Measuring Seat Value in Stadiums and Theaters

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Abstract

We study how the seat value perceived by consumers attending an event in a theater/stadium, depends on the location of their seat relative to the stage/field. We develop a measure of seat value, called the Seat Value Index, and relate it to seat location and consumer characteristics. We implement our analysis on a proprietary dataset that a professional baseball franchise in Japan collected from its customers, and provide recommendations. For instance, we find that customers seated in symmetric seats on left and right fields might derive very different valuations from the seats. We also find that the more frequent visitors to the stadium report extreme seat value less often when compared to first-time visitors. Our findings and insights remain robust to the effects of price and game related factors. Thus, our research quantifies the significant influence of seat location on the ex-post seat value perceived by customers. Utilizing the heterogeneity in seat values at different seat locations, we provide segment-specific pricing recommendations based on a service-level objective that would limit the fraction of customers experiencing low seat value to a desired threshold.

Keywords: Seat Value, Empirical Research, Revenue Management Application, Customer Behavior, Ordinal Logit Models.

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1 Introduction

Theaters and sports stadiums have several characteristics that are well suited to Revenue Management (RM) methods. There are many different customer segments (e.g. season ticket holders, families, students) each with varying usage patterns and willingness to pay. The value experienced by a consumer attending an event depends on several factors, such as the location of his seat, the popularity of the event, and other consumer-related attributes (see Talluri and van Ryzin 2004 for more details). However, there has been limited research on how the value experienced by consumers in such settings is influenced by the aforementioned factors.

According to Talluri and van Ryzin (2004) "*fear of negative customer reactions and consequent loss of customer goodwill are the main reasons firms seem to be avoiding bolder demand management strategies.*" This fear is not unfounded; Anderson et al. (2004) find a positive association between customer satisfaction and long-run financial performance of firms in retail settings. Hence, it is imperative to develop a systematic understanding of seat value experienced by consumers in order to be able to improve ticket selling strategies. This is the main research objective of our paper.

The value of a seat in a stadium/theater is a function of the experience they offer consumers, and could be driven significantly by the location of the seat relative to the stage or playing field. For instance, front row seats in a theater are valued higher as they offer a better view of the performance. This is in stark contrast to airline seats, where seat value in the same travel class is less sensitive to seat location,[1] as airline seats primarily serve as a conduit for transporting a person from an origin to a destination. Consequently, for the most part, the price of a ticket in economy class indicates how much a person values the trip, more than how much he values the seat itself. However, theater/stadium seats might be thought of as experience goods. It is unclear how consumer valuations are distributed across different attributes. Moreover, the dependence of seat value on the location of the seat can be fairly complex. For example, in theaters, seats in the middle of a row might be preferred over seats toward the end of a row further forward, and seats at the front of second-level sections are sometimes preferred to seats at the back of first-level sections (Leslie 2004). This ordering of seat value by location is only understood subjectively by theaters and stadiums. However, there has been little research on developing a measure of seat value in these settings. Measuring seat value and developing a better understanding of how it is driven by seat location would assist theaters and stadiums in formulating their ticket selling strategies.

The relationship between seat value and seat location is not well understood. This has been

[1] Although there are differences between aisle seats and middle seats, most seats in the same travel class (business or economy) are perceived to provide comparable valuations for consumers. Of late, these seat value differences based on seat location are gaining attention. See *www.seatguru.com*.

a focus of subjective discussions recently. We briefly discuss one such case. In 2006, the Oakland Athletics decided to reduce the capacity of McAfee Coliseum (where their home games are played) by covering several of their upper deck seats with tarpaulin sheets, thus reducing the stadium capacity from 44,000 seats to about 34,077 seats (Urban 2005). The Oakland A's announced that the decision was made in order to provide an "intimate" experience to those in attendance, in a smaller field. In fact, when the team moves to a newer field for the 2012 season, they plan to play in a stadium that has lesser capacity (32,000) than the currently used tarpaulin-covered stadium. Bnet.com quoted "*...the fans who are feeling slighted most are the lower-income brackets who feel the third deck was their last affordable large-scale refuge for a seat behind home plate, even one so high.*" The team management contended that people liked the upper deck mostly because of availability, and perhaps not so much because of the view (Steward 2006). One article in Slate Magazine criticized the move, stating "*Some of us want to sit far away*" (Craggs 2006). Thus, the seat value perceived by consumers seated at the upper deck was not only unclear, but also varied among different fans. So is it true that the consumers seated in the upper deck valued those seats highly? Were the upper deck seats being underpriced? How did the seat value perceived by consumers attending the game differ across seat locations? These are some of the questions that will be addressed by our research.

In addition to seat location, there are a number of other factors that might affect the seat value perceived by a customer. For instance, in the case of a sports stadium, the nature of the opposing team, the age of the customer, or whether the customer is a regular or an infrequent visitor, might affect her valuation of the seat. For most theaters and stadiums, understanding heterogeneity in customer valuations is the key to increasing revenues. A clear understanding of the seat valuations would lead to the creation of better "fences" that would provide theaters and stadiums with an opportunity to manage their revenues and customer base better. Our paper sheds more light on the key factors influencing seat value in these settings.

Our research on non-traditional industries (theater and sports) complements current RM literature by (1) developing a measure of seat value (Seat Value Index), (2) establishing the critical relationship between the Seat Value Index and seat locations, and (3) providing *segment-specific* recommendations that would help the firm achieve a service-level objective such as a *"desired level of seat value"*.[2] We apply this research methodology to a proprietary dataset collected by a professional baseball franchise in Japan, from a survey of its customers. Based on the findings from the dataset, we provide various measures by which stadiums/theaters can improve customer satisfac-

[2]This notion is analogous to "fill-rate" measures employed in retail settings. While focusing on a desired fill-rate might be sub-optimal for short-run profit maximization, it improves availability, leading to long-run benefits. Quantity adjustments are more difficult in stadiums/theaters, but price adjustments to "satisfice" value can be made.

tion through better handling of ticket pricing, seat rationing, and seating layout decisions. Since RM practices are not employed on a large scale in these areas of interest, our research fills a gap, both in theory and practice.

To our knowledge, ours is the first paper to study the distribution of consumer seat value and its dependence on seat location in theater/stadium environments. Revenue management practice hinges on the ability to price-discriminate, which is possible only if there is heterogeneity in seat value. Based on service-level objectives, we provide pricing recommendations that a firm may use to improve positive experience from the repeated consumption of the good. We apply our model to a dataset collected by a Japanese baseball franchise and find evidence for heterogeneity in seat value at the stadium. Using our model, we *quantify* this heterogeneity in terms of customer attributes and their seat locations. Pursuant to the results from applying our method, we provide some segment-specific pricing recommendations.

In the following Section §2, we position our paper with respect to the existing literature. In Section §3, we discuss our research design, methodology and its application to a proprietary dataset. In Section §4, we test the robustness of our results to game effects, prices and seat location. In Section §5, we provide segment-specific pricing recommendations and discuss insights from our analysis. We conclude the paper by summarizing the key ideas of our methodology and charting future research directions.

2 Literature Positioning

We analyze seat value perceived by consumers, and the key implications it has for pricing in sports stadiums and theaters. Most of the literature in the sports and entertainment industry has been about secondary markets and ticket pricing in scalping markets (See Courty (2000) for a comprehensive survey). The only paper related to ours is Leslie (2004) which studies the profit implications of price-discrimination based on exogenously defined seat quality and consumers' income levels for a Broadway theater. In contrast to Leslie (2004), we measure seat value based on *consumer perceptions*.

Our paper also contributes to an evolving literature on consumer behavior and empirical modeling in Revenue Management. Shugan and Xie (2000) show that advanced selling mechanisms can be used effectively to improve firm profits as long as (a) consumers have to purchase a product ahead of their consumption, and (b) their post-consumption valuation is uncertain. Xie and Shugan (2001) provide guidelines for when and how sellers should advance sell in markets with capacity constraints. Dana (1998) shows that advance-purchase discounts can be employed effectively in competitive markets, if consumers' uncertain demand for a good is not resolved before the purchase of the good. Su (2007) finds that heterogeneity in consumer valuations, along with waiting time behavior, influences pricing policies of a monopolist. Gaur and Park (2007) consider consumer learning in competitive environments. While most of this literature is analytical, we take an empirical approach to analyze seat values as perceived by customers, and study its implications for revenue management decisions in the sports/theater business.

There has been recent interest in modeling Revenue Management decisions in non-traditional settings. Roels and Fridgeirsdottir (2009) consider a web publisher who can manage online display advertising revenues by selecting and delivering requests dynamically. Popescu and Rudi (2008) study revenue management in stadiums where experience is often dictated by the collective experience of others around a patron.

Methodologically, our paper is related to the literature employing ordinal models to study the antecedents and drivers of customer satisfaction. Kekre et al. (1995) study the drivers of customer satisfaction for software products by employing an ordinal probit model to analyze a survey of customer responses. Bradlow and Zaslavsky (1999) use a Bayesian ordinal model to analyze a customer satisfaction survey with 'no answer' responses. Rossi et al. (2001) propose a hierarchical approach to model customer satisfaction survey data that overcomes reporting heterogeneity across consumers. We use an ordinal logit model similar to the aforementioned papers, taking into account heterogeneity in reporting (across customers) and heterogeneity in the distribution of seat values (across seat locations).

Anderson and Sullivan (1993) note that relatively few studies investigate the antecedents of satisfaction, though the issue of post-satisfaction behavior is treated extensively. They note that disconfirmation of expected valuation causes lower satisfaction and affects future consumption. While previous considerations about a product might affect how consumers value the experience, we mainly focus on how product attributes such as seat location, and personal attributes such as gender, age and frequency of visits affect customer valuations.

Homburg et al. (2005) show that customer satisfaction has a strong impact on willingness to pay. Ittner and Larcker (1998) provide empirical evidence that financial performance of a firm is positively associated with customer satisfaction and customer value perception. We use seat value measures reported by consumers in a survey to recommend changes that would help the firm (a baseball franchise in our context) achieve a chosen service objective on seat value. Hence we believe that this objective would improve customer goodwill, which in turn would lead to better long-run performance.

3 Research Issues and Methodology

3.1 Research Issues

The focus of our research is to understand how the seat value perceived by a customer in a stadium/theater varies based on the location of her seat relative to the stage/field. Since we are interested in post-consumption seat value perceived by customers in attendance, we do not consider the underlying trade-offs made while arriving at the purchase and seat choice decisions. Therefore, we only model the ex-post *net valuations* realized by consumers, in order to understand how they differ based on seat location.

