INVESTIGATING CONSUMER CHOICE PROCESSES FOR EXPERIENCE GOODS: AN ECONOMETRIC ANALYSIS

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The authors are grateful to Pradeep Chintagunta, Erin Anderson, Ben Sacks and Wilfried Vanhonacker for many helpful suggestions.

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Abstract

This research develops and executes an econometric framework to formally model and analyze the consumer choice processes for experience products. A multi-stage model is developed in the context of new movie choices. The modeling framework incorporates psychological variables such as consumer expectations of choice set elements, consumer product preferences and dispositions, and influences of informational sources such as word of mouth within a discrete choice formulation. Model estimation allows for the relationship between different stages of the consumer choice process. An estimation procedure that explicitly accounts for measurement errors in the latent psychological variables is also developed. In particular, a probit measurement error model is proposed which provides unbiased parameter estimates. Data for the model estimation were obtained from a laboratory experiment and a field study. The empirical results provide insights into the role of psychological variables (such as consumer expectations) in consumers' choice decisions for movies and the formation of consumers' post-consumption judgment and word of mouth. A validation exercise shows that model predictions are highly correlated with box office performance of the movies in the sample.

Key Words: Experience Goods, Motion Pictures, Probit Models, Measurement Error, Latent Variables

1. Introduction

Discrete choice models are an important tool employed to understand and predict consumer choice behavior (Cortsjens and Gautchi 1983, Roberts and Lilien 1993, McFadden 1991). These models typically map the relationship between observable market information such as product attributes, marketing activities and observable market behavior of consumers, i.e., their brand choices. They are ideally suited for *search* products where consumers can evaluate product quality *prior* to purchase (Nelson 1974).

In contrast to search goods, there are other products called *experience goods*, for which consumers can evaluate quality only *after* purchase and consumption. Examples of such goods are entertainment products such as movies, concerts, sporting events and services such as vacation packages, hair styling, restaurant meals. For experience goods, consumers have limited tangible cues to quality prior to choice. Hence, they rely on psychological bases such as *expectations* and perceptions of brands in making choice decisions. They confer with previous consumers of the product and solicit and receive *word of mouth* inputs. Additionally, they take into account their own tastes, i.e., *product preferences and dispositions* in making choice decisions. Thus, different information sources (e.g., word of mouth), and psychological variables (e.g., consumers' expectations) influence consumers' choice decisions for experience products. After choosing a particular experience product and consuming it, consumers assess their choices and engage in word of mouth. Thus, post-choice activity is another important facet of consumer behavior for experience products.

The above characteristics of experience products highlight the need for an integrated modeling approach which combines psychological variables and processes with a discrete choice formulation (Cortsjens and Gautchi 1983, McFadden 1986 and 1991, Winer 1989, Ben Akiva et. al. 1994). McFadden (1986), for example, notes that combining the output from traditional market research studies that use psychometric methods to understand latent consumer perceptions with econometric choice models will yield both powerful insights and predictions.

In this paper, we develop and execute a multi-stage econometric model to understand and predict consumer choice for experience products. Specifically, we develop the framework and estimation procedure in the context of new movie choices. Motion pictures are an interesting product category for this research due to the nature of the industry and the underlying consumer characteristics. Decision makers in the motion picture industry require sales and market share predictions for successive introductions of new movies. Industry specialists note, however, that product attributes and marketing activities do not provide clear guidance for making market share predictions (Austin 1989). From the consumers' perspective, new movies are experience goods and are hard to judge prior to viewing. Hence, consumers form expectations about new movies using cues obtained from advertising, critic reviews and word of mouth. These informational sources, together with consumer expectations and dispositions determine their movie choice. After consumers choose and view a movie, they form post-consumption evaluations and convey these to others via word of mouth. Consideration of both pre-choice influential variables and consumers' post-choice evaluations is, therefore, critical to building an analytical model of movie choice.

The key contribution of this research is the proposed modeling framework and estimation methodology. Analytically, the model incorporates psychological variables such as consumer expectations of choice set elements, consumer product preferences and dispositions and influences of informational sources such as word of mouth within a discrete choice formulation. Methodologically, the issues pertinent to the formulation and estimation of this model are three-fold.

The first issue deals with estimating the effects of psychological variables (e.g., consumer expectations) on choice. These variables are latent and inherently unobservable. The psychometric literature identifies causes or indicators of these latent variables and uses techniques like factor analysis and structural equation modeling to arrive at appropriate measures for them. However, these measures are imperfect proxies and error prone. In this research, we develop an estimation procedure that explicitly accounts for measurement errors in the latent variables. Specifically, we develop a probit measurement

error model that modifies the conventional probit model and obtains parameter estimates with desired statistical properties.

The second issue arises from the *multi-stage* nature of the conceptual model. We formally model consumers' choice processes by specifying a system of equations for consumers' pre-choice evaluations, choice decisions and post-purchase activities. While consumers make their choices amongst a set of choice elements, we have data on post-choice evaluations only for the chosen option. In the econometric literature, data of this nature is said to be characterized by *selectivity bias*. We estimate the post-choice models by correcting for selectivity bias and obtain unbiased parameter estimates.

The third issue pertains to data requirements for estimation of the proposed model. Traditionally, econometric choice modeling uses readily available data describing actual behavior (for example, scanner panel data with consumer purchase histories). Psychometric analysis, on the other hand, uses consumer responses obtained through experimental or survey data. Numerous researchers have noted the difficulties in obtaining both choice and perceptual data from the same set of consumers (Winer 1989, Tybout and Hauser 1981). In this research, we overcome these difficulties by combining a laboratory experiment with a field study. The laboratory experiment provides measures of perceptions and choice while the field study allows us to observe choice behavior and obtain post-consumption measures. For each of these two stages, we develop stimuli and measurement instruments and obtain the measures requisite for model estimation.

We add to prior research on the motion picture industry by studying consumer choice processes at a micro level. Previous research on this industry (Sawhney and Eliashberg 1996, Mahajan, Muller and Kerin 1984) has adopted a macro-level modeling approach to analyze sales of new and unlaunched movies. The advantage of a micro-modeling approach is that it provides insights into the role of psychological variables in consumers' movie choice processes. Specifically, it allows us to address these substantive questions: Do psychological variables play an important role in movie choice decisions and how can they be modeled? What is the role of word of mouth in influencing choices of other consumers? What is the role of

psychological variables after film viewing? Is it possible to make predictions of market shares of a set of new movies prior to launch? How do these predictions relate to actual sales figures?

The rest of this paper is organized as follows. In the following section, we present our proposed model and discuss the analytical formulation and estimation procedures. Section 3 outlines the details of the data collection method. Section 4 presents the results and discusses the implications. Finally, Section 5 summarizes the research and outlines future directions.

2. Model Development

2.1 Modeling Framework: The model conceptualization draws on previous research of consumer purchase decision processes (Engel and Blackwell 1982, Howard and Sheth 1969, Nicosia 1966). A basic premise underlying all these models is that consumers go through sequential stages in their brand choice processes. Characteristics of these models (e.g., model elements and stages) are determined by the product category studied (e.g., movies) and phenomenon of interest (e.g., consumer choice). The characteristics of experience products and a behavioral understanding of consumer choice processes lead us to propose the following general framework.[1]

We model consumer choice decisions in two stages: pre-choice and post-choice. In the pre-choice stage, consumers choose from a set of experience goods. Choice in this stage is influenced by expectations, market information about each choice option (e.g., advertising, word of mouth from other consumers), and motivational consumer characteristics (e.g., psychological dispositions). In the post-choice stage, consumers form judgments about their choice based on their consumption experience and engage in word of mouth with other consumers. This word of mouth influences the choices of other consumers. Aggregate market share for each choice option, therefore, depends on the choices of the initial consumers, their post-consumption judgment and word of mouth, and the influence of such word of mouth on subsequent consumers.[2] Figure 1 illustrates the framework discussed above.

