USING EXPECTATIONS DATA TO INFER MANAGERIAL OBJECTIVES AND CHOICES

Tat Y. Chan,* Barton H. Hamilton,* and Christopher Makler**

May 2008

ABSTRACT

We develop a theory-driven empirical framework to analyze managerial decision-making that incorporates subjective 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 expectations. We apply the model to examine the advertising decisions of the marketing manager of a large university performing arts center. The use of expectations data generates more reasonable demand estimates. More importantly, the results show that while the manager's beliefs concerning the price elasticity of demand and advertising effectiveness are unbiased, she is over-optimistic about the appeal of certain product attributes. Subsequent estimates of the model of advertising behavior are quite sensitive to "standard" specifications of beliefs typically made in the literature, such as rational expectations. The results also highlight an interesting agency issue. In response to information on initial ticket sales, the manager will manipulate advertising so that final sales coincide with her ex ante forecast. This latter finding suggests that simply including expectations as an additional variable in reduced-form choice models will generate endogeneity bias.

*Chan and Hamilton – Olin Business School, Washington University in St. Louis, Campus Box 1133, One Brookings Drive, St. Louis, MO 63130. Chan@wustl.edu; HamiltonB@wustl.edu.
**Makler – Aplia Inc. Cmakler@aplia.com.

We are grateful to Andrew Ching, Avi Goldfarb, and Gautam Gowrisankaran for helpful comments, as well as seminar participants at UC Berkeley, UBC, Washington University in St. Louis, and the 2007 QME Conference.

USING EXPECTATIONS DATA TO INFER MANAGERIAL OBJECTIVES AND CHOICES

I. 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 generally 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 then 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 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 long been used to measure consumer preferences and tradeoffs, although the focus of these studies has generally 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 in economics, marketing, and psychology attempts to provide 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 actual choices may depend on the same information (unobserved to the researcher) she uses for updating expectations, 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, implying that reported forecasts may correspond poorly with outcomes (Manski (1990)). Finally, most studies that utilize 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 in the literature 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 our 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 as in the case of professional forecasters, the manager has an incentive to report her true expectations, since these 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 it has not been 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" art to the community.[8] Consequently, we assume that the manager chooses advertising to maximize her utility, and test the relative weights she places on profit maximization vs. community exposure

[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 Jarret and David Sedaris. Avant-garde shows include Vietnamese Water Puppets and La La La Human Steps.

to avant-garde (AG) 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 show 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 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 and significant. More notably, we find that the manager's prior expectations concerning the impact of advertising on ticket sales and the price elasticity of demand are unbiased (ruling out explanation (c)), as is typically assumed in most economic models. The major departure concerns the manager's beliefs regarding the latent appeal of AG shows. The results show that the manager is highly over-optimistic regarding the latent appeal of these performances, leading her to overspend on advertising for AG shows.[10]

When we specify the manager's utility function incorporating the 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 $19 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, we find that this estimate is very sensitive to assumptions regarding her expectations, suggesting potential identification issues in the absence of subjective expectations data. For example, if the manager is assumed to have rational expectations, as is typical in the literature, the estimated additional utility associated with AG shows quadruples to $79 per ticket. Finally, the behavioural model suggests an interesting misalignment of the incentives of the manager and her superiors at the Center. When initial ticket sales for a show are below the manager's reported

[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.

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 II describes the relevant operations of the performing arts center and the timing of the marketing manager's advertising decisions. Section III develops the framework for incorporating subjective expectations data into a structural econometric model of advertising choice, and describes our two step estimation procedure for recovering the parameters of the market demand and managerial objective functions. Section IV estimates the parameters of the demand model and tests whether the manager has biased beliefs, and Section V discusses the empirical results from the behavioural model and the sensitivity of these findings to the specification of managerial expectations. We conclude in Section VI.

II. 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 <u>aesthetic of fusion and diversity</u> — 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 <u>spirit of the avant-garde radiates from dark stages…An incu</u>bator of new ideas, [the Center] is dedicated to radical, genre-bending collaborations and the development of new work."

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 arranged by genre and generally 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:

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 attractiveness 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 (both as part of a series package and individually). No advertising for individual shows is conducted. Note that for shows occurring early (late) in the season, period 1 may be fairly short (long). Overall, 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 ("Period 1 Sales"), and updates her period 0 beliefs concerning the latent attractiveness of the show and the amount she plans to spend on advertising.

---

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

Period 2: Based on her updated beliefs concerning show attractiveness and period 1 sales, the manager decides how much to spend advertising the show, 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 up until the date and time of the performance.

II.A. 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 reported expectations 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 would potentially lead to booking an act in a venue that is too small, implying lost revenue if the performance is a sellout, while overstating her forecast would potentially inflate costs due to the staffing requirements of a larger venue. Unlike survey-based reports of expectations in which respondents may have little incentive to report their true expectations, we view the data in this study as being similar in spirit to expectations data collected from professional forecasters. Because these professionals sell their forecasts, it is argued that they have strong 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.

II.B. 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 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.[13]

Figure 1 shows that there is a strong positive relationship between the manager's expectations regarding ticket sales and actual ticket sales. The correlation between expected and actual tickets sold is high (0.85), with higher projected ticket sales generally associated with higher actual sales. However, the figure also indicates that the manager tends to under-predict ticket sales. In fact, the manager projects more than actual ticket sales for only 26% of shows. She also appears to be substantially more optimistic regarding AG shows. In this case, the manager's projections overstate actual tickets sold in 59% of cases. Figure 1 seems to indicate that the manager is under-biased in her expectation for the total ticket sales but over-biased in her belief of the appeal of avant-garde shows.

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

[13] The manager's updated beliefs regarding ticket sales after Period 1 are not reported in the data.

expenditures by genre may suggest the consequences of the manager's beliefs concerning the latent attractiveness of avant-garde shows -- perhaps in response to slow first period sales, the manager substantially increase the actual advertising for avant-garde shows than what the manager expected. 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.

II.C. 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 some 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 such as show genre and series membership. 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 from column (1) a 10 percent increase in advertising expenditure is associated with a 1.2 percent decline in tickets sold! Even when the advertising effect is allowed to vary by show genre (avant-garde shows vs. non avant-garde shows), the OLS results in column (2) continue to show a negative effect of advertising.

The results in Table 2 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 likely charge a higher price. Conversely, she might have an incentive to advertise more for less attractive shows, generating the negative relationship observed in the table. Other product characteristics are also likely to be endogenous. For example, believing that "Vietnamese Water Puppets" is appealing to the audience the manager might move the show to a large venue. The potential endogeneity of many of the product attributes shown in Table 2 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.

III. AN EMPIRICAL MODEL OF MANAGERIAL CHOICE WITH PARTIAL INFORMATION AND POTENTIALLY BIASED EXPECTATIONS

In this section, we develop a framework for managerial decision-making in which the manager has partial information and may not have rational expectations. We begin by specifying a general parametric demand function for product *j* whose specification is known to both researchers and the manager up to a parameter set Θ:

$$y_j = y(X_j, z_j, \omega_j; \Theta) . \qquad (1)$$

In equation (1), Θ represents the effects of product attributes and managerial policies on the demand function, X_j is a vector of the product attributes (which may include variables describing the competitive environment), and z_j consists of managerial decision variables (e.g., advertising expenditures, prices etc.). The variable ω_j denotes the true product quality or attribute which is unobserved by researchers. Consequently, ω_j will in general be correlated with z_j and X_j, leading to a classical endogeneity problem. Simple linear or non-linear regression of (1) will produce biased estimates of Θ, as illustrated in Table 2 above. Empirical researchers usually assume that ω_j is correlated with z_j but not with X_j. However, in many cases (and most certainly for our data), such an assumption is invalid.

The manager may only partially observe the true ω_j. Let Ω_j be the managers' information set for product j, so that her belief of the true ω_j is a conditional distribution function $F^0(\omega|\Omega_j)$. This belief has uncertainty if the information set is not perfect, i.e., F^0 has positive variance. Let Θ^0 be the set of parameters that represent the manager's perception of the impact of product attributes and managerial policies on the demand. Then the manager's *expected* market demand for product j, y_j^0, is

$$y_j^0 \equiv E[y_j \,|\, \Omega_j] = \int y(X_j, z_j, \omega_j; \Theta^0) dF^0(\omega \,|\, \Omega_j), \qquad (2)$$

This general specification allows Θ^0 to differ from the true parameters Θ, so that the manager may be systematically biased in forming expectations of market demand. We do not impose the rational expectations assumption that $y_j^0 = y_j$.

