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An Automated Valuation Model for Hotels

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A stepwise regression analysis to create an automated valuation model (AVM) for hotels found four significant factors that together provide a reasonable estimate of a property's value. The four factors are the twelve-month lagging averages of net operating income, average daily rate, occupancy, and number of rooms. Number of rooms appears to stand in for the extent of the hotel's facilities. The regression analysis tested the following factors but found that they were not significant: region, location in a metropolitan area, age of property (or date of construction), and date of sale. Even though the regression indicates that the operating ratios capture much of a hotel's value, the AVM is not intended to supplant more-sophisticated methods of hotel valuation (such as discounted cash flow). Moreover, the question remains of how to separate the two aspects of a hotel property's value, that of the real estate and that of the business operation.

Keywords: hotel; value; purchase; sale

This article summarizes recently completed research intended to assist hotel managers, owners, potential purchasers, potential lenders, and analysts with an interest in a hotel with the ability to quickly, cheaply, and objectively estimate the hotel's market value. Using data that are readily available to hotel stakeholders, a quick estimate of the market value of that real property can be made using an automated valuation model (AVM).[1] However, despite the fact that real estate appraisal has gradually evolved from a largely manual process to an automated one (particularly for residential real estate), a usable AVM for hotels has not yet been developed. The purpose of this article is to present a recently developed hotel AVM that has been refined to serve to accelerate the advancement of AVMs for hotels and, perhaps more important, to provide to those with an existing or potential interest in a hotel a model to apply to estimate value.

This research results in a hotel AVM using the statistical application of stepwise multiple linear regression analyses. The goals for this AVM are to be practical (i.e., to provide analysts with a usable formula), to supplement traditional appraisal and valuation training (although the use of AVMs in residential real estate has already gone beyond the supplemental stage), and to be relatively simple to apply (i.e., users of the AVM should be able to use basic math and not need to use the stepwise linear regression analysis). The methodology presented in this article essentially employs the sales comparison approach, a commonly used technique to estimate hotel market value. Another commonly used technique for estimating hotel value, the income capitalization approach, capitalizes a hotel's net operating income (NOI) to arrive at a value estimate. While the model presented in this article does not specifically use the income approach, it does make use of a hotel's NOI as a predictor of value (more on that later).

Under the traditional application of the sales comparison approach to estimate market value (i.e., likely sale price), a real estate appraiser analyzes the economics of recent sales of comparable properties and makes subjective adjustments to the information available from those sale transactions to arrive at an estimate of market value of the subject property or, in many cases, to arrive at a range (high and low) of likely value of the subject. The AVM presented here uses a similar but more mechanized, quicker, cheaper, and objective approach, and it makes use of actual hotel sale transactions that have occurred in the marketplace. That means it does not require analysts who themselves are using it to gather comparable hotel sale transaction data.

The methodology employed in this study is not intended to replace such vital knowledge and skills as real estate appraisal training and professional hotel management experience and education, but it is intended to assist analysts with understanding the dynamics of hotel properties. Analysts conducting hotel appraisal assignments need a better understanding of hotel properties, and much has already been written on the topic to build such understanding, including texts by Stephen Rushmore.[2] Nevertheless, as I said, a usable hotel AVM has not yet been developed despite the high level of interest in, attention to, and importance of hotel valuation. Although computerized valuation methodologies are increasingly available for commercial real estate properties,[3] the development of such methodologies for lodging properties has progressed much more slowly.[4]

A simple-to-use model based on operating ratios gives a reasonably solid estimate of a hotel's value.

