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Multiunit Restaurant Productivity Assessment Using Three-Phase Data Envelopment Analysis

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This paper focuses on uncontrollable variables' effects on multiunit restaurant productivity using data envelopment analysis (DEA). We argue the importance of first considering managerially uncontrollable (nondiscretionary) variables as inputs in the actual DEA model, with managerially controllable variables considered post hoc for their relationship to the efficiency scores. We illustrate the merits of this approach using data from a chain of 62 full-service restaurants. From a large number of candidate inputs, we arrive at a short list of uncontrollable inputs: hourly server wage, restaurant seats, and a coding variable representing whether the restaurant is a stand-alone facility. Output variables in our model were daily sales and tip percentage. We find that just under 12% of the restaurants operate efficiently and that the average efficiency for the chain is 82%.

Keywords
service management, restaurants, productivity, data envelopment analysis

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This paper focuses on uncontrollable variables' effects on multiunit restaurant productivity using data envelopment analysis (DEA). We argue the importance of first considering managerially uncontrollable (nondiscretionary) variables as inputs in the actual DEA model, with managerially controllable variables considered post hoc for their relationship to the efficiency scores. We illustrate the merits of this approach using data from a chain of 62 full-service restaurants. From a large number of candidate inputs, we arrive at a short list of uncontrollable inputs: hourly server wage, restaurant seats, and a coding variable representing whether the restaurant is a stand-alone facility. Output variables in our model were daily sales and tip percentage. We find that just under 12% of the restaurants operate efficiently and that the average efficiency for the chain is 82%.

Keywords: Service management; Restaurants; Productivity; Data envelopment analysis

1. Introduction

Productivity assessment has long been considered important for service-related organizations (Bloom, 1972; Doutt, 1984; Reynolds, 2003). During economic downturns, operators look to increase productivity by attempting to maintain sales while minimizing costs; in economic booms, operators strive to leverage inputs to attain disproportionately greater increases in outputs such as overall sales volume (Brown and Dev, 1999). Moreover, productivity measurement, monitoring, and improvement lead to overall gains in profitability, leading service firms to focus on achieving productivity gains as an overarching objective (Eccles, 1991).

In the foodservice industry, researchers have focused largely on partial-factor productivity indices that stem from Bloom's (1972) definition of productivity: a ratio of output measured in specific units and any input factor also measured in specific units. Such measures include sales per labor hour (Jablonsky, 1994), revenue per available seat hour (Kimes et al., 1998) or transactions per hour (Filley, 1983). While useful for specific intertemporal or intrafirm analyses, these measures have limited utility and frequently do not adequately correlate to technical or operational efficiency, reflecting only specific operational attributes (Reynolds, 1998).

In particular, most partial-factor ratios fail to account for potentially meaningful differences among foodservice operations. For example, sales per labor hour may be subject to differing wage levels. Even total-factor productivity models, as recommended by Brown and Hoover (1990), are not adequate for comparing multiple units with considerably different operating characteristics. Furthermore, both partial- and total-factor ratios statistically generate only an average measure. While useful for comparison purposes, related averages reveal little regarding the best operations—those that might better serve as benchmarks.

While still residing in the output-to-input ratio measurement domain, data envelopment analysis (DEA), which Charnes et al. (1978) first proposed as an evaluation tool for decision units, solves many of the problems associated with the aforementioned measures by integrating multiple outputs and inputs simultaneously. The operations-research-based approach allows for 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 combinations of operating characteristics given that operating conditions are similar (c.f., Sexton et al., 1994). This also allows operators, as recommended by Farrell (1957), to use the best performing units as bases for evaluation.

Researchers interested in service-industry productivity have applied data envelopment analysis to a variety of sectors including banking (Jemric and Vujcic, 2002; Sherman and Ladino, 1995), insurance (Mahajan, 1991), nursing (Nunamaker, 1983), public services (Hammond, 2002), and telecommunications (Uri, 2001). Very few have analyzed the hospitality industry. Morey and Dittman (1995) examined data from 55 hotels while Anderson et al. (2000) applied the technique to a slightly smaller sample. Donthu and Yoo (1998) applied DEA to foodservice, although their study focused on quick-service restaurants only as an example of a general retailing environment.

