Journal of Service Research
Volume 12 Number 1
August 2009 73-86
© 2009 The Author(s)
10.1177/1094670508329224
http://jsr.sagepub.com

The Role of Price Tiers in Advance Purchasing of Event Tickets

Wendy W. Moe
University of Maryland
Peter S. Fader
University of Pennsylvania

This article focuses on the empirical modeling of advance purchasing and the effects of price on purchasing behavior. Because pricing strategies are typically more complex than simply setting a single price point, the authors consider multiple aspects of price: (a) use of multiple price tiers, (b) face value of tickets, and (c) discounts resulting in week-to-week variations in price. They show that failure to account for price tiers can lead to exaggerated inferences about the role of price over time. Findings reflect substantial differences across tiers. Purchasers in the high-priced tier tend to buy earlier in the selling period and are influenced by price discounts and premiums in the spot market. Purchasers in the low- and mid-priced tiers tend to delay purchasing and are influenced only by face value prices in the spot market. The authors discuss the implications of these empirical observations for future researchers and marketing managers.

Keywords: *advance selling; advance pricing; event tickets; price tiers; entertainment marketing*

In recent years, advance purchasing behavior has attracted increased attention from both marketing managers and academics. In the technology and entertainment industries, for example, marketers have been focusing more efforts on announcing and taking orders for products well before they are actually available for consumption (Knowledge@Wharton 2007). These advance orders can provide marketers with actionable information pertaining to overall demand, the diffusion process across customers, and customer responsiveness to marketing efforts (e.g., Moe and Fader 2002).

Recent theoretical research in marketing has studied a number of market environments in which advance purchasing is common (e.g., concerts, air travel) and has delineated key differences among these markets. Desiraju and Shugan (1999) differentiate among advance purchasing markets based on demand characteristics such as the nature of purchase arrivals and consumer price sensitivity, two characteristics they analytically show to drive optimal pricing policies. Other studies (Shugan and Xie 2000; Xie and Shugan 2001) have examined the role of marginal costs and capacity constraints when determining optimal advance pricing policies.

A substantial amount of research on advance purchase markets can also be found in the yield management literature, particularly with respect to airline revenue management, where dynamic pricing policies are designed to maximize revenues given capacity constraints. Many of these studies examine these dynamic pricing policies as a means to price discriminate between high and low valuation customers (e.g., Biyalogorsky et al. 1999; Borenstein and Rose 1994; Dana 1998). A key, but largely untested, behavioral assumption underlying these policy decisions is that low valuation customers purchase earlier while high valuation customers purchase later.

In this article, we take a different perspective in studying pricing in advance markets. Rather than focusing on the optimal pricing policy that would arise from a set of behavioral assumptions, we empirically examine customer purchasing and the role of price in these markets and identify regularities in behavior, particularly as they pertain to the purchase timing and nature of sales arrivals. Without a clear understanding of the underlying customer behavior, the potential benefits of optimal pricing models may be limited. Although our findings may have significant policy implications for practice, our

Authors' Note: The authors would like to thank the anonymous company mentioned in this article for providing the data and for many insightful discussions surrounding the issues tackled in this article. The authors would also like to thank Peggy Tseng for assisting with the preliminary data analysis.

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

objective is not to propose an optimal pricing policy or to provide a forecasting tool. Instead, our objective is to empirically study how customers respond to various aspects of price in the advance purchase market.

Price has several dimensions in many advance markets. The first is the existence of *price tiers,* that is, the variety of prices that are typically offered at any given time. For example, tickets for a given event may vary dramatically in price depending on the quality of the seats. As a result, each price tier tends to attract a different segment of buyers, unique in their valuation for the performance, purchase timing, and price responsiveness over time. The second is the ticket's *face value,* which is set in advance for a given tier of tickets and generally remains unchanged throughout the duration of the selling period. Finally, we model the effects of *price discounting,* a common practice that leads to week-to-week variations in price.

We focus on the advance market for arena events. Like in the airline industry, event tickets are generally available for purchase months before the actual performance takes place. Also like in the airline industry, different price tiers exist for the same performance (or flight). However, the differences across the two industries are stark. Most notable is the fact that strategic dynamic ticket pricing is not a common practice among box offices and major ticket distributors as it is in the airline industry. In the airline industry, a well-known practice is to offer lower prices to leisure travelers who tend to plan their trips well in advance of the travel date while raising prices as the flight time approaches for the last minute business travelers. This is not a pricing policy seen in the event tickets market. Instead, prices tend to be set in advance and remain stable throughout the selling period. Occasionally, some price discounts are offered, but these offerings tend not to be a result of any strategic week-to-week decisions made by the ticket sellers. As a result, price discrimination among ticket buyers occurs primarily when the consumers choose their price tiers or use discount codes and is rarely the result of any strategic dynamic pricing policy.

One relevant empirical article that moves away from the airline setting is that of Leslie (2004), who examined price discrimination in Broadway theater tickets through the use of price tiers and couponing. The focus of his research was on the buyer's price sensitivity and choice of tier. When and what a consumer purchased depended on the ticket price, transaction costs, and (in particular) capacity constraints. Although Leslie examined the consumer's choice of price tiers and response to price discounting, he did not address any differences in purchase timing among the available tiers (which reflect differences between low versus high valuation customers).

Despite the prominent focus on capacity constraints in many of these papers, surprisingly few events actually bump into such constraints. Although the press tends to highlight the sold-out Hannah Montana concert or playoff basketball game, most arena performances (primarily concerts, sporting activities, and family shows) take place with excess capacity. Although Leslie's (2004) study of Broadway shows emphasized the effects of capacity constraints, only 12 of the 199 performances in his data set were sold-out shows—and those were held in theaters with far smaller capacity than most arenas. In our data set, not a single performance sold out its capacity, either for the entire venue or for specific price tiers. Therefore, in this article, we examine advance purchase behavior in the absence of capacity constraints—and we are quite comfortable generalizing from the observations we make here.

We develop a Weibull timing model of purchasing for each tier that describes both the purchase timing decision of buyers in that price tier as well as measuring their responsiveness to various dimensions of price through the use of time-varying (and tier-specific) price-related covariates. We also incorporate into the model a measure of spot market size (i.e., the number of tickets sold in the week of the event). In this component of the model, we allow the pricing schedule employed in the advance selling period to affect the relative size of the spot market.

Although previous research has modeled the nature of sales arrivals in advance markets using stochastic models, authors have done so at the aggregate performance level rather than at the price tier level (for a review, see McGill and van Ryzin 1999). By examining sales arrivals for specific price tiers, we can empirically examine and compare the behaviors of buyers with different valuations for the performance.

