Learning About Computers:
An Analysis of Information Search and Technology Choice

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Very Preliminary Draft: October 2002

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This research is supported by the NSF grant SBR-9812067.
We thank to Sabri Öncü for his extensive programming assistance in this paper.

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Abstract

This paper examines consumer search for high-tech durable goods, in markets characterized by two or more technological alternatives and a rapid pace of technological change. Special emphasis is on how consumers learn about and choose between the Apple/Macintosh and IBM/Compatible technologies. However, the modeling framework we develop can be easily generalized to any product category with more than one competing technology, such as Internet access (cable modem line versus a digital subscriber line), satellite access (cable service versus satellite dish), etc.

For most consumers, making a high-tech purchasing decision involves searching many different types of information channels. In our model, consumers decide in each period whether to obtain information from several sources. After obtaining information, the consumer decides whether (and what) to buy at that time. If the consumer decides to wait, then in the next period he/she again has the option of obtaining information from several different sources, and so on. Waiting has the advantage that more information can be gathered and price may fall. But it has the drawback of delaying the stream of consumption of a new computer.

To estimate the model we use a unique panel data set collected in collaboration with a major U.S. personal computer manufacturer. This data set contains a wealth of information about the search behavior of a set of consumers who were in the market for a personal computer, and who were interviewed at two-month intervals over a one-year period, including the information sources visited each period, search durations, brand purchased and price paid. It also contains measures of price expectations and stated attitudes toward the alternatives during the search process. A major innovation in our work is the incorporation of these expectation and attitudinal measures into the estimation of a dynamic structural model. This allows us to relax some of the assumptions that are typically required to estimate such models.

Our estimated model fits the data very well. Our results imply that consumers have substantial uncertainty about qualities of different computer technologies and information sources differ in regard to the costs associated with obtaining information and accuracy of information these information sources provide. We find preliminary evidence for duration dependence in information search, that is, as time passes by, consumers tend to search less. Given the estimated model, we also run policy experiments to investigate how altering accuracy and cost of various information sources would alter information acquisition and technology choice behavior of consumers.

Key words: Choice Models, Technology Choice, Decision-making under Uncertainty, High-Tech Markets, Information Search, Consumer Expectations, Dynamic Structural Models

"How should we allocate resources between information channels? We really don't know exactly how consumers learn about technology."
-Marketing Manager for a personal computer manufacturer, 1996

I. Introduction

There exists a large body of marketing literature, which focuses on consumers' choice for mature, frequently purchased products. However, the question of what motivates choice of high involvement durables in dynamic markets (e.g. high-tech durable goods) has received very little attention. Given the relative infrequency of purchase occasions for high-tech durable goods and the high switching costs associated with switching between alternative technologies, it is vital for marketers to understand the factors which influence consumers' commitment to one type of technology over another. Specifically, an important question to ask is how consumers form expectations about each competing technology through available information channels.

This paper examines the consumer choice process under uncertainty for high-tech durable goods, which are characterized by two or more technological alternatives and a rapid pace of technological change. In product categories with more than one competing technology such as personal computers (IBM/Compatible vs. Apple), Internet access (cable modem line versus a digital subscriber line) and satellite access (cable service vs. satellite dish), an important decision to make is the technology choice.

In this paper, we develop and estimate a dynamic model of the process by which agents learn about computers and make computer purchase decisions. In our model, agents not only have incomplete information about the products they are interested in buying, but also have several information sources, which vary in the accuracy of the information they provide.

We propose a model with active learning, in which consumers decide in each period whether or not to obtain information from several sources. After obtaining information, the consumer decides whether (and what) to buy at that time. If the consumer decides to wait, then in the next period he/she again has the option of obtaining information from several different sources, and so on. As time passes, the consumer learns about the attributes of various computer systems.

In our model, consumers are not only uncertain about quality levels of alternative technologies but also about future changes in prices. They learn about quality levels, and also form price expectations, over time. In each period consumers decide whether to obtain more information from each of several sources, and whether and what to buy.

We make use of a unique data set collected in collaboration with a major U.S. personal computer manufacturer. Data necessary for the calibration of the proposed models were collected from a random sample of consumers throughout the U.S. who were in the market for a personal computer. These consumers were first contacted by phone using random digit dialing. After passing a screening process and agreeing to participate in our panel, we collected demographic and personal computer use information, including their prior experience with computers, whether they owned a computer, and, if so, its type and age.

After this initial survey, data were collected at two month intervals, lasting for one year or until a purchase was actually made, whichever came first. At each two month interval, each individual was asked the following main questions: (1) Whether he/she had yet bought a PC, and if so its description and cost; (2) Whether he/she had yet decided on the IBM/Compatible or Apple/Macintosh technology; (3) Whether in the previous two month period the person had obtained information from each of five sources: shopping in a retail store, articles in computer publications, articles in general publications, advertisements, conversations with friends and co-workers; (4) to rate his/her quality perceptions for each technology, on a set of 1-7 rating scales; and, finally, (5) the individual's perceived price of the type of configuration he/she is currently thinking of buying, both at the present time and six months earlier, as well as his/her forecast of the price six months ahead. Since we have data on expectations, one of the key innovations of our project will be to model how expectations are formed, rather than assuming a particular structure such as rational expectations.

We know of no other data source that gives such detailed over time information on the whole decision process of an individual in the market for a computer - or for any durable good for that matter. The data set is also reasonably large, containing data on 300 people.

Our estimated model fits the data very well. Our results indicate that consumers are uncertain about quality of computer technology and they form expectations both about quality and future prices. We find that for moderate price declines from t-2 and t-1, which is the case in our price data, consumer future expectations of the price decline is monotonic with fluctuations in the rate of decrease. Given the estimated model, we also run policy experiments to investigate how altering accuracy and cost of various information sources would alter information acquisition and technology choice behavior to illustrate the many experiments that can be run to shed light on how consumer information search and choice behavior would change due to changes in consumer environment (e.g., the variability of the information source).

The rest of the paper is organized as follows. Next, we outline relevant streams of previous literature. Then, we describe our modeling approach and our data. Next, we discuss our empirical results and their managerial, as well as consumer welfare implications. We conclude with a brief summary of our findings and implications for future research.

II. Literature Review

II.1. Consumer Search and Information Source Usage in Durable Goods Market

Research focusing on information search for durable goods has sought to explain the determinants of search, the extent of search, and the returns to search (e.g., Brucks 1985; Furse et al. 1984; Hauser, Urban and Weinberg 1993; Nelson 1970; Ratchford and Srinivasan 1993; Urbany et al. 1989). For example, Srinivasan and Ratchford (1991) used a LISREL model to examine how factors such as knowledge, prior memory, interest, experience, perceived risk and cost of search may affect the amount of search effort consumers expend for information about automobiles. Although there exists a considerable stream of literature in marketing examining consumer search in general, there has been very little research on the allocation of search effort across specific information sources (Moorthy, Ratchford, and Talukdar, 1997).

However, many studies in marketing have examined consumer search behavior with respect to consumer characteristics and information source usage (Beatty and Smith 1987; Claxton et al. 1974; Furse et al. 1984; Kiel and Layton 1981; Newman and Staelin 1973; Westbrook and Fornell 1979). These studies have categorized information sources into the following channels: 1) retail; 2) word-of-mouth; 3) media and 4) neutral (third party or general-purpose publications), but only examined what type of consumer would be more likely to use each type of information source. This stream of research has not examined the process by which consumers use these channels to learn about their decision environment or how this process affects consumers' choice behavior.