Of the handful of DEA studies using hospitality-related business data, all share the commonality of analyzing a combination of controllable and uncontrollable variables in a single step or phase. As noted by Cooper et al. (2000) and explained in greater detail later in this paper, such an approach may lead to inaccurate efficiency scores. Moreover, such an approach may integrate variables that have no causal relationship to the outputs, further confounding the results.

The objective of this study, then, is to first focus on the uncontrollable variables as inputs in the DEA model using similarly positioned restaurants within a single chain. We then explore the effects of controllable variables having leveled the playing field in terms of comparing units with differing features outside of the unit-level management’s purview. 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 service-based operations.

2. Data envelopment analysis

DEA is a linear-programming-based benchmarking technique that explicitly considers multiple outputs and inputs, producing a single measure of performance. In contrast to parametric approaches whose purpose is to optimize 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 et al. (2001), DEA extends the basic output-to-input calculation of productivity by integrating the weighted sum of outputs to the weighted sum of inputs. For example, if Restaurant 1 is evaluated using two output variables, Y_1 and Y_2, and three input variables, X_1, X_2, and X_3, its efficiency (P1) is calculated by

$$P_1 = \frac{U_1Y_1 + U_2Y_2}{V_1X_1 + V_2X_2 + V_3X_3}. \tag{1}$$

In applying DEA, the weights (U_s and V_s) are estimated separately for each restaurant such that the efficiency is the maximum attainable. Moreover, the weights estimated for Restaurant 1 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. On a more general basis, assuming the number of outputs and inputs is conceptually infinite, the maximum efficiency of Restaurant *o* as compared with *n* other restaurants is calculated as follows:

$$\text{Maximize } P_o = \frac{\sum_{r=1}^{s} U_r Y_{ro}}{\sum_{i=1}^{m} V_i X_{io}} \tag{2}$$

$$\text{Subject to } \frac{\sum_{r=1}^{s} U_r Y_{rj}}{\sum_{i=1}^{m} V_i X_{ij}} \leq 1 \text{ for all } j = 1, \ldots, n \tag{3}$$

$$U_r > 0 \text{ for } r = 1, \ldots, s \tag{4}$$

$$V_i > 0 \; for \; i = 1, \ldots, m, \tag{5}$$

where Y_{rj} is the *r*th output for the *j*th restaurant, X_{ij} is the ith input for the jth restaurant, *s* is the number of outputs, *m* is the number of inputs and and U_r are the variable weights estimated and used to determine the relative efficiency of *o*.

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 productivity score (*P*) of 1, suggesting 100% efficiency when compared with those in the competitive set. These optimal units lie on a multidimensional frontier; the efficiency frontier 'envelops' the inefficient units within and quantifies the inefficiency by a relative score of less than 100% and a relational measure on each output and input.

2.1. Using DEA in the service sector

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, if the efficient restaurants in a DEA analysis are those exhibiting best practices. Best practices follow from management decisions. Our investigation, then, is predicated on all inputs being uncontrollable variables. By using an output maximization model, where all the inputs are uncontrollable, each restaurant is matched to others given that operating conditions are similar across units. Here high performance is a function of management decisions, which lead in turn to best practices.

Consider the effect of including controllable variables in the analysis. Even if the controllable variables are verifiably accurate, a restaurant will be matched to other restaurants based on that controllable variable. Thus, a restaurant that uses a small amount of some controllable variable (perhaps the number of part-time employees) can 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.

