

USING EXPECTATIONS DATA TO INFER MANAGERIAL OBJECTIVES AND CHOICES

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ABSTRACT

We develop a theory-driven empirical framework to analyze managerial decision-making that incorporates subjective expectations data. We apply the model to examine the advertising decisions of the marketing manager of a large university performing arts center who reports her demand forecasts as part of the annual budgeting process. We recover parameters of the manager's utility function and assess the sensitivity of estimated preferences to alternative assumptions regarding her expectations. The results from our structural demand model of ticket sales show that the manager is over-optimistic about the appeal of avant-garde art and advertising effectiveness, although her belief concerning the price elasticity of demand is unbiased. Estimates of managerial utility parameters are sensitive to the specification of expectations: Allowing for biased expectations, the manager exhibits strong preference for avant-garde performances, which is consistent with the mission of the performing arts center. Imposing rational expectations reverses the sign of this key behavioral parameter and implies the manager has distaste for avant-garde art. The results also suggest that the manager attempts to manipulate advertising so that final sales coincide with her ex ante forecast, imposing an agency cost on the performing arts center.

Keywords: subjective expectations, biased beliefs, structural choice and demand models, advertising, non-profit, avant-garde art

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1. INTRODUCTION

Empirical models using observed choices to infer agent preferences have a long history in economics (McFadden (2001)). Individuals in these models are generally assumed to have partial information about the outcomes associated with their choices. Agents are assumed to have rational expectations concerning outcomes so that the researcher can focus on the determinants of revealed preference, but the resulting empirical findings may be quite sensitive to assumptions regarding expectations and the elements of the agent's information set.¹ Potential issues of identification arise because different combinations of behavioural parameters and expectations mechanisms may be consistent with observed choices (Keane and Runkle (1990)). Manski (2004) argues that more credible estimates of behavioural parameters may be obtained if subjective expectations data are incorporated into the econometric model, since the researcher can relax or test assumptions regarding expectations formation. To date, however, the use of expectations data in economics remains the exception.²

Economists have been reluctant to use subjective expectations data in empirical studies, in part because early studies found such data to be poor predictors of subsequent

¹ See Manski (2004) for a discussion and examples of the limitations of inferring preferences from choice data alone. Manski (1990) also shows that assumptions concerning expectations formation can have a substantial impact on the factors that are believed to impact educational attainment.

² The economic analysis of poor health behaviors, such as smoking, has incorporated subjective data on beliefs and risk perceptions (see, e.g., Viscusi (1990)). The use of subjective preference and expectations data has a long history in fields such as marketing (see Hensher et al (1999) for a summary that relates these methods to revealed preference analysis). Conjoint analysis has been used to measure consumer preferences and tradeoffs, although the focus of these studies has been the elicitation of preferences rather than an analysis of consumer choice in more realistic multi-product settings (Green and Wind (1971), Louviere (1994)). The literature on behavioral decision theory argues that it provides more realistic models of choice behavior (e.g., Kahneman and Tversky (1979, 1984)).

behaviour (e.g., Juster (1964)).³ However, the use of expectations data requires careful specification of both the agent's information set at the time expectations are reported, and the subsequent evolution of the information set up to the date that the agent makes her choice. For example, some studies have included reported expectations as an additional independent variable in a reduced-form choice model. The agent's expectations formation process and actual choices may depend on the same unobservables (to the researcher), leading to endogeneity bias in estimation (van der Klaauw (2000), Lochner (2007)).⁴ Similarly, an agent may experience shocks that influence her choice behavior after reporting expectations so that reported forecasts may correspond poorly with outcomes (Manski (1990)). Finally, most studies utilizing subjective preference and expectations data derive this information from large-scale surveys where individuals have little incentive to respond accurately, leading some to question whether such reports accurately reflect the true expectations of respondents.⁵ Nevertheless, it has been argued that for some groups of respondents, such as professional forecasters who sell their information on the market, reported expectations are likely to contain accurate information on true expectations (Keane and Runkle (1990)).

In this paper, we develop a theory-driven empirical framework to analyze managerial decision-making that incorporates subjective intentions and expectations data. Our goal is to recover parameters of the manager's utility function and assess the sensitivity of estimated preferences to alternative assumptions regarding the manager's

³ Dominitz and Manski (1997, 1999) discuss the history of the use of expectations data in economics.

⁴ Bernheim and Levin (1989) discuss the use of expectations data as independent variables in models of personal saving and Social Security benefits.

⁵ Dominitz and Manski (1996, 1997) argue that more accurate expectations data may be obtained from surveys if appropriate elicitation methods are utilized. Bernheim (1989) and Hurd and McGarry (1995) are examples where survey respondents report relatively accurate and internally consistent expectations in the cases of retirement date and life expectancy, respectively.

expectations. In this sense our paper is similar in spirit to studies such as Lancaster and Chesher (1983) and Berry, Levinsohn, and Pakes (2004) who use subjective reports of reservation wages and “second choices” to recover structural parameters of job search and consumer choice models, respectively. We use the framework to analyze the advertising decisions of the marketing manager of a large university performing arts center (the “Center”) over a three year period. This application is appealing for a variety of reasons. We utilize a unique (to the literature) source of expectations data. As part of the manager’s annual strategic plan, she reports her expectations of advertising spending and ticket sales for each of the shows presented by the Center in the upcoming year.⁶ We argue that like professional forecasters, the manager has an incentive to report her true expectations: her expectations are used for a variety of planning purposes (e.g., choice of venue and staff size for the performance) that have real economic consequences, and they are reported to the manager’s superiors. While not previously analyzed in academic studies, this type of internal forecast data is routinely collected by a wide variety of firms as part of their annual planning processes in areas such as marketing, R&D, and new product development.⁷

A key element our application is that the Center is a non-profit institution with a mission of bringing both “traditional” and “avant-garde” (AG) art to the community.⁸ We assume that the manager chooses advertising to maximize her utility, and recover the relative weights she places on profit maximization vs. community exposure to avant-

⁶ Textbook treatments of the marketing planning and budgeting process view the construction of accurate product sales forecasts as a key element in deciding upon the associated expected promotional expenditure for each product (Kotler and Keller (2006)).

⁷ The growing interest among firms in internal prediction markets suggests that many firms are seeking more efficient and less biased forecasts of future sales. However, even in these markets, there is evidence of biases such as over-optimism (Cowgill, Wolfers, and Zitzewitz (2008)).

⁸ Examples of “traditional” shows are performances by Keith Jarrett and David Sedaris. Avant-garde shows include Vietnamese Water Puppets and La La La Human Steps.

garde art in her utility function. Inspection of the summary statistics suggests that manager has strong preferences toward promoting AG art that go beyond profit maximization. She spends significantly more on advertising AG performances despite substantially lower attendance at these shows. However, the availability of the expectations data allows us to investigate a richer array of possible explanations for these patterns: (a) as noted above, the manager has preference for AG art, which is consistent with the mission of the Center; (b) the manager is overly optimistic regarding the appeal of AG art in the community and spends more on informative advertising; (c) the manager has biased beliefs about the impact of advertising on ticket sales for AG shows. In the absence of data on expectations, we would be unable to account for explanations (b) and (c) when estimating the behavioural parameters associated with explanation (a).

Our results highlight the value of the subjective expectations data in this setting. The first step in distinguishing between explanations (a)-(c) is to recover the manager's beliefs about the relationship between sales and advertising, pricing, and other show attributes. Simple OLS regressions of demand indicate that more advertising and lower prices lead to reduced ticket sales. These nonsensical results reflect unobserved (to the researcher) attributes that are correlated with both managerial choices and outcomes. For example, when choosing advertising expenditures, a manager may decide to advertise more (less) for products with less (more) latent appeal. We estimate a structural model of demand and use the expectations data to infer the manager's prior beliefs concerning the latent appeal of each show, and specify a learning process in which she updates her ex

ante beliefs prior to making the advertising decision.⁹ In contrast to the initial OLS results, the estimated advertising response using this framework is positive. More notably, we find that the manager's prior expectations concerning the impact of price on demand is unbiased, as would typically be assumed in most economic models. The major departures concern the manager's overly optimistic beliefs regarding advertising response, and the latent appeal of AG shows. The former beliefs lead to over-spending on advertising in general, reducing net revenues, while the latter beliefs generate relatively higher advertising expenditures for AG shows.¹⁰

When we specify the manager's utility function to incorporate information on her beliefs generated from the expectations data, the estimated behavioural parameters show that her preferences for AG art coincide with the mission statement of the Center. An additional ticket sold to an AG show generates an extra \$16 in utility to the manager (over and above the \$30 ticket price), implying that she will spend more on advertising for these shows. More importantly, this estimate is sensitive to assumptions regarding expectations, suggesting potential identification issues in the absence of subjective expectations data. If the manager is assumed to have rational expectations, the estimated additional utility associated with AG shows changes sign and becomes -\$12 per AG ticket.

The behavioral model also suggests an interesting misalignment of the incentives of the manager and her superiors at the Center. When initial ticket sales for a show are

⁹ As described in the next section, advertising decisions are made 1 month prior to the date of the performance. Tickets are sold prior to this date as part of a "pre-season" sales effort in which only the entire season of shows is advertised.

¹⁰ Prior studies have found that same agent may have unbiased expectations for some quantities but not others. For example, Zarnowitz (1985) finds that professional forecasters are more likely to have unbiased expectations concerning real GNP growth but not inflation.

below the manager's reported expectations, she will overspend on advertising in an attempt to raise final ticket sales to a level that corresponds to her ex ante forecasts. This finding emphasizes the value of a well specified model of agent behavior when using subjective expectations data.

