# A Discrete-Choice Analysis for Valuing Opaque Products

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**Abstract**

This paper evaluates a consumer's purchase decision involving a hotel room wherein specific details, such as the exact location or available amenities are hidden prior to completing the transaction. These rooms, referred to as "opaque" properties, are typical of purchases made through online service providers such as Hotwire. The purpose of this research was to determine, via a discrete-choice experiment, the value drivers and subsequent purchase decisions associated with these opaque products, and whether consumers use available information from traditional or "non-opaque" products in their purchase decisions. Specifically we test how knowledge of price and available amenities of the non-opaque products impact the value of a comparable opaque product. We also investigate how lack of knowledge of the location of the opaque property affects value. The results indicate that consumer base their decisions on the price of the opaque product as well as the difference in price for a comparable non-opaque product. This information can then be used by managers is setting appropriate rates on opaque channels in order to maximize revenues. We also established that knowledge of available amenities can drive the value of opaque products. Thus managers should customize the information on available amenities when using opaque channels to sell excess capacity, increasing the probability of a sale while still protecting brand identity.

Keywords: discrete-choice analysis; multinomial logit; opaque product; pricing; hospitality services

**Introduction**

The increased market transparency in the service sector resulting from the availability of various online purchase channels creates both opportunities and risks to service providers (Granados et al., 2005) as they face more knowledgeable and sophisticated consumers. This is consistent with findings reported in the literature, in which the majority of service managers agree the internet has increased price transparency for consumers and has blurred traditional segmentation lines (Garrow et al., 2006). Consumers have available a vast array of data, including both price and inventory availability from multiple providers, along with a host of product attributes (amenities and other services) available when making their purchase decisions. From the perspective of the service provider, it is important to understand customers' willingness to pay in order to determine the benefit of specific services and amenities, as well as setting the right pricing and inventory controls to maximize revenues. This in turn has led to an increased emphasis within the pricing and revenue management literature to focus on various behavioral aspects of the consumer in determining their response to price as well as other service attributes with respect to their final purchase decision.

A related area that has also received increased attention is the use of opaque channels, for example Hotwire and Priceline, in which consumers can often purchase products/services at discounted prices, but the actual product or service is obscured (i.e. limited details provided) until after the final purchase is made. All major service providers (hotels, airlines, car rental agencies) make use of these opaque channels to sell remaining inventories that may otherwise go unsold and increase overall revenues while avoiding 'dilution' across their traditional channels in order to protect brand value. However, there is limited research tying these two streams together, where consumers use both traditional (non-opaque) and opaque channels in determining their final purchase decision. In addition to pricing details available through related searches of traditional sites, opaque sites such as Priceline and Hotwire also provide pricing information on median/average prices of products of similar level and location as a guide in purchasing a particular opaque product.

There are a number of considerations from the perspective of the service provider. The first and most basic is an understanding the consumer's valuation of opaque products so that providers can set rates on the opaque channel appropriately and increase incremental revenues. Only by gaining an understanding of the consumer's decision-making process will service providers be able to determine the impacts on their revenue management systems and overall profitability and to realize the full potential of opaque channel sales. The primary focus of this research to evaluate the choice-process of consumers when deciding on a traditional (non-opaque) service and a similar but opaque service through the administration of a discrete-choice survey. By understanding this process, we acquire valuable information service providers need, but currently lack, in setting rates on opaque channels to improve incremental revenue. By understanding how consumer's value and evaluate options available through non-opaque channels, service providers can determine appropriate rates to maximize overall revenues from both channels. The choice experiment consisted of consumers selecting among a choice-set of traditional (non-opaque) hotel rooms with different attributes. Then, to determine the value of the opaque product, respondents are given the option of purchasing a similar but opaque property. Via this choice process, we can determine how consumers value opaque products in relation to a similar non-opaque property, and through a discrete choice model, estimate the probabilities of sales given posted prices and opaque channel rates.

## Background

There are two primary areas that are related to this work; specifically the development of discrete-choice methods and their application to the service sector as well as the research on opaque channels. We first review the recent contributions to the opaque products literature, in particular those related to the service industries. We then follow with a review of discrete-choice analysis along with recent applications to the service sector.

