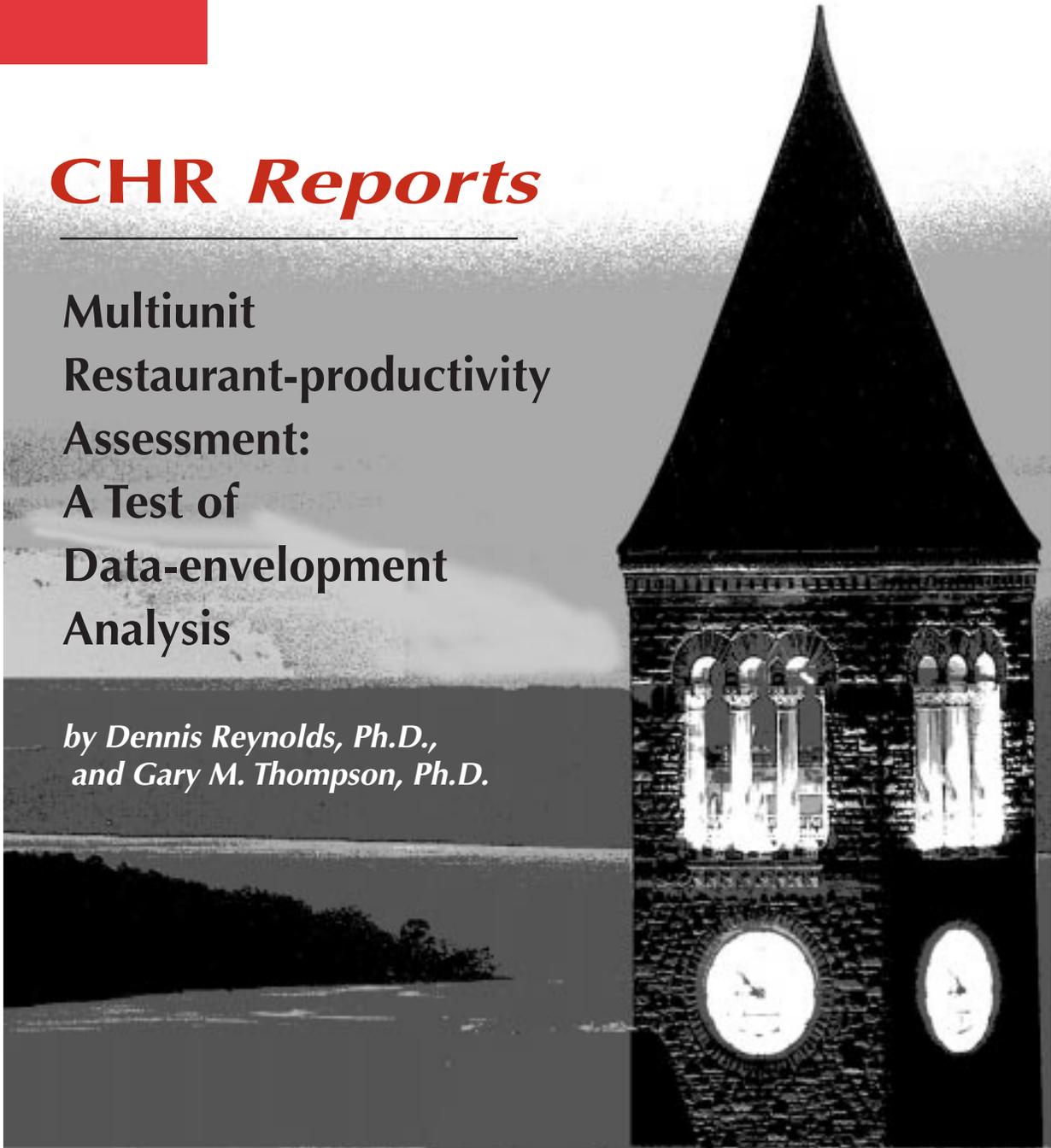


CORNELL

CHR Reports

**Multiunit
Restaurant-productivity
Assessment:
A Test of
Data-envelopment
Analysis**

*by Dennis Reynolds, Ph.D.,
and Gary M. Thompson, Ph.D.*



The Center for Hospitality Research
A T C O R N E L L U N I V E R S I T Y



CHR Reports

**is published for the benefit of the hospitality industry by
The Center for Hospitality Research at Cornell University**

**Cathy A. Enz, Executive Director
Glenn Withiam, Director of Publications Services**

Single-copy price \$50.00

Copyright © 2002 by Cornell University

Multiunit Restaurant-productivity Assessment:

A Test of Data-envelopment Analysis

by Dennis Reynolds, Ph.D., and Gary M. Thompson, Ph.D.

This report describes a three-step process for performing a data-envelopment analysis (DEA) to compare restaurants' efficiency and to examine their best practices. To start with, prospective efficiency factors must be analyzed to ensure that they are relevant. Secondly, to put restaurants on an equal footing the first DEA should consider only managerially uncontrollable (nondiscretionary) factors as inputs. With uncontrollable factors accounted for, managerially controllable factors can then be assessed in terms of their effect on productivity. Best practices can be isolated and assessed in this manner. To illustrate this three-step approach, data from 60 full-service restaurants are analyzed. From a large number of

prospective input factors, the analysis considers a short list of uncontrollable inputs—namely, hourly server wage, number of restaurant seats, and a coding variable representing whether the restaurant is a stand-alone facility. The output variables for this analysis were daily sales and tip percentage. Just over 20 percent of the restaurants operated with maximum efficiency, with the chain's average efficiency hitting 82 percent—good, but leaving room for improvement. However, the two discretionary factors that were proposed as differentiating the restaurants' efficiency—server hours and number of servers—proved not to be significant factors, inviting further analysis of the efficiency effects of additional discretionary factors.

