Consumer Search and Propensity to Buy

Ofer Mintz

Imran S. Currim

Ivan Jeliazkov*

July 2010

* Ofer Mintz (omintz@uci.edu) and Imran S. Currim (iscurrim@uci.edu) are doctoral student in marketing and Chancellor's Professor respectively at the Paul Merage School of Business, and Ivan Jeliazkov (ivan@uci.edu) is Assistant Professor of Economics, all at the University of California, Irvine, CA 92697. We thank Decision Tactics for providing the data and participants at the 2009 INFORMS Annual Meeting, 47th Annual Edwards Bayesian Conference, and the Paul Merage School of Business Brown Bag Series for helpful comments. The first author acknowledges partial financial support provided by a summer grant from the Institute of Mathematical Behavioral Sciences (IMBS) at the University of California, Irvine.

Consumer Search and Propensity to Buy

ABSTRACT

This article investigates the association between consumers' pattern of information search and their propensity to buy in a field setting. We expect that a consumer whose information search pattern is skewed towards alternative-based search will have a greater propensity to buy than a consumer whose search pattern is skewed towards attribute-based search. In addition, we examine whether the price range selected by a consumer influences their subsequent pattern of search. To address these questions, we consider several empirical models that allow us to account for endogeneity and simultaneity in the relationship between pattern of information search and propensity to buy. The results confirm our expectations. The implication is that a manager can now identify a consumer who has a higher propensity to buy while that consumer engages in information search prior to a purchase commitment, an important first step in targeting decisions.

Keywords: Choice Modeling; Digital Strategy; Information Processing; Latent Variable Simultaneous Equations Model; Markov Chain Monte Carlo (MCMC).

INTRODUCTION

Consumers face daily decisions and trade-offs regarding products they want to buy and often search for information, particularly in durable product categories, to aid their decisions. The digital revolution has significantly enhanced consumers' accessibility to information and hence the value they derive from it (Shapiro and Varian 1999, p. 8). As a result, more than 140 million consumers, almost 50% of the total US population, incorporate digital information into their shopping habits (Mendelsohn et al. 2005). While the digital revolution enhances consumers' accessibility to various types of information, in this paper we are mainly interested in objective product information across product alternatives and attributes and focus on a consumer's information search or processing pattern when such information is available.

When evaluating product alternatives across attributes, Bettman (1979, p. 178) indicates that two basic forms of information processing used by consumers are (1) Choice by Processing Brands, when consumers process the available information by examining specific products across attributes (what we call an alternative-based search pattern) and (2) Choice by Processing Attributes, when consumers process the available information by examining specific product attributes across alternatives (an attribute-based search pattern).[1] Consumers could, of course, process the available information using any mix of the two basic patterns, which raises a logical question: If a consumer searches through product information using one pattern to a greater extent than another, would s/he be more, less, or equally likely to buy a product? This is the central question that motivates the current study.

[1] We use the words search and process interchangeably. This is consistent with Bettman (1979, p. 33) who indicates that processing "rules are probably developed simultaneously with search."

Several well-known websites such as Dell, CNET, and Apple offer the consumer a choice to search using alternative-based, attribute-based, or any mix of alternative- and attribute-based patterns. For example, the Apple website menu allows consumers who are mainly interested in the iPod classic to click on the product and be directed to a page that describes only that product in detail (see Figure 1 for a largely qualitative version and Figure 2 for a largely quantitative version). The website also allows consumers who are interested in comparing Apple's several iPod models across attributes to get the information in a format that facilitates that comparison (see Figure 3). These pages provide the consumer the ability to search for their preferred model using any mix of the two basic patterns.

A key challenge for commercial websites is conversion, i.e., converting visitors to buyers. This is an area in which industry-wide metrics have not budged. Since 2001 shopping cart abandonment rates have hovered at a steady 50%, while website conversion rates have never exceeded 3.2% (Mulpuru, Graeber, and Hult 2007). If we can determine which basic search pattern is more likely to result in a purchase, managers will be able to better design the presentation of their products and target their marketing efforts to consumers who are more likely to purchase while these consumers engage in search prior to a purchase. For example, if consumers who are primarily using alternative-based search are found to have a higher propensity to purchase than consumers primarily using attribute-based search, managers could ask consumers to specify their must-have and unacceptable features, and if required, limited information on the tradeoffs they are willing to make across product attributes, so that they can be presented with one alternative, or one alternative at a time, that is customized to their

requirements. And if these consumers abandon their search or shopping carts, they can be prioritized, ceteris paribus, over consumers who use mainly attribute-based search for the purpose of follow-up communications. The ability to target consumers who are more likely to buy prior to their making a purchase commitment is of utmost importance for e-commerce website managers. Even small changes in conversion can result in significant increases in sales revenue. In addition, any research results that can aid presentation decisions made by e-commerce retailers will indeed be timely. The majority of e-retailers surveyed in a recent industry report by Mulpuru, Johnson, and Hult (2008) indicate that they intend to focus on improving the effectiveness of their product detail pages (90%) and search result pages (87%).

Second, we investigate how the price category that shoppers choose affects their information processing pattern. Shoppers that limit themselves to the lowest price category will have fewer options than those that are not limited to that category. Consequently, the choice of a particular price category could influence the type of search conducted. If shoppers who choose a low price category engage in alternative-based search, managers could use the price category selected by consumers as an important proxy for segmenting their customer base. While segmenting consumers based on the basic information search pattern used requires tracking and computations, as we demonstrate later, segmenting consumers based on the price category selected for search is easier to implement since the price category selected is easily observed.

Next we provide background, followed by the development of expectations on the association between search patterns and propensity to buy. We then briefly describe the Decision Board Platform (Mintz et al. 1997), similar to the Mouselab program (Payne,

Bettman, and Johnson 1988) which was installed on an internet retailer's website to collect data. This material is followed by a presentation of our model, estimation methodology, and results. The paper concludes with a summary of the managerial implications and discussion of potential avenues for further research.

BACKGROUND

Information Processing

The information processing literature has provided important contributions on the conditions under which consumers are likely to employ alternative-based, attribute-based, or a mix of alternative and attribute-based processing patterns. For example, laboratory studies have investigated the effect of individual differences (e.g., novices vs. experts), specific properties of the choice task being undertaken (e.g., complexity of the choice task as in the number of alternatives and attributes, and dissimilarity of options), and the type of choice situation (e.g., whether it involves emotion, time pressure, or a certain type of information display). The reader is referred to Bettman (1979), Payne, Bettman, and Johnson (1993), and Bettman, Luce, and Payne (1998) for a review and details. Less attention has been paid to studying how processing patterns affect purchase decisions. To the best of our knowledge, this paper is the first to explore this relationship in a field setting.

Linking the use of information processing patterns to propensity to buy serves as an important first step towards understanding the implications of the conditions studied historically in the information processing literature, for purchase behavior. For example, if complex task environments make it more likely that a consumer will use an attribute-based processing pattern over an alternative-based processing pattern and furthermore,

we find that a consumer who is more likely to use an attribute-based processing pattern has a lower propensity to purchase, the implication will be that managers should attempt to simplify the task environment faced by the consumer to facilitate purchase. Such examples abound in business practice – for instance, the Apple website recommends a particular iPod for a certain type of use, e.g., the iPod shuffle for clipping a light-weight model to a sleeve, belt, or gym shorts (for ultra-portability), the iPod nano for those who want to shake, shuffle, and roll (mainly music lovers), the iPod classic for music, movies, TV shows, games, podcasts, and audio books, and the iPod touch to have fun with the Internet, games, video, and songs.

Models of Consumer Choice Based on Scanner Panel Data

In contrast, household-level scanner panel-based data studies that examine choices of consumers in retail environments (e.g., Guadagni and Little 1983; see Abramson, Andrews, Currim, and Jones 2000 for a review and details), have provided important insights on the effects of brand names, prices, promotions, and consumer characteristics, on propensity to purchase. In these settings, however, search patterns are unobserved, so it is not possible to investigate how purchase behavior is influenced by search.[2] In contrast, on e-commerce websites such as Dell, Apple, etc., consumers today are able to search for information and purchase products, and managers can use technology to observe some of their search patterns, so that it is now possible to explore the relationship between search and propensity to purchase.

Effect of Propensity to Buy on Search

[2] Some studies incorporate consideration sets based on previous purchases (see Abramson, Andrews, Currim, and Jones 2000).

While the type of search conducted could influence the propensity to buy, it is conceivable that propensity to buy may also influence the type of search conducted. For example, a consumer under time pressure to purchase a new digital camera for use on their child's birthday or an upcoming vacation may conduct a search which is more limited than it would have been in the absence of time pressure. In their laboratory-based work on choice deferral, Dhar and colleagues (see Dhar and Nowlis 2004 for a review and details) find that when subjects are in a buy-no buy decision response mode (versus an unconditional brand-choice response mode), decision processes will more likely be characterized by alternative-based evaluations. Consequently, our analysis must allow not only for endogeneity, but also for simultaneity in the relationship between search and propensity to buy. If these aspects are not explicitly accounted for, the models could be fundamentally mis-specified yielding biased parameter estimates and misleading managerial implications. To deal with these concerns, we develop a new Bayesian simultaneous equation model for discrete (buy vs. do not buy) and censored (search pattern) data and propose a new simulation-based estimation method that overcomes the intractability of the likelihood function in this setting.

