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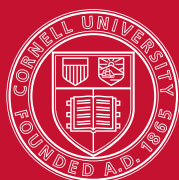


Cornell Hospitality Report

Restaurant Capacity Effectiveness: Leaving Money on the Tables

by Gary M. Thompson, Ph.D.

Vol. 7, No 7, April 2007



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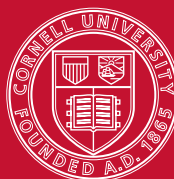
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Restaurant Capacity Effectiveness:

Leaving Money on the Tables

By Gary M. Thompson, Ph.D.

ABOUT THE AUTHOR



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EXECUTIVE SUMMARY

In fall 2005 The Center for Hospitality Research (CHR) at Cornell University released the Restaurant Table Mix Optimizer (or RTMO), which I developed. This tool identifies the best mix of tables for a restaurant, based on a variety of inputs. The tool itself is web-based, with the CHR storing users' data anonymously in a database. As of mid March 2007, a total of 1,543 people had registered to use the RTMO. However, not all of those registrants created a valid table-mix scenario. With unusable scenarios eliminated, the final study analyzed the table mixes of 68 restaurants. While eight of the restaurants had the actual optimum table mix for peak operating times, the other 60 restaurants were leaving some money on the table. That is, most restaurants could improve their table mix. On average, the restaurants in this sample could increase their peak revenue by almost 15 percent by implementing a more effective table mix. Almost one-fifth of the restaurants in this sample could improve revenue by more than 20 percent just by having the appropriate mix of right-size tables. Restaurant operators may be lulled into thinking they are doing as well as possible at peak times when they have full tables and guests waiting, but if that restaurant has empty seats, even at an occupied table, the mix of table sizes probably could be adjusted to seat more diners, even at peak times. Table-mix optimization shows what that mix should be.

Restaurant Capacity Effectiveness:

Leaving Money on the Tables

By Gary M. Thompson, Ph.D.

In fall 2005 The Center for Hospitality Research (CHR) at Cornell University released the Restaurant Table Mix Optimizer (or RTMO), which I developed. This tool, which is web-based, identifies the best mix of tables for a restaurant, based on a variety of inputs. The Center stores RTMO users' data anonymously in a database. As of mid March 2007, a total of 1,543 people had registered to use the RTMO. This report examines the capacity effectiveness of these real restaurants, using the data saved by the tool users. I see both good news and bad news here, depending on one's perspective. The news is good, in that the results I report here show that optimizing restaurant tables mixes can yield significant improvements in restaurant revenue (increasing revenues during peak periods by 14.8 percent, on average). The bad news is that, based on the data provided by users, restaurant owners are leaving a lot of money "on the table" in the sense that they could be doing substantially more business at peak times than they are. They can do this by filling seats rather than filling tables, as I explain here.

The RTMO Tool

The Restaurant Table-Mix Optimizer is designed to help managers find the best mix of tables for their restaurants, based on the mix of customer-party sizes, in terms of revenue (or contribution margin). As inputs, the RTMO requires that users specify information that most managers already have available: the percentage of total parties of each size (e.g., parties of one constitute 20 percent of total parties); the average dining duration by party size; the average check by party size; the space to be allocated in the restaurant; which table sizes can be used; and the space required by each table size allowed.

As outputs, the RTMO identifies the maximum number of parties that can be served per hour; the maximum average value that the restaurant can achieve (contribution margin or revenue) per available space-hour; and which combinations of table sizes will make it possible to best serve the various size parties. As a web-based tool, the RTMO allows users to create, evaluate, and save different scenarios. This enables users to determine the effect on performance of such things as changing the table sizes they have in their restaurants.

Data Collection and Cleansing

Although 1,543 people have registered to use the RTMO as this is written, many people did not create a scenario in which they saved data. Moreover, most of these registrants did not enter data specific to their own restaurants (as indicated by their use of data similar to the example provided as part of the RTMO). To ensure that the cases I evaluated were related to real restaurants, I performed a number of steps to “cleanse” the data. These steps, which are described in the appendix on the next page, resulted in a final sample of 68 restaurants.