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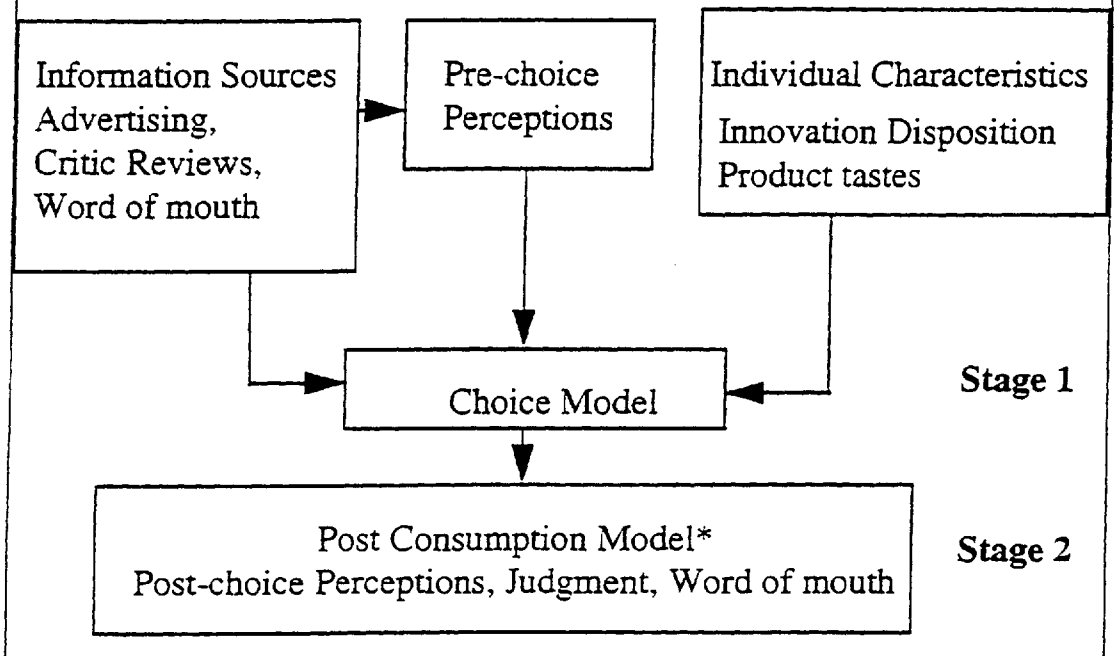
[1] This framework examines consumer choice within a given product category (e.g., choice amongst a set of movies or restaurants).

[2] While we explicitly consider the relationship between the pre-choice and post-choice stages in the individual choice process, we do not account for any updating of information within each stage of the choice process. We

To operationalize the conceptual model for the motion picture industry, we develop a research design that parallels the pre-choice and post-choice stages. We use a laboratory experiment to simulate the pre-choice stage. A sample of potential consumers are exposed to advertising, positive or negative critic reviews and positive or negative word of mouth simulations for three unlaunched movies. They choose amongst these three movies. Next, they view the movie of their choice in a field setting (i.e., movie theater) and fill out a self-administered questionnaire about their post-consumption evaluations.

Figure 1:
Conceptual Framework



* Post consumption refers to the stage after the chosen product has been consumed

take the choice set as given and do not model the derivation of a specific choice set from a larger consideration set. Further, we model individual as opposed to joint choice decisions. This approach is consistent with existing published research on movie viewership (Mahajan, Muller and Kerin 1984, Eliashberg and Sawhney 1994).

In sections 2.2 and 2.3 below, we develop the rationale, operational details and econometric specifications for the pre-choice and post-choice models respectively.

2.2 Pre-Choice Model : In this section, we first discuss the variables which influence movie choice. Next, we specify the utility function that incorporates these variables in a discrete choice framework. Finally, we present the model estimation procedure.

a. Model components:

We model consumer choice in the pre-choice stage as a function of informational inputs, pre-choice expectations, and consumer characteristics. Using previous research, we identify the informational inputs as advertising, critic reviews, and word of mouth (Austin 1989, Mahajan, Muller and Kerin 1984). Consumer characteristics included in the model are consumers' predisposition to innovate and genre preferences (Eliashberg and Sawhney 1994).

Informational inputs: The most influential advertising source for movies is television advertising (Austin 1989). In this research, we use TV advertising as a vehicle to provide a common platform of awareness. Hence, all participants in the experiment viewed the same advertising for each movie and we did not manipulate the role of advertising. To obtain these advertisements, we recorded prime time television shows for three weeks prior to the running of the experiment. These shows contained the advertisements for the movies included in the study.

Both word of mouth and critic reviews have been identified as critical influences on movie viewing behavior by industry observers and academics (Burzynski and Baker 1977; Mizerski 1982; Eliashberg and Shugan 1995). However, evidence on the relative roles of critic reviews and word of mouth is lacking. Models in the marketing literature that relate these variables to movie performance have focused on one or the other of these variables. Mahajan, Muller and Kerin (1984) and Sawhney and Eliashberg (1996), for example, examine the influence of positive and negative word of mouth on movie performance. Eliashberg and Shugan (1995), on the other hand, study the relation between critic reviews and movie performance.

We use an experiment to study the influence of *both* critic reviews and word of mouth on movie choice. They are manipulated as dichotomous variables (i.e., positive or negative). This operationalization is consistent with previous research and it allows a cleaner manipulation of these variables in a laboratory experiment (Roberts and Urban 1988; Mizerski 1982; Herr, Kardes and Kim 1991). We used information about the movies from press kits and reviews in trade press as to develop the content of audio word of mouth simulations. These were recordings of the opinions of a sneak-preview viewer of the movie. Both male and female voices were used and counterbalanced to avoid gender effects. The words and descriptions of each movie were such that the valences in both positive and negative conditions were equally balanced. Further, measures were obtained from the experiment participants on the authenticity and credibility of the word of mouth. Positive and negative versions of critic reviews for the three movies were also prepared based on available information. Pre-tests were conducted to test the stimuli developed and identify credible critics for the sample population. Appendix A provides examples of the stimuli used for the word of mouth and critic review manipulations.

Analytically, the word of mouth condition for individual n for alternative i is a dummy variable denoted by w_{ni}. Negative word of mouth is denoted by $w_{ni} = 1$ and vice versa for positive word of mouth. Similar notation for the critic reviews dummy is c_{ni}. In addition to their direct influence on utility, these informational sources also exert an indirect influence through consumers' pre-choice expectations.

Pre-Choice Expectations: Consumer product expectations are prepurchase beliefs about the product (Oliver 1980). Oliver and Winer (1989) discuss three sources of influence on expectations for a particular brand: (i) prior consumption experiences with that brand (ii) marketing, social and environmental stimuli, and (iii) consumer experiences with other similar brands. Since movies are new products the role of prior consumption experience is non-existent. Expectations for each movie are, thus, based on both informational stimuli (word of mouth, critic reviews and advertising) and consumers' prior experiences with other movies which had the same or similar actors, plot, setting, etc. To measure these latent expectations, we use attitudinal indicators. These

are a series of questions relating to individuals' impressions of various aspects of each movie in the choice set (e.g., acting, costume, appeal). Appendix B provides details of these attitudinal indicators.

Notationally, indicators obtained from individual *n* for alternative *i* are denoted by a_{ni}. These observed indicators (a_{ni}) are linked to latent pre-choice expectations (P_{ni}^*) using factor analysis.

$$a_{ni} = \Pi_1 P_{ni}^* + \zeta_{1ni} \tag{1a}$$

where Π_1 denotes the loading matrix obtained from exploratory factor analysis and ζ_{1ni} is a normally distributed random error term. Estimation of the factor loading matrix (Π_1) together with the responses for each individual (a_{ni}) allows us to obtain a factor score for pre-choice expectations denoted by P_{ni}°. Following the conventions of factor analysis (Morrison 1990), we state this factor score as a linear function of the latent pre-choice expectations and a normally distributed random error (ω_{1ni}).

$$P_{ni}^* = P_{ni}^\circ + \omega_{1ni} \tag{1b}$$

The presence of the random error ω_{1ni} has implications for model estimation which we discuss later.

Genre Preferences: Consumers use genre labels as a simple and convenient way to categorize movie stories and make their choices. In this research, we use the classification provided by Austin and Gordon (1987) to identify the set of relevant genres. We obtained a measure of each individual's liking of different genres (for example, comedy, romance, horror) at the end of the laboratory experiment. We use these ratings to calculate a share of relative genre preference specific to each movie using the following steps. First, individuals' ratings are summed across the different genres to obtain a total genre preference score for each respondent. Next, each movie in the choice set is classified as belonging to one or multiple genres. The classifications of movie critics Ebert, Martin and the Cinemania Index were used for this purpose. After identifying each movie with its genre(s), we sum the ratings of each respondent for the genre(s) specific to each movie. The ratio of this sum to the total genre preference score gives us a movie specific genre preference measure. We provide an example of the way this measure is calculated in Appendix B.