Consumer Information Search

Consumer search has been studied in the context of two basic paradigms, the psychological model of information processing, and the economic model of search. The first paradigm is based on constructs such as beliefs and attitudes, involvement (e.g., Beatty and Smith 1987) and knowledge (e.g., Urbany, Dickson, and Wilkie 1989) and provides excellent descriptions of the psychological processes that accompany search. The second paradigm weighs the costs and benefits of search when making search

decisions (e.g., see Moorthy, Ratchford, and Talukdar 1997 for a review). For example, Moorthy, Ratchford, and Talukdar (1997) study how brand uncertainty, product class involvement, risk aversion, search cost, and experience affect the total amount of search conducted in the automobile category. In our field setting, as is the case in a large variety of commercial websites, consumer variables described above are typically unobserved. As a result, we are not able to study the important insights offered by these two streams of studies. On the other hand, however, search and purchase are observable in our field setting and other commercial websites so that there is a potential that our analysis could be valuable to managers of a large number of commercial websites.

Models of Internet Conversion Based on Clickstream Data

A few works have investigated consumer conversion (i.e., converting store visits into purchases) on the internet by proposing empirical models which have provided important insights. For example, Moe and Fader (2004) posit a model that decomposes an individual's conversion into two components, one for accumulating visit effects (e.g., visits for purchasing vs. visits for hedonic browsing) and another for purchasing threshold effects (e.g., the psychological resistance to online purchasing that evolves with purchasing experience on a given website), and find evidence for both effects in the context of book purchasing at Amazon. Moe (2006) follows up by proposing a two-stage choice model, products viewed and products purchased, and finds that in the earlier stage consumers use simpler decision rules on a subset of attribute information (screening attributes), while ingredient attributes (of nutritional products) are used in both stages (screening and purchase).

Montgomery, Li, Srinivasan, and Liechty (2004) categorize and model the path information at the Barnes and Noble site. They find that the memory component of their model is crucial in accurately predicting a path and after only six viewings, purchaser can be predicted with more than 40% accuracy. Sismeiro and Bucklin (2004) decompose the purchase process into the fulfillment of three tasks, complete product configuration (details of the automobile desired), inputting personal information, and completing the order, and find that their approach better identifies likely buyers relative to a single-stage benchmark. Less attention has been paid to the search or information processing pattern that a consumer uses, that is, whether the consumer searches for or processes information primarily across- or within-brands and how such search or processing patterns are associated with purchase.

Website Morphing

Hauser et al. (2009) provide an innovative model for website morphing which involves automatically matching the basic look and feel of a website, not just content, to cognitive styles. Cognitive style is a person's preferred way of gathering, processing, and evaluating information. For example, impulsive visitors might prefer less detailed information (e.g., fewer alternatives, fewer attributes, or easy to comprehend general content on overall comparisons), whereas deliberative visitors might prefer more information. And, the more focused morph might appeal to visitors that are holistic, while the ability to compare many options in a table might appeal to analytic visitors. They show that morphing based on cognitive style can increase purchase intentions by 20% on the former British Telecom site. Our study is similar in spirit but different in scope. We identify the nature of a customer's information search or processing and connect it to

purchase. Specifically, we focus on the second of the four technical challenges they identify, that is even if we know a customer's search, processing, or cognitive style, website managers must learn which characteristics are best for which customers in terms of sales and profit.

EXPECTATIONS

Building on prior research on information processing, search, and behavioral decision theory, we now propose several hypotheses linking the search pattern that consumers employ and their propensity to buy. Figure 4 illustrates our conceptual framework.

Influence of Information Search Pattern on Propensity to Buy

Previous research has demonstrated that product preferences are often constructed whenever one is searching through a website (Mandel and Johnson 2002), i.e. they are frequently assembled and not just revealed when making a decision (Bettman 1979; Bettman and Park 1980; Bettman, Luce, and Payne 1998; Häubl and Murray 2003; Tversky, Sattah, and Slovic 1988). Therefore, the specific search pattern that a consumer uses to assess product information can influence their propensity to buy.

In particular, we hypothesize that consumers whose search is more alternative-based will be more inclined to purchase a product than consumers whose search is more attribute-based. Consumers who search in an alternative-based pattern assess products individually in isolation or one-at-a-time so that they are able to judge whether that product's features meet their baseline purchasing criteria, with less distraction about whether another competitive product is better (Dhar and Nowlis 2004). As a result, these consumers develop more accurate representations of the products (e.g., Payne, Bettman,

and Johnson 1993) and are better able to judge the overall suitability of each product they examined. Thus, at the conclusion of their search, consumers who search in more alternative-based patterns are more certain of whether a product can be purchased.

Furthermore, consumers often engage in alternative-based search to not even allow the possibility of trade-offs. For example, alternative-based search occurs when consumers perceive an item or brand as superior to other available options. This results in a simple preference validation based search process to ensure that the product they have a preconceived superior perception of does not have any negative properties that discourage purchasing it (Iyengar and Lepper 2000; Moorthy, Ratchford, and Talukdar 1997). Alternative-based search also occurs following a process Simon (1956) identifies as "satisficing", in which alternatives are considered sequentially and the value of each attribute of the alternative is considered to determine whether it meets a pre-determined minimum cutoff level. If any attribute fails to meet the minimum cutoff level, the option is rejected and the next alternative is considered until an option is found in which all attributes meet their minimum cutoff levels.

On the other hand, shoppers whose search is more attribute-based directly compare alternatives to determine for example, which alternative is best on each attribute. If only one attribute is important, such a lexicographic search strategy can be useful. However, in many product categories, and durable product categories in particular, typically more than one attribute is important (e.g., various quality attributes and price). As a result, choice can become more difficult since the consumer usually has to confront the fact that in order to purchase a product that is superior on a particular attribute, certain other superior features of competitive products must be sacrificed. Thus, after completing

search, shoppers who search is more attribute-based may have a more difficult time deciding which product is best for them, and consequently be less likely to purchase.

> **H1:** Consumers engaging in more alternative-based search will have a greater propensity to buy than consumers exhibiting more attribute-based search.

Alternatively, one could argue that attribute-based search increases the certainty that a particular alternative is the "optimal" alternative since the shopper is able to make a judgment about the alternative relative to competitive alternatives, and that such increased certainty results in a greater propensity to buy. In such a case H1 would not be supported.

Influence of Propensity to Buy on Information Search

Although we have just described several reasons for why the pattern that consumers utilize to search can influence their propensity to buy, one could theorize that a consumer's propensity to buy could influence their pattern of search. For example, a consumer who has a high propensity to buy is more likely to know what product or brand they want, the price they want to pay, or features they are most interested in (e.g., Hauser and Wernerfelt 1990; Ratchford 1982; Roberts and Lattin 1991; Simonson, Huber, and Payne 1988). These shoppers use such prior knowledge to efficiently screen out alternatives and subsequently evaluate each remaining alternative in more detail (e.g., Alba et al. 1997). Thus, shoppers may have completed what resembles the first stage of Poliheuristic theory, by which alternatives are ruled out using easier to execute non-compensatory attribute-based processing methods. This first stage is followed by a second stage in which remaining alternatives are assessed using more compensatory alternative-based patterns (Mintz et al. 1997; Payne 1976).

In addition, in their laboratory-based work on choice deferral, Dhar and colleagues (see Dhar and Nowlis 2004 for a review and details) find that when subjects are in a buy-no buy decision response mode (versus an unconditional brand-choice response mode), decision processes will more likely be characterized by alternative-based evaluations. Their theoretical account suggests that a focus on the buy/no-buy decision activates greater use of alternative-based evaluations (i.e., whether an option is acceptable), making purchase deferral more sensitive to the valence of shared features and category reference information. That is, when alternatives are being evaluated in the buy/no-buy mode, shared (unique) good features will lead to lower (higher) deferral than in the unconditional brand-choice response mode. The greater alternative-based evaluation makes it easier for shoppers to compare the options with a category reference (e.g., Kalyanaram and Winer 1995) which can be based on previous experience or externally available information that provides a natural frame of comparison (Bettman and Park 1980).

H2: Consumers who have a higher propensity to buy are more likely to engage in alternative-based search.

Alternatively one could argue that consumers with a higher propensity to buy will be more likely to employ attribute-based search in order to ensure that the product is "optimal" relative to competing alternatives. In such a case H2 will not be supported. Because H1 and H2 are not mutually exclusive the relationship between search and propensity to buy is conceptualized as being simultaneous as depicted in Figure 4.

Influence of Price on Information Search

In their work on the impact of information and learning on consumer choice, Tellis and Gaeth (1990) identify three strategies that consumers use to make choices,

price aversion, best value, and price-seeking. Price aversion involves choosing the lowest price alternative to minimize immediate cost. Best value involves choosing based on price and expected quality. Price-seeking involves choosing the highest price alternative to maximize expected quality. The three choice strategies originate from three different theoretical perspectives. Price aversion originates from the theory of risk aversion which is based on a consumer's preference for a more certain prospect over a more uncertain one even if the expected values of the two prospects are similar (e.g., Kahneman and Tversky 1979; Thaler 1980, 1985). Best value originates from the economic theory of rationality, principles which describe the normatively best or utility maximizing choice (e.g., von Neumann and Morgenstern 1944; Lancaster 1966). Price-seeking originates from the theory of inference, how consumers infer a missing attribute such as quality from price (e.g., Leavitt 1954; Monroe and Petroshius 1981; Zeithaml 1988).