The remainder of the paper proceeds as follows. Section 2 describes the relevant operations of the performing arts center and the timing of the marketing manager's advertising decisions. Section 3 develops the framework for incorporating subjective expectations data into a structural econometric model of advertising choice, and describes our estimation procedure for recovering the parameters of the market demand and managerial objective functions. Section 4 estimates the parameters of the structural demand model and examines whether the manager has biased beliefs, and Section 5 discusses the empirical results from the behavioural model and the sensitivity of these findings to the specification of managerial expectations. We conclude in Section 6.

2. THE EMPIRICAL SETTING

We analyze the advertising decisions of the marketing manager for one of the largest university-based performing arts centers in the United States. The Center presents approximately 60 music, dance, and theatrical events each year, with each event usually running from one to five performances. Unlike commercial presenters, it is a non-profit organization whose mission is to bring to the local community, and especially the university community, performers who reflect a wide range of cultural and artistic backgrounds. In particular, a key objective is to present avant-garde art.¹¹ Consequently,

¹¹ An excerpt from the Mission Statement reads "...[the Center] promotes an aesthetic of fusion and diversity — in which concert hall divas, world-class chamber orchestras and hip-hop dancers share the season—and sometimes the stage—with post-modern dancers, world music superstars, contemporary storytellers, and rock 'n' roll mavericks...the spirit of the avant-garde radiates from dark stages...An

while some performances are by popular artists (e.g., Keith Jarrett, David Sedaris, Mikhail Baryshnikov), others are by relatively unknown artists who are on the very cutting edge of experimental performance art (e.g., La La La Human Steps, Umabatha, Vietnamese Water Puppets). The Center can be considered a local monopoly - although there are a large number of entertainment options in the community, the Center is the only major presenter of AG artists within an easy driving distance of the affluent area of the city in which it is located.

The Center Director hires the artists and books the venue. The Center operates both large and small performance venues, and artists are booked into these venues depending in part on expected ticket sales (based on input from the Marketing Department). The Marketing Department is responsible for generating ticket sales, which account for roughly two-thirds of the Center's operating budget. The marketing manager sets prices for both individual shows and performance series. These series are arranged by genre and feature both well-known and lesser-known artists. Most of the Marketing Department's budget, which is set at the beginning of the year, is spent on advertising in print (the local major newspaper and the campus newspaper), radio, and direct mail. Ticket packages are offered during the pre-season. After the season begins, each event is advertised individually, starting about a month before the show opens.

To model the decision-making of the Center's marketing manager, it is important to specify the sequence of options available to her when advertising each show. The timing these decisions and their outcomes can be divided into three periods:

incubator of new ideas, [the Center] is dedicated to radical, genre-bending collaborations and the development of new work.”

Period 0: Before the season begins, the marketing manager decides on the ticket prices of individual shows and Series ticket packages. Once set, these prices do not change over the course of the season, and the Center does not offer discounts for poorly selling shows (there are student discounts but they are a small proportion of total ticket sales). Consequently, after period 0, the only strategic option available to the manager to increase demand for a particular show is the level of advertising for that show. As part of the venue booking process, the manager generates and reports a forecast of the ticket sales for each performance that is used in deciding which hall to allocate to each show. The manager also uses heuristic “rules-of-thumb” to form expectations concerning advertising expenditures and to decide the preliminary advertising budget for each performance.¹² Her expected ticket sales are a function of venue, time of year (university semester), day and time of week of the performance (weekends, weekdays, daytime, evening), Series, genre (traditional, family, avant-garde), price, the expected advertising expenditure, and the manager’s beliefs concerning the latent appeal of the show before any ticket is sold.

Period 1: At the beginning of period 1, the Center mails circulars describing the upcoming season. Over the course of the period, individuals purchase tickets for each performance (as part of a series package or individually). No advertising for individual shows is conducted. For shows occurring early (late) in the season, period 1 may be fairly short (long). Approximately 36% of tickets sales occur in period 1. At the end of period 1, roughly one month prior to the date of the performance, the manager observes the ticket sales for the show up to that point, and updates her period 0 beliefs concerning

¹² Expected advertising expenditures depend primarily on number of shows for the performance and the venue, as well as the manager’s past experience.

the latent appeal of the show. Further, she may observe new factors (e.g. competition from other entertainment venues, economic shocks etc.) affecting the demand for shows that were unforeseen in period 0.

Period 2: Based on her updated beliefs concerning show quality and other demand shifters, the manager decides on advertising spending and purchases advertising in print and on the radio at the beginning of period 2. Advertising expenditures may also depend on the amount of budgetary funds remaining at the beginning of the period. Ticket sales are then recorded until the time of the performance.

2.1 Reliability of the Expectations Data

The discussion of the Period 0 planning process suggests that the manager has strong incentives to report her expectations accurately. Her forecasts have economic consequences since they are reported to her superior and are used to choose the venue and staff assignment for each performance. Understating expected ticket sales potentially leads to booking an act in a venue that is too small, implying lost revenue if the performance is a sellout; overstating her forecast potentially inflates costs due to the staffing requirements of a larger venue. Unlike survey-based reports where respondents have little incentive to report their true expectations, the data in this study is similar in spirit to expectations data collected from professional forecasters. Because these professionals sell their forecasts, they have stronger incentives to report their true expectations (Keane and Runkle (1990)). The formation of expected sales and marketing expenditures is “textbook” practice in many firms (Kotler and Lane (2006)). At the beginning of our sample period, the manager had been in her position for seven years and so was experienced in making these forecasts. Consequently, we believe that the data

reported here is a more accurate representation of the manager's true expectations than may be commonly elicited from large scale surveys.

2.2 Data and Summary Statistics

We obtained data from the Center regarding show characteristics, prices, and Period 1 and 2 ticket sales for each of the 146 shows staged during the years 1997-1999. No information was available on the characteristics of ticket purchasers. Of key importance for this study, the Marketing manager provided us with her period 0 expectations regarding ticket sales for each show in the data set, as well as her period 0 planned advertising expenditures.

Figure 1 shows a strong positive relationship between the manager's expectations and actual ticket sales. The correlation is high (0.85), with higher projected ticket sales generally associated with higher actual sales. The figure also indicates that the manager tends to under-predict ticket sales. She projects more than actual ticket sales for only 26% of shows. However, she is more optimistic regarding AG shows, where her projection overstates actual tickets sold in 59% of cases.

Table 1 indicates that projected advertising expenditures per performance are roughly equal to actual expenditures. However, though statistically insignificant, actual advertising expenditures are higher than expected expenditures for avant-garde shows, and *vice versa* for other genres. Comparison of the actual and expected advertising expenditures by genre suggests the consequence of the manager's optimistic beliefs concerning the latent appeal of avant-garde shows. Perhaps in response to slow first period sales, the manager may then increase actual advertising for avant-garde shows above her period 0 expectation. The third row of the table shows that the average ticket

price of each show is about \$30, and there is no significant difference in pricing for avant-garde shows vs. other genres.

2.3 OLS Estimates of Ticket Sales

The difficulty faced by the econometrician in evaluating the impact of advertising, pricing, and product characteristics on tickets sold is illustrated by the results in Table 2. Columns (1) and (2) of the table present OLS regression estimates of the price elasticity of demand for tickets sold for each performance, as well as the elasticity of advertising response and the impact of other product characteristics thought to affect demand such as show genre, series membership, day of the performance (weekend vs. weekday), time of day (evening vs. daytime), time of season (early, mid, or late-year), venue, and year. Taken at face value, the price coefficient implies that the demand curve for shows is upward sloping, since a 10 percent increase in price is associated with 3.2-3.4 percent increase in the number of tickets sold. On the other hand, advertising appears to reduce demand, since a 10 percent increase in advertising expenditure is associated with a 1.2 percent decline in tickets sold in column (1)! Even when the advertising effect is allowed to vary by show genre (AG vs. non-AG shows), the OLS results in column (2) continue to show a negative effect of advertising.

These results suggest not surprisingly that pricing and advertising strategies are endogenous. If the manager believes a show is likely to be popular to potential customers, she will charge a higher price. Conversely, she may advertise more for less attractive shows to boost sales, generating the negative relationship observed in the table. The potential endogeneity of price and advertising, as well as other product attributes, makes standard econometric approaches for generating unbiased estimates of the impacts of

prices, advertising, and attributes particularly problematic. One is unlikely to find reasonable instruments for all the endogenous variables. In fact, even if product attributes are assumed to be exogenous, acceptable instruments may not be available for both pricing and advertising. Consequently, an alternative approach is required.

3. MANAGERIAL CHOICE WITH PARTIAL INFORMATION AND POTENTIALLY BIASED EXPECTATIONS

We develop a framework for decision-making in which the manager has partial information and potentially biased expectations. The manager chooses the level of advertising expenditure, A_j , for each of the $j = 1, \dots, J$ shows staged by the Center in a given year, based on the information available to her as of the decision date t during the season (Ω_t) and her beliefs regarding the determinants of demand for the show, which are characterized by a parameter set Θ^0 . Unlike previous research, we allow Θ^0 to differ from the “true” parameter set Θ .

Following models of non-profits in general (e.g., Malani et al (2003)), and performing arts centers in particular (Baumol and Bowen (1965); Hansmann (1981)), the manager has multiple objectives. First, she chooses advertising to maximize the net contribution (R_j) that show j makes to the Center. Net contribution from show j is defined as $R_j = p_j Y_j - A_j - FC_j$, where p_j is the ticket price to show j , set at the start of the year, Y_j is number of tickets sold to j , and FC_j is the fixed cost associated with show j .¹³ As part of the university, Center revenues are used to fund educational activities in the performing arts departments. The Center also receives revenue from donations (D) which we assume are proportional to the total level of advertising (i.e., $D = \rho \sum_j A_j$).