Notationally, let k=1...K denote the genres. If movie i belongs to genre j, then an individual n's liking for genre j to which movie i belongs to is denoted by $g_{j,ni}$. The movie specific genre preference ($G_{j,ni}$) is then given by:

$$G_{j,ni} = g_{j,ni} / \sum_{k=1}^{K} g_{k,ni} \qquad (2)$$

Innovation Disposition: Prior research has highlighted that individual dispositions have an important influence on movie selection and enjoyment (Eliashberg and Sawhney 1994). We propose that an individual's inclination to learn about new movies interacts with the information available about movies and influences his/her choice. We measure such inclination using the domain specific innovativeness scale developed by Goldsmith and Hofacker (1991). These researchers state that "*Domain or product category specific innovativeness reflects the tendency to learn about and adopt innovations (new products) within a specific domain of interest.*" Goldsmith and Hofacker test this scale in a series of six studies administered to different samples for the product categories *rock music* and *designer fashions*. They show the scale to be highly reliable and valid, and adaptable across product domains. Appendix B presents the scale items.

We use the indicators from the Goldsmith and Hofacker (1991) scale and exploratory factor analysis to obtain a measure of the latent trait. Notationally, the relation between the individual's latent predisposition to innovate (I_n*) and the measured indicators (v_n) is given by:

$$v_n = \Pi_2 I_n^* + \zeta_{2n} \qquad (3a)$$

where Π_2 denotes the loading matrix and ζ_{2n} represents the random error component. Further, the relationship between the latent variable innovation disposition (I_n*) and the factor scores (I_n°) is expressed as:

$$I_n^* = I_n^\circ + \omega_{2n} \qquad (3b)$$

where ω_{2n} is a normally distributed error term. Implications of the presence of this term for model estimation are discussed later.

Interactions: An individual's innovativeness is closely linked to the information sources sought and used by the individual to make choice decisions (Midgley and Dowling 1993). This implies that the influence of word

of mouth and critic reviews on movie choice is mediated by the individual's predisposition to innovate. In other words, there is an interaction between word of mouth and critic reviews and individual's innovation disposition score. This interaction influences movie choice. Notationally, these two interaction terms are denoted by:

Critic Reviews and Innovation Disposition $(c_{ni})^* (I_n^*)$ (4a)

Word of mouth and Innovation Disposition $(w_{ni})^* (I_n^*)$ (4b)

b. Model Specification:

We now specify a discrete choice model that incorporates the variables discussed in the previous section. We begin by assuming that each consumer *n* has a feasible choice set C_i, with a fixed number of alternatives. We then represent customer *n*'s utility for alternative *i*, U_{ni}^*, as a function of the indirect utility (V_{ni}^*) and the random error component (e_{ni}). While the utility is not observable, we observe the alternative chosen by each individual. Based on the specification of the utility function we obtain the brand choice probabilities. We represent this formally below.

Utility function $U_{ni}^* = V_{ni}^* + e_{ni}$ (5a)

Choice Decision $C_{ni} = 1 \text{ if } U_{ni}^* > U_{nj}^* \ \forall \ j \neq i$ (5b)

Choice Probability $P(C_{ni}=1) = \Pr[U_{ni}^* > U_{nj}^* \ \forall \ j \text{ element of } C_i]$ (5c)

In order to make inferences about the individual's utility and obtain choice probabilities it is important to specify the indirect utility function (V_{ni}^*). In accordance with the common practice in discrete choice literature, we assume a linear in parameters functional form for V_{ni}^* (Ben-Akiva and Lerman 1985). Specifically, we state V_{ni}^* as a function of: *movie specific constants, genre preferences, pre-choice expectations, word of mouth* and *critic reviews combined with individual's innovation disposition scores.* We estimate a set of unknown parameters (denoted by β) which reflect the impact of each of these variables on the movie choice decision. Formally, we have the following specification,

$$V_{ni}^* = \beta_{0i} + \beta_1 G_{j,ni} + \beta_2 P_{ni}^* + \beta_3 (c_{ni})^*(In^*) + \beta_4 (w_{ni})^*(In^*)$$

Consequently, U_{ni}^* in Equation (5a) can be expressed as:

$$U_{ni}^* = \beta_{0i} + \beta_1 G_{j,ni} + \beta_2 P_{ni}^* + \beta_3 (c_{ni})^*(In^*) + \beta_4 (w_{ni})^*(In^*) + e_{ni} \qquad (6)^3$$

Substituting the relationship between the latent variables and factor scores (equations (1b) and (3b)) in equation (7)), we get

$$U_{ni}^* = \beta_{0i} + \beta_1 G_{j,ni} + \beta_2 P_{ni}^\circ + \beta_3 (c_{ni})^*(I_n^\circ) + \beta_4 (w_{ni})^*(I_n^\circ) +$$

$$[e_{ni} + \beta_2 \omega_{1ni} + (\beta_3(c_{ni}) + \beta_4(w_{ni}))\, \omega_{2n}] \qquad (7)$$

From Equation (8) we can define the probability of alternative 1 being chosen by individual n as follows:

$$P(C_{n1}=1) = P(U_{nj} - U_{n1} \le 0 \quad \forall\ j \ne 1)$$

$$= P\{[(\beta_{0j} - \beta_{01}) + \beta_1(G_{j,nj} - G_{j,n1}) + \beta_2 (P_{nj}^\circ - P_{n1}^\circ) + \beta_3(c_{nj} - c_{n1})^*(I_n^\circ) + \beta_4(w_{nj} - w_{n1})^*(In^\circ)$$

$$+ [(e_{nj} - e_{n1}) + \beta_2[\omega_{1nj} - \omega_{1n1}] + [\beta_3(c_{nj} - c_{n1}) + \beta_4(w_{nj} - w_{n1})]\, \omega_{2n}] \le 0 \quad \forall\ j \ne 1\} (8)$$

For notational convenience,

Let $Z_{nj1} = (\beta_{0j} - \beta_{01}) + \beta_1(G_{j,nj} - G_{j,n1}) + \beta_2 (P_{nj}^\circ - P_{n1}^\circ) + \beta_3(c_{nj} - c_{n1})^*(I_n^\circ) + \beta_4(w_{nj} - w_{n1})^*(I_n^\circ)$

and $\eta_{nj1} = (e_{nj} - e_{n1}) + \beta_2[\omega_{1nj} - \omega_{1n1}] + [\beta_3(c_{nj} - c_{n1}) + \beta_4(w_{nj} - w_{n1})\, \omega_{2n}]$ (9)

Hence, Equation (8) can be written as:

$$P(C_{n1}=1) = P(Z_{nj1} + \eta_{nj1} \le 0 \quad \forall\ j \ne 1)$$

$$= P(\eta_{nj1} \le -Z_{nj1} \quad \forall\ j \ne 1) \qquad (10)$$

A key issue that arises in the estimation of the above specified model is the non-traditional error specification (η_{nj1}) caused due to the presence of measurement errors in the latent variables. Below we discuss the statistical and theoretical reasons that necessitate accounting for this measurement error.

c. Model Estimation

To estimate the choice probabilities it is necessary to specify the distribution of the error term η_{nj1} in Equation (10). From (9) we know that this error term is a linear composite of the random error in the utility function ($e_{nj} - e_{n1}$) and the measurement error terms ($\omega_{1nj} - \omega_{1n1}$) and ω_{2n}, assumed to be normal The

[3] β_2 may represented as a vector to allow for the possibility of multiple factors defining pre-choice expectations. Research by Goldsmith and Hofacker (1991) and a pre-test conducted in the context of motion picture viewing showed the factor defining innovation disposition to be unidimensional.

measurement error arises due to the structural restrictions imposed in Equations (1) - (5). These equations are derived from the model formulation that incorporates critical aspects of consumer behavior for experience products. From a theoretical perspective, it is important to ensure that the structural restrictions implied in Equations (1) - (5) are preserved in the reduced form. From a methodological perspective, ignoring the measurement error in parameter estimation will result in biased estimates (Train, McFadden and Goett 1987, McFadden 1986). Therefore, for both theoretical and methodological reasons we require a specification for the error term (η_{njl}) which allows us to carry forward the structural restrictions into the reduced form.