Analysis

The purpose of the analysis was to compare each restaurant’s existing table mix with the best possible table mix for that restaurant. I wanted to find out whether the restaurants had an appropriate mix of tables, given their customer mix, or whether they were “leaving money on the table” because

their table mix did not match their customer mix. I did this by first simulating 50 days’ worth of peak business for each of the 68 restaurants, using the existing table mix for each. The mix of customers, their dining durations, and value all came from the data provided by the user who created the scenario. Using a procedure to find the best table mix that I have reported on elsewhere,¹ I then found the best table mix for the restaurant, using the given characteristics. The technique I applied was more sophisticated than the RTMO tool. The RTMO implements a search for the naïve table mix.² However, the tool I employed uses the naïve table mix as a starting point, and it then uses simulation and a search strategy to identify, if possible, a better-performing mix of tables.

Let me explain why the RTMO stops with the naïve table mix. In earlier research, Sherri Kimes and I found that the algorithm used in the RTMO typically finds table mixes that yield revenue within 1 percent of the amount possible with the best table mix. In contrast, the procedure I used for this report typically finds table mixes that yield revenue within 0.1 percent of the revenue possible with the best table mix.³ The reason that the RTMO does not use the more sophisticated analysis relates to processing requirements. Because the Center for Hospitality Research cannot dedicate a computer to RTMO, trying to use the sophisticated, simulation-oriented approach is impractical simply due to the computer time needed to identify the recommended table mix. That said, however, the improvement typically to be gained by optimizing the mix of tables in a restaurant using the RTMO (the naïve level) far exceeds the small amount of revenue that RTMO itself may miss. In other words, as I explain below, the RTMO will get restaurateurs most of the way to achieving their optimum peak revenue.

¹ S. E. Kimes and G.M. Thompson, 2005. “An Evaluation of Heuristic Methods for Determining the Best Table Mix in Full-service Restaurants,” *Journal of Operations Management*, Vol. 23, No. 6, pp. 599-617.

² Gary M. Thompson, “Optimizing a Restaurant’s Seating Capacity: Used Dedicated or Combinable Tables?,” *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 44, No. 1 (June 2003), pp. 45-57.

³ Kimes and Thompson, *op.cit.*

Appendix: Data Collection & Cleansing

As stated in the accompanying text, by mid-March 2007, 1,543 people had registered to use the RTMO. However, it became clear that only 369 scenarios had been created by tool users as of mid March 2007. Moreover, inspection of the data made it necessary to eliminate another 300 of those scenarios, as I explain here.

The accompanying table lists the steps that I followed in cleansing the raw data, and the number of scenarios that were eliminated in each step. For example, eliminating any scenarios that did not list the existing numbers of tables dropped 46 scenarios. To make it through the data-cleansing process, a scenario had to accomplish the following. It had to list the number of tables in the restaurant; identify the proportion of each size party (for example, that parties of two represented 35 percent of the total number of parties); specify the space requirements for each table size being considered; have table size and party proportions different from those in the sample scenario provided to all tool users; have more than one valid table size; have a total space of less than 20,000 (units were not specified, so this could be square meters or square feet); and provide information that was consistent with having sufficient space in the restaurant for the optimum numbers of tables.—*G.M.T.*

Step	Observations Removed	Remaining Observations
RTMO Registrants	N/A	1,543
Remove those registrants who have not saved their own scenario	1,174	369
Remove those scenarios without existing numbers of tables	46	323
Remove those scenarios without party-size proportions (i.e., they provided no information like parties of one person represented 20% of total parties)	179	144
Remove those scenarios with no space used (i.e., table space not specified)	5	139
Remove those scenarios with table sizes and total space identical to those in the sample scenario	44	95
Remove those scenarios with party-size distributions identical to those in the sample scenario	20	75
Remove those scenarios with only one valid table size (since the best table mix is trivial when only one size of table is allowed)	4	71
Remove those scenarios with space available > 20,000	1	70
Remove those scenarios with no space available	2	68

The performance metric I focused on was the total achieved revenue. To ensure that I was not cherry-picking only the most valuable customers in the simulation (or the ones that would best fit into the available tables), I simulated the arrival of a number of parties that would, in theory, just fit in the restaurant if its seats were always full.