We expect that price sensitive shoppers or consumers with stringent budget constraints will choose to search in the lowest price category and will largely employ price aversion strategies which involve identification of the lowest price alternative(s) (e.g., Tellis and Gaeth 1990) followed by an alternative-based evaluation strategy to ensure that the option does not have any negative features that detract from purchase (Simon 1956). The theoretical rationale is simply that the consumer is minimizing expenses or losses that are certain.

In contrast, less price sensitive shoppers will consider higher priced options and largely employ best value and price-seeking strategies. Tellis and Gaeth (1990) indicate that when more information is available on relevant attributes, consumers will be able to employ the best value strategy. However, when there is missing information on relevant

attributes, consumers will be more likely to employ price-seeking strategies. Digital information has generally facilitated consumer access to information on relevant attributes so that if such information is accessed the consumer will be able to engage in attribute-based search in order to identify the best value option.

H3: Consumers who shop in higher priced categories are more likely to employ attribute-based search than consumers who shop in the lowest price category.

EMPIRICAL ANALYSIS

Data

To test our theoretical hypotheses, the Decision Board Platform (Mintz et al. 1997), a computerized decision process tracing program similar to Mouselab (e.g., Johnson, Payne, and Bettman 1988), that has been used in a variety of research fields such as political science, engineering safety, and business decision making, in both on- and off-line environments, was installed on the website of a popular computer manufacturer/retailer. Shoppers who visited the website over a 50 hour period during a weekend chose a price category to shop and were able to compare 3 products at-a-glance (presented in columns) on 11 product features including price (presented in rows). The feature values in the corresponding cells were hidden and shoppers were instructed to click on cells that were important to them. Subsequently, they had the option to either buy a specific product or "Customize and Buy". The Decision Board Platform keeps track of the information cells accessed and the final decision of each shopper. The search pattern of 920 shoppers (visitors who had more than one click), who were unaware that their actions were to be analyzed for an experiment, were recorded.

Measures

Information processing patterns. The measure PATTERN (Payne, Bettman, and Johnson 1988) was employed to measure the extent to which shoppers used alternative-based versus attribute-based search. PATTERN is constructed as a ratio, the numerator is the number of alternative-based transitions minus the number of attribute-based transitions, and the denominator is the number of alternative-based transitions plus the number of attribute-based transitions. The resulting scores are censored – i.e. they range from -1.0 to +1.0, with lower numbers representing more attribute-based processing patterns, and exhibit point-masses at both ends of the range [-1,1].[3]

Propensity to buy and Price category. Propensity to buy was recorded as a binary variable, 0 or 1, with 1 indicating that a shopper chose a product. Shoppers entered two price categories to conduct their search, low (less than $999) and high (more than $999).

Overview

Of the 920 shoppers who visited the website, 293 exhibited attribute-based search behavior (had a negative PATTERN score), 612 were alternative-based searchers (had positive PATTERN score), and 15 exhibited neutral search behavior with a PATTERN score of 0. Among the website shoppers, 596 chose to search in the low price category, while 324 searched in the high price category. In addition, 438 shoppers proceeded to buy or customize and buy and 482 did not. Among the shoppers who used the alternative-based strategy, 52% (319 out of 612) proceeded to buy or customize and buy. Similarly, among the shoppers who used the attribute-based search strategy, 40% (119 out of 293) proceeded to buy or customize and buy. Of the 596 shoppers who chose to shop in the low price category, 441 (or 74%) used alternative-based search, while among the 324

[3] As a robustness check, variations on the measure PATTERN were also considered in the subsequent analysis, but the results did not reveal any major qualitative differences.

shoppers in the high price category, 171 (or 53%) used alternative-based search. Overall, the data set exhibits sufficient variability over the constructs being investigated.

Model

Overview. We now present an econometric model that is specifically tailored to the setting considered in this paper. The model is intended to accommodate three particular aspects of the problem at hand. First, our model accounts for the discrete nature of the dependent variables – in particular, propensity to buy is a binary indicator variable, while our measure of search behavior is censored on the interval [-1,1] and exhibits point mass at both endpoints. To deal with this difficulty, our modeling and estimation approach relies on data augmentation techniques (Chib 1992; Albert and Chib 1993) which allow the model to be written in terms of a threshold-crossing latent variable representation that greatly facilitates estimation. A second issue we address is the potential for endogeneity and simultaneity in search behavior and propensity to buy. If these potential features of the theory are not accounted for in the model, they could render it severely mis-specified. Models with endogeneity and simultaneity, however, have been difficult to estimate when the dependent variables of interest are not continuous because standard two-stage estimators are inapplicable in this context. Third, we specifically account for model uncertainty by discussing methods for model comparison based on marginal likelihoods and Bayes factors. These techniques allow us to consider the extent to which the data support the hypotheses about price categories, information search and propensity to buy presented earlier.

Specification. For consumer $i = 1, \ldots, n$, the general specification we consider is given by the following bivariate system:

$$\begin{pmatrix} y_{iIS}^* \\ y_{iPB}^* \end{pmatrix} = \begin{pmatrix} x_{i1}' & 0 \\ 0 & x_{i2}' \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} + \begin{pmatrix} y_{iPB}^* & 0 \\ 0 & y_{iIS}^* \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \end{pmatrix},$$

where y_{iIS}^* and y_{iPB}^* are the latent variables underlying information search and propensity to buy, respectively, and x_{i1} and x_{i2} are exogenous covariates with corresponding parameter vectors β_1 and β_2. For estimation purposes, the model can also be written in any of the following equivalent forms

$$Ay_i^* = X_i\beta + \varepsilon_i \quad \text{or} \quad y_i^* = A^{-1}X_i\beta + A^{-1}\varepsilon_i,$$

where

$$A = \begin{pmatrix} 1 & -\theta_1 \\ -\theta_2 & 1 \end{pmatrix}, \; y_i^* = \begin{pmatrix} y_{iIS}^* \\ y_{iPB}^* \end{pmatrix}, \; X_i = \begin{pmatrix} x_{i1}' & 0 \\ 0 & x_{i2}' \end{pmatrix}, \; \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}, \text{ and } \varepsilon_i = \begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \end{pmatrix}.$$

The observed information processing pattern, y_{iIS}, relates to the latent measure of information search y_{iIS}^* through the two-sided censored (Tobit) relationship

$$y_{iIS} = \begin{cases} -1 & \text{if } y_{iIS}^* \le -1 \\ y_{iIS}^* & \text{if } y_{iIS}^* \in (-1,1) \\ 1 & \text{if } y_{iIS}^* \ge 1 \end{cases},$$

while the binary product selection indicator, y_{iPB}, relates to the latent propensity to buy y_{iPB}^* through the (probit) relationship $y_{iPB} = 1\{y_{iPB}^* > 0\}$, where $1\{\cdot\}$ is the indicator function. In the foregoing system of simultaneous equations, the errors follow

$$\begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \end{pmatrix} \sim N(0,\Omega), \text{ where } \Omega = \begin{pmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & 1 \end{pmatrix}$$

is a symmetric positive definite matrix that incorporates the usual unit variance restriction in binary data probit models. In the specific application that we consider, the vector of

exogenous covariates x_{i1}' contains an intercept and a dummy variable for price category, while x_{i2}' contains an intercept term.

Let $y_i = \left(y_{iIS}, y_{iPB}\right)'$, $y = \left(y_1', \ldots, y_n'\right)'$, and $y^* = \left(y_1^{*\prime}, \ldots, y_n^{*\prime}\right)'$, and let $\psi = \left(\beta, \theta, \omega\right)$ represent the vector of model parameters, where ω contains the unique unrestricted elements of Ω. The likelihood function

$$f\left(y \mid \psi\right) = \prod_{i=1}^{n} f\left(y_i \mid \psi\right)$$

For this the model requires multivariate integration to obtain each likelihood contribution

$$f\left(y_i \mid \psi\right) = \int_{S_i} f\left(y_i^* \mid \psi\right) dy_i^* ,$$

where S_i is the feasible region defined by the mapping between y_i^* and y_i. This feature complicates estimation by maximum likelihood methods. However, using techniques introduced in Chib (1992) and Albert and Chib (1993), estimation can be accomplished in a Bayesian simulation-based framework that specifically introduces the latent $\left\{y_i^*\right\}$ into the estimation algorithm. Bayesian estimation is also useful because it provides finite sample inferences and enables comparisons of nested and non-nested models.