An appealing candidate for the specification of the error term η_{njl} is a *nonlinear probit* model. The conventional probit model assumes that random error (i.e., $\eta_{njl} = e_{nj} - e_{nl}$) has a multivariate normal distribution.[4] The normal distribution provides a good approximation to many multivariate distributions and has the additional feature that sums and differences of normal variates are also normal (Hausman and Wise 1978; Currim 1982). We know already that the errors of the latent factors (ω_{1nj} and ω_{2n}) follow multivariate normal distributions. Assuming a normal distribution for the random error in the utility function (e_{nj}) and adding this to the measurement errors will thus give us a normally distributed composite error (η_{njl}). It is possible, therefore, to develop a special case of the probit model that explicitly allows for the distributional assumptions relating to the latent variables in the model. We call such a model a *probit measurement error model.*

The key feature of the probit measurement error model is that it explicitly accounts for measurement errors through a reparametrization of the error variance-covariance matrix. The specification of the error variance-covariance matrix for probit measurement error model is presented in Appendix C. The intuition underlying this model is as follows. We obtain information about the measurement errors from factor analysis and use these in the probit model estimation. The model estimation thus uses information available from factor analysis to reformulate the probit specification and obtain unbiased parameter estimates. The additional estimation costs of this model have to be weighed against the benefits the insights obtained into the relationship

[4] The conventional logit model assumes the errors ($\eta_{njl} = e_{nj} - e_{nl}$) to follow the weibull distribution.

between choice by explicity modeling the measurement error structure. Standard maximum likelihood methods can be employed to estimate the model parameters. The model and estimation algorithm have been implemented using the Gauss programming language (Aptech Systems 1992) on a personal computer.[5]

2.3 Post-Choice Model : Prior literature differentiates between a consumer's evaluation of the product before it is chosen and after it is consumed (Westbrook 1987, Westbrook and Oliver 1991). Post-consumption evaluation is of interest because it influences both the consumer's repeat purchases and purchases of other consumers through word of mouth (Bayus, Carroll and Rao 1986). We model the determinants of post-consumption evaluation/judgment for movies and build a formal link between such evaluation and consumers' choice decisions. Two important constructs in this model are *post-consumption perceptions* and *judgments*. We present below details of these measures, the analytical formulation and procedure for estimating the model parameters.

Post-consumption perceptions: Perceptions are defined as *"the individual's current feelings about, or appraisal of, the object as experienced in the immediate situation"* (Fazio, Powell, and Williams 1989). Post-consumption perceptions are, therefore, appraisals and feelings about the movie that was chosen and viewed. To obtain a measure for these latent perceptions we use indicators of movie viewers' appraisal of different aspects of the movie (e.g., plot, setting, appeal, costume) along with their emotional responses (happy/unhappy, pleased/annoyed, relaxed/bored, frenzied/sluggish). The details of the items are presented in Appendix B.

We conduct exploratory factor analysis on the observed indicators and obtain a measure of the latent post-consumption perceptions. Notationally, the relation between the individual's latent post-consumption perceptions (PV_{ni}^*) and the measured indicators (pv_{ni}) is given by:

$$pv_{ni} = \Pi_3 PV_{ni}^* + \zeta_{3ni} \qquad (11)$$

where Π_3 denotes the loading matrix and ζ_{3ni} represents the random error component. Further, using factor analysis we also obtain the factor score for post-consumption perceptions (PV_{ni}°).

[5] Interested readers may obtain a copy of the program from the first author on request.

Post-Consumption Judgment: Post-consumption judgment refers to the individual's subjective evaluation of the various outcomes and experiences associated with consuming a specific product (in our case, choosing and viewing a particular movie). Such judgment is influenced by the nature of the consumption experience and pre-choice expectations (Parasuraman, Berry and Zeithaml 1985, Churchill and Suprenaut 1982). We therefore specify a relation between consumers' post-consumption judgments (J_{ni}), perceptions (PV_{ni}^{o}) and also their pre-choice expectations (PX_{ni}^{o}) for that movie. Formally, we state this as a linear regression model with parameter vectors γ_1 and γ_2.[6]

$$J_{ni} = [\gamma_1]' PX_{ni}^{o} + [\gamma_2]' PV_{ni}^{o} + v_i \qquad (12)$$

Note that J_{ni} can be estimated only for those individuals who chose alternative i. This gives rise to the selectivity bias problem (Heckman 1976). The presence of selectivity bias implies that the choice model error in Equation (8) may be correlated with the regression errors in Equation (12). The result of such correlation is that the conditional expectation of the errors in the regression model is nonzero. If ordinary least squares is used to estimate the post-choice model, the parameter estimates obtained will be biased and inconsistent (Lee and Trost 1978). To obtain consistent parameter estimates in problems with this structure, econometricians have proposed a two stage estimation procedure. In the first stage, a discrete choice model is estimated. This provides probabilities and parameter estimates for the choice model. In the second stage, we have to condition the error distribution of the regression equation by the choice decision. Thus, for an alternative i which is chosen we need

$$J_{ni} = [\gamma_1]'PX_{ni}^{o} + [\gamma_2]'PV_{ni}^{o} + E(v_i \mid U_{ni}^{*} > U_{nj}^{*} \text{ for } j \neq i)$$

We obtain this by using the transformation of the error from the choice equation shown in the equation below (Lee 1982).

$$J_{ni} = [\gamma_1]'PX_{ni}^{o} + [\gamma_2]'PV_{ni}^{o} + [\gamma_3][\phi(\Phi^{-1}(P(C_{ni})))/P(C_{ni})] + \xi_{ni} \qquad (13)$$

To estimate Equation (13), we use the following steps. First, we obtain choice probabilities from the

[6] $[\gamma_1]'$ and $[\gamma_2]'$ are represented as vectors to allow for the possibility of multiple factors defining the dimensions of pre-choice expectations and post-consumption perceptions.

discrete choice model estimation, i.e., $P(C_{ni})$. Next, the inverse normal cumulative distribution function of these probabilities are computed. i.e., $\Phi^{-1}(P(C_{ni}))$. A code was written in Gauss programming language (Aptech Systems 1992) based on the algorithm in Kennedy and Gentle (1980) for this purpose. Next, we take the probability distribution function of these transformed probabilities and obtain $\phi(\Phi^{-1}(P(C_{ni}))$. The ratio of this term to the original probabilities gives us the transformation of the choice model error term that appears in Equation (13). Equation (13) can now be estimated by ordinary least squares. The coefficient of the error transformation term (γ_3) indicates the presence or absence of selectivity bias.

In further study of a consumer's post-choice decisions, we examine the valence of outgoing word of mouth. Specifically, the word of mouth measure asked the respondent whether they would recommend the movie they just viewed to a friend. A scale anchored on definitely recommend/definitely not recommend was used to obtain response. These responses were dichotomized to correspond to the positive/negative word of mouth experimental manipulation used in the pre-choice model. This dichotomization provided us with sample probabilities of positive and negative outgoing word of mouth for each of the movies. These probabilities were used to obtain aggregate market share predictions that are presented in the results section. We present below the empirical analysis of this model.

3. Empirical Results and Model Validation

3.1 Data Collection: The data collection was carried out in two stages: pre-choice and post-choice. In the pre-choice stage we ran a laboratory experiment. This consisted of a 2 x 2 design in which subjects were exposed to advertising, critic reviews (positive and negative) and word of mouth (positive and negative). Administration of the experiment took 25 minutes. At the end of the laboratory experiment we provided respondents with gift certificates to view the movie of their choice. We also gave them a self administered questionnaire to fill immediately after viewing the movie. Respondents were told to return this questionnaire along with proof of movie viewership (ticket stub) and collect cash remuneration for their assistance.

Subjects for the study were recruited on the basis of their interest in movies. The respondents were both students (undergraduate or graduate) and professionals. This mix was decided to obtain external validity in the sample. Sample sizes collected were 202 for the first stage and 125 for the second stage.

The three movies used in the experiment were: *Little Big League, Forrest Gump,* and *I Love Trouble.* These movies were chosen on the basis of their launch dates, genres and information from local theaters on whether these movies would be shown by them. An operational constraint on the study was that the choice data had to be obtained prior to the launch of the movies in the choice set. This was necessary to obtain strong experimental manipulation effects and to minimize subjects' exposure to outside information sources (such as word of mouth from viewers who would watch the movies if they had been released). Since the second stage of the study required the subjects to actually view the movie and provide judgment measures, we could not run the choice experiment too far in advance of the movie release date. These considerations meant that the experiment was run a few days prior to the launch of the movies in the choice set. The experiment was run multiple times for three continuous days.

