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Deterministic and Stochastic Approaches for Assessing Marketing Efficiency

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Introduction

One of the key themes of the marketing strategy literature has been to identify sources of competitive advantage for firms. Firms can develop their competitive advantage either by focusing on implementing their strategies efficiently or by focusing on developing capabilities that can enable them to sustain their competitive advantage. In both cases it is important for firms to assess how efficient they have been in implementing their actions or to compare their capabilities to some benchmark. Consider the marketing context: Assessing how well a firm implements its marketing strategy may involve a comparison among different operating units within the firm. Examples are examinations of the relative efficiency of a firm's sales districts (Horsky and Nelson 1996) and the relative efficiency of a firm's retail outlets (Kamakura, Lenartowicz, and Ratchford 1996). Similarly, assessing the quality of a firm's marketing capabilities relative to its competitors requires rigorous estimation of those capabilities and then benchmarking them relative to competitors. As an example, the research and development capability of a firm is compared with that of competing firms later in this chapter.

In this chapter we will discuss two approaches to measuring efficiency: data envelopment analysis (DEA) and stochastic frontier regression (SFE). DEA is a linear programming procedure for determining how efficient a unit or firm is relative to its competitors (Charnes, Cooper, and Rhodes 1978; Charnes, Cooper, Lewin, and Seiford 1994). In its normal application, this approach is nonparametric, in the sense that no explicit assumption or allowance is made for random measurement errors, and only minimal assumptions are made about the shape of the relation between outputs and inputs. The intuition behind DEA is quite simple. A natural way to measure efficiency is to take a ratio of inputs to outputs. But when there are multiple outputs and inputs, forming this ratio requires that some weighting scheme be chosen. The basic idea of DEA is to choose a set of weights for each unit in a given set of peers (be they divisions of an organization, organizations in a given industry, or other entities that make it look the best in comparison with other units). This is the set of weights that maximize the unit's weighted ratio of outputs to inputs, subject to the normalization constraint that this ratio must be less than or equal to one for all units (including the focal unit). If the ratio equals one for that unit, it lies on an efficiency frontier; if it is less than one, it is inefficient because some other unit or combination of units could produce the same output with fewer inputs. This maximization procedure is run for each unit in turn, leading to an efficiency score for each unit under study.

The intuition behind the stochastic frontier estimation (SFE) method is also straightforward. In cases where there is a single output, one can regress output on a set of inputs to determine an output-input relationship. If the stochastic frontier method is employed in this regression, the regression will contain two error terms instead of the standard random-error term in the usual regression (see for example Greene 2000, Ch. 9). One error term is the standard measurement error term, which can take on any value, while the other is an efficiency error term, which is bounded at zero, where zero values of this efficiency term trace out an efficiency frontier. Values of the efficiency error term for each unit estimate its efficiency relative to the frontier. Because of the restriction that the efficiency error term is bounded at zero, all the parameters in the stochastic frontier regression can be identified.

Both the SFE and DEA methods aim to determine a frontier that describes maximum outputs for a given set of inputs and to determine the efficiency of any unit relative to the frontier. Both are easy to implement: As a linear programming procedure, DEA models can be estimated using the Excel Solver or any standard linear programming package. The SFE method is incorporated in readily available econometrics packages, such as LIMDEP.

The differences between the two approaches define their strengths and weaknesses. Because DEA provides a piecewise linear frontier that can approximate any shape, it allows for a flexibly shaped efficiency frontier. Thus it requires a minimum of assumptions for its application. However, one key assumption employed in most versions of DEA is that the efficiency frontier is composed of a linear combination of actual units. For example, if the objective is to determine the efficiency of business schools, New York University's Leonard N. Stern School of Business might be compared with a linear combination of Northwestern University's Kellogg School of Management and Cornell University's Johnson Graduate School of Management in the DEA solution. The implicit assumption that this linear combination of Northwestern and Cornell is feasible may not be realistic. Also, because standard methods of DEA do not allow for an error structure, DEA is susceptible to measurement errors and the effects of omitted outputs or inputs. (As discussed in the next section, however, recent extensions to DEA do allow for measurement errors.)

The SFE method does explicitly account for measurement errors. However, since it requires a priori assumptions about functional form and distribution of error terms, it is susceptible to specification errors. In particular, results may be sensitive to different assumptions about the form of error distributions (Greene 2000, Ch. 9). Another problem is that production function versions of the SFE method do not readily admit more than one output, while DEA is designed to handle multiple outputs.

To understand the implication of these points more fully, let us first turn to an outline of the DEA approach and application, followed by an outline of the SFE approach and application.