Our findings show that advance purchasing behavior tends to vary dramatically across different price tiers even within a single performance. We examine a highly varied set of events and find consistent results across them. Although buying behavior varies across price tiers, buyers are virtually unaffected by the face value price or week-to-week price variations in the advance selling period. The only element of price that is important to these buyers is the price tier. Spot market buyers, on the other hand, are influenced both by face values (in the low- and mid-priced tiers) and the spot market price relative to the advance price (in the high-priced tier). Overall, however, the largest source of variation in behavior arises from the differences across price tiers rather than any pricing strategy within tier. This is a significant finding that we hope will contribute to the extant literature as well as to how event marketers think about pricing.

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Table 1
Descriptive Information for Event Performances

Event Location	Month	Total Sales	Range of Prices Paid	Selling Weeks
1. New York, NY	April 2004	12,252	$5.00–$169.95	18
2. New York, NY	March 2004	9,929	$5.00–$169.95	16
3. San Diego, CA	February 2004	8,247	$7.00–$56.30	10
4. Atlanta, GA	February 2004	7,979	$5.00–$101.35	15
5. Albany, NY	April 2004	7,713	$5.50–$37.15	17
6. Phoenix, AZ	June 2004	7,198	$2.50–$79.75	10
7. Los Angeles, CA	January 2004	6,695	$5.00–$56.30	11
8. Nashville, TN	January 2004	6,336	$5.75–$43.25	10
9. Raleigh, NC	February 2004	6,274	$10.00–$42.80	8
10. Kansas City, MO	March 2004	6,160	$9.50–$48.90	9
11. San Antonio, TX	June 2004	6,048	$5.00–$40.05	10
12. Sacramento, CA	February 2004	5,891	$10.00–$55.00	13
13. Phoenix, AZ	January 2004	5,405	$2.50–$58.90	13
14. Miami, FL	April 2004	5,036	$8.50–$58.00	12
15. Laredo, TX	May 2004	4,845	$8.25–$44.50	7
16. Miami, FL	January 2004	2,866	$2.50–$41.70	9
17. New Orleans, LA	May 2004	2,746	$10.50–$40.50	8
18. Jacksonville, FL	April 2004	1,950	$10.00–$54.25	10
19. Wheeling, WV	March 2004	1,720	$5.00–$23.55	6
20. Atlantic City, NJ	May 2004	1,548	$6.50–$66.00	10
21. Madison, WI	May 2004	561	$6.00–$33.25	5
22. Miami, FL	March 2004	428	$1.50–$58.00	11

The Role of Price Tiers in the Market for Event Tickets

Our Sample

Our analysis focuses on a sample of 22 performances of "family" events (e.g., circus, children's concerts, etc.). The 22 performances in our sample are held in a variety of locations ranging from major markets such as New York and Los Angeles to smaller markets such as Wheeling, West Virginia, and Laredo, Texas. As a result, sales and prices vary substantially across events. The events all took place between January and June 2004, but ticket sales began far earlier with events experiencing as many as 18 weeks of tickets sales leading up to the performance date. Table 1 provides some descriptive information for each of the 22 performances in our sample.

The data were provided to us by a leading nationwide ticketing agency, which at the time served as the dominant distribution channel for the vast majority of tickets at all events. Small numbers of tickets can be held back by the venue, the event promoter, and other local entities. But these tickets are not sold in a conventional manner (e.g., they are used for local radio station giveaways), so there is little "leakage" of these tickets into the general population of buyers. Thus our data set provides a fairly accurate and complete representation of the sales patterns for every event. (Our data period precedes the prominent role of now-popular resellers such as StubHub.)

The price of a ticket has several dimensions in our data. First is the face value of each ticket. The face value is the full price of that ticket prior to any service charges or facilities fees that may be imposed. The face value is set well in advance of the selling period and is fixed for the duration of the selling period. However, this is not to say that consumers see unchanging prices over time. Instead, discounts are common and vary from week to week. The price paid by each buyer is the face value plus any service and facilities charges and less any price discount available that week *and* claimed by the buyer. Because the available discounts vary from week to week, the average price paid also changes from week to week. Therefore, the second dimension of price that we consider is the week-to-week variation in price. We discuss measures of this aspect of price later when we develop our model. The final facet of price is the price tier. For each performance, there are a variety of tickets with different face values and/or seating locations that are defined by the layout of the venue. The number of ticket categories varies across events. Although some had as few as three ticket categories, others had as many as

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

nine. In many cases, multiple categories shared the same face value but were divided into two separate categories to reflect the seating location. In these cases, we collapsed the two categories into one.

To allow for comparability across performances, we grouped ticket categories into three tiers: high-priced, midpriced, and low-priced. Two separate coders independently viewed the floor plans of the venues along with the face-value prices and seating locations of those tickets available for sale. Based on the distribution of ticket prices and seating locations, ticket categories were assigned to one of the three price tiers. The task was surprisingly straight-forward because the face value prices of tickets tended to cluster together.

One final issue that we need to address is that of capacity utilization. As noted earlier, although the perception may be that capacity limitations pose frequent and pressing constraints in this industry, this is rarely the case. The more common events, such as gymnastics competitions, skating shows, circuses, rodeos, and even concerts by less popular artists, are less salient than the sold-out rock concerts that tend to be the focus of news stories and conversations. In our discussions with two separate firms (i.e., our data provider and another nationwide ticketing company), we were told that capacity is rarely an issue for a given performance. With the exception of a handful of popular concerts, venue sizes far exceed demand for most events. Table 2 summarizes the capacity utilization across the performances in our data. These measures show that capacity constraints are nonbinding in our data and therefore should not be the driving force behind the purchasing behavior we model.

Table 2
Capacity Utilization

	High-Priced Tier (%)	Midpriced Tier (%)	Low-Priced Tier (%)
Minimum	22.0	6.3	2.9
25th percentile	81.7	58.0	20.8
Median	88.8	83.5	31.6
75 percentile	91.7	95.7	64.3
Maximum	99.7	98.6	97.3

Note: Percentages are the percentage of tickets available for sale that are actually sold. This measure excludes all those tickets that are held back for special promotions.

Aggregate Sales and Pricing Patterns

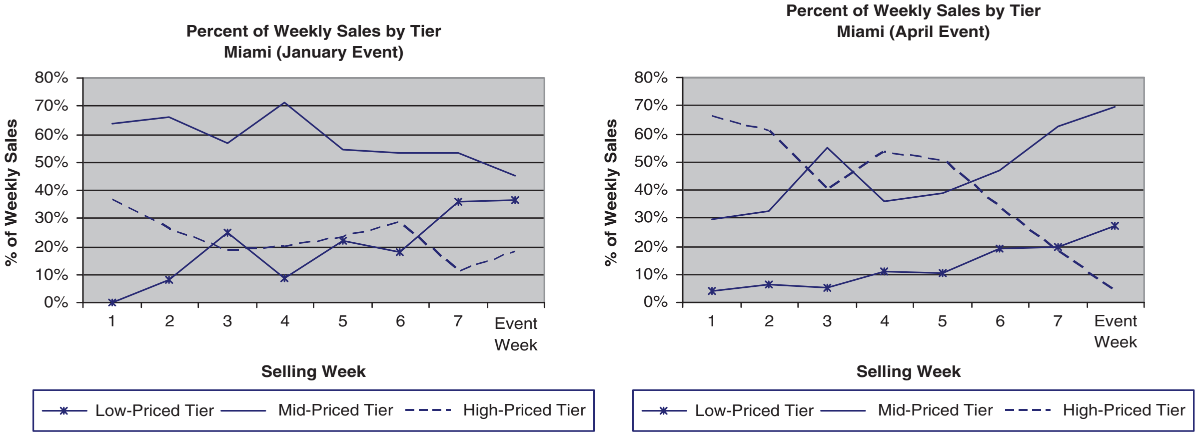
To illustrate the typical sales and pricing patterns observed, consider two different events that took place in Miami, Florida. Figure 1 plots the overall sales and prices (aggregated across price tiers) for each advance selling week, *t*.