Specifically, Bayesian model comparison proceeds on the basis of the posterior model probabilities for the set of competing models, where for any two models M_j and M_k, the posterior odds are defined as

$$\frac{\Pr\left(M_j \mid y\right)}{\Pr\left(M_k \mid y\right)} = \frac{\Pr\left(M_j\right)}{\Pr\left(M_k\right)} \frac{f\left(y \mid M_j\right)}{f\left(y \mid M_k\right)}.$$

The first fraction on the right hand side of this equation is known as the prior odds ratio, while the second fraction is known as the Bayes factor. This expression makes it clear

that the posterior odds incorporate both sample information (because the Bayes factor depends on the data) and non-sample information (through the prior odds that could be based on theoretical considerations, evidence from earlier studies, etc.). Of central importance in determining the Bayes factor is the quantity $f\left(y \mid M_l\right)$, known as the marginal likelihood, which is defined as integral of the likelihood function $f\left(y \mid \psi_l, M_l\right)$ with respect to the prior density $\pi\left(\psi_l \mid M_l\right)$, i.e.,

$$f\left(y \mid M_l\right) = \int f(y \mid \psi_l, M_l)\pi\left(\psi_l \mid M_l\right) d\psi_l \ .$$

Several important properties of this framework deserve attention. Marginal likelihoods and Bayes factors lead to finite sample model probabilities and do not require that the competing models be nested. These properties are in contrast to other model comparison criteria, such as the likelihood ratio test, which are justified only asymptotically (as $n \to \infty$) and are only useful in comparing nested models. As shown by Schwarz (1978), Bayes factors have appealing asymptotic properties and in large samples give rise to the Schwarz Information Criterion (SIC), also known as the Bayes Information Criterion (BIC). Reviews are given in Greenberg (2008, Ch. 3) and O'Hagan (1994, Ch. 3). It is also interesting to note that the marginal likelihood can be viewed as a measure of sequential out-of-sample predictive fit that evaluates how well the model predicts the observed data one observation at a time. This can be seen by writing

$$\begin{aligned} f\left(y \mid M_l\right) &= \prod_{i=1}^{n} f\left(y_i \mid \left\{y_j\right\}_{j<i}, M_l\right) \\ &= \prod_{i=1}^{n} \int f\left(y_i \mid \left\{y_j\right\}_{j<i}, \psi_l, M_l\right) \pi\left(\psi_l \mid \left\{y_j\right\}_{j<i}, M_l\right) d\psi_l, \end{aligned}$$

where the first line uses the law of total probability to represent the marginal likelihood as the product of *n* sequential predictive densities, and the second line offers an

equivalent representation that is quite instructive. Specifically, it shows that the adequacy of a model, as captured by its marginal likelihood, corresponds to its cumulative out-of-sample predictive record, in which the predictive fit of observation *i* is measured with respect to the posterior density based only on information up to the *i*th data point (a thorough discussion is offered in Geweke 1999). Thus, marginal likelihoods formally capture the idea behind out-of-sample prediction comparisons often used in empirical work. When such comparisons are performed, the available data set is split into an estimation sample, used to provide parameter estimates, and a comparison (or validation) sample, where the predictions formed using these parameter estimates are compared with the actual observations.

Under the prior distributions $\pi(\beta) = N(\beta \mid \beta_0, B_0)$, $\pi(\theta) = N(\theta \mid \theta_0, \Theta_0)$, and $\pi(\Omega) \propto IW(r_0, R_0) 1\{\Omega_{22} = 1\}$, we develop a Markov chain Monte Carlo (MCMC) estimation algorithm which proceeds by recursively sampling from the full-conditional distributions of the parameters θ, β, and Ω, and the latent data $\{y_i^*\}$. The latent $\{y_i^*\}$ are specifically introduced in the MCMC algorithm in order to facilitate estimation (Chib 1992; Albert and Chib 1993). Algorithm 1 in the Appendix presents details on the MCMC simulation approach. To gauge the empirical relevance of the benchmark simultaneous equations model and cast light on the hypotheses presented earlier, we also examine several alternative model specifications. These competing models are compared on the basis of their marginal likelihoods which are computed using the techniques of Chib (1995) and Chib and Jeliazkov (2001).

Results

Parameter estimates for the benchmark simultaneous equations model M_1 are presented in Table 1. Inferences are based on an MCMC simulation run of length 50,000 draws, following a burn-in cycle of 5,000 draws. We begin with a discussion of hypothesis H3 because it is the most straightforward among the three hypotheses that we consider. We then focus on H1 and H2, and provide additional evidence and model comparisons to address the issues that arise in the analysis of these two hypotheses.

The results in Table 1 suggest that hypothesis **H3**, which asserted that shoppers in the higher-price category are more likely to engage in attribute-based search (leading to lower values of y^*_{iIS} and y_{iIS}), is supported by the data. Specifically, the coefficient on the price category covariate, β_2, has a posterior mean of -0.76 with a posterior standard deviation of 0.17. Because of the simultaneity between y^*_{iIS} and y^*_{iPB}, the correlation in the errors, and the non-linearity in the relationship between $y^*_i = \left(y^*_{iIS}, y^*_{iPB}\right)'$ and $y_i = \left(y_{iIS}, y_{iPB}\right)'$, interpretation of the magnitude of β_2 in practical terms is not straightforward. However, the simulation techniques presented in Chib and Jeliazkov (2006) and Jeliazkov *et al*. (2008) allow for uncomplicated simulation-based evaluation of the marginal effect. In particular, covariate effect estimation proceeds as a forecasting problem in which, given a draw ψ from the posterior, a value of $y^*_i = \left(y^*_{iIS}, y^*_{iPB}\right)'$ is generated and converted to $y_i = \left(y_{iIS}, y_{iPB}\right)'$ for both the high and low price categories. Performing this simulation multiple times and averaging the resulting differences between the high and low price simulated values of y_i gives an estimate of the average effect of the exogenous covariate price category and is a useful way to interpret the

magnitude of β_2. Using this simulation approach, we have been able to determine that y_{iIS} decreases by approximately 0.35 when price category is changed from 0 (low price) to 1 (high price) suggesting that shoppers utilize more attribute-based search patterns. Because of the simultaneity in the model a change in this covariate also has an effect on y_{iPB}, which decreases by approximately 0.09. Both of these effects are of economically significant magnitudes.

Hypothesis **H1** postulated that shoppers who search in alternative-based patterns will be more likely to purchase a product than shoppers who search in more attribute-based patterns. This hypothesis is supported by the data as it was found to have a robust effect in the baseline model – the posterior mean of θ_2 is given by 0.28 with posterior standard deviation of 0.1. One should keep in mind, however, that because both y^*_{iIS} and y^*_{iPB} are endogenous and simultaneously determined, interpretation of the coefficients θ is not *ceteris paribus*.

A cursory look at Table 1 may lead one to question whether the complexity of the simultaneous equation model is fully warranted in this setting. The fact that both θ_1 and ω_{12} are small relative to their posterior standard deviations calls for examination of simpler model specifications. Several simpler competing models are presented in Figure 5 and Table 2. In particular, model M_2 is a mediated model of consumer behavior in which search is endogenous, but there is no full simultaneity. In that specification θ_1 is restricted to zero, producing a system with recursive endogeneity, but no simultaneity, between the variables – the Tobit equation specifies a link between price category and information search pattern, and the probit equation, in turn, studies the impact of

information search pattern on consumers' propensity to buy but rules out feedback in the reverse direction. Model M_3 offers another simplification: it does not allow for the possibility that the error terms in the two equations may be correlated as Ω is diagonal. Model M_4 goes even further and treats propensity to buy and information search as completely independent of each other. Finally, model M_5 allows for correlation in the errors but restricts both θ_1 and θ_2 to zero, ruling out endogeneity or simultaneity and producing a system of seemingly unrelated Tobit and probit equations. By examining these simpler alternative models, we can gauge the empirical relevance of the benchmark model, M_1, and cast further light on the hypotheses that were discussed earlier.

The marginal likelihood results in Table 2 indicate that the simultaneous equations model M_1 is supported by the data as it has the highest marginal likelihood. One can see that removing the parameters θ_1 and ω_{12} either one at a time or jointly (as in models M_2, M_3, and M_4) reduces overall fit relative to the benchmark model M_1. Removing both θ_1 and θ_2 from model M_1 while still allowing for correlation between the error terms in the two equations (as in model M_5) reduces the fit, but by less than in the other simplifications. As further evidence that θ_1 and ω_{12} play an important role in the benchmark model, we present a bivariate contour plot of their joint posterior distribution in Figure 6. The figure indicates that the mass of this joint posterior distribution is centered away from zero, even though each of the univariate 95% posterior credibility bands include that value, and for this reason the presence of these parameters in the model is supported by the data. The figure is also instructive because it reveals that the modal values of θ_1 and ω_{12} are 0.327 and -0.747, respectively. This is suggestive,

although weak, evidence in support of **H2**; however, more data and further study are needed in order to determine the validity of this hypothesis.

We take the results presented in this section as strong evidence that the two equations should be treated jointly and that correlation in the errors must be properly accommodated. Through formal model comparisons, we have found that data strongly support hypotheses **H1** and **H3** and that further study is warranted to determine the empirical relevance of hypothesis **H2**.

SUMMARY, MANAGERIAL IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

While the information processing literature in marketing has provided several important contributions over the past four decades on why individuals use alternative-based vs. attribute-based strategies (e.g., Bettman 1979; Luce, Payne, and Bettman 1999) in experimental settings, less attention has been paid to the relationship between such information processing or search strategies and product choices in shopping settings. To the best of our knowledge, this is the first work to explore this relationship in a field setting. This work is now possible because digital information is often presented in ways that facilitate such processing patterns and/or because search patterns can be observed or inferred by tracking devices. As a result, there is now a potential to connect all the experimental work over the past four decades on individual differences (e.g., novices vs. experts), properties of the task (e.g., complexity of information or amount of information and dissimilarity of options), and type of choice situation (e.g., whether it involves emotion, time pressure, or a certain type of information display) to product choices in shopping settings.