It is important to note that the best table mix I identified for each restaurant was limited to what would fit into the space of the restaurant (defined by summing the number of the existing tables, times their sizes). Imposing this constraint is another means of ensuring the relevance of the findings.

Results

To begin, I categorized the 68 scenarios in the sample based on the effectiveness of their existing table mix. “Excellent” restaurants were those scenarios where peak revenue was within 1 percent of that provided by the best table mix. Those that were within 2 percent I labeled “very

good”; “good” restaurants hit within 5 percent of the best mix revenue; those within 10 percent were “fair”; and “poor” restaurants yielded peak revenue of within 20 percent of the revenue yielded by the best table mix. Finally, peak revenues at “very poor” restaurants were better than 20 percent lower than those yielded by the best table mix.

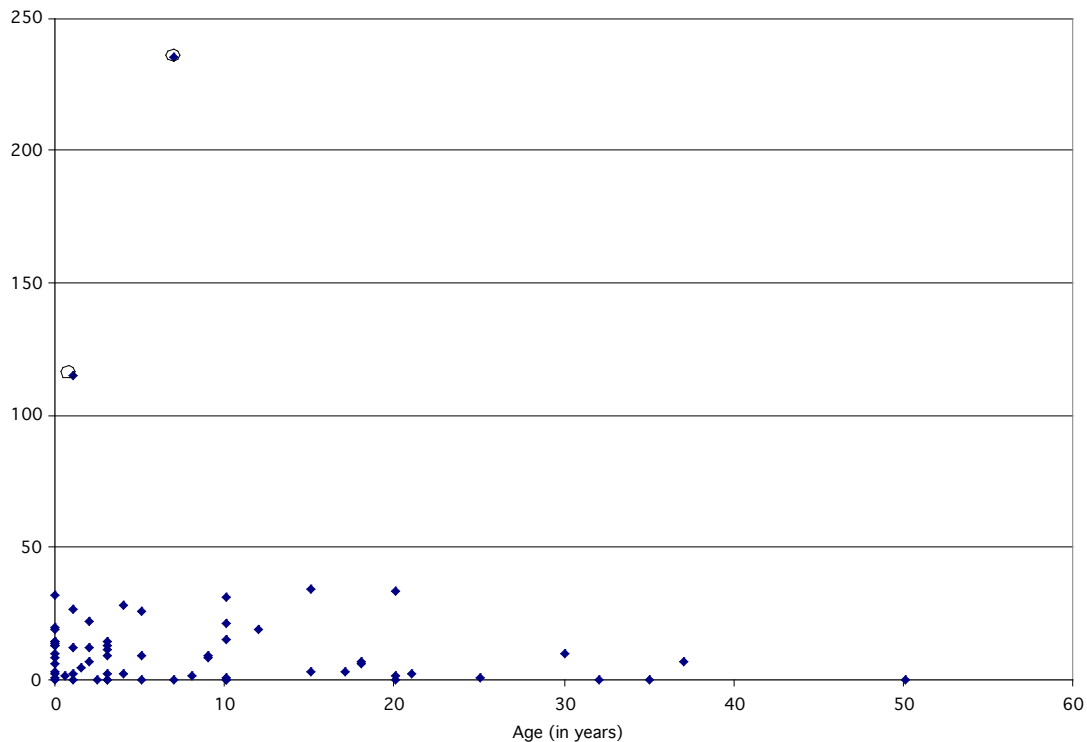
Exhibit 1 shows the 68 restaurant scenarios in the final sample according to the categories that I just explained. Only 39 (31.5%) of the restaurants fell in the “excellent,” “very good,” or “good” levels of performance, while 37 (29.8%) fell in the “poor” category and 29 more (23.4%) fell into the “very poor” level of performance.