For AVM formulation, this study uses a proprietary database compiled at the School of Hotel, Restaurant, and Recreation Management at The Pennsylvania State University to develop and present a model for use by those with an interest in a hotel, such as managers, owners, developers, potential purchasers, potential lenders, and analysts. In other words, users of the formulas presented here do not need access to the proprietary database, but they do need to have an interest in a hotel or at least to have access to fundamental operating figures of the hotel. The database used in this study consists of verified sales of hotels in the United States that include operating information for the twelve months preceding the sale. These properties represent all hotel types (economy, midscale, full service, all-suite without food and beverage, and all-suite with food and beverage) and all regions of the United States (New England, Mid-

Exhibit 1:
Descriptive Statistics of Database Use to Construct the Automated Valuation Model

Statistic	*Rooms*	*Occupancy*	*Average Daily Rate*	*Capitalization Rate*	*Net Operating Income*	*Room Revenue Multiplier*	*Price/ Room*	*Age (years)*
Median	173	70.0	$78.25	10.6	$980,400	3.08	$59,338	11.0
Mean	219	68.7	$83.15	10.7	$1,721,277	3.21	$74,020	16.1
Standard deviation	163	12.2	$37.28	2.2	$2,213,162	1.14	$58,330	15.2
Minimum	35	18.5	$31.50	1.1	$67,840	0.70	$6,931	1.0
Maximum	1,348	96.3	$250.50	20.4	$18,676,000	9.25	$479,167	98.0

dle Atlantic, Southeast, Upper Midwest, Lower Midwest, Southwest, and West).

The database that was used to construct the AVM comprises a sample of 327 hotel sale transactions for which I was able to obtain complete hotel operating and descriptive information—information that would normally be readily available to a party with an interest in a hotel. For each transaction, the database includes (for the trailing twelve months prior to the sale transaction) average daily rate, occupancy percentage, NOI, capitalization rate (cap rate), and room revenue multiplier (RRM), as well as number of guest rooms, sale price, age, sale date, and hotel type, that is, economy (75 properties), midscale (94 properties), full service (111 properties), all-suite without food and beverage (32 properties), and all-suite with food and beverage (15 properties). All sale transaction data were verified with a party involved in the transaction (typically, the seller or purchaser). The database includes information regarding hotel sale transactions from 1990 through 2002, so it subsumes a full economic cycle. Descriptive statistics are presented in Exhibit 1.

Models using regression analysis to predict hotel sale price have been previously developed based on a variety of the factors considered in this study.[5] The current database size of 327 properties provides excellent statistical power—AVMs that have been developed by other researchers for other types of real property (and have had statistical significance using regression analysis) have typically had sample sizes ranging from 143 to 219 properties.[6] Exhibit 2 presents a summary description of the variables used in this study. It is important to note that variables like cap rate, RRM, and price per room were not considered in the model presented here, because although these data were available for each of the 327 hotel sale transactions, they are in fact direct indicators of, and calculated as a function of, actual sale price, and the intent of this study was to develop a model that could be used to predict hotel market value (likely sale price) using other (not directly related) factors.

Using stepwise multiple linear regression analysis, I found there to be four steps resulting in significant regression coefficients.[7] The R^2 (regression coefficient) increased from .791 in the first step, to .892 in the second step, to .897 in the third step, and to .900 in the fourth step, indicating improved predictive ability in each step and showing that in the fourth step, the overall model with four variables

Exhibit 2:
Description of Variables Considered in Developing the Automated Valuation Model

Variable	*Description*
Occupancy	Occupancy percentage rate for trailing twelve months prior to sale
ADR	Average daily rate for trailing twelve months prior to sale
Rooms	Number of guest rooms
NOI/room	Net operating income divided by number of guest rooms
Regcode	Code indicating region of the United States in which hotel is located[a]
Metro	Code indicating whether hotel is located in a major metropolitan area[b]
Type	Code indicating type of hotel[c]
Open year	Calendar year hotel originally opened
Sale year	Calendar year hotel sale transaction occurred

a. Regcode consists of a series of six dummy variables: 1 = New England; 2 = Mid Atlantic; 3 = Southeast; 4 = Upper Midwest; 5 = Lower Midwest/Southwest; and 6 = West.
b. Metro codes are as follows: 1 = hotel is located in a metropolitan area with more than one million permanent residents; 0 = hotel is not located in a metropolitan area with more than one million permanent residents.
c. Type consists of a series of five dummy variables: 1 = economy; 2 = moderate service (midscale); 3 = full service; 4 = all-suite without food and beverage operations; and 5 = all-suite with food and beverage operations.