In both cases, peak sales occur in the performance week. In the advance weeks, sales start relatively low and gradually build as the performance approaches. In contrast, average price paid in the advance weeks starts high and gradually declines as the performance week approaches. These aggregate sales and price patterns are similar across events and are consistent with the analytical findings of Desiraju and Shugan (1999) relating optimal pricing policies to the nature of sales arrivals.

Figure 1
Overall Sales and Pricing Patterns

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Figure 2
Percentage of Weekly Sales by Price Tier

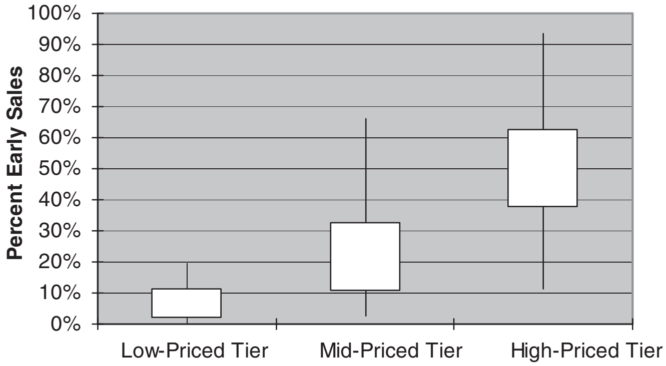


Difference Across Price Tiers

At first glance, the downward sloping price curve seems to suggest that the ticket seller is employing a deliberate pricing policy of decreasing price as the performance nears. However, on further investigation, this trend is primarily an artifact of aggregating across price tiers. Figure 2 plots the percentage of sales attributable to each price tier and shows that tickets in the high-priced tier tend to sell disproportionately in the early weeks of the advance selling period, while tickets in the low-priced tier tend to sell more as the performance approaches. When these differences across price tiers are ignored and aggregated to provide an overall average price paid, the result is what appears to be a schedule of decreasing prices over time.

The same phenomenon can be observed across the remaining events in our data set. Figure 3 shows the percentage of all sales that occur in the early selling period (i.e., all weeks prior to the final month of sales) and provides an overview of how this measure varies across events for each tier. The boxes represent the events in the interquartile range (i.e., the middle 50th percentile), while the lines indicate the full range of observed values. It is quite evident that only a small percentage of the low-priced tickets sell in the early weeks of the advance selling period. In contrast, a significant percentage of high-priced tickets sell in the first four weeks. This pattern is similar to that described above where the proportion of ticket sales in the high-priced tier tend to decrease as the performance approaches, while the opposite is true in the low-priced tier. These sales patterns highlight the potential pitfalls of ignoring price tiers and conducting aggregate level research, as many of the dynamics within price tiers are masked in aggregation. They also highlight one of the key differences, discussed earlier, between demand patterns for events compared to airlines and other industries that rely on traditional notions of yield management.

Figure 3
Summary of Sales Timing by Tier

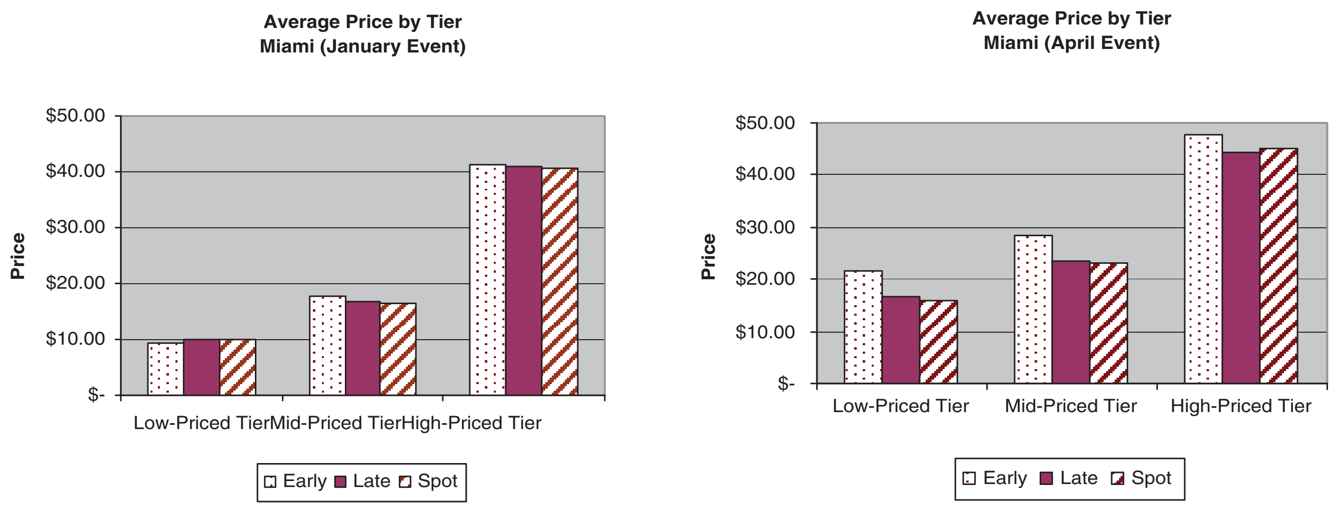


Pricing Over Time

In addition to the price differences across tiers, week-to-week price variations also exist within tiers. However, these variations are not as dramatic and systematic as the price plots in Figure 1 might suggest. For some events and tiers, prices do decline as the performance approaches. However, there are also several instances where an increasing price pattern is observed. In fact, pricing patterns differ

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Figure 4
Average Price Paid by Tier



even across the two Miami events used in our example. In Figure 4, the average price in each tier is charted over time for the same two events presented in Figure 2. For ease of presentation, the selling period is divided into three stages. The spot period represents the week of the performance. The late period represents the month prior to the performance (excluding the spot period), and the early period represents all weeks prior to the final month of sales. Because face values are set before the tickets are made available for sales and remain unchanged throughout the selling period, any variation seen in prices over time are largely because of price discounting. For the January event, tier-specific prices remain quite stable over time, a fact that is lost in the aggregate event-level data (Figure 1). The April event, on the other hand, exhibits slightly more price variation over time. Specifically, tickets in the low- and the mid-priced tiers tend to get less expensive as the performance approaches. Ticket prices for the high-priced tier indicate a more irregular pricing pattern. But these within-tier variations are still quite modest compared to the aggregate patterns shown in Figure 1.