Measurement of information search strategies in the above mentioned literature is censored (in the range -1 to +1), purchase is binary (yes or no), and prior theory suggested a possibility of a relationship between purchase and information search (e.g., Dhar and Nowlis 2004) in addition to the general proposition of a relationship between information search and propensity to purchase. Models with such endogeneity and simultaneity have been difficult to estimate when the dependent variables of interest (purchase and information search) are not continuous, because standard two-stage estimators are inapplicable in such a context. We develop a Bayesian simulation-based estimation methodology that overcomes the analytical intractability of the likelihood function in this class of models.

Our main result is that the type of information processing or search pattern does impact a shopper's propensity to buy. Specifically, shoppers whose search is more alternative-based are found to have a higher propensity to purchase than shoppers whose search is more attribute-based. The main rationale is that shoppers using alternative-based search are evaluating products one-at-a-time and are better able to judge whether the product meets their purchasing criteria or is suitable for them with lesser distraction from other products. Whether these shoppers are displaying a no trade-off approach such as a preconceived preference validation or satisficing strategy or a different search strategy in which they assess some or all of the available products to then select which product was the most suitable, the alternative-based approach is found to more likely result in a purchase decision. We have found that many "brick and click" retailers of durable produce categories (flat panel televisions, computers, etc.) do not present information on many shopper relevant features on the shelf talker. Our main result

suggests that shopper relevant features should be provided and if sales force resources are limited, they need to be allocated to shoppers whose queries focus on one of two products (alternative-based) in contrast to shoppers whose queries are more general (attribute-based) so that the queries cover several products.

Commercial websites usually provide more product selection than brick and mortar stores. Managers of commercial websites, in particular, need to ensure that visitors can easily identify products they are or would be interested in and determine whether these products meet their purchasing requirements (alternative-based processing). This can be accomplished through marketing research and segmentation, in order to identify the major usage or benefit segments so that recommendations of one or a couple products can be made to shoppers who would identify themselves with a particular usage or benefit segment. Alternatively, the shopper could be asked a few questions on whether they are interested in certain products or a few questions about their proposed usage or benefits desired so that recommendations can be made for further alternative-based processing. In addition, if the shopping cart was abandoned, manufacturers and retailers could prioritize alternative-based shoppers over attribute-based shoppers for follow-up or short-term promotional efforts.

Our second finding is that shoppers in low price categories are more likely to employ alternative-based search than shoppers in higher price categories. The main rationale is that shoppers in low price categories will be interested in the lowest price product(s) and will engage in an alternative-based search to ensure that the product does not have any negative features that deter purchase. In contrast, shoppers in higher price categories will be more interested in getting the best value and will conduct an attribute-

search to understand and make trade-offs required to attain best value (e.g., Tellis and Gaeth 1990). While segmentation of shoppers based on the type of search (alternative- vs. attribute-based) requires some tracking and computation, the price category a shopper shops in is easily observable. Many retailers in the brick and click spaces do not organize their presentations based on price. Such an organization could facilitate purchases among low and higher price category shoppers. Low price category shoppers would find it easier to identify the least expensive product. And higher price category shoppers would find it easier to identify alternatives to conduct an attribute-based search in order to understand and make trade-offs required to attain best value. In addition, such an organization would simplify the choice task since shoppers in a certain category consider fewer options. A more complex choice environment with a larger set of unorganized products would require attribute-based evaluations to identify a couple products before subsequent alternative-based evaluations can be performed.

This investigation was conducted in one durable product category offered by a popular retailer. It would be useful to understand whether the relationship between search and choice varies across durable product categories, retailers, and consumers. For example in lower (or higher) price product categories such as small household appliances (luxury watches) which are less subject to technological change, shoppers may search differently and the relationship between search and choice might be different. It would also be useful to understand whether the relationship between search and choice varies across retailers. For example, it is possible that consumers shopping for durables at certain retailers that have developed strong reputations for everyday low prices (e.g., Wal-Mart), product value (e.g., Costco), or luxury (e.g., Louis Vuitton) might modify

their search behavior because of trust in the retailer and the relationship between search and purchase may be different from that when shopping at less differentiated stores. While these directions refer to studies conducted in retailer settings, it would also be useful to conduct studies in a consumer setting, which allow us to follow the digital search conducted by the consumer from the moment they begin thinking about a durable purchase in a certain product category to the moment they make a purchase. Such a study could provide a portrait about how search evolves towards purchase and the differences across product categories and retailers. We hope our efforts will motivate such future research.

APPENDIX

Algorithm 1: MCMC Estimation of the Latent Data Simultaneous Equations Model

1. Sample $[\beta \mid y^*, \theta, \Omega] \sim N\left(\overline{\beta}, \overline{B}\right)$, where

$$\overline{B} = \left(B_0 + \sum_i X_i' \Omega^{-1} X_i\right)^{-1} \text{ and } \overline{\beta} = \overline{B}\left(B_0^{-1}\beta_0 + \sum_i X_i' \Omega^{-1} A y_i^*\right).$$

2. Sample $[\theta \mid y^*, \beta, \Omega]$ by drawing a proposal draw $\theta' \sim T_\nu\left(\overline{\theta}, \overline{\Theta}\right)$ where $T_\nu(\cdot)$ is a multivariate *t* distribution with ν degrees of freedom, mean $\overline{\theta}$ taken to be the maximum, and $\overline{\Theta}$ is the inverse of the negative Hessian, of the complete data log-likelihood function $L\left(\theta; y^*\right)$, i.e. given the latent data $\left\{y_i^*\right\}$ (keep in mind the Jacobian term due to A). Given the proposed draw θ' and the current draw θ in the Markov chain, accept θ' with probability

$$\alpha\left(\theta, \theta'\right) = \min\left\{1, \frac{L\left(\theta'; y^*\right)\pi\left(\theta'\right)}{L\left(\theta; y^*\right)\pi\left(\theta\right)} \frac{f_{T_\nu}\left(\theta \mid \overline{\theta}, \overline{\Theta}\right)}{f_{T_\nu}\left(\theta' \mid \overline{\theta}, \overline{\Theta}\right)}\right\},$$

   otherwise return θ.

3. Sample $[\Omega \mid y^*, \theta, \beta]$ by drawing $\omega_{11\cdot 2} \equiv \omega_{11} - \omega_{12}\omega_{22}^{-1}\omega_{21}$ from $\omega_{11\cdot 2} \sim IW\left(r_0 + n, Q_{11}\right)$, where $Q = R_0^{-1} + \sum_i \left(y_i^* - X_i\beta\right)\left(y_i^* - X_i\beta\right)'$, followed by drawing $\omega_{12} \sim N\left(Q_{22}^{-1}Q_{21}, \omega_{11\cdot 2}Q_{22}^{-1}\right)$, from which Ω can be recovered directly.

4. For $i = 1, \ldots, n,$ sample $[y_{iIS}^* \mid y_{iPB}^*, y_{iIS}, \beta, \theta, \Omega] \sim TN_{S_i}\left(\mu_{1|2}, V_{1|2}\right)$ from a truncated normal distribution, where S_i is the region consistent with the censoring of y_{iIS} and $\mu_{1|2}$ and $V_{1|2}$ are the usual conditional mean and variance for a normal random variable; at each step also sample $[y_{iPB}^* \mid y_{iIS}^*, y_{iPB}, \beta, \theta, \Omega] \sim TN_{S_i}\left(\mu_{2|1}, V_{2|1}\right)$, where S_i is the region $\left(0, \infty\right)$ if y_{iPB} is 1, or it is the region $\left(-\infty, 0\right)$ otherwise.

The first step in Algorithm 1 follows the form used in the sampling of seemingly unrelated regression models (see Chib and Greenberg 1995), the second step relies on the Metropolis-Hastings algorithm to sample θ (resulting in acceptance rates of around 88-

90% in our application), the third follows from the properties of the inverse Wishart distribution (see Dreze and Richard 1983, and Chib, Greenberg, and Jeliazkov 2009), and the final step exploits the data augmentation techniques proposed in Chib (1992) and Albert and Chib (1993). The marginal likelihoods of models fit by Algorithm 1 are evaluated following the approach of Chib (1995) and Chib and Jeliazkov (2001).

REFERENCES

Abramson, Charles, Rick L. Andrews, Imran S. Currim, and Morgan Jones (2000), "Parameter Bias from Unobserved Effects in the Multinomial Logit Model of Consumer Choice," *Journal of Marketing Research*, 37 (November), 410-26.

Alba, Joseph, John G. Lynch, Barton Weitz, Chris Janiszewski, Richard Lutz, Alan Sawyer, and Stacy Wood (1997), "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces," *Journal of Marketing*, 61 (July), 38-53.

Albert, James H. and Siddhartha Chib (1993), "Bayesian Analysis of Binary and Polychotomous Response Data," *Journal of the American Statistical Association*, 88 (June), 669-79.

Beatty, Sharon E. and Scott M. Smith (1987), "External Search Effort: An Investigation Across several Product Categories," *Journal of Consumer Research*, 14 (June), 83-95.