The manager's expected objective function when making decisions for z_j is specified as

$$V(z_j; X_j, W_j; \Theta^0, \Omega_j; \Psi^0) = \int u(X_j, W_j, y(X_j, z_j, \omega_j; \Theta^0); \Psi^0) dF^0(\omega \,|\, \Omega_j) \qquad (3)$$

where W_j is a set of variables excluded from the market demand function (e.g., cost variables) and Ψ^0 is the set of behavioral parameters. Note that specification (3) allows the manager to potentially have objectives other than traditional static profit maximization, such as preferences for market share or particular product attributes X_j. These factors are potentially important in the non-profit setting that we study. [14]

Under this specification, the manager chooses the optimal level of z_j to maximize her objective function. That is

$$z_j^* = \arg\max_{z \in Z} V(z_j; X_j, W_j; \Theta^0, \Omega_j; \Psi^0) \equiv h(X_j, W_j; \Theta^0, \Omega_j; \Psi^0). \quad (4)$$

It is common to write the observed z_j as

$$z_j = z_j^* + \varepsilon_j = h(X_j, W_j; \Theta^0, \Omega_j; \Psi^0) + \varepsilon_j, \quad (5)$$

where the stochastic variable ε_j is assumed to be independent with X_j and W_j. However, equation (5) shows that if $\Theta^0 \neq \Theta$ and the manager's information set Ω_j is not perfect, we cannot separately identify Ψ^0 from her beliefs. For example, observing the manager advertising more for avant-garde shows from data we are unable to infer whether this is because avant-garde shows have more weight in the manager's objective function, or because the manger wrongly believes that advertising is more effective in generating revenue for avant-garde shows.

III.A. Overview of the Econometric Implementation of the Model

We adopt a two-step strategy to estimate the model parameters. Standard econometric approaches find instruments for the endogenous variables in the demand function. However, appropriate instruments may not be available (as in our application). The key difference of our approach is to use the data on the period 0 managerial expectations of outcomes y_j^0 to infer unobservables in the demand function that are independent of observed show attributes X_j and decision variables z_j. We then construct

[14] Even for for-profit firms, a manager's decisions may be inconsistent with the firm's profit maximization objective if there exist agency problems.

moment conditions for the first step model estimation. Specifically, we model the manager's updated beliefs regarding the latent product attribute ω_j after new information arrives in period 1 by combining the observed and expectations data. This allows us to "invert" the unobservables and hence specify the pure demand shock unexpected to the manager in both periods 1 and 2. In this step we obtain consistent estimates for $(\Theta-\Theta^0)$, as well as a subset of the true and perceived demand parameters that relate to the effectiveness of decision variables z_j.[15] Conditional on these estimates, our second step is to recover the preference parameters Ψ^0 in the managerial objective function *V(.)* in equation (3).

In summary, this approach allows us to make the following contributions:

1. We allow for a general case where the unobservable stochastic component ω_j is correlated with X_j as well as z_j. We do not need to impose the restriction that product attributes X_j are exogenous, as is typical in the empirical literature.
2. We allow for a general case where managers may have biased belefs, *i.e.,* $\Theta^0 \neq \Theta$, in decision making, and may have partial information about the unobservables in the demand function.
3. Because of (1) and (2), we are able to estimate the parameters of the manager's objective function without imposing potentially restrictive assumptions, such as rational expectations, for identification. We can recover managerial objectives that are potentially inconsistent with the static profit maximization assumption. We can also examine the sensitivity of the estimated preference parameters to alternative assumptions regarding expectations.

[15] This will be explained more fully below.

IV. DOES THE MANAGER HAVE UNBIASED BELIEFS?

In this section, we use the expectations data to examine whether the manager has biased beliefs for the demand parameters Θ, and recover both the true and her perceived advertising effects. To begin, we adopt a Cobb-Douglas specification for equation (1):

$$Y_j = e^{\alpha + X_j \beta + Ad_j \cdot \gamma + \omega_j} \qquad (6)$$

where Y_j is the total ticket sales of *j*, α is a constant, X_j the show attributes that include genre, series, day of week, show time, venue, period dummies, year dummies, and (log of) prices. The manager's decision variable z_j is the (log of) advertising expenditures for show *j*, Ad_j. Recall that X_j is determined before any tickets are sold (period 0) and cannot be adjusted during the season, while Ad_j is chosen one month before the performance date (period 2), at which time the manager has observed initial ticket sales. Finally, ω_j is a stochastic component representing the appeal of the show which may correlate with X_j and Ad_j.

Demand Functions and Managerial Expectations in Period 0

Given ω_j and Ad_j, the manager believes that total ticket sales are the following:

$$Y_j^0 = e^{\alpha^0 + X_j \beta^0 + Ad_j \cdot \gamma^0 + \omega_j}$$

where the superscript 0 represents the manager's beliefs. The above specification is equivalent to (6) except that the manager's perceptions concerning the effects of show attributes may be different from the actual effects, *i.e.*, $\alpha \neq \alpha^0$, $\beta \neq \beta^0$, and $\gamma \neq \gamma^0$. This allows for the possibility that the manager makes systematic mistakes in forecasting policy implications, perhaps due to her limited information or the lack of experience.

The manager may also be uncertain about the true appeal of show *j* to the public, implying that ω_j is stochastic in the above specification. Similarly, in period 0 the manager is uncertain of Ad_j since she expects that unforeseen demand shocks may occur in period 1 requiring her to adjust her advertising policy. Let $\Omega_{j,0}$ be the manager's information set for performance j in period 0.[16] Based on the above assumptions, the manager's expected total ticket sales is:

$$E[Y_j^0 \mid \Omega_{j,0}] = \int e^{\alpha^0 + X_j \beta^0 + Ad_j \cdot \gamma^0 + \omega_j} dF(\omega_j) dG(Ad_j) \tag{7}$$

where F and G are the distribution functions for ω_j and Ad_j, respectively. We assume that the manager perceives ω_j as normally distributed with prior mean ω_j^0 and prior variance σ_0^2 ($\omega_j \sim N(\omega_j^0, \sigma_0^2)$). We also assume that the manager's beliefs regarding future advertising expenditure are distributed as $N(Ad_j^0, \sigma_{Ad_0}^2)$.

A complicating factor in the analysis is that while the expectations are reported in period 0, the manger makes her advertising decision after observing the number of tickets sold to show j sales in period 1, denoted by $Y_{1,j}$. We now describe how the updating process is incorporated into the econometric model. Recall that advertising for any performance comes only in period 2. We use another Cobb-Douglas function to specify the demand in period 1:

$$Y_{1,j} = e^{\alpha_1 + X_j \beta_1 + \omega_{1,j}} \tag{8}$$

Note that X_j in (8) are the same as in (6) since they cannot be changed after the season starts; Ad_j does not enter (8) because there is no advertising in period 1. The variable $\omega_{1.j}$ is the period 1 unobserved show attractiveness that will be explained in detail later. Our specifications of the total and first period ticket sales allow that $\beta \neq \beta_1$, which is desirable

[16] The information set includes show attributes X_j and the manager's expected advertising spending and expected show appeal.

since some show attributes may have different impacts on ticket sales in the two periods.[17]

From (6) and (8) we can write the ticket sales function in period 2 as:

$$Y_{2,j} = Y_j - Y_{1,j} = Y_{1,j} \cdot (e^{\alpha_2 + X_j \beta_2 + Ad_j \cdot \gamma + \omega_{2,j}} - 1)\,, \qquad (9)$$

where $\alpha_2 = \alpha - \alpha_1,\ \beta_2 = \beta - \beta_1,\ \omega_{2,j} = \omega_j - \omega_{1,j}$.

