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

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Abstract

We estimate a dynamic model of how consumers learn about and choose between different brands of personal computers (PCs), with an emphasis on the choice between the IBM/Compatible and Apple/Macintosh technologies. To estimate the model we use a unique panel data set collected in collaboration with a major U.S. PC manufacturer. The data contain a wealth of information on the search behavior of a set of consumers who were in the market for a PC, and who were interviewed at 7-week intervals over a 10-month period. The data record the information sources visited each period, search durations, brand purchased and price paid, as well as measures of price expectations and stated attitudes toward the alternatives during the search process.

Our model extends recent work on estimation of Bayesian learning models of consumer choice behavior in environments characterized by uncertainty about brand attributes. Specifically, while several authors have recently estimated models of passive learning about brand attributes, the present paper is, to our knowledge, the first attempt to estimate a model of <u>active</u> learning – i.e., a model in which consumers make optimal sequential decisions about how much information to gather prior to making a purchase.

Our work also makes two methodological contributions. Following the suggestion of Manski (2003), we use our data on price expectations to model consumers' price expectation process. To our knowledge, this is the first attempt to estimate a dynamic structural model using such an approach in lieu of the typical rational expectations assumption. Also, following the suggestion of McFadden (1989a), we incorporate the stated brand quality information into our likelihood function, rather than modeling only revealed preference data.

Our analysis sheds light on how consumer forward-looking price expectations and the process of learning about quality influence the consumer choice process. A key finding is that estimates of <u>dynamic</u> price elasticities of demand – i.e., demand elasticities that account for how a price change today alters expectations of future price changes – exceed estimates that ignore the expectations effect by roughly 50%.

This occurs because our estimated expectations formation process implies that consumers expect mean reversion in price changes. That is, if there is an exceptionally large price cut today, consumers expect a price rebound tomorrow. This enhances the incentive to buy now. Clearly, to the extent that estimates of demand elasticities are sensitive to how consumers form price expectations, it becomes important to collect data on expectations in order to learn more about how they are formed.

Finally, while our work focuses specifically on the PC market and on the choice between Apple and IBM compatible technologies, the modeling approach we develop here may be useful for studying a wide range of high-tech, high-involvement durable goods markets where active learning about different technologies is important.

Key words: Brand Choice Models, Technology Choice, Decision-making under Uncertainty, Information Search, Consumer Expectations, Dynamic Programming

I. Introduction

In this paper, we develop and estimate a dynamic model of personal computer (PC) purchase decisions. We model how consumers learn about, and then choose between, the two competing PC technologies: the IBM Compatible/Windows platform vs. the Apple/Macintosh platform. Although this is a very specific market, we believe our modeling framework will be useful across a range of high-tech durable goods markets characterized by three key features: 1) there are two or more technological alternatives, 2) consumers have uncertainty about the quality of each alternative (and/or its suitability to their particular needs), and 3) there is a rapid pace of technological improvement, reflected in a rapid rate of price decline for any given level of quality. Examples of other markets where different technologies compete are Internet access (cable modem vs. DSL) and satellite access (cable service vs. satellite dish).

There is now a significant body of literature in marketing and economics focusing on how consumer learning about brand attributes affects consumer choice behavior in markets for frequently purchased experience goods. Examples include Eckstein, Horsky and Raban (1988), Erdem and Keane (1996), Anand and Shachar (2002), Ching (2002), Ackerberg (2003), and Crawford and Shum (2003). But we are not aware of prior empirical work that examines how learning affects consumer choice behavior in high involvement durable goods markets.

In contrast to experience goods, high-tech durables are characterized by a large number of "search attributes." Thus, we expect that active learning (i.e., information search) should be important. In prior work on frequently purchased goods, learning has been modeled as passive (i.e., coming through use experience and/or the passive reception of advertising messages). Thus, we seek to extend the literature on learning and consumer choice behavior by developing an estimable model of active learning that is more appropriate for high involvement goods.

In our model, consumers have prior uncertainty about the "quality" of the two alternative PC technologies. Our notion of quality is not absolute but, rather, is taken to subsume an individual specific match component. Prior to making a purchase, consumers decide whether to utilize each of several alternative information sources (e.g., store visits, reading computer articles, etc.) in order to learn about the match quality of each technology. The sources vary both in terms of information accuracy and the cost of use.

After obtaining information, the consumer decides whether (and what) to buy. 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. Thus, waiting allows the consumer to gather more information and make a more informed choice. On the other hand, waiting entails an opportunity cost, since the consumer delays obtaining a new computer. The weighing of the benefits from learning vs. the cost of delay is one source of dynamics in our model.

The other key source of dynamics in our model is that PC prices tend to decline over time. In our model, consumers are forward-looking, so they take both current and expected future prices into account when deciding whether today is a good time to buy. If consumers expect prices to decline, this provides another incentive to delay purchase.[1]

A methodologically innovative aspect of our paper is how we model consumer expectations of future prices. Previous work on the role of price expectations in consumer choice behavior, such as Erdem, Imai and Keane (2003), assumes that consumers have rational expectations – meaning they know the true price process and use it to forecast future prices. But here, following the suggestion of Manski (2003), we have collected data on price expectations, and used it to estimate consumers' expectations of future PC prices. By utilizing data on expectations, we can significantly relax the sorts of strong assumptions on expectations that are typically invoked to estimate dynamic structural models of choice behavior.

To estimate our model, we collected a unique data set in collaboration with a major U.S. PC manufacturer. Starting from a random sample of U.S. consumers contacted by random digit dialing, we chose a subset of individuals who we identified as being actively "in the market" for a PC. This produced a sample size of N=281. These panelists were then interviewed at roughly 7-week intervals, for nine months or until they bought a PC, whichever came first. In each wave, they were asked whether they had yet bought a PC, and, if so, its description and cost. They were also asked about which of several information sources they had utilized over the 7-week interval.

In addition, respondents were asked to consider the particular PC configuration they were currently thinking of buying, and to report their perception of its current price and its price six months earlier, as well as their forecast of the price six months ahead. This information on current, past and expected future prices was used to estimate the price process as perceived by consumers. We assume that consumers form price expectations based on this estimated process.

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[1] This aspect of the problem is also modeled by Melnikov (2000) and Song and Chintagunta (2003). But in their models consumers are assumed to have complete information about product attributes, so there is no learning.

A second methodologically innovative aspect of our work is that we incorporate stated preference data into the estimation of the model. This type of procedure has been advocated by McFadden (1989a), who argued that stated preference data may provide important identifying information for the estimation of choice models.[2] In each wave of our survey, the respondents were asked to rate their quality perceptions for each technology on 1-7 Likert scales. We model responses to these questions as functions of consumers' underlying quality perceptions (via an ordered probit specification), and incorporate them into our likelihood function.

We feel that the use of stated quality perception data is quite important here. By observing the extent to which quality perceptions are updated after particular information sources are utilized, we gain important information about the accuracy of those sources.

To preview our results, we note that our estimated model fits the data quite well in a number of important dimensions, including the purchase hazards for each technology, and utilization hazards for each information source by wave. The purchase hazard rises over time, while the rate of information acquisitions falls, and our model captures both these features of the data. Our estimates of the price expectation process imply that consumers expect roughly a 16% annualized rate of price decline. The estimates also imply that consumers expect mean reversion in price declines (e.g., if the decline over the past few months was greater (less) than normal, then consumers expect a lesser (greater) price decline over the next few months.

Given the estimated model, we ran a number of counterfactual experiments to learn more about the nature of the consumer behavior implied by the model. One set of experiments is designed to gauge how expected price declines and opportunities for learning generate incentives for purchase delays.

Another set of experiments examines how price expectations affect demand elasticities. We find that the elasticity of demand with respect to a transitory price cut is 2.5 if expected future price changes are held fixed, while it is 3.6 if expectations of future price changes are allowed to adjust. Given that our estimated expectation process implies mean reversion, this is what one would expect. That is, an exceptionally large price decline today leads consumers to

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[2] Several papers (primarily in the marketing literature) incorporated stated preference and/or attitudinal data into estimation of static choice models. An example is Harris and Keane (1999), who also survey of other work of this type. We are not aware of prior work that incorporates stated preference data into estimation of dynamic structural models, except for van der Klaauw and Wolpin (2003), whose procedure can be interpreted in this way. They fit a dynamic model of retirement behavior to both actual retirement decisions and stated intentions about retirement age.

expect a smaller price decline (or even a price rebound) tomorrow, enhancing the incentive to buy today. Thus, the expectation effect augments the short run demand elasticity by nearly 50%.

We also examine how altering the accuracy and cost of the various information sources would alter information acquisition and technology choice behavior. We find that making information more freely available, either by lowering the cost of a signal or increasing the accuracy of signals, would favor the Apple/Macintosh platform. This occurs because, according to our model, consumers have substantially greater prior uncertainty with respect to the match quality of the Apple/Macintosh platform.

