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An exploratory analysis of resource utilization across organizational units

Understanding the resource-based view

Stewart R. Miller
Management Department, McCombs School of Business, University of Texas-Austin, Austin, Texas, USA, and
Anthony D. Ross
Department of Marketing and Supply Chain Management, Eli Broad Graduate School of Management, Michigan State University, East Lansing, Michigan, USA

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Abstract *This study explores the applicability of the resource-based view at the organizational unit level by investigating why resource utilization, as measured by efficiency, might differ within a firm. Using a downstream petroleum firm as the context for this study, the data envelopment analysis framework is applied to examine resource input congestion of its DCs (i.e. distribution centers). The study also provides a more granular analysis by decomposing distribution efficiency into managerial, scale, and programmatic efficiency, and examines the impact of corporate-level decision making by including non-discretionary variables. The analysis identifies opportunities to improve efficiency at the organizational unit level, using alternative views of the operational problem. The approach also provides practicing managers with an objective means to evaluate performance at the level of the organizational unit. Both the efficiency view and the managerial performance view are discussed simultaneously from a strategic view of firm resources.*

Introduction

A growing number of scholars have integrated economic principles into the strategic management literature (Rumelt *et al.*, 1991). Williamson (1991) underscored the importance of efficiency to the strategic management literature, noting that studies of business strategy tend to fall into two broad categories: strategizing and economizing. The efficiency-based approach to competitive advantage has a long tradition that suggests firms build sustainable competitive advantage only through efficiency and effectiveness (Williamson, 1991). Williamson asserted strategizing would rarely succeed in the face of production, distribution, and/or organizational inefficiencies. He further argued that in the long term, the best strategy is

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to organize and operate efficiently. Economizing also plays a role in the strategizing perspective. Porter (1996, p. 161) contended "operational effectiveness is necessary, but not sufficient". Both operational effectiveness and strategy are vital to a firm's success. Williamson also commented that the efficiency-based approach is also consistent with the resource-based view (RBV) of the firm (Barney, 1991, 2001; Peteraf, 1993; Priem and Butler, 2001a, b; Rumelt, 1984; Teece *et al.*, 1997; Wernerfelt, 1984). Evaluating performance links the components of complex value-creating supply-chain systems at the strategic level by directing strategy formulation and at the operational level by monitoring the implementation of that strategy (Fawcett and Clinton, 1996).

The RBV of the firm has grown in popularity as a paradigm through which to explain sustainable competitive advantage and interfirm performance (e.g. Barney, 1991). Revealed by efficiency, resource utilization is an important aspect of RBV thinking because it reflects productive use of resources. For example, Rumelt *et al.* (1991, p. 13) noted that creation of specialized resources is based on operating efficiently – "properly identifying the existence and quality of resources, and in building product-market positions and contractual arrangements that most effectively utilize, maintain, and extend these resources". Efficiency is also embedded in the notion of resource heterogeneity – resource bundles underlying production differ across firms (Barney, 1991). Peteraf (1993, p. 180) suggested that different production factors used by firms have "intrinsically differential levels of 'efficiency'", since some resources are superior to others. Therefore, firms with superior resources are able to produce more cost effectively and/or enhance customer satisfaction, and therefore achieve rents. According to the RBV, resource heterogeneity and imperfect imitability are essential for sustaining competitive advantage (e.g. Barney, 1991). Yet, Zander and Kogut (1995) posited that a capability that is difficult to imitate by competitors is also inclined to be difficult to replicate within a firm. As such, we contend that imperfect imitability by rivals has an intrafirm counterpart, imperfect replicability, which has received little attention in the literature (see also Szulanski, 1996).

One question that remains unanswered is that if resource heterogeneity and imperfect imitability exists across firms according to the RBV, then what are the implications for resource utilization at the organizational unit level? To address this question, the present study focuses on two issues. First, building and sustaining competitive advantage for a firm requires a deeper understanding of resource utilization within the firm. One means to achieve this end is to examine the efficiency of a firm's decision-making units (DCs) and decompose efficiency so that we can paint a clearer picture of the sources of inefficiency and offer appropriate prescriptions to enhance resource utilization of DCs and the entire organization rather than resorting to broad-based efficiency initiatives with no roadmap to improvement.

Second, resource heterogeneity may occur within the same firm, since managers with different skill levels control facilities with resource of different quality. For example, some DCs may have superior physical resources, but poor managerial resources. Alternatively, other units may have less-than-superior physical resources, but highly skilled managerial resources. Moreover, managers may face corporate restrictions that limit their abilities to manage effectively. To make informed assessments of the performance of a firm's operations, and its managers, it becomes essential to disentangle the different types of inefficiencies, as well as, corporate-level constraints, as they relate to resource utilization. Most studies of resource utilization have been interfirm in nature (e.g. Majumdar, 1998). However, despite the important link between efficiency and competitive advantage, there has been little rigorous analysis of intrafirm resource utilization (e.g. Berger *et al.*, 1997), especially of a firm's distribution system.

The present study addresses the following research question: To what extent does resource utilization differ within a firm (e.g. its supply-chain system)? In addition, we ask two follow-up research questions: To what extent do geographic markets and corporate-level constraints contribute to resource utilization differences within a firm? Are some types of efficiency more important than others when evaluating distribution resource utilization within a firm?

To answer these questions, we use refining distribution centers of a large regional firm in the downstream petroleum industry as the context and examine resource utilization and different types of efficiency with data envelopment analysis (DEA; Farrell, 1957; Charnes *et al.*, 1978). The DEA literature tends to associate the efficient frontier with best-practicing firms. DEA measures input-output efficiency – how effectively a firm's managers are able to economize on the use of inputs to obtain a given level of outputs. DEA relates the performance of companies in an industry to a piecewise linear production frontier, which is an empirically estimated production function based on the inputs and outputs of the most efficient companies. Hence, DEA reveals a firm's capabilities in using its resources (Majumdar, 1998).