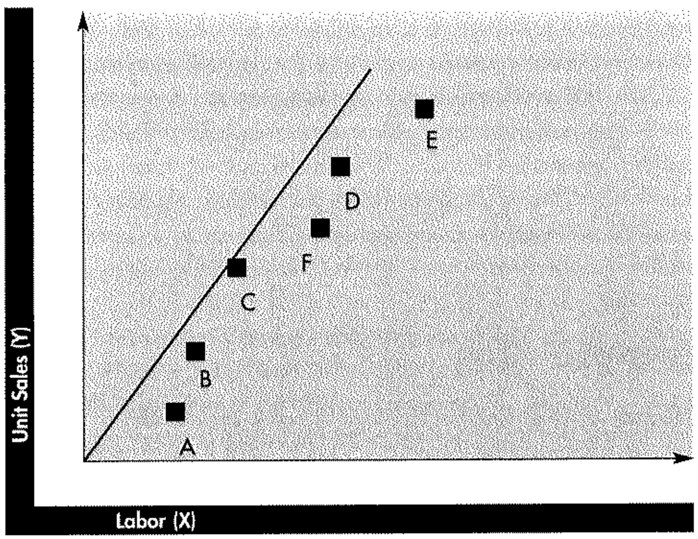
Data Envelopment Analysis

Data envelopment analysis is one of the tools available for identifying the most efficient units and measuring the relative efficiency of other units in relation to the production frontier defined by the efficient ones. If the focus is on measuring the relative efficiency of a set of retail outlets, each retail outlet is called a decision-making unit, or DMU. Resources that are used by the store manager but that are not under the manager's control (such as the characteristics of the trade area, and most physical facilities) are called allocative inputs. Resources directly managed by the DMU are treated as inputs.

Suppose that a retail chain wants to measure the productivity of its retail outlets and to define best practices to be emulated by the less efficient units. It has sales data by department, data on the physical facilities (for example, each unit's number of parking spaces, store frontage, total area, number of checkout counters, and so forth), trade area information (population, per capita income, per capita consumption by product category, and so on), and expenditures (for example, on labor or promotions) by department. What it wants to do is measure how efficiently each retail outlet transforms its inputs (labor, promotion expenditures, and so on) and resources (trade area characteristics, physical facilities) into outputs (sales and contribution in each department).

The simplest and most common way of measuring productivity and relative efficiency is with output-input ratios, illustrated in Figure 1. Here we have six retail outlets (DMUs) represented by the inputs they utilize (say, man-hours of labor) and outputs they produce (unit sales). In terms of the output-input ratio, DMU C is the most efficient.

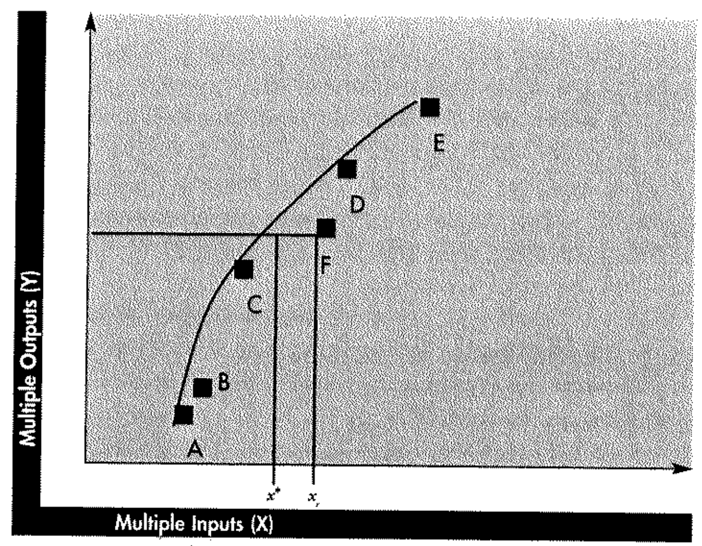
Figure 1
Output-Input Ratio



This example reveals at least two major problems with the use of ratios to measure efficiency, however. First, the figure seems to show (dis)economies of scale: The output-input ratio increases as the sales volume grows from DMU A to C, and decreases as the sales volume grows from DMU C to E. DMUs A and B might have a lower ratio of sales to man-hours because they operate at a lower scale (due to a more limited trade area), and therefore might be unfairly characterized as inefficient because of the economies of scale benefiting DMU C.

The second problem is that computation of a productivity ratio such as the one depicted in Figure 1 becomes complex when there are multiple inputs and outputs, requiring some weighting of both inputs and outputs before a ratio can be computed. DEA addresses these two major issues by treating productivity assessment as an optimization problem. Solving this optimization problem results in the proper weights for the inputs and outputs in the efficiency ratios and also accounts for (dis)economies of scale. Instead of a single line representing the most efficient output-input ratio, DEA produces a piecewise linear production frontier, as shown in Figure 2. Now that economies of scale are taken into account, all DMUs except F are in the production frontier. DMU F is deemed inefficient because it should be able to produce the same level of outputs utilizing fewer inputs (x^* instead of x_f), by combining the production technologies from C and D. Note, however, that while DEA replaces the linear frontier produced by simple output-input ratios with a piecewise linear frontier, there is still an underlying assumption of linearity within each facet of the efficiency frontier.