It should be noted that studies examining information source usage have analyzed search with respect to durable goods with relatively stable technologies. Research in marketing examining consumer behavior with respect to high technology products has demonstrated that differences in the decision environment between high and low tech durable product categories limits the generalizability of results between these two categories (Bridges, Coughlan, and Kalish 1991; Bridges, Yim, and Briesch 1995; Glazer 1991; Glazer and Weiss 1991; Weiss and Heide 1993). Given the inherent product and information complexity and dynamics of high technology products, one may very well expect consumers' search behavior to differ dramatically with that of products traditionally studied in marketing (Robertson and Gatignon 1986).

II.2. Consumer Choice Behavior in High-Tech Durable Markets

There is a dearth of empirical research on consumer choice behavior in high-tech durable goods markets. Bridges et al. (1995) examine factors affecting demand for high-tech durables stressing the importance of consumer expectations in the formulation of choice models for this type of product category. In their reduced form-market share model for personal computers, they construct their price and technology expectation measures using the actual price and technology of each product. They find that price and technology expectations have a significant effect on product market share. Weiss and Heide (1993) look at consumer search behavior in high technology markets and focus on the underlying process that generates decision outcomes for industrial buyers. They examine how search effort and duration of the search is affected by buyers' perception of technological change and the level of technological heterogeneity.

II.3. Consumer Learning and Decision-Making under Uncertainty

There is a large literature on consumer decision-making and learning under uncertainty. The type of work that most closely relates to the issues we analyze in this paper deals with consumer forward-looking expectations under price or quality uncertainty. Erdem and Keane (1996) modeled consumer learning about quality and strategic use of product trial for information-gathering purposes. In this model of consumer choice under quality uncertainty, consumers are forward-looking since in their current decisions, they take into account the effect of the value of information contained in trial on the stream of future expected utilities. In this context, consumers also face a trade-off, that is, there is the possibility of decreased present utility due to consumption of a product that consumers may not necessarily like but the stream of future expected utilities could be higher due to information gained.

Gönül and Srinivasan (1996) modeled expectations of future coupon availability on purchase timing and quantity decisions. Furthermore, models of price uncertainty have been proposed (and empirical implications derived and experimentally tested) where consumer forward-looking expectations affect consumer purchase timing, brand choice and quantity decisions (e.g., Meyer and Assuncao 1990, Krishna 1992). Erdem et. al. (2002) propose such a dynamic structural model and estimate it on panel data. In these models of consumer choice under price or coupon availability uncertainty, consumers are forward-looking since their expectations about future prices affect their current purchase timing, brand choice and quantity decisions. In this context, the trade-off involves the possibility of a stock-out and associated decreased present utility versus the possibility of obtaining a better price and associated increased expected utility in the future.

In dynamic high-tech durable markets, there are often both price and quality uncertainty. Not only do high-tech durable good prices tend to drop over time, generating uncertainty about the extent of future price declines, but consumers may be uncertain about product quality as well. If consumers delay the purchase rather than buying now, prices will tend to drop over time for a given configuration, and uncertainty about quality levels will tend to decrease over tine. However, opportunity costs arise from not having a new computer during the period of delay. Thus, in this context, consumers are forward-looking since their price and quality expectations affect when to buy and what to buy decisions, especially in high-technology markets. Song (2002) analyzed the impact of forward-looking behavior on the diffusion patterns of new high-technology products.

In high-technology markets, the trade-off between buying now and delaying the purchase involves the increased expected utility of getting a better and/or cheaper product versus the forgone utility of consumption during delay. Melinkov (2000) studied this trade-off in the case of quality uncertainty in the printer market and formalized consumers' timing decision as an optimal stopping problem. Below we propose and estimate a model, which not only captures this trade-off in regard to purchase decisions but also the information search process and decisions, as well as formation of price expectations in such markets.

III. A Model of the Information Search and Technology Choice in High-Tech Durable Markets

III.1. Preliminaries

Let U_{ijrt} denote the utility to person i from purchase of technology j, where j=Apple, IBM, in dollar amount P_r at time t=1,T. Let P_r for r=1,R be a set of discrete dollar amounts that the consumer may choose to spend on a computer. Discretizing the spending levels converts our problem into a pure discrete*i* choice problem, which greatly facilitates estimation. Next, we specify utility as:

(1) $$U_{ijrt} = \beta_i (1 - \exp\{-\alpha\pi_{jrt} P_r Q_j\}) - \gamma P_r + \varepsilon_{ijrt}$$

Here, the π_{jrt} are indices of the "size" or "efficiency units" of computer capabilities that one can purchase by spending P_r dollars on technology j at time t. The Q_j are per dollar quality levels of the technologies j=Apple, IBM. It is important to note that the notion of quality here is person specific. It includes not just the absolute quality of the particular technology, but also how well that technology is suited to the particular consumers needs. Thus, the true value Q_j may differ across consumers. In this paper, we will allow for two different types of consumers in regard to their quality beliefs. However, for ease of exposition, we are suppressing the *i* subscript.

The parameter β_i is individual specific, while α and γ are common parameters, and ε_{ijrt} is a stochastic term. We will allow β be a function of observed consumer characteristics (experience with computers, age, education, gender and income). We will allow for unobserved heterogeneity in quality levels by assuming two types of consumers. We now describe each component of (1) in more detail.

The π_{jrt} can be thought of as inverse price indices. These will grow over time as computer prices drop. As with any price index, only percentage changes over time have meaning, so we normalize π for both technologies to 1 in the base period t=1. Note that Q_j, the quality of technology j, is assumed to be constant over time t. Essentially, we are assuming that over a relatively short period of time (e.g., one or two years) the relative qualities of the two technologies remains unchanged.

There are three key sources of dynamics in the consumer choice process in our model:

(i) The agents recognize that computer prices tend to drop over time, causing the π to grow over time. This creates an incentive to delay purchase. Of course, the strength of this incentive depends on agents' forecast of how much prices will drop.

(ii) We assume that agents begin the search process with uncertainty about the quality levels Q_j. In each period t the agents will have the opportunity to learn about the Q_j. To the extent that agents are risk averse, the expected utility obtained from a purchase is a decreasing function of the degree of uncertainty about the Q_j. This also creates an incentive to delay purchase while learning more about quality.

(iii) Working against both of the above incentives for delay is the opportunity cost that arises from not having a new computer during the period of delay.

Continuing with our description of (1), note that we have written a constant (absolute) risk aversion form of the utility function, in which parameter α determines the degree of risk aversion. The parameter β_i is individual specific. For instance, the utility weight β_i on computer capabilities may be larger for agents with more computer experience or more education, since they can get relatively more use out of a larger configuration. Finally, note that the ε_{ijrt} in (1) are i.i.d stochastic shocks to consumer i' s utility from purchase of technology j in dollar amount P_r at time t. These error terms are meant to capture various influences on the agents' decisions that are unobserved by the econometrician.

In addition to equation (1), we need to specify the utility that a consumer gets from no-purchase. The per period utility that the consumer obtains if s/he makes no purchase at time t depends upon whether the consumer already owns a computer and a number of consumer socio-demographics. We denote this by U_{i0}.

We now describe in turn the price forecasting and quality learning aspects of our model.