¹³ Marginal costs of selling additional tickets are close to zero when a show has not achieved a full house, so R_j will be equivalent to net profit for the Center. This is the case for all of the shows in our data.

Advertising heightens awareness of the Center's activities, which in turn may generate additional contributions.¹⁴

The manager's second objective is to fulfill the Center's mission of promoting "an aesthetic of fusion and diversity" and non-mainstream or avant-garde artists when making her advertising decisions.¹⁵ Consequently, we assume that her utility is a function of attendance at avant-garde (AG) performances, $Y_{j|j \in AG}$.

The manager may also have preference for total attendance at show j that is related to her expectations. As discussed in Section 2, the manager's period 0 forecasts of demand for each show are reported to her superiors. Mistakes in her forecasts have readily observable consequences, such as half empty venues. For example, if period 1 ticket sales for show j are unexpectedly low, the manager may prefer to increase advertising expenditures so that final ticket sales more closely correspond to her reported period 0 forecast. We therefore incorporate the manager's reported expectations into the utility function to capture this potential agency issue.

Finally, the manager does not face a "hard" budget constraint since she can spend more than her planned budget.¹⁶ However, excessive over-spending may lead to disciplinary action or confiscation of future resources which the manager may seek to avoid, implying that utility will be a function of the amount of funds remaining in the budget as of date t , B_t .

¹⁴ We do not have information on the amount of donations to the Center in each year. However, advertising may establish the Center's brand name in the community and may impress prospective donors. The relatively high level of the Center's advertising expenditure suggests that they perceive benefits of advertising, such as increased donations, beyond the immediate effect on ticket sales.

¹⁵ The Center's mission corresponds with Hansmann's (1981) view that an objective of a performing arts organization is to spread "culture."

¹⁶ Therefore the manager's problem is not the one with fixed advertising budget.

The manager's choice problem is to decide how to allocate advertising expenditure for all shows scheduled after date t (in a given year) based on her information set, Ω_t , and her beliefs Θ^0 :

$$\max_{\{A_j, j>t\}} \sum_{j>t} E_t[U_j(R_j, D_j, Y_j |_{j \in AG}, Y_j, B_t) | \Omega_t, \Theta^0], \quad (1)$$

where U_j is the utility associated with show j and D_j is the incremental donation associated with advertising for show j .

3.1 Specification of Preferences

We assume that the manager is risk neutral so that the sum of expected utilities for shows performed after t in the school year is given by

$$\begin{aligned} \sum_{j>t} E[U_j | \Omega_t, \Theta^0] &= \sum_{j>t} \{ (p_j \cdot E[Y_j | \Omega_t; \Theta^0] - A_j - FC_j) \\ &\quad + \rho A_j + \psi_{AG} E[Y_j |_{j \in AG} | \Omega_t; \Theta^0] \\ &\quad + \psi_H E[Y_j | \Omega_t; \Theta^0] \cdot 1_{\{(Y_{1,j}/Y_j^0) > c_H\}} + \psi_L E[Y_j | \Omega_t; \Theta^0] \cdot 1_{\{(Y_{1,j}/Y_j^0) < c_L\}} \} \\ &\quad + \psi_{Bt} (\sum_{j>t} A_j - B_t), \end{aligned} \quad (2)$$

where $1_{\{x\}}$ is the indicator function. Equation (2) emphasizes the fact that expected ticket sales for show j , $E_t[Y_j | \Omega_t; \Theta^0]$, depend on the manager's information set at time t (which includes initial ticket sales to j) and her beliefs regarding the determinants of demand.

The first term on the right hand side of equation (2) is the expected net contribution generated by show j , and the second term captures the incremental contribution to annual donations to the Center resulting from advertising for show j .¹⁷

The parameter ψ_{AG} reflects the additional utility the manager receives from a ticket sold

¹⁷ Alternatively, as an art performance promoter the Center may have preference for attendance above the static profit maximization objective (i.e., "art for art's sake"). Since attendance is an increasing function of advertising expenditures in our results (discussed below), our specification for D is consistent with this explanation.

to an AG show. The terms associated with ψ_H and ψ_L in the third line equation (2) capture the potential incentive of the manager to adjust advertising so that final ticket sales correspond more closely to her period 0 reported expectations. We characterize show j as having unexpectedly high (low) period 1 ticket sales if the ratio of observed period 1 sales to expected sales, $Y_{1,j}/Y_j^0$, is in the top (bottom) tercile of all shows (i.e., larger than c_H (smaller than c_L)).¹⁸ The parameters ψ_H and ψ_L represent the additional utility the manager receives from selling a ticket to a show that had unexpectedly high or low period 1 ticket sales, respectively. If $\psi_L > 0$, the manager spends more to advertise a show with slow initial ticket sales than is implied by profit maximization.

The final term of (2) captures the impact of the budget constraint on advertising decisions. The utility cost to the manager of spending more on advertising than the remaining budget B_t is given by ψ_{B_t} . Let OB_t measure the extent to which actual advertising expenditures prior to time t are running above or below planned expenditures.¹⁹ ψ_{B_t} is specified as a function of the extent to which the manager's advertising budget is above or below plan as of date t , so that $\psi_{B_t} = \psi_{OB} + \psi_{1BD}|OB_t| \cdot 1_{OB_t > 0} + \psi_{1BS}|OB_t| \cdot 1_{OB_t < 0}$. In this case, $\psi_{1BD} < 0$ implies the manager reduces subsequent advertising expenditures the more she is over-budget at time t .

The expected demand function for j is assumed to be independent of ticket sales from previous shows k , $k < j$, so that there are no spill-over effects across shows. This

¹⁸ Because we do not observe the manager's forecast of period 1 sales, we use the ratio $Y_{1,j}/Y_j^0$ to compute the measure of whether initial sales are high or low relative to expectations (i.e., above or below the cutoff values c_H and c_L , respectively, that are defined by the appropriate terciles). This will be an accurate measure if the manager's period 0 expectation of period 1 sales is roughly a constant fraction of overall expected sales, i.e., $Y_{1,j}^0 = \delta Y_j^0$. We regressed the ratio of observed period 2 to period 1 ticket sales, $Y_{2,j}/Y_{1,j}$, on observed show characteristics and found no evidence that these factors were significant predictors of the ratio. This evidence supports the assumption that δ is constant, although the possibility that the manager believes it varies with show characteristics cannot be ruled out.

¹⁹ This implies $OB_t = \sum_{k=1}^{t-1} (A_k - A_k^0)$.

seems to be a reasonable assumption; shows of a particular type (e.g., avant-garde) in our data are usually not scheduled close together. Consequently, they are unlikely to substitute or complement each other in ticket sales. Under this condition, solving the advertising expenditure problem in (2) can be reduced to solving the optimal advertising expenditure for each show separately.

3.2 Specification of Demand

Estimation of equation (2) requires the specification of the demand for show j . To be consistent with our empirical context, we specify demand functions in periods 1 and 2 that allow for consumer preference heterogeneity for each show. Further, we distinguish between the manager's perceived demand model, characterized by parameter set Θ^0 , and the actual demand model with the true parameters Θ .

Let ξ_j represent the quality of the show that is unknown to researchers but partially observed by the manager in period 0. ξ_j may thus be correlated with show attributes and prices, which, as observed in Section 2, generates nonsensical estimates in OLS regressions of ticket sales. The indirect utility function of consumer i for show j in period 1 is specified as:

$$V_{ij,1} = X_j \beta + \xi_j + \omega_{j,1} + \zeta_{ij} + \varepsilon_{ij,1}, \quad (3)$$

where X_j is a vector of observed show attributes, including genre, series, day of week, show time, venue, season, year, and (log of) prices. $\omega_{j,1}$ is a period 1 demand shock unexpected by the manager.²⁰ After period 1, $\omega_{j,1}$ is revealed to the manager and so may be correlated with actual advertising spending. Finally, individual preference

²⁰ We use $\omega_{j,1}$ to differentiate from the part of demand disturbance that is predicted by the manager in period 0, which is absorbed into ξ_j .

heterogeneity is assumed to have two components: (a) ζ_{ij} represents individual i 's time-invariant preference for show j that is independently distributed as $N(0, \sigma_\zeta^2)$; (b) $\varepsilon_{ij,1}$ represents a period 1 individual- and time-specific *i.i.d.* preference shock.