To derive sharper insights, we assume that consumers are forward-looking and have rational expectations, i.e. that they do not make systematic forecasting errors about what valuations they might receive from attending a game or seeing a show. The rational expectations assumption is widely employed in empirical research in economics (Muth 1961, Lucas and Sargent 1981, Hansen and Sargent 1991) and marketing literature (for example, Sun et al. 2003). Accordingly, we assume that every consumer has some belief on the distribution of possible valuations that she could realize, conditional on her covariates. Furthermore, the ex-ante distribution of valuations for a rational consumer is identical to the ex-post distribution of valuations realized by the consumer population with identical covariates. Note that rational expectations does not imply that consumers are perfectly informed about their true valuations.

3.2 Methodology

Seat Value: We define the value perceived by a consumer as the valuation realized from her event experience *net* of the price paid (consistent with Zeithaml 1988). We note that the exact valuation realized from the experience cannot be easily quantified, and therefore the value perceived is *latent*. However, the consumer would be able to translate her latent value perceived on some graded scale. In other words, although she cannot describe the *exact* worth of the show she attended, she can usually confirm if the value she perceived was low, medium or high. We define *Seat Value Index* (SVI) as an ordinal measure that captures the post-consumption latent value perceived by a consumer. Let V_i denote the SVI reported by a respondent i. It takes values in $\{1, 2, \ldots, J\}$, $J \in \mathbb{N}$, where $V_i = 1$ corresponds to the lowest SVI (low net value), and $V_i = J$ represents the highest SVI (high net value).

Service Objective

In many operational contexts, firms that seek to improve customer service adopt a service level measure such as *fill rate* or *in-stock* probability (Cachon and Terwiesch 2008). Such decisions are based on the belief that improving availability of products reduces the incidence of costs that might be associated with stockouts, and the resultant loss of goodwill. For instance, a firm might aim to keep the fraction of customers facing stockouts within 1% (i.e., a fill-rate of 99%). Such service level measures that focus on limiting the fraction of customers facing inferior service experience, is commonly applied in several industries. Call centers choose staffing level according to an 80/20 rule (or, some variation thereof) that focuses on limiting the fraction of customers that face waiting times exceeding a certain threshold.

While a newsvendor can adjust quantities of goods produced based on the chosen service level objective, in many RM scenarios, the quantities are unchangeable (for example, the number of seats in a theater cannot be adjusted easily). In such cases, prices are the main lever by which RM firms can attain their service objective. However, in many revenue management scenarios, especially in stadiums/theaters, the value of the product is intrinsically linked to the experience. For example, it is possible that customers who experience low value might switch to other services, or balk from visiting again. Firms would hope to set prices such that the fraction of customers experiencing low seat value could be limited to acceptable levels. Such an objective would be consistent with the models of customer behavior linked to service/stockout experiences considered in previous Operations Management settings (For example, see Hall and Porteus 2000, Gans 2003, Gaur and Park 2007).

Several RM firms desire to limit the fraction of customers experiencing low seat value in order to mitigate the loss of goodwill or to reduce switching. Hence, we consider a service-level objective that aims to set prices to maximize revenues while keeping the probability of a customer reporting low SVI to a maximum threshold level, α_l, at some seat location l. For expositional ease, we shall assume that $\alpha_l = \alpha$ across all seat locations. This clearly need not be the typical case. A theater might be willing to impose more stringent constraints on certain sections of the arena compared to other sections. Therefore, under our service level objective for a particular seat category l, the firm would like to set some price p_l^* under the constraint

$$\Pr[SVI \leq j | p_l^*] \leq \alpha_l \tag{1}$$

The choice of α_l and j are flexible, and could be based on the long term objective of the firm.

We only consider static price adjustments in our setting, since such schemes are consistent with industry practice where we apply our model. It is very common that theaters and sports stadiums announce prices for the entire season; the number of price changes are extremely limited within the selling horizon.

Modeling SVI

Utilizing the service level objective we elaborated, the firm can increase or decrease prices suitably to achieve a desired level of seat value. We describe our model of SVI in the context of our dataset.

3.3 Description of Baseball Dataset

We now illustrate our research issue based on the data from a professional league baseball franchise (equivalent of Major League Baseball) in Japan. The franchise is located in a mid-small city, and hence could not rely on conventional streams of revenue such as broadcasting, merchandizing and advertising. The franchise management decided to focus on ticket sales as it saw an upside potential in considering improvements in pricing and seating layouts.

As the team was a recently established franchise, the management conducted a survey to better understand the traction for the team among its fans. The survey discussed in the paper was designed by the team based on inputs from various departments and team executives in the franchise. The survey was administered to a random sample of consumers at the franchise's stadium on a weeknight game. Only one response was obtained from each consumer.

In the survey, respondents were asked to report the net worth of the seats they sat in as Low, Medium or High. This corresponds to the Seat Value Index (SVI) measure which was defined before as a quantification of a respondent's realized net value. In addition, customers were asked to report their age, gender, hometown, seat, frequency of visits to the stadium and preference for visiting teams. Table 1 provides more details on these variables and how we treat them in our models.

Variable Name	Values	Treatment
SVI	Low, Medium, High	Ordinal (1-3)
Age	$0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60+$	Continuous (1-7)
Gender	Male, Female	Categorical
Hometown	City, Prefecture, Outside	Categorical
Seat	$1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12$ (see Figure 1)	Categorical
Frequency	First Time, Once, Thrice, Five Times, All Games	Continuous (1-5)
Visiting Team	Team 1, Team 2, Team 3, Team 4, Team 5	Categorical

Table 1: Description of Variables in the Dataset

The experience and the resulting value perceived are highly dependent on the location of the seat from which a respondent watched the game. However, this information is not clearly captured by the explanatory variable *Seat*. For example, customers seated in locations 2 and 7 have almost identical views, but this linkage is not apparent in the current coding of the *Seat* variable. Hence, we represented each seat in terms of three location attributes given by **Side** = {1st Base, 3rd Base, Backnet, Field, Grass}, **InOut** = {Infield, Outfield} and **Deck** = {Upper, Lower}.

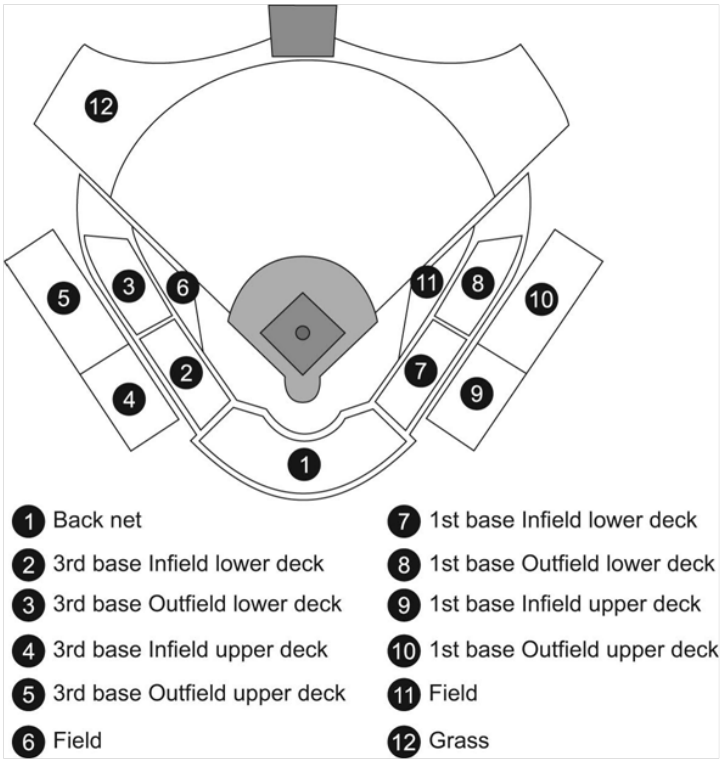


Figure 1: Stadium Seating Layout. **Side** = {1st Base, 3rd Base, Backnet, Field, Grass}, **InOut** = {Infield, Outfield} and **Deck** = {Upper, Lower}

3.4 Preliminary Analysis

From a total of 1397 respondents, 259 responses were dropped due to missing information, resulting in $N = 1138$ responses. A preliminary analysis revealed that the frequency distribution of SVIs was skewed towards the right, as shown in Figure 2. This implies that a higher proportion of consumers reported a low SVI, which underlines the further need for studying seat value.

Figure 2 also reveals some cursory insights. The seat value index reported by older respondents seems to be more homogeneous. Customers seated in Grass seats report higher SVI, while respondents seated at Backnet seem to have a lower SVI. Infield and Lower Deck seats seem to have a higher proportion of respondents reporting low SVI as compared to Outfield and Upper Deck seats. Finally, the season regulars attending all games seem to have more homogeneous SVIs as compared to the first-timers. We now discuss the regression methodology adopted and the estimation of model parameters.

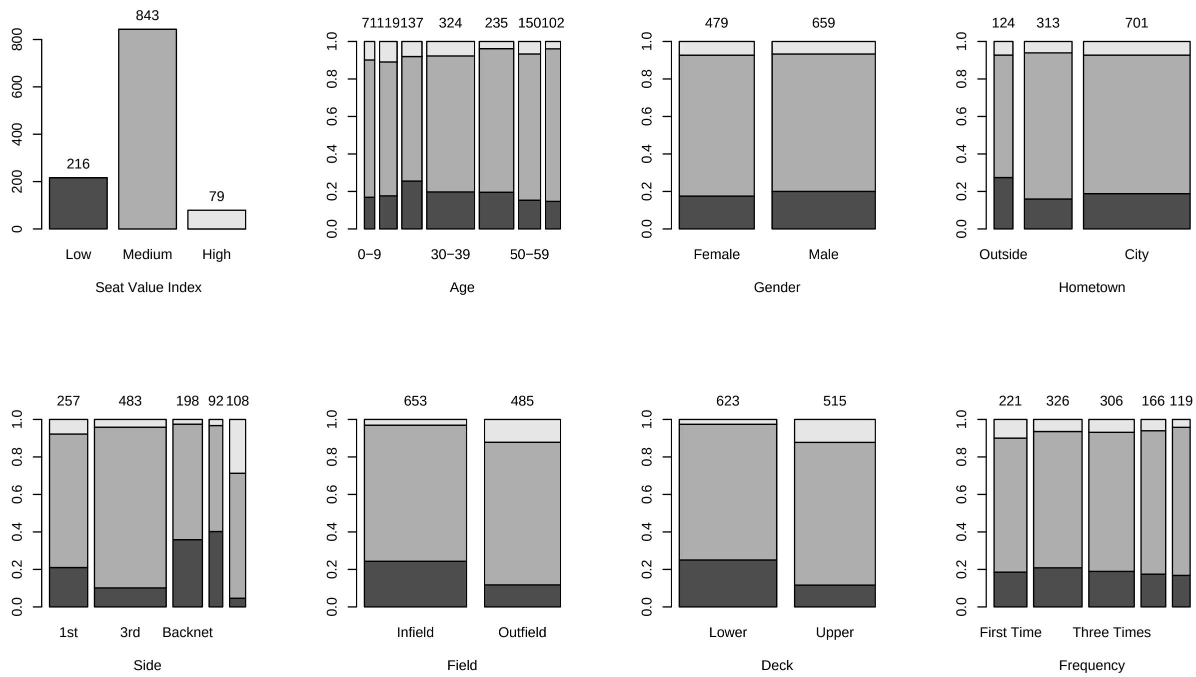


Figure 2: The distribution of Seat Value Indices reported by the respondents for each covariate.The width of the histogram denotes the number of responses (which is also indicated on top for each value of the covariate).