III.2. Forecasting Future Prices

Traditionally, in the estimation of dynamic choice models in economics, one treats uncertainty about future prices by: (1) assuming a stochastic process for prices, and (2) assuming that agents know the true process and generate optimal forecasts accordingly (that is, agents have rational expectations). A key feature of our proposed work is that we depart from this approach. Because we actually have data on consumer expectations of future prices, we can estimate the process that consumers use to forecast prices directly without having to make the further assumption that the forecasts are made optimally.

In our data, the consumer is asked his/her perception of the price of the type of configuration he/she is currently thinking of buying, both at the present time and six months (and 12 months) earlier, as well as his/her forecast of the price six months (and 12 months) ahead. We used these data to calculate consumer expected price decline for a particular configuration. Under the assumption that percentage price declines are expected to be equal for all configurations, this also gives the consumers' expected increase in the π_{jrt} from t to t+1.

Rather than assuming that survey responses measure expectations exactly (which we feel would be unreasonable), we assume the survey responses measure expectations with error. Denote by $\Delta_{ij,t+1}$ the inverse of the consumers' report of his/her expectation of the price decline from t to t+1. We assume that:

(2) $$\ln \Delta_{ij,t+1} = E[\ln(\pi_{jr,t+1} / \pi_{jrt}) \mid I_{it}] + \nu_{ijr,t+1} \qquad \nu_{ijr,t+1} \sim N(0, \sigma_{\nu}^{2})$$

That is, the report is equal to the consumers' actual expectation plus the normally distributed measurement error term ν_{ijrt}. Here E denotes the expectation operator whereas the consumer information set at time t, I_{it}, will be introduced in the next two sections.

Next, since we have actual data on expectations, we can write down directly a specification of the process generating expectations. For instance, we could assume the process:

(3) $$E[\ln(\pi_{jr,t+1} / \pi_{jrt}) \mid I_{it}] = \theta_0 + \theta_1 \ln(\pi_{jrt} / \pi_{jr,t-1}) + \theta_2 \ln(\pi_{jrt} / \pi_{jr,t-2})$$

We can then estimate (3), treating $\Delta_{i,j,t+1}$ as a noisy measure of the left hand side (see (2)). By using reported expectations rather than actual (inverse) prices on the left-hand side, we allow consumers to depart from the optimal forecasting rule an econometrician would construct.

Note that (3) can be interpreted as follows: For example, if $\theta_1 = 1$ and $\theta_0 = \theta_2 = 0$, then consumers simply extrapolate the most recent one period (inverse) price change into the future. Alternatively, if $\theta_0 = 0$, $\theta_1 > 2|\theta_2| > 1$ and $\theta_2 < 0$, then consumers expect that whatever acceleration or deceleration of price changes that occurred from t-2 to t will be continue in the future. If $\theta_0 \neq 0$, $0 < \theta_1 < 1$ and $0 < \theta_2 < 1$ then the consumer expects the rate of price change to revert towards some natural state. Thus, (3) is a fairly flexible model of expectation formation.

It is important to note that having data on expectations does not allow one to avoid making assumptions about how expectations are formed. We still have to specify a process like (3). Rather, having data on expectations simply changes the <u>type</u> of the assumptions the econometrician must make.

At this point we have two remaining problems. First, for estimation of a dynamic model we need measures of consumers' price expectations for all future periods, ranging from 2 months ahead out through the terminal period T. We will need to construct expected price changes over these other horizons using an equation like (3). For example, if the θ values in (3) are such that consumers expect the rate of price decline to accelerate, we can easily work out the extent to which the expected rate of price decline over the next two months is less than that over the next six.

Second, note that point estimates of expected future prices are not sufficient to solve the consumer's dynamic choice problem. We need to specify the expected distribution of future prices. For simplicity, we assume that agents expect that the distribution of future prices be:

(4) $$\ln \pi_{jr,t+1} \sim N(E[\ln \pi_{jr,t+1} \mid I_{it}], \sigma_{\pi}^{2})$$

Here, σ_{π}^{2} is the variance of this distribution.

III.3. Learning About Quality

The key process we focus on in our model is that by which consumers learn about the Q_j - that is, the quality of the IBM/Compatible and Apple/Macintosh technologies. We assume that consumers enter the market with priors on each of the Q_j. These are:

(5) $$Q_j \sim N(Q_{jo}, \sigma_{jo}^{2})$$

Here, Q_{j0} is the consumer's prior expectation of the quality of computers of type j, and σ_{jo}^{2} is the consumer's prior uncertainty about computers of type j. We would like to repeat here that to note that the notion of quality here is person specific. In this paper, we will allow for two different types of consumers in regard to their quality beliefs.

Consumers can learn about Q_j, and thus reduce the variance σ_{jo}^{2}, by sampling from five information sources, which we index by k. The five channels are: (1) retail stores, (2) articles in computer specific sources, (3) articles in general purpose sources, (4) advertisements, and (5) word-of-mouth.[1] Although there are other sources of

[1] The data was collected between August 1995-June 1996. During this period, our panelists consistently ranked the Internet as one of the least important sources of information during their search. Since then, Internet usage has increased. However, many consumers, especially those looking for information on making a high-tech purchase, seem to utilize the on-line versions of the same "core information channels", such as reading Consumer Reports or magazine articles on-line. Thus, the use of the Internet can be viewed as an alternative medium (electronic) to search for each type of channel related information.

information consumers could use to decide on personal computers, based on input from consumer focus groups (comprised of consumers who recently purchased a PC) and managerial interviews, we decided that these information sources represented the major sources consumers use of learn about different computer technologies and brands.

In our model, the consumer has a prior on the variance of the signals provided by each information source. Letting S_{jkt} denote a signal from source k at time t about technology type j, the consumer knows that

(6) $$S_{jkt} \sim N(Q_j, \sigma_k^2),$$

where $1/\sigma_k^2$ is the accuracy or precision of information contained in information source *k*.

Finally, note that our data set contains information on consumers' perceptions of each technology. In the data section, we will discuss the scale for perceived quality of technology. It may suffice to say here that we plan to model the responses to these perceived quality questions as providing noisy information about the consumer's perceptions of the Q_j. One useful set up that would account for this is to assume as before that the consumers distinguish the level of qualities in a low, medium or high range. Denote these as L, M and H, respectively and denote by q_{ijt} these reported quality perceptions. As we will show in section III.5, Bayesian updating indicates that the consumer perceptions at time t obey the distribution

(7) $$E[Q_j | I_{it}] = Q_j + z_{ijt}, \qquad z_{ijt} \sim N(0, \sigma_{ijt}^2),$$

where $E[Q_j \mid I_{it}]$ is the consumer quality expectation conditioned of I_{it} and σ^2_{ijt} is the variance of the associated perception error. In principle, the consumers could have responded to the questionnaire with their own $E[Q_j \mid I_{it}]$. Instead what we observe is

$$q_{ijt} = L \qquad if \quad E[Q_j \mid I_{it}] \leq \mu_{jL},$$

$$(8) \qquad q_{ijt} = M \qquad if \quad \mu_{jL} < E[Q_j \mid I_{it}] < \mu_{jH},$$

$$q_{ijt} = H \qquad if \quad E[Q_j \mid I_{it}] \geq \mu_{jH}.$$

The μ's are unknown parameters to be estimated together with the rest of the parameters. This can be formalized using the Ordered Probit Model:

$$\Pr ob(q_{ijt} = L) = \Phi_{\sigma_{ijt}}(\mu_{jL} - Q_j),$$

$$(9) \qquad \Pr ob(q_{ijt} = M) = \Phi_{\sigma_{ijt}}(\mu_{jH} - Q_j) - \Phi_{\sigma_{ijt}}(\mu_{jL} - Q_j),$$

$$\Pr ob(q_{ijt} = H) = 1 - \Phi_{\sigma_{ijt}}(\mu_{jH} - Q_j),$$

where $\Phi_{\sigma_{ijt}}$ is the cumulative normal distribution function with the mean 0 and variance σ^2_{ijt}. These will contribute to the individual likelihood functions.