In period 2 individual preferences may change due to three sources: (i) a period 2 demand shock, $\omega_{j,2}$, that may be correlated with $\omega_{j,1}$; (ii) the period 2 individual- and time-specific preference shock $\varepsilon_{ij,2}$ (which is uncorrelated with $\varepsilon_{ij,1}$); (iii) advertising for show j that may impact preferences. The period 2 indirect utility function is then:

$$V_{ij,2} = X_j \beta + Ad_j \gamma + \xi_j + \omega_{j,2} + \zeta_{ij} + \varepsilon_{ij,2}, \quad (4)$$

where Ad_j is the log of advertising spending A_j for show j . Following standard assumptions (e.g., Berry, Levinsohn, and Pakes (1995)), $\varepsilon_{ij,2}$ and $\varepsilon_{ij,1}$ are independent and follow extreme value type I distribution. Let M be the potential market size, which we assume to be the total population size in the city where the Center is located. We assume that the consumer will purchase a ticket for show j in period 1 if $V_{ij,1}$ is greater than the value of the no-purchase option, which is normalized to zero. If a ticket is not purchased in period 1, the consumer will again have the option to buy in period 2; i purchases if $V_{ij,2} > 0$.²¹ Using our utility function specifications for $V_{ij,1}$ and $V_{ij,2}$ and appropriate distributional assumptions for ζ_{ij} , $\varepsilon_{ij,2}$ and $\varepsilon_{ij,1}$, the market share functions for period 1 and period 2, conditional on latent show quality and period-specific demand shocks, are

$$s_{j,1} \equiv \frac{Y_{j,1}}{M} = \int \frac{e^{X_j \beta + \xi_j + \omega_{j,1} + \zeta_{ij}}}{1 + e^{X_j \beta + \xi_j + \omega_{j,1} + \zeta_{ij}}} d\Phi(\zeta_{ij}; \sigma_\zeta^2), \quad (5)$$

²¹ Our specification of consumer demand shares some features of Leslie's (2004) model of Broadway theater ticket sales in that we allow for heterogeneous consumer tastes and incorporate temporal demand effects. Unlike Leslie's application, there is no monetary benefit to a consumer of delaying a ticket purchase to a Center performance (e.g., there is no day of show discount ticket booth), except that individuals will be more certain about their preferences for show j closer to the performance date. Our model abstracts away from such dynamic considerations by explicitly assuming that the consumer will not wait until period 2 to purchase a ticket if $V_{ij,1} > 0$.

and

$$s_{j,2} \equiv \frac{Y_{j,2}}{M} = \int \frac{1}{1 + e^{X_j \beta + \xi_j + \omega_{j,1} + \zeta_{ij}}} \cdot \frac{e^{X_j \beta + Ad_j \gamma + \xi_j + \omega_{j,2} + \zeta_{ij}}}{1 + e^{X_j \beta + Ad_j \gamma + \xi_j + \omega_{j,2} + \zeta_{ij}}} d\Phi(\zeta_{ij}; \sigma_\zeta^2) \quad (6)$$

Equations (5) and (6) imply that period 1 ticket buyers are likely to be those with greater preference for the Center's performances than period 2 buyers. Most of the tickets in period 1 are sold to annual subscribers who attend multiple shows during the season. In period 2, tickets tend to be sold to single show buyers who are likely to have less knowledge of the Center's show schedules. Advertising to this consumer segment is important for both persuasive and informative purposes.

3.3 *The Manager's Expectations of Demand*

We allow the manager's period 0 expectations of demand to depart from the "true" demand model in two ways. First, the manager's perceptions concerning the effects of show attributes and advertising on ticket sales may be different from their actual effects. Denoting the parameter set in the above demand model by $\Theta = \{ \beta, \gamma, \sigma_\zeta^2 \}$, and the manager's beliefs concerning these parameters by $\Theta^0 = \{ \beta^0, \gamma^0, \sigma_\zeta^{02} \}$, this possibility implies Θ^0 may not equal Θ . If $\Theta^0 \neq \Theta$, the manager makes systematic mistakes in forecasting policy implications for demand, perhaps due to innate biases or lack of experience. In addition, the manager's perception of show appeal may be different from that actually held by consumers due to limited information, so that $\xi_j^0 \neq \xi_j$.

Because the manager decides on X_j and the advertising plan Ad_j^0 before the season starts, these quantities together with ξ_j^0 become her information set for performance j in period 0, $\Omega_{j,0}$. Using specifications (5) and (6) and her report of

expected ticket sales for show j , Y_j^0 , the manager's period 0 belief of the market share for show j , s_j^0 , is given by:

$$E[s_j | \Omega_{j,0}] \equiv s_j^0 \equiv \frac{Y_j^0}{M} = \int \left[\frac{e^{X_j \beta^0 + \xi_j^0 + \zeta_{ij}}}{1 + e^{X_j \beta^0 + \xi_j^0 + \zeta_{ij}}} + \frac{1}{1 + e^{X_j \beta^0 + \xi_j^0 + \zeta_{ij}}} \cdot \frac{e^{X_j \beta^0 + Ad_j^0 \gamma^0 + \xi_j^0 + \zeta_{ij}}}{1 + e^{X_j \beta^0 + Ad_j^0 \gamma^0 + \xi_j^0 + \zeta_{ij}}} \right] d\Phi(\zeta_{ij}; \sigma_\zeta^{02}) \quad (7)$$

The demand disturbances $\omega_{j,1}$ and $\omega_{j,2}$ do not enter (7) because they are unexpected to the manager. Furthermore, if $\sigma_\zeta^2 \neq \sigma_\zeta^{02}$ the manager's perception of the heterogeneity in consumer tastes is different from the true level.

3.4 Overview of the Econometric Implementation of the Model

Our goal is to estimate the managerial preference parameters $\Psi^0 = \{\rho, \psi_{AG}, \psi_H, \psi_L, \psi_{OB}, \psi_{1BS}, \psi_{1BD}\}$ in equation (2), allowing for the general case where the manager may make systematic errors concerning the determinants of demand and have partial or biased information about the unobservables in the demand function. In fact, we are able to test whether the manager has biased beliefs concerning the impact of advertising and various product attributes (such as avant-garde) on ticket sales. It is clear from equation (2) that in the absence of the expectations data, identification of Ψ^0 rests on assumptions regarding expectations formation. For example, observing that the manager excessively spends on AG shows, we cannot distinguish whether this is because she has unique preference for AG performances or because she is over-optimistic about the appeal of AG to the audience. By employing expectations data, we can assess the sensitivity of the preference parameter estimates to assumptions such as rational expectations that are typically found in the literature.

The standard approach to infer Θ is to find instruments for the endogenous decision variables in the demand function. However, appropriate instruments may not be available (as in our application). The key insight of our approach is that combining the data on the period 0 managerial expectations with observed market outcomes allows us to infer the demand shocks that are independent of observed show attributes X_j and the advertising decision variable Ad_j . The independence of these shocks helps to construct moment conditions in model estimation. Specifically, we model the manager's updated beliefs regarding the demand in period 2 after new information arrives in period 1, and specify the pure demand shock unexpected to the manager in period 2. This step provides consistent estimates for $(\beta - \beta^0)$, as well as the true and perceived effectiveness of advertising, γ and γ^0 , respectively. With these estimates, we then recover the preference parameters Ψ^0 in equation (2).²²

Three sets of moment conditions are created to estimate the parameters in demand functions and managerial objective function. Although the model is estimated simultaneously using all moments, for expositional purposes we first describe in the next section how to estimate the demand parameters using the first two moment conditions. Section 5 then describes the estimation of the managerial objective function parameters using the third moment condition, conditional on the demand estimates. Further details concerning the estimation of the model are provided in Appendix A.

4. DOES THE MANAGER HAVE UNBIASED BELIEFS?

We use the expectations data to examine whether the manager has biased beliefs for the demand parameters. A complicating factor in the analysis is that while

²² This will be explained more fully below.

expectations are reported in period 0, the manager makes her advertising decision after observing the number of tickets sold to show j in period 1. Consequently, we must specify how the information set evolves from $\Omega_{j,0}$ to $\Omega_{j,1}$. The remainder of this section describes the econometric implementation of the model, and then discusses the demand estimates.

4.1 Econometric Implementation

Let $\delta_{j,1} = X_j\beta + \xi_j + \omega_{j,1}$ and $\delta_{j,2} = X_j\beta + Ad_j\gamma + \xi_j + \omega_{j,2}$ denote the mean utility levels of show j in periods 1 and 2. Given the variance σ_ζ^2 , we calculate the simulated market share functions (see equations (5) and (6)) by drawing a set of ns pseudo-random ζ 's from the assumed distribution:

$$\tilde{s}_{j,1}(\sigma_\zeta^2) = \frac{1}{ns} \sum_{s=1}^{ns} \frac{e^{\delta_{j,1} + \zeta_{ij}^s}}{1 + e^{\delta_{j,1} + \zeta_{ij}^s}} \quad \text{and} \quad \tilde{s}_{j,2}(\sigma_\zeta^2) = \frac{1}{ns} \sum_{s=1}^{ns} \frac{1}{1 + e^{\delta_{j,1} + \zeta_{ij}^s}} \cdot \frac{e^{\delta_{j,2} + \zeta_{ij}^s}}{1 + e^{\delta_{j,2} + \zeta_{ij}^s}}$$

The above expressions indicate that $\tilde{s}_{j,1}$ and $\tilde{s}_{j,2}$ are calculated conditional on σ_ζ^2 . We then use a contraction mapping algorithm to invert $\delta_{j,1}$ and $\delta_{j,2}$ by matching $\tilde{s}_{j,1}$ and $\tilde{s}_{j,2}$ with actual market shares $s_{j,1}$ and $s_{j,2}$ (for detailed description see Berry (1994)).

Similarly, let $\delta_j^0 = X_j\beta^0 + \xi_j^0$ denote the manager's perceived mean utility level of show j . Given the variance parameter σ_ζ^{02} (see equation (7)) we simulate another set of ns pseudo-random variables $\{\zeta^{01}, \zeta^{02}, \dots, \zeta^{0ns}\}$. Conditional on the manager's perceived advertising effects γ^0 , the simulated expected total market share is calculated as

$$\tilde{s}_j^0(\gamma^0, \sigma_\zeta^{02}) = \frac{1}{ns} \sum_{s=1}^{ns} \left[\frac{e^{\delta_j^0 + \zeta_{ij}^{0s}}}{1 + e^{\delta_j^0 + \zeta_{ij}^{0s}}} + \frac{1}{1 + e^{\delta_j^0 + \zeta_{ij}^{0s}}} \cdot \frac{e^{\delta_j^0 + Ad_j^0\gamma^0 + \zeta_{ij}^{0s}}}{1 + e^{\delta_j^0 + Ad_j^0\gamma^0 + \zeta_{ij}^{0s}}} \right],$$

where \tilde{s}_j^0 is a function of γ^0 and σ_ζ^{02} . We again use the contraction mapping algorithm to invert δ_j^0 by matching \tilde{s}_j^0 with the manager's reported expectation s_j^0 .