3.5 Estimation of Parameters

Let V_i denote the SVI reported by respondent i, $i = 1, 2, \ldots, N$. Note that V_i can take the rank-ordered values $j = 1, 2, 3$ corresponding to *Low, Medium* and *High*, respectively. Given that our response variable is ordinal, we follow McCullagh (1980) and use ordinal regression to model our data. The reader is directed to Liu and Agresti (2005) for a detailed overview and survey of ordinal data analysis.

Following the specification of the ordinal regression model, we assume that a respondent i derives her SVI, $V_i \in \{1, 2, 3\}$, by categorizing her post-consumption *latent* net value realized (valuation of the experience net of the price paid), V_i^*, into buckets defined by the thresholds $\{\tau_i^0, \tau_i^1, \tau_i^2, \tau_i^3\}$, where it is understood that $\tau_i^0 = -\infty$ and $\tau_i^3 = +\infty$. Hence, respondent i reports her SVI as $V_i = j$, if and only if $\tau_i^{j-1} < V_i^* \leq \tau_i^j$, for $j = 1, 2, 3$.

The net value experienced by the customer can be expressed as $V_i^* = \mathbf{x}_i^T \beta + \epsilon_i$, where the vector of covariates $\mathbf{x}_i$ consists of *Age, Gender, Hometown, Side, InOut, Deck, Frequency* and *Team 1.* β is the associated vector of parameters, and ϵ_i is a stochastic term that captures the idiosyncratic value derived from the experience, which is assumed to follow a standard logistic distribution (Λ). Following McCullagh (1980), we assume that $\tau_i^j = \tau^j$ for all consumers i. We can now write down the cumulative probability distribution of V_i as

$$\Pr(V_i \leq j \mid \mathbf{x}_i) \quad = \quad \Lambda(\tau^j - \mathbf{x}_i^T \beta) \ \forall j = 1, 2, \tag{2}$$

where $\mathbf{x}_i^T\beta = \beta_1\text{Age}_i + \beta_2\text{Male}_i + \beta_3\text{City}_i + \beta_4\text{Prefecture}_i + \beta_5\text{3rdBase}_i + \beta_6\text{Backnet}_i + \beta_7\text{Field}_i + \beta_8\text{Grass}_i + \beta_9\text{Outfield}_i + \beta_{10}\text{UpperDeck}_i + \beta_{11}\text{Frequency}_i + \beta_{12}\text{Team1}_i$.[3]

Prior to running the regression model, we first tested for the usual symptoms of multi-collinearity (Greene 2003): (1) high standard errors, (2) incorrect sign or implausible magnitude of parameter estimates, and (3) sensitivity of estimates to marginal changes in data. We found no evidence of these symptoms in our dataset. We computed the Variance Inflation Factors (VIF) for every covariate and found all of them to be less than two (i.e. $\max(VIF) < 2$), which again suggests that multi-collinearity is not an issue. In addition, we added random perturbations to the independent variables and re-estimated the model (Belsley 1991). We determined the changes to the coefficients of those variables to be insignificant on repeated trials, thus further supporting that multicollinearity might not be a significant concern.

We use the *OLOGIT* routine in STATA 10.0 to estimate the parameters of the model using the maximum likelihood approach. The results are summarized in Table 2. The standard ordinal model implicitly assumes proportional-odds.[4] To validate this assumption, we applied a likelihood ratio test and found that the standard ordinal logit model is strongly rejected in favor of an expanded model that allows for the slope coefficients to differ across threshold levels ($\chi^2_{(12)} = 46.74, p < 0.0001$). Consequently, we conducted a test proposed by Brant (1990), to find that the proportional-odds property is violated for the coefficients β_1 (Age), β_5 (Side) and β_{10} (Deck).[5] To rule out the possibility of a misspecified link, we applied the Brant test to ordinal models with different link functions (probit, log-log and complementary log-log), but still found the same violations of the

[3] Note that the actual price paid may have an effect on consumer valuations and the ex-post survey scores reported. While our approach can easily incorporate price into the regression model, our dataset lacks granular price data at the consumer level. Therefore, we do not explicitly consider price in our model. Instead, we study the effects of seat price on SVI and test the robustness of our model to price effects in Section 4.4. We find that our conclusions remain unchanged even when price dependencies are considered. We thank an anonymous reviewer for pointing out this aspect.

[4] The proportional-odds property implies that all respondents have the same ratio of odds of reporting a low SVI to odds of not reporting a high SVI.

[5] A likelihood ratio test confirms that a partially constrained model that allows only for β_1, β_5 and β_{10} to depend on j cannot be rejected in favor of an unconstrained model that allows all the β's to depend on j ($\chi^2_{(9)} = 6.33, p = 0.71$).

proportional-odds property.

Variable		Standard Ordinal Logit	Generalized Ordinal Logit		Heteroskedastic Ordinal Logit
		$j = 1, 2$	$j = 1$	$j = 2$	$j = 1, 2$
Threshold: Low-Medium	τ^1	-1.215***	-0.761**		-0.748***
Threshold: Medium-High	τ^2	3.387***	2.071***		2.067***
Age	β_1^j	0.048	0.127**	-0.172**	0.034
Male	β_2^j	-0.019	-0.026	-0.026	-0.034
City (vs. Outside)	β_3^j	0.083	0.029	0.029	0.011
Prefecture (vs. Outside)	β_4^j	0.192	0.166	0.166	0.102
3rd Base (vs. 1st Base)	β_5^j	0.428**	0.873***	-0.727**	0.145
Backnet (vs. 1st Base)	β_6^j	-0.730***	-0.678***	-0.678***	-0.440***
Field (vs. 1st Base)	β_7^j	-0.893***	-0.824***	-0.824***	-0.509***
Grass (vs. 1st Base)	β_8^j	1.816***	1.206***	1.206***	0.919***
Outfield	β_9^j	0.215	0.211	0.211	0.171
Upper Deck	β_{10}^j	0.246	0.066	0.947***	0.263**
Frequency	β_{11}^j	-0.126**	-0.093	-0.234**	-0.081**
Team 1	β_{12}^j	0.249*	0.250*	0.250*	0.185**
Age	γ_1		-NA-		-0.075***
3rd Base (vs. 1st Base)	γ_5		-NA-		-0.324***
Upper Deck	γ_{10}		-NA-		0.208***
Frequency	γ_{11}		-NA-		-0.057*
Log Likelihood	LL	-748.12	-727.18		-726.27
Likelihood Ratio χ^2	LR	149.02	190. 90		192.72
No. of Parameters		12	16		16
McFadden Pseudo R^2		9.06%	11.60%		11.71%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2: Parameter Estimates for All Models

The deviation from proportional-odds suggests the presence of heterogeneity across consumers and seat locations. Hence, we consider two different modifications to the standard ordinal logit model to account for this.

1. The first modification is a generalized threshold model that addresses the possibility of customers using different thresholds in reporting their responses, by relaxing the assumption that the thresholds, τ_i^j, are identical for all respondents.

2. The second modification is a heteroskedastic model that addresses the inherent differences in the distribution of net value across seat locations, by allowing the variance of the idiosyncratic

value term, ϵ_i, to systematically vary across respondent groups.

We now discuss these two sources of heterogeneity and the modeling strategies that can account for them.

Heterogeneity in Response Thresholds: Generalized Threshold Model (Peterson and Harrell 1990)

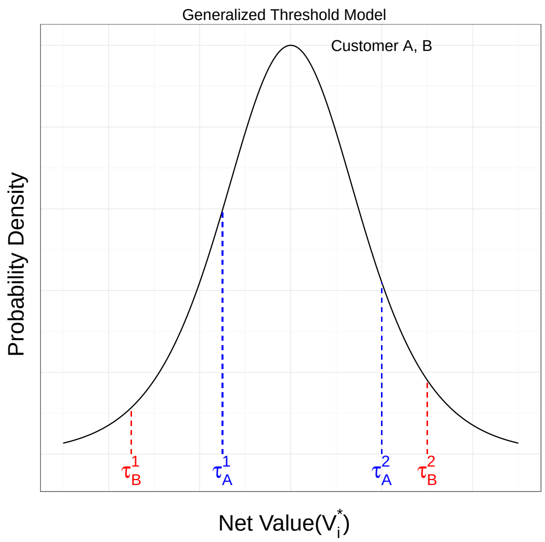
It is not uncommon for people to use different thresholds in reporting their ordinal responses.[6] The generalized threshold ordinal logit model retains the idea that consumers realize their net value from a common distribution, $V_i^* \sim \Lambda(\mathbf{x}_i^T\beta, \frac{\pi^2}{3})$, but assumes that they use systematically different thresholds, τ_i^j, while reporting their net value. A common approach to model generalized thresholds is to make the threshold parameters linear (Maddala 1983, Peterson and Harrell 1990) or polynomial functions of the covariates. We choose the linear specification and accordingly let $\tau_i^j = \tilde{\tau}^j + \mathbf{x}_i^T\delta^j$, where $\mathbf{x}_i$ is the set of covariates and $\delta^j, j = 1, 2$, are vectors of the associated parameters that capture the effect of the covariates in shifting the thresholds. Substituting the expression for τ_i^j in place of τ^j in Equation (2), we can write the defining set of equations for the generalized ordinal logit model as

$$\Pr(V_i \leq j \mid \mathbf{x}_i) \quad = \quad \Lambda(\tilde{\tau}^j - \mathbf{x}_i^T\beta^j),\ \beta^j = \beta - \delta^j\ \forall j = 1, 2. \tag{3}$$

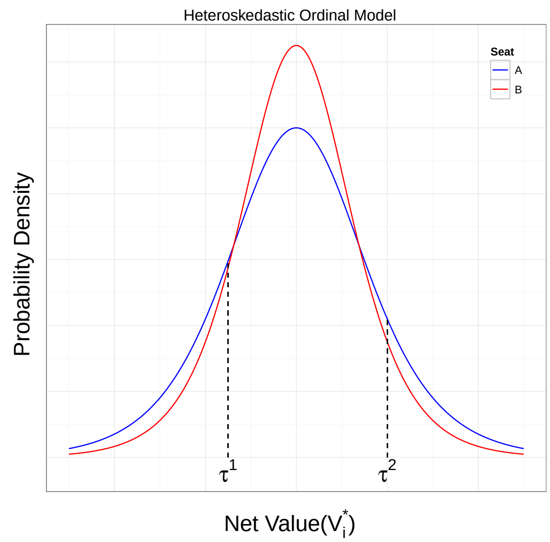
According to the generalized threshold ordinal logit model, the net effect of any covariate k, β_k^j on SVI, is a combination of two effects (a) the real effect (β_k) and (b) the threshold-shifting effect (δ_k^j). It is the threshold-shifting effect (δ_k^j) that leads to the manifestation of unequal slopes detected by the Brant test. Thus, two groups of customers might have identical distributions of net value, but the distributions of their reported SVIs might differ because of different reporting thresholds. Figure 3 illustrates this case for two customers, A and B, seated at identical locations.