Multiunit Restaurant-productivity Assessment:

A Test of Data-envelopment Analysis

by Dennis Reynolds, Ph.D., and Gary M. Thompson, Ph.D.

Productivity assessment is important for service organizations in good times and bad.¹ During economic downturns, operators look to increase productivity by maintaining sales while minimizing costs. In economic booms, operators strive to make the most of their resources to grab market share and expand overall sales volume.² In either case, productivity measurement, monitoring, and improvement lead to overall gains in profitability.³

¹ G.F. Bloom, *Productivity in the Food Industry: Problems and Potential* (Cambridge, MA: MIT Press, 1972).; J.T. Doutt, "Comparative Productivity Performance in Fast-food Retail Distribution," *Journal of Retailing*, Vol. 60 (1984), pp. 98-106; and D. Reynolds, "Productivity Analysis in the On-site Food-service Segment," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 39, No. 3 (June 1998), pp. 22-31.

² J.R. Brown and C. S. Dev, "Looking beyond RevPAR: Productivity Consequences of Hotel Strategies," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 40, No. 2 (April 1999), pp. 23-33.

³ R.G. Eccles, "The Performance-measurement Manifesto," *Harvard Business Review*, Vol. 69 (1991), pp. 131-137.

Productivity can be measured in many ways, however. In the food-service industry, for instance, researchers have focused largely on partial-factor productivity indices that stem from Bloom's definition of productivity, which is a ratio of output (measured in specific units) to any input factor (also measured in specific units).⁴ Analyses of this kind that have been applied to the food-service industry include sales per labor hour,⁵ revenue per available seat hour,⁶ and transactions per hour.⁷ While useful for specific intertemporal or intrafirm analyses, measures of this kind offer limited utility and frequently do not

⁴ Bloom, *op. cit.*

⁵ M. Jablonsky, "Productivity in Industry and Government," *Monthly Labor Review*, Vol. 117, No. 8 (1994), pp. 49-57.

⁶ S.E. Kimes, R.B. Chase, S. Choi, P.Y. Lee, and E.N. Ngonzi, "Restaurant Revenue Management: Applying Yield Management to the Restaurant Industry," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 39, No. 3 (June 1998), pp. 32-39.

⁷ R.D. Filley, "Putting the 'Fast' in Fast Foods: Burger King," *Industrial Engineering*, Vol. 15, No. 1 (1983), pp. 44-47.

correlate adequately with true efficiency, but instead they reflect only specific operational attributes.

In particular, most partial-factor ratios fail to account for potentially meaningful differences in the circumstances facing various food-service operations. For example, sales volume per labor hour may not be a helpful comparison measure if the restaurants being compared are subject to widely differing wage levels. Even total-factor-productivity models, such as the one recommended by Brown and Hoover, are not adequate for comparing multiple units with considerably different operating characteristics.⁸ Furthermore, both partial- and total-factor ratios statistically generate only an average (mean) measure. While useful for comparison purposes, related averages reveal little regarding the best operations, which can serve as benchmarks for weak performers.

In contrast to the above approaches, data-envelopment analysis, which we discuss here, integrates multiple outputs and inputs into one calculation.⁹ Residing in the domain of output-to-input-ratio measurement, data-envelopment analysis (DEA), which Charnes, Cooper, and Rhodes first proposed as an evaluation tool

⁸ M.D.M. Brown and L.W. Hoover, "Productivity Measurement in Food Service: Past Accomplishments—A Future Alternative," *Journal of the American Dietetic Association*, Vol. 90 (1990), pp. 973–981.

⁹ A.C. Charnes, W.W. Cooper, and E. Rhodes, "Measuring Efficiency of Decision-making Units," *European Journal of Operations Research*, Vol. 2 (1978), pp. 429–449.

for decision units, solves many of the problems associated with the aforementioned measures by integrating multiple outputs and inputs simultaneously. This operations-research-based approach allows consideration of both controllable (discretionary) and uncontrollable (nondiscretionary) variables, producing a single relative-to-best productivity index that relates all units under comparison. Thus,

DEA allows for assessment of contingent productivity, which takes into account the performance of each restaurant despite differing environmental or situational factors.

DEA allows for assessment of contingent productivity, which takes into account the performance of each restaurant despite differing environmental or situational factors. This also allows operators to use the best-performing units as bases for evaluation, as recommended by Farrell.¹⁰

Researchers interested in service-industry productivity have applied data-envelopment analysis to a variety of sectors, including banking;¹¹ insur-

¹⁰ M. Farrell, "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society, Series A, General*, 120, Part 3 (1957), pp. 253–281.