In this section, we have shown that aggregate performance-level trends in sales and pricing often mask the more complex dynamics that occur because of the existence of price tiers. Therefore, in the next section, we model ticket sales at the tier level. We hope to complement the existing research that relates optimal pricing policies to buyer behavior by empirically modeling and highlighting differences in behavior across tiers.

Model Development

Our proposed model has several important characteristics that we develop in turn. First, it explicitly models sales of tickets in each price tier. Second, it differentiates between the advance selling market and the spot market. Finally, we capture the effects of face value and week-to-week variations in price and measure their impact on the advance market as well as the spot market.

The Advance Market

We start by modeling the timing of sales arrivals for each tier as a Weibull process. This process governs *when* buyers in the advance market purchase their tickets. This may be as early as several months prior to the performance or as late as a few days before the performance. We chose the Weibull for its flexibility in accommodating a variety of shapes that are consistent with what we see empirically in our data. The associated hazard function $h_i(t|j)$, survival function $S_i(t|j)$, and cumulative distribution function $F_i(t|j)$ for each event i and tier j are as follows,

$$h_i(t \mid j) = \lambda_{ij} c_{ij} t^{c_{ij}-1}$$
$$S_i(t \mid j) = e^{-\int h_i(t \mid j)} = e^{-\lambda_{ij} t^{c_{ij}}}$$
$$F_i(t \mid j) = 1 - S_i(t \mid j) = 1 - e^{-\lambda_{ij} t^{c_{ij}}}$$

where t = advance selling week

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

λ_{ij} = slope parameter for event i purchases in tier j ($\lambda_{ij} > 0$)
c_{ij} = shape parameter for event i purchases in tier j ($c_{ij} > 0$)

Modeling ticket sales is different from most other purchasing contexts in that all purchases must be made by a predetermined time—the time of the performance. However, if purchase timing were modeled to strictly follow a Weibull timing process, ticket sales could theoretically extend beyond the performance date. Because the occurrence of the performance effectively right censors the selling period, buyers who would have preferred to delay purchase are forced to purchase at or before the time of the performance. To accommodate this, we assume that the remainder of the cumulative distribution function (cdf) at the time of the performance is compressed and materializes at the last minute.

$$F_i(t \mid j) = 1 - S_i(t \mid j) = 1 - e^{-\lambda_{ij} t^{c_{ij}}} \text{ if } t < T \qquad (1)$$
$$F_i(t \mid j) = 1 \text{ if } t = T$$

where T is the time of the performance.

The Spot Market

In addition to the advance-purchase market, there is also a substantial spot market that is not fully captured by the model developed thus far. Therefore, we model the large number of buyers who buy in the spot market by inflating the probability of purchase at $t = T$ (i.e., the performance week) in the same way that a zero-inflated Poisson inflates the probability at zero. After accommodating both the spot market buyers and the discrete-time nature of our observed data (i.e., weekly counts), we can write the probability of observing a tier j ticket purchase at time t as:

$$P_i(t|j) = \phi_{ij} I_t + (1 - \phi_{ij}) \cdot [F_i(t|j) - F_i(t-1|j)] \qquad (2)$$

where $I_t = 1$ for $t = T$ ($I_t = 0$, otherwise), ϕ_{ij} represents the proportion of sales from strictly spot buyers and $F_i(t \mid j)$ is defined above in Equation 1. Because the size of the spot market can be influenced by the pricing policy, we further define ϕ_{ij} in the next section.

The Role of Price

Our objective in this article is to better understand the role of price in an advance market.[1] This objective is partly satisfied by modeling the differences among price tiers as we have done above. However, two other aspects of price remain: face value and week-to-week variations because of discounting.

Sales in the advance market are modeled as a Weibull timing process. Incorporating covariates in a Weibull hazard model is a straightforward process. The first covariate effect we consider is the effect of face value. Because there are some slight variations in face value within a given price tier, we calculate the average face value (AFV) for each performance-tier combination. This value is unchanged over time within a given performance-tier and captures the primary impact of price level on advance buying behavior. The second covariate effect we consider is that of week-to-week variations in price. The proportional hazards framework allows us to easily incorporate time-varying covariates and provides coefficients that reflect the effect of week-to-week changes in the covariates. However, the coefficients reflect the overall level of the covariates as well. Therefore, to separate the effect of week-to-week variations in price from the effect of overall price level, we use the average percentage discount (DISCOUNT) instead of average price paid as a time-varying covariate. We also include the number of advance selling weeks (PREWK) and seasonality variables (THANKS and XMAS) as control covariates. We include all of these covariates through the Weibull hazard function as follows,

$$h_i(t|j) = \lambda_{ij} c_{ij} t^{c_{ij}-1} \exp\{\boldsymbol{\beta}_{\mathbf{ij}} \mathbf{X}_{\mathbf{ijt}}\}$$

where $\mathbf{X}_{\mathbf{ijt}}$ is a vector of covariates that includes,

THANKS_{it} = an indicator variable for the week before Thanksgiving
XMAS_{it} = an indicator variable for the week before Christmas
PREWK_i = number of advance selling weeks
AFV_{ij} = average face value of tickets sold in tier j for performance i
DISCOUNT_{ijt} = the average percentage discount for a tier j ticket for performance i at week t

Using standard proportional hazard methods, we fine-tune the cumulative distribution functions (cdfs) shown in Equations 1 and 2 to incorporate these covariates as follows.

$$F_i(t|j) = 1 - \exp\left\{-\lambda_{ij} \sum_{u=1}^{t} \left([u^{c_{ij}} - (u-1)^{c_{ij}}] \cdot e^{\boldsymbol{\beta}_{\mathbf{ij}} \mathbf{X}_{\mathbf{iju}}}\right)\right\}, \text{ if } t < T$$

Our modeling objective in the spot market is the same as that in the advance market: to capture the effects of face value as well as week-to-week price variations in the

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

weeks leading up to the performance. To model the effect of face value, we again use AFV as a covariate. However, to capture the effect of week-to-week variations in price, we need to consider a new measure that compares the spot market price to earlier prices. As a time-varying covariate in the advance-selling period, the DISCOUNT covariate reflects the effect of week-to-week changes in price as well as the size of the discount. However, as a covariate for spot market size, the DISCOUNT measure would not provide any comparison to earlier prices. Therefore, in the spot market component of the model, we use Spot Price Index (SPI) as a covariate and calculate it for each tier as the average price paid in the spot market ($t = T$) divided by the average price paid in the advance market ($t < T$). If pricing strategies are unchanged between the advance market and the spot market, we would have SPI = 1. An SPI < 1 indicates additional discounting in the spot market. An SPI > 1 indicates that spot market tickets are selling at a premium relative to the tickets sold in earlier weeks.