From the results of the Brant test, we infer that the covariates *Age*, *3rd Base* and *Upper Deck* could be driving the shift in thresholds. In addition, we believe that repeated visits help respondents learn the true value of the game experience and would induce them to use different

[6] For example, despite having the same level of 'true' health, older people may report their health differently from younger people. This phenomenon of subgroups of population using systematically different thresholds when assessing some latent quantity is referred to as *Response Category Threshold Shift* or *Reporting Heterogeneity*. It is also possible that some respondents are biased and answer questions on latent factors (such as the value of a seat) by comparing themselves with a reference group or a situation, that may be unobservable to the researcher (*Scale of Reference Bias* Groot 2000). In addition, respondents could display systematic biases in using different portions of the scale, e.g. the lower and upper ends. For instance, some discerning consumers attending a play might be quite strict on reporting 'high' responses (hard to please critics). This is referred to as *Scale-Usage Heterogeneity* (Rossi et al. 2001).



Generalized Threshold Model



Heteroskedastic Ordinal Regression

Figure 3: **Generalized Threshold Model:** The figure on the left compares SVIs at the same seat location for two different customers, A and B. Although the distribution of net value is identical for both customers, the difference in reporting thresholds causes them to report different SVI for the same realization of net value. **Heteroskedastic Ordinal Logit Model:** The figure on the right compares SVIs for the same customer at two different seat locations, A and B. Although the mean realization of net value and the response thresholds are identical at both seat locations, the difference in variances causes the customer to report a particular SVI with different probabilities across the two locations.

thresholds. Accordingly, we let the thresholds depend on the subset of covariates $\mathbf{z}_i = \{$Age, 3rd Base, Upper Deck, Frequency$\}$, and set $\delta_k^j = 0, j = 1, 2$ for $k \notin \mathbf{z}_i$.

We estimate the parameters of this generalized threshold model using the *GOLOGIT2* routine (Williams 2006a) in STATA 10.0. The results are summarized in Table 2. We observe that in addition to *Side* and *Frequency, Age* also becomes a significant predictor now. A standard measure of fit for ordinal regression models is the McFadden pseudo-R^2 which is defined as $1 - \frac{LL_{Model}}{LL_{Null}}$, where LL_{Model} refers to the model log-likelihood. It indicates the improvement in likelihood due to the explanatory variables over the intercepts-only (null) model. We find the pseudo-R^2 for the generalized threshold model to be 11.60%.[7]

[7]This value needs to be interpreted with caution as it is not directly comparable to the R^2 obtained in OLS, which is a measure of the proportion of variance in the responses explained by the predictors. In fact, it is possible to obtain low values for the pseudo-R^2, even when the explanatory power of the model is good (Hauser 1978). Hence we analyzed more detailed fit statistics in Section 4.1 to support the predictive power of the model. When we compared the actual number of respondents at a given seat location reporting a particular SVI, with those predicted by the model, we observed a high degree of correlation. This suggested that the model provides a pretty good fit.

Heterogeneity in Net Value Distribution: Hetetoskedastic Ordinal Logit (McCullagh and Nelder 1989)

In the previous subsection, we considered customers using different thresholds to report different levels for the same realized experience. However, it is also possible that the distribution of values, ϵ_i, realized by different consumer groups might, themselves, be different. Consumers seated in different locations could have different variabilities in their experience depending on their seat location. Such occurrences are very likely in several Revenue Management settings. It is likely that consumers seated in some sections such as dress circles may have smaller differences in the value experienced than those consumers seated at farther sections of the same theater. Therefore, we believe that it is important for firms to account for such systematic differences in the variance of the distribution of idiosyncratic value, to obtain meaningful parameter estimates.[8]

We capture the dependence of the error variance on the covariates using a skedastic function $h(.)$ that scales the iid ϵ_is in the standard ordinal logit model. Mathematically, we write $V_i^* = \mathbf{x}_i^T\beta + h(\mathbf{z}_i)\epsilon_i$, where $\mathbf{z}_i$ is the vector of covariates upon which the residual variance depends. Following Harvey (1976), we parametrize $h(.)$ as an exponential skedastic function given by $h(\mathbf{z}_i) = \exp(\mathbf{z}_i^T\gamma)$. We can now rewrite Equation (2) to obtain the defining set of equations for the heteroskedastic ordinal logit model as

$$\Pr(V_i \leq j \mid \mathbf{x}_i) = \Lambda\left(\frac{\tau^j - \mathbf{x}_i^T\beta}{\exp(\mathbf{z}_i^T\gamma)}\right) \;\forall j = 1, 2. \tag{4}$$

The heteroskedastic ordinal logit model belongs to a larger class of models known as location-scale models, and the reader is directed to McCullagh and Nelder (1989) for more details.[9]

Since the explanatory variables *Age*, *3rd Base* and *Upper Deck* violated the Brant test, we include these covariates in the expression for variance of idiosyncratic value. In addition, we also include the covariate *Frequency* in the variance expression, as we believe that repeated visits should help respondents learn the "true value" of the game experience, and consequently reduce the residual variation in their net value perceived. We estimate the parameters of the heteroskedastic ordinal

[8]Ignoring systematic differences in variances across seat locations might lead to incorrect conclusions in some cases. For instance, consider two identical groups of consumers in a theater, who are seated at locations A and B, who have the same mean idiosyncratic value, but group A has twice the variance realized by group B, i.e., $\beta_A = \beta_B$, but $\sigma_A = 2\sigma_B$. This case is illustrated in Figure 3. Now, if we assumed that variances are equal at both locations, it would lead us to the erroneous conclusion that $\hat{\beta}_A = 0.5\hat{\beta}_B$, where $\hat{\beta}_i$ is an estimate of the true parameter β_i. Hence, accounting for heteroskedasticity is critical.

[9]Note that the heteroskedastic ordinal logit model does not display proportional odds for the covariates in $\mathbf{z}_i$. This can be seen by writing out the expression for log-odds of $V_i \leq j$ conditional on $\mathbf{x}_i$, and observing that the effect of the covariates $\mathbf{z}_i$ on the log-odds is now dependent on the threshold level j:

$$\log(\text{Odds}(V_i \leq j \mid \mathbf{x}_i)) = \frac{\tau^j - \mathbf{x}_i^T\beta}{\exp(\mathbf{z}_i^T\gamma)}.$$

logit model using the *OGLM* routine (Williams 2006b) in STATA 10.0.

From the results summarized in Table 2, we observe that the covariates *Frequency*, *Side* (except *3rd Base*) and *Upper Deck* have significant β coefficients. All the γ coefficients included in the variance equation are significant. We can draw several interesting inferences from these results.

Controlling for heteroskedasticity, we find that respondents at the third base have the same average net value as respondents at the first base, as $\hat{\beta}_5$ is not significant. However, the respondents seated on the third base side have *significantly less* variance in the net value realized (standard deviation is 1-exp($\hat{\gamma}_5$) = 28% lower) as compared to those seated on the first base side. This could be due to the location of the home team dugout and/or the relative incidence of foul balls/home runs on the left field. Figure 3 details a comparison of reported SVIs for a customer located on the first base side and the third base side.

We find that the net value experienced by respondents seated at the upper deck has a higher mean ($\hat{\beta}_{10} = 0.263, p = 0.04$), as well as a higher variance ($\hat{\gamma}_{10} = 0.208, p = 0.0408$), when compared to the net value experienced by respondents seated at the lower deck. The net value experienced by customers visiting more frequently has a lower mean ($\hat{\beta}_{11} = -0.081, p = 0.028$) and a lower variance ($\hat{\gamma}_{11} = -0.058, p = 0.074$). Age of a respondent does not affect the mean of net value experienced, but older respondents tend to have lower variance in the net value experienced.

The current dataset has only one response for each consumer. Hence, it is not possible to econometrically distinguish between the Generalized Threshold Model and the Heteroskedastic Model. The observed deviation from proportional-odds could be a manifestation of consumers using different thresholds, or of the value distribution being heteroskedastic across seat locations. Hence, the applicability of either model must depend on the appropriate interpretation. For example, it is more likely that heterogeneity across consumers is explained by thresholds, while heterogeneity across seat locations is better explained by differences in the idiosyncratic value distribution. We interpret our results accordingly.

3.6 Achieving the Service Objective

Let us now consider the aforementioned service-level objective that we discussed before, where the firm aims to set prices such that the probability of a customer reporting low SVI is limited to a maximum threshold level, α, at all seat locations l. In Lemma 1, we derive an expression for the price change at each seat location that would help the firm achieve this objective, using the heteroskedastic ordinal logit model specification.