### *Opaque Channels*

With the growth of opaque channels, there has been a corresponding increase in the related published research, though the existing literature is still somewhat limited with most focusing on structural issues. For example, in Fay (2004), the author develops a model for a monopolist on a Name-your-own-price

(NYOP) channel similar to Priceline and investigates the issue of repeat bidding. The results show that partial repeat bidding by knowledgeable consumers may reduce profitability as compared to allowing for complete repeat bidding and therefore provides guidance to NYOP channels on how to structure the bid-process. In Fay (2008), the author develops a model for, and evaluates the impact of, multiple service providers selling a product in an opaque market. Results indicate that although the opaque channel can lead to increased segmentation and sales, for industries with low brand-loyalty these channels can reduce overall profit. Jiang (2007) develops a Hotelling-type (Hotelling, 1929) model to determine under what conditions a firm should utilize opaque channels. They provide guidelines for service providers to effectively segment the market as well as how these firms should price on traditional versus opaque channels. Similarly, Wang et al. (2009) develop an analytic model of a service provider using both traditional as well as an opaque NYOP channel. They evaluate trade-offs in the use of opaque channels and provide insights into key drivers for contracting with NYOP retailer.

In a number of recent articles, the models presented have become more prescriptive, providing specific direction on optimal pricing as well as inventory decisions to service providers using opaque channels. In Anderson (2009), using data from Priceline for a boutique hotelier, the author develops a model for the pricing and inventory allocation problem. A spreadsheet algorithm is presented to implement the model to determine optimal pricing and inventory in order to maximize revenues over the opaque channel. In Wilson et al (2011), the authors also evaluate a set of Priceline data and compare revenues from the joint price-inventory problems applying different mathematical models. Results indicate that more recent general class of price-dependent demand models typically performs the best. In Anderson and Xie (2012) a nested logit model is used to illustrate how a service provider can dynamically set optimal prices on an opaque sales channel. Using data from a specific provider on Hotwire.com, they show how the approach would be applied.  In an extension (Anderson and Xie, 2014), the authors develop a stylized consumer choice model of market segmentation and develop optimal pricing strategies for sellers using both regular and opaque sales channels.

***Discrete Choice Analysis***

Discrete Choice Analysis (DCA) provides a systematic way to model the relative weights of various attributes in the decision making process, and has found application across a number of fields in the social sciences since its introduction by McFadden (1974). An introduction to the theory and methods of DCA can be found in multiple sources, including texts by Ben-Akiva and Lerman (1985), Louviere et al (2000) and Hensher et al. (2005) as well as the recent overview by Verma et al. (2008). In the following, we thus provide a brief overview of the DCA method and present some recent applications in the services and hospitality sector.

In large part, the appeal of discrete-choice methods is the models are consistent with random utility theory (RUT) (see Ben Akiva and Lerman, 1985), which provide a theoretical basis for DCA. In economics, choice theory assumes that individuals' choice behavior is determined through the maximization of preferences or utility. Often, utility is expressed as a simple linear-in-attributes model, with the utility for alternative 'j' specified as

$$U_j = V_j + \varepsilon_j = \sum \beta_j X_j + \varepsilon_j \tag{1}$$

where $V_j$ is a deterministic component assumed to be linear in the explanatory variables ($X_j$) and the weights of the individual attributes given by $\beta_j$. The unobserved random utility component is given by $\varepsilon_{ij}$.

Different assumptions on the distribution of the error component give rise to different classes of models. One of the most common of these models is the multinomial logit (MNL) model, in which the random term is taken as an i.i.d. Type I extreme value or Gumbel distribution. From this assumption, the conditional probability in MNL models of choosing an alternative 'j' from a given set of 'n' alternatives can be expressed as:

$$P_j = \frac{e^{\mu V_j}}{\sum_{i=1}^{n} e^{\mu V_i}} \tag{2}$$

where μ represents the constant scale for the underlying Gumbel distribution.

To meet the data requirements for estimation of the required model parameters ($\beta_j$) in equations (1) and (2) above, two common approaches have been used in practice. They are either transactional data based upon actual purchases, often referred to as revealed preference data, or data collected through choice experiments or stated preference data. Though there are advantages to both that often guide the decision to select one approach over the other, a commonly discussed advantage of the stated-preference approach is that it allows for wider variation in available attributes (MacDonald et al., 2010). In addition, it allows for specifically testing attributes or combinations of attributes, including pricing, that may not exist in the market. This allows estimation of attributes and provides the required understanding of the consumer's choice behavior that may not be otherwise possible (see Train, 2005). For this research a stated-preference approach, through the application of a discrete-choice experiment, was employed. A detailed description of the choice experiment is given in the subsequent methodology section.