We analyze efficiency, in the form of resource input congestion, within a firm using a supply chain distribution system as the test bed. Using a firm's DCs (i.e. its distribution centers) as the context for the present study, we are better able to identify best practices and areas in need of improvement in terms of resource utilization within the supply chain. In addition, such analysis improves our understanding of efficiency at the firm level. In this study, we do not challenge Porter's (1996) arguments by suggesting that efficiency is a strategy, rather, we attempt to highlight the importance of operational effectiveness to achieving and sustaining competitive advantage.

Resource utilization within the firm

A fundamental underpinning of the RBV of the firm is that superior performance is achieved because of resource heterogeneity (e.g. Barney, 1991; Peteraf, 1993; Rumelt *et al.*, 1991), as well as uncertain imitability (Lippman and Rumelt, 1982). Resource heterogeneity can arise due to the presence of a unique coordination process within firms (Majumdar, 1998). Coordination involves allocation of specific resources toward activities. Majumdar (1998) further commented that, "The function of identifying how one activity may impact others becomes important (Kaldor, 1934), so that interdependent resources can be optimally combined together via activities". From an intra-organizational perspective, two issues arise. First, the coordination process may limit the discretionary activities of business unit managers, resulting in shortfalls in efficiency. Second, interdependent resources can lead to intrafirm differences in performance. Barney (1991, p. 101) suggested that firm resources include "all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable it to conceive of and implement strategies that improve its efficiency and effectiveness (Daft, 1983)". Majumdar (1998, p. 811) suggested that resources can be unbundled to include "physical, intangible human and organizational resources". Although corporate managers may be focused on overall firm performance, the allocation of tangible and intangible resources can influence system performance due in part to causal ambiguity (Alchian, 1950; Rumelt, 1984), which exists when "the link between the resources controlled by a firm and a firm's sustained competitive advantage is not understood or understood only very imperfectly" (Barney, 1991, pp. 108-9). As such causal ambiguity can produce various combinations of tangible and intangible resources within the firm, that result in differences in intra-firm performance.

RBV scholars have argued that unique historical conditions represent an important source of imperfect imitability (Barney, 1991; Dierickx and Cool, 1989). According to RBV thinking, a firm obtains valuable and rare resources because of its unique historical trajectory. The firm can exploit these resources that cannot be replicated by rivals because firms without the same unique historical path are unable to obtain the necessary resources to implement their strategy. We assert that the historical conditions argument can be applied at organizational unit level. Thus, unique historical conditions at the time of an organizational unit's establishment can influence its ability to replicate a best-practice template within the firm. Organizational units with unique histories may be unable to perfectly replicate a best practice template due to their existing resource bundle. Best practices developed for a specific set of resources may result in shortfalls in resource utilization by the organizational unit without the same desirable combination and quality of resources.

Historical conditions may also contribute to variance in resource utilization across regions (i.e. programs) of the firm. A firm that establishes facilities in more valuable locations than anticipated at the time the location was selected has an imperfectly imitable physical resource (Barney, 1991). Similarly, a firm with researchers uniquely positioned within the organization to produce scientific discoveries may have imperfectly imitable human resources (Winter, 1988). As a result, region-specific differences can lead to variance in the ability to replicate best practices within the firm and to regional differences in resource utilization of organizational units, as measured by scale, managerial, and programmatic inefficiency.

Context for the hypotheses

Higher customer expectations, shrinking profit margins and little brand loyalty create challenges and opportunities to achieving superior performance. Operations size, workforce knowledge, direct salaries (influenced by experience), geographic market differences, vehicle costs (capital, maintenance and repair, fuel, insurance), load time at the distribution center, discharge time/rate into customer facilities, customer densities and many other factors can influence performance. In some cases, resource decisions are determined by top management and inherited by local managers. These decisions are strategic in nature and classified as non-discretionary. Alternatively, discretionary resource decisions are tactical in nature and determined by local managers (e.g. workforce profiles in the form of driver experience). Thus, the sheer number of potentially relevant variables complicates most any approach to measuring performance. Empirical research applying the DEA methodology is vast (Seiford, 1996). Recent studies have examined efficiency among libraries, schools, hospitals, consumer product vendors, software services, and telecommunications firms (Chen, 1997; Hartman and Storbeck, 1996; Mahmood *et al.*, 1996; Majumdar, 1998; Sexton *et al.*, 1994; Weber, 1996). We build on these prior studies by specifically exploring the internal dimensions of resource efficiency among intra-business units and by testing the following hypotheses:

H1a. On average, the managerial inefficiency of intra-business units within a region will be positive.

H1b. Managerial inefficiency of intra-business units will differ across regions.

H2a. On average, the programmatic inefficiency of intra-business units within a region will be positive.

H2b. Programmatic inefficiency of intra-business units will differ across regions.

H3. Scale inefficiency of intra-business units will differ across regions.

Evaluating the efficiency of a supply chain system is difficult for several reasons. First, efficiency is generally evaluated in relative rather than absolute terms. Second, the DCs are generally within a larger organizational hierarchy where multiple inputs are used to produce multiple outputs. Thus, there is a need to address and understand both managerial and program efficiencies among the units in the firm. Corporate planning managers want to know what fundamental change in distribution strategy was required (if any), while DC managers are concerned primarily with the tactical issues reflecting only on their individual performance. Also, DC managers compete internally for allocation of resources from corporate managers and externally for market share. In terms of this study, we illustrate these needs with Figure 1. Here we illustrate that each of the major market regions is described by best-performing DCs in the region. These DCs form the efficient frontier for the associated region. Thus the efficient input and output levels vary by region. Strategic resource decisions are often made without understanding the unique, and sometimes, subtle operating differences that lead to high performance or poor performance. Unraveling this mystery from the resource allocation perspective is a central theme of this paper.