The rest of the paper is organized as follows. In section II we outline relevant streams of previous literature. In section III we describe our model. Sections IV and V describe the solution and estimation process. Section VI discusses our survey data on computer search behavior that we use to estimate the model. Section VII presents our estimates, and Section VIII presents the counterfactual experiments. We conclude in section IX with a brief summary of our findings.

II. Literature Review

II.1. Consumer Search Behavior in Durable Goods Markets

There is a large body of literature in marketing examining consumer search behavior in general (see Moorthy et al. (1997) for a survey). Several papers examine determinants of search intensity in markets for durable goods. For example, Srinivasan and Ratchford (1991) examine how prior knowledge, memory, interest, experience, perceived risk and cost of search affect the effort that consumers devote to searching for information about automobiles (see also Brucks (1985), and Urbany et al. (1989)). Weiss and Heide (1993) look at search behavior of industrial buyers in high technology markets. They examine how buyers' perception of technological change and the level of technological heterogeneity affect search effort and duration.

A number of studies have also examined the relation between consumer characteristics and what information sources they utilize when searching for information.[3] These studies have categorized information sources into the following channels: 1) retail; 2) word-of-mouth; 3) ads, and 4) articles in "neutral" sources (i.e., third party or general-purpose publications).

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[3] See, for instance, Beatty and Smith (1987), Claxton et al. (1974), Furse et al. (1984), Kiel and Layton (1981), Newman and Staelin (1973) and Westbrook and Fornell (1979).

Neither of these streams of research has integrated active information search into estimable models of consumer choice behavior. Roberts and Urban (1988) proposed a Bayesian learning model with myopic agents, which integrated consumers' (passive) learning about car attributes through test-drives and word-of-mouth into a model of choice behavior.[4] However, they did not model consumers' decisions to engage in active information acquisition.

Other studies have compared consumer search behavior in markets for durable goods with relatively stable technologies vs. those with a rapid pace of technological progress (see, e.g., Bridges, Coughlan, and Kalish (1991), Glazer (1991), Glazer and Weiss (1991)). This work typically concludes that differences in the decision environment between high and low tech durable product categories limits the generalizability of results between the two categories.

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. An exception is Bridges, Yim, and Briesch (1995), who examine how consumer expectations affect demand for high-tech durables. Specifically, in reduced form-market share model for PC's, they construct price and technological change expectations based on the actual price and technology of each product; i.e., they assume perfect foresight. They conclude that expectations significantly affect market shares. Holak, Lehmann and Sultan (1987) also found evidence that consumer forward-looking expectations affect consumer durable purchases.

II.3. Consumer Choice Behavior under Uncertainty about Quality and Future Prices

There is a large literature on consumer decision-making under uncertainty about product quality. For instance, Erdem and Keane (1996) modeled consumer learning about quality of alternative brands of an experience good. The consumers in their model are forward-looking since, in making current period purchase decisions, they take into account how the value of information that obtained through a trial purchase would affect the expected future utility stream.

A number of authors have also considered models of consumer-decision making under uncertainty about future prices. Researchers have proposed models where consumer price expectations affect purchase timing, brand choice and quantity decisions, and the predictions from such models have been experimentally tested (see, e.g., Meyer and Assuncao (1990), Krishna (1992)). Erdem, Imai and Keane (2003) estimate such a dynamic structural model on

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[4] See also Hauser, Urban and Weinberg (1993).

scanner panel data for frequently purchased consumer goods. Hendel and Nevo (2002) estimate a related type of model.[5]

A key feature of high-tech durables markets is the tendency for prices to fall quickly over time, creating an incentive to delay purchases. Melinkov (2000) models consumer behavior in this context using data from the computer printer market. Song and Chintagunta (2003) analyze the impact of price expectations on the diffusion patterns of new high-technology products using aggregate data. But these models differ fundamentally from ours in that they do not model how consumers search for information.

We are not aware of prior empirical work that integrates both learning about quality and the expectations about future prices into a single model of consumer decision-making. Our main contribution is to include both these features in a single model. It is important to note that both learning and expectations of declining prices can generate incentives to delay purchase of a durable. Our results imply that both mechanisms help to generate positive duration dependence in the purchase hazard for consumers in the PC market, and this is a salient feature of the data.

III. A Model of Learning and Technology Choice in High-Tech Durable Goods Markets

III.1. The Utility Specification

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. For convenience, in the model development section, we refer to the Apple/Macintosh technology as simply "Apple," and the IBM Compatible/Windows Platform as simply "IBM." We 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 possible spending levels converts our problem into a pure discrete choice problem, which greatly facilitates estimation. In estimation we set R=5 (the choice of the price categories is discussed further in the data section).

Consumers have a utility function defined over the efficiency units of computer capabilities they possess, E, and consumption of an outside good, C. If a consumer spends P_r dollars on a PC, then his/her consumption of the outside good is $C_{ir} = I_i - P_r$, where I_i is the consumer's income. The efficiency units of computer capabilities that the consumer obtains by spending P_r on technology j depends on the current price per efficiency unit of that technology.

[5] Gönül and Srinivasan (1996) model how expectations of future coupon availability affect purchase decisions.

Let π_{jt} denote an <u>index</u> of the efficiency units of computer capabilities that one can purchase by spending one dollar on technology j at time t. The π_{jt} can be thought of as inverse price indices. Thus, they will grow over time as computer prices drop. We normalize the inverse price indices π_{jt} for j=Apple, IBM equal to 1 in the base period t=1, so that changes in these indices reveal changes in prices over time, but not absolute price levels.

Next, we let Q_j denote the efficiency units of computer capabilities that one can purchase by spending one dollar on technology j at time t=1. We will call Q_j the per dollar "quality" of technology j, and assume it is constant over time t. Essentially, we are assuming that over a relatively short period of time the relative qualities of the two technologies remain unchanged.

Thus, the product of π_{jt} and Q_j gives the efficiency units of computer capabilities that one can purchase by spending one dollar on technology j at time t. Hence, we have that:

$$G_{ijrt} = \pi_{jt} P_r Q_j$$

is the efficiency units of computer capabilities that one can purchase by spending P_r dollars on technology j at time t. Note that by spending one dollar at t=1, one obtains $\pi_{j1}Q_j$ efficiency units, but since we have normalized π_{jt} =1 at t=1, this is just Q_j (consistent with our definition of Q_j).

Next, we assume the utility function U_{ijrt} is given by:

$$U_{ijrt} = \beta_i (1 - \exp\{-\alpha G_{ijrt}\}) + \gamma C_{ijrt} + \varepsilon_{ijrt} \tag{1}$$

where the parameter β_i is individual specific, while the parameters α and γ are common across all consumers. ε_{ijrt} is an *iid* stochastic term that captures i's idiosyncratic taste for alternative j,r at time t. These error terms are meant to capture miscellaneous influences on consumers' decisions that are unobserved by the econometrician.

Substituting for G_{ijt} and C_{ijrt} in (1) we obtain:

$$U_{ijrt} = \beta_i (1 - \exp\{-\alpha \pi_{jt} P_r Q_j\}) - \gamma P_r + \varepsilon_{ijrt} \tag{2}$$

where we have dropped the γI_i term because it is constant across alternatives j,r and therefore will not affect choices.

A key aspect of our model is that consumers do not know the attributes of the two available technologies perfectly. Thus, they have uncertainty about the true quality levels Q_j for for j=Apple, IBM. Below, in section III.3, we will describe in detail the process by which consumers learn about quality. At this point, it is sufficient to note that in a model of Bayesian learning in which consumers have a normal prior on quality and receive normally distributed noisy signals of quality, consumer perceptions at time t will obey the distribution:

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

where I_{it} denotes the consumer's information set (i.e., the set of signals received), $E[Q_j \mid I_{it}]$ is the consumer quality expectation conditioned on I_{it}, and σ^2_{ijt} is the perception error variance.

Together, (2) and (3) imply that a consumer's expected utility conditional on purchase of technology j at time t is given by:

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

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 known to the consumer.

Several aspects of this specification are worth commenting upon:

First, note that the exponential (CARA) form for the sub-utility function for G (the efficiency units of computer capability) that we specify in (1) implies that consumers are risk averse with regard to uncertainty in Q_j. This form for the sub-utility function has been used in previous (Roberts and Urban 1988) as well as more recent work (Crawford and Shum 2003). The parameter α determines the degree of risk aversion. We see from (4) that, when $\alpha>0$, expected utility is increasing in expected quality and decreasing in the perceived variance of quality, σ^2_{ijt}.