In recent years, a number of applications from related fields have used DCA, though only more recently have we seen it applied to the hospitality service sector. A recent article by Verma (2010) provides an overview of the applicable literature. Below we highlight a few of the recent relevant research papers, in addition to Anderson and Xie (2012) previously described above.

The first application is from the airline industry. In Garrow et al (2007), the authors design a stated-preference survey to examine airline customers' willingness to pay for products offered through an online channel for business and leisure travelers. In addition to price, the survey evaluated departure and total travel time as well as qualitative issues such as legroom. They then estimate price sensitivity to the varying combinations via MNL and nested logit (NL) models and how the different attributes affect final preferences. From the hotel sector, Bodea et al (2009) collected data from existing revenue management systems at 5 select hotel properties and evaluate the application of choice-based revenue management algorithms. The paper focused on the complexities of extracting required information and other practical issues in implementing a choice-based system. In MacDonald et al (2010), the authors present an overview of discrete-choice modeling using revealed and stated preference data for hotel properties. They discuss the strengths and weaknesses of each method and how both can be combined to provide a more complete modeling approach. Vulcano et al (2010) use a maximum likelihood estimation algorithm with an expectation-maximization method to account for censured demand to estimate parameters based upon revealed-preference data on airline routes. The resulting discrete choice model was tested in a simulation to assess the revenue impact of the approach and was shown to increase revenues by 1-5%.

Above, a number of models are proposed to provide guidance for pricing of products on opaque channels. However, none explicitly evaluate how consumers use available information on traditional channels to value the opaque product. Also lacking is how amenities and other non-price attributes are considered in the purchase decision. The goal of this research endeavor is to use discrete-choice analysis to evaluate this aspect of the consumer's decision making process.

**Methodology**

To evaluate the everyday trade-offs consumers make in determining their final hotel purchase decision, a discrete-choice analysis (DCA) approach was selected. This methodology has been used extensively in marketing, transportation, hospitality, etc. to model the choice processes of consumers. In DCA, a carefully designed discrete-choice experiment is conducted to determine the valuation for specific attributes of interest for a product or service. Individual respondents are presented with scenarios designed to mimic realistic choice decisions. Various attributes deemed important in both the analysis and decision-making process are presented, with the levels of the attributes varied based upon the experimental design. Depending upon the design of the DCA experiment, respondents are then asked to select one of the alternatives or none at all. Based upon the responses and attribute levels, a multinomial logit (MNL) model can be estimated and used to predict aggregate behavior based upon the levels of the attributes.

For the survey, the population of interest consisted of business and leisure travelers representative of the general population, based upon various demographic criteria as compared to U.S. census data. To obtain a representative sample, the choice experiment was administered via a web-based interface through a marketing firm specializing in survey and data collection. An initial screening of respondents confirmed that they had purchased hotel accommodations at least once in the past twelve months, as well as setting limits on various demographic measures (age groups, income distribution, etc.). The firm identified an initial contact list of 2,000 potential respondents distributed across the U.S from its database. Each of the potential respondents received an email invitation to participate in the survey, and in return for their participation were offered rewards points that could be redeemed for products and services from the firm's catalog.

The e-mail list contained a sample of respondents balanced according to US census data validated by various demographics criteria. Approximately 40% of the respondents answered negatively to the screening question (have you taken a business or leisure trip during the last 1 year which required a hotel stay?) and were not allowed to continue with the survey. A total of 444 respondents completed the online survey within the 1-week collection period. Of these, 12 surveys were incomplete and were thus discarded, leaving a total sample size of 432 respondents, almost equally split along gender lines (217 female and 215 male respondents), with 20% being identified as predominately business travellers and the remaining as leisure travellers. The distribution of the respondents for income, education, and age are presented in Appendix A. As there was no indication of any response bias, all subsequent analysis is based on the survey data collected all 432 respondents.

For our experiment, both the relevant attributes as well as the appropriate levels for each were required for traditional as well as opaque product types. This process naturally requires a compromise between inclusion of every possible attribute specified at multiple levels and the required number of combinations required and resultant number of respondents, as well as the time and expense, to carry out the experiment. The final experimental design was based upon orthogonal block design, with 27 possible scenarios (9 per respondent). The final survey consisted of 3 hotel-types (star ratings), 3 amenities packages, and 3 price points for the traditional product and 3 hotel-types (star ratings), 3 distance variables, and 3 price points for the opaque product.

