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Pricing in the Hospitality Industry: An Implicit Market Approach

Abstract

The authors apply economic theory to an analysis of industry pricing. Data from a cross-section of San Francisco hotels is used to estimate the implicit prices of common hotel amenities, and a procedure for using these prices to estimate consumer demands for the attributes is outlined. The authors then suggest implications for hotel decision makers. While the results presented here should not be generalized to other markets, the methodology is easily adapted to other geographic areas.

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Pricing in the Hospitality Industry: An Implicit Markets Approach

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The authors apply economic theory to an analysis of industry pricing. Data from a cross-section of San Francisco hotels is used to estimate the implicit prices of common hotel amenities, and a procedure for using these prices to estimate consumer demands for the attributes is outlined. The authors then suggest implications for hotel decision makers. While the results presented here should not be generalized to other markets, the methodology is easily adapted to other geographic areas.

Developers in the hotel industry, as in any real estate enterprise, are faced with numerous questions, one of which is what type of hotel would be most profitable in this particular market and where should it be built. Hotel development has long relied on the results of marketing studies as a guide to these questions. These studies often employ an ad hoc analysis of the local competition, including such instruments as surveys of travelers at area airports and assessments of trends in hotel occupancy rates to determine hotel site selections and amenity structures. In addition, decisions regarding repositionings, i.e., the upscaling or improving of a hotel, also employ methodologies which largely ignore the actual revealed preferences of the area's hotel consumers.

There are available methodologies, however, that provide a more structured and accurate approach to this issue. Profit-enhancing policy decisions in the hotel industry concerning site selection, amenity structures, and repositionings are all functions of correctly providing consumers with the amenities for which they are willing to pay. Having some knowledge of consumer willingness to pay (demand) for individual amenities is crucial to this decision-making process. Determining this willingness to pay requires that decision makers have an idea of the prices of these amenities. It is possible to estimate attribute prices from market data and use them to estimate attribute demands.

Hotel developers can incorporate the prices of attributes into

their capital budgeting decisions. Those amenities that provide marginal room revenues in excess of their marginal cost over the life of the project will be incorporated into the project's development while those that do not will be excluded.

For example, a hotel located closer to a city's financial district might be able to sell its rooms at higher rates. But this additional revenue must be weighed against the additional cost of building on that site versus the next best alternative. A similar analysis can be performed whenever a hotel is undergoing a repositioning by adding or removing attributes. When the marginal revenue from adding an attribute exceeds its marginal cost, the amenity should be added.

Basic Hedonic Price Theory Provides Model

Rosen's pathbreaking work on the theory of implicit markets provides a novel method for analyzing pricing in the hospitality industry.¹ This work has shed considerable light on the problem of analyzing markets in which heterogeneous commodities, such as hotel rooms, are exchanged.

The basic theory describes markets in competitive equilibrium. It defines the price of one unit of a heterogeneous commodity as a hedonic price function as follows:

Equation 1

$$P = P(z_1, \dots, z_n)$$

This equation includes n objectively measured homogeneous attributes, with each z measuring the amount of some attribute contained in each unit of the commodity. This hedonic price function results from the interactions of the preferences of buyers and the cost functions of sellers in implicit markets for the attributes. Generally, it will be nonlinear.² By itself, it is nothing more than a locus of equilibrium attribute prices, a market clearing function between individual buyers' willingness to pay for attributes and individual suppliers' offer functions for the same attributes. By itself, the function says nothing about the underlying demand and supply functions for each attribute that determine $P(z_1)$, although they can be estimated.

It is possible to estimate from Equation 1 the implicit prices of each of the attributes that comprises a commodity using regression analysis. Regressing commodity price on the quantities of the attributes contained in the hedonic price function provides estimates of the rate at which price changes when the amount of an attribute contained in a commodity changes holding the amounts of the other attributes fixed. The estimates are interpreted as the set of marginal, or implicit, prices of the attributes. Since the hedonic function is nonlinear, each implicit attribute price depends on the quantities of all attributes contained in the heterogeneous commodity bundle. The estimated implicit prices, while interesting and important by

themselves, can then be used to estimate individuals' willingness to pay (demand) functions or supplier offer functions for each of the attributes. Since the procedure for estimating demand and supply functions is the same, and since estimates of willingness to pay for attributes would seem to be of more interest in the hotel industry, the focus then turns to demand estimation.