Figure 2
Efficiency Frontier



Formulation of the DEA Model

Key notations:

k = Decision-Making Unit (DMU)
x_{ik} = i-th input used by DMU k
z_{lk} = l-th allocative input used by DMU k
y_{jk} = j-th output produced by DMU k

Suppose the retail chain is interested in evaluating a particular outlet—DMU o. The problem then is to find the proper weights for each input (v_i) and output (w_j) that would result in an output-input ratio defining the best practice to which DMU o could aspire. This problem can be written as:

$$\max \frac{\sum_j w_j y_{jo}}{\sum_i v_i x_{io}} \tag{1}$$

subject to

$$\max \frac{\sum_j w_j y_{jk}}{\sum_i v_i x_{ik}} \le 1 \quad \text{for all outlets } k \tag{2}$$

$w_j, v_i \ge 0$ for all inputs i and outputs j.

Instead of solving the nonlinear optimization above, we transform it into a linear programming problem:

$$\max \sum w_j y_{jo} - \phi_0 \tag{3}$$

subject to

$$\sum_i v_i x_{io} = 1 \tag{4}$$

$$\sum_j w_j y_{jo} - \phi_0 \le \sum_i v_i x_k \quad \text{for all DMUs } k \tag{5}$$

$w_j, v_i \ge 0$ for all inputs i and outputs j.

And, instead of solving the linear programming problem above, we solve its dual:

$$\min T_o$$

subject to

$$y_{jo} \le \sum_k \lambda_k y_{jk} \quad \text{for all outputs } j \tag{7}$$

$$T_o x_{io} \ge \sum_k \lambda_k x_{ik} \quad \text{for all inputs } i \tag{8}$$

$$z_{lo} \ge \sum_k \lambda_k z_{lk} \quad \text{for all allocative inputs } l \tag{9}$$

$\lambda_k \ge 0$ for all DMUs k

$$\sum_k \lambda_k = 1 \tag{10}$$

where T_o is the technical efficiency ratio. Constraint 7 specifies that the DMU under evaluation cannot produce more outputs than those observed in the efficiency frontier. Constraint 8 specifies that the DMU under evaluation cannot use fewer inputs than those utilized at the efficiency frontier, even after accounting for its technical (in)efficiency. Since allocative inputs are not under the DMU's direct control, they do not affect technical efficiency directly (Constraint 9). Solution of this linear programming problem will produce a weight (λ_k) for each DMU k and the technical efficiency ratio (T_o) for the DMU being evaluated. The set of weights (λ) defines a convex combination of efficient DMUs forming the facet of the production frontier to which the focal DMU will be compared. If the focal DMU is in the frontier, its efficiency ratio will be equal to 1 and its own weight λ_o will be also equal to 1, indicating that this DMU forms the production frontier.

A Simple Illustrative Example

Table 1 shows the activities report for 10 salespeople, including the number of customers visited, the number of customers called on the phone, market potential index for each salesperson's territory, the number of new accounts created, and unit sales.

We will use DEA to measure how efficiently these salespeople translated their efforts (visits and phone calls) and the resources at their disposal (market potential) into new accounts and sales. The DEA model for John would be:

Table 1

Inputs and Outputs for a Hypothetical Example

Salesperson	Personal visits	Phone calls	Market potential	New accounts	Sales
John	70	20	50	68	55
Mary	53	62	80	21	32
Jane	20	50	93	81	16
Paul	33	27	77	63	11
Mike	25	45	38	43	58
Jill	30	30	55	65	39
Peter	32	3	36	82	38
Don	11	79	91	98	53
Jack	26	30	75	39	72
Tony	14	50	98	90	83

$\min T_o$

subject to

$$Sales_{John} \le \sum_{k=1}^{10} \lambda_k Sales_k \qquad (11)$$

$$Accounts_{John} \le \sum_{k=1}^{10} \lambda_k Accounts_k \qquad (12)$$

$$T_{John} Personal_{John} \ge \sum_k \lambda_k Personal_k \qquad (13)$$

$$T_{John} Phone_{John} \ge \sum_k \lambda_k Phone_k \qquad (14)$$

$$Potential_{John} \ge \sum_k \lambda_k Potential_k \qquad (15)$$

$\lambda_k \ge 0$ for all salespeople k

$$\sum_k \lambda_k = 1.$$

The production frontier for the 10 salespeople is defined by the following weights (λ) in Table 2 indicating that John, Mike, Peter, Don, Jack, and Tony are at the frontier.

Table 2

Efficiency Frontier

	Efficiency	John	Mary	Jane	Paul	Mike	Jill	Peter	Don	Jack	Tony
John	**1.000**	1.000									
Mary	.428							.494			.506
Jane	.848							.159			.841
Paul	.759							.621			.379
Mike	**1.000**					1.000					
Jill	.832							.657	.209		.134
Peter	**1.000**							1.000			
Don	**1.000**								1.000		
Jack	**1.000**									1.000	
Tony	**1.000**										1.000

As shown in Table 2, the efficiency ratio for Mary was .428, relative to a combination of the performances by Peter and Tony with weights .494 and .506, respectively. This suggests that by combining the technologies used by Peter and Tony, Mary should be able to produce her current sales and new accounts using only .428 of her current inputs. Peter and Tony define the best practice that Mary should emulate to become more efficient.