To determine the appropriate levels for each of the traditional products, we conducted a review of available online properties at each of the star-level in several major cities to provide a description of "typical properties", including available amenities and price points. The three pricing levels for each of the hotel property types were then set at the 25$^{th}$ 50$^{th}$ and 75$^{th}$ percentile based upon the results of the review. This resulted in the following three pricing levels for each property: 2-star: \$65, \$80, \$95; 3-star:

$105, $120, $140; and 4-star: $150, $165, $190. Similarly, we created a “base” amenities package for each star-level by including amenities that were found to be available in at least two-thirds of the properties reviewed. The remaining amenities packages were then created by adding a single amenity to this base package by selecting the next two most commonly available amenities. A list of amenities for each property are given in Table 1

For the opaque properties, the prices were taken at 40, 60 and 80%, or equivalently discounts of 60, 40 and 20%, of the comparable (same star level) traditional product being displayed. For setting the distance from the desired location, a similar approach to setting the levels in the traditional products was used. We surveyed the maps of several cities of online opaque properties to determine typical distances of area maps presented to their customers. Based upon our review, maximum distances of 1, 3 and 6 miles from the desired location were selected.

Table 1: Amenities groupings for each property type:

| | 2-star | 3-star | 4-star |
|---|---|---|---|
| Group 1<br>(base pkg) | Parking<br>High-Speed Internet<br>Fitness Facility<br>Courtesy Breakfast<br>Coffee Maker | Parking<br>High-Speed Internet<br>Pets Allowed<br>Swimming Pool<br>Business Center<br>Dry Cleaning/Laundry<br>Fitness Facility<br>Courtesy Breakfast<br>Coffee Maker | Parking<br>High-Speed Internet<br>Pets Allowed<br>Business Center<br>Dry Cleaning/Laundry<br>Fitness Facility<br>Restaurant On Site<br>Coffee Maker |
| Group 2 | Parking<br>High-Speed Internet<br>Fitness Facility<br>Courtesy Breakfast<br>Coffee Maker<br>Swimming Pool | Parking<br>High-Speed Internet<br>Pets Allowed<br>Swimming Pool<br>Business Center<br>Dry Cleaning/Laundry<br>Fitness Facility<br>Courtesy Breakfast<br>Coffee Maker<br>Restaurant | Parking<br>High-Speed Internet<br>Pets Allowed<br>Business Center<br>Dry Cleaning/Laundry<br>Fitness Facility<br>Restaurant On Site<br>Coffee Maker<br>Swimming Pool |
| Group 3 | Parking<br>High-Speed Internet<br>Fitness Facility<br>Courtesy Breakfast<br>Coffee Maker<br>Laundry/Dry Cleaning | Parking<br>High-Speed Internet<br>Pets Allowed<br>Swimming Pool<br>Business Center<br>Dry Cleaning/Laundry<br>Fitness Facility<br>Courtesy Breakfast<br>Coffee Maker | Parking<br>High-Speed Internet<br>Pets Allowed<br>Business Center<br>Dry Cleaning/Laundry<br>Fitness Facility<br>Restaurant On Site<br>Coffee Maker<br>Hot Tub |

| | | | |
|---|---|---|---|
| | | Kitchenette | |

For the experimental design of the traditional products, star-level or rating, available amenities and price were assigned to the product mix. Respondents were also presented with a general description for each type of property (see Figure 1). In each discrete-choice experiment, respondents randomly presented with possible scenario combinations and asked to select the preferred option amongst the three hotel properties (2-star, 3-star or 4-star) in each scenario, based upon the price and listed amenities. A sample scenario is presented in Figure 2. After selecting the best option from the traditional products, a follow-up scenario involving a random opaque product in a similar location was offered. For the opaque product, star-level, maximum distance from desired location and price were selected as the attributes of interest. An example of the opaque property description and details are shown in Figure 3. Respondents are informed that details of the room will be provided after they have committed to the purchase of this property. Prices for the opaque properties were taken at levels of 40, 60 and 80% of the equivalent traditional property of the same star-rating.

| RATING | DESCRIPTION |
|---|---|
| 2-star | Satisfies traveler's basic needs. Moderate aesthetics in the property grounds, room decor, and quality of furnishings. |
| 3-star | Higher level of service with improved features/facilities. Grounds and decor are a noticeable upgrade. |
| 4-star | Superior properties with a high level of service/hospitality. Upscale facilities including room decor and landscaping. |