To incorporate spot market covariates, we define the spot market parameter, ϕ_{ij}, from Equation 2 as follows,

$$\phi_{ij} = \frac{e^{\theta_{ij}}}{1+e^{\theta_{ij}}} \quad \text{where } \theta_{ij} = \gamma_{\mathbf{ij}}\mathbf{Z}_{\mathbf{ij}}$$

where Z_{ij} is a vector of covariates that includes an intercept and the following[2]:

PREWK_i = number of advance selling weeks
AFV_{ij} = average face value
SPI_{ij} = spot price index

Heterogeneity Across Events

To accommodate heterogeneity across events, we assume that both the slope (γ_{ij}) and shape (c_{ij}) parameters of the Weibull process governing sales within each performance tier are drawn from independent normal distributions as follows,

$$\text{In}(\lambda_{ij}) \sim Normal\ (\mu_{\lambda j},\ \sigma_{\lambda j})$$
$$\text{In}(c_{ij}) \sim Normal\ (\mu_{cj},\ \sigma_{\lambda j})$$

In addition, we allow covariate effects to vary across events according to independent normal distributions,

$$\beta_{kij} \sim N(\bar{\beta}_{kj}, s_{kj}) \text{ and } \gamma_{rij} \sim N(\bar{\gamma}_{rj}, s_{rj})$$

where k indexes the covariates in the Weibull hazard model and r indexes the covariates (including the intercept) in the spot market component of the model.

To complete the model specification, we chose appropriately diffuse and uninformative priors for each of our parameters. We estimate this model using WinBUGS and run 20,000 iterations, discarding the first 15,000 for burn in. Trace plots and Monte Carlo standard errors were monitored to ensure convergence.

We also estimated a number of benchmark models, including one that allowed for correlations among parameters and another that did not allow for parameter differences across tiers. In the correlated model, we found that most correlations were statistically insignificant, and most of the exceptions were not substantially different from zero (i.e., the largest correlation was 0.0089). In the "homogeneous-tiers" model, all price tiers shared the same Weibull parameters and price coefficients. This model performed far worse than the proposed model (as indicated by the fit measures described in the next section). Because our objective here is to focus more on empirical regularities rather than model comparison, per se, we limit our discussion to the results of the proposed model alone because it outperforms our benchmarks while providing an accurate and parsimonious description of buyer behavior in this market.[3]

Results

Model Validation

Figure 5 presents tracking plots for the same two events shown in Figure 1. It is clear that the proposed model fits the data quite well. In fact, because the week-to-week fit is so accurate, it is difficult to distinguish the actual sales line from the estimated sales line.

To further illustrate the quality of the model, Figure 6 shows the model fit for the same two events by tier. Again, for ease of presentation purposes, we divide the advance selling period into early, late, and spot periods.

Figures 5 and 6 show that the model provides a very good fit for the two events displayed despite the earlier discussion that the two events exhibit slightly different sales patterns at the tier level. For the January event, sales of tickets in the high-price tier increase as the performance approaches.[4] In contrast, sales of tickets in the high-price tier decrease as the performance approaches in April. Despite these differences, the model presented in this article fits both events very well.

To extend the analysis presented in Figure 6 to the complete set of events, we calculate RMSE (root mean squared error) as an indicator of model fit and present the results in Table 3. We use the selling period (i.e., spot, late, and early) as our unit of analysis and then average across periods as follows,

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Figure 5
Tracking Plots for Miami Events

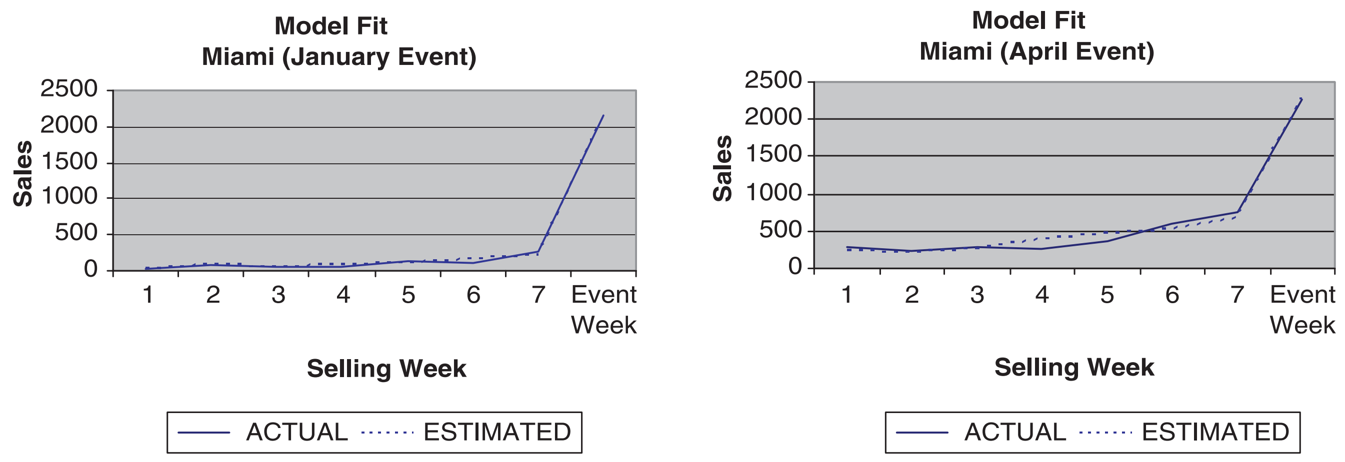
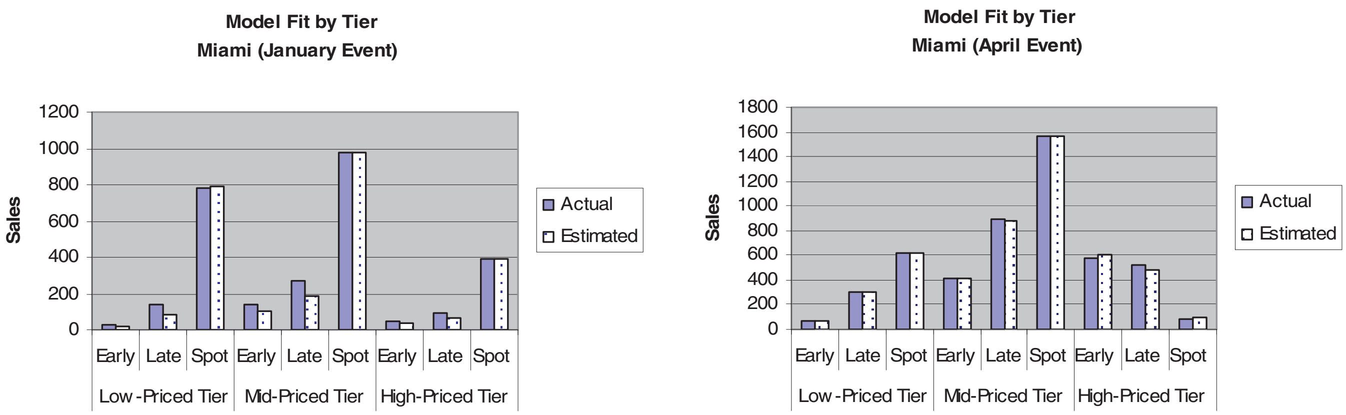