With the computed $\delta_{j,1}$ and δ_j^0 we have

$$\delta_{j,1} - \delta_j^0 = X_j(\beta - \beta^0) + \nu_{j,1}, \quad (8)$$

where $\nu_{j,1} = \xi_j - \xi_j^0 + \omega_{j,1}$ is a shock to the manager in period 0 that is independent of the decisions of show attributes, pricing and planned advertising spending. Let ν_l be a vector which j -th element is $\nu_{j,1}$, and $Z_l = \{X, Ad^0\}$ be the set of these decisions for all shows. The first moment condition we use in model estimation is:

$$E[\nu_l | Z_l] = 0. \quad (9)$$

Actual advertising spending Ad_j is not independent of ν_l . After period 1 the demand shock $\omega_{j,1}$ is revealed and with this new information the manager adjusts her advertising spending to maximize her objective function in (1) and (2). Consequently, to estimate the actual advertising effect, we need to model how her expectations change after period 1.

Updating Managerial Expectations in Period 1

Equation (7) implies that the manager expects the market share of show j in period 1 to be

$$E[s_{j,1} | \Omega_{j,0}] \equiv s_{j,1}^0 \equiv \frac{Y_{j,1}^0}{M} = \int \left[\frac{e^{\delta_j^0 + \zeta_{ij}}}{1 + e^{\delta_j^0 + \zeta_{ij}}} \right] d\Phi(\zeta_{ij}; \sigma_\zeta^{02}) \quad (10)$$

We infer the manager's perceived mean utility level of show j in period 1, $\delta_{j,1}^0$, after observing market share $s_{j,1}$, using a procedure similar to previous discussion. We first

draw ns pseudo-random variables $\{\zeta^{01}, \zeta^{02}, \dots, \zeta^{0ns}\}$ from $N(0, \sigma_\zeta^{02})$ to form the simulated market share function

$$\tilde{s}_{j,1}(\sigma_\zeta^{02}) = \frac{1}{ns} \sum_{s=1}^{ns} \frac{e^{\delta_{j,1}^0 + \zeta_{ij}^{0s}}}{1 + e^{\delta_{j,1}^0 + \zeta_{ij}^{0s}}}.$$

The contraction mapping method is then used to invert $\delta_{j,1}^0$. Note that $\delta_{j,1}^0$ may be different from the true $\delta_{j,1}$ if σ_ζ^{02} differs from σ_ζ^2 . The quantity $\nu_{j,1}^0 = \delta_{j,1}^0 - \delta_j^0$ represents the shock viewed by the manager after period 1.²³

If the manager expects the demand shocks in the two periods to be correlated, she will use the new information $\nu_{j,1}^0$ to update her belief regarding ticket sales for show j in period 2. We model the manager's updated belief of $\delta_{j,2}^0$ following the specification in Olley and Pakes (1996):

$$\delta_{j,2}^0 = \delta_j^0 + g(\nu_{j,1}^0), \quad (11)$$

where $g(\nu_{j,1}^0)$ is an unknown function. This is estimated by a series estimator using a fifth order polynomial expansion in $\nu_{j,1}^0$:

$$g(\nu_{j,1}^0) = \sum_{l=1}^5 \theta_l \cdot \text{sign}(\nu_{j,1}^0) \cdot |\nu_{j,1}^0|^l$$

where $\text{sign}(\cdot)$ equals 1 if the expression inside brackets is positive, and -1 otherwise.²⁴

With this updating of managerial expectations, let $\nu_{j,2} = \xi_j + \omega_{j,2} - (\xi_j^0 + g(\nu_{j,1}^0))$ represent the shock to the manager in period 2 that is independent of show attributes, pricing and planned advertising spending. It is also independent of actual advertising

²³ We use this notation to differentiate from the "true" demand shock $\nu_{j,1}$ described earlier.

²⁴ The criterion function value, parameters of interest, and θ_l 's are almost the same between the fifth and fourth order expansion in our model estimation.

spending since the decision is made at the beginning of period 2. Using the contraction mapping techniques discussed above, we compute $\delta_{j,2}$ and δ_j^0 from observed ticket sales and the manager's reported expected ticket sales, respectively, to construct

$$\delta_{j,2} - \delta_j^0 = X_j(\beta - \beta^0) + Ad_j\gamma + g(\nu_{j,1}^0) + \nu_{j,2}. \quad (12)$$

Define ν_2 as a vector with j -th element $\nu_{j,2}$, and Z_2 be a set of the set of managerial decisions (including X_j , Ad_j^0 , and Ad_j) together with the basis functions of $g(\cdot)$,

$sign(\nu_{j,1}^0) \cdot |\nu_{j,1}^0|^l$, for all j . The second moment condition used in model estimation is then:

$$E[\nu_2 | Z_2] = 0. \quad (13)$$

The moment conditions in (9) and (13) are used to identify the parameters $(\beta - \beta^0)$, γ and γ^0 .

In summary, the manager's expected show attractiveness ξ_j^0 may be correlated with performance attributes X_j as well as planned and actual advertising expenditures Ad_j^0 and Ad_j , respectively. However, the shock in period 1, $\nu_{j,1}$, is unexpected to the manager in period 0; hence it is uncorrelated with X_j and Ad_j^0 . Nevertheless, $\nu_{j,1}$ may affect Ad_j since the manager may update her belief about ticket sales at the end of period

1. Conditional on information set Ω_{j1} , the shock in period 2, $\nu_{j,2}$, is unexpected to the manager after period 1 and so is uncorrelated with X_j , Ad_j^0 , and Ad_j . These become the identification conditions for our estimation of the demand parameters. We can estimate from the data the true and expected advertising effects γ and γ^0 , respectively, but we can only recover the differences $(\beta - \beta^0)$. In general, the parameters are identifiable with expectations data if policies are dynamically adjusted in response to changing market

conditions. However, only the differences between actual and perceived effects of product attributes, including price, can be estimated when the decisions are fixed from period 0.^{25,26}

4.2 Estimation Results

Table 3 presents GMM estimates of the demand model for tickets, based on the above moment conditions. As discussed above, we are unable to consistently estimate the impact of time-invariant show attributes, including price, on demand. However, we are able to estimate the extent to which the manager's beliefs concerning the effect of these attributes on demand are biased. Column (1) of Panel A suggests that while the manager over-estimates the price elasticity of demand for Center performances, the difference is not statistically significant. Her period 0 expectations concerning the demand curve appear to be borne out by the actual data.

²⁵ If we followed the standard assumptions in the previous literature that product attributes are exogenous (and therefore uncorrelated with the unobserved demand shocks), we could directly estimate the impacts of product attributes on demand after obtaining the estimate of the advertising effect.

²⁶ Our estimation approach is similar in many respects to the strategies used by Olley and Pakes (1996) and Levinsohn and Petrin (2003) to estimate production functions. These papers decompose the unobserved state variables in the production function into two components. The first, ω_t is the firm's unobserved productivity shock in period t . Its expected value conditional on the past shock, $E[\omega_t | \omega_{t-1}]$, affects capital input decisions k_t (analogous to show quality ξ_j^0 in our model), while the realized value affects labor input decisions l_t (analogous to the impact of $\nu_{j,1}$ on advertising decisions in our model). Another state variable η_t (similar to our $\nu_{j,2}$) has no effect on both k_t and l_t . Their estimation strategy is to first use other inputs, such as investment i_t or intermediate inputs l_t , in their data as instruments and invert ω_t as a non-parametric function of inputs (except l_t). Conditional on the estimated labor coefficient obtained from the first step, their second step is to assume that ω_t follows a first-order Markov process, $\omega_t = E[\omega_t | \omega_{t-1}] + \xi_t$, where ξ_t is an unexpected productivity shock uncorrelated with k_t . Similarly, we model how the manager updates her belief of demand after observing first period ticket sales, using the manager's expectations data instead of instrumental variables. Our method does not require other conditions such as monotonicity that relates to the objective function of decision makers, since the manager in our application may not maximize profits. Further, the availability of prior expectations data allows manager to have imperfect information and potentially make systematic errors in our model.

The positive coefficient for avant-garde (AG) suggests that the manager is over-optimistic concerning the appeal of this type of show in the Center's market. This follows from the observation in Figure 1 that the manager tends to over-predict ticket sales for AG shows. The finding is consistent with what psychologists term "desirability bias" (Hogarth (1987)), which posits that preferences for outcomes cause over-optimism on the part of the decision-maker.²⁷ This hypothesis implies that if the manager prefers higher attendance at AG shows, she will have upward biased forecasts of ticket sales.²⁸

We are able to recover from our model both the manager's beliefs concerning the impact of advertising on demand, and an unbiased estimate of the true advertising response. From Panel B of Table 3 (column (1)), the manager believes that advertising generates additional demand. Moreover, the (expected) marginal effect of advertising is the same for AG and non-AG shows, implying that the manager believes she is allocating advertising dollars efficiently across show types. Panel C of Table 3 demonstrates the value of our approach in generating plausible estimates of the impact of advertising. While the simple OLS estimates in Table 2 indicated that advertising had a significant and negative impact on demand, we now find that increased advertising expenditure generates more ticket sales to the Center's performances, particularly in the case of AG shows. This is perhaps because AG performers are relatively unknown; advertising may thus generate more informative and persuasive effects. Comparison of Panels B and C

²⁷ Krizan and Wenschitl (2007) provide an excellent summary of the literature on desirability bias.