Figure 1: General description of hotel property type

| HOTEL | RATING | AMENITIES | | PRICE |
|---|---|---|---|---|
| A | 2-star | Free Parking<br>High-Speed Internet<br>Fitness Facility | Courtesy Breakfast<br>Coffee Maker<br>Swimming Pool | $80 |
| B | 3-star | Free Parking<br>High-Speed Internet | Dry Cleaning/Laundry<br>Fitness Facility | $150 |

| | | | | |
|---|---|---|---|---|
| | | Pets Allowed<br>Swimming Pool<br>Business Center | Courtesy Breakfast<br>Coffee Maker | |
| C | 4-star | Valet Parking<br>High-Speed Internet<br>Pets Allowed<br>Business Center<br>Dry Cleaning/Laundry | Fitness Facility<br>Restaurant/Room Service<br>Coffee Maker<br>Swimming Pool | $180 |

Figure 2: Example traditional product scenario

| RATING | TYPICAL AMENITIES | | DISTANCE |
|---|---|---|---|
| 3-Star | High-Speed Internet<br>Coffee Maker<br>Restaurant | Cable TV<br>Iron /Ironing Board | 3 mile |
| Amenities given are typically available; actual amenities will vary by property.<br>The property is guaranteed to be within the distance listed of your desired location. | | | |

Figure 3: Example opaque product scenario

Finally, a series of follow-up questions were presented at the end of the discrete-choice experiment to provide a more complete picture of the choice process. In addition to collecting standard demographic data, responders we queried on their attitude towards purchasing opaque properties and primary drivers for and against such a decision.

**Results**

We first evaluated the traditional property results as a test of the choice experiment, as well as to estimate the value and importance placed upon specific amenities packages based upon price and star rating. The parameters for price, hotel type (star level) and amenities of a multinomial logit (MNL) model were estimated using maximum likelihood, with all analysis performed using the MDC procedure in SAS 9.2. Table 2 presents results for price and rating, where the lowest (2-star) rated property was taken as the reference. The estimated parameters were all found to be highly significant. In addition, as would be expected, the rating of a given property affected the estimated probability of purchase, with a 4-star property being more likely at a given price, followed by 3 and 2 star properties. These intuitive results help in validating the approach taken in the discrete choice experiment, including the selection of pricing levels.

The next step was to determine whether, within a given rating, the associated amenities (as described in Table 1 above) available are a consideration in the final purchase decision. Here we interpret the hotel rating data and associated amenities as categorical, i.e. as separate properties, with the 4-star rating with the group 3 amenities selected as the reference category. These results are presented in Table 3. Estimated parameters signs and magnitude are as expected, with significance levels generally <0.05 and all <0.1. Based upon the results, respondents place value not only on the hotel's rating, but also on the known amenities available. This, though again intuitive, is important to demonstrate within the choice experiment as it is relevant in the comparison of opaque products where amenities are not known with certainty.

Table 2: Estimated Parameters for Traditional Properties based on Price and Rating

| Attribute | Estimate | Std Error | t-value | P>\|t\| |
|---|---|---|---|---|
| Price | -0.0327 | 0.001497 | -21.83 | <.0001 |
| 3 Star | 0.7752 | 0.0699 | 11.09 | <.0001 |
| 4 Star | 0.8558 | 0.1166 | 7.34 | <.0001 |

Table 3: Estimated Parameter with Amenities

| Attribute | Estimate | Std Error | t-value | P>\|t\| |
|---|---|---|---|---|
| Price | -0.0301 | 0.001597 | -18.86 | <.0001 |
| 2-Star Amenities 1 | -0.9708 | 0.1387 | -7 | <.0001 |
| 2-Star Amenities 2 | -0.7318 | 0.1414 | -5.18 | <.0001 |
| 2-Star Amenities 3 | -1.1366 | 0.1278 | -8.89 | <.0001 |
| 3-Star Amenities 1 | -0.4965 | 0.1147 | -4.33 | <.0001 |
| 3-Star Amenities 2 | -0.2148 | 0.11 | -1.95 | **0.0508** |
| 3-Star Amenities 3 | -0.1541 | 0.0927 | -1.66 | **0.0963** |
| 4-Star Amenities 1 | -0.6322 | 0.1623 | -3.9 | <.0001 |
| 4-Star Amenities 2 | -0.5192 | 0.156 | -3.33 | 0.0009 |

Having determined the significance of the key parameters from a traditional product perspective, we now examine the results of the second stage of the choice experiment. Here, as described above, respondents were presented with the option of selecting an alternative opaque product. A similar estimation approach was applied to the opaque survey, to determine the value of different opaque products based upon star rating, available amenities as well as distance from the desired location on the impact on the purchase of the opaque service. The primary distinction being that the choice process is now modeled as a binary choice (i.e. accept/reject opaque product).