This second step estimation is done by regressing the estimated implicit attribute prices on the quantities of the attributes contained in the hedonic price function that are purchased by individuals and on a set of other household characteristics such as income and number of children. The results of the second step thus estimate the inverse relationship between attribute price and the quantity demanded of that attribute in a given time period while holding the other variables constant.

Since the set of implicit attribute prices estimated in the first step is market clearing prices, each of these prices equates quantity demanded with quantity supplied for a particular attribute. This poses a problem for the estimation of the demand functions. Since both demand and supply posit functional relationships between price and quantity, and since these equilibrium prices and quantities are points on both the demand and supply curves, one does not know if the regression is estimating the parameters of demand or supply. Estimates of the parameters of these functions would likely be misleading (the estimates would be statistically inconsistent).

Identifying the demand functions so that consistent estimates can be obtained requires data on variables that influence the implicit attribute prices, yet do not enter these demand functions. Rosen proposed using information on firm cost functions to identify demand.³ More recent work by Diamond and Smith, however, shows that the Rosen solution is inappropriate.⁴ They argue that identifying demand requires data from more than one market.⁵

Application to the Hotel Industry Involves Preferences

The application of implicit markets theory to the hospitality industry deals with these estimation issues by identifying two types of hotel guests with two distinct sets of preferences. In effect, this defines two markets for hotel rooms in a given geographic area at the same point in time. The first type of guest, the business traveler, maximizes the following utility function:

Equation 2

$$U_b = U_b(Z_b, C)$$

while the second type, the tourist traveler, maximizes:

Equation 3

$$U_t = U_t(Z_t, C)$$

U_b and U_t are utility functions for business travelers and tourist travelers respectively; Z_b is a set of hotel attributes that provides utility only to business travelers; Z_t is a set of attributes that provides utility only to tourist travelers, and C is a set of common attributes that provides utility to both types of travelers. Examples of elements of Z_b are the availability of office facilities like secretarial pools and personal computers, exercise facilities, and free local calls, while examples of elements of Z_t might be distance to popular tourist spots and complimentary breakfasts. C might include things like a concierge service and the availability of transportation to and from airports. Maximizing both equations subject to the usual budget constraints yields the attribute demand functions discussed above.

For each hotel there exists a hedonic price function analogous to Equation 1 which can be expressed as the following regression:

Equation 4

$$P = P(C, Z_b, Z_t, v),$$

where v is a random disturbance term. Since no hotel caters exclusively to either type of guest, Equation 4 indicates that price is a function of all three types of attributes.

Estimation of Equation 4 yields the set of implicit attribute prices. The results provide hotel decision makers with information previously unknown to them, namely estimates of the prices of each individual attribute contained in their hotel. This information can be very useful when deciding how to adjust room rates when attributes are either added to or eliminated from a hotel. It can largely eliminate the short run cost involved with a trial and error process of rate adjustment.

These implicit prices can then be used in a second step estimation of willingness to pay. Data from the tourist market on attributes that influence the marginal prices of attributes demanded by business travelers yet do not enter business traveler demand functions can be used to identify these demand functions. Tourist traveler demand functions can be estimated similarly.

Hedonic Estimation Uses Data from San Francisco Market

The hedonic estimation uses monthly data on attributes of 20 hotels in San Francisco, California, for the years 1982 through 1986. The data come from three sources: survey files provided by the School of Hotel Administration at Cornell University, telephone surveys conducted with the managers of the hotels included in the sample, and the annual *TourBook: California-Nevada*, published by the American Automobile Association (AAA).

According to the Convention and Visitors Bureau, there is no well-defined tourist season in San Francisco. Tourists who stay in the city's hotels generally come all year long. Also, for the hotels in this study, room rates do not change during the year. Because of this, the monthly data will be used to estimate Equation 4. For purposes

of comparison, however, the hedonic equation is also estimated using yearly averages of the monthly data.

Besides a measure of room rates and data on the physical attributes of the hotel, the estimation of Equation 4 also includes information on the distance of the hotel from various popular tourist spots in the city.⁶ Table 1 lists, defines, and provides summary statistics for the variables used to measure the characteristics.