²⁸ Since the manager had been in her position for a number of years by 1997, we assume that her beliefs regarding the appeal of AG shows were stable during our sample period. An obvious question is why her apparent biases persist over time. Kahneman and Lovall (1993) argue that decision-makers have a tendency to view problems as unique and to anchor their forecasts on plans rather than past results. Consequently, the manager may not appropriately update her beliefs about the appeal of AG shows. Conversely, Caskey (1985) shows that the under-prediction by forecasters of inflation during the 1970s is consistent with models of Bayesian learning and appropriately chosen priors, and does not necessarily reflect irrational behavior on the part of forecasters.

indicates that the manager is too optimistic about advertising effectiveness, particularly in the case of non-AG performances. This partly explains the relatively high level of advertising spending on the part of the manager. The results in Panel C also suggest that if the manager knew the actual effectiveness of advertising, she would allocate more of the advertising budget to AG shows.

The manager under-estimates the extent of consumer heterogeneity in the market, according to Panel D. She apparently believes there is a larger mass of marginal arts consumers who are potentially responsive to advertising. This may also support higher advertising expenditures. In actuality, there are more individuals with either strong taste or distaste for the Center's offerings. In summary, while the manager is biased in her beliefs concerning the appeal of some show attributes such as AG genre and advertising effectiveness, the expectations she has regarding the price sensitivity and other product characteristics appear to be unbiased. The finding that the manager has biased beliefs concerning some variables but not others is similar to the results of Zarnowitz (1985), who shows that forecasters have rational expectations about real GNP growth but not inflation.

4.3 Robustness Checks

Our approach requires us to explicitly model the manager's expectations in equation (7). Estimates may be biased if the manager's forecasting model for ticket sales is mis-specified in our framework. To investigate the extent of this issue, we estimated several alternative models to assess the robustness of the results under different specifications.

First, it is possible that art performances are not appealing to many individuals so they will never attend these shows. These individuals may not be considered by the manager as potential consumers, so the potential market size M is smaller than the city population that we assumed. We re-estimated the model using one-tenth and one-twentieth of the city population for M . The coefficients of interest were qualitatively similar, providing evidence that the major findings are robust to various market size assumptions.

We are also concerned that equation (7) does not account for the impact of the manager's uncertainties regarding true show quality, demand shocks, and her final advertising decisions when forming expectations. The manager does not report the uncertainty associated with her expectations, implying that they are not identifiable when included in the model.²⁹ We conduct a sensitivity analysis to check how the estimation results differ when expectations uncertainty is incorporated into the model. Since the value of period 1 demand shock $v_{j,1}^0$ is calculated in model estimation, we can compute its variance, σ_{v1}^2 . We assume in our sensitivity analysis that when forming expectations, the manager believes a demand shock, v_j , may exist and is distributed as $N(0, \sigma_{v1}^2)$:

$$s_j^0 = \int \left[\frac{e^{X_j \beta^0 + \xi_j^0 + v_j + \zeta_{ij}}}{1 + e^{X_j \beta^0 + \xi_j^0 + v_j + \zeta_{ij}}} + \frac{1}{1 + e^{X_j \beta^0 + \xi_j^0 + v_j + \zeta_{ij}}} \cdot \frac{e^{X_j \beta^0 + Ad_j^0 \gamma^0 + \xi_j^0 + v_j + \zeta_{ij}}}{1 + e^{X_j \beta^0 + Ad_j^0 \gamma^0 + \xi_j^0 + v_j + \zeta_{ij}}} \right] d\Phi(v_j; \sigma_{v1}^2) d\Phi(\zeta_{ij}; \sigma_\zeta^2)$$

The estimates from this model, shown in column (2) of Table 4, are generally quite close to those from the base model in column (1). The notable exception is the estimate of the manager's beliefs concerning the extent of individual preference heterogeneity, σ_ζ^2 . As

²⁹ The identification issue is driven by our reluctance to impose restrictive assumptions on how the manager perceives the extent of these uncertainties, e.g., rational expectations on the variances. This is the same issue in our discussion regarding how the managerial biases in expectations cannot be identified unless we have data on the manager's expectations.

we allow for uncertainty regarding the manager's expectations, σ_{ζ}^{02} begins to converge on σ_{ζ}^2 .

Finally, we assess the sensitivity of our findings to the structural specification of demand given by equations (5)-(7). There may be concern that the structural framework explicitly constrains the types of ticket buyers in the two periods, or that equation (7) is simply too complicated for the manager to actually use to compute her expectations. As an alternative, we re-estimated the model assuming reduced-form, Cobb-Douglas models of actual and expected ticket sales.³⁰ The results from the reduced form model of demand are quite similar to the structural estimates. In particular, the estimates show that the manager is overly optimistic about the appeal of AG shows to consumers.³¹ Overall, the major findings concerning the impact of show characteristics and advertising on actual and expected ticket sales appear to be robust to alternative specifications of market size, uncertainty regarding beliefs, and the demand function. We now turn to the estimation of managerial preference parameters.

5. ESTIMATING MANAGERIAL PREFERENCES

We now examine the manager's objective function and the implications for advertising decisions, incorporating her beliefs concerning demand estimated in Section 4. One of our main interests is to determine whether the manager incorporates the Center's mission of promoting "an aesthetic of fusion and diversity" and non-mainstream or avant-

³⁰ Total ticket sales for show j in the reduced form Cobb-Douglas model are given by $Y_j = e^{\alpha + X_j\beta + \gamma Ad_j + \bar{\omega}_j}$, where $\bar{\omega}_j$ is a stochastic component representing show appeal as well as other demand shocks. The manager's expectations of ticket sales to show j are obtained by replacing the parameter set $\Theta = \{\alpha, \beta, \gamma\}$ with Θ^0 and allowing her to have her own beliefs regarding the distribution of the stochastic component. One advantage of this reduced-form specification is that "nuisance" parameters, such as the manager's uncertainty regarding her forecasts, can be reduced to a single constant parameter in the estimation model.

³¹ Detailed derivation of the reduced-form model and results are contained in an Appendix available from the authors.

garde artists when making her advertising decisions. We then examine the sensitivity of the estimated behavioral parameters to assumptions regarding expectations. Finally, we conduct simulation exercises to assess the magnitude of the impact of the manager's over-optimism, preferences, and agency costs on the Center's net revenues.

5.1 Econometric Implementation

After observing period 1 ticket sales, the manager updates her beliefs regarding the mean utility levels of show j to be $\delta_{j,2}^0$ (see equation (11)). Her expectation of period 2 ticket sales becomes

$$\begin{aligned} E[Y_j | \Omega_{j,1}, Ad_j] &= Y_{j,1} + E[Y_{j,2} | \Omega_{j,1}, Ad_j] = Y_{j,1} + E[s_{j,2} | \Omega_{j,1}, Ad_j] \cdot M \\ &= Y_{j,1} + \int (1 - s_{j,1}) \cdot \frac{e^{\delta_{j,2}^0 + Ad_j \gamma^0 + \zeta_{ij}}}{1 + e^{\delta_{j,2}^0 + Ad_j \gamma^0 + \zeta_{ij}}} d\Phi(\zeta_{ij}; \sigma_\zeta^2) \cdot M, \end{aligned} \quad (14)$$

where $s_{j,1}$ is the market share of show j in period 1. Substituting this expression into equation (2) in Section 3, we can derive the optimal level of advertising spending for j , A_j^* , conditional on the managerial objective function parameters Ψ^0 .

Let observed advertising spending be $A_j = A_j^* + \nu_{j,3}$, where $\nu_{j,3}$ is a stochastic component in the advertising decision unobserved to researchers (e.g. it may not be possible to buy advertising at some media channels exactly at the desired levels). Define ν_3 to be a vector of which j -th element is $\nu_{j,3}$, and Z_3 be a set of variables that will influence the manager's utility function. From the discussion in Section 3, Z_3 includes indicators for AG show (AG_j), unexpectedly high and low period 1 ticket sales (H_j and L_j), and the extent which the advertising budget is above or below plan when advertising

decision is made ($OB_j \cdot 1_{OB_j > 0}$ and $OB_j \cdot 1_{OB_j < 0}$). By construction, our third moment condition in model estimation is

$$E[v_3 | Z_3] = 0. \quad (15)$$

Conditional on the values of the parameter set Ψ^0 , we numerically compute the value of A_j^* . In the model estimation, we search in the parameter space until our criterion function value based on the moment conditions (9), (13) and (15) is minimized. Technical details are provided in Appendix A.

5.2 Estimation Results

Column (1) of Table 4 presents the results from the structural estimation of the manager's objective function given by equation (2). The manager places substantial weight on increasing attendance at avant-garde shows, which is consistent with the Center's mission. Since the average ticket price to a performance is \$30, the estimates imply that each additional ticket sold to an AG show has a marginal value to the manager of $\$30 + \$16.60 = \$46.60$, or approximately 55% more than an additional ticket sold to a non-AG show. This additional utility benefit provides an incentive to overspend for AG advertising from a static net revenue maximization perspective. However, the manager's preference for AG shows may be consistent with profit maximization in the long run. The promotion of AG shows may build a unique position for the Center in the local market, generating future ticket sales and donations. On the other hand, her biased belief concerning the appeal of AG shows leads to advertising expenditures for AG shows that are sub-optimal.