Bettman, James R. (1979), *An Information Processing Theory of Consumer Choice*. Reading, Massachusetts: Addison-Wesley Publishing Company.

———, Mary Frances Luce, and John W. Payne (1998), "Constructive Consumer Choice Processes," *Journal of Consumer Research*, 25 (December), 187-217.

——— and C. Whan Park (1980), "Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis," *Journal of Consumer Research*, 7 (December), 234-48.

Chib, Siddhartha (1992), "Bayes Inference in the Tobit Censored Regression Model," *Journal of Econometrics*, 51 (January), 79-99.

——— (1995), "Marginal Likelihood from the Gibbs Output," *Journal of the American Statistical Association*, 90 (December), 1313-21.

——— and Edward Greenberg (1995), "Hierarchical Analysis of SUR Models with Extensions to Correlated Serial Errors and Time-Varying Parameter Models," *Journal of Econometrics*, 68 (August), 339-60.

———, ———, and Ivan Jeliazkov (2009), "Estimation of Semiparametric Models in the Presence of Endogeneity and Sample Selection," *Journal of Computational and Graphical Statistics*, 18 (June), 321-48.

——— and Ivan Jeliazkov (2001), "Marginal Likelihood from the Metropolis-Hastings Output," *Journal of the American Statistical Association*, 96 (March), 270-81.

——— and ——— (2006), “Inference in Semiparametric Dynamic Models for Binary Longitudinal Data,” *Journal of the American Statistical Association*, 101, 685-700.

Dhar, Ravi and Stephen Nowlis (2004), "To Buy or Not to Buy: Response Mode Effects on Consumer Choice," *Journal of Marketing Research* , 41 (November), 423-32.

Dreze, Jacques H., and Jean-Francois Richard (1983), “Bayesian Analysis of Simultaneous Equation Systems,” in *Handbook of Econometrics*, Vol. 1, Zvi Grilches and Michael D. Intriligator, eds. Amsterdam, The Netherlands, 517-98.

Geweke, John (1999), “Using Simulation Methods for Bayesian Econometric Models: Inference, Development, and Communication”, *Econometric Reviews*, 18 (1), 1-73.

Greenberg, Edward (2008), *Introduction to Bayesian Econometrics*. New York: Cambridge University Press.

Guadagni, Peter and John D.C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (March), 203-38.

Häubl, Gerald and Kyle B. Murray (2003), "Preference Construction and Persistence in Digital Marketplaces: The Role of Electronic Recommendation Agents," *Journal of Consumer Psychology*, 13 (January), 75-91.

Hauser, John R. and Birger Wernerfelt (1990), "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, 16 (March), 393-408.

———, Glen L. Urban, Guilherme Liberali, and Michael Bruan (2009), “Website Morphing,” *Marketing Science*, 28 (March), 202-23.

Iyengar, Sheena S. and Mark R. Lepper (2000), "When Choice is Demotivating: Can One Desire Too Much of a Good Thing?" *Journal of Personality & Social Psychology*, 79 (December), 995-1006.

Jeliazkov, Ivan, Jennifer Graves and Mark Kutzbach (2008), “Fitting and Comparison of Models for Multivariate Ordinal Outcomes,” *Advances in Econometrics: Bayesian Econometrics*, 23, 115-156.

Kahneman, Daniel and Amos Tversky (1979), “Prospect Theory: An Analysis of Decisions Under Risk,” Econometrica, 47 (March), 263-91.

Kalyanaram, Gurumurthy and Russell S. Winer (1995), Empirical Generalizations from Reference Price Research,” *Marketing Science*, 14 (March), G161-G169.

Lancaster, Kelvin J. (1966), “A New Approach to Consumer Theory,” *Journal of Political Economy*, 74 (April), 132-57.

Leavitt, Harold (1954), “A Note on Some Experimental Findings About the Meaning of Price,” *Journal of Business*, 27 (July), 205-10.

Luce, Mary F., John W. Payne, and James R. Bettman (1999), "Emotional Trade-Off Difficulty and Choice," *Journal of Marketing Research*, 36 (May), 143-59.

Mandel, Naomi and Eric J. Johnson (2002), "When Web Pages Influence Choice: Effects of Visual Primes on Experts and Novices," *Journal of Consumer Research*, 29 (September), 235-45.

Mendelsohn, Tamara, Nikki Baird, Carrie Johnson, and Sean Meyer (2005), “How The Web Is Changing In-Store Experiences: Early Signs Of Shopping Convergence Appear In Stores,” research report, Forrester Research (October).

Mintz, Alex, Nehemia Geva, Steven B. Redd, and Amy Carnes (1997), "The Effect of Dynamic and Static Choice Sets on Political Decision-Making: An Analysis using the Decision Board Platform," *American Political Science Review*, 91 (September), 553-66.

Moe, Wendy W. (2006), "An Empirical Two-Stage Choice Model with Varying Decision Rules Applied to Internet Clickstream Data," *Journal of Marketing Research*, 43 (November), 680-92.

——— and Peter S. Fader (2004), "Dynamic Conversion Behavior at E-Commerce Sites," *Management Science*, 50 (March), 326-35.

Monroe, Kent B. and Susan M. Petroshius (1981), “Buyers’ Perception of Price: An Update of the Evidence,” in *Perspectives in Consumer Behavior*, 3rd ed., Harold H. Kassarjian and Thomas S. Robertson, eds. Glenview, IL, Scott Foresman and Company, 43-55.

Montomery, Alan , Shibo Li, Kannan Srinivasan, and John C. Liechty (2004), “ Modeling Online Browsing and Path Analysis Using Click Stream Data,” *Marketing Science*, 23 (4), 579-595.

Moorthy, Sridhar, Brian T. Ratchford, and Debabrata Talukdar (1997), "Consumer Information Search Revisited: Theory and Empirical Analysis," *Journal of Consumer Research*, 23 (March), 263-77.

Mulpuru, Sucharita, Catherine Graeber, and Peter Hult (2007), “The Checkout Tools that Boost eBusiness: Why Paypal, Bill Me Later, and Google Checkout Work,” research report, Forrester Research (January).

———, Carrie Johnson, and Peter Hult (2008), “The State of Retailing Online 2008: Profitability, Economy, and Multichannel Report,” research report, Forrester Research (October).

O'Hagan, Anthony (1994), *Kendall's Advanced Theory of Statistics: Bayesian Inference*. New York: Wiley.

Payne, John W. (1976), "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," *Organizational Behavior & Human Performance*, 16 (August), 366-87.

———, James R. Bettman and Eric J. Johnson (1988), “Adaptive Strategy Selection in Decision Making,” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14 (3), 534-52.

———, ———, and ——— (1993), *The Adaptive Decision Maker*. Cambridge, UK: Cambridge University Press.

Ratchford, Brian T. (1982), "Cost-Benefit Models for Explaining Consumer Choice and Information Seeking Behavior," *Management Science*, 28 (February), 197-212.

Roberts, John H. and James M. Lattin (1991), "Development and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, 28 (November), 429-40.

Schwarz, Gideon (1978), “Estimating the Dimension of a Model,” *The Annals of Statistics*, 6 (March), 461-64.

Shapiro, Carl and Hal R. Varian (1999), *Information Rules: A Strategic Guide to the Networked Economy*. Boston: Harvard Business School Press.

Simon, Herbert A. (1956), “Rational Choice and the Structure of the Environment,” *Psychological Review*, 63 (2), 129-38.

Simonson, Itamar, Joel Huber, and John W. Payne (1988), "The Relationship between Prior Brand Knowledge and Information Acquisition Order," *Journal of Consumer Research*, 14 (March), 566-78.

Sismeiro, Catarina and Randolph E. Bucklin (2004), "Modeling Purchase Behavior at an E-Commerce Web Site: A Task-Completion Approach," *Journal of Marketing Research*, 41 (August), 306-23.

Tellis, Gerard J. and Gary J. Gaeth (1990), "Best Value, Price-Seeking, and Price Aversion: The Impact of Information and Learning on Consumer Choices," *Journal of Marketing*, 54 (April), 34-45.

Thaler, Richard (1980), “Towards a Positive Theory of Consumer Choice,” *Journal of Economic Behavior and Organization*, 1 (March), 39-60.

——— (1985), “Mental Accounting and Consumer Choice,” *Marketing Science*, 4 (Summer), 199-214.

Tversky, Amos, Shmuel Sattath, and Paul Slovic (1988), "Contingent Weighting in Judgment and Choice," *Psychological Review*, 95 (3) 371-84.