In addition to the efficiency frontier, the DEA model provides other useful insights about the inefficient DMUs. Table 3 shows the slacks that are needed to make each of the input and output constraints in equations 11 through 15 bind-

Table 3

Output and Input Slacks

	New accounts	Sales	Visits	Sales calls	Market potential
John	.0	.0	.0	.0	.0
Mary	**64.8**	**28.8**	.0	.0	**12.8**
Jane	**7.9**	**59.9**	.0	.0	**5.7**
Paul	**21.2**	**44.0**	.0	.0	**17.9**
Mike	.0	.0	.0	.0	.0
Jill	**20.7**	**8.6**	.0	.0	.0
Peter	.0	.0	.0	.0	.0
Don	.0	.0	.0	.0	.0
Jack	.0	.0	.0	.0	.0
Tony	.0	.0	.0	.0	.0

ing (the typical result produced by any linear programming algorithm). These slacks indicate that in order to be as efficient as Peter and Tony, Mary would not only need to use only 42.8% of her current inputs, but also produce 64.8 more new accounts and 28.8 more sales than she currently produces. These slacks also show that with her current output levels, Mary is not fulfilling 12.8 units of her market potential.

The DEA model described above is the basic model proposed by Charnes, Cooper, and Rhodes (1978). Extensions to incorporate qualitative (ordinal) inputs and outputs have been proposed by Banker and Morey (1986) and Kamakura (1988). A simpler but quite effective way of handling qualitative inputs and outputs is to restrict the linear programming problem such that a DMU is only compared with units that use equal or better qualitative inputs and produce equal or worse qualitative outputs (Charnes et al. 1994).

DEA has been applied in a wide range of contexts, both in the profit and nonprofit sectors. In marketing, DEA has been used to compare the performance of salespeople (Mahajan 1991), bank branches (Kamakura, Lenartowicz, and Ratchford 1996), sales districts (Horsky and Nelson 1996), and retail outlets (Grewal, Levy, Mehrotra, and Sharma 1999). It has also been used to measure consumer welfare loss due to price inefficiencies (Kamakura, Ratchford, and Agrawal 1988), to assess the service profit chain across retail outlets (Kamakura, Mittal, Rosa, and Mazzon 2002), and to evaluate subsidiaries of a global corporation (Grewal, Iyer, Kamakura, Mehrotra, and Sharma 2003). These marketing applications are described in Table 4.

A major limitation of the DEA model is that it is deterministic, assuming that the production process under assessment is fully characterized by the observed inputs and outputs, and that they are free of measurement errors. The deterministic nature of the DEA model makes it highly susceptible to measurement error and to outliers. This weakness is illustrated in Figure 3. Suppose the inputs utilized by C are erroneously measured, moving this DMU to the position C′. This single measurement error will render B, F, and (to some extent) D inefficient, when in reality only F should be deemed inefficient.

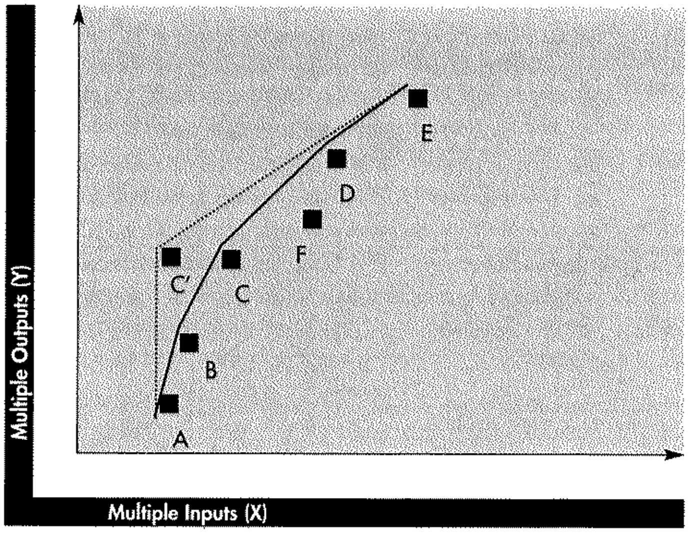
Stochastic DEA models that explicitly incorporate measurement errors have already been proposed in the literature (e.g., Land, Lovell, and Thore 1994; Gong and Sun 1995; Cooper, Huang, Lelas, Xi, and Olsen 1998; Gstach 1998; Li 1998). These extensions of the DEA model involve the introduction of stochastic components in the input and output constraints and corresponding modifications of the objective function of the linear programming model to reflect violations of these constraints. As these extensions go beyond the scope of this introduction to productivity assessment, we refer the reader to the literature for more details about stochastic DEA. We now