¹¹ I. Jemric and B. Vujcic, "Efficiency of Banks in Croatia: A DEA Approach," *Comparative Economic Studies*, Vol. 44, Nos. 2–3 (2002), pp. 169–193; and H.D. Sherman and G. Ladino, "Managing Bank Productivity Using Data-envelopment Analysis," *Interfaces*, Vol. 25, No. 2 (1995), pp. 60–73.

ance,¹² nursing,¹³ public services,¹⁴ and telecommunications.¹⁵ We have found few studies, however, that have analyzed the hospitality industry. Among those that we did find are those of Morey and Dittman, who examined data from 55 hotels, and Anderson, Fok, and Scott, who applied the technique to a smaller sample.¹⁶ Donthu and Yoo applied DEA to food service, although their study focused on quick-service restaurants only as an example of a retailing environment.¹⁷

¹² J. Mahajan, "Data-envelopment Analytic Model for Assessing the Relative Efficiency of the Selling Function," *European Journal of Operational Research*, Vol. 53 (1991), pp. 189-205.

¹³ T.R. Nunamaker, "Measuring Routine Nursing-service Efficiency: A Comparison of Cost per Patient-day and Data-envelopment Analysis Models," *Health Services Research*, Vol. 18, No. 2, Part 1 (1983), pp. 183-205.

¹⁴ C.J. Hammond, "A Data-envelopment Analysis of U.K. Public-library Systems," *Applied Economics*, Vol. 34, No. 5 (2002), pp. 649-657.

¹⁵ N.D. Uri, "Changing Productive Efficiency in Telecommunications in the United States," *International Journal of Production Economics*, Vol. 72, No. 2 (2001), pp. 121-137.

¹⁶ R.C. Morey and D.A. Dittman, "Evaluating a Hotel GM's Performance: A Case Study in Benchmarking," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 36, No. 5 (October 1995), pp. 30-36; and Anderson, Fok, and Scott, "Hotel Industry Efficiency: An Advanced Linear Programming Approach," *American Business Review*, Vol. 19, No. 1 (2000), pp. 40-48.

¹⁷ D.N. Donthu and B. Yoo, "Retail-productivity Assessment: Using Data-envelopment Analysis," *Journal of Retailing*, Vol. 74, No. 1 (1998), pp. 89-105.

Of the handful of DEA studies using hospitality-related business data, all analyzed a combination of controllable and uncontrollable variables in a single step or phase. However, as noted by Cooper, Seiford, and Tone and explained in greater detail later in this report, such an approach may lead to inaccurate efficiency scores.¹⁸ Moreover, a single-phase DEA approach may integrate variables that have no causal relationship to the outputs, further confounding the results.

With those concerns in mind, we set the following twofold objectives of this study. First, we introduce a three-step approach to DEA, based on a fundamental insight that we explain in a moment. Second, we apply our three-step approach to DEA to a comparison of similarly positioned restaurants (all operated by one chain, just for this example) with the goal of identifying the best practices in this particular multiunit organization. We believe our approach and our results will be of interest to researchers in DEA and in other envelopment-related approaches, with particular relevance to multiphase, nonparametric approaches to productivity analysis, and to practitioners concerned about maximizing productivity across operations.

¹⁸ W.W. Cooper, L.M. Seiford, and K. Tone, *Data-envelopment Analysis: A Comprehensive Text with Models, Applications, References, and DEA-solver Software* (Boston: Kluwer Academic Publishers, 2000).

Data-envelopment Analysis

DEA is a linear-programming-based benchmarking technique that explicitly considers multiple outputs and inputs to produce a single measure of performance. In contrast to parametric approaches that have the purpose of optimizing a single regression plane through the data, DEA optimizes on each individual observation with an objective of calculating a discrete piecewise frontier occupied by the most efficient units. This frontier—and the associated measure for each unit, which is generally referred to as relative efficiency or productivity—has particular managerial relevance in that it allows for comparison of disparate operating units.

As fully described by Charnes, Cooper, Lewin, and Seiford, DEA extends the basic output-to-input calculation of productivity by integrating the weighted sum of outputs to the weighted sum of inputs (see Exhibit 1).¹⁹ In applying DEA, the weights are estimated separately for each restaurant such that the resulting efficiency is the maximum attainable. Moreover, the weights estimated are such that when they are applied to corresponding outputs and inputs from other units in the analysis the ratio of weighted outputs to weighted inputs is less than or equal to 1.

¹⁹ *Data-envelopment Analysis: Theory, Methodology, and Application*, ed. A.C. Charnes, W.W. Cooper, A.Y. Lewin, and L.M. Seiford (Norwell, MA: Kluwer Academic Publishers, 2001).

EXHIBIT 1 DEA equations

As related in the accompanying text, data-envelopment analysis integrates the weighted sum of outputs to the weighted sum of inputs. Say that a restaurant is using two output variables, Y_1 and Y_2 , and three input variables, X_1 , X_2 , and X_3 . Its efficiency (P) is calculated as follows:

$$P_1 = \frac{U_1 Y_1 + U_2 Y_2}{V_1 X_1 + V_2 X_2 + V_3 X_3}$$

The weights U_s and V_s are estimated separately for each restaurant such that the efficiency is the maximum obtainable, with a maximum ratio of 1.