A key question is whether there were systematic differences between restaurants, related to their characteristics. In particular, I wanted to find out whether the restaurants that already had a top-performing table mix had characteristics in common that made them different from restaurants that did not have effective table mixes. To undertake this phase of analysis, I used information about the restaurants that were provided by RTMO users, such as the age of the restaurant,

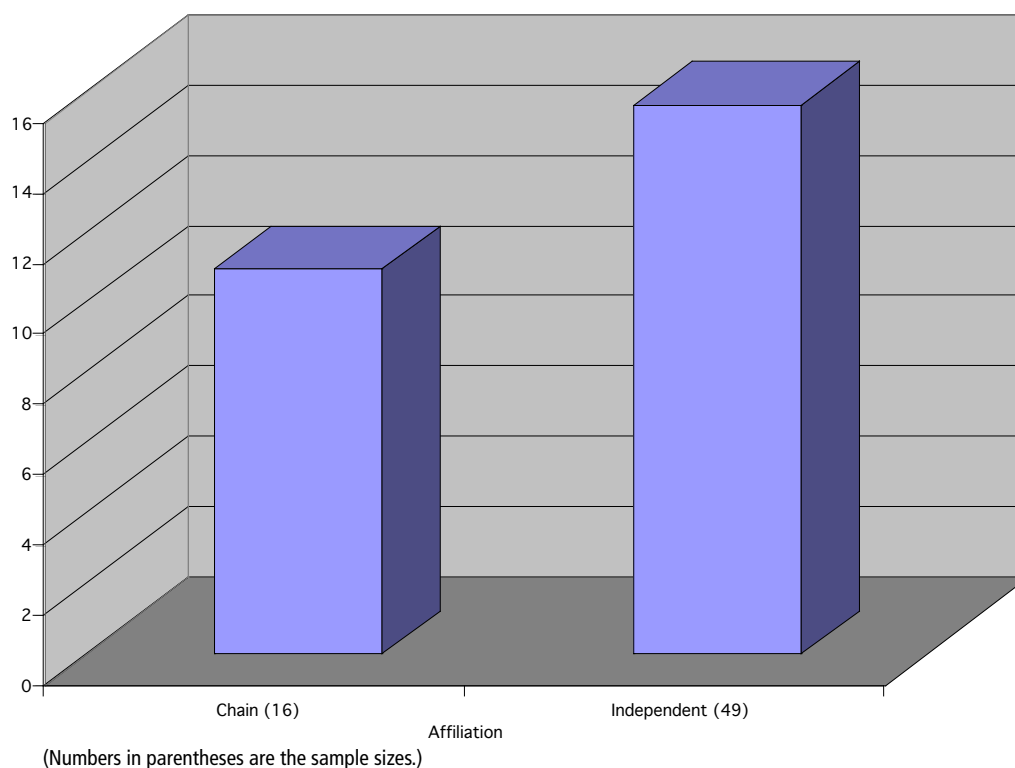
EXHIBIT 1**Restaurants in the sample, by table-mix performance**

Performance Category	Performance Level*	Number of Restaurants (%)
Excellent	< 1%	15 (22.1%)
Very Good	1-2%	4 (5.9%)
Good	2-5%	10 (14.7%)
Fair	5-10%	10 (14.7%)
Poor	10-20%	16 (23.5%)
Very Poor	≥ 20%	13 (19.1%)

*Capacity effectiveness of the best-identified table mix for the restaurant, compared to the restaurant's existing table mix. Thus, a score of 4 percent would mean the restaurant could increase sales by 4 percent over that provided by its existing table mix.