Second, the assumption that utility is linear in consumption of the outside good is quite standard in brand choice modeling. It can be motivated as an approximation under the assumption that the marginal utility of consumption is roughly constant over the range of outside good consumption levels generated by different choices of expenditure on computers (since spending on computer equipment will typically be a rather small fraction of total expenditure).

Third, our notion of the "quality" of a technology is person specific. It includes not just the absolute quality of the particular technology, but also how well that technology is suited to a particular consumer's needs. Thus, the Q_j are best interpreted as match specific quality levels that may differ across consumers. In our estimation, we will allow for two different types of consumers in terms of "true" quality of the two technologies. However, for ease of exposition, we will suppress the type specific subscripts on the Q's.

Fourth, we allow β_i to vary across consumers to capture the fact that some consumers may derive greater marginal utility from additional computer capability (at any given level of G). 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. Thus, we write $\beta_i = \beta_0 + \tilde{\beta} X_i$, where X_i is a vector of observed consumer characteristics (experience with computers, age, education, gender and income).

There are three key potential sources of dynamics in the consumer choice process in our model that we will focus on:

(i) Consumers may recognize that computer prices tend to drop over time, causing the π_{jt} to grow over time. This creates an incentive to delay purchase. Of course, the strength of this incentive depends on consumers' forecast of how quickly prices will drop.

(ii) We assume that agents begin the search process with uncertainty about the quality levels Q_j. In each period t they 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 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.

Thus, in addition to equation (4), 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 $U_{i0}(X_i)$.

At this point, a discussion of a key identification issue is in order. In sections I and II, we noted that positive duration dependence in the purchase hazard is a key feature of our data. Any model that includes a mechanism whereby consumers have an incentive to delay purchases can generate such positive duration dependence. But we have noted that both expectations of falling prices and the desire to acquire more information about quality create incentives for delay. Since either mechanism alone can generate this key qualitative feature of the data, one might question how it is possible to distinguish the two mechanisms (absent strong auxiliary assumptions).

For instance, if price expectations are treated as unobservable, one might suspect that any desired extent of purchase delay (and positive duration dependence in the purchase hazard) could be achieved simply by assuming that agents expect a sufficiently rapid rate of price decline. Similarly, one could presumably generate any desired extent of delay via the learning mechanism as well, simply by increasing the assumed level of prior quality uncertainty confronting the consumers, thereby increasing the value of information acquisition.

Intuitively, we resolve this fundamental identification problem in two ways: First, we use data on expectations to identify the rate of price decline that consumers actually expect (as opposed to say, just fitting an expectation process using the choice data alone). Second, we incorporate data on consumer perceptions of the quality of each technology and how this evolves over time. If quality perceptions change little over time, then prior uncertainty is not a plausible story for purchase delay.

Finally, we note that even a model with myopic agents could generate positive duration dependence in the purchase hazard, simply because prices do, in fact, fall over time. The strength of this effect is governed by the price elasticity of demand. However, the demand elasticity is not free to adjust simply to fit this one aspect of the data. It must also capture how the quantity of computer capabilities that consumers buy varies with price. Furthermore, prices do not decline steadily over time – rather they fall more over some time intervals than others – nor do prices fall by the same amount for both the IBM and Apple technologies in each period. A myopic model would generate purchase hazards that rise closely in step with price declines, while a dynamic model, because it incorporates incentives for purchase delay, can generate a hazard that rises substantially even between periods where prices are relatively flat.

Next, we describe how agents forecast prices and learn about quality in 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 work is that we depart from this approach. Because we actually have data on consumer expectations of future prices, we can attempt to estimate the process that consumers use to forecast prices directly, without having to make the further assumption that consumers have rational expectations.

Manski (2003) has argued that this type of strategy may make results from dynamic structural models more "credible," both because the RE assumption may be intrinsically implausible in many contexts, and because data on expectations allows one to bring more information to bear, enabling one to achieve identification under weaker assumptions. We think the later point is especially salient in the present context, particularly in light of the heuristic discussion of identification issues in section III.1.

In our data, a consumer is asked his/her perception of the price of the type of PC configuration he/she is currently thinking of buying, both at the present time and six months earlier. The consumer is also asked for his/her forecast of the price six months ahead. We used these data to calculate consumer's expected price decline for a particular PC configuration. We then used the answers to these questions to construct consumer specific measures of the perceived change in the π_{jt} from t-1 to t, as well as of the expected change in the π_{jt} from t to t+1.

There are three reasons we asked consumers to think about a particular PC configuration when answering the price perceptions/expectations questions. First, we felt it would be easier for consumers to report perceived/expected price changes for PC configurations they were familiar with, rather than trying to form some abstract construct of computer prices in general. Second, we felt that focusing on a particular configuration would provide a more accurate measure of the relevant prices facing the particular consumer (e.g., If a consumer felt that PC prices would fall in general over the next 6 months, but that the price of the system he was interested in would not fall, we would argue that it is the latter forecast that is more relevant to his/her purchase timing).

Third, by trying to isolate the price of a particular system, we hoped to avoid quality bias in our price indices. For example, suppose a consumer expects the price of a "typical" PC configuration to stay constant from this year to next, but also expects that the "typical" PC next year will have a faster CPU. If this consumer uses a "typical" PC as his/her point of reference, he might say he expects no price change. By asking the consumer to focus on a fixed configuration, we hoped to elicit an expected price decline under scenarios like this.

In our view, it would be implausible to assume that respondents respond to survey questions in exactly the way we intend (regardless of how carefully the questions are phrased), or that they will necessarily report their perceptions and expectations with a high degree of precision. Thus, rather than assuming that survey responses measure expectations exactly, we assume expectations are measured with error. This means we have to assume a measurement error process. Clearly, while having data on expectations may allow us to <u>relax</u> assumptions on how expectations are formed, we can never escape entirely from *a priori* assumptions.

We specify our measurement error process as follows: Denote by $\Delta_{ij,t+1}$ the inverse of the consumer's report of his/her expectation of the price decline from *t* to *t*+1. That is, if π^*_{jt} denotes the consumer's (error laden) survey response π_{jt} regarding his/her perception (or forecast) of the price level at time *t*, we define $\Delta_{ij,t+1}=\pi^*_{j,t+1}/\pi^*_{jt}$. We then assume that:

(5) $$\ln\Delta_{ij,t+1}=E[\ln(\pi_{j,t+1}/\pi_{jt})\,|\,I_{it}]+\nu_{ij,t+1} \qquad \nu_{ij,t+1}\sim N(0,\sigma^2_\nu)$$

where $E[\ln(\pi_{j,t+1}/\pi_{jt})\,|\,I_{it}]$ denotes consumer *i*'s <u>subjective</u> expectation of the log price change conditional on his/her information set I_{it}, and ν_{ijt} is measurement error.

Another key issue is that solution of the optimization problem confronted by the agents in our model requires that we specify the entire predictive distribution of future prices. It is clearly not sufficient that we have data on point estimates of expected price changes for 6 months ahead. We need to extrapolate from this information to the entire predictive distribution. This means we need to make another *a priori* assumption that facilitates the extrapolation.[6]

Our approach to this problem is to write down a flexible specification for the process generating expectations. Specifically, we will assume the process:

(6) $$E[\ln(\pi_{j,t+1}/\pi_{jt})\,|\,I_{it}]=\theta_0+\theta_1\ln(\pi_{jt}/\pi_{j,t-1})+\theta_2\ln(\pi_{jt}/\pi_{j,t-2})$$

We will estimate (6), treating $\ln\Delta_{i,j,t+1}$ as a noisy measure of the left hand side (see (5)). By using reported expectations rather than actual (inverse) price indices in (6), we allow consumers to depart from the optimal forecasting rule an econometrician would construct.

To gain some intuition about what equation (6) implies for the properties of price expectations, consider the following: If θ_1=1 and θ_0=θ_2=0, then consumers simply extrapolate the most recent one period (inverse) price change into the future. Alternatively, if θ_0=0, θ_1 >2|θ_2|>1 and θ_2<0, consumers expect any acceleration (deceleration) of the rate of price change

[6] We hasten to add that, in our view, this need to make additional assumptions does not arise just because of some shortcoming of our data collection effort. Rather, we feel it will be a rather general feature of modeling efforts that seek to estimate dynamic models using survey data on expectations. The key problem is that, to solve a dynamic model, one needs agent's subjective distribution over all future realizations of the forcing processes, and this is, in general, a very complex object. There is simply no practical way to elicit such a complex object completely using survey questions. Thus, given some data measuring a few features of this joint distribution, one will typically need to make assumptions that enable one to extrapolate to the whole distribution. Still, in many contexts, these types of assumptions may seem more credible *a priori* than do rational expectations assumptions.

that occurred from t-2 to t to continue into the future. If θ_2<0 and $|\theta_2|>|\theta_1+\theta_2|$, consumers expect mean reversion in the rate of price change towards the "natural rate" $\theta_0/(1-\theta_1-2\theta_2)$. Given the range of processes it can encompass, (6) is a fairly flexible model of expectation formation.