Analogous to equation (7), we assume that the manger's expected first period ticket sales, given the information set $\Omega_{j,0}$, is the following:

$$E[Y_{1,j}^0 \mid \Omega_{j,0}] = \int e^{\alpha_1^0 + X_j \beta_1^0 + \omega_{1,j}} dF^1(\omega_{1,j})\,, \qquad (10)$$

where F^1 is the manager's perceived distribution of $\omega_{1,j}$. The manager only reports the total expected ticket sales for each show in the data. Given that she may update her beliefs of the show attractiveness if the first period ticket sales are different from her expectation, we must make an assumption in the model regarding her beliefs of show appeal in period 1. We assume that the manager expects show attractiveness to have equal multiplicative effect on ticket sales in periods 1 and 2. The manager's prior belief of the show attractiveness in period 1, $\omega_{1,j}$, is distributed as $N(\omega_j^0, \sigma_1^2)$, where the variance σ_1^2 for first period ticket sales may be different from that for total ticket sales σ_0^2. Note that we do not restrict the realized value ω_j to be equal to $\omega_{1,j}$ in equations (6) and (8).

Updating Managerial Expectations in Period 1

[17] For example, series package, in which shows that belong to same genre are bundled together and sold before the season starts, may affect ticket sales positively in period 1 but negatively in period 2. In this case β_1 for series package is positive and β_2 is negative.

Define $\xi_{1,j} = \omega_{1j} - \omega_j^0$ as the deviation of the show attractiveness from the manager's expected period 1 ticket sales, and the analogous period 2 deviation, $\xi_{2,j} = \omega_j - \omega_j^0 - \xi_{1,j}$. Note that $\xi_{1,j}$ is a pure demand shock to the manager in period 0 when X_j are determined; hence, $\xi_{1,j}$ is uncorrelated with X_j. The additional shock $\xi_{2,j}$ occurs in period 2. As $y_{1,j}$ is known to the manager when she makes advertising decisions in period 2, $\xi_{1,j}$ may be correlated with the actual advertising expenditures Ad_j. Let $V_{1j} = \{X_j, Ad_j^0\}$. We follow the standard assumption that $E[\xi_{1,j} | V_{1j}] = 0,$ and $E[\xi_{2,j} | V_{1j}] = 0.$ These assumptions are very reasonable since in the model we allow the intercepts in the expected and true demand functions to be different, i.e., $\alpha \neq \alpha^0$ and $\alpha_1 \neq \alpha_1^0$. If the manager constantly over- or under-estimates the true show attractiveness ω_j, such a difference should be reflected in differences $\alpha - \alpha^0$ and $\alpha_1 - \alpha_1^0$.

Let $\xi_{1,j}^0$ be defined as the demand shock perceived by the manager after period 1. This can be expressed as

$$\xi_{1,j}^0 = (\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0) + \xi_{1,j}.$$

Such a demand shock comes from two sources: the true shock, $\xi_{1,j}$; and the systematic error in predicting the true impact of show attributes of which the manager is unaware, $(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0)$. Therefore, even though $E[\xi_{1,j}] = 0$, $E[\xi_{1,j}^0]$ may not be zero. For example, if the appeal of AG shows is over-estimated, ticket sales of AG shows in period 1 are more likely to become negative shocks to the manager.

We decompose the difference between the show attractiveness and the manager's expectation into two components, $\xi_{1,j}^0$ and $\xi_{2,j}^0$ where $\xi_{2,j}^0 = \omega_j - \omega_j^0 - \xi_{1,j}^0$ [18]. After observing $\xi_{1,j}^0$, the manager may use this new information to update her belief regarding $\xi_{2,j}^0$. Let $\Omega_{1,j}$ be the information set for the manager after period 1, which now includes the ticket sales information in period 1. We assume a linear updating rule of the following form:

$$E[\xi_{2,j}^0 \,|\, \Omega_{1,j}] = \theta \cdot \xi_{1,j}^0 \quad \text{and} \quad \text{var}[\xi_{2,j}^0 \,|\, \Omega_{1,j}] = \sigma_2^2 .$$

Suppose $\xi_{1,j}^0$ is positive. This means that first period ticket sales are $\xi_{1,j}^0$ percent higher than expected. If θ is zero, this updating rule implies that the manager now expects that the final ticket sales will also be $\xi_{1,j}^0$ percent higher than expected. If $-1<\theta<0$, the manager expects higher total ticket sales but the magnitude will be smaller than $\xi_{1,j}^0$ percent. This is perhaps because the manger expects a certain degree of substitution between period 1 and period 2 ticket sales. If θ is -1, the manager does not update her belief of the total ticket sales; instead, she expects that the increase in period 1 only comes from those consumers who would have purchased in period 2.

Next, define $\tilde{\eta}_j = \xi_{2,j} - \xi_{2,j}^0 = \xi_{2,j} - \theta \cdot \xi_{1,j}^0$. This is an unexpected demand shock from the manager's perspective after period 1 when she makes the advertising decisions. If the manager's beliefs of the impacts of show attributes are biased, $E[\tilde{\eta}_j]$ will be equal to $-\theta \cdot [(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0)]$. Let $\eta_j = \tilde{\eta}_j + \theta \cdot [(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0)]$, and

[18] Similar to $\xi_{1,j}^0$, we use $\xi_{2,j}^0$ to distinguish from another stochastic variable $\xi_{2,j} = \omega_j - \omega_j^0 - \xi_{1,j}$ when there are no biased beliefs.

$V_{2j} = \{X_j, Ad_j^0, Ad_j\}$, we have another moment condition, $E[\eta_j \mid V_{2j}] = 0$, that may be used to estimate the demand and expectation parameters

In summary, the manager's expected show attractiveness, ω_j^0, may be correlated with performance attributes X_j as well as expected and actual advertising expenditures Ad_j^0 and Ad_j, respectively. However, the stochastic variable $\xi_{1,j}$ is unexpected to the manager; hence it is uncorrelated with X_j and Ad_j^0. Nevertheless, $\xi_{1,j}$ may affect Ad_j since the manager may update her belief about the true show attractiveness ω_j at the end of period 1. This implies that using expectations data $E[Y_j^0 \mid \Omega_{j,0}]$ together with Ad_j and other show attributes X_j as independent variables to estimate the demand function is problematic: Even that $E[Y_j^0 \mid \Omega_{j,0}]$ helps to "control" for the unobservable ω_j, $\xi_{1,j}$ may correlate with advertising decisions; hence, estimated advertising effects may still be biased. However, conditional on information set Ω_1, the stochastic variable η_j is unexpected to the manager and so is uncorrelated with X_j, Ad_j^0, and Ad_j. As a result, we have the following moment conditions: (i) $E[\xi_{1,j} \mid V_{1j}] = 0,$ and (ii) $E[\eta_j \mid V_{2j}] = 0$. These are the identification conditions for the model estimation in the first step (see the detailed discussion of the econometric implementation in Appendix A).

It is important to note that the true data generating process for ($\xi_{1,j}, \xi_{2,j}$) need not be specified, except that their expectations conditional on V_{1j} are zero. Although we parametrically model the updating of ω_j for the manager, this is consistent with various updating rules in the literature (see our discussion in Appendix B). If there are no systematic bias in the manager's beliefs, ($\xi_{1,j}, \xi_{2,j}$) are equivalent to ($\xi_{1,j}^0, \xi_{2,j}^0$).

From the models we can estimate the true and expected advertising effects γ and γ^0, respectively, but we can only recover the differences ($\beta - \beta^0$) (see our discussion in Appendix A). We can identify the effects if decision variables can be adjusted as new information in period 1 arrives, but not for product attributes, including price, that are fixed overtime. In general, if policies such as prices are dynamically adjusted in response to changing market conditions, we could recover their effects with expectations data. However, for decisions that are fixed after a product is introduced into the market (e.g., product designs) only the difference between expected and actual effects can be estimated.[19]

Our model is similar in many respects to the strategy used in Olley and Pakes (1996) and Levinsohn and Petrin (2003) that estimates the production function. These papers decompose the unobserved state variables in the production function into two components. First, ω_t is the firm's unobserved productivity shock in period t. Its expected value conditional on the past shock, $E[\omega_t|\omega_{t-1}]$, will affect capital input decisions k_t (analogous to ω^0 on performance attributes in our model), while it's realized value will affect the labor input decisions l_t (analogous to the impact of ($\omega^0 + \theta \cdot \xi_1^0$) on advertising decisions in our model). Another state variable η_t (similar to our η) has no effect on both k_t and l_t. Their estimation strategy, as the first step, is to use other inputs such as investment i_t or intermediate input ι_t in their data as an instrument, and invert ω_t as a non-parametric function of inputs except l_t. Conditional on the estimated labor

[19] 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 from equation (6) after obtaining the estimate of the advertising effect.

coefficient obtained from the first step, their second step is to assume that ω_t follows a first-order Markov process, i.e., $\omega_t = E[\omega_t \mid \omega_{t-1}] + \xi_t$, where ξ_t is an unexpected productivity shock uncorrelated with k_t. Instead of instrumental variables, we use the manager's expectations data. We model how the manager updates her belief of the unobserved show attractiveness, ω, after observing the first period ticket sales. This is similar to the second step in Olley and Pakes and Levinsohn and Petrin, but we use a linear updating rule. Though our method may be more restrictive than the non-parametric specification,[20] it does not require other potentially restrictive conditions in the model, e.g., the *monotonicity* condition that relates to the objective function of decision makers.[21] Further, because we have the prior expectations data, our model allows that the manager may not have perfect information and may make systematic errors.