III.4. Solving the Consumer's Dynamic Choice Problem

We first need to characterize the state of a consumer at each point in the choice process. The consumer's state is fully characterized by I_{it} where I_{it} is the information set introduced in the previous section. As we have discussed above, several of the model parameters, including consumers' priors about the different technologies, will be allowed to differ according to these personal characteristics.

The consumer's choice set at each time t includes $32(2^5)$ combinations of information source visits he/she can choose. After deciding on which of the five information sources to sample, and seeing the resultant signals, the consumer can decide either to buy a computer or wait until the next period. If the consumer decides to buy, there are 2xR possible choices (2 technologies at each of R price levels). If the consumer decides to wait, he/she will face the same choices in the next period. The value of each of the 32 options for information acquisition is:

$$(10) \qquad V_{imt}(I_{it}) = -\sum_{k=1}^{5} J_{km} c_k + E\max\{V_{it}^{P}(I_{it}, m), V_{it}^{N}(I_{it}, m)\} + \xi_{imt}$$

Here, the c_k for k=1,5 are the costs of obtaining information from each source k, which we treat as parameters to be estimated. The index m is the index of 32 combinations of information sources. J_{km} is an indicator for whether source k is included in combination m. ξ_{imt} is an iid stochastic shock to the cost of search option m at time t.

In the above, V_{it}^{P} is defined as follows:

$$(11) \qquad V_{it}^{P} = \max_{\{j,r\}} E[U_{ijrt} | I_{it}, m]$$

This is the maximum over all possible technology and price choices {j, r} of the expected utilities of those choices. Note that the expected utilities are conditional on the initial information-state I_{it} as augmented by signals obtained in search option m. The augmented state is denoted by (I_{it}, m). The consumer does not know what signals will be obtained if search option m is chosen, so he/she must take an expectation over the possible signals. Finally V_{it}^{N} is the value of making no purchase at time t and waiting until the next period. This is:

$$(12) \qquad V_{it}^{N} = U_{i0} + \delta E \max_{m} V_{im,t+1}[I_{i,t+1}] + e_{it}$$

This recognizes that if no purchase is made at t, then the consumer gets the per-period utility from his/her current computer if any, which we denoted by U_{i0}. And at t+1, the consumer will face the same choice over the m=1,32 search options, except that he she will have the augmented information set I_{it+1} generated by I_{it} plus the information received from the search option chosen at time t.

Together, (10), (11) and (12) give the Bellman equation for the consumer's dynamic optimization problem. This problem can be back solved from the terminal period T using backward recursion in the usual way. Once the dynamic optimization problem is solved, it is obvious from the above discussion how the data elements (1), (2), (3), (4) and (5) described in section 1.2 will all enter the likelihood for our model. Note that our dynamic model with forward-looking consumers nests the myopic model that is obtained if δ equals zero. Thus, we can test if consumers are forward-looking by testing whether δ is significantly different from zero. More generally, small estimated values of δ would imply that consumers care little about the future when making current decisions.

III.5. Bayesian Updating and Expected Utilities

In Section III.3 we have assumed that the consumers are Bayesian updaters and their prior quality perceptions obey the distribution given by Equation (5). At later times > 0, their quality perceptions are updated and obey the distribution

(13) $$Q_j \sim N(E[Q_j | I_{it}], \sigma^2_{ijt}).$$

This can be rewritten as

(14) $$E[Q_j | I_{it}] = Q_j + z_{ijt}, \qquad z_{ijt} \sim N(0, \sigma^2_{ijt}),$$

where

(15) $$\sigma^2_{ijt} = E\{(Qj - E[Q_j | I_{it}])^2 \mid I_{it}\},$$

and z_{ijt} are the perception errors.

To write down the Bayesian updating formulae let us rewrite (6) as

(16) $$S_{jkt} = Q_j + x_{ijkt} \qquad x_{ijkt} \sim N(0, \sigma^2_{kt}).$$

Using the standard techniques of Kalman filters, we obtain

(17) $$\sigma^2_{ijt} = \frac{1}{\dfrac{1}{\sigma^2_{j0}} + \sum_{s=1}^{t}\sum_{k=1}^{5}\dfrac{L_{ks}}{\sigma^2_k}},$$

(18) $$z_{ijt} = z_{i,j,t-1} + \sum_{k=1}^{5} L_{kt}\frac{\sigma^2_{i,j,t-1}}{\sigma^2_{i,j,t-1} + \sigma^2_k}(x_{ijkt} - z_{i,j,t-1}).$$

Where L denotes whether a particular information source is chosen. Equation (18) gives the evolution of the accuracy of the perception errors whereas Equation (19) tells us how perception errors themselves are updated given the quality signals. A fairly extensive account of the derivation of such updating formulae can be found, for example, in Erdem (1998).

Given the above perceived quality distributions, the expected utilities for the technologies j, where j= IBM, Apple, are then

(19) $$E[U_{ijrt} \mid I_{it}] = \beta_i \{1 - \exp\{-\alpha\pi_{jrt} P_r E[Q_j \mid I_{it}] + (\alpha\pi_{jrt} P_r)^2 \sigma_{ijt}^2 / 2\}\} - \gamma P_r + \varepsilon_{ijrt}$$

where we have used the properties of the log-normal distribution in obtaining the above result. Note that ε_{ijrt} is not affected by the expectation operator because it is stochastic only for the analyst but known to the consumer. We see from (18) that, when $\alpha>0$, the larger the expected quality the higher the expected utility whereas the higher the quality perception variance the lower the expected utility.

For convenience in the discussion of the next section, we rewrite (19) as

(20) $$E[U_{ijrt} \mid I_{it}] = E[W_{ijrt} \mid I_{it}] + \varepsilon_{ijrt}$$

where

(21) $$E[W_{ijrt} \mid I_{it}] = \beta_i \{1 - \exp\{-\alpha\pi_{jrt} P_r (Q_j + z_{ijt}) + (\alpha\pi_{jrt} P_r)^2 \sigma_{ijt}^2 / 2\}\} - \gamma P_r$$

whereas W_{ijrt} is given by

(22) $$U_{ijrt} = W_{ijrt} + \varepsilon_{ijrt} .$$

For further convenience, we rewrite also the equation (10) as

(23) $$V_{imt}(I_{it}) = X_{imt}(I_{it}) + \xi_{imt}$$

where X_{imt} is read from (9); and Equation (12) as

(24) $$V_{it}^N = Z_{it} + e_{it}$$

(25) $$Z_{it} = U_{i0} + \delta\, E \max_m V_{im,t+1}[I_{i,t+1}]$$

We should note here that if a consumer does not buy at the terminal period T, then our model specification will imply that the person's expected future utility stream at T would be the discounted net present value of U_{i0}.