If the controllable variables are not to be included in the DEA analysis, how then should they be used? Logically, if the controllable variables represent the best practices themselves, or management's decisions that lead to best practices, we would expect that there is a measurable relationship between the controllable variables and performance (we address this more fully in the discussion). These relationships can be examined once the DEA (based on the uncontrollable variables) has identified the efficiency of the restaurants. This leads to the following DEA methodology:

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

It is important that the linkage between input and outputs specified in Step 1(a) exist. For example, a restaurant manager might argue that performance is linked to the number of shrubs around the restaurant (particularly if his or her restaurant had few shrubs). 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. Unless the number of shrubs really has a measurable effect on one or more of the output variables, though, the input is spurious and so it should not be included in the analysis because including the input in the DEA model artificially raises efficiency scores.

We acknowledge that this is an unconventional approach to using DEA. While most envelopment techniques provide provocative results, they share the common assumption that controllable and uncontrollable variables should be included at the onset (Cazals et al., 2002). For example, Jayashree (1991) explored the efficiency of insurance companies by integrating a variety of factors under management's control, such as number of sales employees in a given service center, and uncontrollable, environmental factors such as the number of nearby branches occupied by competitors.

Furthermore, it is important to note that uncontrollable variables may become controllable at some point during the operating lifetime of the restaurant. For example, if a given restaurant requires additional capacity, it may become an option for the unit manager to expand the seating area using current and projected profit to fund the capital improvement. Hence, a variable that we treat here as uncontrollable may need to be reassigned in future analyses.

This phased approach used in this study reflects Norman and Stoker's (1991) assertion that measurement in respect to uncontrollable variables is more important because such variables represent a more influential effect on the efficiency frontier. Our approach is different from the stepwise approach detailed by these researchers, however, in that we make the determination of including uncontrollable variables based first on the a priori assumptions stated earlier in concert with the existence of the causal relationships apparent in the regression analyses.

Our approach offers other benefits when it comes to convincing restaurant managers that the analysis makes sense and should be used. When the results of a DEA analysis is presented to unit managers, our experience has been that they often offer reasons (excuses) why they did not perform better. For example, a manager might say that 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.’’ If you examine these excuses, they are typically uncontrollable variables, since a manager is not going to say that his or her restaurant performed poorly because of his or her bad decisions. From the list of excuses, we can then perform the analysis again: Validate the new inputs (the excuses) to see if they are related to some output measure and verify that they are independent of other inputs; if they meet the inclusion criteria, run the DEA output model again to develop the revised efficiency scores. Our experience has been that even a single iteration of the process yields much better buy-in among unit managers.

In the foodservice industry, uncontrollable variables might include a restaurant’s maximum seating capacity, parking availability, and number of nearby competitors; these 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. Controllable variables include those within management’s purview, such as labor hours, number of servers during a given shift, or wages paid to employees.

While the number of potential variables is relatively limitless, a review of the literature suggests some essential factors. In terms of uncontrollable variables, for example, Doutt (1984) demonstrated that service capacity is fundamental to any measure of productivity. Such measures might include number of seats or overall square footage. Information relative to environmental characteristics, such as location—including such building characteristics as freestanding or building adjacency—and competitive conditions, such as the number of similarly positioned competitors in the surrounding area, also appears pertinent (e.g., Goldman, 1992; Ortiz-Buonafina, 1992). A related uncontrollable environmental characteristic that may affect productivity is parking availability, as posited by Broholm (1991).

The correlation between wages and productivity, particularly for skilled workers, is well established in the literature (e.g., Bayard and Troske, 1999). In the restaurant industry, however, the common practice is to pay minimum wage particularly for low-skill jobs, especially when the position also includes gratuities (Sturman, 2001). Thus, even when the standard is to pay minimum wage, these amounts vary by state and are beyond management's control.

As for controllable variables, Reynolds (1998) asserted that labor hours is one of the key elements in calculating foodservice productivity, while Yoo et al. (1997) suggested front-of-the- house labor as a decisive variable. Similarly, Powers (1974) indicated that the number of servers is influential in predicting unit-level productivity. Another issue that appears to have a direct influence on productivity, but one that is fully under management's control, is the amount of training provided to the staff. In a sales setting, for example, Pullig et al. (2002) illustrated the positive effects of training on firm-wide productivity, while Barrett and O'Connell (2001) provided empirical evidence for the efficacy of training as it pertains to productivity, including a wide range of types of training.