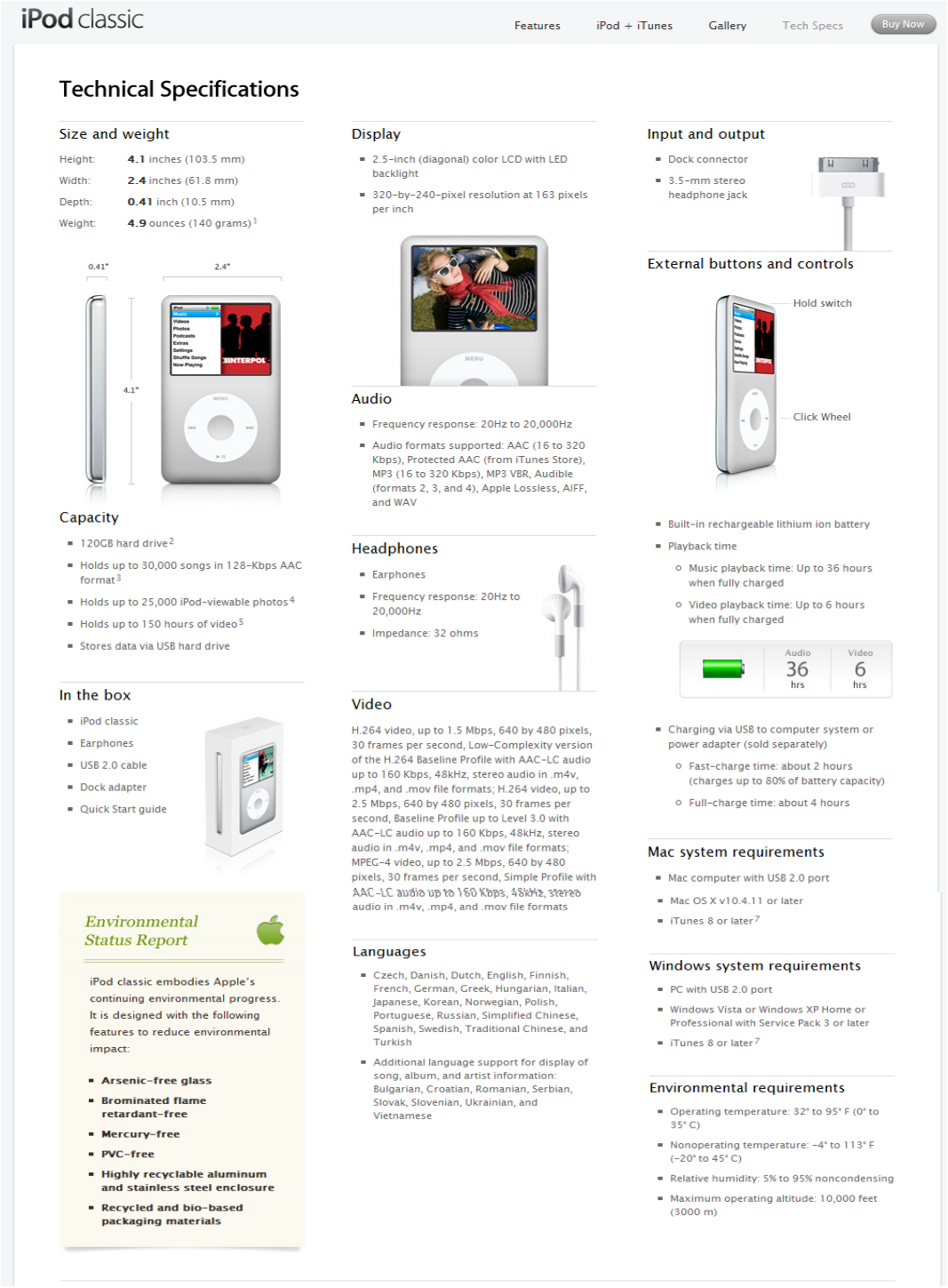
Urbany, Joel E., Peter R. Dickson, and William L. Wilkie (1989), "Buyer Uncertainty and Information Search," *Journal of Consumer Research*, 16 (September), 208-15.

von Neumann, J. and O. Morgenstern (1944), *Theory of Games and Economic Behavior*, Princeton, NJ: Princeton University Press.

Zeithaml, Valarie A. (1988), "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence," *Journal of Marketing*, 52 (July), 2-22.

Figure 1. Presentation which offers Alternative-based Qualitative Information

Figure 2. Presentation which offers Alternative-based Quantitative Information



iPod classic

Features | iPod + iTunes | Gallery | Tech Specs | Buy Now

Technical Specifications

Size and weight

Height: **4.1** inches (103.5 mm)
Width: **2.4** inches (61.8 mm)
Depth: **0.41** inch (10.5 mm)
Weight: **4.9** ounces (140 grams)[1]

Capacity

- 120GB hard drive[2]
- Holds up to 30,000 songs in 128-Kbps AAC format[3]
- Holds up to 25,000 iPod-viewable photos[4]
- Holds up to 150 hours of video[5]
- Stores data via USB hard drive

In the box

- iPod classic
- Earphones
- USB 2.0 cable
- Dock adapter
- Quick Start guide

Environmental Status Report

iPod classic embodies Apple's continuing environmental progress. It is designed with the following features to reduce environmental impact:

- **Arsenic-free glass**
- **Brominated flame retardant-free**
- **Mercury-free**
- **PVC-free**
- **Highly recyclable aluminum and stainless steel enclosure**
- **Recycled and bio-based packaging materials**

Display

- 2.5-inch (diagonal) color LCD with LED backlight
- 320-by-240-pixel resolution at 163 pixels per inch

Audio

- Frequency response: 20Hz to 20,000Hz
- Audio formats supported: AAC (16 to 320 Kbps), Protected AAC (from iTunes Store), MP3 (16 to 320 Kbps), MP3 VBR, Audible (formats 2, 3, and 4), Apple Lossless, AIFF, and WAV

Headphones

- Earphones
- Frequency response: 20Hz to 20,000Hz
- Impedance: 32 ohms

Video

H.264 video, up to 1.5 Mbps, 640 by 480 pixels, 30 frames per second, Low-Complexity version of the H.264 Baseline Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; H.264 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Baseline Profile up to Level 3.0 with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; MPEG-4 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Simple Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats

Languages

- Czech, Danish, Dutch, English, Finnish, French, German, Greek, Hungarian, Italian, Japanese, Korean, Norwegian, Polish, Portuguese, Russian, Simplified Chinese, Spanish, Swedish, Traditional Chinese, and Turkish
- Additional language support for display of song, album, and artist information: Bulgarian, Croatian, Romanian, Serbian, Slovak, Slovenian, Ukrainian, and Vietnamese

Input and output

- Dock connector
- 3.5-mm stereo headphone jack

External buttons and controls

- Built-in rechargeable lithium ion battery
- Playback time
  - Music playback time: Up to 36 hours when fully charged
  - Video playback time: Up to 6 hours when fully charged

Audio	Video
36 hrs	6 hrs

- Charging via USB to computer system or power adapter (sold separately)
  - Fast-charge time: about 2 hours (charges up to 80% of battery capacity)
  - Full-charge time: about 4 hours

Mac system requirements

- Mac computer with USB 2.0 port
- Mac OS X v10.4.11 or later
- iTunes 8 or later[7]

Windows system requirements

- PC with USB 2.0 port
- Windows Vista or Windows XP Home or Professional with Service Pack 3 or later
- iTunes 8 or later[7]

Environmental requirements

- Operating temperature: 32° to 95° F (0° to 35° C)
- Nonoperating temperature: -4° to 113° F (-20° to 45° C)
- Relative humidity: 5% to 95% noncondensing
- Maximum operating altitude: 10,000 feet (3000 m)

Figure 3. Presentation that offers Alternative-based and Attribute-based Information

Comparison Chart

	iPod shuffle		iPod nano		iPod classic	iPod touch		
Storage	1GB	2GB	8GB	16GB	120GB	8GB	16GB	32GB
Songs	240	500	2,000	4,000	30,000	1,750	3,500	7,000
Price	$49	$69	$149	$199	$249	$229	$299	$399
Color								
Battery life	Up to 12 hours of music playback		Up to 24 hours of music playback; up to 4 hours of video playback		Up to 36 hours of music playback; up to 6 hours of video playback	Up to 36 hours of music playback; up to 6 hours of video playback		
Display			2-inch (diagonal) color LCD with LED backlight		2.5-inch (diagonal) color LCD with LED backlight	3.5-inch (diagonal) widescreen Multi-Touch display		
Ports	Stereo minijack		Dock connector, stereo minijack		Dock connector, stereo minijack	Dock connector, stereo minijack		
Connectivity	USB through included dock		USB through dock connector; component and composite video through dock connector (with AV cables, sold separately); audio through headphone jack		USB through dock connector; component and composite video through dock connector (with AV cables, sold separately); audio through headphone jack	USB through dock connector; component and composite video through dock connector (with AV cables, sold separately); audio through headphone jack		
Wireless data						Wi-Fi (802.11b/g) Nike + iPod support built in Maps location-based service		
Charge time	About 4 hours (2-hour fast charge to 80% capacity)		About 3 hours (1.5-hour fast charge to 80% capacity)		About 4 hours (2-hour fast charge to 80% capacity)	About 4 hours (2-hour fast charge to 80% capacity)		
Audio support	AAC (8 to 320 Kbps), Protected AAC (from iTunes Store), MP3 (8 to 320 Kbps), MP3 VBR, Audible (formats 2, 3, and 4), WAV, and AIFF		AAC (16 to 320 Kbps), Protected AAC (from iTunes Store), MP3 (16 to 320 Kbps), MP3 VBR, Audible (formats 2, 3, and 4), Apple Lossless, WAV, and AIFF		AAC (16 to 320 Kbps), Protected AAC (from iTunes Store), MP3 (16 to 320 Kbps), MP3 VBR, Audible (formats 2, 3, and 4), Apple Lossless, WAV, and AIFF	AAC (16 to 320 Kbps), Protected AAC (from iTunes Store), MP3 (16 to 320 Kbps), MP3 VBR, Audible (formats 2, 3, and 4), Apple Lossless, WAV, and AIFF		
Photo support			Syncs iPod-viewable photos in JPEG, BMP, GIF, TIFF, PSD (Mac only), and PNG formats		Syncs iPod-viewable photos in JPEG, BMP, GIF, TIFF, PSD (Mac only), and PNG formats	Syncs iPod-viewable photos in JPEG, BMP, GIF, TIFF, PSD (Mac only), and PNG formats		
Video support			H.264 video, up to 1.5 Mbps, 640 by 480 pixels, 30 frames per second, Low-Complexity version of the H.264 Baseline Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; H.264 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Baseline Profile up to Level 3.0 with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; MPEG-4 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Simple Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats		H.264 video, up to 1.5 Mbps, 640 by 480 pixels, 30 frames per second, Low-Complexity version of the H.264 Baseline Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; H.264 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Baseline Profile up to Level 3.0 with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; MPEG-4 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Simple Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats	H.264 video, up to 1.5 Mbps, 640 by 480 pixels, 30 frames per second, Low-Complexity version of the H.264 Baseline Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; H.264 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Baseline Profile up to Level 3.0 with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats; MPEG-4 video, up to 2.5 Mbps, 640 by 480 pixels, 30 frames per second, Simple Profile with AAC-LC audio up to 160 Kbps, 48kHz, stereo audio in .m4v, .mp4, and .mov file formats		
Size	1.07 x 1.62 x 0.41 inches (27.3 x 41.2 x 10.5 mm) including clip		3.6 x 1.5 x 0.24 inches (90.7 x 38.7 x 6.2 mm)		4.1 x 2.4 x 0.41 inches (103.5 x 61.8 x 10.5 mm)	4.3 x 2.4 x 0.33 inches (110 x 61.8 x 8.5 mm)		
Weight	0.55 ounce (15.6 grams)		1.3 ounces (36.8 grams)		4.9 ounces (140 grams)	4.05 ounces (115 grams)		
Included accessories	Earphones, USB dock		Earphones, USB cable, dock adapter		Earphones, USB cable, dock adapter	Earphones, USB cable, dock adapter, polishing cloth		