Using (6) we can construct estimates of consumers' point expectations of price changes from the current period to all future periods, ranging from 2 months ahead to the terminal period of the planning problem, which we denote by T. For example, if the θ values in (6) are such that consumers expect the rate of price decline to accelerate, we can calculate the extent to which the expected rate of price decline over the next two months is less than that over the next six. Thus, we can use (6) to construct $E[ln\pi_{j,t+j}/\pi_{jt}|I_{it}]$ for j=1, …, T-t. Furthermore, $E[ln\pi_{j,t+j}|I_{it}]$ for any $t+j$ can be constructed from $E[ln\pi_{j,t+j}/\pi_{jt}|I_{it}]$ because the current price levels π_{jt} for j=IBM, Apple are assumed to be elements of I_{it}.

Finally, note that having point estimates of a consumer's price expectations at all time horizons (out through T) is still not sufficient to solve the consumer's dynamic choice problem. We need to specify the subjective <u>distribution</u> of future prices at each horizon. For simplicity, we will assume that agents' subjective expectation of the distribution of prices at $t+j$ is given by:

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

where σ_π^2 is the subjective variance of the log price distribution. Unlike the θ's in (6), σ_π^2 is not identified by the data on price perceptions/expectations, since we only have data on point estimates and not measures of dispersion. It is identified in the complete structural model, because it affects the option value of waiting and hence reservation prices.

III.3. Consumer Learning About Quality

The other 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 are Bayesians (although, as we discuss below, our estimation procedure does not strictly impose this). They enter the market with priors on the Q_j for j=IBM, Apple. We assume that consumers have normal priors, given by:

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

where 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.

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 sources are: (1) retail stores, (2) articles in computer specific publications, (3) articles in general-purpose publications, (4) advertisements, and (5) word-of-mouth. Based on input from focus groups of recent PC buyers, managerial interviews, and the literature reviewed in Section II.1, we concluded these are the primary information channels consumers use to gather information about PCs.[7]

In our model, these five information sources provide noisy signals of product quality. Each source provides signals of different accuracy. Letting S_{jkt} denote a signal from source *k* at time *t* about technology type *j*, the consumer knows that:

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

where $1/\sigma_k^2$ is the precision of information contained in information source *k*, and Q_j is the "true" quality level of technology *j*=Apple/IBM. In estimation, we will allow for two different types of consumers in regard to these true quality levels. Treating the consumer type as a latent variable, we also estimate the population proportion of each type. However, in expositing the model, we suppress the type specific subscript on the Q_j for notational convenience.

At each time *t*, the consumer decides which set of information sources to visit. He/she receives a quality signal from each visited source. The consumer then updates his/her quality prior using standard Bayesian updating formulas. To write these formulas, it is convenient to rewrite (9) as:

(9') $$S_{jkt} = Q_j + x_{ijkt} \qquad x_{ijkt} \sim N(0, \sigma_{kt}^2).$$

and to recall equation (3), in which z_{ijt} denoted a consumer's quality perception error for technology *j* at time *t*:

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

where:

(10) $$\sigma_{ijt}^2 = E\{(Qj - E[Q_j | I_{it}])^2 \mid I_{it}\}.$$

[7] The data were collected from Sept. 1995 to June 1996. Panelists consistently ranked the Internet as one of the least important sources of information, so we do not include it. Since then, Internet usage has increased. However, many consumers, especially those looking for information on high-tech durables, 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 Internet can be viewed as an alternative medium (electronic) to obtain information from each channel.

Then, letting L_{ikt} be a dummy variable indicating whether consumer *i* visits information source *k* at time *t*, and assuming the signals are independent, we obtain the Bayesian updating formulas:

(11) $$\sigma_{ijt}^2 = \left[\frac{1}{\sigma_{j0}^2} + \sum_{s=1}^{t} \sum_{k=1}^{5} \frac{L_{iks}}{\sigma_k^2} \right]^{-1}$$

(12) $$z_{ijt} = z_{i,j,t-1} + \sum_{k=1}^{5} L_{ikt} \frac{\sigma_{i,j,t-1}^2}{\sigma_{i,j,t-1}^2 + \sigma_k^2} (x_{ijkt} - z_{i,j,t-1})$$

Equation (11) gives the evolution of the accuracy of the perception errors, whereas equation (12) describes how perception errors themselves are updated given the quality signals. The consumer's subjective quality distribution for technology *j* at time *t* is then:

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

Note that the perception errors z_{ijt} retain a normal distribution throughout the updating process.

One mechanism generating positive duration dependence in the purchase hazard is that σ_{ijt}^2 will fall over time as more information is acquired. From (4), we see that this increases expected utility conditional on making a PC purchase. This suggests the following intuitive argument for identification of the precisions $1/\sigma_k^2$ for *k*=1,5: If an information source is more (less) accurate, the perception error variance σ_{ijt}^2 will fall more (less) after that source is visited. This, in turn, is reflected in the extent to which the purchase hazard rises after a source is visited.

The use of stated preference data provides us with an additional source of information to help identify the precisions. The basic idea is that, if an information source is very inaccurate, then consumers will be very unlikely to update their quality perception substantially after visiting that source. This is because the Kalman gain coefficient $\sigma_{ij,t-1}^2/(\sigma_{ij,t-1}^2 + \sigma_k^2)$ associated with that source in equation (12) will tend to be small. Thus, survey measures of how consumers' quality perceptions evolve over time should help to identify the precisions. Furthermore, as we argued earlier, the extent that perceived quality ratings change over time should help identify the extent of prior uncertainty captured by the parameters σ_{jo}^2.

In each survey wave, we asked consumers to rate each technology on 7-point Likert scales. More details on the questions will be provided in section VI. At this point, it suffices to say that we treat responses to these perceived quality questions as providing measures of the consumer's underlying subjective quality perceptions E[Q_j | I_{it}] for j=IBM, Apple.

Specifically, we divide reported quality into a low, medium or high range. Denote these as L, M and H, respectively. Let q_{ijt} denote consumer i's reported quality perceptions at time t. We assume these survey responses are generated by a quantal response model where:

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

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

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

The μ's are threshold parameters to be estimated. Of course, the E[Q_j | I_{it}] are random variables from the perspective of the econometrician, because we observe only the number of signals a consumer has received from each source, not their actual content. According to equation (3'), the E[Q_j | I_{it}] are normally distributed with variance σ_{ijt}^2. Thus, we obtain the ordered probit model:

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

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

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

where $\Phi_{\sigma_{ijt}}$ is the normal distribution function with the mean 0 and variance σ_{ijt}^2. The response probabilities in (14) will contribute to the likelihood function we construct in Section V.[8]

Finally, we note that that our estimation procedure does not actually impose that consumers update in a strict Bayesian manner. El-Gamal and Grether (1995), in their experiment on Bayesian learning, found that, while Bayes' rule was the most commonly used rule, subjects often used a "representativeness heuristic." This means they update too much when they receive new information. Since we do not observe precisions of the information sources in our data, the estimated precisions are free to depart from their "true" values. Increasing the estimated precisions above their true values leads to behavior that is observationally equivalent to excessive updating. Whether consumers are strictly Bayesian is not identified in our framework.

[8] Note: In (14) we could have added an additional source of measurement error, so that consumer responses would be random even conditional on a known E[Q_j | I_{it}]. But we suspected that this would have little effect on the results.

IV. The Consumer's Dynamic Optimization Problem

The state of a consumer at each point in the choice process is characterized by the information set I_{it} introduced in the previous section. To be precise, I_{it} contains the complete set of signals received by consumer *i* up through period *t*, which we denote by $\tilde{x}_{it}$, for which the subjective mean and variances of quality are sufficient statistics. It also contains the current and lagged inverse price indices, and the consumer's observed characteristics and latent type. That is:

$$I_{it} = \{\{E[Q_j \mid \tilde{x}_{it}], \sigma^2_{ijt}, \pi_{jt}, \pi_{j,t-1}\}_{j=IBM,Apple}, X_i, \tau\} \quad . \tag{15}$$

where X_i is a vector of consumer characteristics and τ=1,2 denote the latent type (see Section II.1). Note that $E[Q_j \mid \tilde{x}_{it}] = E[Q_j \mid I_{it}]$.