explains approximately 90 percent of the variance in the hotel sale price per room. This R^2 statistic exceeds the range of R^2 results of AVMs previously developed for other types of real property, where R^2 results have ranged between .772 and .888.[8]

Specifically, after a constant (*y*-intercept) of –$42,873, the NOI-per-room variable was automatically entered in the first step, and in subsequent steps, average daily rate (ADR), rooms, and occupancy percentage were automatically added. Thus, the model found NOI, on a per-guest-room basis, to be the best predictor of hotel sale price per room, as might be expected. After NOI per room was entered into the model, the hotel's ADR was found to be the next most significant predictor of sale price per room. Thus, the two most significant predictors of a hotel's sale price appear to be its "bottom line" (i.e., NOI) and its "top line" indicator of ADR. After NOI and ADR, the number of guest rooms was the next most significant predictor of sale price, probably because the number of guest rooms serves as a proxy for the extent and level of services and amenities offered by a hotel (e.g., the number of food and beverage outlets, business amenities, and recreational amenities) because all other things being equal, larger hotels usually (though, granted, not always) contain more amenities. Finally, another top-line indicator, the hotel's occupancy level, is a significant predictor of hotel sale price per room, most likely because along with ADR, occupancy is a determinant of hotel room revenues per available room (RevPAR). These results indicate that hotel purchasers may give "credit" to the upside potential of a property—that is, the anticipated ability to improve on a hotel's bottom line is reflected in sale price if occupancy rate or ADR is relatively strong, even when NOI is not. A summary of the results of the stepwise multiple lin-

Exhibit 3:
Summary of Overall Stepwise Multiple Linear Regression Analysis

Step	*Variable Added*	*Beta Coefficient*	*t*	*Significance*
1	NOI/room	5.615	16.492	$p < .001$
2	ADR	615.039	12.310	$p < .001$
3	Rooms	33.693	3.751	$p < .001$
4	Occ	234.891	2.343	$p < .05$

Note: See Exhibit 2 for descriptions of variables.

ear regression analysis is presented in Exhibit 3.

Thus, stepwise multiple linear regression analysis found that region code, metro, type, open year, and sale year were not overall significant predictors of sale price per guest room after the other four variables had been automatically included. While differences were found in the summary statistics for sale price by region (e.g., properties in New England tended to sell for higher prices per room than properties in the Southeast), apparently when hotel NOI, occupancy, ADR, and number of guest rooms are included in the model, region is not a significant predictor of sale price, because variations in economics by region are captured in the model by the variations in those monetary measures. Similar results were found regarding the variable for large metropolitan areas (more than one million permanent residents). While properties in larger metro areas may sell for higher prices, the model captures these differences through variations in its monetary measures. Similarly, while different types of hotels average different prices on a per-guest-room basis, the model captures these differences with the four variables included in the stepwise regression.

The open-year variable was not significant, even when this variable was converted to age by subtracting the opening year from the sale year. In other words, there appear to be many relatively old hotels that do not significantly lose value over time. Furthermore, the extent to which age affects a hotel's economics appears to be captured by the model's other four variables.

The sale-year variable also was not significant. The database that was used to construct the AVM includes data regarding hotel sale transactions dating as far back as 1990, and clearly, there was a trend of increasing hotel sale prices between 1990 and 2002, a period that includes both the trough of an economic recession and the peak of an economic expansion. However, those increasing sale prices correlated with the changes in occupancy, ADR, and NOI, statistics that capture the increase in sale prices stemming from improved operating performance. Therefore, sale year was ultimately excluded as a variable in the model. This result is interesting and practical for analysts because it indicates that the model of best fit (with the four variables included) may actually be applied to the coefficients presented here, relatively independent of time period.