As a primary focus was on predicting opaque purchases based upon prices of available similar traditional or alternative products, we evaluate those results first. In comparing two of the best known opaque sites, Priceline and Hotwire, prices of opaque products on Priceline are often represented as a percentage savings over comparable products (i.e. “save up to 60%”), while Hotwire often lists the price of comparable non-opaque products and thus a price savings or differential. We therefore compared results using both the ratio and difference of opaque and traditional price products. The results for the opaque difference and ratio models are presented in Tables 4 and 5 respectively for each property type. Both models include the opaque price as a variable. For each parameter estimate, Akaike's Information Criteria (AIC) and MacFadden’s Likelihood Ratio Index ($\rho^2$), often interpreted as a pseudo-$R^2$, are reported as model comparison criteria.

Table 4: Opaque Price Difference Model

| Attribute | Estimate | Std Error | t-value | P>\|t\| |
|---|---|---|---|---|
| **2-Star (**$\rho^2$=0.3368; AIC=2180**)** | | | | |
| Opaque Price | -0.0394 | 0.001835 | -21.48 | <.0001 |
| Opaque Price Difference | 0.0843 | 0.003348 | 25.18 | <.0001 |
| **3-Star (**$\rho^2$=0.2409; AIC=2972**)** | | | | |
| Opaque Price | -0.028 | 0.001121 | -24.98 | <.0001 |
| Opaque Price Difference | 0.0393 | 0.00157 | 25.01 | <.0001 |
| **4-Star (**$\rho^2$=0.2657; AIC=2997**)** | | | | |
| Opaque Price | -0.0237 | 0.000897 | -26.41 | <.0001 |
| Opaque Price Difference | 0.0242 | 0.001067 | 22.65 | <.0001 |

Table 5: Opaque Price Ratio Model

| Attribute | Estimate | Std Error | t-value | P>\|t\| |
|---|---|---|---|---|
| **2-Star (**$\rho^2$=0.0212; AIC=3216**)** | | | | |
| Opaque Price | -0.0362 | 0.005556 | -6.51 | <.0001 |
| Opaque Price Ratio | 3.2867 | 0.4589 | 7.16 | <.0001 |

| | | | | |
|---|---|---|---|---|
| **3-Star (**$\rho^2$=0.0477; AIC=3726**)** | | | | |
| Opaque Price | -0.0455 | 0.004502 | -10.1 | <.0001 |
| Opaque Price Ratio | 4.9747 | 0.5471 | 9.09 | <.0001 |
| **4-Star (**$\rho^2$=0.1272; AIC=3561**)** | | | | |
| Opaque Price | -0.041 | 0.004234 | -9.68 | <.0001 |
| Opaque Price Ratio | 5.5754 | 0.7036 | 7.92 | <.0001 |

In comparing the model results, we first note that all estimated coefficients are highly significant, with all reported p-values <0.0001. However, the goodness of fit measures ($\rho^2$ and AIC) indicate that the price difference based models provide for a better fit of the experimental data. In particular, all of the $\rho^2$ values fall between 0.2 and 0.4, often considered to be indicative of a very good fit, approximate to an $R^2$ of 0.7 to 0.9 in linear regression (Louviere et al., 2000).

We next evaluate results and interpret the impact of amenities on the opaque purchase decision. Given the above results and comparison of the two pricing models, we restrict the price variables to Opaque price and the Opaque difference. For each hotel star rating, the base package or grouping of available amenities were selected as the reference category to allow for ease of interpretation. Specifically we want to determine whether the addition of the particular amenity was significant in the purchase behavior. The results for specific amenities within each star rating are mixed, with both amenities (swimming pool, hot tub) in the 4-star category having p-values less than 0.05, while only swimming pool and restaurant are significant at this level for 2-star and 3-star properties respectively. Thus, while amenities may play a role in the final purchase decision of an opaque product, the impact is specific to a particular amenity. The role and specificity of amenities is discussed further below.