IV.A. Estimation Results

Table 3 presents the GMM results of the analysis of the demand 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. The first row of Panel A suggests that while the manager slightly underestimates the price elasticity of demand for Center

---

[20] It is possible to use a non-parametric updating rule such as $E[\omega \mid \Omega_1] = g(\omega^0, \xi_1^0)$. We choose a more restrictive linear rule because we do not have as many data points as in their data; hence, estimator efficiency is critical.
[21] As a non-profit organization, the Center is very likely to have objectives other than profit maximization. A lot of research has been done related to the comparison of the objective functions between for- and non-profit organizations.

performances, the difference is not statistically significant. Her period 0 expectations concerning the demand curve appear to be borne out by the actual data.

In contrast to the findings concerning price, the positive and significant coefficient for AG shows suggests that the manager is over-optimistic concerning the appeal of this type of show in the Center's market. The magnitude of this effect is substantial; the manager initially believes that, holding prices and other attributes constant, AG shows will generate 25.9% more ticket sold than they actually do. This is consistent with the observation in Figure 1 that the manager tends to over-predict ticket sales for AG shows. This 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.[22] This hypothesis implies that if the manager prefers higher attendance at AG shows, she will have upward biased forecasts of ticket sales.[23]

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 elasticity. Panel B of Table 3 indicates that the manager believes that advertising generates additional demand. Moreover, the results suggest that the manager believes that the marginal effect of advertising is roughly the same for AG and non-AG shows, since the difference in the elasticities across show types is not statistically significant. Panel C of Table 3 demonstrates the value of our approach in generating plausible

[22] Krizan and Wenschitl (2007) provide an excellent summary of the literature on desirability bias.
[23] An obvious question is why these 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. Unfortunately, we lack sufficient data to model the formation of the manager's expectations over time since she had been in her position for a number of years at the start of our sample period in 1997.

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 a 10% increase in advertising expenditure generates 0.7-0.8% more tickets sold. The manager's expectations concerning advertising effectiveness is also consistent with actual effectiveness in two ways. First, the marginal effect of actual advertising effectiveness does not differ significantly across performance type. Second, although the manager appears to be slightly optimistic concerning the advertising effectiveness, the differences in the corresponding coefficients in Panels B and C are not statistically significant.[24] In summary, while the manager is biased in her beliefs concerning the appeal of some show attributes such as AG genre, the expectations she has regarding the price sensitivity and advertising effects 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.

Panel D of Table 3 reports the estimates of the coefficient in the linear updating rule $E[\xi^0_{2,j} | \Omega_{1,j}] = \theta \cdot \xi^0_{1,j}$. The result implies that, if the first period ticket sales are 10% higher than expectation, the manager would update her expectations of the total ticket sales by about 8% ($1+\theta$). This is perhaps because the manger expects certain degree of substitution between period 1 and period 2 ticket sales.

V. ESTIMATING MANAGERIAL PREFERENCE PARAMETERS

We now examine the manager's objective function and the implications for advertising decision-making, incorporating her estimated beliefs described in Section IV.

---

[24] For example, the difference between expected and actual advertising effectiveness for non-AG shows reported in Panels B and C is -0.041 with a standard error of 0.030.

One of our main interests is to determine the extent to which the manager incorporates the Center's mission of promoting "an aesthetic of fusion and diversity" and non-mainstream or avant-garde artists when making her advertising decisions. We then examine the sensitivity of the estimated behavioral parameters to assumptions regarding expectations.

For the purpose of maximizing profit for each show, the estimated advertising effects suggests that, if marginal cost of additional tickets sold is close to zero, the optimal level of advertising expenditures should be about 7-8% of ticket revenues, or 8-11% under the perceived advertising effectiveness of the manager. This is much lower than the actual advertising expenditures from the data, which is about 30% on average. Models of non-profit firm behavior suggest that managerial objectives in these organizations incorporate factors such as output quality and donations to the firm in addition to profits (Malani et al. (2003)). In this vein, we assume that the manager chooses a level of advertising for show *j* that maximizes her utility, which consists of (a) the profit associated with show *j*; (b) donations to the Center that are a function of total advertising expenditures; and (c) attendance at AG performances, which fulfills the Center's stated mission of bringing avant-garde art to the community.

Two additional "non-standard" features are incorporated into the manager's objective function. First, we allow her utility to depend on her period 0 forecast of demand for show *j*. These expectations are reported to the manager's superiors, and mistakes in her forecasts have readily observable consequences, such as half empty venues. This also raises agency concerns. If, for example, period 1 ticket sales for show *j* are unexpectedly low, the manager can increase advertising expenditure so that final ticket sales more closely correspond to her reported period 0 forecast. Finally, excessive over-spending above the annual budget may be penalized by Center management, which may negatively affect the manager's utility.

We incorporate the above factors into the empirical specification of the manager's objective function, and we assume that she is risk-neutral. At time *t*, the manager must decide how to allocate the advertising budget for all shows scheduled after date *t* in the season, based on her information set at *t*, Ω_t. Her problem is specified as

$$\begin{aligned}
\max_{\{Ad_j, j>t\}} V_t &\equiv \sum_{j>t} E[U_j | \Omega_t] \\
&= \sum_{j>t} \Big\{ \big(p_j \cdot E[y_j | \Omega_t; \Theta^0] - Ad_j - FC_j \big) \\
&\quad + \rho \cdot Ad_j + \psi_{AG} \cdot E[y_j | \Omega_t; \Theta^0] \cdot 1_{j \in AG} \\
&\quad + \psi_H E[y_j | \Omega_t; \Theta^0] \cdot 1_{(Y_{1,j}/Y_j^0) > c_H} + \psi_L E[y_j | \Omega_t; \Theta^0] \cdot 1_{(Y_{1,j}/Y_j^0) < c_L} \Big\} \\
&\quad + \psi_{Bt} \cdot (\sum_{j>t} Ad_j - B_t)
\end{aligned} \tag{11}$$

where *j>t* denotes all performances after time *t*, 1_x is the indicator function, FC_j is the fixed cost associated with show *j*, and B_t is the advertising budget remaining in the season at time *t*. Equation (11) highlights the fact that expected total ticket sales, $E[y_j | \Omega_t; \Theta^0]$, depend on the manger's information set at time t, Ω_t, and her beliefs regarding the determinants of demand, $\Theta^0 = \{\alpha^0, \beta^0 ', \gamma^0, \theta, \sigma_2^2\}$.

The first term on the right hand side of equation (11) is the profit generated by show *j*. We assume that total donations (*D*) are proportional to the level of advertising (i.e., $D = \rho \sum_j Ad_j$), so that the second term captures the incremental contribution to annual donations to the Center resulting from advertising for show *j*.[25, 26] The parameter ψ_{AG} reflects the additional utility the manager receives from a ticket sold to an AG show. The terms associated with ψ_H and ψ_L in equation (11) captures the potential agency conflict described above. 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)).[27] The parameters ψ_H and ψ_L represent the additional utility the manager receives from selling an additional ticket to a show that had unexpectedly high or low period 1 ticket sales, respectively. If $\psi_L > 0$, the manager will spend more advertising a show with slow initial ticket sales than is implied by profit maximization.