The outputs used to assess productivity in service industries, and particularly the restaurant industry, are sales and customer satisfaction. Pilling et al. (1999) used DEA and demonstrated the importance of sales as an output variable. Similarly, Thore et al. (1996) used DEA and longitudinal data and reported on the pertinence of sales as an output.

As for customer satisfaction, a number of studies have demonstrated its importance in terms of the productivity associated with service-related functions. Notably, one study provided empirical results that a DEA model incorporating customer satisfaction as an output variable was superior (Lothgren and Tambour, 1999). Related studies on productivity have also demonstrated the importance of customer-satisfaction indices (Parasuraman et al., 1994). Specific to the service sector, Bolton (1998) illustrated the importance of satisfaction in the customer's relationship with a service provider.

4. Methodology

Given the research objective to measure efficiency among similarly positioned restaurant operations, we performed a pilot study by collecting data from 60 same-brand units of a 62-unit chain located throughout the United States. (The data from the two units not included in the study were unavailable.) The period of time 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 third-party data provider. This data set contains point-of- sale (POS) reports generated by the corporate office and data pertaining to square footage and number of seats. We augmented this third-party data with data gathered from phone surveys with unit managers.

We made a number of assumptions. First, since we do not have access to profitability data, we assumed that sales was a reasonable surrogate for profitability. While this may be true in general, it does mean that our results could be corrupted by managers making decisions to drive sales at the expense of profitability. Second, we assumed that gratuities serve as an adequate surrogate measure of customer satisfaction, which is supported by the literature (e.g., Bodvarsson and Gibson, 1997). 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 that patrons using a credit card tip similarly as 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. Third, we assumed that back-of-the-house labor hours were relatively constant among stores; this assumption was based on information supplied by the company. Officials of the organizations also noted that while most front-of-the-house employees are part-time, the majority of back-of-the-house employees are full-time employees and work according to structured staffing schedules that are very similar throughout the chain.

Fourth, we assumed that since all restaurants included in the study were in suburban settings and all sites were selected according to a well-defined set of site-selection criteria, the operating conditions across units are similar including traffic patterns and related environmental factors. The last assumption pertains to competitors. 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).

Table 1 presents the complete list of variables for which we obtained data. We had to remove the 'turnover' data field, since it was not numeric. (For example, some respondents reported 'frequent turnover' while others reported it as an annual percentage.) We also removed the 'competitors' data field, since the numbers, which ranged from 0 to 225, appeared unrealistic. Since we hold the

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INSERT TABLE 1 HERE

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controllable variables for later analysis, we were left with Sales and Tips as output variables and Server Wage, Seats, Square Feet, In State, ST1, ST2, ST3, Years, Parking and Stand Alone as input variables. We included coding variables for the three states with the largest number of units (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. Our next step, then, was to perform stepwise multiple regressions, with Sales and Tips as dependent variables and Server Wage, Seats, Square Feet, In State, ST1, ST2, ST3, Years, Parking and Stand Alone as independent variables. Table 2 reports the results of those regressions. Only Server Wage, Seats and Stand Alone were significantly related to either output. Consequently we eliminated Square Feet, In State, ST1, ST2, ST3, Years, and Parking from further consideration.

The results of the regression with Sales as the dependent variable offer interesting insights. The results tell us that sales are higher in high-wage locations, 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 (coded using a binary variable), by almost $1300 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 counts from the other buildings.

The negative relationship between Server Wage and Tips is somewhat problematic from a DEA perspective. Given the relationship Server Wage has with sales, however, we decided to keep Server Wage as an input factor.

Table 3 reports the correlations between the remaining candidate input variables and between the output variables. Since all correlations are low, the independence requirements identified in steps 1(b) and 1(c) are satisfied. Our preliminary DEA model is based, then, on Sales and Tips as output variables and Server Wage, Seats, and Stand Alone as input variables.