The consumer's choice set at time *t* includes 2^5=32 combinations of the five potential information sources that he/she may choose to utilize. After deciding which 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 2·*R* possible choices (2 technologies and *R* expenditure levels). If the consumer decides to wait, he/she will face the same choices at *t*+1. The value of each of the 32 options for information acquisition is:

$$V_{imt}(I_{it}) = -\sum_{k=1}^{5} J_{km} c_k + E\max\{V_{it}^P(I_{it}, m), V_{it}^N(I_{it}, m)\} + \xi_{imt} \qquad m=1,32 \tag{16}$$

Here, the c_k for *k*=1,5 denote the costs of obtaining information from each source *k*, which we treat as parameters to be estimated. 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 using search option *m* at time *t*.

In (16), V_{it}^P denotes the value of the purchase option. It is defined as follows:

$$V_{it}^P(I_{it}, m) = \max_{\{j,r\}} E[U_{ijrt} \mid I_{it}, m] \tag{17}$$

This is the maximum over all possible technology and expenditure options {*j*=IBM, Apple, *r*=1,*R*} of the expected utilities of those choices. These expected utilities were given in (4). The expectations in (17) are conditional on the start of period information set I_{it} as augmented by signals obtained from choosing 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. The expectation operator in (16) incorporates this integration over the distribution of the signals that may be received under search option *m*.

Finally V_{it}^{N} in (16) denotes the value of making no purchase at time *t*. This is:

(18) $$V_{it}^{N}(I_{it},m)=U_{i0}+\delta E\max_{m} V_{im,t+1}[I_{i,t+1}]+\varepsilon_{i0t}$$

Thus, if no purchase is made at *t*, the consumer gets the per-period utility flow denoted by $U_0(X_i)=\gamma_0+\tilde{\gamma}X_i$, where X_i is a vector of individual characteristics. Then at t+1, he/she will repeat the process of deciding which information sources to visit, followed by the decision whether or not to buy. The parameter δ is the discount rate. We discuss the contents of the X_i vector in detail below. Here we note that it includes an indicator for whether the consumer already has a home computer. Obviously this may be an important determinant of the flow utility under the no-purchase option. The stochastic term ε_{i0t} can be interpreted as a shock to the value of the no purchase option at time *t*, known to consumer *i* but unobserved by the econometrician.

The expectation in (18) is taken over realizations of the price indices $\pi_{j,t+1}$ at time t+1. Given $(\pi_{j,t-1}, \pi_{j,t}) \in I_{it}$, the consumer forms a subjective distribution over $\pi_{j,t+1}$ using (6) and (7). 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*, plus the actual realization of $\pi_{j,t+1}$.

Together, (16), (17) and (18) give the Bellman equations for the consumer's dynamic optimization (DP) problem. In order to solve the DP problem, we specify a finite terminal period *T* and then construct the period specific value functions using backward recursion in the usual way. We assume that if a consumer still does not buy in the terminal period *T*, then he/she receives the discounted value of the per-period utility stream $U_0(X_i)$ over an infinite horizon.

Given that we have 6 waves of data covering roughly 10 months, we decided to specify a terminal period of T=12, which corresponds to a 20-month planning horizon. As we'll see, the model predicts that the large majority of consumer will have bought a computer within 12 periods, so, not surprisingly, changing the terminal period seems to have little effect on our results.

Finally, we note that, since the four state variables in (15) that characterize the evolution of quality perceptions and prices are continuous, it is not possible to solve the DP problem exactly. We use the Keane and Wolpin (1994) approach, which involves solving for the value functions on a grid of state points and then extrapolating to the remaining points.

V. Consumer Choice Probabilities and the Construction of the Likelihood Function

Recall that, in each period, consumers make two sequential decisions. The first of these is the information gathering choice, whereas the second is the purchase/no purchase/expenditure level quantity choice. We'll describe the purchase choice probabilities first.

Let D_{ijrt} be a dummy variable equal to 1 if consumer i chooses to buy technology j at time t and his/her chosen expenditure amount, which must belong to the discrete set $\{P_1,\ldots, P_R\}$, is P_r. Let D_{i0t} be a dummy equal to 1 if the consumer chooses not to make a purchase at time t. In order to obtain more compact expressions for the purchase choice probabilities, we rewrite (4) as

(4') $$E[U_{ijrt} \mid I_{it}] = E[\overline{U}_{ijrt} \mid I_{it}] + \varepsilon_{ijrt}$$

where $\overline{U}_{ijrt} \equiv \beta_i \{1 - \exp\{-\alpha\pi_{jrt} P_r (Q_j + z_{ijt}) + (\alpha\pi_{jt} P_r)^2 \sigma_{ijt}^2 / 2\}\} - \gamma P_r$, and rewrite (18) as:

(18') $$V_{it}^N = \overline{V}_{it}^N + \varepsilon_{i0t}$$

where $\overline{V}_{it}^N = U_{i0} + \delta E \max_m V_{im,t+1}[I_{i,t+1}]$. We then assume that the $2{\cdot}R+1$ vector of stochastic terms $\{\{\{\{\varepsilon_{ijrt}\}_{j=\text{IBM, Apple}}\}_{r=1,R}\}, \varepsilon_{i0t}\}$, which is known to the consumer but unobserved by the econometrician, is distributed i.i.d extreme value. This generates multinomial logit choice probabilities (see McFadden 1974) of the form:

(19) $$\Pr(D_{ijrt} = 1 \mid \theta, z_{it}, \tau) = \frac{\exp(E[\overline{U}_{ijrt} \mid I_{it}])}{\exp(\overline{V}_{it}^N) + \sum_{l=1}^{2} \sum_{q=1}^{R} \exp(E[\overline{U}_{ilqt} \mid I_{it}])}, \qquad j=\text{IBM, Apple},\ r=1,R$$

(20) $$\Pr(D_{i0t} = 1 \mid \theta, z_{it}, \tau) = \frac{\exp(\overline{V}_{it}^N)}{\exp(\overline{V}_{it}^N) + \sum_{l=1}^{2} \sum_{q=1}^{R} \exp(E[\overline{U}_{ilqt} \mid I_{it}])},$$

where θ denotes the complete set of model parameters, z_{it} is the vector or perceptions errors (z_{ijt} for j=IBM, Apple), and τ is the consumer's latent type.

We turn next to the expressions for the information choice probabilities. Let M_{imt} be a dummy variable equal to 1 if consumer i chooses information acquisition option m at time t. For convenience, rewrite equation (16) as:

(16') $$V_{imt}(I_{it}) = \overline{V}_{imt}(I_{it}) + \xi_{imt} \qquad m=1,32$$

where:

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

We assume the vector of stochastic terms (ξ_{i1t}, …,$\xi_{i,,32,t}$), which is revealed to the consumer at the start of period *t*, but which is unobserved by the econometrician, is distributed i.i.d extreme value. This again generates multinomial logit choice probabilities of the form:

$$\text{(21)} \qquad \Pr(M_{imt} = 1 \mid \theta, z_{i,t-1}, \tau) = \frac{\exp(\overline{V}_{imt}(I_{it}))}{\sum_{l=1}^{32} \exp(\overline{V}_{ilt}(I_{it}))}, \qquad m=1,32$$

Note that, by our timing conventions, $z_{i,t-1}$ is the vector of quality perception errors at the start of period t, prior to gathering any additional information.

Given (19)-(21), along with the equations in sections III.2 and III.3 that characterize the distributed of reported price expectations and quality perceptions, the likelihood contribution for consumer *i* at time *t*, <u>conditional</u> on his/her quality perceptions and latent type can be written:

$$\text{(22)} \qquad L_{it}(\theta, z_{it}, z_{i,t-1}, \tau) = L_{1it}(\theta, z_{i,t-1}, \tau) L_{2it}(\theta, z_{it}, \tau) L_{3it}(\theta, z_{it}, \tau) L_{4it}(\theta)$$

where the L_1, L_2, L_3 and L_4 components correspond to information choices, purchase decisions, reported quality ratings, and reported price expectations, respectively, and are given by:

$$\text{(23)} \qquad L_{1it}(\theta, z_{i,t-1}, \tau) = \prod_{m=1}^{32} \Pr(M_{imt} = 1 \mid \theta, z_{i,t-1}, \tau)^{M_{imt}}$$

$$\text{(24)} \qquad L_{2it}(\theta, z_{it}, \tau) = \Pr(D_{i0t} = 1 \mid \theta, z_{it}, \tau)^{D_{i0t}} \prod_{j=1}^{2} \prod_{r=1}^{R} \Pr(D_{ijrt} = 1 \mid \theta, z_{it}, \tau)^{D_{ijrt}}$$

$$\text{(25)} \qquad L_{3it}(\theta, z_{it}, \tau) = \Pr(q_{ijt} = L)^{I[q_{ijt} = L]} \Pr(q_{ijt} = M)^{I[q_{ijt} = M]} \Pr(q_{ijt} = H)^{I[q_{ijt} = H]}$$

$$\text{(26)} \qquad L_{3it}(\theta) = \prod_{j=1}^{2} \frac{\exp(\nu_{ijt}^{2} / 2\sigma_{\nu}^{2})}{(2\pi)^{1/2} \sigma_{\nu}}$$

where ν_{ijrt} in (26) denotes the measurement error term in the price forecasting equation (5), while the response probabilities in (25) were given in equation (14).