III.6. Consumer Choice Probabilities and the Likelihood Function

Recall that for each period, consumers make two consecutive choices. The first of these is the information gathering choice, whereas the second is the purchase/no purchase choice. Denote by P_{ijrt} the purchase choice probability for technology j and configuration r at time t whereas by N_{it} the no purchase choice probability at time t. Also denote by M_{imt} the probability of consumer making the information choice m at time t as described in section III.4. Under the assumption of i.i.d extreme value error terms ε_{ijrt} and ξ_{imt} these probabilities take the form of a standard multinomial logit choice probabilities (McFadden 1974):

(26) $$M_{imt}(\theta, z_i) = \frac{\exp(X_{imt})}{\sum_{l=1}^{32} \exp(X_{ilt})},$$

(27) $$P_{ijrt}(\theta, z_i) = \frac{\exp(E[W_{ijrt} \mid I_{it}])}{\exp(V_{it}^{N}) + \sum_{l=1}^{2}\sum_{q=1}^{R} \exp(E[W_{ilqt} \mid I_{it}])},$$

(28) $$N_{it}(\theta, z_i) = \frac{\exp(Z_{it})}{\exp(Z_{it}) + \sum_{l=1}^{2}\sum_{q=1}^{R} \exp(E[W_{ilqt} \mid I_{it}])},$$

where θ is the vector of parameters that were introduced in the previous sections whereas z_i is the vector of perception errors z_{ijt}.

We define K_{imt} as the indicator variable which takes the value 1 if the information combination m is chosen at time t, 0 otherwise. We also define G_{ijnt} as the indicator variable which takes the value 1 if the quality perception level n is reported, 0 otherwise. Here n = L, M, H. Lastly, we define Y_{ijrt} as the indicator variable which takes the value 1 if the technology j, configuration r is chosen at time t, 0 otherwise and Y_{iNt} as the indicator variable which takes the value 1 if the no-purchase option is chosen, 0 otherwise. With these definitions the individual likelihood function can be written as

(29) $$L_i(\theta, z_i) = L_{1i}(\theta, z_i) L_{2i}(\theta) L_{3i}(\theta)$$

where

(31) $$L_{1i}(\theta, z_i) = \prod_{t=1}^{T} N_{it}(\theta, z_i)^{Y_{iNt}} \prod_{m=1}^{32} M_{imt}(\theta, z_i)^{K_{imt}} \prod_{j=1}^{2} \prod_{r=1}^{R} P_{ijrt}(\theta, z_i)^{Y_{ijrt}} ,$$

(32) $$L_{2i}(\theta) = \prod_{j=1}^{2} \prod_{t=1}^{T} \Pr ob(q_{ijt} = L)^{G_{ijLt}} \Pr ob(q_{ijt} = M)^{G_{ijMt}} \Pr ob(q_{ijt} = H)^{G_{ijHt}} ,$$

and

(33) $$L_{3i}(\theta) = \prod_{j=1}^{2} \prod_{r=1}^{R} \prod_{t=2}^{6} \frac{\exp(\nu_{ijrt}^2 / 2\sigma_\nu^2)}{(2\pi)^{1/2} \sigma_\nu} ,$$

whereas ν_{ijrt} is measurement error term in the price forecasting equation (2). Hence we estimate the coefficients of price equation together with the rest of the model parameters.

It is seen from (28) and (29) that the above likelihood function is not only conditioned on the model parameters but also on the perception errors z_i. Therefore, to obtain the likelihood function conditioned on the model parameters only, this likelihood function must be integrated over the error terms z_i as follows:

(34) $$L_i(\theta) = \int_{z_i} L_i(\theta, z_i) f(z_i) dz_i$$

where $f(z_i)$ is the probability density function of the z_i. The log-likelihood *LogL(θ)* for the entire set of consumers is then

$$(35) \qquad LogL(\theta) = \sum_{i=1}^{I} \ln L_i(\theta).$$

where I is the number of consumers.

Unfortunately, the calculation of (34) requires the evaluation of *12*-dimensional integrals. The evaluation of such integrals by traditional methods is computationally impossible. Because of this, one must employ simulation techniques to maximize (33) (e.g., Keane 1993, Lerman and Manski 1987, McFadden 1989). Here, we use the simulated maximum likelihood approach (see, for example, Erdem 1998).

There are many alternative methods to maximize this log-likelihood function. Among these, the Quasi-Newton method with line search is used to maximize (33). In conjunction with this method, the BHHH algorithm is employed to approximate the Hessian. Finally, we use the Keane and Wolpin (1994) method to solve and estimate the DP problem.

IV. Data

Data necessary for the calibration of the proposed model was collected from a random sample of consumers throughout the U.S. who were in the market for a personal computer. The panel members were first contacted by telephone using random digit dialing. Consumers were invited to participate in the panel if they met the following conditions: 1) they stated they were extremely or very likely to buy a personal computer for their homes within the next six to eight months; 2) they were the member of the household most responsible for making the purchasing decision; 3) they were planning to spend more than $1,200 dollars on a computer. If the potential panel member passed the screening process, she or he was invited to become one of the 350 participants in the research project.

The duration of this project was based on the estimated average time a typical consumer spends searching for information and deciding on personal computers[2]. It was decided to create a panel of six waves. Six waves, distributed over the course of ten months, were considered sufficient to capture detailed search data without a high rate of perceived repetition. Given the length of the survey and the repetition of questions, it was decided panelist should be given at least six weeks between surveys to minimize burnout.

Starting in September 1995 and ending in June 1996, panel members were asked to complete six surveys (approximately one every seven weeks). To reduce the problem of attrition we provided a variety of incentives to retain panel members. Panelists were paid $5 dollars for each completed survey. The first wave of the panel consisted of 345 members. Given that the project's duration was almost a year and that the survey asked for at least 15 minutes of the panelist's time, a high percent (59%) was retained for the entire study. Respondent attrition was not sufficient to change the composition of the sample (e.g., all dependent variables retained approximately the same percent composition of consumer characteristics; Winer 1983).

The sample consisted of consumers who have a higher than average level of education (61% undergraduate or graduate degree) and have a much higher income level than the average American (80% reported annual income between $35,000 and $80,000). The panel members reported their levels of expertise at 34% novices, 52% intermediate abilities and only 14% considered themselves experts. The sample was evenly split on

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2 At the time of this project, the marketing managers that we were working with estimated the purchase cycle for a personal computer to be on average six months. We wanted to capture the entire process for the majority of our panel. Therefore, the panel was run for ten months.

past purchase experience, with 45% of the panel reporting this was their first time purchasing a personal computer. These statistics are reported in table 1.

Panel members were asked to report whether or not they had purchased a computer within the last eight weeks. If they had, we asked each panelist to report detailed information on the configuration purchased, the brand and purchase price.

There are five channels of information through which consumers may access information about technologies and brands. Usage of the five information channels were defined to the panelist as: (1) retail stores (e.g., any type of store which sells computers), (2) articles in computer specific sources (e.g., have you spent any time looking at computer information in computer magazine articles, mail order catalogs or computer books?), (3) articles in general purpose sources (e.g., have you spent any time reading articles on computer information in newspapers, general purpose magazines or consumer guides?), (4) advertisements (e.g., have you spent any time reading advertisements about computers in newspapers, computer magazines, general purpose magazine, or viewing TV commercials?) , and (5) word-of-mouth (e.g., during the last eight weeks, about how many people including friends, family, co-workers or others, have you talked with about the different types of computers?).

To construct a measure of perceived average quality for technology respondents were asked to think about all they had heard, read or experienced with each technology and rate each of the following four items: 1) Will meet my needs for a long time to come; 2) user friendly; 3) powerful; 4) a large number of software titles and; 4) All components operate together without any problems (hardware, software, peripherals). A 7-point Disagree/Agree scale was used for each item. Once again, these items were factor analyzed and found to be measuring a unidimensional construct. The reliability of the final construct was tested using coefficient alpha (See Table 2). The results show high reliability and a high level of internal consistency across both technologies and each wave of the panel.