EXHIBIT 2**Achievable restaurant improvement, by restaurant age**

Note: Circled points are outliers which were eliminated from consideration.

EXHIBIT 3**Achievable restaurant improvement, by affiliation (chain or independent)**

its sales level, the number of seats it contains, the number of peak weekly hours, whether it was independent or affiliated with a chain, and whether it was a full- or limited-service.

For this analysis, I focus on achievable restaurant improvement, which is defined as the revenue increase that would be yielded by the best possible table mix for the restaurant at the peak period, measured as a percentage of the peak revenue yielded by the restaurant's existing table mix. Thus, for example, an achievable restaurant improvement score of 12 percent would indicate that the restaurant's peak revenue could increase by 12 percent compared to its existing peak revenue, if the table mix were changed to the best-possible mix.

Measured according to achievable restaurant improvement, the average restaurant in the sample could increase its peak revenue by 14.8 percent compared to that achieved using its existing table mix. Below I describe the relationship

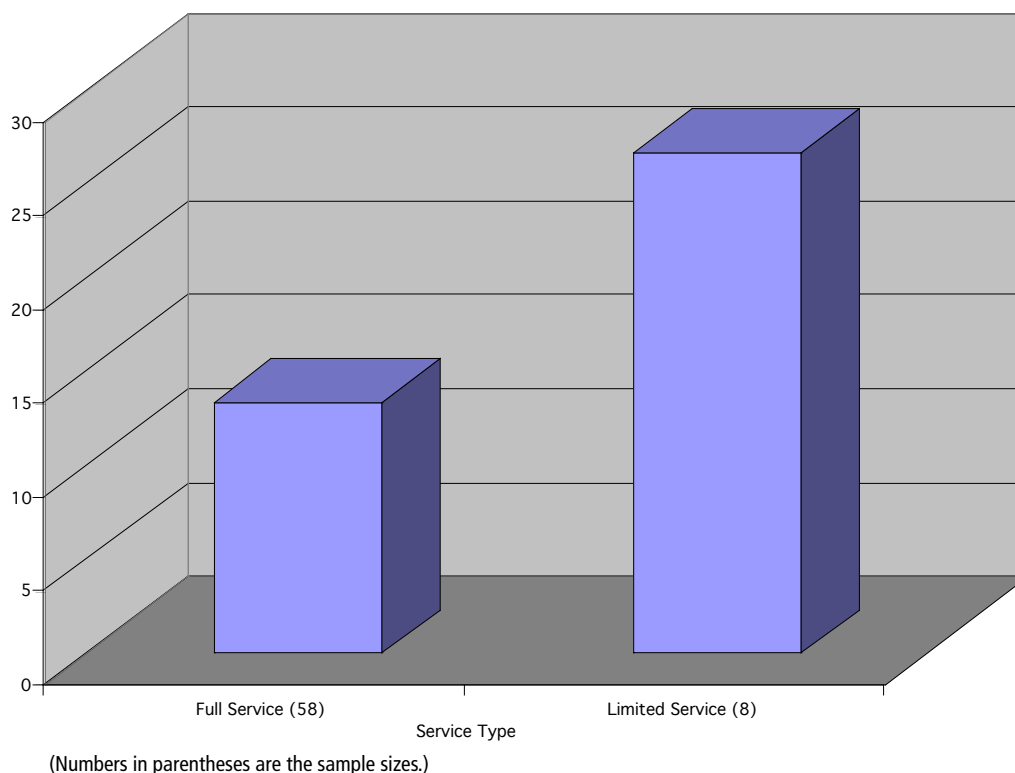
between the achievable restaurant improvement and various restaurant characteristics, based on data provided by RTMO users.

To do this, I developed least-squares regression models linking achievable restaurant improvement to the number of seats in the restaurant, the number of peak weekly hours, and the age of the restaurant. Only restaurant age had a statistically significant relationship to improvement (and the relationship was only weakly significant, at that). A scatter plot of the data is shown in Exhibit 2 on the previous page.