Table 5: Opaque Price and Amenities Model

| Attribute | Estimate | Std Error | t-value | P>\|t\| |
|---|---|---|---|---|
| **2-Star (**$\rho^2$=0.3383; AIC=2179**)** | | | | |
| Opaque Price | -0.0411 | 0.002073 | -19.84 | <.0001 |
| Opaque Price Difference | 0.0828 | 0.003439 | 24.08 | <.0001 |
| 2-Star Amenities 2 (+swimming pool) | -0.2787 | 0.1275 | -2.19 | 0.0288 |
| 2-Star Amenities 3 (+laundry/dry cleaning) | -0.1196 | 0.129 | -0.93 | 0.3541 |
| **3-Star (**$\rho^2$=0.2488; AIC=2945**)** | | | | |
| Opaque Price | -0.0301 | 0.001279 | -23.5 | <.0001 |

| | | | | |
|---|---|---|---|---|
| Opaque Price Difference | 0.0381 | 0.001635 | 23.31 | <.0001 |
| 3-Star Amenities 2 (+restaurant) | -0.5593 | 0.1107 | -5.05 | <.0001 |
| 3-Star Amenities 3 (+kitchenette) | -0.0607 | 0.1105 | -0.55 | 0.5827 |
| **4-Star (**$\rho^2$=0.2679; AIC=2992**)** | | | | |
| Opaque Price | -0.0248 | 0.000997 | -24.89 | <.0001 |
| Opaque Price Difference | 0.0232 | 0.001114 | 20.86 | <.0001 |
| 4-Star Amenities 2 (+swimming pool) | -0.1946 | 0.1101 | -1.77 | 0.0774 |
| 4-Star Amenities 3 (+hot tub) | -0.3308 | 0.1097 | -3.01 | 0.0026 |

The final variable in the opaque product category to analyze was the distance from a desired location for the property. As described above, opaque products are typically defined to be within specific region (for example downtown, city center, etc) or within a maximum distance of a specific landmark to maintain the anonymity of the property. Our results indicate that, the distances selected (within 1-mile; within 3-miles; within 6-miles) were not statistically significant for the opaque properties defined in our choice experiment. This was a somewhat surprising result as location is often considered an important criterion is selecting a hotel property. We discuss further below within the section on contextual questions posed to respondents upon completion of the discrete choice experiment.

In addition to the above, respondents were asked questions regarding their interest in opaque products, including listing specific drivers that would encourage/discourage an opaque purchase. The primary driver, as anticipated, was the prospect of a low price/good deal. On the other side, reasons for not purchasing included uncertainty regarding specific location, hotel brand, and amenities, as well as policies regarding acceptance of pets. When asked regarding specific amenities required, the top four were given as high-speed internet, restaurant available, swimming pool and complimentary breakfast. This is generally consistent with the amenities results above, as the amenities tested that were significant were those that were deemed important. The location issue is more complicated. Though uncertainty regarding the exact location was considered important, this was not observed based upon the distance variable. The problem is likely that, though somewhat related, distance does not translate or is not interpreted as location. That is, being further away with respect to distance is not as important as the location itself being physically desirable.

Based upon these results, we observe a decrease in likelihood of opaque purchase at different star ratings (decrease at higher rating) at different price points. More importantly is at least an equally significant impact of the price differential (i.e. savings) between the comparable traditional and opaque products for all three hotel ratings. Thus consumers are basing their opaque purchase decision on both cost as well as the perceived savings over a similar available traditional product. As well, we were also able to determine that the likelihood of an opaque purchase over that of a traditional product is affected by information on the availability of specific amenities within the competing traditional hotel property. For example, the presence of a swimming pool in a two-star hotel decreases the likelihood of selecting an opaque property for which this information is not available. However, this impact was found to be amenity specific, with no significant impact on the purchase decision for availability of laundry/dry cleaning in a two-star hotel. Thus managers can use the above results as a decision aid in setting prices for opaque products for their particular hotel type. In addition, this information allows an opaque service provider to potentially tailor opaque offerings by determining for different regions what information regarding amenities to make available while still disguising the final product. For example, in a region with a large number of product offerings, it may be possible to provide further information on available amenities to induce purchase without revealing the final product.