Table 1
Variables in the Hedonic Price Equation

Variable and Definition	Mean	Std. dev.	Min.	Max.
Rate: Monthly room revenue/ number of rooms sold per month.	62.54	12.49	39.42	93.94
Food sales: Monthly food sales in dollars/number of rooms sold per month.	18.09	10.15	0	75.55
Gift sales: Monthly revenue from gift shop and boutique sales/ number of rooms sold per month.	4.29	7.02	0	101.17
Conc: Dichotomous variable equal to 1 if the hotel provides a concierge service.	0.38	0.49	0	1
Gym: Dichotomous variable equal to 1 if the hotel provides an area with exercise equipment.	0.46	0.50	0	1
Vdc: Dichotomous variable equal to 1 if the hotel provides a valet dry cleaning service.	0.91	0.28	0	1
Local: Dichotomous variable equal to 1 if the hotel allows free local calling.	0.19	0.39	0	1
Freeb: Dichotomous variable equal to 1 if the hotel provides a complimentary breakfast.	0.19	0.39	0	1
Rating: Measures the AAA hotel rating system. Values range from 1 = one diamond rating through 5 = five diamond rating.	3.10	0.30	2	5
Wharf: Straight line distance in miles from the hotel to the geographic center of the area defined as Fisherman's Wharf.	11.01	6.51	0	20.07

The dependent variable, Rate, is a measure of the average room rates actually paid by hotel guests and is computed by dividing total monthly room revenue by the number of rooms sold per month.⁷ These attributes included in the hedonic regression can be grouped into the categories mentioned above. For example, it seems reasonable that Gym, Vdc, and possibly Local are demanded solely by business travelers, while Gift sales, Freeb, and Wharf are valuable only to tourists. Food sales, Conc, and Rating arguably belong in the set of common attributes.⁸

Hedonic estimation requires a specific functional form for Equation 4. While Rosen shows that in general the hedonic price function is nonlinear, the theory does not suggest any specific nonlinear form.⁹ Quadratic specifications are sufficiently general to allow estimated hedonic functions to be linear, concave, or convex. A quadratic function that specifies room rate as a function of attributes and attributes squared has been adopted (squared terms are not included for the dichotomous variables or Rating as they would result in perfect collinearity between regressors). A linear specification is also used so that one can gauge the robustness of the estimates. Column 1 of Table 2 presents implicit price estimates for Equation 4 using the monthly data to estimate the nonlinear hedonic. Estimates for a linear specification of Equation 4 using the monthly data are given in column 3. The t-statistics in columns 2 and 4 measure if the estimates are statistically significantly different from zero.

A few technical aspects of the estimation process should be mentioned at this point. Estimating a pooled cross-section time series data set using ordinary least squares imposes a restriction on the implicit price estimates. Specifically, the estimation procedure does not allow the price estimates to change over the five-year time span studied. Although it seems reasonable that prices would not change much during this relatively short time period, one should not base decisions on this assumption without first doing more sophisticated regression analysis.¹⁰ The time series component of the data also causes an autocorrelation problem. The results reported in Table 2 are corrected for autocorrelation by using a routine that estimates a coefficient of autocorrelation and then uses the estimate to delete the autocorrelated component of the data.

As Table 2 shows, the difference in the explanatory power between the linear and quadratic specifications is small as measured by adjusted R^2 . A formal test of increased explanatory power is the standard test for linear restrictions, where the linear equation is the restricted regression and the restrictions are that the coefficients of the squared terms are all equal to zero. The calculated F-statistic, equal to .245, does not reject the hypothesis that the coefficients of the squared terms are all zero.¹¹ It therefore appears that the linear hedonic is a good approximation of the quadratic.

Table 2
Hedonic Regression Results

Variable	1 quadratic equation	2 (t)	3 linear equation	4 (t)
Intercept	12.280	1.19	18.342	3.56
Foodsales	0.102 ¹	1.27 ²	0.006	0.17
Giftsales	0.173 ¹	1.76	0.032	1.16
Conc	9.693	2.70	11.721	9.63
Gym	-2.378	-2.39	-2.592	-2.50
Vdc	6.402	2.20	4.839	2.48
Local	-7.383	-5.15	-8.347	-6.23
Freeb	-2.056	-1.37	-2.727	-2.22
Rating	16.033	3.98	14.203	7.93
Wharf	-.075 ¹	-1.16 ²	0.518	-5.60
Food sales ²	-0.002 ¹	-1.50 ²		
Gift sales ²	-0.001 ¹	-1.46 ²		
Wharf ²	0.024 ¹	0.55 ²		
adj. R ²	.59		.62	
sample size	567		567	