Although Table I reports initial results from evaluations relative to each DC's efficient frontier for each model considered, the interpretation depends on the distributions of the inefficient DCs. In Figure 1, the horizontal is axis (x) and the vertical axis (y) represent the inputs and outputs, respectively. The figure

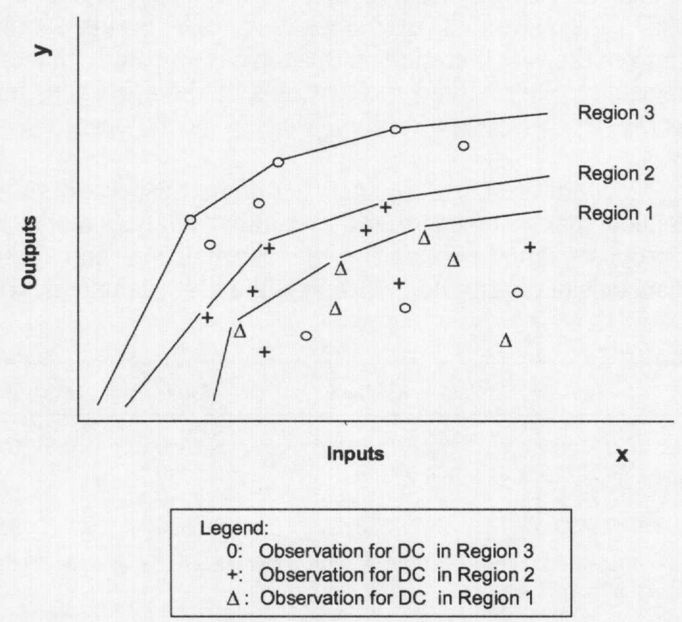

Figure 1. Efficient frontiers of DC regions

shows an efficiency frontier for each of the three operating regions used considered. Regions similarly situated to number 3 seem to dominate number 2, and those similar to region 2 seem to dominate number 1. This phenomenon, however, may be obscured by the inefficient DCs not demonstrating their full capabilities possible. As was noted earlier, however, understanding why and in what form such dominance (or differences) exists is at the heart of this exploratory investigation. More specifically, we investigate each region and attempt to unravel the behavior of the efficient and inefficient DCs using several decompositions of efficiency (managerial, programmatic, or scale), which are defined later in our presentation of the methodology.

As will be shown later in the paper, we eliminate this programmatic inefficiency by separately evaluating each region using the ideas discussed later in our presentation of the methodology to project each DC onto its respective frontier. We then re-evaluate the adjusted observations by combining the frontiers. When this is done, the efficient frontier can be comprised of DCs from any of the regions. We will then apply parametric tests on the rankings of the DCs. This scenario occurs in cases where the efficient frontier of one region strictly dominates the efficiency of other regions. It is more likely, however, that the frontiers intersect or crossover. In any such case of multiple comparisons, the parametric tests (of means) and non-parametric tests (of ranks) can be applied to explore differences in resource efficiency and capabilities.

Studies in the general operations management and banking literature have partially addressed these supply chain system issues (Kleinsorge *et al.*, 1989; Berger *et al.*, 1997; Gillen and Lall, 1997; Ross *et al.*, 1998; Sarkis, 2000). What seems to absent from the vast literature on this topic is any study that explores resource heterogeneity, alternative process views of the operations, and the impact of corporate-level decisions on the efficiency of the operating system simultaneously.

Drawing on this literature base, we analyze different aspects of efficiency. However, please note that we do not offer the definitive analysis model. Rather, our research proposes another step in the constructing and testing of comprehensive models of distribution efficiency. We first evaluate distribution

Table I. Operating efficiency results

Region	Model 1	Model 2	Model 3	Model 4
1	0.74 (0.26)	0.74 (0.26)	0.65 (0.35)	0.80 (0.20)
2	0.75 (0.25)	0.81 (0.19)	0.62 (0.38)	0.82 (0.18)
3	0.75 (0.25)	0.70 (0.30)	0.72 (0.28)	0.87 (0.13)
Total sample	0.74 (0.26)	0.75 (0.25)	0.66 (0.34)	0.82 (0.18)

Notes: Efficiency is measured using initial DEA with constant returns to scale models (1-4). Operating inefficiency in parentheses performance from several strategic process views in order to understand the general nature of efficiency. Second, we identify and differentiate managerial efficiency, scale efficiency, and programmatic efficiency using a firm's distribution operation as our testbed. Finally, we explore (using parametric tests) the efficiency impact of non-discretionary and regional variables that may not be directly controlled by DC managers.

The remainder of this paper is organized as follows. First, we summarize the DEA methodology. Second, we discuss efficiency measurement in supply chains. Third, we present the results and discussion. We conclude by highlighting contributions, managerial implications, limitations, and opportunities for future research.

Methodology

Data

All data for this study was obtained directly from a large regional firm in the downstream petroleum industry. This Midwest-based firm provided operating data for its 207 distribution centers, which are located in three geographical regions.

DEA efficiency: the general formulation

Data envelopment analysis (DEA) has become an important way to evaluate efficiency (Charnes *et al.*, 1978). As competition continues to intensify, many manufacturing and service enterprises have expressed concerns about their ability to efficiently transform various inputs into valued outputs. DEA efficiency is a critical methodology for performance evaluation because it is based on the ratio of inputs to outputs. DEA accommodates differences in size, management, objectives or other characteristics with the flexibility to include only the relevant inputs and outputs. Finally, DEA requires no statistical assumptions about the underlying data.

Charnes *et al.* (1978) developed a mathematical programming model (CCR) useful for evaluating the efficiency of DCs that assumes constant returns to scale. As stated earlier, the DC is a petroleum DC. By employing DEA, the efficiency of each DC is evaluated by comparing it to a group of other DCs having the same set of inputs and outputs, as will be described later.