**Conclusions**

The purpose of this research was to evaluate, through the implementation of a discrete-choice experiment, the value drivers and subsequent purchase decisions associated with opaque products in the hotel industry. The results indicate that consumers base their decisions on the price of the opaque product as well as the difference in price for a comparable non-opaque product. This information can then be used by property managers is setting appropriate rates on opaque channels in order to maximize sales and revenues based upon the specific type of property. We were also able to establish that knowledge of available amenities also drive the value of opaque products. Given this information, managers may find it valuable to customize information on available amenities within specific markets, increasing the probability of a sale while still protecting brand identity. One limitation, and possible avenue for future research, would be establishing how lack of knowledge regarding property location plays into the decision-making process. Using the distance variable in our current research was not effective. A possible approach that may be effective is the use of maps or graphics of actual physical locations. A final consideration, both with respect to future research as well as the applicability of the above analysis, is that of the impact of specific hotel brands. Given that brand identity is obscured for the opaque product, it would be interesting to evaluate the impact, if any, on final opaque purchase decisions of specifying the hotel brand for the non-opaque products.

**Appendix A: Summary of Survey Respondents – Demographics**

Figure A1: Respondent Education Levels

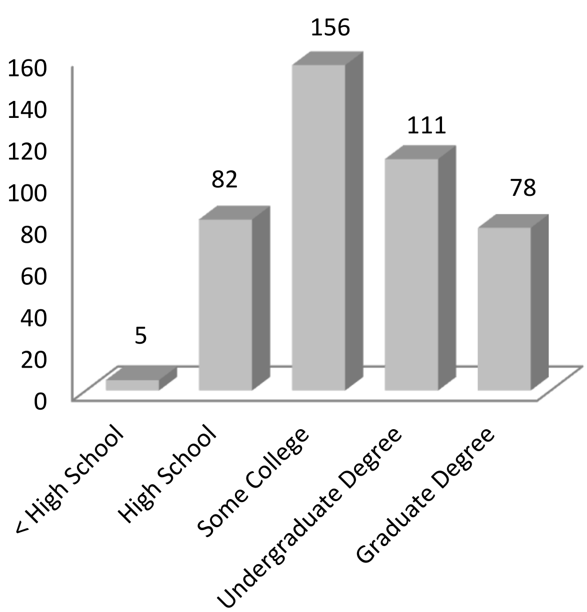



Figure A2: Respondent Income Levels

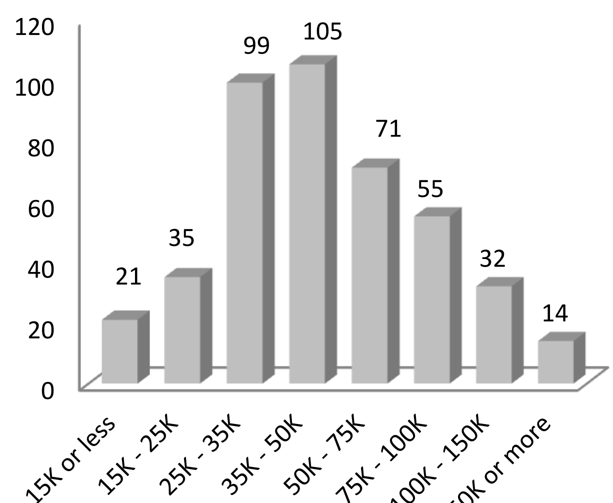
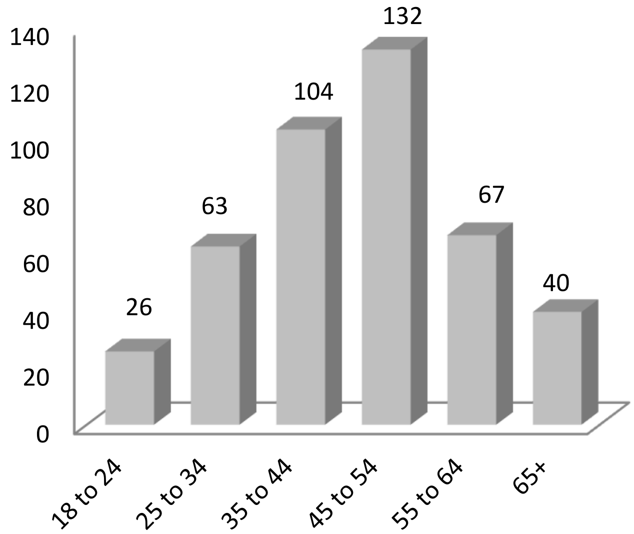



Figure A3: Respondent Age Distribution

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