3.2 Pre-Choice Model: We first discuss the measures obtained for the variables which influence choice i.e., pre-choice model components. Next, we present the probit measurement error model that incorporates these measures and provides choice predictions. Finally, we discuss issues pertaining to model comparison and validation of the probit measurement error model.

a. Model components

The pre-choice model discussed in section 2.2 consisted of the following components: *Information sources* (word of mouth and critic reviews), *pre-choice expectations, genre preferences* and *innovation disposition.* In the empirical analysis, we use dummy variables to denote positive and negative word of mouth and critic reviews and obtain a measure of the interaction between these variables and innovation disposition. We use factor analysis to obtain measures for pre-choice expectations and innovation disposition. The results of the factor analysis are discussed below.

Consumer Pre-Choice Expectations (P_{ni}*): Table 1 shows the results of the factor analysis of the indicators c pre-choice expectations. These indicators were a series of questions on the individual's expectations from eacl movie in the choice set on various dimensions. The factor pattern loadings were obtained using maximum likelihood estimation procedure. A study of the inter-factor correlation matrix led us to conclude the appropriate rotation method for this data is the promax rotation (Morrison 1990).

TABLE 1
PRE- CHOICE MODEL:
FACTOR ANALYSIS OF THE VARIABLES DEFINING PRE-CHOICE EXPECTATIONS

	Rotated Factor Pattern		Standardized Scoring Coefficients	
Dimensions on which the movies were rated	Factor 1	Factor 2	Emotional Stimulation	Tangible Product Attributes
Interesting/Boring	**.937**	.004	.325	.052
Appeal	**.929**	.002	.293	.046
Fascinating/Dull	**.825**	-.016	.120	.015
Fun	**.811**	-.057	.128	.005
Excitement	**.804**	-.039	.114	.008
Costumes	.114	**.802**	.023	.126
Sets	.026	**.788**	.016	.141
Acting	-.202	**.739**	-.018	.240
Supporting Cast	-.180	**.680**	-.010	.139
Special Effects	-.090	**.654**	.001	.096
Music	.011	**.561**	.006	.058
Plot/Story	-.383	**.545**	-.047	.130

The results in Table 1 reveal two underlying factors. The table shows that the indicators that loaded highly on the first factor related to respondents' feelings about the movies in the choice set. An example of an indicator that loaded highly on this factor is a question that asked the respondent whether he/she thought the movie would be fascinating or dull. This factor was, therefore, named *emotional stimulation*. The indicators that loaded highly on the second factor related more to specific product characteristics as opposed to consumer's feelings. For example, these indicators obtained the respondents' impressions about the acting, costumes, sets, etc. This factor was named *tangible product attributes*. Results from this analysis are

consistent with previous research on entertainment products and suggests that both an individual's own feelings and known product attributes determine expectations (Hirschman 1985).

Innovation Disposition (I_n*): The observed indicators for the individual characteristic of innovation disposition were items from the scale of domain specific innovation (Goldsmith and Hofacker 1991). Exploratory factor analysis of these items revealed that all the items on the scale load on to a single factor that defines the individual disposition to innovative behavior in movie consumption (Table 2). A single factor defining domain specific innovativeness for movies is in line with the findings of Goldsmith and Hofacker (1991) for the product categories rock music and designer fashions.

TABLE 2
PRE- CHOICE MODEL: DOMAIN SPECIFIC INNOVATIVENESS TRAIT

Variables[@]	Factor Pattern: Innovation Predisposition	Standardized Scoring Coefficients
Watch a lot more movies than others	.819	.306
First in circle of friends to watch new releases	.814	.304
Interested in watching new movies	.673	.252
Do not like watching movies before others	-.577	-.216
Last among my friends to know about new movies	-.074	-.279

[@] Statements described different aspects of an individual's domain (movie consumption) specific innovativeness and subjects stated their agreement/disagreement with the statements mentioned above.

Since innovation disposition is an individual specific trait there is no variation in the distribution of this latent factor across alternatives. Below we present results from the probit measurement error model that incorporates the variables specified in the indirect utility function (Equation 6) and accounts for measurement error in the latent variables.

b. Probit Measurement Error Model

The probit measurement error model provides parameter estimates for the following: brand constants for the movies *Little Big League* and *Forrest Gump*, genre preferences, factors defining pre-choice expectations

(i.e., emotional stimulation and tangible product attributes), interaction between critic reviews and innovation disposition and interaction between word of mouth and innovation disposition and the error covariance terms.[7] Table 3 reports the results from the probit measurement error model.

TABLE 3
PROBIT MEASUREMENT ERROR MODEL
Parameter Estimates and (Standard Errors)

Little Big League	Forrest Gump	Pre-choice Expectations: Emotional Stimulation	Pre-choice Expectations: Tangible Attributes	Genre Pref.	Innovation Disposition Trait * Critic Review	Innovation Dispositio n Trait* Word of mouth	Error term $\tilde{\Gamma}_{11}$ [a]	Error term $\tilde{\Gamma}_{12}$
-1.249*	.112	-.202*	-.171**	.044	.0176*	-.01128**	.740	1.35*
(.249)	(.120)	(.099)	(.096)	(.096)	(.009)	(.007)	(.458)	(.445)

* Significant at 5% ** Significant at 10%
• Base Movie is *I Love Trouble*
[a] $\tilde{\Gamma}_{11}$ and $\tilde{\Gamma}_{12}$ represent elements of the probit measurement error covariance matrix (Σ_η) explained in Appendix C.

- Log likelihood	165.728
Sample Size	202

Table 3 shows that all the parameter estimates have correct signs. Further, the variables emotional stimulation, interactions between innovation disposition and critic reviews and word of mouth, and the movie constants for *Little Big League* are significant at the 5% level, while tangible attributes variable is significant at the 10% level. A major finding that emerges from this model is the significant influence of the consumer's expectation of emotional fulfillment in making the choice decision. This result provides strong empirical support for discussions in prior literature on the role of emotional variables in consumer behavior for experience products (Iacobucci 1992). Another interesting finding is the importance of external information sources such as critic reviews and word of mouth on movie choice in contrast to genre preferences.[8] This suggests that direct information about a movie (e.g., movie specific word of mouth) is a better predictor of

[7] The base movie for this model is *I Love Trouble*.
[8] We also estimated a model with critic reviews and word of mouth as independent variables (i.e. without multiplying these with innovation disposition trait) and found these variables to be a statistically significant influence on choice.

choice as compared to more general indicators of movie preferences such as genre preferences. Comparisons of the model in Table 3 with a model which does not incorporate innovation disposition showed the significant influence of this latent consumer trait as a moderator of the word of mouth and critic review influences. Thus there is a systematic variation in the taste of consumers for different information sources.

The measures of pre-choice perceptions were obtained after respondents were exposed to experimental manipulations of critic reviews and word of mouth. Hence there is a possibility of multicollinearity between these two sets of variables which implies that not all the parameters in the model can be estimated precisely. To examine this issue, we regressed the factor scores for pre-choice expectations on dummies for word of mouth and critic reviews and used the residuals from this regression as inputs in the discrete choice model. This procedure ensured that the factor scores were orthogonal to the word of mouth and critic review inputs. The results from this analysis were substantively identical to the results presented in Table 3.

We now turn to a discussion of the error covariance terms. Table 3 reports two error covariance terms $\left(\tilde{\Gamma}_{11} \text{ and } \tilde{\Gamma}_{12}\right)$ which reflect both the structure of the latent factors in the model as well as the conventional probit error covariances. As explained in Appendix C, these estimates are obtained by reparametrizing the probit error terms using structural information from factor analysis. In particular, the estimated error terms are the summation of the conventional probit error covariance matrix and the covariance matrix of the measurement errors obtained from factor analysis. Hence, to interpret the estimated error parameters, it is important to understand the structure of the underlying latent factors.

We present below the variance-covariance matrices for the latent factors, conditional on observed indicators of pre-choice expectations for the three movies in the study. These matrices are calculated using factor loadings, inter-factor correlations and standardized coefficients.[9]

	Little Big League		*Forrest Gump*		*I Love Trouble*	
Emotional Stimulation	.047	.004	.058	.008	.044	.008
Tangible Product Attributes	.004	.086	.004	.045	.008	.086

[9] A test for difference between the three covariance matrices was conducted and a significant difference was found between the three covariance matrices.