This initial DEA model was then examined for potential problems such as those made evident through outliers or potentially biasing variables. While no outliers were found, the issues associated with integrating binary variables, as explained fully by Bankerv and Morey (1986), became evident. That is, when efficiency scores were segregated based on the stand alone designation, the zero value for the

INSERT TABLE 2 HERE

INSERT TABLE 3 HERE

corresponding units appeared to skew the respective efficiency scores. Thus, this variable was eliminated from the final DEA model. To test the potential effect of units' free-standing characteristics, we regressed this variable during post-hoc analyses on the efficiency scores, which is discussed later in this paper.

When we ran the final DEA model, which included sales and gratuities as output variables and server wage and number of seats as inputs, 7 of the 60 restaurants were judged to be efficient, with 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 24%. Fig. 1 shows the efficiency scores of the restaurants, which are rank-ordered based on declining efficiency scores. The lowest scoring restaurant had an efficiency score of 0.527.

As for application and model specification, we used Frontier Analyst as this software appeared well-suited to handle the computation-intensive linear programming models. Regarding model specification, we employed an output-oriented model given the assumptions discussed earlier. To that end, radial efficiency measures were taken using the CCR model to provide an aggregate measure of technical efficiency, which resulted in the ranking shown in Fig. 1. This approach, as discussed by Ferrier, Kerstens, and Vanden Eeckaut (1994), was logical as the inputs are not subject to radial reductions. Furthermore, the constant returns to scale is appropriate here since our focus was on the macro-level effects where the observed variability of outputs and inputs is independent and homothetic. It should also be noted that there was no non-radial slack, as calculated using the BCC model.

The final step in our three-step analysis is to examine the relationship between restaurant efficiency scores and the values of the controllable inputs as well as the binary ‘stand alone’ uncontrollable input. To this end, we performed two types of tests. First, we ran a stepwise multiple regression with the efficiency score as the dependent variable and Server Count, Server Hours, and Stand Alone as independent variables. The results of this analysis were that the efficiency score was not related significantly to either controllable variable but did portend a negative relationship with Stand Alone. Second, we performed paired t-tests on the means of the controllable variables. The samples were the seven efficient units and the seven least-efficient units. As with the related regression analyses, the paired t-tests did not indicate significant differences between the controllable variables. Finally, we repeated the regression analysis, this time including the variables that appeared insignificant in the initial analysis (as noted in Table 1). No relationships were noted.

5. Discussion

While the potential for DEA in foodservice management is evident, there are a number of limitations, both with the empirical illustration provided and the method of analysis. Regarding the pilot study presented here, the number of restaurants was relatively small. This was the result of the limited size of the organization, which is comprised of only 62 units, and a larger number of operations would likely provide more depth to the findings. In addition, the similarities shared by a single chain likely belie the absence of other variables in the final model.

Other related limitations pertain to the assumptions described earlier. Are sales a reasonable proxy for profits? Are charged gratuities equivalent to satisfaction? While earlier studies suggest the validity of such an assumption, some researchers contend gratuities are not correlated highly with satisfaction (e.g., Lynn, 2001). A better, more aptly defined measure of customer satisfaction would be desirable. Finally, are there other variables of greater importance in assessing productivity? The number and experience of managers in the restaurant is one possibility; another is the experience of the management team. Finally, how does employee turnover affect productivity? Anecdotal evidence suggests that turnover can serve as a significant and possibly fatal detriment to restaurant productivity. Inclusion of such information would likely provide more provocative results. Had we had full access to primary data from the restaurant we would have been able to include more appropriate variable choices. As such, readers should view our actual application of our advocate approach to DEA as illustrative, rather than exemplary.