The (conditional) likelihood for consumer *i*, using data from all 6 survey waves, is then:

$$\text{(27)} \qquad L_i(\theta, z_i, \tau) = \prod_{t=1}^{6} L_{it}(\theta, z_{it}, z_{i,t-1}, \tau)$$

where z_i denotes the entire sequence of consumer *i*'s perception errors for both technologies.

Since the econometrician does not observe either z_i or τ, we must integrate them out as follows:

$$L_i(\theta) = \sum_{\tau=1}^{2} \lambda_\tau \int_{z_i} L_i(\theta, z_i, \tau) f(z_i) dz_i \tag{28}$$

where λ_τ is the population type proportion of consumer type τ, and $f(z_i)$ denotes the joint density of the perception errors. We know from section II.3 that $f(z_i)$ is a multivariate normal density, with a rather complex intertemporal variance-covariance pattern governed by (11) and (12).

Unfortunately, z_i is a 12-vector (there are 6 periods and two perception errors each period – one for each technology) so the integral over z_i in (28) is 12-dimensional. The evaluation of such an integral by traditional methods is computationally impractical. Thus, we adopt the simulated maximum likelihood (SML) approach, using 100 draws from the z_i distribution to simulate the integral (see, e.g., Lerman and Manski (1981), Pakes (1987), McFadden (1989), Keane (1993)). This simulator is smooth, so a gradient-based method can be used to maximize the simulated log-likelihood function. We used the Quasi-Newton method with line search. In conjunction with this method, the BHHH algorithm is employed to approximate the Hessian.

VI. The Survey Data

In order to estimate the proposed model, we sought to construct a representative sample of consumers throughout the U.S. who were in the market for a personal computer. Potential panel members were first contacted in September 1995 by telephone using random digit dialing. They were invited to participate in the panel if they met the following criteria: 1) they stated they were extremely or very likely to buy a PC for their home 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. Of 7,733 contacted individuals, 345 passed the screening process and were invited to participate in the panel.

The duration of our survey was based on prior information concerning the time that a typical consumer spends making a PC purchase decision. Marketing managers at the PC manufacturer we were working with estimated the purchase cycle for a personal computer to be on average six months. Thus, in an attempt to capture the entire process for the majority of our panel, we decided to collect data over a period of nine months.

Starting in October 1995 and ending in June 1996, panel members were asked to complete six surveys, approximately one every seven weeks. To reduce attrition we provided a variety of incentives to retain panel members. Panelists were paid $5 dollars for each completed survey. Of the 345 individuals who received the first wave survey, 300 responded. However, we eliminated 19 individuals due to missing information, leaving a sample size of N=281.

Table 1 describes the socio-demographic characteristics of the sample. The panelists tend to have a higher level of education (61% possess an undergraduate or graduate degree), and a higher income level (80% reported annual income between $35,000 and $80,000), than the average American. The panel members reported their levels of computer expertise as 34% "novices," 52% "intermediate abilities," and 14% "experts." Slightly less than half the sample (45%) reported this was their first time purchasing a personal computer.

In each survey, respondents were asked about their search activity since the last survey, and whether they had yet made a PC purchase. They were re-surveyed at 7-week intervals until they report a purchase, at which point detailed information on the configuration, brand, and price were obtained. Once a purchase is reported, data collection on the individual ceases.

The top panel of Table 4 shows choice distributions by wave. That is, it shows how many panelists were interviewed in each wave, and, of these, how many purchased an IBM/compatible or Apple PC in each wave. "Wave 1" refers to the October 1995 survey. Interestingly, there are no purchases in this wave, suggesting that the panelists tended to be at a relatively early stage of the search process when they were selected for the project. This is a good thing from our perspective, since we would like to capture search from an early stage.[9]

"Wave 2" refers to the second survey that respondents completed roughly seven weeks later.[10] Note that, since no purchases were reported in wave 1, all 281 panelists were surveyed again in wave 2 (with no attrition). Of these 281 panelists, 19 bought an IBM and 1 bought an Apple PC during period covered by the second wave survey. In the absence of sample attrition, there should therefore have been 261 panelists surveyed in wave 3. However, as we see in Table 4, only 245 responded, giving a 6% attrition rate in wave 3. Attrition rates in the subsequent three waves were 10%, 9% and 17% respectively.

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[9] On the other hand, it must be admitted that, unlike the other waves, the initial survey was sent out only 3 to 4 weeks after panelists were selected (and then had to be returned within two weeks). This creates a bias towards not finding as many purchases in the first wave as in subsequent waves, since a respondent who had made a purchase 5 or 6 weeks prior to the first survey could have been screened out of the panel during the initial phone interview.

[10] We say "roughly" because respondents were allowed to return the survey within a two-week window. A respondent who returned the survey immediately would tend to have had a shorter gap since the previous survey.

Overall, the statistics in Table 4 indicate that, of the 281 original panelists, 102 made no purchase by the end of wave 6, while 98 had bought a PC, and 81 had left the sample due to attrition. Thus, attrition affects 29% of the original panelists. Given that the project's duration was almost 10 months and that the survey required at least 15 minutes of the panelist's time, we view this is a relatively good retention rate. Comparing the characteristics of subjects who attrite vs. those who stay in the sample in each wave, we do not find evidence of significant differences.

The second panel of Table 4 presents attrition-adjusted calculations of the number of panelists making each choice in each wave. That is, we treat the purchase hazard presented on the right-hand side of the top panel as given, and adjust the sample size in each wave for attrition. These calculations imply that, in the absence of attrition, 119 out of the original 281 panelists would have made a purchase by the 6th wave survey. In other words, if the purchase hazard was the same for those who attrite as for those who remained in the survey, 21 out of the 81 attritors would have made a purchase by the 6th wave. This calculation implies that 40% of the respondents have made a purchase by wave 6, which is 10 months after the original survey. This suggests that managers we interviewed may have underestimated typical search durations.

In each survey we asked panelists if, during the previous 7-week period, they had gathered information about PCs through: (1) store visits, (2) articles in general publications, (3) articles in computer publications, (4) advertising and (5) word-of-mouth. Our questions were phrased in such a way as to try to capture active search, as opposed to purely passive exposure to signals. For example, regarding articles in general publications, we asked: "Have you spent any time reading articles on computer information in newspapers, general purpose magazines or consumer guides?" And, regarding advertising, we asked: "Have you spent any time reading advertisements about computers in newspapers, computer magazines, general purpose magazines, or viewing TV commercials?" Thus, we asked if respondents had actually *spent time* reading articles or reading/viewing ads, as opposed to merely being casually exposed to them.

We also asked panelists about their quality perceptions for both the IBM compatible and Apple technologies. To construct a measure of perceived quality, respondents were asked to rate each technology on 7-point Likert disagree-to-agree scales for the following five items: 1) "will meet my needs for a long time to come," 2) "is user friendly," 3) "is powerful," 4) "has a large number of software titles," and 5) "all components operate together without any problems (hardware, software, peripherals)." Factor analysis suggested that the five items measured a unidimensional construct. Thus, we constructed an overall quality measure by averaging the five items. We report the reliability of the quality construct, as measured by the Cronbach's alpha, in Table 2. The alpha coefficients imply a high level of reliability and a high level of internal consistency for the items. This is consistent across technologies and waves of the panel.

Recall that we incorporate in the likelihood whether a consumer reports a "low," "medium" or "high" quality level for each technology in each period (see equation (14)). Taking our 7-point quality scale, we classified values in the [1-3), [3, 5] and (5,7] intervals as low, medium, and high, respectively.

Finally, we also needed to collect data on actual and expected prices. We have already described the construction of the price expectation data at some length in Section III.2, so we will not repeat that here. We will instead describe how we constructed the actual realized price indices for each technology in each period. Recall that the (inverse) price indices π_{jt} for j=IBM, Apple that we need to construct are normalized to 1.0 at t=1 (i.e., in the first wave). Thus, we need to construct measures of how prices changed from each wave to the next.

In order to measure how PC prices moved over the sample period, we first looked at the PC configurations that panelists reported they were considering in the first wave. We matched these with retail prices obtained from industry data to measure their prices. We then chose 5 representative configurations that cost approximately \$1500, \$2000, \$2500, \$3000 and \$3500 in October 1995, one each for IBM and Apple. Next, we used industry data to examine how prices of each configuration moved over the sample period. Using a sales weighted average of the configuration prices, our calculations implied that prices fell approximately 10% from October 1995 through June 1996. This translates into a 15% annual rate, which is quite close to the 16% annual rate that consumers expected on average.