Figure 6
Model Fit by Tier for Miami Events



$$RMSE_{ij} = \sqrt{\frac{\sum\limits_{\tau \in \{spot, late, early\}} (Sales_{ij}(\tau) - E[Sales_{ij}(\tau)])^2}{3}}$$

Overall, the RMSE measures provided in Table 3 show that the model fits the data very well. The overall fit for all performances, regardless of price tiers, generates an RMSE of 45.41. The model fit by price tier is just as impressive with RMSE ranging from 11.55 for the low-priced tier to 72.51 for the mid-priced tier. To better evaluate RMSE, we also provide in Table 3 the percentage of total performance tier sales the RMSE represents. Given the volume of sales for each performance tier, the RMSE reported in Table 3 indicate an excellent fit with overall and tier-specific errors falling within 2.5% of sales across performances.

Parameter Results: The Advance Market

We begin our discussion of results by examining the baseline Weibull parameters for each price tier, λ_j and c_j. These parameters represent the underlying purchase timing process absent of any covariate or spot market effects (see Table 4 for all parameter estimates).

Figure 7 plots the theoretical Weibull distributions that result from the parameter estimates presented in

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Table 3
Model Fit

	Low-Priced Tier	Midpriced Tier	High-Priced Tier	Overall
RMSE	11.55	72.51	15.49	45.41
RMSE (% of sales)	1.25	1.69	2.35	0.77
# of performances with RMSE < 2.5%	20	17	16	21
# of performances with RMSE 2.5%–5.0%	1	4	4	1
# of performances with RMSE > 5.0%	1	1	2	0

Note: RMSE = root mean squared error.

Table 4. These distributions assume steady pricing in the advance selling weeks and median values for the number of advance selling weeks, AFV, and SPI for each tier. From this figure, we can see that tickets in the high-priced tier tend to sell earlier. In contrast, buyers of the mid- or low-priced tickets tend to delay their purchases. This is the underlying dynamic that results in the perception that prices decline as the performance approaches. This result is also consistent with Desiraju and Shugan's (1999) contention that for this class of products (e.g., concerts, fashion, etc.), buyers who have the greatest value for the service buy earlier in the advance selling period.

For the most part, the seasonality covariates for Thanksgiving and Christmas have no effect on the timing of ticket purchases for any tier of tickets. We see an effect of Thanksgiving on the mid-priced tier that is marginally significant (the coefficient is significant at $p = .10$ but not at $p = .05$). The number of advance selling weeks has a significant and negative effect on the Weibull hazard across all three price tiers. In other words, the earlier that the tickets are made available for sale, the more gradual is the pattern of sales arrivals.

Interestingly, the price of the tickets also has no significant impact on sales in the early market once price tiers are taken into account. Neither the face value nor any price discounting influences the purchasing decision in the advance market. This suggests that price promotions in the early market only serve to decrease margins.

Parameter Results: The Spot Market

In contrast to the results for the advance market, several covariates influence the size of the spot market. The number of advance selling weeks has a significantly negative effect on the size of the spot market for all three price tiers. In other words, the longer tickets for an event have been available for sales, the smaller the spot market. This makes intuitive sense because the longer selling period prior to the scheduled performance provides more opportunities for consumers to buy early.

Pricing, unlike in the advance market, has a significant effect in the spot market. The face value of the ticket influences the size of the spot market in the low- and mid-priced tiers, while the spot price (SPI) has an influence on the size of the spot market in the high-priced tier.

Figure 8 summarizes the pricing policies in the spot market across performances for each of the three price tiers. The figure illustrates that additional price discounting in the final selling week (SPI < 1) is a common practice in all three tiers, with the most severe discounting occurring in the mid-priced tier. However, there are also instances of tickets selling at a price premium in the spot market (SPI > 1). In our sample of 22 performances, all of them had one or more price tiers selling at a price discount in the spot market. Fourteen performances had one or more price tiers selling at a price premium in the spot market. (Perhaps these events had discount coupons that expired before the performance date but other fees that continued to apply.)

Despite all the price variability shown in Figure 8, spot market prices have very little impact on the relative size of the spot market in the low- and mid-priced tiers. For these two tiers, the only facet of price that has an impact on purchasing is the ticket's face value, which remains unchanged throughout the selling period. The model results ($\bar{\gamma}_{AFV,\ LOW} = -5.03$, $\bar{\gamma}_{AFV,\ MID} = -3.82$) indicate that face value has a significant and negative effect in both the low- and the mid-priced tiers, suggesting that higher face values encourage consumers to buy in the advance market rather than in the spot market. This could be because higher prices require a bigger commitment (and more advance planning) by the consumer. SPI, however, has no significant effect on the relative size of the spot market in these two tiers. This result, coupled with the Weibull parameter estimates, indicates that price discounting, and the week-to-week price variations that result, appear to have no impact on ticket buying behavior in either the advance or the spot market for the low- and mid-priced tiers.

Customer behavior in the high-priced tier presents a sharp contrast to that seen in the other two tiers. In the high-priced tier, face value has no significant impact on the size of the spot market, while a discounted spot market price can significantly increase the relative size of the

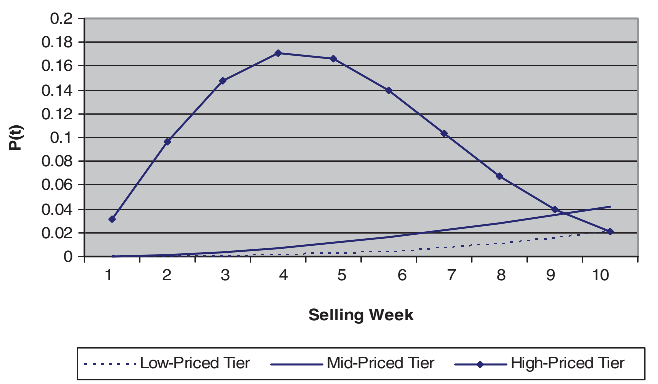
Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Table 4
Parameter Estimates