Table 4
Marketing Applications of Data Envelopment Analysis

Authors and Study Year	Application Focus	Other Details
Kamakura, Ratchford, and Agrawal (1988)	Price efficiency of brands competing in the same product categories	DEA is utilized to determine the extent to which competing brands in the same product category are overpriced for the attributes they offer and to measure welfare loss due to price inefficiencies.
Mahajan (1991)	Relative sales productivity of insurance agents	DEA is used to assess the relative efficiency of the sales function across multiple insurance agencies.
Kamakura, Lenartowicz, and Ratchford (1996)	Relative efficiency of multiple bank branches operating in diverse markets	DEA is used as a benchmark in comparison to clusterwise stochastic frontier estimation, which allows for multiple frontiers, depending on latent (unobservable) market characteristics.
Horsky and Nelson (1996)	Redeployment of a salesforce	DEA is used to assess the relative efficiency of sales districts and as the basis for reallocating the salesforce to improve profitability.
Grewal, Levy, Mehrotra, and Sharma (1999)	The sales performance of retail outlets of a national chain	DEA is utilized to measure relative efficiency and to identify best practices that inefficient outlets can emulate. The production frontier is also utilized to establish performance goals for the future.
Kamakura, Rosa, Mittal, and Mazzon (2002)	The service-profit chain of bank branches	This is a two-stage model that compares how efficiently branches of a retail bank produce high-quality services and how well they translate satisfied customers into profitable ones.
Grewal, Iyer, Kamakura, Mehrotra, and Sharma (2003)	Relative efficiency of subsidiaries of a global corporation	This is a two-stage model that examines subsidiaries' efficiency in customer acquisition (market growth) and development (market yield).

turn to an overview of stochastic frontier estimation (SFE), which provides another way of incorporating measurement errors in productivity assessment.

Figure 3
Sensitivity of the DEA Frontier to Outliers



Stochastic Frontier Estimation

Stochastic frontier estimation adopts an input-output approach to estimate how well the unit has achieved its stated targets. SFE enables such an assessment by relating resources used to the optimal attainment of objectives or targets. This approach is very general, and all it requires is measurable objectives (outputs) and measurable resources (inputs) employed in achieving those objectives.[1]

To illustrate, assume that a given firm would like to estimate how efficient it is in utilizing the resources at its disposal for developing innovative technologies. Assume that the resources that the firm has at its disposal are its past research and development expenditure ($CUM\_R\&DEXPENSE_{it}$) and its base of technologies ($TECHBASE_{it}$). Further, its goal is to develop innovative technologies ($TECH\_INNV_{it}$).[2]

Now, the econometric task described below shows how one can use the firm's observed resources—its R&D expenditure and existing technological knowledge base—to infer the maximum amount of innovative technologies it *could have* produced. After inferring the maximum, the difference between the actual output and maximum is our measure of firm-specific inefficiency in its ability to attain its R&D objective.

To start, consider the simple log-linear specification, that is, the OLS model:

$$\ln TECH\_INNV_{it} = \alpha_0^r + \alpha_1^r.\ln CUM\_R\&DEXPENSE_{it} + \alpha_2^r.\ln TECHBASE_{it} + \varepsilon_{it} \quad (16)$$

where ε_{it} represents the random-error term, reflecting stochasticity in the environment. It has a normal distribution, with zero mean (similar to an OLS assumption) and variance σ_ε^2.

Now, simply estimating Equation 16 using OLS with the error term as above would not give us a clear idea of firm-specific inefficiency.[3] This is because all we have is the OLS residual, ε_{it}, which could be due to random shocks or luck (or both) just as much as inefficiency. To incorporate the notion of inefficiency explicitly, we need another error term. Further, this second error term must always be positive, since inefficiency represents a shortfall from the optimum. Thus, we can rewrite Equation 16 as follows:

$$\ln TECH\_INNV_{it} = \alpha_0^r + \alpha_1^r.\ln CUM\_R\&DEXPENSE_{it} + \alpha_2^r.\ln TECHBASE_{it} + \varepsilon_{it} - \eta_{it} \quad (17)$$

where η_{it} represents the inefficiency error term, which is the key to our measurement of firm efficiency. It has a truncated normal distribution, with mode μ and variance σ_η^2. Formally:

$$\phi^+(\eta_{it}) = \frac{1}{[1-\Phi(-\mu/\sigma_\eta)]\sqrt{2\pi}\sigma_\eta} \exp\left[-\frac{1}{2}\left(\frac{\eta_{it}-\mu}{\sigma_\eta}\right)^2\right] \quad \text{for } \eta_{it} \in [0,+\infty] \quad (18)$$

$$= 0 \text{ else}$$

where $\Phi(.)$ is the standard normal distribution function.

While our interest is in estimating the inefficiency error term, η_{it}, what we actually observe is the composite error term, e_{it}. To see the composition of the composite error term, rewrite Equation 17 as follows:

$$\ln TECH\_INNV_{it} = \alpha_0^r + \alpha_1^r.\ln CUM\_R\&D_{it} + \alpha_2^r.\ln TECHBASE_{it} + e_{it} \tag{19}$$

where the two error terms, ε_{it} and η_{it} have been written as:

$$\varepsilon_{it} - \eta_{it} \equiv e_{it} \tag{20}$$

We know the distributions of ε_{it} and η_{it} individually. Hence, we can compute the distribution of e_{it}. This distribution is given by the following equation (see Stevenson 1980):

$$g(e_{it}) = \frac{1}{\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} \left[1 - \Phi\left(\frac{e_{it}\sigma_\eta}{\sigma_\varepsilon\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} - \frac{\sigma_\varepsilon\mu}{\sigma_\eta\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}}\right)\right] \phi\left(\frac{e_{it} + \mu}{\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}}\right)\left[1 - \Phi\left(-\frac{\mu}{\sigma_\varepsilon}\right)\right]^{-1}. \tag{21}$$