Lemma 1 *Let* $\mathbf{x}_l$ *denote the vector of covariates for a customer seated at location* l*. Let* α, β, γ *and* $\mathbf{z}_l$ *be defined as in the heteroskedastic ordinal logit model, and* θ *denote the price elasticity of*

V_l^*. *To limit the probability of this customer reporting SVI=1 at seat location* l *to a threshold* α, *the required price change* Δp_l *is given by*

$$\Delta p_l = \frac{1}{\theta}\left\{-\tau^1 + \mathbf{x}_l^T\beta + \Lambda^{-1}(\alpha)\exp(\mathbf{z}_l^T\gamma)\right\} \tag{5}$$

Proof : At current prices, the probability of a typical customer reporting SVI as low is given by

$$\Pr(V_l^* \leq \tau^1) = \Lambda\left(\frac{\tau^1 - \mathbf{x}_l^T\beta}{\exp(\mathbf{z}_l^T\gamma)}\right) \tag{6}$$

Increasing the ticket price for seat location l by Δp_l would change this probability to

$$\Pr(V_l^* - \theta\Delta p_l \leq \tau^1) = \Lambda\left(\frac{\tau^1 + \theta\Delta p_l - \mathbf{x}_l^T\beta}{\exp(\mathbf{z}_l^T\gamma)}\right).$$

Equating this to α, we can calculate the desired price change Δp_l shown in Equation (5).

We apply the results of this lemma in Section §3.8 to derive price changes for a baseball franchise. Note that we could allow the service-level thresholds to differ across seat locations by specifying different αs.

3.7 Calculating Marginal Probabilities

The main purpose of our model is to predict the probability that a consumer seated at a particular seat location reports a certain SVI. In order to manage SVI, it is crucial to understand how these probabilities of a consumer reporting a certain SVI change with seat location and other covariates. Regression coefficients only explain the mean effects. In contrast, marginal probabilities measure how a change in a covariate impacts the distribution of the response variable.[10] Hence we calculated the marginal probabilities of the impact of different covariates on SVI. While measuring the marginal probability effects of any covariate, we define a *typical customer* for every covariate by fixing the rest of the covariates at their mean (or their mode for categorical covariates).

We use the MFX2 routine in STATA 10.0 to estimate the marginal probability effects and the results are summarized in Table 3, and interpreted in Section §5. Note that both the generalized threshold and heteroskedastic models provide comparable marginal probability estimates. Therefore, irrespective of the non-proportional-odds model considered, we obtain the same qualitative insights. As indicated before, we employ the threshold interpretation for consumer attributes (such as age, gender, frequency of visit, etc.), and the heterogeneity interpretation for all seat attributes.

[10]If we let x_{il} denote the value of the l^{th} covariate for respondent i, then the marginal probability effect is given by $\frac{\partial \Pr(V_i=j|\mathbf{x}_i)}{\partial x_{il}}$ for a continuous covariate and $\Delta \Pr(V_i = j \mid \mathbf{x}_i)$ for a categorical covariate.

Table 3: Marginal Probability Effects of Ordinal Logit Models for Select Covariates[a]

SVI	Variable	Standard	Generalized	Heteroskedastic
Low	Age	-0.006	-0.017**	-0.024***
	3rd Base	-0.056**	-0.114***	-0.102***
	Backnet	0.114***	0.107**	0.116***
	Field	0.151***	0.139**	0.143***
	Grass	-0.149***	-0.118***	-0.136***
	Upper Deck	-0.033	-0.009	-0.013
	Frequency	0.017**	0.013	0.006
	Team 1	-0.034*	-0.035*	-0.043**
Medium	Age	0.004	0.024***	0.030
	3rd Base	0.035**	0.143***	0.131***
	Backnet	-0.086**	-0.084**	-0.090**
	Field	-0.120**	-0.114**	-0.120**
	Grass	-0.023	0.039**	0.011*
	Upper Deck	0.021	-0.032	-0.036
	Frequency	-0.011**	-0.003	0.008
	Team 1	0.022*	0.025	0.030**
High	Age	0.002	-0.007**	-0.0087**
	3rd Base	0.021**	-0.029**	-0.031**
	Backnet	-0.029***	-0.023***	-0.026***
	Field	-0.031***	-0.025***	-0.027***
	Grass	0.172***	0.079***	0.120***
	Upper Deck	0.012	0.041***	0.048***
	Frequency	-0.006**	-0.010**	-0.013**
	Team 1	0.012*	0.010*	0.013**

[a] *Gender, Hometown and InOut did not have significant effects.*
* p<0.1, ** p<0.05, *** p<0.01

In addition to the calculation of marginal probabilities for a typical customer, we also calculate the marginal probabilities for different customer segments (Age, Geography, Frequency of Visits). We discuss these results and their implications for *segment-specific* pricing in Section §5.1.

3.8 Calculating Price Adjustments to Achieve the Service Objective.

Suppose that the franchise wants to keep the probability of a specific customer reporting SVI = Low to a threshold α at all seats. The current probability of a specific customer seated at location l reporting SVI = Low, can be calculated using Equation (6). We can then use Equation (5) to calculate the price change required at each seat location, that would equate the probability of this customer reporting SVI = Low, to the threshold value α. The parameters (β, γ) are known from the regression estimates, while the price elasticity of SVI (θ) can be estimated using the price variation observed across seat locations.

Seat Location/ Frequency of Visits	$\Pr(V_l^* \leq \tau^1)$	$\theta\Delta p_l$	Δp_l ('000 Yen)
1st Base, Lower Deck, Infield/Outfield	20.8%	−0.249	−25.9
3rd Base, Lower Deck, Infield/Outfield	10.3%	0.197	20.5
Backnet, Lower Deck, Infield	34.7%	−0.689	−71.8
Field, Lower Deck, Infield/Outfield	37.2%	−0.758	−79.0
1st Base, Upper Deck, Infield/Outfield	19.3%	−0.236	−24.6
3rd Base, Upper Deck, Outfield	9.7%	0.278	29.0
Grass, Upper Deck, Outfield	6.8%	0.683	71.1
One Additional Visit	20.8%	−0.269	-28.0

Table 4: Calculation of Price Increase that keeps the Probability of a typical customer reporting a Low SVI, to $\alpha = 15\%$.

We now illustrate this calculation for a typical customer of the franchise (Age=4.22, Gender=Male, Hometown=City, Frequency=2.68) and a threshold of $\alpha = 15\%$. Table 4 summarizes the current service levels and the price changes (Δp_l) that achieve the threshold service level of $\alpha = 15\%$ for a typical customer. Note that the franchise might be interested in achieving this service objective for different consumer segments. We discuss this in Section 5.1.

4 Validation: Effects of Game, Seat Location and Prices

In this section, we validate our empirical results using various robustness checks. Specifically, we study game related effects with an additional dataset and the effects of price on seat value. In addition, we compare the effect of seat specific attributes (such as seat location) vs. customer specific attributes (such as age) on SVI.

4.1 Model Validation

The standard approach to validate regression models is to estimate the model parameters on a calibration sample and validate those results on a hold-out sample. Accordingly, we constructed a calibration sample and a validation sample by randomly splitting our data-set into two equal parts. We measured the predictive accuracy of our model using an R^2 measure (see Equation 7), and find that $R_H^2 = 57.1\%$, which implies that the model significantly improves prediction accuracy over a naive model. Figure 4 shows a comparison of the actual number of respondents at each seat location reporting a particular SVI, with the expected numbers predicted by the model for the hold-out sample. These predictions generally match the distribution of the SVI for various seat locations.

While the R^2 is an indirect measure of predictive accuracy computed at a highly disaggregated

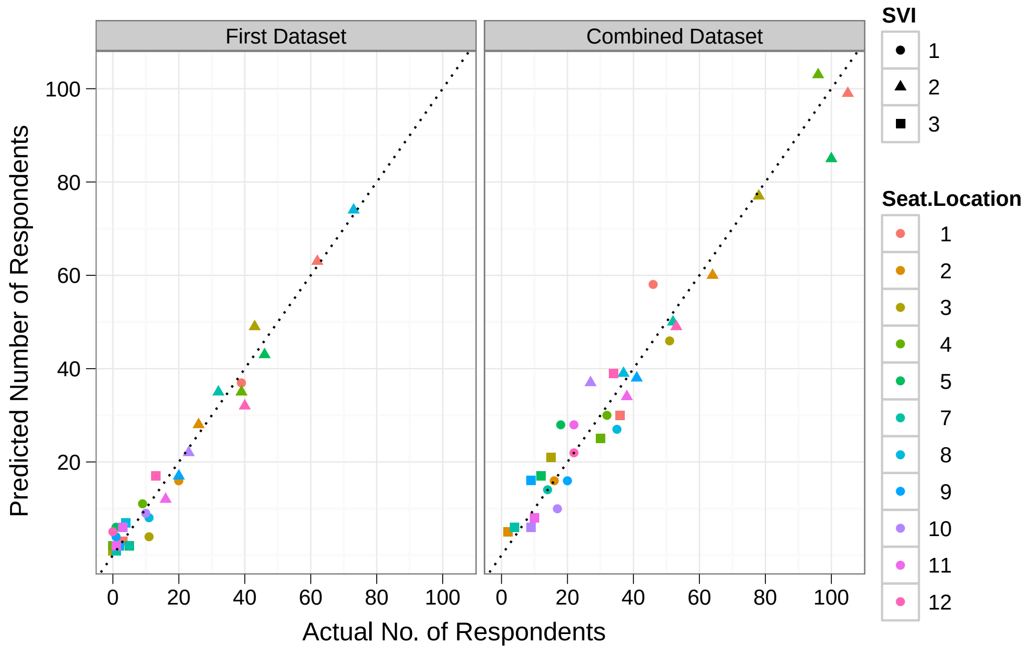


Figure 4: Comparison of the actual number of respondents at a given seat location reporting a particular SVI with those predicted by the model for a hold-out sample. The graph on the left shows the comparison for the first dataset, while the graph on the right shows the comparison for the combined dataset.

level, a more direct measure is the accuracy of the predicted service level, $\Pr(SVI = 1)$. Computing the predicted service level for the hold-out sample, we find that while the actual service level is 19.6%, our model predicts a service level of 19.2%, thereby providing further confidence on the predictive power of our model.

We now briefly describe how we calculate our R^2 measure of predictive accuracy.

Calculating R^2: To calculate a measure of predictive accuracy, we ran the heteroskedastic ordinal logit model (M) on the calibration sample (C) to obtain estimates of the parameters β, γ and $\tau^j, j = 1, 2$. We then computed the expected number of respondents reporting SVI$= j \in 1, 2, 3$ at each seat location l, for the hold-out sample (H), using the following expressions.

$$E^M_{lH}[SVI = j] = \sum_{i \in H, Location = l} \Pr(SVI_i = j|\mathbf{x_i}).$$

A naive model (N) would estimate this probability of reporting SVI$= j$ as $\frac{1}{|C|}\sum_{i\in C}\mathbf{I}(SVI_i = j)$, which would predict the expected number of respondents reporting SVI$= j$ at seat location l as

$$E^N_{lH}[SVI = j] = \frac{n_{lH}}{|C|}\sum_{i\in C}\mathbf{I}(SVI_i = j),$$

where n_{lH} is the number of respondents in the hold-out sample, seated at location l.