More generally, assuming an infinite (or incalculable) number of outputs and inputs, the maximum efficiency for restaurant o , as compared with n other restaurants is calculated as follows:

$$\text{Maximum } P_o = \frac{\sum_{r=1}^s U_r Y_{ro}}{\sum_{i=1}^s U_r Y_{io}}$$

$$\text{subject to: } \frac{\sum_{r=1}^s U_r Y_{rj}}{\sum_{i=1}^s V_r X_{ij}} \leq 1 \text{ for all } j = 1, \dots, n$$

$$U_r, V_i > 0, r = 1, \dots, s, \text{ and } i = 1, \dots, m$$

where:

Y_{rj} is the r^{th} output for the j^{th} restaurant;

X_{ij} is the i^{th} input for the j^{th} restaurant;

U_r and V_i are the variable weights estimated and used to determine the relative efficiency of o ;

s is the number of outputs; and

m is the number of inputs.

Since DEA seeks optimization contingent on each individual restaurant's performance in relation to the performance of all other units, those with the greatest productivity have a score (P) of 1.0, suggesting 100-percent efficiency. These optimal units lie on the top edge, or frontier, of the multidimensional efficiency measure. One could say that this efficiency frontier "envelops" the

To compare management decisions one must first account for the uncontrollable elements that affect restaurant operations.

inefficient units within and quantifies their inefficiency by giving them a relative overall score (of less than 1.0) and a relative measure of each output and input.

A Fundamental DEA Insight

As noted earlier, the goal of our analysis is to identify the best practices as they exist in the restaurant chain. DEA offers the means to accomplish this, *provided* the efficient restaurants are, in fact, those exhibiting best practices (and not merely those that are in such a good position that their sloppy operations are masked). Best practices follow from management decisions, but to compare those decisions one must first account for the uncontrollable elements that affect restaurant operations. This leads to our fundamental DEA insight. For

this analysis, *all inputs must be uncontrollable factors*. That is, the DEA inputs represent the restaurants' operating environments (at least, initially), allowing us to control for the competition or other environmental factors that the restaurant faces and to put each restaurant on an even footing. By using an output-maximization model, where all the inputs are uncontrollable, each restaurant is matched to others in equally difficult or more-difficult operating environments. When the uncontrollable factors are thus accounted for in the model, high performance becomes a function of management decisions (regarding controllable factors), which lead in turn to identifying best practices.

On the other hand, consider the effect of mixing controllable factors into the analysis. Even if a given controllable factor is verifiably accurate, a restaurant will be matched to other restaurants based (at least in part) on that controllable factor. Thus, if the DEA analysis for a particular restaurant includes a controllable factor in its efficiency analysis (perhaps the number of part-time employees), that restaurant can spuriously show up as efficient. To put it another way, restaurants whose managers make bad decisions are matched to other restaurants where managers make bad decisions—and it becomes impossible to identify the best practices.

Once the DEA analysis is completed with uncontrollable factors, one can turn to the controllable factors for

analysis. Logically, if the controllable factors represent the best practices themselves, or management decisions that lead to best practices, we would expect that there is a statistically significant relationship between the controllable factors and performance (we address this matter more fully later on). These relationships can be examined once the DEA has identified the efficiency of the restaurants (based on the uncontrollable factors). This leads us to the following three-step DEA methodology:

- (1) Examine the data to ensure that:
 - (a) There is a statistically significant relationship between each input and at least one output;
 - (b) All candidate input factors are independent of each other; and
 - (c) All candidate output factors are independent of each other.
- (2) Run an output-maximizing DEA model using only uncontrollable factors as inputs.
- (3) Perform multiple-regression analyses examining the effect of the controllable factors on restaurant efficiency.

It is important that one can, in fact, establish a linkage between the input and outputs specified in Step 1a. For example, a restaurant manager might argue that her unit's performance is linked to the number of shrubs around the restaurant (particularly if that restaurant is in the midst of a highway strip's parking-lot desolation). Including additional inputs or outputs in DEA will never reduce the efficiency score of a unit. The efficiency scores will either stay the same

or increase. Thus, if the number of shrubs were included in the DEA as an input, then the restaurant's reported efficiency would probably improve because of its small number of shrubs. So, one must first test to see whether shrubs actually are linked to performance. Unless the number of shrubs really has a measurable effect on one or more of the output variables, it should not be included in the analysis—because including the input in the DEA model could artificially raise efficiency scores.

To our knowledge, we are the first to arrive at the above fundamental insight regarding DEA. Indeed, while most envelopment techniques provide provocative results, they share the common assumption that controllable and uncontrollable variables should be included at the onset.²⁰ For

When the uncontrollable factors are accounted for, high performance becomes a function of management decisions.

example, Jayashree explored the efficiency of insurance companies by integrating a variety of factors under management control, such as number of sales employees in a given service center, along with (uncontrollable)

²⁰ For example, see: C. Cazals, J.P. Florens, and L. Simar, "Nonparametric Frontier Estimation: A Robust Approach," *Journal of Econometrics*, Vol. 106, No. 1 (2002), pp. 1-25.

environmental factors, such as the number of nearby branch offices operated by competitors.²¹

This phased approach reflects Norman and Stoker's assertion that measurement that accounts for uncontrollable factors is more vital than a

DEA can analyze managers' performance excuses to see whether those factors are, in fact, related to the restaurant's output.

mixed analysis, because uncontrollable variables are most influential in establishing an efficiency frontier.²² However, our approach is different from the stepwise approach detailed by those two researchers in that we make the determination of which uncontrollable factors to include based on the *a priori* assumptions stated earlier in concert with the existence of the causal relationships apparent in the regression analyses.