As an extension to the constant returns to scale model, Banker *et al.* (1984) developed a general model formulation follows below for m inputs, p outputs and n DCs that assumes that variable returns to scale exist. In the variable returns to scale (BCC) model, DEA determines a measure of the relative efficiency of each DC in comparison to all remaining DCs considered (the analysis set). Mathematically, it is:

$$\begin{aligned} \text{Min} \quad & \Theta - \textstyle\sum_{i=1}^{m} e_i - \sum_{r=1}^{p} s_r \\ \text{subject to}: \quad & \textstyle\sum_{j=1}^{n} X_j\lambda_j + e_i = \Theta x_{i0}, i = 1, 2, \ldots, m, \\ & \textstyle\sum_{j=1}^{n} Y_j\lambda_j - s_r = y_{r0}, r = 1, 2, \ldots, p, \\ & \textstyle\sum_{j=1}^{n} \lambda_j = 1 \\ & \Theta, e_i, s_r, \lambda_j \geq 0, \forall i, r, j \end{aligned} \tag{1}$$

where:

θ = aggregate efficiency score for DC_o, the unit under consideration.

y_{ro} = amount of output r generated by DC_o.

x_{io} = amount of input i consumed by DC_o.

X_j = the actual inputs consumed by DC_j. Each problem has ($x_{1j}, x_{2j}, \ldots, x_{mj}$).

Y_j = the actual outputs generated by DC_j. Each problem has ($y_{1j}, y_{2j}, \ldots, y_{pj}$).

e_i = amount of excess input i for DC_o.

s_r = amount of slack in output r for DC_o.

λ_j = the weights assigned to the inputs and outputs at DC_j.

The objective function is oriented toward minimizing the levels inputs consumed, and thus is specified as input-oriented. In order, the remaining constraints:

(1) ensure that the input level for input i is a linear combination of the inputs from the analysis set, plus the excess input of i; and

(2) specify that the optimal output of r at DC_o should also be a convex combination of the outputs from the analysis set, minus its slacks.

The weights, λ_j, are generated by solving the DEA equations simultaneously. The optimal solution to the objective function implies that DC_o is efficient if and only if the following hold: $\theta^* = 1.00$; and $e_i^* = s_r^* = 0.00$. The reader may consult the above-cited works for additional background, or Charnes *et al.* (1994). As is discussed later in the paper, much of our analysis is based on the variable returns to scale assumption of equation (1) to account for varying DC sizes. However, we accomplish the constant returns to scale portion of analysis by omitting the convexity constraint (2) below from equation (1):

$$\sum_{j=1}^{n} \lambda_j = 1. \quad (2)$$

Models analyzed

We evaluate several DEA models involving pairings of the input variables with the same set of output variables. Table II lists these eight distinct process models. Process models 1-4 assume variable returns to scale. Process models 1*-4* assume constant returns to scale. The purpose of using eight models, which include different-input-output permutations, is to obtain an overall view of efficiency, regardless of the perspective, rather than rely on only one benchmark. By using alternative process views, we are better able to form conclusions on the nature of efficiency and illustrate an integrated evaluation approach.

Modeling scale efficiency and programmatic efficiency

Both scale differences and programmatic (regional) differences existed among the DCs, and these were caused by local competition, the effectiveness of local management, and other factors. For managers, an analysis of the results can help determine policies regarding input mix for resources so that operating performance of the DC improves.

Scale efficiency

To analyze scale efficiency, constant returns to scale (models 1*, 2*, 3* and 4*) and variable returns to scale (models 1, 2, 3 and 4) results are required. For a given set of data, scale efficiency is expressed as a ratio of constant returns efficiency to variable returns efficiency, or $EFF_j^{scale} = EFF_j^{constant} / EFF_j^{variable}$. If EFF_j^{scale} is equal to 1.0, it indicates that DC $\boldsymbol{j}$ is operating at its most productive scale. EFF_j^{scale} greater than 1.0 indicates DC $\boldsymbol{j}$ operates on a scale greater than the most productive. Finally, EFF_j^{scale} less than 1.0 indicates that DC $\boldsymbol{j}$ operates on a scale less than the most productive.

Inputs	Model 1 (and 1*)	Model 2 (and 2*)	Model 3 (and 3*)	Model 4 (and 4*)
Vehicle fleet size			Excluded	
Average driver experience		Excluded		
Regional market index	Excluded			
Outputs identical across models				

Notes: Models 1 to 4 were solved using variable returns to scale. Models 1* to 4* used constant returns to scale

Table II. Descriptive statistics and process models (alternative process models)

Programmatic efficiency

Within an organization, there is typically a managerial layer responsible for overseeing the strategies and tactics of some group of units (group of DCs) sharing similar operating characteristics (e.g. production technology, market characteristics, resource technology, geography, etc.). In general, the intermediate level of management overseeing a group may be called a program. In this study, the 207 DCs are grouped by sub-market within the Midwest: Region 1, region 2, and region 3, and so there are three programs defined by region, each with accountability and management control. In general, not all programs are the same. There may be a larger number of good (or poor) managers in one region than in the others; there may also exist superior (or inferior) combinations of resource inputs (a management decision). Performance evaluations across programs (in our case, across regions) require controlling for programmatic differences so that the DCs can be fairly compared (Ganley and Cubbin, 1992). Charnes *et al.* (1981), Byrnes *et al.* (1988), and Banker *et al.* (1990) study efficiency within programs. But not until the paper by Brockett and Golany (1996) was is possible to extend DEA analyses further. They developed the theoretical and statistical basis for inter-program efficiency comparisons where non-discretionary variables can be incorporated. Thus, their study opened up the opportunity to extend the DEA methodology even further into the strategy field.