The relationship is as follows:

$$\text{Achievable Improvement (\%)} = 11.01 - 0.167 * \text{Age (in years)} \\ (p < 0.15, \text{adjusted } R^2 = 0.019)$$

This relationship indicates that older restaurants had better table mixes than younger restaurants, but that restaurant age explained only a small amount (i.e., under 2%) of the difference in achievable improvement across restaurants.

EXHIBIT 4**Achievable restaurant improvement, by service type**

An examination of the other characteristics of the restaurants yielded no indication that certain restaurant types had consistently superior table mixes. For example, 65 of the 68 restaurants in the sample provided affiliation information. As may be seen in Exhibit 3, the average achievable improvement was similar for the two categories. Chain-affiliated restaurants had an achievable improvement of 10.9 percent, compared to 15.6 percent for independents, a difference that was not statistically significant.

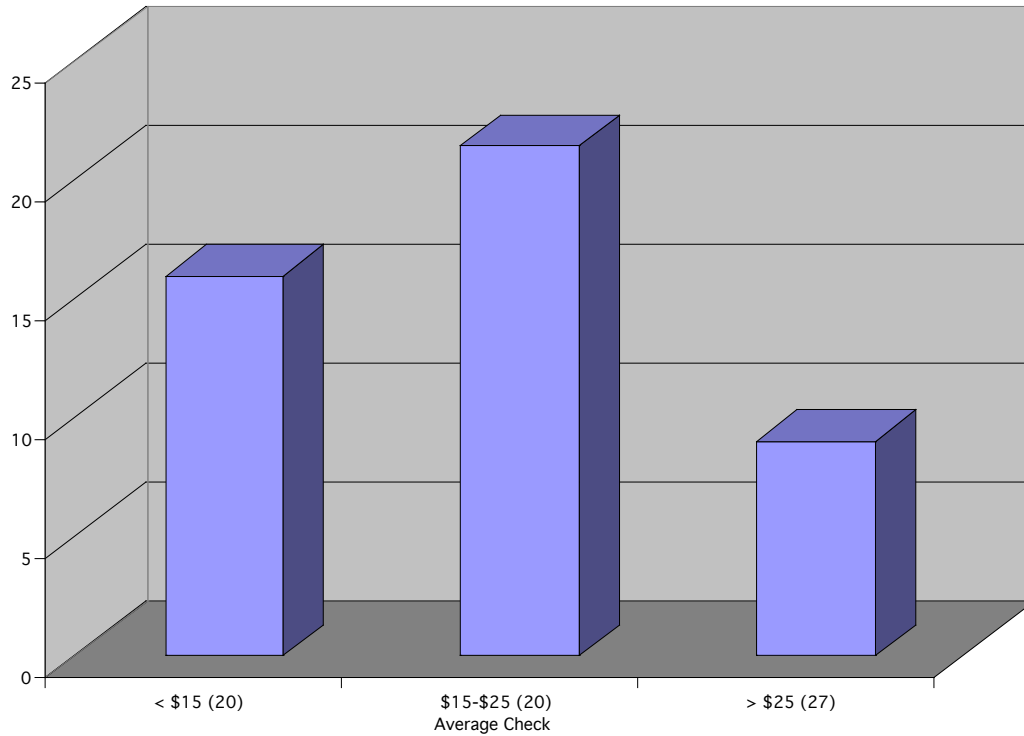
One characteristic that did turn up considerable differences was the type of service. The relationship between achievable restaurant improvement and service type is illustrated in Exhibit 4. Sixty-four of the 68 users provided this information, and 58 of those 64 were full-service restaurants. The difference in average achievable improvement is quite marked; full-service restaurants have an average achievable improvement of 13.4 percent, compared to 26.7 percent for

the six limited-service restaurants (again, though, this difference was not statistically significant).