How to Apply the Model

In short, a hotel's value per guest room may be estimated using the following AVM formula:

A Sample Calculation

An actual fifty-seven-room Hampton Inn in Ohio that operated with an annual NOI of approximately $450,000, ADR of $76.81, and annual occupancy rate of 72.8 percent would be valued as follows:

Coefficient				–$42,873
+ $450,000/57	x	5.615	=	+$44,329
+ $76.81	x	615.039	=	+$47,241
+ 57	x	33.693	=	+$1,921
+ 72.8%	x	234.891	=	+$17,100
			=	$67,718/room

Thus, in the previous example, the subject fifty-seven-room hotel would have an estimated value of approximately $3,860,000 ($67,718 x 57). In fact, the hotel actually sold in 2003 for $64,912 per room, or within 5 percent of the likely sale price predicted by the AVM presented here. Thus, there are reasons why the actual value of this Hampton Inn may not be exactly $67,718 per room. An analyst could construct confidence intervals, for example, the use of 95 percent confidence intervals would allow analysts to be essentially 95 percent sure that the hotel value is actually within a calculated range.

To determine confidence intervals for the results of a multiple regression analysis, analysts must calculate both the low and the high boundaries of the likely value range using unique coefficients developed through matrix algebra, which in this case would involve constructing a four-by-four matrix with sixteen terms, which is unwieldy.[a]

Most analysts would prefer using statistical software such as SPSS to determine confidence intervals. In the SPSS Data Editor (SPSS 11.0 for Windows), one would select *Analyze*, *Regression*, *Linear*, and then select *Case Labels Variable* (if a case labels variable is not selected, the confidence interval values will not be added to the spreadsheet). Next, one would click on *Statistics* and select which statistics one would want to have appear in the output (e.g., covariance matrix, descriptives, collinearity diagnostics) and then click on *Save*. Next, one would select *Predicted Values Unstandardized* and then *Predicted Intervals Mean* and *Individual*. The default confidence interval is 95 percent. The unstandardized predicted values represent the regression line. The mean interval represents the confidence bands around the regression line. The individual interval represents the confidence interval for any new predictions based on the regression solution. These selections will result in five new variables being added to the spreadsheet: pre_1 is the predicted value, lmci_1 is the lower bound of the 95 percent confidence interval for the mean (i.e., regression line), umci_1 is the upper bound, lici_1 is the lower bound of the 95 percent prediction confidence interval (i.e., for new values), and uici_1 is the upper bound.

—*J.W.O.*

a. See, for example: Neter, Kutner, Nachtsheim, and Wasserman, *Applied Linear Statistical Models*, 4th ed. (Chicago: Irwin, 1996).

–$42,873 (the constant from the regression)

+ NOI per room	x	5.615
+ ADR	x	615.039
+ rooms	x	33.693
+ occ[9]	x	234.891

= estimated value per room

In summary, in the overall model, the predictor variables (NOI per room, occupancy, ADR, and number of rooms) correlated with the response variable (sale price per room) with a regression coefficient, or R^2, of .900 (i.e., 90 percent). Considering all of the hotel sale transactions, the average actual sale price per room varied from the predicted sale price per room by a mean of 9.8 percent (the median was 7.5

Exhibit 4:
Analysis of Residuals

Statistic	*Amount*
N	327
Minimum	$5
Maximum	$58,815
Median (50th percentile)	$7,710
75th percentile	$11,978
90th percentile	$16,798
95th percentile	$28,526

percent). Previous research has found that actual real estate appraisals of commercial properties differ from sale prices by a variance of only about 5 percent.[10] Thus, while the model presented here results in a hotel value estimate that comes close to the level of accuracy achieved by actual hotel appraisals, it is not quite so accurate on average.

Since the model I propose here naturally results in some differences between actual and predicted sale prices, it is helpful to analysts to know what factors are most likely to cause the model to be most accurate. Therefore, I conducted an analysis of the residuals (the difference between predicted and actual hotel sale price for each sale transaction in the database used to construct the AVM). This analysis revealed that the number of hotel guest rooms, occupancy, ADR, and NOI appear to predict residuals. This analysis, which applied multiple regression analysis with the residual serving as the response variable, revealed that residuals are smallest (i.e., predictions are most accurate) for hotels with relatively more guest rooms, higher occupancy, higher ADR, and higher NOI. Exhibit 4 summarizes key statistics from the analysis of residuals. In short, 50 percent of the actual hotel sale prices used to construct the AVM were within $7,710 per room of the value estimated by the AVM (i.e., the median difference between the actual and predicted sale price was $7,710 per room), 75 percent were within $11,978, 90 percent were within $16,798, and 95 percent were within $28,526 per room.