The major substantive finding from these matrices is the contrast in the size of the variances of both factors between *Forrest Gump* and the other two movies. Comparing across movies, we note that *Forrest Gump* has the highest variance for the emotional stimulation factor and the lowest variance for the tangible product attributes factor. We conjecture that these differences are caused due to the following. The tangible product attributes for *Forrest Gump* (e.g., acting by Tom Hanks and Sally Field) were recognized as being of superior quality compared to a movie like *Little Big League* which does not have any big-name stars. Thus the variance in this factor is the least for *Forrest Gump* followed by *I Love Trouble* and then *Little Big League*. The emotional stimulation factor, on the other hand, is a reflection of the subjects' anticipated emotional response to the movie. Depending upon the movie concept presented in the advertisements, critic reviews and word of mouth there might be variations in the anticipation emotional response. The results suggest that the more non-standard movie concept of *Forrest Gump* leads to a larger variance in emotional stimulation as compared to the concepts of the other movies. [10] Overall, examining the distribution of these factors provides an understanding of their varying role in the formation of pre-choice expectations for each of the movies in the choice set.

Additionally, the assumptions and output of factor analysis provide structural information on the conditional distribution of the measurement errors in the model. This information allows for the identification of the error parameter estimates in the probit model. Further, the parameter estimates obtained from such a procedure are unbiased and consistent (Hsiao 1996). The results in Table 3 show that after accounting for measurement error, one of the error terms $\left(\tilde{\Gamma}_{11}\right)$ is significant. This implies that the assumption of zero covariance that is made in logit estimation does not hold for this data.

[10] This result finds corroboration in the movie industry discussions of high concept movies. In industry parlance a high concept movie is one which has a high appeal, easy to communicate core proposition. In other words, a film which is promotable using a key phrase of ten or fewer words is called a high concept film (Austin, 1989). Examples of some high concept movies would be *Terminator 2* and *Jurassic Park*. Expected variation in consumers' emotional expectations for a high concept movie would be less than for other movies. *Forrest Gump* was not marketed with just one simple core selling proposition. Thus it cannot be readily classified as a high concept movie. This implies a large variation in emotional stimulation which is consistent with our findings.

Comparisons with existing models: To investigate the merits of the proposed model, we compare the results of this model with other commonly used models, viz. conventional logit and probit models. Table 4 presents the results of the estimation of the conventional logit and probit models. Both these models do not incorporate the effects measurement errors in latent variables and innovation disposition as a systematic taste variation.[11]

TABLE 4
MODEL COMPARISONS: CONVENTIONAL PROBIT AND LOGIT MODELS
Parameter Estimates and (Standard Errors)

Little Big League	Forrest Gump•	Pre-choice Expectations: Emotional Stimulation	Pre-choice Expectations: Tangible Attributes	Genre Pref.	Critic Review (Base: Negative)	Word of mouth (Base: Positive)	Error term Γ_{11}[a]	Error term Γ_{12}
Probit								
-1.218*	.220**	-.168*	-.117**	.063	.409*	-.237*	.931*	1.32*
(.322)	(.114)	(.062)	(.071)	(.085)	(.144)	(.093)	(.405)	(.639)
Logit								
-1.372*	.542*	-.329*	-.237*	.123	.725*	-.438*		
(.253)	(.132)	(.085)	(.101)	(.145)	(.105)	(.131)		

* Significant at 5% ** Significant at 10%
• Base Movie is *I Love Trouble*
[a] Γ_{11} and Γ_{12} represent elements of the probit error covariance matrix (Σ_ε)explained in Appendix C.

Probit Model	-Log likelihood	169.9	Sample Size	202
Logit Model	-Log likelihood	170.3	Sample Size	202

The results from Table 4 highlight the role played by the two factors emotional stimulation and tangible product attributes in movie choice. Both the logit and probit models indicate the important role played by the information obtained from critic reviews and word of mouth for the choice decision. The error covariance parameters in the probit model are significant implying the violation of the IIA property for this data set. In contrast to the conventional logit and probit models, the probit measurement error model provides a more realistic representation of consumers' choice process. Thus, the parameter estimates in Table 3 incorporate the

[11] Simpler "naive" logit and probit models were also estimated which did not include the latent factors as explanatory variables. The negative log likelihoods of the naive logit and probit models are 173.60 and 172.57. Chi-square tests show that the hypothesis that the latent factors are an important influence for movie choices is supported 5% level for the logit model at the 10% level for the probit formulation.

underlying structure of the latent variables and are unbiased and consistent. Further comparison of the log likelihoods of the probit measurement error model (-165.7) and the equivalent conventional probit model (-167.8) show that the former has a lower log likelihood with the same numbers of parameters. Hence the probit measurement error model provides a better fit for these data.

Pre-choice Model Validation: To compare the predictive ability of the different model formulations we used two procedures. First we calculated the in-sample hit rates. [12] The hit rate is defined as the proportion of correct choice predictions made by a model. The hit rates for the conventional logit, probit, and probit measurement error models are .58, .60 and .62 respectively. These results indicate that the probit formulations perform better than the logit model.

To investigate further the predicitve performance of the proposed formulation versus the conventional probit model we employed a jackknife-like cross-validation procedure (Efron and Tibshirani, 1993). This procedure evaluates the predictive accuracy of a model by using multiple hold out samples. A major advantage of this procedure is that it makes more efficient use of available information than the traditional split-half cross-validation. This advantage is critical in the face of small sample sizes (Rust and Schmittlein 1985).

The procedure involves the following steps. First, for each observation in the data set a sub-sample is created. This sub-sample consists of all the remaining observations in the sample. The total number of sub-samples thus equals the total number of observations in the data set. Second, the probit measurement error and conventional probit model are estimated using data from each sub-sample (i.e., each of these models is estimated 202 times). Third, the parameters obtained from each estimation are used to calculate predicted probabilities for the observation in the corresponding hold out sample. Fourth, the predicted probabilities are compared with the actual choice for that observation. For the entire sample the hit ratio is calculated as the proportion of the number of correct predictions to the total sample size. The hit ratios obtained from the different models are compared to gauge the relative predictive performance of the models. From this analysis we obtained a hit ratio of .56 for the probit measurement error model and .54 for the conventional probit model.

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[12] All three models used for comparison were equivalent and had the independent variables shown in Table 3.

Thus on both critereon of predictive accuarcy, we find evidence of superior performance by the probit measurement error model.

Overall, the probit measurement error model uses information from factor analysis about the underlying structure of latent variables and hence is based on a truer representation of consumers' choice processes. The econometric formulation allows us to take advantage of information within the data set which might otherwise have been ignored. The estimation procedure provides unbiased and consistent parameter estimates. Further, the model performs better on data fit and prediction criteria as compared to the conventional probit model.

3.3 Post-Choice Model: The data used to estimate the models in this section were obtained from the respondents after they had viewed the movie of their choice. Prior to estimating the post-choice model, it was necessary to discern the underlying dimensions of post-consumption perceptions. The results of an exploratory factor analysis reveal that three underlying dimensions describe the manner in which consumer's perceive movies. The first dimension relates to the different *product characteristics* such as acting, plot, supporting cast, etc. The second and third dimensions both relate to the emotional fulfillment that the viewer obtained from the movie. These dimensions are obtained from items of the Mehbrian-Russell scale and are identified as *pleasure* and *arousal* (Havlena and Holbrook 1986). The second factor, labelled *pleasure*, is defined by variables such as "While watching the movie how excited or calm were you feeling?" An example of the indicators that load highly on the *arousal* factor is: "While watching the movie how happy or melancholy were you feeling?"

Table 5 shows the results of the two stage estimation of the post-choice model. The model R-square of .626 is a good performance for a cross sectional study. The table reveals that the critical influencers of the post-consumption judgment for movies are consumers' post-choice perceptions of the chosen movie (i.e., product characteristics, arousal and pleasure). Furthermore, this model is not characterized by selectivity bias since the term associated with selectivity bias is not statistically significant. Presence of selectivity bias would suggest that if a certain individual decided to choose a particular movie (say, *Forrest Gump*) s/he is more likely

to judge the movie as a good one. Lack of significance of this term is intuitively appealing for experience products such as movies. Since experience products are hard to judge prior to choice, the nature of the product experience is an overwhelmingly important determinant of post-consumption judgment. Overall, the results from this model suggest that once consumers' choose a particular movie, their consumption experience as opposed to pre-choice expectations determine their evaluation of the movie.

