, 5%, 1% level, respectively.

### Table 6

A DEA-based multi-method approach for competitive environment analysis.

<table>
<thead>
<tr>
<th>Index</th>
<th>Steps</th>
<th>Research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Factor identification</td>
<td>For a specific research problem, we identify nondiscretionary factors for competitive environment analysis and discretionary factors for main decisions.</td>
</tr>
<tr>
<td>Step 2</td>
<td>Data collection</td>
<td>We collect the real data for discretionary factors, nondiscretionary factors, and other relevant variables.</td>
</tr>
<tr>
<td>Step 3</td>
<td>Model building and nonparametric methods</td>
<td>We build nondiscretionary DEA models to describe the research problem. For different problems, we can use nondiscretionary network DEA models.</td>
</tr>
<tr>
<td>Step 4</td>
<td>Model Analysis</td>
<td>We solve and analyze nondiscretionary DEA models, calculate efficiency measuring, and assess organizational performance.</td>
</tr>
<tr>
<td>Step 5</td>
<td>Result verification and exploration with parametric methods</td>
<td>We use other quantitative methods to verify the results of nondiscretionary DEA models and further explore the information from the DEA study. For example, we can consider the MNL, PLS, and hierarchical regression methods or other quantitative methods in the literature.</td>
</tr>
<tr>
<td>Step 6</td>
<td>Result explaining</td>
<td>The advantages of DEA models are in performance evaluation and efficiency measurement, not in further mechanism discovery. We integrate with other quantitative methods to further explain the results of nondiscretionary DEA models or provide new findings relevant to the research question.</td>
</tr>
</tbody>
</table>
DEA models and use quantitative methods to further verify the results and provide new findings for the research question.

5.2. Implications in theories

According to (Whetten, 1989) (p. 493), introducing a new variable that can significantly change the understanding of the phenomenon is a type of theoretical insights. While classical environment-relevant measures and constructs such as environmental dynamism, introduced 34 years ago by (Miller and Friesen, 1983), have advantages in general application in multiple industries (Ward and Duray, 2000), they are not regularly used in retailing practices, which creates a practical gap for retailing practitioners. Considering a PBV (practice-based view), a rising theory in strategy management (Bromiley and Rau, 2014) when studying the effect of organizational environment, we consider measures in Planet Retail, a major database used by retailing practices and consulting. With the support of the PBV theory and keeping consistent with retailing practices, we introduced indicators and measures of industrial environment.

Previous competitive environment analysis is based on a number of influential theories, including strategic fit, contingency theory, industrial organization economics, institutionalization theory, ecological theory, and resource dependence theory (Zajac et al., 2000; Van de Ven et al., 2013; Meyer and Rowan, 1977; Astley and Fombrun, 1983; Hillman et al., 2000). We provide a new nondiscretionary DEA view rooted in production economics and microeconomics for competitive environment analysis.

Our new framework based on nondiscretionary DEA, considering multiple input and output measures and environmental impacts, can measure operational efficiency and provide an estimation of the influence of environmental factors. Without assuming parameter values, DEA assesses the performance of an organization by calculating and comparing it with the efficiency frontier, which is a function that indicates the maximum attainable level of output corresponding to a given quantity of inputs.

Prior research found the different roles, mechanisms, and functions of environmental factors, including the moderating effect of environmental factors, control variables, and factors leading to a complex nonlinear relationship. We can find knowledge regarding some environmental factors as nondiscretionary factors and then build a new framework to understand a competitive environment in a retailing operations strategy.

5.3. Implications in practices

Our studies show that operational efficiencies of global retailers show significant regional difference, which offers nontrivial management insights to retailing practitioners in setting objective for local operational units. Standardized versus localized objective setting in an operations strategy is a classical decision for global operations (Van Mieghem, 2008). Considering that “operating efficiencies are not a competitive advantage because they can be and usually are adopted by other companies” (Greenwald and Kahn, 2005) (p.4), we suggest that global retailers with operating units in different regions do not adopt a standardized objective in operating efficiencies for sustaining competitive advantages in different regions.

Our research shows that: inputs relevant to outside environment can influence operational efficiency and business performance more than inputs in internal supply chain (e.g., warehouses). The inputs in suppliers can improve the structure of upstream supply chain, manage inter-organization resources, and fit industrial environment. The inputs in outlets can optimize the structure of downstream supply chain, improve customer relationship management, and fit marketing environment. This new finding provides practical implication to retailing decision-makers: to increase efficiency and business performance, they can increase inputs relevant to outside environment. However, based on our data and analysis, practitioners cannot overplay to reduce inputs in internal resources since the relationship between the number of warehouses and efficiency is insignificant, not significantly negative.