The positive and significant estimate of ψ_L in column (1) highlights the potential agency issue that the Center faces *vis-a-vis* the manager. If period 1 sales for show j are

relatively low, the manager gains substantial additional utility from increasing ticket sales to that show (an additional ticket sold has marginal utility = $\$30 + \$10.95 = \$40.95$). The estimate is reversed for shows whose initial sales substantially exceed expectations: $\psi_H < 0$ implies that an additional ticket sold to one of these performances reduces managerial utility relative to that generated by other shows. Expectations that differ sharply from actual sales may indicate that the manager lacks the expertise to understand the true appeal of each show. The manager's reported expectations potentially expose her incompetence to her superiors at the Center. Consequently, the manager may have an incentive to manipulate advertising spending so that final demand accords with her forecast, but the inefficient expenditure allocation is potentially costly to the Center.³²

The remaining parameters in column (1) suggest that the manager feels some pressure not to over-spend her budget, since ψ_{IBD} is negative and significantly different from zero. However, the magnitude of this effect is relatively small. We are unable to separately identify ψ_{OB} and ρ due to the lack of data on donations. However, if the pressure of over-budgeting is small, so that ψ_{OB} is close to zero, the estimate of constant term implies that ρ is in the range of 0.6 to 0.7. This is consistent with the view that advertising plays a valuable role in raising the profile of the Center in the community, thereby generating charitable donations.³³

5.3 Sensitivity to Expectations Assumptions

In the remainder of Table 4, we investigate the sensitivity of the behavioral estimates to alternative assumptions regarding managerial expectations. In column (2),

³² Because shows are never sold out in our data, the marginal cost of an additional ticket sold to a show exceeding expectations is negligible.

³³ The estimates of Ψ^0 obtained when the reduced-form model of demand described in Section 4.3 is used are quite similar to those reported in Table 4.

the manager is assumed to have unbiased expectations regarding the latent appeal of AG shows, rather than the over-optimistic beliefs reported in Table 3. Imposing this assumption increases the estimate of the additional utility the manager receives from selling tickets to AG shows, ψ_{AG} . The restricted model in column (2) therefore rationalizes the high advertising expenditures observed for AG shows by even greater managerial preferences for attendance at AG performances.

The results in column (3) highlight the value of the expectations data in recovering behavioral parameters. When we assume that the manager has unbiased beliefs concerning all demand parameters, the estimate of ψ_{AG} changes sign and becomes negative and significant. An additional ticket sold to an AG show now reduces the manager's utility by \$12.80! The estimate reflects the implication from Panel C of Table 3 that the manager should be spending more advertising AG shows because AG advertising is actually 3 times more effective than that for non-AG shows. By specifying unbiased beliefs in column (3), the only avenue to rationalize the observed allocation of advertising expenditures across genres is through managerial distaste for AG performances. This seems implausible given the mission of the Center to promote avant-garde art. Overall, the analyses presented in Table 4 suggest that estimates of the managerial preference parameters are sensitive to the specification of expectations. These results highlight the value of subjective expectations data in recovering key parameters of the behavioral model.

5.4 Simulations

To understand the magnitude of the impact of the manager's over-optimism concerning the appeal of AG shows and advertising effectiveness, and the additional

preference weight for increasing demand for AG performances, we conduct counter-factual policy experiments. For the simulations reported in Table 5, we assume that the manager optimally chooses advertising expenditures for each show to maximize her utility, and compute the associated net revenue (total ticket sales revenue – advertising expenditure) using the estimates from column (1) of Table 3 and column (1) of Table 4.³⁴

The totals for baseline net revenue amounts, overall and by show type, are presented in column (1) of Table 5. The simulation in column (2) assumes that the manager has unbiased beliefs concerning the appeal of AG shows and calculates her utility maximizing advertising expenditures and associated net revenues. Because informative advertising is actually less effective in generating demand, Panels A-C indicate that the manager could increase the Center’s net revenue by \$192K, primarily by reducing advertising expenditures for AG shows. The impact of the manager’s optimistic expectations concerning advertising effectiveness is even more substantial: If the manager knew the true values of γ , column (3) shows that net revenues for AG shows increase by 30.9%, since advertising is actually more effective for this genre than for non-AG performances. Overall net revenues increase by 23% if she had unbiased expectations and adjusted advertising expenditures accordingly.

The final two simulations in Table 5 examine the impact of the manager’s preferences on net revenues. Column (4) shows that if the manager did not have special preference for increasing attendance at AG performances (i.e., $\psi_{AG} = 0$), net revenues would be \$247K higher. Consequently, following the Center’s mission reduces revenues by approximately 5.1% relative to that generated by a profit maximizing level of

³⁴ We do not observe the fixed costs associated with each show, so we cannot simulate the impact on overall profitability. The difference between revenue and advertising expenditure measures the contribution to the coverage of these fixed costs.

advertising. Column (5) assesses the magnitude of the agency cost to the Center due to the manager's incentive to manipulate advertising so that final demand meets her reported expectations. Panel C suggests that the implicit agency cost is substantial, approximately \$249K over the three year period. Comparison of Panels A and B indicates that the majority of this implicit cost reflects inefficient allocation of advertising expenditure towards AG shows, since the manager is too optimistic in her reported forecasts of demand for these performances. To summarize, the simulations show that the manager's biased beliefs concerning demand parameters have a significant impact on the net revenue of the Center. Preference for AG shows and agency costs also have substantial effects.

6. CONCLUSION

This paper develops an empirical framework that combines observed market data with reports of subjective expectations to estimate demand and utility function parameters, which may be used to assess theories of managerial choice. Our approach highlights the value of reported expectations data in addressing a number of critical issues in the estimation of empirical models of behavior: (1) endogeneity problems that arise when product attributes and managerial choices are correlated with unobserved (to the researcher) product quality and sufficient instrumental variables are unavailable; (2) uncertainty on the part of the decision-maker regarding true product quality, and biases in managerial beliefs regarding the appeal of certain product attributes; (3) potentially biased expectations concerning the outcomes associated with managerial actions; (4) managerial preferences that may deviate from static profit maximizing behavior. As noted by Manski (2004), problems (2) and (3) are often addressed by assuming that

agents have rational expectations, creating a potential problem in identifying utility parameters. Subjective expectations data allow us to relax strong assumptions regarding expectations and assess the sensitivity of the empirical findings to alternative specifications of the agent's beliefs.

We apply our methodology to the analysis of the advertising decisions of the marketing manager of a large university performing arts center that stages both traditional and avant-garde performances. Our findings highlight the value of our approach. We obtain estimates of the true impact of advertising on demand accounting for potential endogeneity issues and the manager's beliefs regarding this relationship. While we find that the manager's beliefs concerning the price elasticity of demand are unbiased, she over-estimates both the effectiveness of advertising for AG and non-AG shows and the appeal of avant-garde shows to the public. These biased beliefs partly explain her observed overspending on advertising, particularly for AG performances. Incorporating these beliefs into the estimation of the manager's objective function, the manager exhibits special preference for promoting AG shows that coincides with the stated mission of the Center. However, the estimate of the incremental utility to the manager associated with AG shows is sensitive to assumptions regarding her expectations. When we assume she has rational expectations regarding the determinants of demand, the estimated marginal utility of additional sales to AG performances becomes negative and significant, which seems implausible in this context. The results also emphasize the care that must be taken when incorporating expectations data into the empirical model. The manager has an incentive to manipulate advertising for shows with poor (or high) initial sales so that final

sales match her ex ante forecast. Simply using expectations data as an additional variable in a reduced-form advertising model fails to account for such agency issues.

The results of the paper raise important questions about the formation of expectations, such as how an experienced manager may continue to hold biased beliefs concerning the appeal of particular product attributes or advertising effectiveness. While theoretical and experimental studies have addressed this issue (e.g., Kahneman and Lovallo (1993); Van den Steen (2004)), availability of panel data covering multiple managers would allow closer examination of the determination and evolution of beliefs over time. A related issue concerns the non-profit context examined in the paper. Our simulations suggest that eliminating the bias in expectations would increase net revenue for the Center. However, as part of a major university the Center may have other objectives aside from profit maximization. On the other hand, the implicit cost associated with biased expectations may be less sustainable for a for-profit firm. The agency issues discussed here should be present in the for-profit sector, where managers may have stronger incentives manipulate their choices such that outcomes “justify” their reported ex ante beliefs.

We emphasize that the approach taken in this paper may be used in a wide range of applications. While not typically utilized in academic studies, expectations data of the type used here is collected by many firms as part of their planning and budgeting processes. For example, empirical researchers may gain access to firm expectations of future sales, market share growth, and profitability through internal financial reports. Use of such subjective data in the context of a well developed empirical model of

behaviour may allow researchers to relax key assumptions, permitting the application of these choice models in more general contexts.