From the distribution of e_{it} above, we can form the required likelihood function as follows:

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T} \frac{1}{\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} \times \left[1 - \Phi\left(\frac{\sigma_\eta[Y_{it} - f(X_{it},\alpha)]}{\sigma_\varepsilon\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}} - \frac{\sigma_\varepsilon\mu}{\sigma_\eta\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}}\right)\right] \times \phi\left(\frac{Y_{it} - f(X_{it},\alpha) + \mu}{\sqrt{\sigma_\eta^2 + \sigma_\varepsilon^2}}\right) \times \left[1 - \Phi\left(-\frac{\mu}{\sigma_\varepsilon}\right)\right]^{-1}. \tag{22}$$

But this likelihood function still does not give us an estimate of η_{it}, which is what we are interested in. To get that we need to derive the conditional distribution of η_{it}, given e_{it}. Formally:

$$\hat{\eta}_i = E[\eta \mid e_i = \hat{e}_i] = \hat{\mu}_i^{**} + \sigma_{**}^2\left\{\phi\left(-\frac{\hat{\mu}_i^{**}}{\sigma_{**}^2}\right)\left[1 - \Phi\left(-\frac{\hat{\mu}_i^{**}}{\sigma_{**}^2}\right)\right]^{-1}\right\} \tag{23}$$

where:

$$\hat{\mu}_i^{**} = \left[-\sigma_\eta^2\bar{\hat{e}}_i + \frac{\hat{\mu}_i\sigma_\varepsilon^2}{T_i}\right]\left[\sigma_\eta^2 + \frac{\sigma_\varepsilon^2}{T_i}\right]^{-1}; \quad \text{and,} \quad \sigma_{**}^2 = \frac{\sigma_\eta^2\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T_i\sigma_\eta^2}. \tag{24}$$

The term $\hat{\eta}_i$ is precisely what we want. It measures how far away the firm's actual performance is from its best possible performance. The greater the gap between its maximum achievable objective and its actual performance, the lower its efficiency in attaining its R&D objective. The asymmetric error term allows us to estimate firm-level inefficiency in attaining its R&D goal. Thus if one firm has a higher level of $\hat{\eta}_i$ than another, this implies that it has lower efficiency in utilizing its R&D resources to achieve its R&D goal of producing innovative technologies.

Applications of SFE to Marketing Strategy

The marketing strategy literature has long highlighted that firm capabilities are an important source of competitive advantage (Wernerfelt 1984; Day 1994). Firm capabilities represent the ability of the firm to combine a number of resources efficiently to engage in productive activity and attain a certain objective (Amit and Shoemaker 1993). A firm's resources are assets that it owns along with assets that are externally available and transferable (Amit and Shoemaker 1997). Examples of resources would include capital equipment, innovative patents, and brand names. Capabilities, in contrast, consist of tangible and intangible combinative skills; they are information based. While resources such as innovative patents confer great advantages upon a firm in and of themselves, the firm's ability to come up with such patents consistently can be a source of even longer-term sustainable competitive advantage.

SFE enables estimation of firm capabilities that is consistent with the theory of capabilities. As discussed in the previous section, the asymmetric error term $\hat{\eta}_i$ measures the distance between actual performance and maximum achievable performance. Since it captures how efficiently a firm attains its goals, this asymmetric term captures the notion of capabilities. Note that this method controls for the amount of input a firm uses to achieve its goal, so a firm like Intel, which can spend several million dollars to develop innovative patents, will be expected to produce more innovative patents than a smaller firm with more limited R&D resources. In other words, the higher number of patents by itself does not indicate that Intel is more efficient in utilizing its R&D resources to generate innovative technologies: Any estimation of efficiency has to account for varying levels of inputs or resources. The SFE estimation of $\hat{\eta}_i$ ensures that scale differences between firms are taken into account.

SFE has been used in recent research to estimate different types of capabilities. It offers many advantages to managers and complements other techniques for assessing firm capabilities. For example, recent research has used the SFE approach to estimate functional capabilities in marketing, R&D, and operations (see Dutta, Narasimhan, and Rajiv 1999, 2004). For each function, one can define the inputs or resources that are used to achieve a measurable objective. Then, for each firm and for each function, one can estimate the inefficiency term $\hat{\eta}_i$ to capture the firm's level of functional capability.

The SFE approach can also be used to estimate a firm's dynamic capabilities. For instance, one dynamic capability is the firm's ability to regenerate its technological know-how base. For this type of dynamic capability, one can define the resources that would enable the firm to regenerate its technological know-how base, and one can develop an objective output measure that reveals how successfully the firm is accomplishing that goal. Having defined measurable inputs (resources) and measurable outputs, one can estimate the inefficiency term $\hat{\eta}_i$ to capture the firm's level of efficiency in using resources available to attain its objective of regenerating its technological base. Recent work has used estimation of the term $\hat{\eta}_i$ to reveal firm-level efficiency in accessing and utilizing technological know-how from outside (Narasimhan, Rajiv, and Dutta 2003).