The final term in (11) captures the impact of the budget constraint on advertising decisions. The Center allows realized total advertising expenditures to be over the planned budget if necessary.[28] However, excessive over-spending may lead to disciplinary action or confiscation of future resources, which the manager may seek to avoid. The utility cost to the manager of spending more on advertising than the remaining budget B_t is given by ψ_{Bt}. Let OB_t measure the extent to which actual

[25] For example, 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 increased ticket sales.
[26] 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, our specification for *D* is consistent with this explanation.
[27] 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 δ. This provides some evidence in support of the assumption that δ is constant, although we cannot rule out the possibility that the manager believes it varies with show characteristics.
[28] Therefore the manager's problem is not the one with fixed advertising budget.

advertising expenditures prior to time t are running above or below planned expenditures.[29] ψ_{Bt} 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 $\psi_{Bt} = \psi_{0B} + \psi_{1BS} OB_t \cdot \mathbf{1}_{OB_t > 0} + \psi_{1BD} OB_t \cdot \mathbf{1}_{OB_t < 0}$. In this case, $\psi_{1BD} < 0$ implies that the manager will reduce subsequent advertising expenditures the more she is over-budget at time t.

Note that equation (11) assumes zero marginal cost for additional tickets sold.[30] Further, the expected demand function for show j, $E[y_j \mid \Omega_t; \Theta^0]$, is independent of ticket sales of previous shows y_k, $k<j$. In other words, we assume that there is no spill-over effect across shows. Solving the advertising expenditure problem in (11) can be reduced to solving the optimal advertising expenditure for each show separately.

V. A. Estimation Results

Conditional on the estimation results in the first step, we use non-linear least squares (NLS) to estimate the simultaneous equation system that we derive from (11). We again employ the observed ticket sales and the manager's expectations data. The details of the econometric approach we take to estimate the behavioral parameters are described in Appendix C. Column (1) of Table 4 presents the results from the structural estimation of the manager's objective function given by equation (11). The table shows that the manager places substantial weight on increasing attendance at avant-garde shows, which is consistent with the Center's mission. Given that the average ticket price to a performance is $30, the estimates imply that each additional ticket sold to an AG show

---

[29] This implies $OB_t = \sum_{k=1}^{t-1} (Ad_k - Ad_k^0)$.

[30] This is a reasonable assumption when a show has not achieved a full-house, which is the case for all of the shows in our data.

has a marginal value to the manager of \$30 + \$19 = \$49, or approximately 63% 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 profit 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 show *j* (additional tickets sold will have a marginal value = \$30 + \$23 = \$53). As noted above, actual attendance that is below expectations may have easily observed and costly consequences. Consequently, the manager has a strong incentive to spend more on advertising than from the Center's perspective. Not surprisingly, the effect is not symmetric for shows exceeding expectations. In this case, the additional utility gain associated with additional attendance is virtually zero.

The remaining parameters in column (1) suggest that the manager does feel some pressure not to over-spend her budget, although the coefficient estimate for ψ_{1BD} is not significantly different from zero. We are unable to separately identify ψ_{0B} and ρ due to the lack of data on donations. However, if the pressure of over-budgeting is small, so that ψ_{0B} is close to zero, the estimate of constant term implies that ρ is relatively close to one. 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.

Making use of both observed ticket sales and the manager's expectations data, we construct two sets of regression equations both derived from (11). This allows us to conduct an over-identification test (see our discussion at the end of Appendix C). The F-statistic from the test is 0.36, which is far below the critical value for the 0.1 significance level. This provides some evidence that our model in (11) has not been mis-specified.

V. B. 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), we assume that the manager has unbiased expectations regarding the latent appeal of AG shows, rather than the over-optimistic beliefs reported in Table 3. Imposing this assumption sharply 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.

In column (3), we assume that the manager has unbiased beliefs concerning all demand parameters. In this case, the estimate of ψ_{AG} is four times the estimate in column (1). The estimate in this specification implies that the manager receives utility from attendance at AG shows that is three times that for non-AG shows, which seems implausibly high in magnitude. This finding is a result of the fact that in column (3) the only avenue to generate the observed high levels of AG advertising expenditures is through managerial preferences. Overall, the sensitivity analyses presented in Table 4 suggest that estimates of the managerial preference parameters are quite sensitive to the specification of expectations. These results highlight the value of subjective expectations data in recovering the parameters of the behavioral model.

V. C. Simulations

In order to understand the magnitude of the impact on advertising decisions of the manager's over-optimism concerning the appeal of AG shows and the additional preference weight for increasing demand for them, we conduct counterfactual policy experiments. For the simulations reported in Table 5, we fix the total advertising expenditures for each season from 97-99 at the same level as in the data, \$1.236 million dollars. We use the estimates from Table 3 and column (1) of Table 4 to compute the optimal advertising expenditures and revenues for each show.[31] The totals for these baseline values, overall and by show type, are presented in column (1) of Table 5. In column (2) we assume that the manager has unbiased beliefs concerning the appeal of AG shows and conduct similar calculations, holding overall advertising expenditure constant. The results in Panels A and B show that the manager re-allocates \$84K from AG to non-AG advertising when she has unbiased beliefs, while Panel C indicates that this change in advertising policy would generate an additional \$29K in revenues. These patterns are accentuated when the manager also does not have special preferences for increasing demand for AG shows ($\psi_{AG} = 0$); advertising expenditure for AG performances declines 31.6% relative to baseline, and revenues are \$47K higher.

In column (4) we specify that the manager has no additional preference for increasing sales for shows with unexpectedly low period 1 sales. In this case, Panel C

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

suggests that the implicit agency cost to the Center is approximately $31K in lost revenues from the manager's attempts to manipulate advertising so that final ticket sales are closer to her period 0 forecasts. Overall, the simulations suggest that changes in beliefs and preferences generate substantial changes in the mix of advertising expenditures across AG and non-AG shows. The impact of changes in beliefs and preferences on revenues is modest, reflecting the relatively low marginal benefit of an additional dollar spent on advertising for either AG or non-AG shows.

VI. **CONCLUSION**

This paper develops an empirical framework that combines observed market data with reports of subjective expectations to estimate demand and objective functions and assess theories of managerial choice. Our approach highlights the value of reported expectations data in addressing a number of critical issues of great concern in the estimation of empirical models of behavior: (1) endogeneity problems that arise when almost *all* product attributes and managerial choices are correlated with unobserved (to the researcher) product quality, implying that sufficient instrumental variables are unlikely to be available; (2) the decision-maker may be uncertain of true product quality, and may be biased in her beliefs regarding the appeal of certain product attributes; (3) she may also have biased beliefs concerning the outcomes associated with her actions. 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 the behavioral model. 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. 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 and the impact of other product attributes on ticket sales. While we find that the manager's beliefs concerning advertising effectiveness are unbiased, she is over-optimistic regarding the appeal of avant-garde shows to the public. These biased beliefs explain in part her observed overspending on advertising for these performances. Incorporating these beliefs into the estimation of the manager's objective function, we find that the manager exhibits special preference for promoting AG shows that coincides with the stated mission of the Center. However, our estimates of the incremental utility to the manger associated with AG shows are sensitive to assumptions regarding her expectations. When we specify that she has rational expectations regarding the determinants of demand, as is typical in the literature, the estimate quadruples in magnitude. The results also emphasize the care that must taken when incorporating expectations data into the empirical model, since the manager appears to manipulate advertising for shows with poor 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 will fail 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. 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. While our simulations suggest that eliminating the bias in expectations changes the advertising mix, the resulting increase in overall revenues is modest. A for-profit firm is unlikely to over-spend as much on advertising as the Center, implying that the impact of biased beliefs on revenues and profits may be much greater. However, the agency issues discussed here should also be present in the for-profit sector, where managers may 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 used in academic studies, expectations data of the type used in the paper is collected by a number of firms as part of their planning and budgeting processes. For example, empirical researchers may have access to the consumer expectations of future income, health, or education through surveys, or to firm expectations of future sales, market share growth, and profitability through company 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: Estimation of Ticket Sales Function Parameters

From equation (6) we have

$$\ln(Y_j) \equiv y_j = \alpha + X_j\beta + Ad_j \cdot \gamma + \omega_j \, . \tag{A.1}$$

Based on the distribution assumptions of the manager's beliefs for ω_j and Ad_j in period 0, we can derive the manager's (*ln* of) expected total ticket sales from equation (7) as

$$\ln(E[Y_j^0 \,|\, \Omega_{j,0}]) \equiv y_j^0 = a^0 + X_j\beta^0 + Ad_j^0 \cdot \gamma^0 + \omega_j^0 \tag{A.2}$$

where $a^0 = \alpha^0 + \frac{(\gamma^0)^2 \cdot \sigma_{Ad^0}^2}{2} + \frac{\sigma_0^2}{2}$.