TABLE 5
POST-CHOICE MODEL

Independent Variables	Parameter Estimates and (Standard Errors)
Constant	7.205* (.389)
Post-Consumption Evaluation Factors:	
Product Attributes	1.446* (.077)
Arousal	-.394* (.072)
Pleasure	-.554* (.075)
Prior Expectations:	
Emotional Stimulation	-.041 (.087)
Tangible Product Attributes	.007 (.094)
Selectivity Bias	1.239 (1.058)
R^2	.626
Sample Size	125

* Significant at 5%

In further analysis of consumers' post-choice behavior, we use consumer responses to obtain probabilities of outgoing positive and negative word of mouth. These are used to make aggregate market share predictions. We provide below details of such prediction and validation with box office performance.

3.4 Market Share Predictions and Model Validation: Initial market share predictions are obtained by estimating the pre-choice model. The initial choice probabilities obtained from the pre-choice model estimation (Section 3.2) are as follows: *Little Big League* .09, *Forrest Gump* .56, and *I Love Trouble* .35. To obtain predictions for subsequent time periods we combine the probabilities of positive and negative outgoing word of mouth with conditional choice probabilities obtained from the pre-choice model. The

positive and negative outgoing word of mouth probabilities for the three movies are as follows: *Little Big League* .92 and .08, *Forrest Gump* .93 and .07, *I Love Trouble* .73 and .27. We multiply these word of mouth probabilities with initial choice probabilities for each of the movies to obtain a measure of the *extent* of positive and negative word of mouth for each movie in the market. For example, the *extent* of positive word of mouth for *Forrest Gump* is the product of is .56 * .93 = .52 and the *extent* of negative word of mouth equals .04. The sum of the *extent* of positive and negative word of mouth of the three movies equals one.

We use the data from the pre-choice model to obtain probabilities of choice conditional on either positive or negative word of mouth. This is done by creating subsets of the data for responsdents exposed to either positive or negative word of mouth for a particular movie. Choice models were estimated for each of these subsets. From this, the choice probabilities we obtain for each of the three movies conditional on positive and negative word of mouth repectively are: *Little Big League* .142 and .042, *Forrest Gump* .629 and .491, *I Love Trouble* .438 and .280. Market share for each movie is obtained by combining these conditional choice probabilities with the *extent* of word of mouth. Since the *extent* of word of mouth at each point in time is determined by the choice probabilities in the previous time period. we update it and obtain estimates of market share at different points in time.

To validate the predictions obtained from the proposed model we collected data on box office performance for the three movies from *Variety Magazine*. Sales data for all three movies were available for 12 weeks after their release. After the twelfth week data for Little Big League was not reported. We converted the sales data for these 12 weeks into market share figures for the three movies. We compared the actual and predicted market shares for each of these twelve weeks and calculated the correlations between these two sets of figures for each of the three movies. The correlations for the three movies are *Little Big League* .93 *Forrest Gump* .93 *I Love Trouble* .95. We carried out the same analysis using box office data from the previous week as an input to calculate the *extent* of word of mouth. The correlations between

actual sales and these predictions for the three movies were: *Little Big League* .96, *Forrest Gump* .98, *I Love Trouble* .97. These results clearly attest the predictive performance of the proposed model.

In conclusion, the results of the pre and post choice models taken together provide the following insights. Choice of a movie is determined both by direct information that the consumers' have on the products (through advertising, critic reviews and word of mouth) and their expectations on emotional and tangible product attribute dimensions. Post-choice judgment of is determined by consumers' post-consumption perceptions as opposed to pre-choice expectations. Further, aggregate market share predictions can be obtained by combining post-consumption word of mouth inputs and conditional choice probabilities.

Given the resounding success of Forrest Gump in the box office, a pertinent question that needs to be answered is "*What made Gump happen?*" The empirical results provide the following explanation. Prior to choice of the movie, consumers' expectations of the tangible product attributes of Forrest Gump were uniformly higher than to other movies in the choice set. Post consumption, consumers had extremely favorable emotional response to the movie. Thus while the tangible product attributes convinced the movie goers to pick Forrest Gump initially, it was the favorable emotional response to the movie that kept the crowds coming.

4. Summary and Future Directions

This paper develops and executes an econometric framework to formally model and analyze the multi-stage consumer choice processes for experience products. The modeling framework incorporates latent psychological variables within a discrete choice formulation. These psychological variables are inherently unobservable and measures obtained for them at various stages of the choice process are error prone. In this research, we develop a methodology that explicitly accounts for such measurement errors in the latent variables. Specifically, we propose a probit measurement error model that modifies the conventional probit model and obtains parameter estimates with desired statistical properties. Further, our estimation procedures also account for relationships between different stages of consumers' choice process. The empirical analysis is conducted for new movie choices.

The empirical findings provide strong support for the key role played by psychological variables (such as expectations of emotional stimulation and tangible product attributes) in the choice process for new movies. Another interesting result is the importance of movie-specific external information sources such as critic reviews and word of mouth in contrast to consumers' genre preferences. The psychological trait measure of innovation disposition also influences choice of movies. Unlike the services literature where pre-choice expectations play an important role in post-purchase evaluations, in the case of movies, consumers' pre-choice expectations are not as critical. Post-choice judgments for a movie are influenced by consumers' post-consumption perceptions as opposed to pre-choice expectations. Further, the empirical results also provide estimates of outgoing word of mouth probabilities which are a critical input in making aggregate market share predictions.

Comparing the proposed probit measurement error model with conventional logit and probit models, we find that the *IIA* assumption is violated for this data set making the logit formulation inappropriate. Further, the parameters that account for measurement errors in latent variables are significant indicating the inadequacy of conventional probit model. These additional parameter estimates provide substantive insights into our understanding of consumer choice processes for experience products. Combining inputs from both the pre-choice and the post-choice models, we obtain aggregate market share predictions. A validation exercise reveals high correlations between these model predictions and actual box office data.

The structure of the modeling framework proposed in this paper can be used to study a variety of marketing problems where understanding consumer psychological processes is critical to managerial decision making. While the focus of this research is on the motion picture industry, an interesting and worth while extension of this work is the application of this model to related industries such as music (e.g. CDs). These industries are similar to movies and yet characterized by unique consumer behavior (e.g., consumers buying multiple CDs of the same music group). Analyzing consumer choice for new services which are also affected by intangibilities in product perceptions and word of mouth influences is another interesting avenue for future research.

The estimation procedure developed in this paper addresses questions that arise due to the presence of measurement errors in the independent variables. Existence of measurement errors is common to all research which uses either consumer based psychological measures or variables which cannot be measured precisely. This is the case with most survey-based research. By presenting a way to correct for the measurement errors and obtain unbiased parameter estimates this research provides a methodology to estimate discrete choice modeling using different types of data sources (Ben Akiva et. al. 1994). Finally, while the problem studied in this work looks at consumer choice processes at one point in time, a possible extension is a dynamic model which incorporates learning effects within a latent variable framework.

To summarize, this research develops a multi-stage econometric framework that incorporates latent psychological variables in a discrete choice framework. The model estimation in the context of new movie choices provides both substantive and methodological insights. It adds to the marketing literature by taking a first step at micro-level modeling of the important but little modeled area of experience products and services.

APPENDIX A

WORD OF MOUTH AND CRITIC REVIEW STIMULI

Word of mouth simulations and critic reviews were created for positive and negative conditions for each of the three movies (*Little Big League, Forrest Gump* and *I Love Trouble*). We present below excerpts from the negative version of the word of mouth simulation for *Little Big League* and the positive version of the critic review for *I Love Trouble.*

A. Word of Mouth Simulations

Subjects were told that a research assistant interviewed people as they left the theater after a sneak preview of Little Big League. They were told that they would be listening to excerpts from one such interview.

Research Assistant:	What did you think of the sneak preview of Little Big League?
Viewer:	I just saw the movie. Wasn't very good. It was pretty predictable. It is the same old baseball story – This kid inherits the Minnesota twins from his grandfather and so on. It was pretty sentimental.
Research Assistant:	What about the acting?
Viewer:	Oh....they developed just one character. And the rest of the acting wasn't any good either.
Research Assistant:	Was there anything good? Enjoyable about the movie?
Viewer:	Well...the music was okay. But I don't think I would go to see a movie for the music. I'd buy the soundtrack instead!

B. Critic Reviews

Please read below the review of this movie from the *New York Times*.