If we let n_{lH}^{j} be the number of respondents in the hold-out sample seated at location l reporting SVI= j, then we can calculate the squared error of predicting n_{lH}^{j} using the ordinal logit model (M) as $\epsilon_H^M = \sum_{l \in AllLocations} \sum_{j \in 1,2,3} \left(n_{lH}^{j} - E_{lH}^{M}[SVI = j] \right)^2$. We can compute an R^2 measure of predictive accuracy by comparing the ratio of ϵ_H^M to the squared errors of the naive model $\epsilon_H^N = \sum_{l \in AllLocations} \sum_{j \in 1,2,3} \left(n_{lH}^{j} - E_{lH}^{N}[SVI = j] \right)^2$, which gives us

$$R_H^2 = 1 - \epsilon_H^M / \epsilon_H^N. \tag{7}$$

4.2 Game Effects

Clearly, SVI is influenced by the actual game/event and hence it is important to consider the robustness of our results to variations across games. For instance, the outcome of the game, the composition of the playing teams, or the weather could have affected the seat value distribution customers reported. However, this limitation could be easily overcome by surveying consumers from multiple games and employing the same methodology to analyze the collected data and explore specific recommendations.

While the ideal way to test this would be to conduct the same survey across multiple games, record key game related attributes (result, attendance, visiting team, etc.) and use them as control variables in the regression equation, for reasons beyond our control, the franchise chose to vary some aspects of the survey across multiple games. For instance, a survey conducted during a different game included many of the same questions as before (Age, Gender and Seat Location), but did not capture a few variables like Hometown and Frequency. We decided to combine the data from these two surveys to check the robustness of our results, especially the relationship between SVI and Seat Location, to inter-game variations.

We modify our regression equation for the HOLM by including only the common covariates across the two surveys and adding a fixed effects parameter to control for difference in valuations across games. The modified regression equation can be written as

$$\begin{aligned} V_i^* \; = \; & \beta_1 \text{Age}_i + \beta_2 \text{Male}_i + \beta_5 \text{3rdBase}_i + \beta_6 \text{Backnet}_i + \beta_7 \text{Field}_i + \beta_8 \text{Grass}_i + \\ & \beta_9 \text{Outfield}_i + \beta_{10} \text{UpperDeck}_i + \beta_{13} \text{Game}_i + \sigma_i \epsilon_i, \end{aligned}$$

where ϵ_i is a standard logistic random variable, and σ_i is a heteroskedastic variance scaling factor given by

$$\sigma_i = \exp(\gamma_1 \text{Age}_i + \gamma_5 \text{3rdBase}_i + \gamma_{10} \text{UpperDeck}_i + \gamma_{13} \text{Game}_i).$$

Note that the parameter γ_{13} captures differences in the variance of the distribution of seat values across the games. Table 5 shows a comparison of the parameter estimates obtained using the combined dataset with those obtained from the single game. Note that all our verifiable conclusions hold even after we control for variations across games. Customers seated on the 3rd Base continue to experience lower variance in the seat value perceived ($\gamma_5 = -0.319, p < 0.001$), while the means show no statistically significant differences. Similarly, customers seated on the Upper Deck continue to have higher mean valuations ($\beta_{10} = 0.303, p < 0.001$) as well as higher variance ($\gamma_{10} = 0.140, p < 0.05$). This suggests that our findings might be robust across games.

It is interesting to note that while the mean valuations across games are not significantly different ($\beta_{13} = 0.055, p = 0.64$), the variances are significantly different ($\gamma_{13} = 0.854, p < 0.001$). In other words, the shape of the distribution of seat values is significantly influenced by the game. For instance, the first survey was conducted during a game that the home team lost, while the second survey was conducted during a game that the home team won. The result of the game could explain a portion of the difference in variances. Nevertheless, even after controlling for differences across the games, our seat value results remain largely unchanged.

Repeating the validation analysis discussed in Section 4.1, we find that even for the combined dataset, the model significantly improves the predictive power over the naive model ($R^2_H = 56.1\%$, see Table 4 for a summary of the results).

4.3 Seat Location Effects

The experience in such entertainment settings is clearly a function of the product (the game in the context of our paper), the consumer and her seat location. Hence it is important to investigate how much of SVI is accounted for by each of these factors (game attributes, consumer attributes and seat location attributes). We study the relative impact of each of these three factors in influencing SVI, by following a three-step approach:

1. First, we ran several heteroskedastic ordinal regressions using a combination of these three factors as explanatory variables, both on the original dataset as well as the combined dataset.

2. Second, we measured the ability of each of these models to predict the number of consumers reporting a particular SVI at each seat location, using the R^2 defined in Equation (7).

3. Third, we compared the computed R^2 across the different models to understand the contribution of each of the three factors in predicting SVI.

Variable		Single Game	Combined
Age	β_1	0.034	-0.007
Male	β_2	-0.034	-0.146
City (vs. Outside)	β_3	0.011	
Prefecture (vs. Outside)	β_4	0.102	
3rd Base (vs. 1st Base)	β_5	**0.145**	**0.080**
Backnet (vs. 1st Base)	β_6	-0.440***	-0.126
Field (vs. 1st Base)	β_7	-0.509***	-0.449**
Grass (vs. 1st Base)	β_8	0.919***	1.055***
Outfield	β_9	0.171	-0.153
Upper Deck	β_{10}	0.263**	0.303***
Frequency	β_{11}	-0.081**	
Team 1	β_{12}	0.185**	
Game	β_{13}		0.055
Age	γ_1	**-0.075*** **	**-0.062** **
3rd Base (vs. 1st Base)	γ_5	**-0.324*** **	**-0.319*** **
Upper Deck	γ_{10}	**0.208*** **	**0.140** **
Frequency	γ_{11}	-0.057*	
Game	γ_{13}		0.854***
Log Likelihood	LL	-726.27	-2043.87
Likelihood Ratio χ^2	LR	192.72	364.82
No. of Parameters		16	18
McFadden Pseudo R^2		11.71%	8.19%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Comparison of Parameter Estimates for the Single Dataset vs. the Combined Dataset

Applying this analysis to the original dataset, we find that while the model consisting of both consumer and seat-location factors had an R^2_H of 57.1%, a *major portion of SVI is accounted for by seat location attributes* (with an R^2 of 56.1%*)*, while consumer attributes have almost insignificant predictive power ($R^2 = 6\%$).

To investigate how seat location factors influence SVI once we control for game related attributes, we applied the same analysis to the combined dataset. We find that while all three factors combined together have an R^2_H of 56.1%, *seat location attributes still account for a major portion of the SVI*, with an R^2_H of 38.5%, even after controlling for game related factors (See Table 6).

The analysis summarized in Table 6 emphasizes that seat location factors explain a significant portion of SVI. Game and Consumer attributes do matter, but explain a smaller portion. This finding underscores the importance of seat location factors in influencing seat value. It also strengthens the case for the need for studies like ours that shed more light on the drivers of seat value. Finally, firms have reasonable control over seat location factors, and hence can take advantage of these findings to manage SVI.

Explanatory Variables	First Dataset R_H^2	Combined Dataset R_H^2
Consumer Attributes	6.0%	9.1%
Seat Location Attributes	56.1%	38.5%
Game Attributes		17.3%
Consumer + Seat Location Attributes	57.1%	51.1%
Consumer + Game Attributes		17.7%
Seat Location + Game Attributes		55.6%
All Attributes		56.1%

Table 6: Predictive Accuracy of Consumer Attributes, Seat Location Attributes and Game Attributes. Note that sub-models that include seat location attributes have higher predictive accuracy than those models that do not include them.

4.4 Seat Price Effects

In order to properly estimate the relationship between seat value and seat location, we need to further isolate the effect of the location-dependent price variable. We address this issue by studying the relationship between SVI and Seat Location, controlling for the price variable. To achieve this, we consider three versions of the Heteroskedastic Ordinal Logit Model.

1. The original model described in Section 3.5 that does not include ticket price.

2. A model that included the ticket price for each seat section in addition to all the other covariates.

3. A model that includes ticket price for each seat section, but excludes all the seat location attributes.

The motivating question behind this analysis is to determine the extent to which the introduction of ticket prices impact our results. From Table 7, we observe that seat location attributes continue to explain a significant portion of SVI even after controlling for ticket price, as can be seen by comparing the McFadden Pseudo-R^2 of Models (b) and (c). In fact, adding seat location attributes to Model (c), which uses only ticket price, increases the pseudo-R^2 from 5.5% to 12.4%. Finally, we find that most of our results and inferences made in Section 3.5 continue to hold.

1. The effect of Age on SVI remains almost unchanged, as seen by the β and γ coefficients in Models (a) and (b).

2. Frequency of Visits have almost the same effect on SVI as before. The estimates for both the mean effect and the variance effect remain almost unchanged.

Variable		HOLM[a]	HOLM with Price[b]	HOLM with Price and NO Seat Attributes[c]
Threshold: Low-Medium	τ^1	-0.748***	-2.71***	-1.34***
Threshold: Medium-High	τ^2	2.067***	0.09	1.24***
Age	β_1^j	0.034	0.03	-0.02
Male	β_2^j	-0.034	-0.03	-0.02
City (vs. Outside)	β_3^j	0.011	0.009	0.010
Prefecture (vs. Outside)	β_4^j	0.102	-0.101	-0.100
3rd Base (vs. 1st Base)	β_5^j	0.145	0.110	
Backnet (vs. 1st Base)	β_6^j	-0.440***	4.642***	
Field (vs. 1st Base)	β_7^j	-0.509***	-0.311	
Grass (vs. 1st Base)	β_8^j	0.919***	0.722***	
Outfield	β_9^j	0.171	-0.221	
Upper Deck	β_{10}^j	0.263**	-0.042	
Frequency	β_{11}^j	-0.081**	-0.071***	-0.053
Team 1	β_{12}^j	0.185**	0.184***	0.224**
Price	β_{13}^j		-0.01***	-0.001***
Age	γ_1	-0.075***	-0.080***	-0.071***
3rd Base (vs. 1st Base)	γ_5	-0.324***	-0.367***	
Upper Deck	γ_{10}	0.208***	0.223***	
Frequency	γ_{11}	-0.057*	-0.062***	-0.072***
McFadden Pseudo R^2		11.71%	12.4%	5.5%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Parameter Estimates

3. The asymmetry that we identified in the paper still holds, as can be seen from the γ coefficient for the 3rd Base. The mean effect still stays insignificant.