We collected prices for each brand/configuration the panelist were considering each period.[3] Panelist were asked to report the price they would expect to pay today for each brand they were considering given their preferred set of characteristics. The panel members also reported detailed information about the brand of computer they eventually purchased. This price included all the features bundled with their system such as modem, CD-ROM, and software and was before tax. Additionally, data was collected on consumers' price expectations. Given the type of configuration each panelist was planning on purchasing, they were asked to report how much they would have expected to pay six months ago for each of the brands they were considering and how much they would expect to pay six months in the future.

V. Empirical Results

V.1. Parameter Estimates

Table 3 reports the parameter estimates. We start by discussing the estimates of the consumer price expectation process parameters. It is useful to first rewrite equation (3) in terms of prices:

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[3] To fill in any missing price data, information was collected about each aspect of the configuration consumers were considering. Consumer were asked to report every alternative they were considering in the following seven categories: 1) processor; 2) CPU speed; 3) RAM; 4) hard disk; 5) monitor; 6) computer style; and; 7) built-in components. For each wave, the exact configuration was matched with reported street prices obtained from industry data. Whenever possible, we tried to match the advertised street prices by area code to the area the panel member lived.

$$E[\ln(P_{jr,t+1} / P_{jrt}) \mid I_{it}] = -\theta_0 + \theta_1 \ln(P_{jrt} / P_{jr,t-1}) + \theta_2 \ln(P_{jrt} / P_{jr,t-2})$$

$$= -\ \theta_0 + (\theta_1 + \theta_2)\ ln\ (P_{jrt}/P_{jr,t-1}) + \theta_2\ ln\ (P_{jr,t-1}/P_{jr,t-2})$$

Since our estimate of θ_0 is 0.043, if price stayed constant from t-2 to t then consumers would expect a 4.3% price decline from t to t+1 (i.e., over the next two months). Since θ_2 is negative and larger in absolute value than θ_1, this process implies that consumers expect mean reversion in price declines: That is, loosely speaking, if the decline over the past four months had been exceptionally rapid, then consumers expect only a small decline (or even an increase) over the next two months. Conversely, if there had been little or no price decline over the recent past four months, then consumers expect an above average price decline over the next two months. The process implies a steady state expected rate of price decline of roughly 2.6% per two-month period. If price had declined at a constant rate from t-2 to t, and this rate was greater (less) than 2.6%, then consumers expect a price decline of less (more) than 2.6% over the next two months. The standard deviation on the estimated price process is 0.071, implying there is substantial measurement error in consumer's reports of their own expectations.

The price coefficient is statistically significant and, given equation 1, it suggests that utility is decreasing in price. Initially, we allowed the price coefficient to depend on a number if socio-demographics. However, due to low significance levels, we dropped these for parsimony.

The equation for the No-purchase utility has a statistically significant positive constant. No-purchase utility is affected by ownership of a computer, age, gender and income. Specifically, as one would expect, no-purchase utility is higher for individuals who already own a computer. Furthermore, older people, men and lower income people have a higher No-Purchase utility than younger people, women and higher income people. Education and experience do not have a statistically significant effect on No-Purchase Utility.

Mean quality estimates suggest that the first segment prefers IBM over Apple whereas the opposite is true for the second segment. However, the first segment constitutes 91% of the individuals. We should note here that our quality measures are not unidimensional. Rather, they have a match component (e.g. one of the scale items was "Will meet my needs for a long time to come"); hence, our quality estimates just reflect the fact that the majority of consumers feel that IBM/compatibles serve their needs better than Apple technology. The prior standard deviation of quality perceptions is statistically significant, and very large relative to the true quality levels of the two technologies. This indicates that there is substantial quality uncertainty in this market.

The estimates of the equation for the utility weight parameter (β_i) indicate that consumers get more utility from home computer capabilities: 1) the more experienced they are with computers, 2) the older they are, 3) the less educated they are, and 4) if they are male. The effect of income on utility weight is statistically insignificant. Note that the constant term for utility weight was set to 1 for identification reasons, and the same is true for the risk coefficient. The fact that more educated people get less marginal utility from additional home computer capability may reflect the fact that they are more likely to have access to computers at work.

Table 3 also reports the estimated standard deviations for the signals received from each of the information channels. The estimates imply that computer magazines, and general sources and advertising provide the noisiest information, whereas store visits provide the most precise information.[4] Note that precision of information level refers here to the noise level contained in the information source and not to the usefulness of information, *per se.*

In regard to costs associated with information sources, reading computer articles, followed by store visits, seem to be the most costly sources, whereas obtaining word of mouth information seems to be the least costly one, followed by reading advertisements.

V.2. Model Fit

Table 4 reports the sample proportions of people who make each choice (No-purchase, IBM, Apple) in each two-month period (or "wave"). It also reports simulated choice probabilities based on our estimated model, based on simulated choice paths for 2000 hypothetical consumers. We refer to this as the "baseline" simulation of the model. We use 2000 individuals in the baseline simulation (rather than 281 as in our sample size) to reduce simulation noise.

To see how the model fits the data, one needs to compare the percentage figures reported in the last three columns of Table 4 for the sample vs. the baseline model. The Model fits the data extremely well. It slightly underpredicts the No-Purchase option (89.6% vs. 90.3%) and slightly overpredicts the IBM-technology choices (9.8% vs. 9.2%). The percent choosing Apple (0.5%) is predicted precisely

Table 5 reports the same type of information, except for the information acquisition process. We report the sample frequencies of people who used each information source in each two-month period (wave) along with the model predictions

[4] During the estimation, we set the variability terms for advertising and store visits to be the same; and computer and general sources to be the same since the model was having difficulty in

from the baseline simulation. The predicted percentage of people using each information source in each period is very close to sample frequency.

A key point is that the percentage of people who use each information source declines over time, both in the data and according to the model. Thus, the intensity of search declines over time among consumers who have not yet made a purchase, and our model successfully predicts this pattern.

Of course, there are multiple explanations for this pattern. Consumers with given characteristics could be searching less intensely over time (duration dependence). Alternatively, the explanation could be purely heterogeneity: those consumers who search less intensely stay in the market longer. However, currently we have unobserved heterogeneity only in consumer quality perceptions, which is unlikely to underlie this result. Indeed, we repeated the simulations we reported above for each quality perception type and the same result holds for each type. Finally, the finding that the intensity of search declines over time among consumers who have not yet made a purchase might be sensitive to T=6. Thus, in our current estimation, the terminal period is wave 6 (please recall that six waves of surveys were sent out with two month intervals). We are in the process of re-estimating our model with T=12 to see the sensitivity of the results to T.

V.3. Policy Experiments

Table 6 reports a series of policy experiments that involve the effects of a 20% decrease in the cost of using each information source on purchase probabilities. Note that the baseline simulation results for purchase probabilities were reported in Table 4. Thus,

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separately identifying these terms and the initial magnitudes suggested that advertising and store visits were subject to similar variabilities. The same was true for computer and general sources.

these numbers should be compared with the numbers in Table 6 to see the effects of each experiment.