Parameter	Variable	Low-Priced Tier	mid-priced Tier	High-Priced Tier
Baseline Weibull parameters				
$\mu(\lambda)$	Slope parameter	0.0065*	0.043*	0.16*
		(0.0018, 0.029)	(0.031, 0.058)	(0.10, 0.26)
$\mu(c)$	Shape parameter	4.16*	2.94*	2.12*
		(3.31, 5.23)	(2.39, 3.63)	(1.35, 3.22)
Advance market parameters				
$\bar{\beta}_{THANKS}$	Thanksgiving effect	0.20	1.17*	1.79
		(–1.30, 1.36)	(0.086, 2.08)	(–0.33, 3.04)
$\bar{\beta}_{XMAS}$	Christmas effect	0.69	0.78	0.90
		(–1.83, 2.80)	(–0.45, 1.97)	(–0.75, 2.48)
$\bar{\beta}_{PREWK}$	# of adv. selling weeks	–0.65*	–0.33*	–0.19*
		(–0.84, –0.44)	(–0.46, –0.19)	(–0.34, –0.039)
$\bar{\beta}_{AFV}$	Average face value	–0.074	–0.12	0.0069
		(–0.19, 0.040)	(–0.46, 0.15)	(–0.21, 0.21)
$\bar{\beta}_{DISCOUNT}$	Percentage price discount	1.97	2.08	–0.59
		(–2.31, 6.25)	(–0.21, 4.30)	(–4.88, 3.79)
Spot market parameters				
$\bar{\gamma}_{INT}$	Intercept	–0.61	–0.17	2.00*
		(–5.06, 4.20)	(–6.27, 4.96)	(0.71, 3.54)*
$\bar{\gamma}_{PREWK}$	# of adv. selling weeks	–1.76*	–3.05*	–0.83*
		(–4.12, –0.032)	(–5.86, –0.29)	(–1.37, –0.35)
$\bar{\gamma}_{AFV}$	Average face value	–5.03*	–3.82*	–0.031
		(–8.54, –1.89)	(–7.31, –0.30)	(–0.56, 0.39)
$\bar{\gamma}_{SPI}$	Spot market index	–0.25	0.14	–3.17*
		(–4.56, 4.41)	(–4.67, 9.46)	(–4.80, –0.65)

Note: Values in parentheses represent the 90% confidence range.
*Significant at $p = .10$.

Figure 7
Baseline Weibull Process by Tier



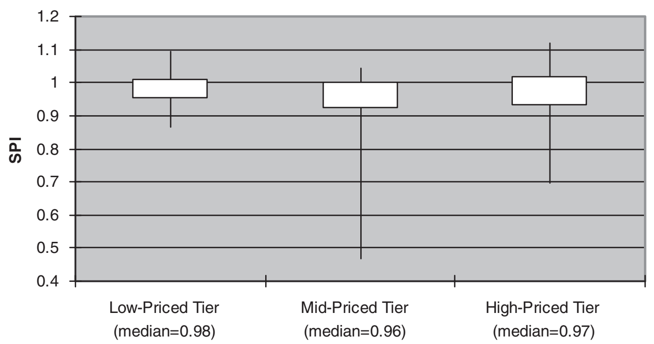
spot market ($\bar{\gamma}_{SPI,\ HIGH} = -3.17$). This result is consistent with the asymmetric price effects found by Blattberg and Wisniewski (1988), who showed that price discounts are more effective when applied to high-quality products than when applied to low-quality products. In the context of event tickets, discounting spot market prices for high-priced (and high-quality) tickets expands the spot market much more effectively than if the same discounts were applied to the other tiers.

Summary and Discussion of Pricing Effects

Overall, there seem to be significant differences in purchasing behavior across price tiers (see Table 5 for a summary). High-priced tier consumers tend to buy earlier, while low- and mid-priced tier consumers are more likely to delay their purchases. To better understand this empirical finding, let us consider the consumer's buying decision. The decision to purchase a ticket is the outcome of a trade-off between the utility value held for the event itself and the cost of committing to this future event (Desiraju and Shugan 1999). When the value for the event exceeds any costs of commitment, purchase occurs. Consumers who bought early in the selling period are likely to be those who have a higher value for the event and/or lower costs of commitment and are able to easily make the trade-off. With their higher valuation for the event, these consumers are also more willing to

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Figure 8
Summary of Spot Market Pricing



Note: SPI = Spot Price Index.

Table 5
Summary of Pricing Effects

	Low-Priced Tier	Midpriced Tier	High-Priced Tier
Advance market effects			
Higher face values	—	—	—
Larger price discounts	—	—	—
Spot market effects			
Higher face values	smaller spot mkt	smaller spot mkt	—
Spot market discounts	—	—	larger spot mkt

pay higher prices for the event, leading to the empirical finding that higher-priced tickets sell earlier than the low-priced tickets. Factors that reduce the consumer's cost of commitment may also induce an earlier purchase. For example, refund policies may make it less costly to purchase in advance and would result is a higher proportion of tickets (regardless of price tier) to sell early in advance selling period. Consumer characteristics, in particular those associated with one's opportunity costs of time, may also influence the costs of commitment and consequently the timing of purchase.

Associated with this idea of cost of commitment are capacity constraints. When faced with capacity constraints, the costs of commitment are also weighed against the costs of delaying associated with the inability to secure a seat at the performance. These costs are greater for those consumers who hold higher valuations for the event. The result again is that higher valuation consumers buy earlier in the selling period. Although capacity constraints are not binding in the performances and events studied in this article, the cost of delaying may still factor into the consumer's decision. However, it is likely not the driving force for the empirical findings presented in this article because most events (including those analyzed in this article) sell far fewer tickets than the venue capacity would allow.

The finding that high valuation customers purchase earlier than low valuation customers is one that contradicts the behavior observed in the airline industry where low-value customers purchase earlier. However, the behavior seen in the airline industry may actually be driven by pricing policies employed in that industry. Airlines tend to price lower early in the advance selling prices and raise prices as the travel date approaches. They do this as part of a revenue management system that assumes leisure travelers (or price-sensitive travelers) plan well in advance, while business travelers (price-insensitive travelers) tend to make last-minute travel arrangements. However, this behavior has never been empirically documented and may have actually been a result of savvy consumers learning and adapting to the pricing policies employed by the airlines. In fact, in recent years, airlines have begun to offer last-minute fares at a dramatically reduced price to fill their excess capacity. The result was that more price-sensitive and leisure travelers purchased closer to the travel date. So although customer behavior in the travel industry appears to differ from that in the event tickets market, it may be the case that this behavior is a consequence of the policies employed and may not actually reflect the true underlying tendencies of travelers. The empirical results presented in this study, however, reflect consumer behavior in the absence of capacity constraints and strategic dynamic pricing policies and as a result are a more accurate indicator of the true underlying behavior of advance purchasers.

In addition to differences across tiers, the prices themselves also have effects that vary across tiers. Although none of the pricing covariates has an impact on *when* tickets are purchased in the advance market, we do see significant effects in the spot market. Although the face value of the tickets affects the spot market for the low- and mid-priced tiers, only the spot price premium or discount (SPI) influences buying behavior in the high-priced tier. Overall, it appears to be difficult to influence sales in the low- and mid-priced tiers once a face value has been set. Sales of tickets in the high-priced tier can, however, be influenced by discounting in the spot market, but this has a limited impact because of the

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

smaller number of consumers in this tier, particularly as the performance gets closer. These findings have significant implications for pricing policies. They suggest that price reductions and price discounting are ineffective in selling more low-priced and mid-priced tier tickets. In contrast, discounting high-priced tier tickets in the spot market can increase ticket sales. To fully evaluate the effectiveness of such a discounting strategy, however, the ticket seller would need to consider both the increase in the number of tickets sold and the decrease in the price per ticket.