However, to analyze programmatic efficiency, we conducted initial DEA and final DEA estimates. Initial DEA differs from final DEA since the linear programming formulations have completely different dimensions and reference sets. For initial DEA, the three Midwest regions were analyzed and projected independently of each other. For final DEA however, all DCs were combined into one super region. Several intermediate steps were required to eliminate managerial inefficiencies. First, the inefficient DCs were projected separately for each region by adjusting input levels to their efficient levels as reported in initial DEA. This is known as frontier projection. It removes the managerial component of inefficiency, leaving programmatic inefficiencies unaltered. Second, regions 1, 2 and 3 were pooled and all 207 scores were recomputed together instead of separately (final DEA):

- *Step 1 (initial DEA).* Apply DEA to each region (region 1, 2, 3) separately to examine operational efficiency (with descriptive statistics).
- *Step 2 (adjust inputs).* For each region separately, project inefficient DCs as close as possible to the efficient frontier. For models with the non-discretionary variable (i.e. the regional market index), complete projection onto the frontier may not be possible.
- *Step 3 (final DEA).* Apply DEA again after adjusting the inputs and pooling the DCs. Compute the final DEA scores and descriptive statistics.

- *Step 4 (parametric test).* Identify programmatic differences by determining if efficiency differences exist across the regions. Tests of significance based on Kruskal-Wallis tests.
- *Step 5.* Recommend input mix policies that can improve programmatic efficiency.

Programmatic efficiency ($EFF_j^{Programmatic}$) is measured using the Final DEA measure of efficiency with the variable returns to scale models to ensure that we control for scale efficiency. Programmatic inefficiency equals $1 - EFF_j^{Programmatic}$. Lastly, managerial efficiency is measured using both the Initial DEA and Final DEA. We compute managerial inefficiency, which equals Final DEA − Initial DEA = $\text{In-EFF}_j^{Managerial}$. If Final DEA ≤ Initial DEA, then $\text{In-EFF}_j^{Managerial} = 0.00$. Managerial efficiency, which is represented by $EFF_j^{Managerial}$ equals $1 - \text{In-EFF}_j^{Managerial}$.

Distribution operations

Efficiency: inputs and outputs. Earlier studies used diverse sets of input and output factors in evaluating efficiency, suggesting that such analyses are contextual (e.g. Bhargava *et al.*, 1994). According to these studies, resource inputs can include any combination of labor (e.g. workforce size, experience, man-hours required or dollar cost), vehicles (e.g. fleet size or capacity), equipment (e.g. size or capacity, machine availability), capital (e.g. net present value), and/or information (e.g. demand requirements). Likewise, there are several classes of outputs such as aggregate revenue, profits, quality, utilization, flow time, fill rates, customer satisfaction, delivery performance, worker satisfaction, and inventory. Given that the context of this study is distribution centers of a firm, the input variables available for this research are vehicle fleet size, average driver experience, and regional market index (see Tables II and III).

Vehicle fleet size. Vehicle fleet size (number of vehicles) represented the delivery capacity for each delivery cycle and the number of people assigned to

	Region 1 ($n = 100$)	Region 2 ($n = 58$)	Region 3 ($n = 49$)	Overall ($n = 207$)
Vehicle fleet size	3.43 (1.44)	2.97 (0.84)	2.90 (1.03)	3.18 (1.23)
Avg. driver experience (years)	7.05 (2.14)	7.12 (1.64)	6.92 (1.89)	7.04 (1.95)
Regional market index	2.87 (1.29)	3.36 (1.16)	2.88 (1.09)	3.01 (1.22)
Commodity 1 (thousands of gallons)	33.2 (2.5)	25.3 (3.9)	33.7 (2.3)	31.2 (4.6)
Commodity 2 (thousands of gallons)	92.9 (1.6)	80.4 (10.2)	78.1 (15.0)	86.1 (11.3)
Commodity 3 (thousands of gallons)	129.9 (9.1)	63.9 (11.5)	91.5 (9.1)	102.8 (30.1)
Commodity 4 (thousands of gallons)	102.1 (12.7)	136.3 (32.0)	162.4 (20.4)	125.5 (32.8)
Run-miles	282.5 (17.4)	283.0 (8.8)	257.5 (25.7)	276.8 (20.8)
No. of deliveries	22.0 (4.1)	28.0 (2.4)	33.0 (2.5)	26.0 (5.8)

Table III. Descriptive statistics and process models (means and standard deviations (in parentheses)) the DC. The fleet is assumed homogeneous. We represented the labor input at each DC using average driver experience (the average years of experience of the personnel assigned to each DC). Workers' process knowledge and expertise were captured using this variable.

Regional market index. Regional market index was provided by executive-level management. It is used as a non-discretionary input to account for unique DC characteristics such as the number of competitors, customer densities, customer switching patterns, the hardware technology in use for fuel transfer facilities, and delivery economics (Banker and Morey, 1986). If the impact of non-discretionary variables can be isolated, then efficiency performance can be objectively compared while still accounting for inherent DC differences. Hence, we are revealing the extent to which discretionary inputs can be reduced by the DC manager while keeping this non-discretionary input at is current level.

The output variables used for each of the models incorporated product delivery volumes and vehicle usage. These data were used primarily because the firm faced considerable competitive pressure to reduce specific resource levels (downsize) in the DC system, but lacked the strategic roadmap for doing so. Product delivery volumes are classified as four types of commodity deliverables: commodity 1, commodity 2, commodity 3, commodity 4. The use of four separate volumes avoids any oversight arising from aggregating outputs, (e.g. total volume). Vehicle usage is measured using average vehicle run-miles and average vehicle number of deliveries, which capture delivery resources associated with a delivery cycle, and customer market size differences across the entire system. Table III lists the means per region for the input and output variables.

Results

Table I presents results for estimating efficiency of DCs in each of the three regions and for the total sample. In region 1, average efficiency ranged from a low of 0.65 (using model 3) to a high of 0.80 using model 4. In region 2, average efficiency ranged from 0.62 to 0.82. Average efficiency in region 3 ranged from 0.70 to 0.87. For the total sample, the results indicate that average operating ranged from 0.66 (using model 3) to a high of 0.87 (using model 4). Model 3, which included drivers experience (input) and the regional market index (non-discretionary variable), generally reported the lowest efficiency for each region. Model 4, which include both input variables (drivers experience and vehicle fleet size) and the regional market index variable, generally reported the highest efficiency.