Our research indicates that nondiscretionary factors significantly influence operational efficiency of global retailers (Greenwald and Kahn, 2005). So environmental contingency and nondiscretionary factors are not only critical for decision makers at the level of business strategy (Miller and Friesen, 1983) but also important for practitioners at the level of operations strategy (Ward and Duray, 2000). We particularly show that retailers located at a higher-level market concentration and consumer spending per capita with a smaller population are more likely to achieve high operational efficiency, which provides practical implications in setting operational objectives and selecting markets.

6. Concluding remarks

This paper studies the competitive environment analysis in a global operations strategy by integrating a DEA methodology and econometric analysis to explore the relationship between competitive environmental factors, inputs, and operational efficiency in different industrial environments. The main contribution is to develop a new six-step methodological framework based on nondiscretionary DEA and econometric models, considering multiple nondiscretionary inputs and multiple outputs, to study and understand the role of the environmental impact in a retailing supply chain strategy and to integrate efficiency analysis and competitive environment analysis in a global operations strategy. Our multi-method approach is essentially a multi-method approach integrating non-parametric and parametric methods for a global operations strategy. Using a sample of 124 firms from Asia, Europe, America, and other regions, we assessed retailing firms’ performance and compared the nonlinear relationships between facility inputs and productivity by region and environmental factor. We presented region-level profiles and analyzed the impact of an industrial environment on operational efficiency. This research has potential applications in a global operations strategy and competitive environment analysis.

Our study has many limitations, some of which can be extended for future research. Our data are limited to retailing, a single industry. It is interesting to explore whether such methodological framework can be applied in other industries. This research focuses on just the level of operations strategy, and it is unclear if the same approach can be applied in competitive environment analysis for different levels of strategies, such as global strategy, corporate strategy, and business strategy. Furthermore, while current research just considers operations strategy, these integrated DEA methods have potential applications in competitive environment analysis for other functional strategies like marketing strategy, IT strategy, and technology strategy.

Acknowledgement

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Table EC.1
Past research in competitive environment analysis∗.

<table>
<thead>
<tr>
<th>Research</th>
<th>Research theme</th>
<th>Method</th>
<th>Sample Size</th>
<th>Regions</th>
<th>Industry</th>
<th>Nondiscretional factors or inputs</th>
<th>Performance or outputs</th>
<th>Roles and functions of environmental factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pang et al. (2014)</td>
<td>IT and administrative efficiency&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Stochastic&lt;sup&gt;b&lt;/sup&gt; Frontier Approach</td>
<td>428 state-years</td>
<td>50 states of U.S.</td>
<td>IT Industry in Public Service</td>
<td>(1) Three factors with contextual effect: private-sector IT industry, share of rural population, and political dividedness of state government; (2) Control variables like Population, Household income, and GDP.</td>
<td>Education, Public welfare, Transportation, Public safety</td>
<td>(1) Some factors like government dividedness have moderating effect, (2) some factors are efficient control variables, (3) some factors may lead to nonlinear relationship such as complementarity. The relationship between business global integration strategy and performance varied significantly by industrial environments.</td>
</tr>
<tr>
<td>Grossman et al. (1999)</td>
<td>Public sector technical inefficiency</td>
<td>Stochastic frontier production function</td>
<td>49 U.S. central cities</td>
<td>Government sector</td>
<td>Average population, Local income tax, State grants, Federal grants, Years for mayor’s term of office</td>
<td>Aggregate market value of local property</td>
<td>Large city governments are operating at different degrees of technical inefficiency and the degree of technical inefficiency varies inversely with measured levels of competitive pressures. There are four general business-level strategies for operating in global environments: domestic product specialization strategy; Exporting high quality offerings strategy; International product innovation strategy; Quasi-global combination strategy. Operational efficiency of retailers has significant regional difference; Firms in an environment with higher market concentration, higher consumer spending per capita with smaller population are more likely to achieve higher efficiency.</td>
<td></td>
</tr>
<tr>
<td>This paper</td>
<td>Competitive environment analysis in GOS</td>
<td>Integrated DEA and econometric methods</td>
<td>124 firms America, Europe, Asia and other regions</td>
<td>Retailing</td>
<td>Market concentration, consumer spending per capita, inhabitants’ population</td>
<td>Operational efficiency; sales, market share, ROI</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<sup>a</sup> Not a comprehensive listing of prior research (chronologically ordered in each group).

<sup>b</sup> While Pang et al. (2014) study non-for-profit environment and the research is not about typical Competitive Environment Analysis, it presents a good example to study environmental factors with regarding them as either control variables and interaction variables.
We collected data across in retailing industry. Table EC.2 shows the sample profile.

Table EC.2
Sample profile of 124 organizations.