The AVM formula presented here generally should be used in addition to the three traditional real estate valuation approaches of income capitalization, sales comparison, and cost. Despite the fact that more-sophisticated real estate valuation techniques exist than AVMs, executives, investors, and real estate appraisers frequently use simpler methods,[11] like AVMs. Licensed real estate appraisers who use AVMs should, however, be aware of Uniform Standards of Professional Appraisal Practice Advisory Opinion 18 that states,

> The output of an AVM is not, by itself, an appraisal. An AVM's output may become a basis for appraisal, appraisal review, or consulting opinions and conclusions if the appraiser believes the output to be credible and reliable for use in a specific assignment.[12]

In short, because AVMs do not in themselves constitute appraisals, they technically should be considered limited or supplemental analyses.

A Reliable Estimate

The AVM formula presented in this article should be useful to hotel analysts who desire a low-cost and objective estimate of hotel value. Also, this formula should be beneficial for hotel stakeholders who wish to acquire a quick value estimate prior to obtaining a complete appraisal, which would normally consume several weeks of time, cost several thousand dollars, and may not be entirely objective.

The research summarized in this article found that the AVM formula presented here has a high level of validity, though the average level of accuracy is not quite as good as an actual hotel appraisal. Analysts should use such models as a reality check for more-sophisticated valuation analyses and perhaps use them in meetings and in the field when computer technology is not readily available. In addition, through an analysis of residuals, this research found that the AVM presented here possesses the greatest degree of accuracy when used to estimate the value of hotels that have relatively more guest rooms, higher occupancy, higher ADR, and higher NOI.

One of the limitations of this research is that even though the analysis subsumes both the realty and the nonrealty aspects of hotels, it does not consider each of those two components separately, which is often necessary for actual hotel sale transactions. This limitation has long been a challenge with the valuation of operating businesses such as hotels. Previous research attempted to separate the real estate and operating components of a given hotel through evaluating the occupancy and ADR premiums that a single hotel achieves in comparison to its competitors and then concluded that such premiums are attributable to the value of the property name, reputation, and affiliation (i.e., nonrealty).[13] This conclusion is not supported in practice, however, because such occupancy and ADR premiums are in fact often attributable to a hotel's physical location in its market (in other words, realty). Future research should empirically consider the effects that such elements as hotel brand names have on overall hotel market value (i.e., sale price) on a national basis. Evaluating the nonrealty-value contribution of hotel brand names in such a manner may hold the greatest level of promise for providing empirical and valid support for separating the realty and nonrealty components of hotels.

In conclusion, the research presented here found statistical support for the use of a hotel's trailing twelve-month occupancy percentage, ADR, NOI, and number of guest rooms as predictors for estimating a hotel's current market value. Such AVMs will probably always be useful for quick analysis and for assessing the appropriateness of more-detailed analysis. Those who are in an industry or who are analyzing an industry should not ignore simple methodologies or rules of thumb that are becoming commonplace in the industry, like AVMs are in commercial real estate analysis.[14] However, in the analysis of commercial real estate, the identification of the macroeconomic and local economic factors that affect it should always be considered as well.[15] AVMs are probably most beneficial for analyzing portfolios of hotels rather than individual properties. Previous research has found that most idiosyncratic risk in individual properties is diversified away at the portfolio level.[16] In short, commercial real estate valuation remains "art" as well as "science." The accuracy of analysis will therefore always, to some extent, be based on the artistry of the analyst.

Endnotes

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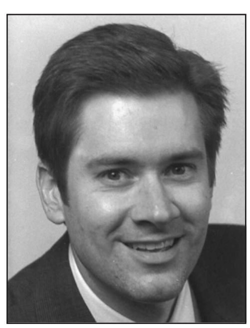

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