Our fundamental insight also offers benefits when it comes to convincing restaurant managers that this analysis makes sense and should be used. When the results of a DEA analysis are presented to unit managers, our experience has been that they

²¹ M. Jayashree, "A Data-envelopment Analytic Model for Assessing the Relative Efficiency of the Selling Function," *European Journal of Operational Research*, Vol. 53, No. 2 (1991), pp. 189-206.

²² M. Norman and B. Stoker, *Data-envelopment Analysis: The Assessment of Performance* (New York: John Wiley and Sons, 1991).

often offer reasons (excuses) for why they did not perform better. For example, a manager might say: "The analysis did not consider the effects of competition. I'm right next to Competitor X, and that makes it hard for me to do better." Those excuses typically relate to uncontrollable factors, since a manager is not going to say that his or her restaurant performed poorly because of his or her bad decisions.

In this case, though, we can perform the three-step analysis again using the list of excuses! Indeed, we can validate the new inputs (the excuses) to see whether they are related to some output measure and verify that they are independent of other inputs. If they meet the inclusion criteria, we can run the DEA output model again to develop revised efficiency scores based on those factors. Our experience has been that even a single iteration of the process yields much better buy-in among unit managers, because they can see that we have isolated the effects of the uncontrollable factors that they were blaming for their problems.

In the food-service industry, uncontrollable factors might include a restaurant's maximum seating capacity, parking availability, and the number of nearby competitors. Factors of that type are typically ignored in other methods of productivity assessment owing to the difficulty in making comparisons across units, particularly when units possess dissimilar uncontrollable characteristics. Needless to say, controllable factors include those

within management's purview, such as labor hours, number of servers during a given shift, or (with some limitations) wages paid to employees.

While the number of potential variables is almost unlimited, the literature suggests essential factors to consider. In terms of uncontrollable variables, for example, Douitt demonstrated that service capacity—usually measured by number of seats or square footage—is fundamental to any measure of productivity.²³ Information relative to environmental characteristics, such as location (solitary or adjacent to demand generators), and competitive conditions, such as the number of similarly positioned competitors nearby, also appears to be pertinent.²⁴ Another uncontrollable characteristic that may affect productivity is the availability of parking.²⁵

The correlation between wages and productivity, particularly for skilled workers, is well established in the literature.²⁶ In the restaurant

industry, however, the common practice is to pay minimum wage (or close to it) for line-level jobs, especially when compensation also includes gratuities.²⁷ Thus, in this sense, pay levels are beyond management's control, because the wages (and tip credits) vary according to state laws.

As for controllable variables, labor hours has been considered to be a key element in calculating food-service productivity,²⁸ while Yoo, Donthu, and Pilling suggested front-of-the-house labor as a decisive variable.²⁹ Similarly, Powers indicated that the number of servers influences unit-level productivity.³⁰ Another direct influence on productivity that is under management's control is the amount of training provided to staff members. In a sales setting, for example, Pullig, Maxham, and Hair showed the positive effects of training on productivity,³¹ while Barrett and

²³ Douitt, *op. cit.*

²⁴ For example, see: A. Goldman, "Evaluating the Performance of the Japanese Distribution System," *Journal of Retailing*, Vol. 68 (1992), pp. 11-39; and M. Ortiz-Buonafina, "The Evolution of Retail Institutions: A Case Study of the Guatemalan Retail Sector," *Journal of Macromarketing*, Vol. 12 (1992), pp. 16-27.

²⁵ As posited by: A.A. Broholm, "Selecting Sites for Restaurant Chains," *Commercial Investment Real Estate Journal*, Vol. 10, No. 1 (1991), pp. 43-46.

²⁶ K. Bayard and K.R. Troske, "Examining the Employer-size Wage Premium in the Manufacturing, Retail-trade, and Service Industries Using Employer-Employee Matched Data," *American Economic Review*, Vol. 89, No. 2 (1999), pp. 99-103.

²⁷ M.C. Sturman, "The Compensation Conundrum: Does the Hospitality Industry Shortchange Its Employees—and Itself?," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 42, No. 4 (August 2001), pp. 70-76.

²⁸ Reynolds, *op. cit.*

²⁹ B. Yoo, N. Donthu, and B.K. Pilling, "Channel Efficiency: Franchise versus Non-franchise Systems," *Journal of Marketing Channels*, Vol. 4, No. 1 (1997), pp. 211-223.

³⁰ T.F. Powers, "Productivity in the Service Restaurant," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 15 No. 3 (November 1974), pp. 49-54, 64.

³¹ C. Pullig, J.G. Maxham, and J.F. Hair, "Sales-force-automation Systems: An Exploratory Examination of Organizational Factors Associated with Effective Implementation and Sales-force Productivity," *Journal of Business Research*, Vol. 55, No. 5 (2002), pp. 401-415.