While DEA may address many of the problems of conventional productivity measures, it has limitations as well. For example, DEA is extremely sensitive to outliers, as these serve to influence the optimal frontier. Thus, it is possible that one restaurant could anomalously create a benchmark—potentially resulting from a variable not included in the analysis—that no other operation can match. 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 lack of a significant relationship between the restaurant efficiency scores and the values of the controllable inputs. We do not believe that this refutes the merits of our approach. Rather, it indicates to us that there are other controllable variables (i.e., general best practices) that are driving the restaurant's efficiency. There are two avenues open to elucidate the relevant controllable variables. First, if data on other controllable variables exists in the chain, these variables can also be examined. Second, a sample of the efficient and inefficient restaurants could be visited 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—including human capital—ultimately leading to more profitable operations.

It is in fact possible that the Server Count and Server Hours controllable variables are relevant, because they are unit-specific best practices and not general best practices (cf., Reynolds, 2003). Unit-specific best practices are the decisions that managers make in certain environmental situations 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 factor against efficiency (or performing paired t-tests on the stratified sample) 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 approach in assessing restaurant productivity cannot be applied successfully to other chains and to other service businesses. DEA, when applied effectively, represents an invaluable tool in the multi-services arena with particular utility for multiunit operations.

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Table 1
Candidate input and output data

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

*POS = point of sale system. Call = telephone questionnaire.

Table 2
Relationships between inputs and outputs

Variable	Sales	Tips
Server wage	$310.84*	−.00225***
Seats	$20.43***	N/A
Square footage	N/A	N/A
In State	N/A	N/A
ST1	N/A	N/A
ST2	N/A	N/A
ST3	N/A	N/A
Years (Q1)	N/A	N/A
Parking (Q3a)	N/A	N/A
Stand alone (Q4)	$1,268.07*	N/A

*$p<0.05$, **$p<0.01$, ***$p<0.001$.

Table 3
Correlations between the candidate inputs and between the candidate outputs

	Seats	Stand alone	Tips
Server wage	0.06281	0.12208	
Seats		0.03697	
Sales			−0.05762

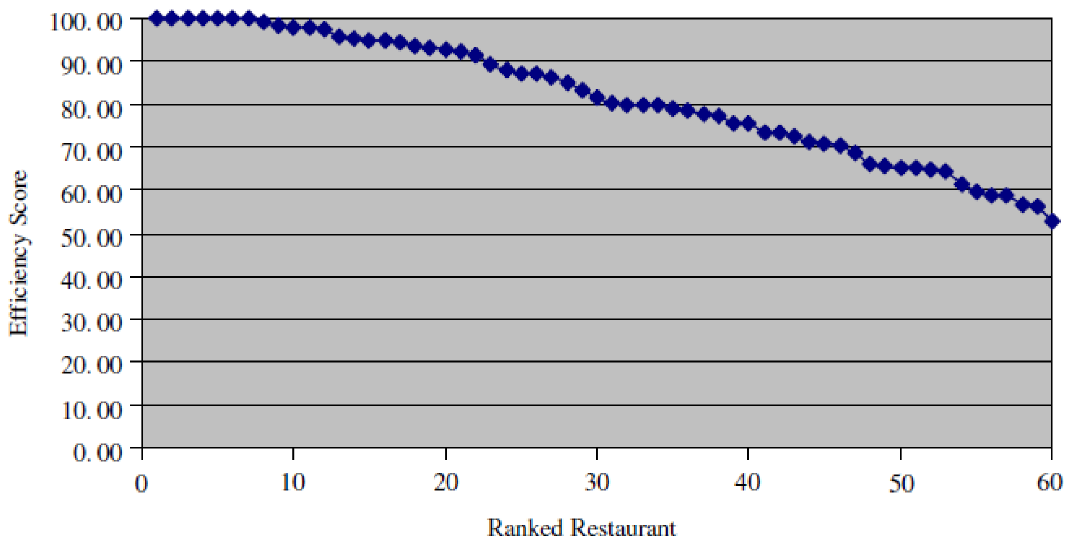

Fig. 1. DEA efficiency scores of the 60 restaurants, rank-ordered in terms of declining score.