An exciting and glamorous movie which delightfully combines the best of romance and action. Julia Roberts and Nick Nolte are at their best in this fast paced breathtaking film as reporters from warring newspapers competing for the same story. The suspenseful plot, great action sequences and remarkable acting make this a not-to-be missed movie. Rated ****

Rating Scale

* Poor ** Fair *** Good **** Excellent

APPENDIX B
DESCRIPTION OF MEASURES FOR MODEL COMPONENTS

Construct	Description	Typical Statement
Pre-choice Expectations (P_n*)	Respondents expectations on different dimensions of each movie were collected using: Attribute-specific and emotion eliciting scales (Examples of Items: plot, acting, supporting cast, appeal, fun, excitement)	Very poor — Excellent Plot ___ ___ ___ ___ ___ ___ ___
Genre Preference ($G_{j,m}$)	Calculated using data obtained from a like-dislike scale (Austin and Gordon 1987). *Example*: Consider a movie X which has been classified as a Drama-Comedy. Suppose individual n's preference for Drama is 5 and Comedy is 7 and the summation of his ratings across genres is 32. Then his score for movie X is calculated as: (7+5)/2)/32=6/32.	Dislike very much — Like very much Comedy ___ ___ ___ ___ ___ ___ ___
Innovation Disposition (I_n*)	Domain Specific Innovativeness Scale (Goldsmith and Hofacker 1991). *Scale Items:* Watch a lot more movies than others First in circle of friends to watch new releases Interested in watching new movies Do not like watching movies before others Last among my friends to know about new movies	Totally agree — Neither agree nor disagree — Totally disagree ___
Post-choice Perceptions (PV_{ni}*)	Respondents perceptions on different dimensions of movie viewed were collected using: * 7 item attribute-specific scale (Items: plot, acting, supporting cast, sets, costumes, music, special effects) * 8 item doubly anchored scale (Russell and Mehbrian 1984) (Items: happy/unhappy, pleased/annoyed, satisfied/unsatisfied, contended/melancholic, stimulated/relaxed, excited/calm, frenzied/sluggish, aroused/unaroused)	Very poor — Excellent Plot ___ ___ ___ ___ ___ ___ ___ Excited ___ ___ ___ ___ ___ ___ ___ Calm
Judgment (J_m)	Global Evaluation	Very poor — Excellent Overall Movie ___ ___ ___ ___ ___ ___ ___
Outgoing Word of mouth	Recommendation of movie to a friend (single item scale)	Definitely recommend — Probably recommend — Probably not recommend — Definitely not recommend ___ ___ ___ ___ ___ ___ ___

APPENDIX C

PROBIT MEASUREMENT ERROR MODEL: ERROR VARIANCE-COVARIANCE MATRIX

(i) *Specification of choice probabilities*

Central to the development of the probit measurement error model is the reparametrization of the error variance-covariance matrix. In the conventional probit model the error term is distributed normally with mean zero and covariance matrix Σ_ε. Here Σ_ε is the covariance matrix of the difference in the error terms (e_j). In the measurement error case (Equation (9)), the distribution of the error term (η_{nj1}) is normal with a mean and covariance that are different from the conventional probit model.

For expositional reasons, the model developed in this appendix is for the three alternative case in the presence of a single measurement error. Generalizations to both larger number of alternatives and measurement errors are possible. Let us consider the case where η_{nj1} is defined as below.

$$\eta_{nj1} = [(e_{nj} - e_{n1}) + \beta_2 [\omega_{2nj} - \omega_{2n1}]] \qquad j=2, 3 \qquad \text{(C.1)}$$

The mean of η_{nj1} in Equation (C.1), M_η and the covariance matrix Σ_η are given as:

$M_\eta = E[\omega_{1j} - \omega_{11}]\beta_2$

$\Sigma_\eta = \Sigma_\varepsilon + \beta_2 \Sigma_{\omega 1} \beta_2$ where $\Sigma_{\omega 1}$ is the covariance matrix of the measurement errors.

In particular, if we let σ_j^2 be the variance of e_j and σ_{ij}^2 be the covariance of e_i and e_j, then the variance-covariance matrix of the random error in the utility function is given by:

$$\Sigma_\varepsilon = \begin{bmatrix} \sigma_1^2 + \sigma_2^2 - 2\sigma_{12} & \\ \sigma_1^2 - \sigma_{13} - \sigma_{12} + \sigma_{23} & \sigma_1^2 + \sigma_3^2 - 2\sigma_{13} \end{bmatrix} \qquad \text{(C.2)}$$

Similarly, we specify the variance-covariance matrix for measurement errors. Let δ_i^2 be the variance of ω_{1j} and δ_{ij}^2 be the covariance of ω_{1i} and ω_{1j}, then variance-covariance matrix of the measurement errors is given by:

$$\Sigma_{\omega 1} = \begin{bmatrix} \delta_1^2 + \delta_2^2 - 2\delta_{12} & \\ \delta_1^2 - \delta_{13} - \delta_{12} + \delta_{23} & \delta_1^2 + \delta_3^2 - 2\delta_{13} \end{bmatrix} \qquad \text{(C.3)}$$

The above lead us to the following specification for the probability of choice of alternative 1 by individual n as below.

$$P_1 = \begin{bmatrix} \int_{-\infty}^{\frac{Z_{12} - M_{\eta 12}}{\sqrt{(\sigma_1^2+\sigma_2^2-2\sigma_{12}) + \beta_2(\delta_1^2+\delta_2^2-2\delta_{12})\beta_2}}} \int_{-\infty}^{\frac{Z_{13} - M_{\eta 13}}{\sqrt{(\sigma_1^2+\sigma_3^2-2\sigma_{13}) + \beta_2(\delta_1^2+\delta_3^2-2\delta_{13})\beta_2}}} b_1(\eta_{21};\eta_{31};r_1)\, d\eta_{21}\, d\eta_{31} \end{bmatrix} \qquad \text{(C.4)}$$

where b_1 is a standardized bivariate normal distribution for η_{21} and η_{31} with correlation coefficient (r_1), Z_{12} and Z_{13} are as defined in the text in Equation (10), and $M_{\eta 12}$ and $M_{\eta 13}$ are the mean of the error term shown in Equation (C.1). Similarly we can obtain the probabilities of alternatives 2 and 3. In conventional probit model, the upper limits of the integral would not contain the terms associated with measurement error.

(ii) *Normalization and estimation of parameters reported in Tables 3 and 4*

For identification purposes, it is conventional in probit model estimation to use one of the terms in this variance-covariance matrix for normalization. We use the term $(\sigma_1^2 + \sigma_3^2 - 2\sigma_{13})$ for normalization and obtain a variance-covariance matrix with two identifiable parameters and a one as the bottom right diagonal term. To ensure that this variance-covariance matrix is symmetric and positive definite we employ the cholesky factorization and obtain the following estimable parameters. Formally, we state the reformulation of the variance-covariance matrix and the cholesky factorization as follows:

$$\Sigma_\varepsilon = \begin{bmatrix} \Gamma_{11} & \Gamma_{12} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \Gamma_{11} & 0 \\ \Gamma_{12} & 1 \end{bmatrix} \tag{C.5}$$

where $\Gamma_{11}^2 + \Gamma_{12}^2 = \Gamma_1$ and $\Gamma_{12} = \Gamma_2$. The results for the conventional probit model in Tables 4 report the two terms Γ_{11} and Γ_{12}.

Using the same normalization practice discussed above (Equation (C.5)), in the case of the probit measurement error model, we obtain two additional parameters for each latent variable measured with error as shown below:

$$\Sigma_{\omega 1} = \begin{bmatrix} \delta_{11} & \delta_{12} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta_{11} & 0 \\ \delta_{12} & 1 \end{bmatrix} \tag{C.6}$$

where $\delta_{11}^2 + \delta_{12}^2 = \delta_1$ and $\delta_{12} = \delta_2$. These parameters are identified using the structural information obtained from factor analysis. In particular, we use the definition of conditional normal density, to obtain the variance-covariance matrix of the measurement errors. This provides us with estimates for δ_1 and δ_2. As shown Equation (C.4), the reparametrized error terms reported in Table 3 (i.e., $\tilde{\Gamma}_{11}$ and $\tilde{\Gamma}_{12}$ are the summation of (a) conventional probit error terms and (b)measurement error variances weighted by the relevant parameters. Standard errors of the parameter estimates in this model are corrected to account for the presence of estimated variables.

In sum, the probit measurement error model reparametrizes the error variance-covariance matrix and obtains choice probabilities. The estimated parameters reflect the structure of the measurement errors associated with the latent variables for different alternatives and are unbiased and consistent.

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