Similarly, from equation (8) we have

$$\ln(Y_{1,j}) \equiv y_{1,j} = \alpha_1 + X_j\beta_1 + \omega_{1,j} \, . \tag{A.3}$$

Based on the distribution assumption of the manager's belief for $\omega_{1,j}$ in period 0, we can derive the manager's (*ln* of) expected ticket sales in period 1 from equation (10) as

$$\ln(E[Y_{1,j}^0 \,|\, \Omega_{j,0}]) \equiv y_{1,j}^0 = a_1^0 + X_j\beta_1^0 + \omega_j^0 \, , \tag{A.4}$$

where $a_1^0 = \alpha_1^0 + \frac{\sigma_1^2}{2}$. Note that ω_j^0 in (A.2) and (A.4) are the same.

As the first step in model estimation, we subtract the ticket sales function in period 1 in (A.3) from the manager's expected total ticket sales function (A.2):

$$y_j^0 - y_{1,j} = (a^0 - \alpha_1) + X_j(\beta^0 - \beta_1) + Ad_j^0 \cdot \gamma^0 - \xi_{1j} \, , \tag{A.5}$$

where $\xi_{1j} = \omega_{1j} - \omega_j^0$ is the deviation of the show attractiveness from the manager's expectation in period 1. Let $V_{1j} = \{X_j, Ad_j^0\}$. As ξ_{1j} is the demand shock unexpected to the manager when decisions for X_j and Ad_j^0 are made, we have the following moment condition:

$$E[\xi_{1j} | V_{1j}] = 0$$

which can be used to obtain consistent estimates for the parameters { $(a^0 - \alpha_1)$, $(\beta^0 - \beta_1)$, γ^0 } from (A.5).

Define $\omega_j = \omega_j^0 + \xi_{1,j} + \xi_{2,j} = \omega_j^0 + \xi_{1,j} + \theta \cdot \xi_{1,j}^0 + \tilde{\eta}_j$, where as discussed in the paper $\tilde{\eta}_j = \xi_{2,j} - \xi_{2,j}^0$ is an unexpected demand shock to the manager when she makes the advertising decision after period 1. We substitute $\xi_{1,j}^0 = (\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0) + \xi_{1,j}$ into the above expression and further substitute into the total ticket sales function in (A.1) to have

$$y_j = \alpha + X_j\beta + Ad_j \cdot \gamma + \omega_j^0 + \xi_{1,j} + \theta \cdot [(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0) + \xi_{1,j}] + \tilde{\eta}_j .$$

Further substitute equations (A.3) and (A.4) into the above expression for unobservables ω_j^0 and $\xi_{1,j}$. After some algebraic manipulation we obtain

$$\begin{aligned} y_j &= (1+\theta) \cdot y_{1,j} - \theta \cdot y_j^0 + \mu + X_j\chi + Ad_j \cdot \gamma + Ad_j^0 \cdot (\theta \cdot \gamma^0) \\ &\quad + \tilde{\eta}_j + \theta \cdot [(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0)] \end{aligned} \qquad \text{(A.6)}$$

where $\mu = \alpha - (1+\theta) \cdot \alpha_1 + \theta \cdot a^0$, and $\chi = \beta - (1+\theta) \cdot \beta_1 + \theta \cdot \beta^0$. Let $\eta_j = \tilde{\eta}_j + \theta \cdot [(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0)]$. As we discussed in the paper $E[\eta_j]$ is equal to 0. This is an unexpected demand shock to the manager after period 1. Hence, let $V_{2j} = \{X_j, Ad_j, Ad_j^0\}$, we have the following moment condition:

$$E[\eta_j | V_{2j}] = 0$$

that can be used to obtain consistent estimates of $\{\mu, \chi, \gamma, \theta \cdot \gamma^0\}$ from (A.6). The above two moment conditions, $E[\xi_{1j} | V_{1j}] = 0$ and $E[\eta_j | V_{2j}] = 0$ can be used to recover consistent estimates of { $(a^0 - \alpha_1)$, $(\beta^0 - \beta_1)'$, γ^0 ; $(\alpha - a^0)$, $(\beta - \beta^0)'$, γ , θ }.

Appendix B: Rationales for the Manager's Linear Updating Rule

Define $\xi_{1,j}^0$ as the demand shock perceived by the manager after period 1, and let $\xi_{2,j}^0 = \omega_j - \omega_j^0 - \xi_{1,j}^0$. Define $\Omega_{1,j}$ be the information set for the manager after period 1, which now includes the ticket sales information in period 1. We assume that the manager use the following linear updating rule to update her belief regarding $\xi_{2,j}^0$:

$$E[\xi_{2,j}^0 \mid \Omega_{1,j}] = \theta \cdot \xi_{1,j}^0 \text{ and } \mathrm{var}[\xi_{2,j}^0 \mid \Omega_{1,j}] = \sigma_2^2$$

This linear updating rule is general enough to include various types of updating rules used in the learning literature. The following are some examples:

Example 1: Simple Adaptive Learning. Let $\omega_{1,j}^0 = \omega_j^0 + \xi_{1,j}^0$ be the effect of show attractiveness on ticket sales in period 1 perceived by the manager. To update her belief of the final show attractiveness, ω_j, suppose the manager uses a simple adaptive learning as $E[\omega_j \mid \Omega_{1,j}] = \upsilon \cdot \omega_j^0 + (1-\upsilon) \cdot \omega_{1,j}^0$, where υ is between 0 and 1. In this case θ in our linear updating rule is equal to $-\upsilon$ which is within the range of -1 and 0.

Example 2: Bayesian Updating. Suppose that in period 0 the manager's prior belief of the period 2 demand shock is $\xi_{2,j}^0 \sim N(0, \tilde{\sigma}_2^2)$ and the manager uses the Bayesian rule to update her beliefs. Together with her belief that $\omega_j \sim N(\omega_j^0, \sigma_0^2)$ we can show that $E[\omega_j \mid \Omega_{1,j}] = \omega_j^0 + \upsilon \cdot \xi_{1,j}^0$, where $\upsilon = \dfrac{\sigma_0^2}{\sigma_0^2 + \tilde{\sigma}_2^2}$. In this case θ in the linear updating rule is equal to $\upsilon - 1$, which is in the range of -1 and 0, and $\sigma_2^2 = \dfrac{\sigma_0^2 \cdot \tilde{\sigma}_2^2}{\sigma_0^2 + \tilde{\sigma}_2^2}$.

Example 3: Linear Least Square Updating. Suppose the manager has prior beliefs $\begin{pmatrix} \xi_{1,j}^0 \\ \xi_{2,j}^0 \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tilde{\sigma}_1^2 & \tilde{\sigma}_{12} \\ \tilde{\sigma}_{12} & \tilde{\sigma}_2^2 \end{pmatrix}\right)$. The linear least square updating rule for the manager will be $E[\xi_{2,j}^0 \mid \Omega_{1,j}] = \frac{\tilde{\sigma}_{12}}{\tilde{\sigma}_1^2} \cdot \xi_{1,j}^0$, and $\text{var}[\xi_{2,j}^0 \mid \Omega_{1,j}] = \tilde{\sigma}_2^2 \cdot (1 - \frac{\tilde{\sigma}_{12}^2}{\tilde{\sigma}_1^2 \cdot \tilde{\sigma}_2^2})$. In this case, $\theta = \frac{\tilde{\sigma}_{12}}{\tilde{\sigma}_1^2}$, which is in the range of 0 and 1 if $\tilde{\sigma}_{12}$ is positive, and -1 and 0 if negative.