<table>
<thead>
<tr>
<th>Product sectors</th>
<th>Observations</th>
<th>%</th>
<th>Region</th>
<th>Observations</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fast-moving Consumer Goods</td>
<td>39</td>
<td>31.20</td>
<td>Asia</td>
<td>37</td>
<td>29.60</td>
</tr>
<tr>
<td>Fashion Goods</td>
<td>31</td>
<td>24.80</td>
<td>Europe</td>
<td>33</td>
<td>26.40</td>
</tr>
<tr>
<td>Hardlines &amp; Leisure Goods</td>
<td>30</td>
<td>24.00</td>
<td>America</td>
<td>26</td>
<td>20.80</td>
</tr>
<tr>
<td>Diversified</td>
<td>25</td>
<td>20.00</td>
<td>Others</td>
<td>29</td>
<td>23.20</td>
</tr>
<tr>
<td>In total</td>
<td>124</td>
<td>100.00</td>
<td>In total</td>
<td>124</td>
<td>100.00</td>
</tr>
</tbody>
</table>

We apply the following bootstrap procedure based on Simar and Wilson (2007), Algorithm 1, using 2000 bootstrap replications for the confidence intervals of the estimated coefficients:

Step 1. Using the original data of inputs and outputs, compute the efficiency score \( \tilde{\theta}_k \) for DMU\(_k\).
Step 2. We estimate the following equation to re-identify the efficiency score \( \hat{\theta}_k = Z_k \beta + u_k \), where \( \hat{\theta}_k \) is the efficiency score for DMU\(_k\). \( X_k \) is a vector of explanatory variables, including a constant term. \( u_k \) is an error term with a standard error of \( \sigma_u \). Since efficiency scores \( \hat{\theta}_k \) are truncated below from zero and above from unity, \( u_k \) is an error term with double truncation. Use the method of maximum likelihood to obtain an estimate \( \beta \) and an estimate \( \tilde{\theta}_k \) in the truncated regression of \( \hat{\theta}_k \) on \( Z_k \).
Step 3. For each \( k = 1, \ldots, n \) draw \( \epsilon_k \) from the \( N(0, \sigma^2_{\epsilon}) \) distribution with truncation at \( (1 - Z_k \hat{\beta}) \), then compute \( \hat{\theta}_k^* = Z_k \beta \epsilon_k + \tilde{\theta}_k \) and estimate the truncated regression of \( \hat{\theta}_k^* \) on \( Z_k \), yielding estimates \( (\beta^*, \sigma^2_{\epsilon}^{*}) \).
Step 4. Loop over step 3 for 2000 times to obtain a set of bootstrap estimates \( (\beta^*, \sigma^2_{\epsilon}^{*})_{i=1}^{2000} \).
Step 5. Use the bootstrap values in \( (\beta^*, \sigma^2_{\epsilon}^{*})_{i=1}^{2000} \) for each element of \( \beta \) and for \( \sigma^2_{\epsilon} \).

Table EC.3 reports regression results derived from the estimation of two models and their bootstrapped confidence intervals. The column (EC1) presents the basic regression model that includes outlets, warehouses and suppliers variables (model EC1). The next column (EC2) includes non-discretionary variables to control the effect of environmental characteristics on operational efficiency (model EC2). We also present the mean and standard deviation for lower and upper bounds of the efficiency measures based on a bootstrapping method at a confidence level of 95%.

Table EC.3
Truncated regression analysis.

<table>
<thead>
<tr>
<th>Dep. var. ( \hat{\theta}_k )</th>
<th>(EC1)</th>
<th>(EC2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outlets</td>
<td>0.378*</td>
<td>0.389*</td>
</tr>
<tr>
<td>Warehouses</td>
<td>0.170</td>
<td>0.120</td>
</tr>
<tr>
<td>Suppliers</td>
<td>0.361*</td>
<td>0.326*</td>
</tr>
<tr>
<td>Inhabitants population</td>
<td>– 0.182</td>
<td>0.213***</td>
</tr>
<tr>
<td>Market concentration</td>
<td>0.256***</td>
<td></td>
</tr>
<tr>
<td>Consumer spending</td>
<td>– 0.384*</td>
<td>– 3.347*</td>
</tr>
<tr>
<td>Constant</td>
<td>0.45(0.23)</td>
<td>0.78(0.19)</td>
</tr>
<tr>
<td>95% C.I. lower bound</td>
<td>Mean (Standard deviation)</td>
<td></td>
</tr>
<tr>
<td>95% C.I. upper bound</td>
<td>Mean (Standard deviation)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables. *p < 0.1, **p < 0.01, ***p < 0.001.

References

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Joe Zhu is Professor of Operations Analytics in the Foisie Business School, Worcester Polytechnic Institute. He is an expert in methods of performance evaluation and benchmarking using Data Envelopment Analysis (DEA) and developed the DEA Frontier software. He has published extensively on peer reviewed journals such as Management Science, Operations Research, European Journal of Operational Research, Journal of Operational Research Society, IIE Transactions, Sloan Management Review, OMEGA, and others.