1- parameter estimates that measure the effect of both the linear and squared terms are computed by differentiating the quadratic hedonic with respect to each of the three attributes containing squared terms. The partial derivative is

$$b_1 + 2g_1 z,$$

where z represents the mean values of Food sales, Gift sales, and Wharf, and b_1 and g_1 are parameter estimates given in column 1 above. The parameter estimates are:

Food sales:	.030
Gift sales:	.164
Wharf:	-.547

2- t-statistics that test the significance of the impact of both the linear and squared terms are computed as

$$t = \frac{b_1 + 2g_1 z}{\sqrt{\text{var}(b_1) + (2z)^2\text{var}(g_1) + 4zcov(b_1, g_1)}}$$

The computed t-statistics are:

Food sales:	0.85
Gift sales:	1.78
Wharf:	-5.19

Amenities Affect Rates

The implicit price estimates are interesting and worthy of mention. A concierge service adds between \$11.72 (linear) and \$9.69 (quadratic) to room rates, while a valet dry cleaning service adds between \$4.84 and \$6.40. Both of these attributes are statistically significant in both equations. The AAA rating scheme adds between \$14.20 and \$16.03 to room rates “per diamond.” These estimates are also statistically significant. The distance of the hotel from Fisherman’s Wharf also significantly affects room rates. The linear specification shows that rates drop by about 52 cents for each mile further from the wharf that the hotel is located. With the quadratic equation, for a hotel located at the mean distance from the wharf, rates fall by about 55 cents per mile further away (see Table 2 for a description of how this price is computed). This implicit price of access to the wharf suggests that commuting costs play a role in deciding where to stay and is consistent with the spatial aspect of the utility maximization problem first introduced into modern urban economics by Alonso,¹² Mills,^{13, 14} and Muth.¹⁵

Food sales proves to be statistically insignificant in both equations and Gift sales does no better with the linear equation. However, Gift sales is significant at the 10 percent level in the quadratic equation. The estimate suggests that, for a hotel with gift sales equal to the sample mean, an increase in rates of about \$16.40 occurs for an extra \$100 spent per occupied room. The lack of explanatory power in these estimates can be due to a number of things, not the least of which is the fact that these variables are probably crude measures of hotel quality. Larger per room sales can reflect many things. Data are not available on the number of restaurants and shops in each hotel, so it cannot be determined if larger sales are due simply to the fact that some hotels have more of these establishments. Reestimating these prices with more detailed data should improve the explanatory power of these attributes.

Local and Freeb provide curious results. The availability of free local calling is responsible for lowering rates approximately \$8, while a complimentary breakfast lowers rates by more than \$2. Except for Freeb in the quadratic, all of these estimates are significant. Since these commodities are relatively inexpensive, they may be attractive only to those guests who must economize by staying at cheaper hotels. Finally, exercise facilities also lower rates in excess of \$2. This finding is unintuitive and is lacking an adequate explanation.¹⁶

One possible statistical explanation for these last three estimates is that there is a high degree of correlation between these three variables and the other regressors in the equation. This correlation would make the parameter estimates very sensitive to model specification and thus present the possibility of the estimates changing sign and giving an unintuitive result. Pairwise correlation coefficients show that Gym is indeed significantly correlated with Rating and Wharf.

While this correlation may help explain the strange results, it is not the main cause for two reasons. First, the ordinary least squares procedure implies large standard errors for highly correlated variables, which would result in small t-statistics. This is not the case here. The parameter estimates for Gym, Rating, and Wharf are all statistically significant. Secondly, the high correlation should cause the magnitude of the parameter estimates to change noticeably if even one of the correlated variables is dropped from the equation. Again, this is not the case. When Gym is dropped the estimates on Rating and Wharf (and all of the other variables) remain virtually unchanged. In the quadratic, the estimate for Rating suggests that an additional "diamond" now adds \$14.02 to the room rate, while the estimate for Wharf shows rates falling by 53 cents for each mile further from Fisherman's Wharf that the hotel is located.

Another more likely statistical explanation for the negative parameter estimate associated with Gym is that attributes omitted from the regressions that impact room rates are correlated with Gym. This could bias the reported estimate enough to give such anomalous results. That other pertinent attributes are omitted from these regressions is also suggested by the fact that both the linear and quadratic regressions explain only about 60 percent of the variation in room rates. More thought should be given to what other attributes are relevant. This will likely explain the anomaly.

Implicit prices of hotel attributes for one area have been estimated and a procedure for using these price estimates to estimate attribute demands has been outlined. The actual price estimates should not be generalized to other markets in different areas since quite a bit of diversity may exist across markets. The procedure, however, could be easily applied to other areas.