Appendix C: Estimation of Objective Function Parameters

Let *t* be the time when the manager has to make advertising choice for a particular show *j*, when she has the information of the first period ticket sales, *i.e.*, $\Omega_t = \Omega_{1,j}$. Also let the updated expectation for the show attractiveness be $E[\omega_j \mid \Omega_{1,j}] = \omega_j^0 + \xi_{1j}^0 + \xi_{2j}^0 \equiv \omega_j^1$, with variance $\text{var}[\omega_j \mid \Omega_{1,j}] = \sigma_2^2$. We can write, conditional on Ad_j, $E[y_j \mid \Omega_{1,j};\Theta^0]$ = $\int e^{\alpha^0 + X_j\beta^0 + Ad_j\gamma^0 + \omega_j}\phi(\omega_j^1, \sigma_2^2)d\omega_j = e^{\alpha^0 + \frac{\sigma_2^2}{2} + X_j\beta^0 + Ad_j\gamma^0 + \omega_j^1}$, then derive the first-order condition for the optimal level of advertising spending for *j*, Ad_j^*, in (11) as the following:[32]

$$(p_j + \psi_{AG}\cdot 1_{j\in AG} + \psi_H \cdot 1_{(Y_{1,j}/Y_j^0)>c_H} + \psi_L \cdot 1_{(Y_{1,j}/Y_j^0)<c_L})\cdot e^{\alpha^0 + \frac{\sigma_2^2}{2} + X_j\beta^0 + Ad_j^*\cdot(\gamma^0 - 1) + \omega_j^1}\cdot\gamma^0 - 1 + \rho + \psi_{0B} + \psi_{1B}\cdot OB_j = 0$$
$$\Rightarrow (\gamma^0 - 1)\cdot Ad_j^* = \ln(1 - \rho - \psi_{0B} - \psi_{1B}\cdot OB_j) - \ln(p_j + \psi_{AG}\cdot 1_{j\in AG} + \psi_H\cdot 1_{(Y_{1,j}/Y_j^0)>c_H} + \psi_L\cdot 1_{(Y_{1,j}/Y_j^0)<c_L})$$
$$- \ln\gamma^0 - (\alpha^0 + \frac{\sigma_2^2}{2} + X_j\beta^0 + \omega_j^1)$$

We assume that the observed advertising spending is $Ad_j = Ad_j^* + \tilde{\varepsilon}_j$, where the stochastic component $\tilde{\varepsilon}_j$ is uncorrelated with show attributes X_j.[33] Then we have the following condition:

$$(\gamma^0 - 1)\cdot Ad_j = \ln(1 - \rho - \psi_{0B} - \psi_{1B}\cdot OB_j) - \ln(p_j + \psi_{AG}\cdot 1_{j\in AG} + \psi_H\cdot 1_{(Y_{1,j}/Y_j^0)>c_H} + \psi_L\cdot 1_{(Y_{1,j}/Y_j^0)<c_L}) - \ln\gamma^0 - (\alpha^0 + \frac{\sigma_2^2}{2} + X_j\beta^0 + \omega_j^1) + \varepsilon_j \tag{C.1}$$

where $\varepsilon_j = (\gamma^0 - 1)\tilde{\varepsilon}_j$. Since ω_j^1, another stochastic component in (C.1) may be correlated with X_j and Ad_j, a simple regression of (C.1) will produce biased estimates.

---

[32] We can write the first-order condition for each *j*>*t* in (11) separately since we assume no dynamic linkage between shows except from the budget constraint. If, for example, there is a spill-over advertising effect from one show to another, advertising for *j* will have an impact on future performances and the problem will become one of true dynamic optimization.

[33] This assumption is reasonable since the above expression for Ad_j^* has included the expected show attractiveness.

As we have discussed, the updated expectation for total show attractiveness, ω_j^1, can be expressed as follows,

$$\omega_j^1 = \omega_j^0 + (1+\theta)\cdot \xi_{1,j}^0 = \omega_j^0 + (1+\theta)\cdot[(\alpha_1 - \alpha_1^0) + X_j(\beta_1 - \beta_1^0) + \xi_{1,j}].$$

We substitute these into (C.1) to obtain the following expression:

$$\begin{aligned}(\gamma^0 - 1)\cdot Ad_j &= \ln(1-\rho-\psi_{0B}-\psi_{1B}\cdot OB_j) - \ln(p_j + \psi_{AG}\cdot 1_{j\in AG} + \psi_H \cdot 1_{(Y_{1,j}/Y_j^0)>c_H} + \psi_L \cdot 1_{(Y_{1,j}/Y_j^0)<c_L}) - \ln\gamma^0 \\ &\quad -(\alpha^0 + \frac{\sigma_2^2}{2} + X_j\beta^0) - \omega_j^0 - (1+\theta)\cdot[(\alpha_1-\alpha_1^0) + X_j(\beta_1-\beta_1^0) + \xi_{1,j}] + \varepsilon_j\end{aligned}$$

(C.2)

We then invert ω_j^0 by making use of the expectations data. Substitute $\omega_j^0 = y_j^0 - a^0 - X_j\beta^0 - \gamma^0\cdot Ad_j^0$ into the above equation and, after some algebraic manipulation, we have the following regression model:

$$\begin{aligned}&y_j^0 + \gamma^0\cdot(Ad_j - Ad_j^0) - Ad_j + \ln\gamma^0 \\ &= \ln(\tilde{\psi} - \psi_{1B}\cdot OB_j) - \ln(p_j + \psi_{AG}\cdot 1_{j\in AG} + \psi_H\cdot 1_{(Y_{1,j}/Y_j^0)>c_H} + \psi_L\cdot 1_{(Y_{1,j}/Y_j^0)<c_L}) \\ &\quad + \varphi - (1+\theta)\cdot X_j(\beta_1 - \beta_1^0) + e_{1,j}\end{aligned} \qquad (C.3)$$

where $\tilde{\psi} = 1-\rho-\psi_{0B}$, $\varphi = (\frac{\sigma_0^2}{2} - \frac{\sigma_2^2}{2}) + \frac{(\gamma^0)^2\cdot\sigma_{Ad^0}^2}{2} - (1+\theta)\cdot(\alpha_1 - \alpha_1^0)$,

$e_{1,j} = -(1+\theta)\cdot\xi_{1j} + \varepsilon_j$, and all other variables same as previously defined. By assumption $e_{1,j}$ is uncorrelated with the variables on the right-hand side of (C.3).

We can also invert ω_j^0 from the true market demand function. Substitute $\omega_j^0 = y_j - \alpha - X_j\beta - Ad_j\cdot\gamma - \xi_{1,j} - \xi_{2,j}$ into (C.2) and, after some algebraic manipulation, we have another regression equation:

$$\begin{aligned}&y_j - (\gamma - \gamma^0)\cdot Ad_j - Ad_j + \ln\gamma^0 - (\alpha - a^0) - X_j(\beta - \beta^0) \\ &= \ln(\tilde{\psi} - \psi_{1B}\cdot OB_j) - \ln(p_j + \psi_{AG}\cdot 1_{j\in AG} + \psi_H\cdot 1_{(Y_{1,j}/Y_j^0)>c_H} + \psi_L\cdot 1_{(Y_{1,j}/Y_j^0)<c_L}) \\ &\quad + \varphi - (1+\theta)\cdot X_j(\beta_1 - \beta_1^0) + e_{2,j}\end{aligned} \qquad (C.4)$$

where $e_{2,j} = -\theta \cdot \xi_{1j} + \xi_{2j} + \varepsilon_j$. Again based on model assumptions $e_{2,j}$ is uncorrelated with the variables on the right-hand side of (C.4).

We plug in the estimates of $\{\gamma^0, (\alpha - a^0), (\beta - \beta^0)', \gamma, \theta\}$ from the first stage, and then estimate the non-linear simultaneous equation system (C.3) and (C.4). The set of parameters to be estimated is $\{\tilde{\psi}, \psi_{1B}, \psi_{AG}, \psi_H, \psi_L, \varphi, (\beta_1 - \beta_1^0)'\}$, which is related to the managerial advertising decision-making. Note that the right-hand specifications in (C.3) and (C.4) are the same except the error terms $e_{1,j}$ and $e_{2,j}$, but the left-hand dependent variables are different (the former associates with the manager's expectations and the latter uses observed ticket sales data). We can estimate (C.3) and (C.4) separately without restricting the right-hand side parameters to be equal. We use this procedure to perform an over-identification F-test for the model specification of the manager's objective function.