A 15% price decline may seem small, but it is important to note that this refers to the price of an entire configuration, not just the CPU. According to National Income and Product Account (NIPA) data, PC prices fell by 31% from 1995 to 1996, but the price of terminals was flat, while that of storage devices fell only 13%, and that of other peripheral equipment fell 22%. The NIPA data also show that price declines for PCs, monitors, memory and other peripheral equipment accelerated substantially beginning in 1997, after our sample period had ended.

The five discrete dollar amounts noted above were also what we assumed as the elements of agents' discrete consumption choice set $\{P_1, \ldots, P_R\}$ in solving and estimating the model.

VII. Empirical Results

VII.1. Parameter Estimates

Table 3 reports the simulated maximum likelihood estimates of our model parameters. We start by discussing the price expectation process parameters. To facilitate interpretation it is useful to rewrite equation (6) in terms of prices (rather than the inverse price indices):

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

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

Our estimate of θ_0 is 0.041. Thus, if price were constant from *t*-2 to *t* (zeroing out the 2nd and 3rd terms), consumers would expect a 4.1% price decline from *t* to *t*+1 (i.e., over the next 2 months).

Since our estimate of θ_2 is negative and larger in absolute value than $\theta_1+\theta_2$, our estimated expectations process implies that consumers expect mean reversion in price changes. The process implies a steady state expected rate of price decline of 2.5% per two-month period. Since consumers expect mean reversion, if prices had declined at a rate that was greater (less) than 2.5% from *t*-2 to *t*, then consumers would expect a price decline of less (more) than 2.5% over the next two months. The expectations process implies a 16% annualized rate of expected price decline, which is similar to what actually occurred (see Section VI).

The estimate of the standard deviation of measurement error for reported price change expectations (i.e., the σ_ν in equation (5)) is 0.088, implying substantial measurement error in consumers' reports of their own expectations. Our estimate of the perceived standard deviation of future price changes around consumers' point expectations (i.e., the σ_π in equation (6)) is 0.076. Thus, consumers perceive substantial volatility in price changes around their means.

Next we discuss the parameters that determine expected utility conditional on purchase (see eqn. (4)). The price coefficient is statistically significant and positive, implying the conditional indirect utility function is decreasing in price, as we would expect. The estimates of the equation for the utility weight parameter, $\beta_i = \beta_0 + \tilde{\beta} X_i$, indicate that consumers get more utility from home computer capabilities if they are: 1) more experienced with computers, 2) older, 3) less educated,[11] and 4) male. The effect of income on the utility weight is statistically

[11] The age variable was entered as Age/35. The education variable ranged from 0 to 6 (for the seven ascending categories listed in Table 1. This was entered as education/6, giving a variable ranging from 0 to 1.

insignificant. 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.

The parameter α was normalized to 1.0 (without loss of generality) for identification. Note that we cannot identify α, the scale of the quality variables Q_j, and the scales of the prior and signal standard deviations, at the same time. For instance, one could double α while halving the Q_j, halving the prior standard deviations σ_{j0}, and halving all the signal standard deviations σ_k. This would halve the σ_{ijt} in (4), and leave expected utility unchanged. Since we resolve this identification problem by normalizing α, the extent of risk aversion is subsumed in the scale of the quality measures and the scale of the prior and signal standard deviations. This does not alter the behavioral implications of the model.

We also had to normalize the constant term in the β_i equation. While technically identified, the likelihood was quite flat over a range of values for this parameter and the same set of quality level and quality variance parameters discussed above. A first order Taylor series expansion of the utility function in (2) around Q=0 gives $U(Q) \approx \pi P \beta Q - \gamma P + \varepsilon$. This suggests that it may be difficult to distinguish the scale of β from the scale of the Q's, which is indeed what we find. Thus, we normalized β_0 =1.

The equation for the No-purchase utility implies, as one would expect, that the No-purchase utility is higher for individuals who already own a computer. Furthermore, older people, women and lower income people have a higher No-purchase utility than younger people, men and higher income people. Education and experience do not have a statistically significant effect on No-Purchase Utility.

We turn next to the estimates of the quality of each technology. Recall that we allow for two latent types of consumers in terms of their match quality with each technology. Our estimates imply that consumers who belong to the first latent segment perceive a higher match quality for the IBM compatible technology, while type 2 consumers prefer the Apple technology. However, the first segment constitutes 88% of the population, implying 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 prior quality uncertainty in this market. Note that the prior uncertainty for Apple is larger than for IBM. Since the Windows platform is more widely used than the Apple platform, consumers presumably have more prior exposure to information about IBM compatibles.

Table 3 also reports the estimated characteristics of each of the five information sources. The estimates imply that store visits provide the most precise information. Word-of-mouth is the next most accurate information source. Articles in computer magazines, articles in general publications, and advertising provide the noisiest information.[12]

In regard to costs associated with information sources, the estimates imply that store visits are the most costly way to gather information. The least costly method is word-of-mouth. Interestingly, reading articles in computer magazines is estimated to be quite a bit more costly than reading computer articles in general publications, or reading ads.

VII.2. Model Fit

Table 4 provides evidence on how the model fits the data on purchase decisions. The top panel of the table describes the data itself. It reports the sample proportion of consumers who make each choice (No-purchase, IBM, Apple) in each 7-week period (or "wave"). The second panel provides attrition adjusted estimates of the choice frequencies, as discussed in section IV.

The bottom panel of Table 4 reports simulated choice frequencies based on our estimated model. We simulated choice paths for 2000 hypothetical consumers, and then re-based the statistics from this simulation to an initial sample size of N=281 (for comparability with the observed data). We refer to the bottom panel of Table 4 as the "baseline" simulation of the model. We extend the simulation for 12 waves, which corresponds to roughly $12 \cdot 7 = 84$ weeks, or about 20 months. Since the data used in estimation extend for only 6 waves, the first 6 waves of the simulation are an in-sample forecast, while the last 6 waves are an out-of-sample forecast.

To see how the model fits the data, one needs to compare the middle and bottom panels of Table 4. The model fits most of the broad features of the data rather well. After 6 waves, or roughly 10 months, the model predicts that 39.9% of consumers would have bought an IBM (or IBM compatible) computer, while 1.9% would have bought an Apple. The corresponding figures in the data are 40.2% and 2.1%, respectively.

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[12] During the estimation process, we decided to set the precisions for advertising, general sources and computer sources to be equal. We were having numerical difficulties in trying to pin down all three of these terms separately, and we could not reject a specification where these three channels had equal signaling variances.

A striking feature of the data is the clear positive duration dependence in the purchase hazard. The no-purchase frequency declines almost monotonically from 100% in wave 1, to 92.9% in wave 2, …, to 89.5% in wave 5, and to 85% in wave 6. The model captures this overall pattern rather well. For instance, it predicts a no-purchase rate of 93.0% in wave 2, falling gradually to 89.7% in wave 5, and these figures are very close to the actuals.

The model predicts that 5.7% of consumers buy in wave 1, whereas, as we discussed in section IV, no survey respondents reported buying during the first wave.[13] Of course, any model with a significant stochastic component to choice behavior would likely have difficult generating such an extreme outcome in a particular period. In addition, the model somewhat overstates the no-purchase rate in wave 6 (89.2% vs. 85% in the data). Thus, the model somewhat understates the degree of positive duration dependence that we see in the data. However, given sampling error in the sample purchase frequencies, the discrepancies do not appear to be serious.[14]

Table 5 provides evidence on how the model fits the data on search behavior. The layout of this table is just like Table 4, except that the choices now are whether or not to utilize each of the 5 information sources in each wave. Again, the model fits the broad features of the data reasonably well. The model slightly underpredicts the extent of search. For instance, it predicts that, over the first 6 waves, households visit a store in 36.2% of the periods, whereas in the data the frequency of store visits is 40.1%. This pattern of under-predicting the utilization rate by about 3 or 4 percentage points holds across all five information sources.

The model accurately predicts the relative utilization of each information source. The most widely used source is word-of-mouth (66.5% utilization in the data vs. 62.1% in the model), while the least utilized source is articles in computer magazines (38.9% utilization in the data, vs. 35% in the model). Of course, these utilization differences are generated by the differential costs and precisions of the information sources, as estimated in Table 3.[15]

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[13] As we discussed earlier, the first wave interview came only a few weeks after the screening interview, so any consumer who bought 5 to 7 weeks before the first survey would have been screened from the data set. This would have biased downward the number of purchases in wave 1, but we abstracted from this in setting up our model.

[14] The standard error on the 85% sample frequency for wave 6 is 2.6%.