Panel A of Table IV presented the scale efficiency results for each region and for the total sample. All four models for the variable returns to scale (models 1 to 4) and the constant returns to scale models (models 1* to 4*) were required to compute scale efficiency. In region 1, the results indicate that the average scale

Region	Model 1	Model 2	Model 3	Model 4
Panel A: scale efficiency/(inefficiency)				
1	0.76 (0.24)	0.77 (0.23)	0.67 (0.33)	0.82 (0.18)
2	0.81 (0.19)	0.94 (0.06)	0.69 (0.31)	0.95 (0.05)
3	0.78 (0.22)	0.74 (0.26)	0.77 (0.23)	0.91 (0.09)
Total sample	0.78 (0.22)	0.81 (0.19)	0.70 (0.30)	0.87 (0.13)
Panel B: programmatic efficiency/(inefficiency)				
1	0.98 (0.02)	0.97 (0.03)	0.98 (0.02)	0.99 (0.01)
2	0.96 (0.04)	0.92 (0.08)	0.94 (0.06)	0.95 (0.05)
3	0.94 (0.06)	0.98 (0.02)	0.95 (0.05)	0.98 (0.02)
Total sample	0.97 (0.03)	0.96 (0.04)	0.96 (0.04)	0.98 (0.02)
Panel C: managerial efficiency/(inefficiency)				
1	0.99 (0.01)	1.00 (0.00)	0.99 (0.01)	0.99 (0.01)
2	0.96 (0.04)	0.94 (0.06)	0.95 (0.05)	0.91 (0.09)
3	1.00 (0.00)	0.97 (0.03)	0.99 (0.01)	0.98 (0.02)
Total sample	0.98 (0.02)	0.97 (0.03)	0.98 (0.02)	0.98 (0.02)

Note: Inefficiency in parentheses

Table IV. Scale, programmatic, and managerial efficiency results

efficiency of the DCs ranged from 0.67 to 0.82 (average scale inefficiency: 0.18 to 0.33). In region 2, scale efficiency of the DCs ranged from 0.69 to 0.95 (average scale inefficiency: 0.05 to 0.31). Average scale efficiency for DCs in region 3 ranged from 0.74 to 0.91 (average scale inefficiency: 0.09 to 0.26). When we pooled across all three regions, average scale efficiency of DCs ranged from 0.70 to 0.87 (average scale inefficiency: 0.13 to 0.30).

Panel B of Table IV presents the results for programmatic efficiency for each region, as well as for the total sample. These results are based on the variable returns to scale models (1* to 4*) in order to exclude scale efficiency effects. In region 1, programmatic efficiency ranges from 0.97 to 0.99 (average programmatic inefficiency is 0.01-0.03). In region 2, programmatic efficiency is somewhat lower, ranging from 0.96 to 0.92 (average programmatic inefficiency was 0.04 to 0.08). Programmatic efficiency in region 3 ranged from 0.94 to 0.98 (average programmatic inefficiency ranged from 0.02 to 0.06). Lastly, for the total sample of DCs, average programmatic efficiency was 0.94 to 0.98 (average programmatic inefficiency ranged from 0.02-0.04). In general, programmatic inefficiency tended to be highest in region 2. Moreover, model 4 tended to produce the lowest programmatic inefficiency.

Panel C of Table IV reports the results for managerial efficiency and inefficiency for each region and the total sample. In region 1, managerial efficiency was at least 0.99 for each of the models. In region 2, managerial efficiency reached a high of 0.96 with model 2 and a low of 0.91 with model 4. In region 3, the minimum average managerial efficiency was 0.97. Across all three regions, managerial efficiency ranged from 0.97 to 0.98.

We now revisit our earlier hypotheses and discuss the results of our tests on each of *H1a*, *H1b*, *H2a*, *H2b*, and *H3* respectively. Table V reports the sample size, mean, sample deviation, and computed *p*-values for *H1a*. Our one-tailed tests show that the probability that these observed values occurred randomly are very low (*p*-values less than 0.01). Since all mean values are positive, we can conclude that there is varying levels of managerial inefficiency in the regions, particularly region 2 is characterized with some 18.6 percent to 35.6 percent inefficiency. Thus, the results support *H1a*.

For *H1b*, we ran simple one-way ANOVA on the managerial inefficiency for the data. Based on these initial results, we then analyzed the difference in mean values across the regions using Tamhane's multiple comparisons to isolate these differences across the regions for models one through four. Table VI reports our summary ANOVA results (*F*-values and significance levels), which show that the mean differences between the regions are significant for all models. Using Tamhane's tests (alpha = 0.05), we detected statistically

Table V.
Managerial inefficiency results (*t*-tests on managerial inefficiency (*H1a*))

		Sample	Mean	SD	*p*-value
Region 1	Model 1	100	0.01834	0.0321	5.83945E-08
	Model 2	100	0.0093	0.03867	0.009016069
	Model 3	100	0.02	0.036	1.16781E-07
	Model 4	100	0.0083	0.01999	3.49424E-05
Region 2	Model 1	49	0.186	0.04488	2.17999E-32
	Model 2	49	0.3594	0.0859	1.41527E-32
	Model 3	49	0.04	0.075	0.000250422
	Model 4	49	0.0329	0.0803	0.003060358
Region 3	Model 1	58	0.0513	0.10467	0.000219612
	Model 2	58	0.0883	0.1878	0.000354415
	Model 3	58	0.08	0.101	6.36678E-08
	Model 4	58	0.1	0.1942	0.000119357

Table VI.
Managerial inefficiency results (ANOVA: managerial inefficiency across regions (*H1b*))

		Sum of squares	df	Mean square	*F*	Sig.
Model 1	Between groups	0.045	2	0.023	5.593	0.004
	Within groups	0.824	204	0.004		
	Total	0.869	206			
Model 2	Between groups	0.230	2	0.115	9.319	0.000
	Within groups	2.513	204	0.012		
	Total	2.743	206			
Model 3	Between groups	0.129	2	0.065	13.491	0.000
	Within groups	0.977	204	0.005		
	Total	1.106	206			
Model 4	Between groups	0.312	2	0.156	12.735	0.000
	Within groups	2.501	204	0.012		
	Total	2.813	206			

significant differences between regions one and three in 3 out of 4 of the models with region one having less managerial inefficiency. Region 2 also contain less managerial inefficiency than region three, however the results suggest those differences were not significant. In fact, when we compared managerial inefficiency across all regions: region 1 vs 2 (0.01 vs 0.05, $p < 0.01$); region 1 vs 3 (0.01 vs 0.02, not significant); and region 2 vs 3 (0.05 vs 0.02, $p < 0.10$). Thus, there is modest support for *H1b*.