REFERENCES

Bernheim, R. Douglas. (1989). "The Timing of Retirement: A Comparison of Expectations and Realizations," in *The Economics of Aging*, David Wise, ed. Chicago: University of Chicago Press.

Bernheim, R. Douglas, and Lawrence Levin. (1989). "Social Security and Personal Saving: An Analysis of Expectations," *American Economic Review* 79(2), 97-102.

Berry, Steven, Levinsohn, James, and Ariel Pakes. (2004). "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market," *Journal of Political Economy* 112, 68-105.

Caskey, John. (1985). "Modeling the Formation of Price Expectations: A Bayesian Approach," *American Economic Review* 75, 768-776.

Cowgill, Bo, Wolfers, Justin, and Eric Zitzewitz. (2008). "Using Prediction Markets to Track Information Flows: Evidence from Google," working paper, Department of Economics, Dartmouth College.

Dominitz, Jeffery, and Charles F. Manski. (1996). "Eliciting Student Expectations of the Returns to Schooling," *Journal of Human Resources* 31, 1-26.

Dominitz, Jeffery, and Charles F. Manski. (1997). "Using Expectations Data to Study Subjective Income Expectations," *Journal of the American Statistical Association* 87, 855-867.

Dominitz, Jeffery, and Charles F. Manski. (1999). "Several Cultures of Research on Subjective Expectations," in *Wealth, Work, and Health*, ed. by R. Willis and J. Smith. Ann Arbor: University of Michigan Press.

Green, P. and Y. Wind. (1971). *Multiattribute Decisions in Marketing: A Measurement Approach*. Hinsdale, IL: Dryden Press.

Hensher, David, Louviere, Jordan, and Joffre Swait (1999). "Combining Sources of Preference Data," *Journal of Econometrics* 89, 197-221.

Hogarth, Robin M. (1987). *Judgment and Choice*, 2nd ed. New York: Wiley.

Hurd, Michael, and Kathleen McGarry. (1995). "Evaluation of the Subjective Probabilities of Survival in the Health and Retirement Study," *Journal of Human Resources* 30, S268-S292.

Juster, Thomas. (1964). Anticipations *and Purchases: An Analysis of Consumer Behavior*. Princeton: Princeton University Press.

Kahneman, Daniel and Dan Lovallo. (1993). "Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk Taking," *Management Science* 39, 17-31.

Keane, Michael and David Runkle. (1990). "Testing the Rationality of Price Forecasts: New Evidence from Panel Data," *American Economic Review* 80(4), 714-735.

Kotler, Philip and Kevin Lane. (2006). Marketing *Management, 12th ed.* New Jersey: Pearson Prentice Hall.

Krizan, Zlatan, and Paul D. Windschitl. (2007). "The Influence of Outcome Desirability on Optimism," *Psychological Bulletin* 133, 95-121.

Lancaster, Tony and Andrew Chesher. (1983). "An Econometric Analysis of Reservation Wages," *Econometrica* 51, 1661-1676.

Levinsohn J. and Petrin, A. (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, Vol. 70(2), No. 243 (April), pp.317-342.

Lochner, Lance. (2007). "Individual Perceptions of the Criminal Justice System," *American Economic Review* 97, 444-460.

Louviere, J.J. (1994). "Conjoint Analysis," in *Advanced Methods of Marketing Research*, ed. by R. Bagozzi. Cambridge, MA: Blackwell Publishers.

Malani, Anup, Tomas Philipson, and Guy David. (2003). "Theories of Firm Behavior in the Nonprofit Sector: A Synthesis and Empirical Evaluation," in *The Governance of Not-for-Profit Organizations*, Edward Glaeser, ed. Chicago: The University of Chicago Press.

Manski, Charles (1990): "The Use of Intentions Data to Predict Behavior: A Best Case Analysis," *Journal of the American Statistical Association*, 85, 934-940.

Manski, Charles (1993): "Adolescent Econometricians: How Do Youth Infer Returns to Schooling," in *Studies of Supply and Demand in Higher Education*, ed. by C. Clotfelter and M. Rothschild. Chicago: University of Chicago Press, 43-57.

Manski, Charles (2004): "Measuring Expectations," *Econometrica*, 72, 1329-1376.

Olley, Steve and Pakes, Ariel (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, Vol. 64, No. 6, pp. 1263-98.

van der Klaauw, Wilbert. (2000). "On the Use of Expectations Data in Estimating Structural Dynamic Models: An Analysis of Career Choices," working paper, University of North Carolina.

Zarnowitz, Victor. (1985). "Rational Expectations and Macroeconomic Forecasts," *Journal of Business and Economic Statistics* 3, 293-311.

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	
Panel A: Deviation of Manger's Expectations from Actual Impact of Selected Show Characteristics on Demand ($\beta^0 - \beta$)	
ln(Price)	-0.020 (0.085)
Avant-Garde	0.259 (0.043)
Traditional	-0.039 (0.031)
Series 1	-0.167 (0.086)
Series 2	-0.078 (0.034)
Daytime	-0.139 (0.065)
Weekend	0.042 (0.035)
Mid-Year	-0.013 (0.022)
Late Year	-0.022 (0.024)
Year 98	0.056 (0.025)
Year 99	-0.0004 (0.023)
Panel B: Manager's Beliefs Concerning Advertising Effectiveness (γ^0)	
Avant-Garde Shows (elasticity)	0.082 (0.037)
Non Avant-Garde Shows (elasticity)	0.108 (0.032)
Panel C: Actual Advertising Effectiveness (γ)	
Avant-Garde Shows (elasticity)	0.076 (0.016)
Non Avant-Garde Shows (elasticity)	0.067 (0.014)
Panel D: Difference Between Beliefs and Actual Ad Effectiveness	
$(\gamma - \gamma^0)\vert$ AG = 1	-0.006 (0.032)
$(\gamma - \gamma^0)\vert$ AG = 0	-0.041 (0.030)
Panel E: Period 1 to Period 2 Updating Parameter	
θ	-0.156 (0.049)

Note: Standard errors in parentheses. Estimates based on 146 observations. Model also includes a constant and indicators for venue size.

TABLE 4
STRUCTURAL ESTIMATES OF MANAGERIAL UTILITY PARAMETERS

Variable	Model (1)	Model (2)	Model (3)
Constant (1 - ρ - ψ_{0B})	0.025	0.022	0.957
	(0.014)	(0.012)	(0.184)
Avant-Garde Show (ψ_{AG})	19.141	31.117	79.146
	(8.610)	(7.043)	(11.289)
High Period 1 Sales (ψ_{H})	-0.946	12.339	9.568
	(2.980)	(4.919)	(4.292)
Low Period 1 Sales (ψ_{L})	23.151	15.684	31.077
	(5.725)	(5.236)	(7.845)
ln(Budget Deficit) (ψ_{1BD})	-0.0008	-0.0007	0.0200
	(0.0007)	(0.0006)	(0.167)
ln(Budget Surplus) (ψ_{1BS})	-0.000	-0.0003	0.031
	(0.0006)	(0.0005)	(0.019)
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 ADVERTISING EXPENDITURES, REVENUES, AND CONTRIBUTIONS FOR ALTERNATIVE BELIEFS AND PREFERENCES

Measure (in $1000)	***Simulation***			
	Baseline	Unbiased AG Appeal	ψ_{AG} = 0 and (2)	ψ_L = 0
	(1)	(2)	(3)	(4)
		Panel A: AG Shows		
Advertising $$	$610	$526	$417	$577
(% change)		(-13.8%)	(-31.6%)	(-5.4%)
Revenues	$2276	$2248	$2201	$2268
(% change)		(-1.2%)	(-3.3%)	(-0.4%)
		Panel B: Non-AG Shows		
Advertising $$	$626	$710	$819	$659
(% change)		(13.4%)	(30.8%)	(5.3%)
Revenues	$4252	$4309	$4375	$4292
(% change)		(1.3%)	(2.9%)	(0.9%)
		Panel C: All Shows		
Advertising $$	$1236	$1236	$1236	$1236
Revenues	$6528	$6557	$6575	$6559
(% change)		(0.44%)	(0.72%)	(0.47%)

Note: Table entries in $1000s. Simulations conducted using parameter estimates from Table 3 and Model (1) from Table 4.

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