4. Consumers still find Grass seats very valuable, as seen from the β coefficient.

5. The mean effect of Backnet has changed significantly (β is now positive). This might be because price affects SVI non-linearly, or that Backnet customers are significantly different. The variance effect that we identified, on the other hand, remains almost unchanged.

6. The β parameter corresponding to the Upper Deck is no longer significant. However, the heterogeneity effects still persist. In fact, the parameter estimates show no significant change. ($\gamma_{10}^a = 0.208, \gamma_{10}^b = 0.223$)

The surveys did not ask consumers for the actual price that they paid, as the franchise felt that consumers might be more biased in their responses if price related information was asked. Hence, we only had seat prices at each section. The absence of variation in price across consumers seated at the same location renders any regression involving location and seat prices susceptible to the effects

Age	3rd Base	Backnet	Field	Grass
0-9	-10.6%	12.4%	14.6%	-17.4%
10-19	-10.8%	13.0%	15.2%	-17.0%
20-29	-10.8%	13.5%	15.8%	-16.3%
30-39	-10.6%	13.8%	16.3%	-15.3%
40-49	-10.2%	14.0%	16.6%	-14.2%
50-59	-9.6%	14.0%	16.7%	-12.8%
60+	-8.7%	13.8%	16.6%	-11.2%

Table 8: Marginal Probability of SVI=Low by Age (Reference: 1st Base, Infield, Lower Deck)

of multicollinearity. This also makes it difficult to isolate the effects of price from seat location. Hence, we study the impact of different prices paid by consumers, by adding a random noise term to perturb the ticket price specified for each seat section. Accordingly, the price paid by consumer i for a seat in section l was modeled as $p_{il} = p_l * (1 - \psi_i)$, where p_l is the ticket price specified for section l and ψ_i is the noise term distributed uniformly over $[0, m]$. Based on conversations with the franchise management on the range of discounts provided to consumers, we varied m from 5% to 20%. We repeated the analysis discussed above with these prices, and find that our results remain unchanged.

5 Findings and Pricing Recommendations

Based on robustness checks in Section §4, we are able to underline the importance of seat location in influencing consumer experience. Hence it is appropriate to consider seat-location specific prices for each consumer segment.

5.1 Segment Specific Pricing

In Sections 3.7 and 3.8, we discussed the calculation of marginal probability effects for a typical consumer and the price changes across seat locations required to achieve a service-level objective of $\alpha = 15\%$. However, the firm could engage in more targeted pricing schemes based on how the marginal probabilities varied across consumer segments. We now calculate the marginal probability effects for different seat locations for each consumer segment based on age groups (Table 8) and visiting frequencies (Table 9).

From the marginal probability tables, we infer that customers in the age group 40 - 49 years and 50 - 59 years tend to have the highest probabilities of reporting low SVI for the Backnet and Field seats, as compared to a similar seat on the 1st Base side. Hence, the franchise could offer reduced prices for these customers for the Backnet and Field seats.

Frequency	3rd Base	Backnet	Field	Grass
First Time	-10.0%	12.0%	14.2%	-13.6%
Once	-10.3%	13.1%	15.5%	-14.4%
Thrice	-10.7%	14.3%	16.9%	-15.4%
Five Times	-11.1%	15.6%	18.5%	-16.6%
All Games	-11.5%	17.2%	20.2%	-18.0%

Table 9: Marginal Probability of SVI=Low by Frequency of Visits (Reference: 1st Base, Infield, Lower Deck)

We also infer that the regulars to the games have a much higher propensity to report a low SVI for the pricier Backnet and Field seats. Given that it is important for the franchise to manage the satisfaction levels of its most loyal customers, the franchise could offer discounts for multi-game tickets for selected stadium seats on the Backnet and Field, and set prices such that the dissatisfaction levels are below an appropriate threshold.

It is also interesting to note that for the Grass and 3rd Base seats, the first-timers are more likely to report a low SVI. Hence the franchise can encourage people to start watching games in the stadium by offering special discounts to newcomers, on the Grass and 3rd Base seats, or reserving a portion of these seats at lower prices for the first-timers.

The recommended segment-specific price changes for each seat section are summarized in Tables 10 (for consumer segments based on age) and Table 11 (for consumer segments based on frequency of visits).

Table 10: Price Change Percentage to set Pr(SVI=Low) to $\alpha = 15\%$

Age	3rd Base	Backnet	Field	Grass
0-9	-6.0%	-14.8%	-52.7%	25.1%
10-19	-1.0%	-13.0%	-46.6%	37.7%
20-29	3.8%	-11.3%	-40.9%	49.7%
30-39	8.3%	-9.7%	-35.5%	61.1%
40-49	12.7%	-8.1%	-30.3%	71.8%
50-59	16.8%	-6.7%	-25.4%	82.1%
60+	20.8%	-5.3%	-20.8%	91.8%

Table 11: Price Change Percentage to set Pr(SVI=Low) to $\alpha = 15\%$

Frequency	3rd Base	Backnet	Field	Grass
First Time	12.0%	-8.9%	-33.1%	66.1%
Once	10.5%	-9.1%	-33.8%	64.6%
Thrice	8.8%	-9.4%	-34.6%	62.9%
Five Times	6.9%	-9.7%	-35.6%	60.8%
All Games	5.0%	-10.0%	-36.7%	58.4%

5.2 Actionable Pricing Recommendations

We now develop more concrete and actionable pricing recommendations that would help a franchise achieve a specified threshold service level on any given set of seat products that they might make available. In Lemma 1 in the paper, we derived an expression for the price change at each seat location that would help the firm achieve its service level objective of keeping $\Pr(SVI_l \leq 1 \mid p_l^*)$ to a threshold α. If we let p_l denote the current seat price, then we can use Lemma 1 to calculate the new price p_l^* to be charged at each seat location as:

$$p_l^* = p_l + \frac{1}{\theta}\left\{\mathbf{x}_l^T\beta - \tau^1 + \ln\left(\frac{\alpha}{1-\alpha}\right)\exp(\mathbf{z}_l^T\gamma)\right\}$$

This equation prices each seat location for a specific consumer whose characteristics are known. However, we can use this equation to price any set of seat products that a baseball firm could make available. For example, a firm is interested in setting a single price for each seat location such that the service level constraint is met. We can derive the new price p_l^* to charge consumers by taking a weighted average of the new prices derived using Lemma 1 over the distribution of consumer characteristics. Alternately, if the firm wants to provide targeted prices for specific consumer segments (e.g. Age, Frequency, Age-Frequency combination), then the new price to charge each segment can be derived by taking a weighted average of the new price over the distribution of the remaining consumer characteristics.

We now illustrate the application of this method in calculating seat prices. First, we calculate the location specific seat prices that the firm should set in order to achieve the service level objective for each seat location. The results are summarized in Table 12. From the seat location specific prices calculated in Table 12, we observe that the seat prices across 3rd base and 1st base are asymmetric. In fact, the seats located on the 3rd base command a 33% premium on average as compared to those on the 1st base. Moreover, as one would expect, seats on the lower deck continue to be priced higher than those on the upper deck.

Now, the firm can do better by setting targeted prices for specific consumer segments. For instance, as suggested by you, the firm can target specific age groups such as students, regulars and retirees. The price to charge each group for a particular seat location are calculated as in Table 12. Note that, as expected, student tickets are heavily discounted across seat locations, while retirees are made to pay a premium.

In addition, the firm might also consider targeting consumers based on their frequency of visits by setting different prices for five game packs and season passes. From the seat prices based on frequency, as summarized in Table 12, we observe that season passes are discounted, compared to single game tickets. An interesting thing to note is that the maximum discount for season passes occurs for 3rd base tickets, which suggests that the firm stands to gain by exploiting the asymmetry in more than one way.

While we have illustrated price calculations for some specific instances of variable pricing, our method is general enough to accomodate more complex forms. For example, the firm might want to offer price bundles based on combination of age and frequency of visits. In this case, we can integrate the consumer specific seat prices across the distribution of remaining consumer characteristics (Gender, City, Team1 etc.) to derive the best price for each bundle that achieves a given service level.

					Price ('000 Yen)				
Seat	**Location**	**Section**	**Row**	**Seat Price**	**Student**	**Regular**	**Retirees**	**Five Game**	**Seasons**
1	Backnet	Infield	Lower	698	667	693	727	694	692
2	3rd	Infield	Lower	242	216	236	263	238	234
3	3rd	Outfield	Lower	165	147	167	194	162	158
4	3rd	Infield	Upper	174	148	171	203	170	167
5	3rd	Outfield	Upper	185	166	189	220	182	179
7	1st	Infield	Lower	198	166	192	226	195	192
8	1st	Outfield	Lower	126	97	123	157	123	120
9	1st	Infield	Upper	123	87	117	157	122	120
10	1st	Outfield	Upper	127	103	133	172	127	126
11	Field	Infield	Lower	149	119	145	179	145	143
12	Grass	Outfield	Upper	200	167	197	235	200	198

Table 12: Seat Prices by Consumer Segment to Achieve Service Level Objective of $\alpha = 15\%$

The ideal way to test the impact of our recommendations would have been to offer the new prices to consumers and observe the resulting distribution of SVIs. However, that approach was not feasible, in our case, as it required the franchise to implement price changes across the board, and conduct the survey post implementation. Hence, we used the demographic profile of consumers in our validation sample to calculate the achieved service levels, assuming that consumers had paid these set prices. From Table 13, we clearly observe that the new prices achieve a service level very close to the threshold of $\alpha = 15\%$ that we set out to achieve.

					Pr(SVI = 1|Validation Sample)				
Seat	**Location**	**Section**	**Row**	**Seat Price**	**Student**	**Regular**	**Retirees**	**Five Game**	**Seasons**
1	Backnet	Infield	Lower	0.143	0.146	0.150	0.163	0.152	0.127
2	3rd	Infield	Lower	0.162	0.162	0.155	0.155	0.161	0.141
3	3rd	Outfield	Lower	0.150	0.150	0.144	0.146	0.131	0.127
4	3rd	Infield	Upper	0.140	0.137	0.155	0.166	0.152	0.115
5	3rd	Outfield	Upper	0.151	0.144	0.143	0.121	0.129	0.124
7	1st	Infield	Lower	0.151	0.151	0.155	0.144	0.161	0.132
8	1st	Outfield	Lower	0.180	0.169	0.167		0.167	0.112
9	1st	Infield	Upper	0.170	0.163	0.157	0.156	0.165	0.162
10	1st	Outfield	Upper	0.160	0.147	0.154		0.145	0.119
11	Field	Infield	Lower	0.141	0.149	0.151	0.155	0.151	0.126
12	Grass	Outfield	Upper	0.148		0.144	0.172	0.148	

Table 13: Service Levels Achieved in the Validation Sample for each Segment based on New Prices

5.3 Insights and Recommendations

Based on the results obtained, we gather several interesting insights on the net value perceived by consumers who attended the game. Our results help quantify seat value in terms of seat location characteristics and consumer attributes. Furthermore, we also characterize the distribution of SVIs that helps us determine the probability of customers reporting low SVI. We make several recommendations based on our empirical results and the service objective considered, and these are being implemented by the franchise.