The results reported in Table 6 suggest that in decreasing information costs leads to acceleration of purchases. For instance, with a 20% decrease n the cost of a store visit, 879 out of the 2000 consumers (44%) have still not made a purchase by the end of wave 6. In this baseline, this is 1129 out of 2000 (or 56%). Decreasing the cost of gathering information from word-of-mouth and advertising has little effect, presumably because these costs are small to begin with. A striking result is that decreasing the cost of gathering information has a much more positive effect for Apple sales than for IBM sales, at least over the 6 wave horizon. In the simulation where cost of store visits is reduced by 20%, Apple sales over the 6 waves increase from 46 to 90 (+96%) while IBM sales increase from 825 to 1031 (+25%).

Furthermore, Apple technology seems to benefit most from a decreased variability of word of mouth information, followed by a decreased variability of information contained in advertising, general and computer articles. IBM benefits most from a decreased variability of information contained in advertising, general and computer articles, followed by decreased variability of information contained in word of mouth.

Finally, comparing the results in Table 8 with the base line numbers in Table 5 reveals that decreasing the variability of information sources encourages people to search slightly more for information. The own-effects (e.g., the impact of decreased variability of an information source on the usage of that information source) are positive. The biggest cross-effect is the <u>positive</u> impact of decreased variability of word of mouth information on store visits. Thus, when consumers have accurate word of mouth information, they are more likely to then visit a store to learn more.

VI. Conclusion

Although this paper focused on the process of learning about and purchasing computers, with an emphasis on the choice between the IBM/Compatible and Apple/Macintosh platforms or standards, our results and modeling approach will be relevant for many durable goods purchase situations, particularly those that involve choice among alternative standards. Thus, our approach can help marketers to understand the information search and the decision-making process of consumers in regard to high-technology durable goods and the impact of the marketing strategy on consumer choices. Our analysis has shed light on issues such as how consumer forward-looking price expectations, the precision of information and costs of information associated with various information channels, some of which are under the –at least partial- control of firms, affect consumer choices. Due to space limitations, we reported only a sub-set of experiments. However, we should note that a very large number of experiments can be run to investigate issues such as how the cost and variabilities associated with each information source may change the pattern of information acquisition behavior (that is, which out of the 32 information search combinations are selected over time and how is that affected, for example, by variability of information).

Our research has a number of managerial implications. For example, we found that word of mouth is the least costly information source whereas obtaining information in computer related articles is perceived to be the most costly source of information, followed by store visits and general purpose articles. These results suggest that managers should focus on providing information in computer specific sources to innovators and opinion leaders and that consumers less involved in the product category are more likely to use word of mouth, advertising and general purpose articles. Thus, in the pre-announcement and introduction stages marketing managers may want to focus their communication spending on computer specific sources.

Our results indicate that increasing the precision (accuracy) of information obtained in information channels increases consumer search, as well as accelerating computer purchases (i.e., more consumers purchase within a one year time frame). We also found a relatively large symmetric cross channel effect for retail stores and word of mouth channels. Thus, if marketing managers can decrease the variability of information obtained in the retail environment consumers will seek more information from family and friends2 (and if the precision of information obtained from word of mouth increases, this encourages consumers to visit stores). These findings support increased spending on recruiting and training of a firm's retail sales force. Furthermore, these results may also provide insight for transitioning sales from brick and mortar to the Internet. One of the most difficult tasks facing marketing mangers on the Internet is driving business to their web site. Our results suggest that focusing spending on simulating clear and concise word of mouth information in chat rooms or consumer-rating sites may provide more motivation for consumers to visit a firm's web site than similar investment in advertising or public relations.

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TABLE 1:
Summary Statistics

EDUCATION	%	INCOME	%	AGE	%
Elementary school through 6th	0	Under $20,000	3.6	Under 18	7
Junior high school (7-8)	1.0	$20,000 to $34,999	13	18 - 24	4
High School (9-12)	13.7	$35,000 to $49,999	27	25 - 34	24
Trade or vocational school	3.3	$50,000 to $64,999	24	35 - 44	34
Some college	21.4	$65,000 to $79,999	14	45 - 54	23
Undergraduate degree (bachelors)	34.1	$80,000 to $99,999	6	55 - 64	7
Graduate School (Ph.D. or Masters)	26.4	$100,000 or over	13	65 or over	2

EXPERTISE	%	PAST PURCHASE	%	GENDER	%
Novice	34	First time buyer	45	Male	62
Intermediate	52			Female	38
Expert	14				

TABLE 2

Quality of Technology: Coefficient Alpha

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
IBM/Compatible	.76	.80	.79	.83	.81	.80
Apple/Macintosh	.79	.80	.82	.84	.83	.80

Table 3. Parameter Estimates

MODEL FIT		
Log of the Likelihood	-2008.8	
PARAMETER ESTIMATES		
Price Process Coefficents		
$Theta_0$	0.043	(0.015)
$Theta_1$	1.260	(0.166)
$Theta_2$	-0.962	(0.197)
$Sigma_v$	0.087	(0.013)
Future Price Process Standard Deviation	0.071	(0.042)
Price Coefficent	0.423	(0.189)
No Purchase Utility Coefficients		
Constant	3.758	(1.206)
Ownership of Computer	0.155	(0.063)
Experience	0.006	(0.052)
Age	0.586	(0.287)
Education	-0.017	(0.086)
Gender	0.516	(0.237)
Income	-0.256	(0.129)
Quality Coefficients		
Mean Quality(IBM, First latent class)	0.917	(0.427)
Mean Quality(Apple, First latent class)	-0.917	-
Mean Quality(IBM, Second latent class)	-0.258	(0.131)
Mean Quality(Apple, Second latent class)	0.258	-
Prior Standard Dev. of Quality Perception	1.268	(0.212)
Quality Perception Interval Coefficients		
IBM-Left	-1.936	(0.240)
IBM-Right	2.695	(0.386)
Apple-Left	-3.118	(0.356)
Apple-Right	2.468	(0.202)
Utility Weight		
Constant	1.000	-
Experience	0.479	(0.238)
Age	0.207	(0.103)
Education	-0.734	(0.257)
Gender	0.639	(0.283)
Income	-0.670	(0.399)
Risk Aversion Coefficient	1.000	-
Variability of Information from Information Sources		
Store Visit	1.705	(0.491)
Advertising, General and Computer Articles	5.076	(1.695)
Word of Mouth	3.398	(1.175)
Information Costs		
Store Visits	1.131	(0.142)
General Articles	0.766	(0.066)
Computer Articles	1.284	(0.164)
Advertising	0.404	(0.058)
Word of Mouth	0.343	(0.065)
Latent Class Probabilities		
1st Latent Class	0.914	(0.133)
2nd Latent Class	0.086	-
Discount Factor	0.990	-

Table 4. Sample Frequencies and Base Line Simulation

Sample frequencies

Wave	Sample Size	Number of Purchases			Percentage of Purchases		
		No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281	281	0	0	100.0	0.0	0.0
2	281	261	19	1	92.9	6.8	0.4
3	245	225	18	2	91.8	7.3	0.8
4	202	179	22	1	88.6	10.9	0.5
5	162	145	17	0	89.5	10.5	0.0
6	120	102	17	1	85.0	14.2	0.8
Total	1010	912	93	5	90.3	9.2	0.5

Base line

Wave	Sample Size	Number of Purchases			Percentage of Purchases		
		No Purchase	IBM	Apple	No Purchase	IBM	Apple
2	2000	1853	140	7	92.7	7.0	0.4
3	1853	1698	139	16	91.6	7.5	0.9
4	1698	1498	191	9	88.2	11.2	0.5
5	1498	1333	162	3	89.0	10.8	0.2
6	1333	1129	193	11	84.7	14.5	0.8
Total	8382	7511	825	46	89.6	9.8	0.5