O’Connell provided empirical evidence for the efficacy of training as it pertains to productivity, including a wide range of types of training.³²

The outputs used to assess productivity in service industries, and particularly the restaurant industry, are sales and customer satisfaction. Using DEA, Pilling, Donthu, and Henson and demonstrated the importance of sales as an output variable.³³ Similarly, Thore, Phillips, Ruefli, and Yue used DEA and longitudinal data

Sales and customer satisfaction are two common measurements for assessing restaurants’ productivity.

and reported on the pertinence of sales as an output.³⁴

As for customer satisfaction, a number of studies have demonstrated its importance in terms of the productivity associated with service-related

³² A. Barrett and P.J. O’Connell, “Does Training Generally Work? The Returns of In-company Training,” *Industrial and Labor Relations Review*, Vol. 543 (2001), pp. 647-662.

³³ B.K. Pilling, N. Donthu, and S. Henson, “Accounting for the Impact of Territory Characteristics on Sales Performance: Relative Efficiency as a Measure of Salesperson Performance,” *Journal of Personal Selling and Sales Management*, Vol. 19, No. 2 (1999), pp. 35-45.

³⁴ S. Thore, F. Phillips, T.W. Ruefle, and P. Yue, “DEA and the Management of the Product Cycle: The U.S. Computer Industry,” *Computers and operations Research*, Vol. 23, No. 4 (1996), pp. 341-347.

functions. Notably, one study provided empirical results that a DEA model incorporating customer satisfaction as an output variable was superior.³⁵ Related studies on productivity have also demonstrated the importance of customer-satisfaction indices.³⁶

Methodology

Given our research objective of applying a three-phase DEA approach to measure efficiency, we collected data from 60 same-brand units of a 62-unit chain located throughout the United States. (The data from two units were not available.) The sample period included up to 180 consecutive days during the summer and fall of 2001. All of the units are operated by the same company, and all share the same menu and operating structure. Thus, the resulting analyses are best described as internal benchmarking.

The primary data source was a set of point-of-sale (POS) reports generated by the corporate office, which also contain data pertaining to square footage and number of seats. The information was augmented through data gathered from phone surveys with unit managers.

³⁵ M. Lothgren and M. Tambour, “Productivity and Customer Satisfaction in Swedish Pharmacies,” *European Journal of Operational Research*, Vol. 115, No. 3 (1999), pp. 449-458.

³⁶ A. Parasuraman, V.A. Zeithaml, and L.L. Berry, “Alternative Scales for Measuring Service Quality: A Comparative Assessment Based on Psychometric and Diagnostic Criteria,” *Journal of Retailing*, Vol. 70 (1994), pp. 193-199.

EXHIBIT 2
Prospective input and output factors

Output Variables	Measurement	Data Source
Sales	\$/Day	POS
Tips	Proportion of check (for credit-card purchases only)	POS
Turnover	Percentage of staff	Call
Input Variables (Uncontrollable)	Measurement	Data Source
Server wage	\$/Hr	POS
Seats	Number	POS
Square footage	Ft ²	POS
In State	Units (within the same state)	POS
ST1	Coding variables for state 1 with a large number of units	POS
ST2	Coding variables for state 2 with a large number of units	POS
ST3	Coding variables for state 3 with a large number of units	POS
Years	Years restaurant has been open	Call
Parking	0 (street), 1 (parking lot)	Call
Stand alone	0 (stand alone) or 1 (adjacent to other buildings)	Call
Competitors	Number within a two-mile radius	Call
Input Variables (Controllable)	Measurement	Data Source
Training	Number of shifts	Call
Server count	Number	POS
Server hours	Hours per week	POS

We made a number of assumptions. First, we assumed that gratuities serve as an adequate surrogate measure of customer satisfaction. While such an assumption is supported by a number of researchers, others argue that gratuity variability is not consistently associated with service.³⁷ Given the exploratory nature of the study and the interest in using objective data sources, however, this assumption appears logical. In addition, since a calculation of total gratuities would require self-reports of all servers, we used only charged gratuities as a proportion of charged sales, operating under the assumption (reasonable, we think) that patrons using a credit card tip similarly to those paying cash. In addition, while some guests use a credit card for the meal but tip in cash, we assumed that such practices would be proportionately similar across units. Finally, while it is arguable that any restaurant is a competitor of any other, we identified only those within the same segment (with correspondingly similar positioning strategies).

Exhibit 2 (on the previous page) presents the complete list of factors for which we obtained data. We had

³⁷ For examples on both sides of the argument, see: O.B. Bodvarsson, and W.A. Gibson, "Economics and Restaurant Gratuities: Determining Tip Rates," *American Journal of Economics and Sociology*, Vol. 56, No. 2 (1997), pp. 187-203; and M. Lynn, "Restaurant Tipping and Service Quality: A Tenuous Relationship," *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 42, No. 1 (February 2001), pp. 14-20.

to remove the "turnover" data field, since it was not numeric. We also removed the "competitors" data field, since the numbers, which ranged from 0 to 225, appeared unrealistic. Since we held the controllable factors for later analysis, we were left with sales and server tips as output variables, and, as input variables, server wages, number of seats, square footage, in-state presence, coding variables for each of three of the states in which the company has the most restaurants (coded as ST1, ST2, ST3), years in operation, availability of parking, and whether the restaurant stands alone. We included those coding variables for the three states with the largest number of units (that is, ST1, ST2, and ST3) as a way of evaluating whether local market conditions might affect the results.