1. **Seats are Asymmetric:** We find that consumers seated on opposite sides of the ball park report *asymmetric* SVIs. Thus, the distribution of SVIs reported by customers seated on the third base side is significantly different from that of customers seated on the first base side. In fact, *any* customer located on the third base side has a *lower* probability of reporting low Seat Value Index as compared to an identical customer seated in a symmetric location on the first base side. This asymmetry is intriguing. Although every professional baseball team prices its tickets identically for left field and right fields, there are several underlying asymmetries in the game/ballpark that could possibly explain this difference in perceived value. First, the incidence of foul balls is generally higher in right field, which could influence how customers respond to their experience of the game. Second, for the stadium of the franchise we study, the location of the home-team dugout was on the third base side, which possibly provided higher value for some of the fans. Third, weather related factors like sunlight, wind, etc. can affect the viewing experience across seat locations. Finally, in many professional ball parks, although the prices are always symmetric, the views from the seats are not. In fact, to many players and baseball fans, the fundamental asymmetries in the design of a ballpark add to the idiosyncratic charm of the game (Maske 1992).

Asymmetric seat values provide the franchise with an opportunity to price tickets differently while maintaining identical probabilities of experiencing low seat value on both sides of the stadium. Our recommendations would initiate differential pricing across symmetric locations and achieve two goals. First, they eliminate the *inherent asymmetry* in net value perceived (and SVIs). Secondly, they also help the franchise achieve a certain desired level of customer service. The franchise is currently implementing our recommendation of pricing the single-game tickets asymmetrically for the upcoming season.

2. **Value of Seat Locations for Consumer Segments (based on Age):** Conventional wisdom provides some guidelines on valuable seat locations in a baseball stadium. For example, Backnet seats are considered quite valuable to customers. In the introduction, we raised the question: "Do the customers seated at the upper deck value those seats highly?". Equipped with our analysis, we can now summarize the value perceived by customers at those seats, and compare our findings with

common notions of seat value. Moreover, we can do this analysis across each consumer segment.

Upper Deck Seats: First, we consider upper deck seats that are generally inexpensive, and located further away from the playing field. Our results suggest higher mean SVI for customers seated at the upper deck. While higher mean seat values are interesting in their own right, our analysis of marginal probabilities reveals a subtler insight. For example, considering a customer in the age group 30-39, we find that he has the same probability of reporting his SVI as Low (or Medium) whether he is seated at the lower deck or the upper deck. However, the probability of reporting SVI as High increases as he moves from a lower deck seat to a similar upper deck seat. In other words, the higher value perceived at the upper deck is almost entirely driven by a significantly higher proportion of customers reporting their seat value as high. Thus, our results argue for the continued availability of upper deck seats for customers.

Backnet Seats: Backnet seats are often considered to be the best seats in the stadium. However, it is unclear how the franchise should price them across consumer segments.

Our analysis implies that the franchise can offer age based discounts as summarized in Table 10. For consumers in the age group 10-19, the recommended segment-specific prices are 13% lower than the current single ticket Backnet prices, whereas for the age group 30-39, the recommended prices are 9.7% lower than current prices (see Table 10). In effect, according to our segment-specific pricing scheme, high-school/college students (in age group 10-19) should receive roughly a 5% discount for single-ticket Backnet prices, compared to the age group 30-39. The franchise can achieve the service-level objective of $\alpha = 15\%$ by suitably *discounting* the backnet seat prices, as indicated in Table 10.

Grass Seats: Grass seats located further in the outfield are similar to upper deck seats. Customers perceive significantly higher value at grass seats. In contrast to upper deck seats, this higher value is driven by a mean shift in its distribution. Conducting a segment-specific pricing analysis similar to that carried out for the Backnet seats, we find that we can increase the grass seat ticket prices and still keep the probability of low SVI within 15%.

3. **Segment Specific Prices based on Frequency of Visits:** We find that repeated visits to the ballpark reduce the probability that a customer would report extreme SVI. For example, we find that a customer visiting the ball-park for the eighth time has an 8% lower probability of reporting SVI = High as compared to a first-time visitor (Table 3 shows that the probability of reporting SVI = High reduces by 1% for every additional visit). Looking at the results of the Generalized Threshold Model in greater detail, we infer that a likely explanation for the reduced tendency of the more frequent customers to report extreme SVIs is that they use stricter thresholds

($\hat{\delta}^2_{11} - \hat{\delta}^1_{11} = \hat{\beta}^1_{11} - \hat{\beta}^2_{11} = 0.141$).[11] In other words, for the same experience and realization of net value, the more frequent customers are less likely to be 'surprised' and are therefore less likely to respond with extreme reactions.

While the difference in reporting thresholds seems to be the most likely explanation for the observed distribution of SVIs, one cannot rule out the possibility that the distribution of net values might be heteroskedastic with respect to frequency of visits. In fact, the results of the heteroskedastic model would suggest that the distribution of realized values for the more frequent customers does have a lower variance ($\hat{\gamma}_{11} = -0.057$) as well as a lower mean ($\hat{\beta}_{11} = -0.081$). This would support the notion that baseball games are experience goods with residual uncertainty that decreases with repeated visits to the ballpark.

Based on the segment-specific pricing analysis, we can recommend price discounts for each seat location based on frequency of visits. These prices are summarized in Table 11. First, we find that the recommended price discounts increase with increasing frequency of visits. Second, we observe that the recommended ticket prices can be higher or lower compared to the current prices. For example, at the 3rd Base, the recommended prices are $5 - 12\%$ higher, whereas at the Backnet, they are $9 - 10\%$ lower than the current prices. This leads to a subtler third insight, that the price discounts offered to a season regular (relative to a first-timer) can be as high as 6% (for the 3rd Base) and as low as 2% (for the Backnet).

6 Conclusions and Future Direction

In this paper, we first developed Seat Value Index, a measure of net value perceived by a consumer after attending an event. Then, we established the relationship between the SVIs reported by consumers and their seat locations. Finally, we provide directions that would help the firm achieve a *"desired level of seat value"* by suitably increasing or decreasing ticket prices in each segment. The key steps of our approach and methodology can be summarized as:

1. Capture on some ordinal scale, the net value perceived by consumers, using a survey instrument.

2. Design a Seat Value Index (SVI) measure.

3. Investigate how the Seat Value Index is influenced by consumer characteristics, seat location attributes and event-related factors, using a series of Ordinal Logit Models. Deviation from proportional-odds (verified using Brant test) suggests the presence of heterogeneity in the

[11] By "stricter thresholds", we mean that consumers use a higher threshold to report Low SVI, and a lower threshold to report High SVI (i.e., consumers are more likely to respond "Low", and less forthcoming to respond "High").

model, which can be incorporated in two ways: (i) The Generalized Threshold Model, which assumes that consumers use different thresholds, and (ii) The Heteroskedastic Model, which assumes that the variance of the idiosyncratic value term differs across covariates.

4. Estimate current service-levels as the probability of a given customer seated at a particular location reporting SVI=Low. Then, optimize the prices to achieve the aforementioned probability threshold acceptable to the firm (as derived in Lemma 1).

We illustrated the application of our methodology by applying it to two survey datasets collected by a professional league baseball franchise in Japan. Our findings provide a characterization of seat value perceived by consumers in a stadium based on their age, location of the seat, and the number of visits. We showed that a careful study of the interactions between SVI and the explanatory variables, specifically accounting for systematic heterogeneity in response thresholds and distributions of seat value across customer segments, reveals some relatively unexpected dependencies (asymmetries, etc.). Detailed analysis reveals that the seat location plays a crucial role in how seat values are distributed, which enables us to consider pricing based on individual segments.

The insights on seat value that we derive in this paper provide the crucial initial steps in planning how seats should be sold, and how to price tickets based on segment-specific and consumer-specific information for different sections of the stadium/theater.

Limitations: Finally, our paper is not without limitations, typical for a paper exploring empirical RM aspects. Although we know the recommended price changes from the study, to further estimate the changes in demand or customers' future valuations, firms need to perturb prices, observe resulting demand, and re-evaluate customers' responses.

The second limitation is that consumer responses to price changes might change the optimal assortment of different ticket categories both in prices and capacity offered at that price. The assortment decision can be studied with additional data on how customers arrived at their revealed preferences. Analyzing Capacitated Multinomial Logit assortment problems is a challenging stream of research. For example, see Rusmevichientong et al. (2008), and references therein. Due to paucity of data on how consumers chose their seats, we did not model the optimal assortment decision in this paper.

A third limitation is around the design of the survey. Most customers in the survey reported SVI = 2. Although this may be a natural response of consumers in our context, we cannot rule out the possibility that respondents avoided using extreme response categories (referred to as central tendency bias). Future work can focus on improved survey design and better measurement of consumer responses in order to counter these biases.

Furthermore, Neelamegham and Jain (1999) argue that modeling customers' expectations (through emotional stimulation and latent product interest) before the choice is made, and modeling post choice evaluations (determined by consumers' post consumption experience) are both important in modeling the consumption of experience goods. Thus our findings on post-consumption perceived value, combined with the decision-models of customers' revealed preferences, would allow firms to explore the impact of subsequent decisions in greater detail.

Finally, SVI is clearly influenced by the actual price paid by consumers. However, we were unable to incorporate seat prices directly into our model and study its effects in detail, as our dataset lacked granular prices at the consumer level. This presents an opportunity for future work, where more granular price data could be gathered to simultaneously study the impact of price and seat location on consumer valuations.

Nevertheless, we hope that our analysis of differing seat values provides sports franchises and theater establishments with the first steps in analyzing customer perceptions of different seats, and factoring those perceptions while making their pricing decisions. In a variety of sporting events/performances, the attending customers value their experience differently based on their seat locations. Although some seats might appear similar, they might provide different valuations for long-time patrons who have a well-developed sense about which seats have better value. Exploring such non-obvious differences in the value perceived by customers located in different seats provides sports and theater establishments with an opportunity to improve their customer base through more efficient pricing, or better selling mechanisms.

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