This estimation of capabilities can be done at any level of analysis provided there are measurable outputs and measurable inputs that go to achieving the stated objectives. For example, one could think of capabilities as being at the project level, and then analyze a firm's capabilities across projects within a business unit. One could also assess the performance of different product lines in achieving their objective given the resources that have been allocated to them.

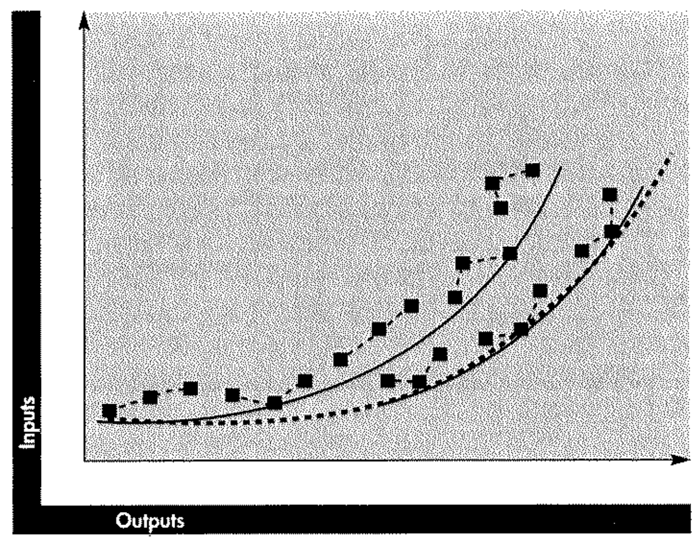
Estimating different types of capabilities from archival data makes it easier to track those capabilities over time. Tracking helps us do three things. First, managers can see which capabilities have the biggest impact on performance and can allocate resources accordingly. Second, managers can assess whether actions taken at a particular point to enhance these capabilities have had any impact on the firm's overall capability. For instance, if the senior management has reconfigured its technology development teams to be cross-functional in nature, then one way to see if this action leads to enhanced quality of product or technology output is to measure the firm's R&D capability before or at the time of the change and then again after some period of time. Third, managers can assess to what extent there is persistence in the firm's capabilities (Dutta, Narasimhan, and Rajiv 2004) and if this persistence varies depending on the type of capability. Assessment of this persistence enables managers to judge the extent of path dependence and how quickly one can succeed in changing the firm's capabilities.

Research using the SFE approach to estimating capabilities complements the literature on market orientation (Deshpandé, Farley, and Webster 1993; Jaworski and Kohli 1993; Day 1994) by suggesting a way to infer the market orientation of a firm, namely, by measuring its marketing capability. One would expect a superior market orientation to be reflected in a higher marketing capability.

Finally, given the data requirements of this approach (secondary data, preferably in a panel setting), we feel that this method is an ideal complement to more detailed firm-level studies (e.g., Helfat 1994; Henderson and Cockburn 1994; McGrath, MacMillan, and Venkataraman 1995) that focus on particular capabilities and attempt to uncover the underlying reasons for differences in those capabilities.

While SFE is extremely flexible and allows for statistical error, it does suffer from some limitations. Notably, it imposes a single parametric structure on the production technology and on the distribution of efficiency, implying that all units being evaluated use the same production technology and face the same long-run cost function. This assumption of a common production technology is likely to be violated when the units being evaluated operate under different market conditions, as is the case, for example, in service operations, where the customer is an integral component of the production process. While some of these market conditions can be treated as allocative inputs, many are unobservable and could result in multiple production frontiers. This situation is illustrated in Figure 4, where the connected points represent longitudinal observations for the same DMU.

Figure 4
Multiple Stochastic Frontiers



The traditional stochastic frontier approach, through a translog cost function, would produce the production frontier represented by the dark traced line, identifying many of the DMUs as inefficient. Kamakura, Lenartowicz, and Ratchford (1996) proposed a multiple-frontier extension to the traditional stochastic frontier estimation approach, which in the illustrative example above identified two frontiers, represented by the continuous lines. These authors argue that their approach can identify latent differences in production technology arising from factors that are not directly observable by the researcher. They apply the multiple stochastic frontier approach to longitudinal data on the performance of 188 bank branches, identifying five groups with distinctive production frontiers. These multiple production frontiers are subsequently validated by secondary data and by interviews with the bank's managers.

Conclusion

The two methods discussed in this chapter are viable and widely used approaches to the measurement of technical efficiency, that is, to the measurement of how efficient a firm or unit of a firm is at using its inputs to produce a given set of outputs. Measures of technical efficiency are also useful for assessing a firm's capabilities relative to those of other firms in specific areas, such as R&D. Further, these measures are also useful for comparing the efficiency of different elements in a firm, such as salespeople, sales districts, retail outlets, divisions, or subsidiaries.