Table 5. Sample Frequencies and Base Line

Wave	Sample Size	Number of consumers collecting information: Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth	Percentage of consumers collecting information: Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth
Sample frequencies											
1	281	181	164	148	188	247	64.4	58.4	52.7	66.9	87.9
2	281	115	116	98	163	204	40.9	41.3	34.9	58.0	72.6
3	245	82	101	87	132	136	33.5	41.2	35.5	53.9	55.5
4	202	77	87	83	121	116	38.1	43.1	41.1	59.9	57.4
5	162	46	64	53	77	94	28.4	39.5	32.7	47.5	58.0
6	120	35	50	41	59	76	29.2	41.7	34.2	49.2	63.3
Total	1010	355	418	362	552	626	35.1	41.4	35.8	54.7	62.0
Base line											
1	2000	1206	1162	994	1333	1652	60.3	53.4	56.9	62.3	94.3
2	2000	745	790	631	1158	1323	37.3	37.4	35.9	55.2	76.5
3	1853	579	728	652	956	963	31.2	38.8	35.9	51.0	57.6
4	1698	622	675	636	992	963	36.6	42.1	42.1	58.9	61.4
5	1498	409	555	467	657	826	27.3	35.8	32.7	46.9	58.6
6	1333	360	504	423	609	797	27.0	40.8	35.8	45.0	69.2
Total	10382	3921	4414	3803	5705	6524	37.8	42.5	36.6	55.0	62.8

Table 6. Information Costs Simulations

20% decrease in the cost of information from store visit

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
2	2000	1780	212	8	89.0	10.6	0.4
3	1780	1574	171	35	88.4	9.6	2.0
4	1574	1307	254	13	83.0	16.1	0.8
5	1307	1091	209	7	83.5	16.0	0.5
6	1091	879	185	27	80.6	17.0	2.5
Total	7752	6631	1031	90	85.5	13.3	1.2

20% decrease in the cost of information from general articles

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
2	2000	1834	158	8	91.7	7.9	0.4
3	1834	1618	193	23	88.2	10.5	1.3
4	1618	1356	238	24	83.8	14.7	1.5
5	1356	1163	186	7	85.8	13.7	0.5
6	1163	880	256	27	75.7	22.0	2.3
Total	7971	6851	1031	89	85.9	12.9	1.1

20% decrease in the cost of information from computer articles

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
2	2000	1817	168	15	90.9	8.4	0.8
3	1817	1649	141	27	90.8	7.8	1.5
4	1649	1404	233	12	85.1	14.1	0.7
5	1404	1217	184	3	86.7	13.1	0.2
6	1217	955	234	28	78.5	19.2	2.3
Total	8087	7042	960	85	87.1	11.9	1.1

20% decrease in the cost of information from advertising

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
2	2000	1833	154	13	91.7	7.7	0.7
3	1833	1647	161	25	89.9	8.8	1.4
4	1647	1427	208	12	86.6	12.6	0.7
5	1427	1259	163	5	88.2	11.4	0.4
6	1259	1045	197	17	83.0	15.6	1.4
Total	8166	7211	883	72	88.3	10.8	0.9

20% decrease in the cost of information from word of mouth

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
2	2000	1851	142	7	92.6	7.1	0.4
3	1851	1674	158	19	90.4	8.5	1.0
4	1674	1472	193	9	87.9	11.5	0.5
5	1472	1303	165	4	88.5	11.2	0.3
6	1303	1081	205	17	83.0	15.7	1.3
Total	8300	7381	863	56	88.9	10.4	0.7

Table 7. 20% decrase in the variability of information							
Store visit							
		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	2000	2000	0	0	100.0	0.0	0.0
2	2000	1760	227	13	88.0	11.4	0.7
3	1760	1567	170	23	89.0	9.7	1.3
4	1567	1337	209	21	85.3	13.3	1.3
5	1337	1070	261	6	80.0	19.5	0.4
6	1070	855	202	13	79.9	18.9	1.2
Total	7734	6589	1069	76	85.2	13.8	1.0
Advertising, General and Computer articles							
		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	2000	2000	0	0	100.0	0.0	0.0
2	2000	1772	199	29	88.6	10.0	1.5
3	1772	1564	164	44	88.3	9.3	2.5
4	1564	1171	385	8	74.9	24.6	0.5
5	1171	892	270	9	76.2	23.1	0.8
6	892	671	213	8	75.2	23.9	0.9
Total	7399	6070	1231	98	82.0	16.6	1.3
Word of mouth							
		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	2000	2000	0	0	100.0	0.0	0.0
2	2000	1748	225	27	87.4	11.3	1.4
3	1748	1541	150	57	88.2	8.6	3.3
4	1541	1217	286	38	79.0	18.6	2.5
5	1217	937	275	5	77.0	22.6	0.4
6	937	742	186	9	79.2	19.9	1.0
Total	7443	6185	1122	136	83.1	15.1	1.8

Table 8. 20% decrase in the variability of information

Store visit

		Number of consumers collecting information					Percentage of consumers collecting information				
Wave	Sample Size	Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth	Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth
1	2000	1314	1100	1136	1267	1861	64.7	53.4	56.9	62.3	87.4
2	2000	892	747	724	1107	1660	44.1	37.4	35.9	55.2	69.5
3	1760	600	702	667	878	1193	37.1	38.8	35.9	51.0	52.0
4	1567	626	611	651	863	971	40.3	42.1	42.1	58.9	56.8
5	1337	368	462	401	559	830	31.0	35.8	32.7	46.9	54.2
6	1070	277	371	331	452	630	29.4	40.8	35.8	45.0	58.3
Total	9734	2763	2893	2774	3859	5284	37.1	38.9	37.3	51.8	71.0

Advertising, General and Computer articles

		Number of consumers collecting information					Percentage of consumers collecting information				
Wave	Sample Size	Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth	Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth
1	2000	1314	1181	1105	1518	1912	65.7	59.1	55.3	75.9	95.6
2	2000	820	899	767	1231	1595	41.0	45.0	38.4	61.6	79.8
3	1772	617	898	789	1183	996	34.8	50.7	44.5	66.8	56.2
4	1564	609	818	657	949	972	38.9	52.3	42.0	60.7	62.1
5	1171	348	546	483	645	702	29.7	46.6	41.2	55.1	59.9
6	892	273	432	332	535	599	30.6	48.4	37.2	60.0	67.2
Total	9399	3981	4774	4133	6061	6776	42.4	50.8	44.0	64.5	72.1

Word of mouth

		Number of consumers collecting information					Percentage of consumers collecting information				
Wave	Sample Size	Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth	Store Visits	General Articles	Computer Articles	Advertising	Word of Mouth
1	2000	1306	1165	992	1255	1858	65.3	58.3	49.6	62.8	92.9
2	2000	830	681	679	1125	1546	41.5	34.1	34.0	56.3	77.3
3	1748	588	629	575	876	1031	33.6	36.0	32.9	50.1	59.0
4	1541	614	574	632	840	923	39.8	37.2	41.0	54.5	59.9
5	1217	355	466	384	530	758	29.2	38.3	31.6	43.5	62.3
6	937	293	339	316	445	596	31.3	36.2	33.7	47.5	63.6
Total	9443	3986	3854	3578	5071	6712	42.2	40.8	37.9	53.7	71.1