Step one required that we ensure that each input was related to at least one output, that the inputs are independent, and that the outputs are independent. We then performed stepwise multiple regressions, with sales and tips as dependent variables, and server wage, seats, square feet, in-state presence, the three largest states in terms of presence (ST1, ST2, and ST3), years in operation, parking, and standing alone as independent variables. Exhibit 3 reports the results of those regressions. Only server wage, seats, and whether the restaurant stands alone were significantly related to either output. Consequently, we eliminated square feet, in state (along with ST1, ST2, ST3), years, and parking from further consideration.

The results of the regression with sales as the dependent variable offer interesting insights. We found that sales are higher in high-wage locations, and that sales increase \$20.43 for each additional seat (which means that the restaurant is getting about two covers per seat per day in the dinner meal period). Also, sales are lower in stand-alone restaurants, by almost \$1,300 per day. This suggests that there are benefits to be derived from locating a restaurant adjacent to other buildings, probably because of the increased traffic generated from those other buildings.

The negative relationship between server wages and tips is problematic from a DEA perspective. Given the relationship that server wage has with sales, however, we decided to keep server wage as an input factor.

Exhibit 4 reports the correlations between the remaining prospective input factors and between the output factors. Since all correlations are low, the independence requirements identified in steps 1b and 1c are satisfied. Our DEA model is based, then, on sales and tips as output variables and, as input variables, server wages, number of seats, and whether the restaurant stands alone.

When we ran the DEA model, 13 of the 60 restaurants were judged to be at top efficiency and gained efficiency scores of 1.0. The average efficiency score across all 60 restaurants was 0.820, suggesting that revenue and tips could be increased by about 22 percent systemwide.

EXHIBIT 3
Relationships between input and output factors

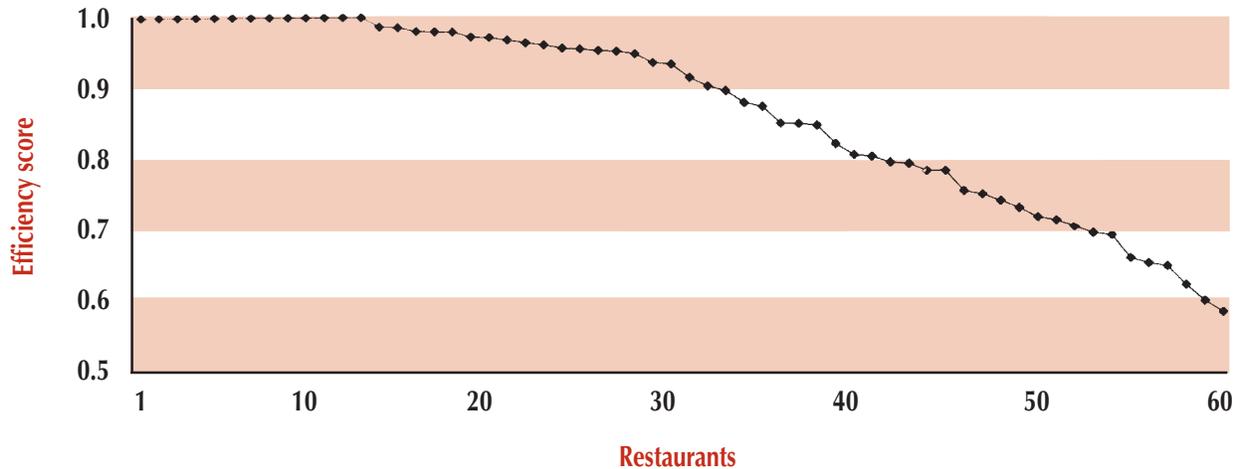
Variable	Sales	Tips
Server wage	\$310.84*	-0.00225**
Seats	\$20.43**	—
Square footage	—	—
In state	—	—
ST1	—	—
ST2	—	—
ST3	—	—
Years	—	—
Parking	—	—
Stand alone	\$1,268.07*	—

* Significant at $p < 0.05$; ** significant at $p < 0.00$; based on stepwise multiple regressions as described in the text at left.

EXHIBIT 4
Correlations between prospective input and output factors

Variable	Seats	Stand alone	Tips
Server wage	0.06281	0.12208	—
Seats	—	0.03697	—
Sales	—	—	-0.05762

EXHIBIT 5
DEA efficiency scores of the 60 restaurants



Note: The above plot demonstrates how a company might compare the efficiency of its individual restaurants using data-envelopment analysis. Each dot represents one restaurant. Efficiency is calculated first on the items outside management’s control to account for those factors. As a result, all restaurants are judged on an equal basis, leaving only factors under management control to differentiate the restaurants.

Exhibit 5 shows the restaurants’ efficiency scores, which are ranked from most to least efficient. The lowest-scoring restaurant had an efficiency score of 0.527.

The final step in our three-step DEA analysis is to examine the relationship between restaurants’ efficiency scores and the values of their controllable inputs. To this end, we ran a stepwise multiple regression with the efficiency score as the dependent variable and server count and server hours as independent variables. The results of this analysis were that the efficiency score was not related signifi-

cantly to either controllable variable (which means that something else is at work, as we discuss next).