Appendix A: Econometric Details

Suppose there are J shows in the data. Let $\nu = [\nu_1, \nu_2, \nu_3]$ be the shocks in the demand and advertising decision models, where the j -th row of ν_1 is

$(\delta_{j,1} - \delta_j^0) - X_j(\beta - \beta^0)$, that of ν_2 is $(\delta_{j,2} - \delta_j^0) - X_j(\beta - \beta^0) - Ad_j\gamma - g(\nu_{j,1}^0)$, and that

of ν_3 is $A_j - A_j^*$. Let $Z = [Z_1, Z_2, Z_3]$ be the set of variables independent of ν (see the

discussion in sections 4 and 5). The moment conditions used in model estimation are

$$E[\nu | Z] = 0 \tag{A.1}$$

We estimate this model using a minimization routine similar to Berry, Levinsohn, and Pakes (1995). Let $\Delta^1 = \{ \sigma_\zeta^2, \sigma_\zeta^{02}, \gamma^0, \psi_{0B}, \psi_{1BS}, \psi_{1BD}, \psi_{AG}, \psi_H, \psi_L \}$, $\Delta^2 = \{ (\beta - \beta^0), \gamma, \theta_1, \dots, \theta_5 \}$. The parameter set to be estimated is $\Delta = [\Delta^1, \Delta^2]$. Assume that

$$E[(\nu_1, \nu_2, \nu_3)'(\nu_1, \nu_2, \nu_3) | Z] = \Omega(Z) \tag{A.2}$$

is finite with every Z , our estimator $\hat{\Delta}$ is obtained by minimizing a criterion function

$$G(\Delta) = \nu'Z(Z'\Omega(Z)Z)^{-1}Z'\nu \tag{A.3}$$

To evaluate $G(\Delta)$, dependent variables $(\delta_{j,1} - \delta_j^0)$ in equation (8) and $(\delta_{j,2} - \delta_j^0)$ in

equation (12) have to be first calculated based on the parameter set Δ^1 . We use a nested

algorithm in model estimation: Given value of Δ^1 , an “inner” algorithm uses the

contraction mapping procedures we described in the paper to calculate $\delta_{j,1} - \delta_j^0$ and

$\delta_{j,2} - \delta_j^0$. The first order conditions for the minimum of (A.3) are linear in Δ^2 . Given the

computed values of ν_1 and ν_2 , we next numerically compute the optimal advertising

spending A_j^* .³⁵ This generates the values of ν_3 . With $\nu = [\nu_1, \nu_2, \nu_3]$ the criterion function value G is evaluated as a function of Δ^1 . An outer algorithm is employed to search for the optimal Δ^1 in the parameter space until G is minimized. This search is performed using the Nelder-Meade (1965) simplex method.

Given that the variance-covariance matrix $\Omega(Z)$ is unknown, we first estimate a consistent estimator $\tilde{\Delta}$ by setting $\Omega(Z)$ to be an identity matrix. Then we use $\tilde{\Delta}$ to compute a consistent estimator for $\tilde{\Omega}(Z)$. Finally we estimate Δ again by substituting $\tilde{\Omega}(Z)$ into the criterion function in (A.3).

³⁵ In practice we use a contraction mapping algorithm that is derived from the first-order condition of equation (2). We find this method computes A_j^* much faster than other numerical methods and, independent from starting values, it always converges to the same solution.

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TABLE 1
SUMMARY STATISTICS PER SHOW
Overall and by Genre

Variable	Show Type		
	All	Not Avant-Garde	Avant-Garde
Advertising \$ (actual)	\$5,654 (2798)	\$5127 (2557)	\$6,495 (2971)
Advertising \$ (expected)	\$5,587 (1747)	\$5619 (1575)	\$5,536 (1999)
Price	\$30.26 (8.07)	\$30.49 (9.27)	\$29.89 (5.68)
# Performances	2.39 (2.15)	1.49 (0.99)	3.83 (2.67)
Genre – Avant-Garde	0.39 (0.49)	0	1
Genre – Traditional	0.44 (0.50)	1	0
Series 1	0.05 (0.21)	0.05 (0.22)	0.04 (0.19)
Series 2	0.72 (0.45)	0.81 (0.39)	0.56 (0.50)
Small Venue	0.33 (0.47)	0.34 (0.48)	0.31 (0.47)
Large Venue	0.60 (0.49)	0.62 (0.49)	0.57 (0.50)
Weekend	0.62 (0.49)	0.59 (0.49)	0.67 (0.47)
Daytime	0.04 (0.19)	0.04 (0.19)	0.04 (0.19)
Mid-Year	0.32 (0.47)	0.37 (0.48)	0.25 (0.44)
Late Year	0.18 (0.38)	0.18 (0.38)	0.18 (0.39)
Year 1998	0.31 (0.46)	0.36 (0.48)	0.23 (0.42)
Year 1999	0.21 (0.41)	0.23 (0.42)	0.17 (0.37)
N	146	112	34

Note: Standard deviations are in parentheses.

TABLE 2
OLS ESTIMATES OF DETERMINANTS OF TICKETS SOLD
(Dependent Variable is ln(Tickets Sold))

Variable	(1)	(2)
ln(Advertising \$)	-0.122 (0.045)	
ln(Advertising \$)*Avant-Garde		-0.064 (0.076)
ln(Advertising \$)*not Avant-Garde		-0.146 (0.052)
ln(Price)	0.343 (0.182)	0.324 (0.183)
Avant-Garde	-0.101 (0.086)	-0.796 (0.731)
Traditional	-0.053 (0.091)	-0.057 (0.092)
Series 1	0.416 (0.175)	0.417 (0.175)
Series 2	0.200 (0.089)	0.193 (0.089)
Daytime	0.115 (0.169)	0.099 (0.170)
Weekend	0.026 (0.066)	0.025 (0.066)
Mid-Year	-0.017 (0.074)	-0.012 (0.074)
Late Year	0.057 (0.094)	0.049 (0.094)
Year 98	0.173 (0.078)	0.167 (0.078)
Year 99	0.088 (0.090)	0.086 (0.090)
R ²	0.585	0.584

Note: Standard errors in parentheses. Each model also includes a constant and indicators for venue size.

TABLE 3
MANAGERIAL EXPECTATIONS AND ADVERTISING EFFECTS

Variable	Specification	
	(1)	(2)
<i>Panel A: Deviation of Manger's Expectations from Actual Impact of Selected Show Characteristics on Demand ($\beta^0 - \beta$)</i>		
In(Price)	0.259 (0.198)	0.058 (0.214)
Avant-Garde	0.244 (0.129)	0.302 (0.155)
Traditional	-0.055 (0.085)	-0.053 (0.105)
Series 1	0.065 (0.229)	0.213 (0.258)
Series 2	0.082 (0.131)	0.180 (0.165)
Multi Show	-0.310 (0.110)	-0.201 (0.130)
Daytime	0.319 (0.455)	0.326 (0.480)
Weekend	0.104 (0.082)	0.017 (0.095)
Mid-Year	-0.143 (0.073)	-0.068 (0.088)
Late Year	0.085 (0.138)	0.228 (0.128)
Year 98	0.039 (0.080)	-0.126 (0.097)
Year 99	0.083 (0.095)	0.103 (0.110)
Constant	1.090 (0.717)	0.807 (0.794)
<i>Panel B: Manager's Beliefs Concerning Advertising Effectiveness (γ^0)</i>		
AG Shows	0.214 (0.003)	0.173 (0.003)
Non-AG Shows	0.214 (0.002)	0.188 (0.002)
<i>Panel C: Actual Advertising Effectiveness (γ)</i>		
AG Shows	0.102 (0.059)	0.102 (0.055)
Non-AG Shows	0.038 (0.063)	0.036 (0.058)
<i>Panel D: Consumer Heterogeneity (σ_ξ^2)</i>		
Manager's Belief	0.685 (0.331)	1.327 (0.188)
Actual	1.796 (0.129)	2.755 (0.101)

Note: Standard errors in parentheses. Estimates based on 146 observations. Model also includes a fifth-order polynomial for the updating function and indicators for venue size.

TABLE 4
STRUCTURAL ESTIMATES OF MANAGERIAL UTILITY PARAMETERS

Variable	Model		
	(1)	(2)	(3)
Constant ($-1 + \rho + \psi_{OB}$)	-0.336 (0.014)	-0.371 (0.014)	-0.159 (0.007)
Avant-Garde Show (ψ_{AG})	16.606 (1.365)	25.776 (1.261)	-12.795 (0.628)
High Period 1 Sales (ψ_H)	-10.468 (1.021)	-11.877 (0.951)	-7.205 (0.787)
Low Period 1 Sales (ψ_L)	10.953 (2.562)	7.706 (2.259)	2.856 (1.776)
Budget Deficit (ψ_{IBD})	-0.004 (0.001)	0.0002 (0.001)	-0.000 (0.001)
Budget Surplus (ψ_{IBS})	0.001 (0.002)	0.005 (0.002)	0.002 (0.001)
Assume Unbiased Expectations for:			
Appeal of AG Shows	No	Yes	Yes
All Other Demand Parameters	No	No	Yes

Note: Standard errors in parentheses. Estimates based on 146 observations.

TABLE 5
SIMULATIONS OF NET REVENUES FOR ALTERNATIVE BELIEFS AND
PREFERENCES
(Net Revenue = Total Sales Revenue – Advertising Expenditure)

	<i>Simulation</i>				
	Baseline (1)	Unbiased AG Appeal (2)	Unbiased Ad Effects (3)	$\psi_{AG} = 0$ (4)	$\psi_L = \psi_H = 0$ (5)
<i>Panel A: AG Shows</i>					
Net Revenue	\$1547	\$1739	\$2026	\$1794	\$1694
(% change)		(12.4%)	(30.9%)	(16.0%)	(9.5%)
<i>Panel B: Non-AG Shows</i>					
Net Revenue	\$3260	\$3260	\$3887	\$3260	\$3363
(% change)		(0.0%)	(19.2%)	(0.0%)	(3.1%)
<i>Panel C: All Shows</i>					
Net Revenue	\$4808	\$5000	\$5913	\$5055	\$5057
(% change)		(4.0%)	(23.0%)	(5.1%)	(5.2%)

Note: Table entries in \$1000s. % change is relative to Baseline amount in column (1). Simulations conducted using parameter estimates from Table 3, column (1), and Table 4, column (1).

FIGURE 1
TICKETS SOLD PER SHOW: ACTUAL vs. MANAGER'S EXPECTATION