Which of the two approaches is preferred in a given situation depends on the characteristics of the data at hand. DEA more readily incorporates multiple outputs and requires only minimal assumptions about the shape of the efficiency frontier. These factors make DEA a good choice for cases in which measurement errors are likely to be small and the data are unlikely to contain outliers. On the other hand, if measurement errors are likely to be large, the SFE method may be a better choice, especially if one is comfortable about making assumptions about functional form and distribution of error terms. Since good approximations to general functions are available (for example, translog), and since specification testing is possible, assumptions about functional form may not be a critical issue for most applications. Perhaps the best strategy for determining technical efficiency is to apply both methods and to look for convergence in the results.

In the stochastic frontier model, although a production function form that relates an output to a set of inputs cannot readily accommodate multiple outputs, a cost function that relates total cost to multiple outputs and input prices can readily handle multiple outputs. Since the cost function is related to the production

function by duality (Caves, Christensen, and Swanson 1981), it provides an alternative to the production function for measuring technical efficiency. Intuitively, minimizing cost by holding input prices constant is equivalent to minimizing the inputs needed to produce a given set of outputs. Thus, if good data on input prices are available, the cost function can be used to measure technical efficiency, and the SFE measure is no longer restricted to a single output.[4]

A potential application of the techniques discussed in this chapter that has not been investigated in detail is for studying the efficiency of offerings in a product category from the consumer's standpoint (see Kamakura, Ratchford, and Agrawal 1988 for an example). That is, the consumer could be seen as receiving a bundle of attributes as outputs produced by prices and other inputs, such as time. Alternatives that lie on an efficiency frontier as determined by either of the methods discussed in this chapter would be utility maximizing for at least some consumers and therefore viable in the market at the going price. The viability of alternatives that fall well below the frontier would be questionable. This approach might be useful for obtaining a preliminary determination of the viability of product concepts. If a concept were very inefficient at prices required to make it profitable, its viability would be doubtful. On the other hand, if a concept could be priced so that it shifted the efficiency frontier outward, then it would be promising. In this case the efficiency analysis would also make it possible to determine which existing products would be rendered inefficient by the new concept and therefore most likely to be affected by its introduction.

We would like to point out that the discussion in this chapter is limited to technical efficiency, which refers to the unit's ability to produce its current levels of outputs with the most economical use of inputs. Because a technical efficiency measure eliminates the confounding effect of differences in output and input prices, it is generally superior to standard profit measures for making efficiency comparisons between units or firms. This is especially true if the managers of the units in question do not have control over prices. For example, managers of a branch bank are unlikely to have control over how the deposits they obtain are invested, and, on the input side, salaries of their employees may be set by the bank's human resources staff. Salaries for a given type of employee may differ because of geography or seniority. Moreover, larger branches may have a cost advantage because of economies of scale. In this case the profitability of a given branch is out of the immediate control of the manager, but he or she does have control over the ratios of deposits and other outputs to employees and other inputs. It is therefore appropriate to use an efficiency measure in evaluating the relative performance of different bank branches.

Similarly, since its outputs are generally not priced and sold in a competitive market, the profitability of a firm's R&D efforts cannot be measured directly.

Moreover, the impact of R&D on the firm's overall profitability depends on the ability of other units in the firm to successfully commercialize R&D outputs. But the efficiency with which the R&D manager utilizes the resources at his or her disposal to produce measured outputs (for example, in the form of patents) is under his or her control, and differences in this efficiency are potential sources of competitive advantage or disadvantage for the firms in an industry. Therefore relative technical efficiency is an appropriate standard for comparing the efficiency of R&D across firms. However, while technical efficiency can assure those concerned that the unit is producing its current outputs with the least waste of resources, it does not guarantee that the unit is operating at optimal levels—that it has allocative efficiency. The assessment of allocative efficiency requires determination of whether the optimal combination of inputs was chosen given their prices, as well as whether the combination of outputs that is produced is optimal from the standpoint of the buyer's welfare. Technical efficiency is a necessary but not sufficient condition for economic or allocative efficiency. A firm can be technically efficient because it produces the maximum outputs for the set of inputs it chooses but still fail to choose the most cost-effective combination of inputs or to produce the most valuable set of outputs. As discussed above, the approaches covered in this chapter are most appropriate for cases in which the manager has control over the efficiency with which a given set of inputs is used to produce a given set of outputs, but does not have direct control over the combinations of inputs or outputs that are employed.

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Notes

1. Further details on SFE can be found in Stevenson (1980), Battese and Coelli (1988, 1992), and Greene (2000, 2001).
2. One could also estimate how efficient the firm is at minimizing its costs. In such a case the firm objective would be to minimize costs, and the predictors would be total output and factor prices.
3. It is possible in an OLS setting to offer some idea of inefficiency by constraining the residuals to be positive (e.g., half-normal distribution; see Kalita 1994). However, this residual consists of both inefficiency and random shocks or luck, and it is not possible to disentangle the two sources of error. Disentanglement can be achieved only if there are two separate types of errors, as discussed in Equation 17 in the text.
4. If input prices do not vary across the firms or units under study, the cost function reduces to a regression of total costs on outputs, with the two error terms associated with the SFE procedure.

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