Another factor I examined was the restaurant's average check. All but one of the 68 restaurants in my sample provided the average check of their restaurant, using the following categories: less than US\$15, between \$15 and \$25, and more than \$25. Similar numbers of restaurants fell into each category, as shown in Exhibit 5 (overleaf). On average, restaurants with the low average checks could improve revenues by 16.0 percent, those with medium average checks could achieve an improvement of 21.4 percent, and high-average-check restaurants could gain 9.0 percent in revenues with the best-possible table mix.

Implications for Managers

My analysis in this report shows that restaurants generally could improve their revenue if they implemented an ideal

EXHIBIT 5**Achievable restaurant improvement, by average check**

(Numbers in parentheses are the sample sizes.)

table mix. The convenience sample of 68 diverse restaurants, all of which used the Restaurant Table Mix Optimizer tool, were leaving a considerable amount of revenue “on the table.” On average, these restaurants could increase their peak revenue by almost 15 percent by implementing a more effective table mix. More than 19 percent of the restaurants in this sample could improve revenue by better than 20 percent just by having the right-size tables, and another 23 percent could increase their revenue by more than 10 percent. Barely one-fourth of the restaurants which I analyzed could be judged as having a table mix that is optimal or near-optimal.

As has been discussed elsewhere,⁴ increasing a restaurant’s capacity by changing table mix is relatively inexpensive

and simple. One does not have to change the restaurant’s footprint, for example. While more wait staff and additional back-of-house capacity may be necessary to handle the increased business, the gain in revenues will almost certainly exceed those increased expenses.

With the exception of age, I found no single factor that could distinguish a restaurant as doing well in terms of its table mix—and even veteran restaurants could still improve. That is, substantial improvements in peak-period revenue were possible regardless of which characteristic I considered, including restaurant size, number of peak hours, average check, service type, and chain affiliation. While long-standing restaurants tended to have more effective table mixes than new restaurants, as a group the older restaurants still could do much better.

⁴S.E. Kimes and G.M. Thompson, “Restaurant Revenue Management at Chevys: Determining the Best Table Mix,” *Decision Sciences*, Vol. 35, No. 3 (2004), pp. 371-392.

The puzzlement here is why restaurant managers are leaving this revenue untapped. I think the key reason has to do with the way restaurants measure their success. Typically, restaurant managers will consider check averages and note how full their tables are. I'm sure the restaurants in the sample are running at capacity (meaning all their tables are full) during peak times, with people waiting. As long as average checks stay high and tables are occupied, it's easy to assume that all is well. The problem is, those occupied tables probably have empty seats. What I have done here is to turn away from table utilization, and focus instead on seat (or space) utilization. Only by changing the metric will one begin to notice that the space could be used better, by matching the mix of table sizes to the mix of party sizes, which in turn drives higher revenue. I suspect that the restaurants with effective table mixes have managers who have figured this out.

While sub-optimal performance is never good, there is the following upside to the report's finding. The RTMO tool, which is designed to identify top-performing table mixes for each restaurant, is available for use at no charge from the CHR at www.chr.cornell.edu. As a manager, if you use it, perhaps you'll find that your restaurant is one of the few

that already have a revenue-maximizing table mix. If you're not in that category, you've taken a first and important step toward raising your restaurant's revenue.

A better mix. With publication of this *Center Report*, I am announcing an added aspect to the RTMO. To this point, RTMO users have entered data anonymously (and can still do so, if they so choose). However, the CHR now allows users to save their email address along with the rest of their data (or soon will have this feature). Those users will be given an analysis using the more sophisticated tool that I used for this report. Thus, when a user saves an email address with a scenario, I will include that scenario in a bimonthly analysis I perform using the enhanced table mix optimizer. I will then send the user the table mix recommended by the enhanced tool. In addition, these data will enable me to perform a follow-up study that examines the characteristics of the restaurants and managers who already have the ideal table mix in place. My expectation is that these restaurants have other best practices, in addition to their table mixes, and that, consequently, these restaurants can serve as true benchmarks for the industry. ■

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