For *H2a*, we calculated the test statistics, using the same approach in *H1a* above (Table VII). Since all mean values are positive, we can conclude that there are varying levels of programmatic inefficiency in the regions, particularly region 3 seems to have the largest degree of such inefficiency (4 percent to 8 percent). Programmatic inefficiency is significantly different from zero across all regions, supporting *H2a*.

For *H2b*, we ran the same procedure as above. Table VIII reports our summary ANOVA results (*F*-values and significance levels). They show that the mean differences between the regions are significant for most models. Using Tamhane's tests (alpha = 0.05), we detected statistically significant differences between regions. Region 1 was less than region three in all cases, but significant in models two and four (alpha = 0.05). Similarly, region two dominated region three in model 2.

For *H3*, we again used one-way ANOVA and Tamhane's tests on the mean scale inefficiency scores across the regions. The results suggest that scale inefficiency tended to be highest in region 2 and lowest in region 1, and with models incorporating non-discretionary variables. Moreover, scale efficiency tended to be highest for model 4, which included both inputs and the regional market index. Table IX reports our summary ANOVA results (*F*-values and significance levels), which show that the mean differences between the regions are generally significant for three of the four model scenarios. Using

		Sample	Mean	SD	*p*-value
Region 1	Model 1	100	0.01538	0.04225	0.000218
	Model 2	100	0.025	0.0508	1.72E-06
	Model 3	100	0.01691	0.044	0.000107
	Model 4	100	0.00956	0.0285	0.000564
Region 2	Model 1	49	0.0586	0.1081	0.000207
	Model 2	49	0.0246	0.07352	0.011682
	Model 3	49	0.0474	0.1093	0.001935
	Model 4	49	0.02055	0.055	0.005937
Region 3	Model 1	58	0.0415	0.0769	6.41E-05
	Model 2	58	0.0835	0.1227	1.5E-06
	Model 3	58	0.0618	0.1783	0.005343
	Model 4	58	0.0515	0.0971	8.11E-05

Note: *H2a* tests whether programmatic inefficiency is significantly different from zero

Table VII. Programmatic inefficiency results (programmatic inefficiency (*H2a*))

Tamhane's tests (alpha = 0.05) to further explore these relationships, we detected statistically significant differences between the regions. Region 1 was more scale efficient than region three in all cases (models), and more scale efficient than region two all but one case (model 3). Region 3 dominated region two in only two of the scenarios. In model three below, Tamhane's results showed significant difference only in region one over region three. With scale inefficiency differences across all regions: region 1 vs 2 (0.18 vs 0.05, $p < 0.01$); region 1 vs 3 (0.18 vs 0.09, $p < 0.01$); and region 2 vs 3 (0.05 vs 0.09, $p < 0.10$), we find support for *H3*.

Discussion

Resource utilization is critical to RBV logic (Majumdar, 1998). Ineffective use of resources negatively affects a firm's ability to sustain competitive advantages. Our study sought to apply RBV thinking at a lower level of analysis – the

Table VIII. Programmatic inefficiency results (ANOVA: programmatic inefficiency across regions (*H2b*))

		Sum of squares	df	Mean square	*F*	Sig.
Model 1	Between groups	0.067	2	0.034	6.387	0.002
	Within groups	1.075	204	0.005		
	Total	1.142	206			
Model 2	Between groups	0.144	2	0.072	10.670	0.000
	Within groups	1.373	204	0.007		
	Total	1.516	206			
Model 3	Between groups	0.081	2	0.041	3.219	0.042
	Within groups	2.577	204	0.013		
	Total	2.658	206			
Model 4	Between groups	0.065	2	0.033	8.700	0.000
	Within groups	0.764	204	0.004		
	Total	0.829	206			

Table IX. Scale inefficiency results (*H3*)

		Sum of squares	df	Mean square	*F*	Sig.
Model 1	Between groups	4.901	2	2.450	109.707	0.000
	Within groups	4.557	204	0.022		
	Total	9.457	206			
Model 2	Between groups	2.939	2	1.470	68.574	0.000
	Within groups	4.372	204	0.021		
	Total	7.311	206			
Model 3	Between groups	1.568	2	0.784	1.259	0.286
	Within groups	127.085	204	0.623		
	Total	128.653	206			
Model 4	Between groups	1.022	2	0.511	30.416	0.000
	Within groups	3.428	204	0.017		
	Total	4.450	206			

organizational units of a firm. In doing so, we found empirical evidence of scale, managerial, and programmatic inefficiencies that varied across regions of the firm. We infer from the results that traditional RBV logic may contribute to divergent outcomes for interfirm analysis and intrafirm analysis of resource utilization.