Conclusions and Discussion

In this article, we model the effects of pricing on the advance purchase of event tickets. To the best our knowledge, it is the first to empirically document the advance purchasing behavior of consumers (with respect to price) in the absence of any influencing factors such as capacity constraints and strategic dynamic pricing policies. As a result, our results offer the most accurate reflection of underlying consumer behavior in an advance selling market to date.

The findings presented in this article have significant implications for pricing policies. They demonstrate that differences across price tiers are far greater than any differences seen by week-to-week price changes within tier. For marketers, that means that strategies and policies should focus on differentiating among tickets tiers rather than manipulating the week-to-week prices of tickets within tier. Again, we see some of this occurring in the airline industry where frequent business travelers are given special privileges and better seating. In the event tickets market, that may mean offering special gift bundles for the high-valuation customers (a practice that has started to gain popularity with some events).

The results presented in this article also raise interesting issues for further research. Although we have documented the empirical behavior of customers in the advance selling market and have speculated as to the customer decision process, future research to study the consumer decision process in more depth would contribute greatly to our knowledge of how advance markets really work. In particular, the consumer's trade-off between the utility value of the performance and the costs of commitment (and delay) is an important issue that can have significant implications for how marketers manage the advance selling market.

In addition, we have raised questions about the effectiveness of the strategic dynamic pricing strategies currently employed by the airlines. Although these strategies are currently aligned with consumer behavior in the travel industry, it may be the case that the consumers have simply adapted their behavior to take advantage of the pricing schemes presented by the airlines. The true underlying preferences of the air travel customer are still unknown. As a result, it is possible that an alternate pricing policy that better serves these customers preferences (and addresses the differences across customers) might generate increased customer satisfaction and greater profitability for the airlines.

Our objective in this article was to study the underlying customer behavior in an advance selling market, especially as it pertains to price. The empirical results presented may seem somewhat intuitive for the event tickets market but present some challenges to the assumptions made in other industries. The hope is that these results will generate additional discussion and future research on advance purchasing behavior. Studies of the consumer decision process in this domain are virtually nonexistent despite the impact that it would have on marketing practice. In addition, our study focuses on an environment where there are minimal capacity constraints and virtually no strategic pricing policies in place. The impact of these constructs on consumer behavior also warrants further investigation and could significantly shape future pricing policies in advance selling markets.

Notes

1. One potential concern is that pricing (i.e., discounting) strategies might not be independent of the expected market response to price. Therefore, we also tested a model that treats price as nonrandom. Specifically, we followed the approach taken by Manchanda, Rossi, and Chintagunta (2004) and simultaneously modeled price as a function of the expected effect of price and expected baseline sales. None of these factors have a significant effect on price. Therefore, for the remainder of the article, we focus only on the model that treats price variations as exogenous and random.

2. We do not include Thanksgiving or Christmas as covariates because none of the events in our data set have scheduled performances during those weeks.

3. Comparison measures among the models are available from the authors.

4. Although the number of tickets sold in the high-price tier increases as the event approaches, it represents a decreasing percentage of all tickets sold because sales in the low- and midprice tiers increase dramatically.

References

Biyalogorsky, E., Z. Carmon, G. Fruchter, and E. Gerstner (1999), "Overselling and Opportunistic Cancellations," *Marketing Science*, 18, 605-610.

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009

Blattberg, Robert C. and Kenneth J. Wisniewski (1988), "Priced-Induced Patterns of Competition," *Marketing Science,* 8 (4), 291-309.

Borenstein, S., and L. R. Rose (1994), "Competition and Price Dispersion in the U.S. Airline Industry," *Journal of Political Economy*, 102, 653-683.

Dana, J. D. (1998), "Advance-Purchase Discounts and Price Discrimination in Competitive Markets," *Journal of Political Economy*, 106, 395-422.

Desiraju, Ramarao and Steven M. Shugan (1999, January), "Strategic Service Pricing and Yield Management," *Journal of Marketing,* 63, 44-56.

Knowledge @ Wharton (2007, June 13), "New Products (Like the iPhone): Announce Early or Go for the Surprise Rollout?" http://knowledge.wharton.upenn.edu/article.cfm?articleid=1752.

Leslie, Philip (2004), "Price Discrimination in Broadway Theater," *RAND Journal of Economics,* 35 (3), 520-541.

Manchanda, Puneet, Peter E. Rossi and Pradeep Chintagunta (2004), "Reponse Modeling with Non-Random Marketing Mix Variables," *Journal of Marketing Research,* 41, 467-478.

McGill, J. I., and G. J. van Ryzin (1999), "Revenue Management: Research Overview and Prospects," *Transportation Science*, 33, 233-256.

Moe, Wendy W. and Peter S. Fader (2002), "Using Advance Purchase Orders to Forecast New Product Sales," *Marketing Science,* 21 (3), 347-364.

Shugan, Steven M. and Jinhong Xie (2000), "Advance Selling for Services," *California Management Review,* 46 (3), 37-54.

Xie, Jinhong and Steven M. Shugan (2001), "Electronic Tickets, Smart Cards, and Online Prepayments: When and How to Advance Sell," *Marketing Science,* 20 (3), 219-243.

Wendy W. Moe is an associate professor of marketing at the Robert H. Smith School of Business at the University of Maryland. She obtained her PhD from the Wharton School at the University of Pennsylvania. Her research interests lie in modeling online consumer shopping behavior and early sales forecasting. Some of her previous work has focused on developing statistical methods and models for Internet clickstream data. She has also developed several early forecasting models that can predict the sales of entertainment products early in their lifecycles and, in some cases, even before the actual launch of the product. Her research has appeared in *Marketing Science*, *Journal of Marketing Research*, *Management Science*, *Journal of Marketing, Journal of Interactive Marketing*, *Journal of Consumer Psychology*, and *Journal of Public Policy and Marketing*.

Peter S. Fader is the Frances and Pei-Yuan Chia Professor of Marketing at the Wharton School of the University of Pennsylvania. His expertise centers around the analysis of behavioral data to understand and forecast customer shopping and purchasing activities. Much of his research highlights the common behavioral patterns that exist across seemingly different purchasing contexts. Many of these cross-industry experiences and observations are currently being channeled toward the development of the Wharton Interactive Media Initiative (http://wimi.wharton.upenn.edu), a new research center that aims to revolutionize current thinking and managerial practices within the media, entertainment, and e-commerce industries.

For reprints and permissions queries, please visit SAGE's Web site at http://www.sagepub.com/journalsPermissions.nav

Downloaded from http://jsr.sagepub.com at UNIV OF MARYLAND on October 5, 2009