Figure 4. Conceptual Framework

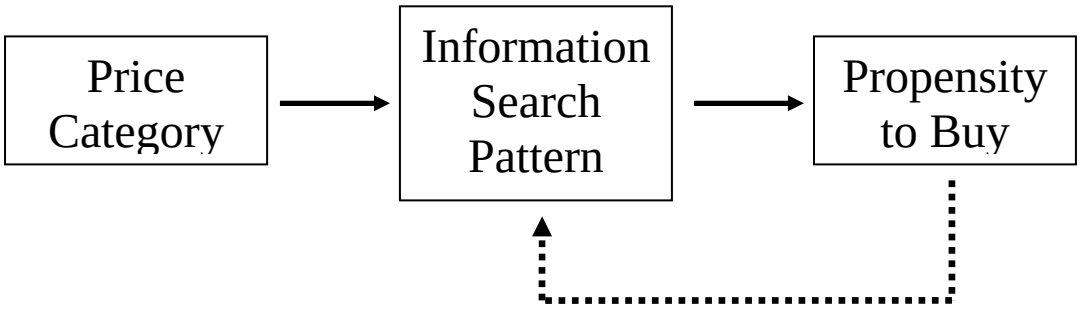
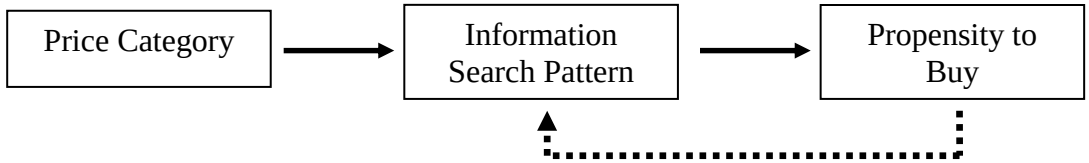
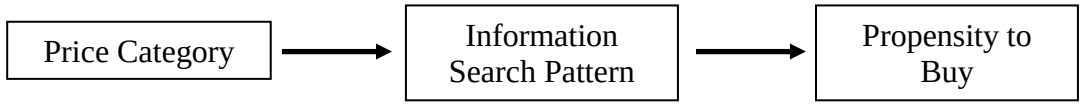


Figure 5. Overview of Models

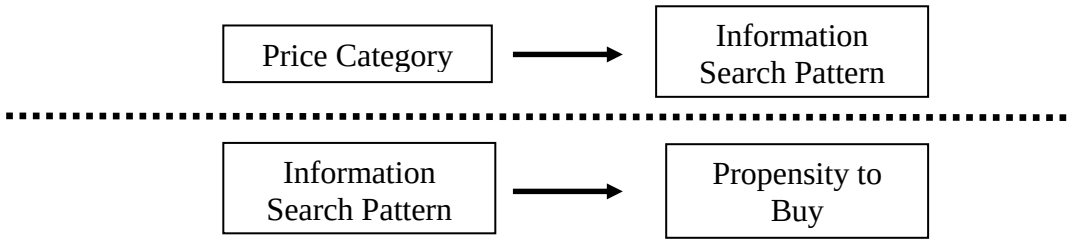
M_1 : Simultaneous Equations Model



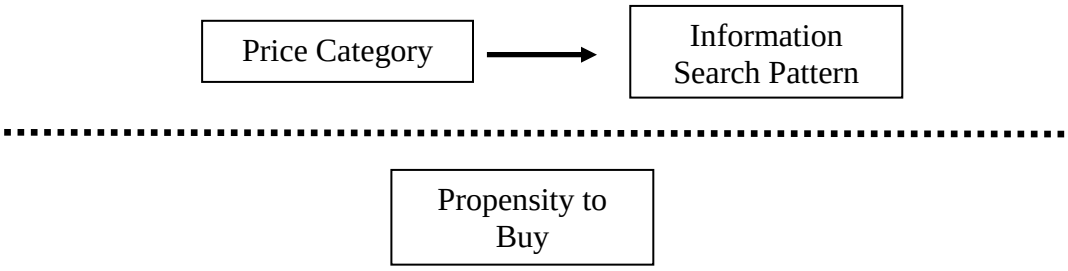
M_2 : Recursive Endogeneity or Mediated Model



M_3 : Recursive Model with Independent Errors



M_4 : Independent Equations Model



M_5 : Seemingly Unrelated Regression Model for Discrete Data

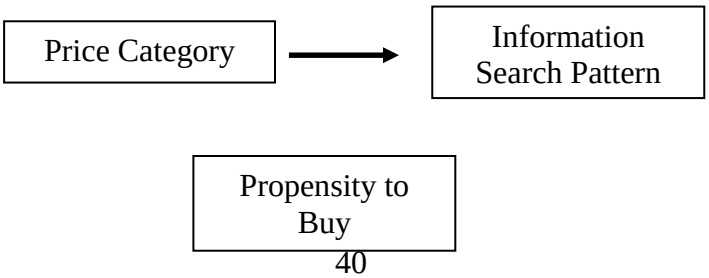


Table 1: Parameter Estimates for Model M_1.

Parameter	Covariate	Mean	SD	Median	95% posterior interval
β	eq. 1: intercept	0.93	0.08	0.93	(0.78, 1.09)
	price category	-0.76	0.17	-0.74	(-1.12, -0.47)
	eq. 2: intercept	-0.25	0.08	-0.25	(-0.39, -0.09)
θ	y^*_{iPB}	-0.04	0.60	0.02	(-1.29, 0.98)
	y^*_{iIS}	0.28	0.10	0.28	(0.08, 0.46)
ω_{11}		2.74	0.67	2.55	(2.07, 4.55)
ω_{12}		-0.41	0.54	-0.49	(-1.26, 0.82)

Table 2: Model Comparisons.

Model	A	Ω	ln(marginal likelihood)
Simultaneous equations model			
M_1	$A=\begin{pmatrix} 1 & -\theta_1 \\ -\theta_2 & 1 \end{pmatrix}$	$\Omega=\begin{pmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & 1 \end{pmatrix}$	-1284.59 (0.02)
Recursive endogeneity or mediated model			
M_2	$A=\begin{pmatrix} 1 & 0 \\ -\theta_2 & 1 \end{pmatrix}$	$\Omega=\begin{pmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & 1 \end{pmatrix}$	-1288.64 (0.01)
Recursive endogeneity or mediated model with independent errors			
M_3	$A=\begin{pmatrix} 1 & 0 \\ -\theta_2 & 1 \end{pmatrix}$	$\Omega=\begin{pmatrix} \sigma^2 & 0 \\ 0 & 1 \end{pmatrix}$	-1292.36 (0.01)
Independent equations model			
M_4	$A=\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$	$\Omega=\begin{pmatrix} \sigma^2 & 0 \\ 0 & 1 \end{pmatrix}$	-1297.93 (0.01)
Seemingly unrelated regression model for discrete data			
M_5	$A=\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$	$\Omega=\begin{pmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & 1 \end{pmatrix}$	-1285.87 (0.01)

Figure 6: Bivariate contour plot of the joint distribution of θ_1 and ω_{12} in model M_1.