Strengths and Limitations

While the potential for using DEA in food-service management is evident, we identified a number of limitations, both with the empirical illustration provided and the method of analysis. For example, we wonder whether gratuities are truly representative of satisfaction, or whether customers are dutifully adding 15 or 20 percent to their check? We believe that a better,

more aptly defined measure of customer satisfaction would be desirable. Perhaps of greater importance, are there variables other than the ones we examined that are of greater importance in assessing productivity? The number and experience of managers in the restaurant is one possibility, for example, and another is the experience of the entire management team. Another concern pertains to differences in traffic patterns and related environmental factors that may be influential. Finally, how does employee turnover affect productivity? Anecdotal evidence suggests that turnover can serve as a significant and possibly fatal detriment to restaurant productivity.³⁸ Inclusion of such information would likely provide more provocative results.

Moreover, DEA itself has flaws. While DEA may address many of the problems of conventional productivity measures, it is extremely sensitive to outliers, as these serve to influence the optimal frontier (that is, outlying variables can raise the supposed efficiency bar). Thus, it is possible that one restaurant could anomalously create a benchmark—say, potentially resulting from a variable not included in the analysis—that no other operation can match. Of course, this is addressed largely through the iterative analysis, including manager input that

³⁸ For example, see: Timothy R. Hinkin and J. Bruce Tracey, “The Cost of Turnover: Putting a Price on the Learning Curve,” *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 41, No. 3 (June 2000), pp. 14–21.

we described earlier. Finally, DEA does not allow for an error structure. Hence, there is no goodness-of-fit information as is found in more traditional statistical techniques (e.g., structural equations).

An interesting outcome of our three-step DEA analysis was the absence of a significant relationship between the restaurant-efficiency scores and the values of the controllable inputs that we identified. We do not believe that this refutes the merits of our three-step approach. Rather, it indicates to us that there are other controllable factors (that is, general best practices) that are driving the restaurants’ efficiency. There are two avenues open to elucidate the relevant controllable factors. First, if data on other controllable factors exist in the chain, these factors can also be examined. Second, one could visit a sample of the efficient restaurants and compare them to a group of inefficient restaurants to identify differences in decisions and practices among the high- and low-performing restaurants.

The findings of such research will likely provide the necessary impetus for managers to more accurately focus on maximizing the requisite assets—

In appreciation to Gazelle Systems

The CHR Report is made possible through an alliance between The Center for Hospitality Research and Gazelle Systems. Through this alliance, Gazelle makes available its data for the use of CHR researchers under non-disclosure and confidentiality agreements that guide the scope of data reporting. The authors gratefully acknowledge the support of Gazelle Systems and the CHR.

including human capital—that ultimately lead to more-profitable operations.

It is possible that the server count and server hours (which are controllable factors) are actually relevant to restaurant efficiency, because they are unit-specific best practices and not general best practices. Unit-specific best practices are the decisions that managers make in certain environments that lead to their high performance levels. These decisions might well be polar opposites of decisions that managers of other high-performing restaurants make in their different

circumstances. In cases like these, performing a regression of the controllable factors against efficiency will not show significant results. However, the interaction term of environment (uncontrollable) and decisions (controllable) should have a statistically significant effect on efficiency scores.

Although we have focused on a single restaurant chain, we see no reason why our three-step approach cannot be applied successfully to several restaurant chains or to other service businesses. DEA, when applied effectively, represents an invaluable tool in multiunit operations. □

About the Authors

Dennis Reynolds, Ph.D., is an assistant professor of food and beverage management in the Cornell University School of Hotel Administration (der17@cornell.edu). His doctoral degree is from Cornell University in hospitality management. His research focuses on pathways leading to enhanced managerial efficiency and effectiveness with specific application to food-service organizations. Reynolds's research has been published in *Advanced Management Journal*, *Cornell Hotel and Restaurant Administration Quarterly*, *Journal of Hospitality and Tourism Research*, and *Journal of Food Service Business Research*. He is also the author of *On-Site Food Service Management: A Best Practices Approach*.



Gary M. Thompson, Ph.D., is associate professor of operations management in the Cornell University School of Hotel Administration (gmt1@cornell.edu). His Ph.D. is in operations management from Florida State University. Thompson's research interests are in applying quantitative techniques to hospitality problems. His research has appeared in *Cornell Hotel and Restaurant Administration Quarterly*, *Decision Sciences*, *Journal of Operations Management*, *Journal of Service Research*, *Management Science*, and *Naval Research Logistics*. He is also founder and CEO of *SchedulExpert, Inc.*, a small software firm focused on scheduling products.

About

The Center for Hospitality Research at Cornell University

The Center for Hospitality Research is the premier source for in-depth research on the hospitality industry. The Center constitutes a community of researchers and industry sponsors working in concert to develop and dispense new knowledge that directly bears on the hospitality industry. Membership in the Center is open to any individual or corporation interested in furthering high-quality research for the betterment of the hospitality industry.

Our corporate sponsors include the following firms.



Bartech Automatic Systems



The Food and Beverage Forum



Cornell Hotel Society Foundation

Four Seasons Hotels and Resorts

Richmond Events

Willowbend Golf Management



Windsor Hotels

The Center for Hospitality Research

A T C O R N E L L U N I V E R S I T Y