We have presented and evaluated several process views of a large-scale service operation, illustrating that it is imperative to unbundle operations inefficiency in order to make informed decisions regarding improving resource utilization of DCs and the firm as a whole. Our study also underscores the managerial complexity of objectively accounting for programmatic, scale, and non-discretionary differences while evaluating DCs. These process models corresponded to alternative paradigms for measuring operations performance. In general, the supply chain system appeared to be operating at less than productive size, but some caveats should be offered. A comparison of models 1 and 4 reveals the importance of including non-discretionary variables in estimation of scale efficiency. Models 1 and 4 include both inputs, but only the latter model includes the regional market index. Scale efficiency was higher when the regional market index was included (model 4) than when it was excluded (model 1). We infer from this finding that researchers and managers may underestimate scale efficiency when relevant non-discretionary variables are available but excluded from consideration. Indeed, results comparing models 1 (non-discretionary variable excluded) and 4 (non-discretionary variable included) indicated that scale efficiency was substantially lower in region 1 ($0.06 = 0.82 - 0.76$), region 2 ($0.14 = 0.95 - 0.81$) and region 3 ($0.13 = 0.91 - 0.78$), respectively.

The empirical results revealed several key operational insights into the problem environment. These insights were developed from the separation of managerial and programmatic efficiency, the investigation of scale efficiency, and development of performance improvement alternatives through input mix changes. Consider, for example, the case of inefficient DCs. The models generally suggested a reduction in inputs, such as fleet size, reduces the congestion (i.e. excessive inputs) and, therefore improves resource utilization. Realistically, reduction in fleet size may be very difficult, and the question remains as to what exactly should be done with excess vehicles, and precisely how would managers reduce the experience level.

The scale efficiency results also highlight the challenges faced by firms in determining the optimal number of distribution centers. Berger *et al.* (1997) found that in the banking industry, banks may incur a small cost of "overbranching" in order to gain additional revenues due to having facilities closer to the customer. That is, company executives need to weigh the benefits of expanding in order to be close to consumers, with the costs (e.g. cannibalization and scale inefficiency). To achieve substantial scale economy savings, companies may need to consider closing DCs, though careful analysis is required because the costs of opening and closing petroleum distribution centers are high compared to other distribution networks such as banking facilities. If this alternative is considered, other DCs that are below efficient scale need to be in close proximity to absorb the additional output from the closed facilities. In some instances, the remaining DCs may incur higher transportation costs that offset savings from scale economies. Moreover, the company also needs to consider managerial resources from the remaining DCs in the event of downsizing – cost savings from improving scale efficiency cannot be offset by high managerial inefficiency. As such, downsizing to improve scale efficiency may require shifting input to other DCs and possible reallocation of DC managers so that the best managers are in charge of the remaining DCs. In the present study, we found that scale efficiency could be greatly improved, especially in region 1. However, the results show that attempts to improve scale efficiency in region 2 and 3 can actually be counterproductive as the projections indicate substantial reductions in scale efficiency (14 percent in region 2 and 5 percent in region 3).

The findings raise some interesting questions regarding the linkages between efficiency of the DCs and firm as a whole. Berger *et al.* (1997) suggested that scale inefficiencies at the distribution-center (business-unit) level can explain scale inefficiency and operating inefficiency at the firm level. Therefore, a firm can improve its overall efficiency, scale efficiency, managerial efficiency, by concentrating on making efficiency improvements at the DC level.

Concluding remarks

This research used the downstream petroleum industry as the backdrop for measuring efficiency of a firm's supply chain. The particular sample firm is actually a cooperative in which the customers are also the stakeholders of the firm. Customers are the beneficiaries of superior performance of decision makers in manufacturing or service environments. It has been well documented that resource performance drives competitive results, and this study shows how analysis of scale, programmatic and managerial differences in the entire supply network are of strategic benefit. In addition, our analysis demonstrated that intra-firm analysis of resource utilization must incorporate relevant non-discretionary variables to prevent overestimating scale inefficiency and perhaps, unjustly penalizing DC managers with respect to their performance.

Our study extends the important work of Majumdar (1998) by shifting the level of analysis of resource utilization to the organizational unit level, or in our case, the distribution center level and by examining three types of efficiency – scale, programmatic and managerial. Our results confirm that the composition of efficiency varies across the regions of the firm. This granular level of analysis can, in turn, help corporate executives customize strategies to improve resource utilization at the DC level. Furthermore, our intrafirm analysis highlights problems often associated with rationalizing logistics resources.

Our study has important implications for managers. First, by identifying variations in the composition of efficiency, corporate executives may be able to apply managerial and programmatic best practices from one region throughout the supply chain in order to improve resource utilization of the entire firm. Second, managers need to consider the implications of closures in order to improve resource utilization. Closure decisions cannot be based solely on a DC's level of scale efficiency (that is, close the least scale efficient DCs). Careful consideration needs to be given to the location and efficiency of remaining DCs because expected cost savings from scale economies may be more than offset by higher costs (increased transportation costs) or managerial inefficiencies (reallocating resources to a DC with poor managerial resources).

For DCs with opportunities to improve efficiency, our study demonstrates that decomposition into scale, managerial, and programmatic efficiency enable DC managers to target problem areas. However, DC and corporate managers need to work together in determining the best way to maximize efficiency – develop new routines, imitate routines of highly efficiency rivals, or imitate highly efficient DCs within the firm (Ross and Droge, 2002). The challenge arises from inertia – resistance or inability to change from existing, inefficient routines. Inertia is the norm rather than the exception in many large companies because changing course is often difficult, costly, risky, and time-consuming (Rumelt, 1995). For firms operating on the efficient frontier, Rumelt (1995, p. 103) suggested, "inertia is costless and arguably beneficial". We caution firms and business units, however, to be wary of complacency since an efficient routine today may not be an efficient routine in the future.

We recognize that there are limitations to the present study. First, a dynamic analysis of efficiency with the use of Malmquist indices may reveal the effects of operations scale changes by DC managers and corporate executives as suggested by Sueyoshi and Aoki (2001). Second, we employed input-based DEA analysis – managers could change the level or mix of inputs. However, this approach was appropriate given that DC managers have little discretion regarding outputs. Nevertheless, future research may consider scenarios in which managers can influence both input and output decisions. Therefore, our results need to be viewed with the above limitations in mind.

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