The estimation of Equation 4 seems to provide reasonable estimates of the implicit prices of some attributes offered by hotels. This appears to be the first attempt to do so. This information would seem to be useful to an industry whose pricing schemes have largely ignored the implicit markets inherent in the heterogeneous commodities they sell.

The logical next step in this work is to use the implicit price estimates to estimate the attribute demand functions. It would seem a worthy endeavor for decision makers in the industry to collect data on individual hotel guests so that this more complete hedonic price study can be done.

The findings reported here must be considered suggestive. No hedonic model can claim that all relevant attributes have been included or that the chosen functional form for the regression equation is the most appropriate one. However, this is an interesting first step and more work should ensue. Only further efforts will shed more light on the plausibility of the findings.

References

¹ Sherwin Rosen, "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, (January/February 1974), pp. 34-55.

² This nonlinearity results since bundles of attributes are not costlessly separated and repackaged. Thus arbitrage between bundles cannot operate to guarantee that the marginal price of an attribute will be independent of the amount of that attribute and others contained in the bundle.

³ Rosen, *op. cit.*, pp. 50-51.

⁴ Douglas B. Diamond and Barton A. Smith, "Simultaneity in the Market for Housing Characteristics," *Journal of Urban Economics*, (May 1985), pp. 280-292.

⁵ Different markets are defined as separate geographical areas, the same geographical area at different points in time, or the same geographical area at the same point in time provided that different consumer groups with distinctly different preferences can be identified.

⁶ The San Francisco Convention and Visitor's Bureau provided data showing that the three most popular tourist spots visited by hotel guests are, in descending order of popularity, Fisherman's Wharf, the downtown area, and the Golden Gate Bridge. Distances to these spots are calculated as simply the straight line distance in miles from the hotel to the center of the geographic area that defines the attraction.

⁷ This measure of room rates is an approximation for two reasons. First, rates vary according to the number of persons checked into the room and, secondly, rates vary based on the type of room that is rented. The AAA TourBook, however, shows that for the hotels in our sample, 90 to 98 percent of all units are of the same type. Hopefully, this largely mitigates the second source of the approximation error. Even though an approximation error exists, this approximation of per room revenue is better than using the rates quoted by the hotels (rack rates), since rack rates are rarely ever paid.

⁸ Other attributes that seem intuitively to belong in any hedonic price function for hotel rooms were not statistically significant at at least the 15 percent level. Some of these attributes are an express checkout system, the availability of secretarial services including personal computers and FAX machines, distance to the downtown area, the Golden Gate Bridge, and Chinatown, and whether or not the hotel provides airport shuttle service. This is likely a sample problem since there is a very high degree of multicollinearity between these variables.

⁹ Rosen, *op. cit.*, pp. 37-38.

¹⁰ An attempt was made to see how restrictive this assumption is by estimating a more sophisticated (covariance) model that allows prices to change over time. However, perfect multicollinearity rendered the test impossible. It must be emphasized, however, that while multicollinearity is a problem inherent in the data set used here, there is no reason to expect this problem to manifest itself in other data. Other more esoteric estimation techniques that would allow prices to change over time are currently not available on the commonly used statistical packages.

¹¹The test is done by calculating the following F-distributed variable:

$$F_{r, s-w} = \frac{(e_0'e_0 - e_1'e_1)/r}{e_1'e_1/(s-w)}$$

where $e_0'e_0$ and $e_1'e_1$ are, respectively, the sum of squared residuals for restricted and unrestricted regressions, r is the number of restrictions, s is the number of observations, and w is the number of parameters estimated in the unrestricted regression.

¹²William Alonso, *Location and Land Use*, (Cambridge: Harvard University Press, 1964).

¹³Edwin S. Mills, "An Aggregative Model of Resource Allocation In A Metropolitan Area," *American Economic Review Papers and Proceedings*, (May 1967), pp. 197-210.

¹⁴Edwin S. Mills, *Studies in the Structure of the Urban Economy*, (Baltimore: Johns Hopkins University Press, 1972).

¹⁵Richard F. Muth, *Cities and Housing*, (Chicago: University of Chicago Press, 1969).

¹⁶The same regressions run on yearly averages of the monthly data yield essentially the same results. Interestingly enough, the statistical significance of the parameter estimates for Gym and Local disappears.