[15] An interesting question is how the model can distinguish if one information source is less utilized than another because it is more expensive or less accurate (or some combination of both). The distinction would obviously not be identified (absent strong functional form assumptions) using data on information source utilization alone. However, our estimation brings two additional sources of information to bear: purchase decisions and stated quality ratings. If an information source is more accurate than another, quality ratings will be more likely to move, and perceived risk of a brand will be more likely to fall (implying a greater increase in the purchase hazard), after that source is visited.

Another striking feature of the data is negative duration dependence search intensity. For instance, the percentage of consumers who gather information via store visits drops from 64.4% in wave 1 to 29.2% in wave 6. The model predicts a decline from 60.5% to 25.5%. Thus, aside from the tendency to under-predict utilization by a few percent in each period, the model captures the time path of utilization very well. The same is true for all five information channels.

One reason for search intensity to fall over time is that the marginal value of search tends to fall as consumers acquire more information. This is a direct consequence of the Bayesian variance updating formula (equation 11), which implies that each additional signal has a smaller variance reducing effect. That is, if N_k denotes the number of signals received from source k, then $\partial\sigma^2 / \partial N_k = -\sigma^4 / \sigma_k^2$, and this is decreasing in N_k since σ^4 is decreasing in N_k.

But this can't be the whole story, because this intuition is purely static. In a dynamic setting, negative duration dependence in search intensity seems to contradict the flavor of results in Moscarini and Smith (2001), to the effect that search should be concentrated into the period just prior to making a decision. Basically, if one discounts the future, it doesn't make sense to engage in costly search today, and then delay a decision for several periods. But two factors alter this logic in the present context: price fluctuations and taste shocks. Intuitively, in our model, it makes sense to acquire good information about brand attributes quickly, enabling one to form a clear idea of which brand one prefers. One may then delay purchase until one sees a good price for the preferred brand, or until one receives a good positive taste shock.

Of course, an alternative explanation for negative duration dependence in search intensity is a compositional effect. Specifically, those consumers who search less intensely may stay in the market longer. However, this story does not seem consistent with the data. Fixed effects logit models for whether a consumer utilizes an information source in each wave show negative time effects, similar in magnitude to the patterns in Table 5. Compositional effects are not important in the model either. We only allowed for unobserved heterogeneity in consumer preferences for Apple vs. IBM, and negative duration dependence is present for each type separately.

VIII. Counterfactual Experiments

In this section we present a number of counterfactual experiments designed to clarify the nature of consumer behavior implied by the model. These experiments are all based on simulated choice histories for 2000 hypothetical agents. These agents are presented with the same random draws for the stochastic terms of the model as were the 2000 hypothetical agents used in the baseline simulation reported in the bottom panels of Tables 4 and 5. Thus, any differences in choice behavior between the experimental treatments and the baseline model simulation will be due entirely to differences in the economic environment.

VIII.1. Effects of Expected Price Declines and Learning on Purchase Delay

The first set of experiments is designed to examine the roles of expected price declines vs. learning in generating purchase delay. The top panel of Table 6 presents a simulation where, in each wave *t*, consumers assume that the mean of the price distribution will remain at the present level for all future periods. That is, we modify equation 7 so that, at time *t*, consumers' subjective expectation of the distribution of future prices is given by:

$$ln\ \pi_{j,t+k} \sim N(ln\ \pi_{jt}|\sigma_\pi^2) \quad \text{for j=IBM, Apple, } k=1,2,\ldots,T$$

where π_{jt} is the current price index. Note that consumers still expect prices to fluctuate over time, according to the variance σ_π^2, but they no longer expect a downward trend in prices. Another way to describe this experiment is that we set $\theta_0 = \theta_1 = \theta_2$ in equation 6.

According to the top panel of Table 6, taking away the expectation of a downward trend in prices results in acceleration of purchases. The purchase hazard shifts up in the first 6 periods, stays about the same in periods 7-9, and shifts down in periods 10-12. The percentage of consumers predicted to buy by the end of wave 6 increases from 41.8% (see Table 4) to 46.3%. But the percentage of consumers who are predicted to buy by the end of wave 12 remains almost unchanged (81.6% vs. 81.9%). Note, however, that positive duration dependence in the purchase hazard remains strong even under this counterfactual experiment. Thus, most of the positive duration dependence in the hazard does not appear to be due to the expectation of falling prices.

We don't find this relatively small effect of expected price declines on purchase timing surprising for two reasons. First, as we noted earlier, another factor inducing positive duration dependence in the purchase hazard is simply that prices do fall over time, a factor that would be present even in a static model. Second, learning is another source of duration dependence.

The bottom panel of Table 6 reports the results of an experiment designed to evaluate the role of learning in generating purchase delay. In this experiment, we implement a substantial increase in the cost of search. Specifically, we increase the cost visiting all five information sources by 60%. Making learning more expensive leads to a noticeable flattening of the purchase hazard. While the hazard rises from 5.7% in wave one to 20.1% in wave 12 under the baseline (an increase by a factor of 3.5), the increase under the experiment is from 5.2% to 14.4% (a factor of only 2.8). Making learning more expensive also shifts the purchase hazard downward, leading to lower computer sales overall. The percentage of consumers who buy by the end of 6 waves is predicted to decline from 41.8% (see the bottom panel of Table 4) to 38.5%, while the percentage predicted to buy by the end of wave 12 drops from 81.6% to 73.7%.

Conversely, a reduction in search costs, which leads to more search, accentuates the positive duration dependence in the purchase hazard. Thus, our results imply that both expected price declines and the desire to gather information both contribute to purchase delay.

VIII.2. How Price Expectations Affect Price Elasticities of Demand

In this section we present two experiments designed to examine how price expectations affect demand elasticities. Recall that our estimates of consumers' subjective price expectation process imply that consumers expect a steady state rate of price decline of roughly 2.5% per two-month period, and that they expect mean reversion in price declines. Thus, if price were to fall by some much larger amount in a particular wave, consumers would expect a price rebound in the following wave. This should augment the demand response to the price cut. In Table 7 we report two experiments designed to evaluate the magnitude of this type of effect.

In the top panel of Table 7, we simulate the effect of a 20% transitory price cut for both IBM and Apple in wave 2, holding prices fixed in all other waves. In this experiment, consumers are assumed to form expectations according to our estimates of their subjective price expectations process. As a result, since the 20% price decline in wave 2 is so unusually large, consumers expect a price rebound in wave 3. Our estimates imply that the price cut induces the percentage of consumers who buy in wave 2 to increase from 7.0% (baseline model) to 11.7%. This is a 67% increase in sales, implying a short run price elasticity of demand with respect to a transitory price cut of roughly 3.4.

In the bottom panel of Table 7, we report the results of an experiment in which prices are cut by 20% in wave 2, but expectations are held fixed. That is, consumers' expectations of the price decline from wave 2 to waves 3, 4, …, T are held fixed at their pre-experimental levels. In other words, consumers view the dramatic price decline in wave 2 as a one time structural break in the price process, which will have no bearing on future price changes. Our estimates imply that this type of price cut induces the percentage of consumers who buy in wave 2 to increase from 7.0% to 10.2%. This 46% increase in sales implies a short run price elasticity of demand with respect to a transitory price cut, holding expectations fixed, of roughly 2.3.

Thus, our results imply that expectations play a major role in how consumers respond to a price change. The elasticity of demand with respect to a transitory price cut is nearly 50% greater if we incorporate how the price cut alters consumers' expectations of future price changes than if we hold those expectations fixed (i.e., 3.4 vs. 2.3). This suggests that static models may potentially give rather misleading estimates of price elasticities of demand. It also suggests that estimates of demand elasticities in dynamic models could be quite sensitive to our assumptions about expectations, thus highlighting the importance of collecting subjective expectations data.

Another issue that the simulations in Table 7 address is the extent to which a temporary price cut leads to purchase acceleration vs. incremental sales. That is, to what extent does the price cut simply cannibalize future sales? Comparing the baseline simulation (Table 4) with the experiment (Table 7), we see that the price cut induces 12.4 additional consumers to buy in wave 2. Looking further out, we see that 117.3 consumers buy a PC by the end of wave 6 in the baseline, compared to 127.3 in the experiment, an increase of 10.0.[16] Thus, by wave 6, 10.0 out of 12.4, or 80%, of the additional period 2 sales induced by the price cut represent incremental sales, while only 20% represent cannibalization of sales from waves 3 through 6.

This story changes if we extend the analysis through to the terminal period (wave 12). 229.3 consumers buy a PC by the end of wave 12 in the baseline, compared to 233.9 in the experiment, an increase of 4.6. Thus, by wave 12, only 4.6 out of the extra 12.4 sales induced by the wave 2 price cut (or 37%) represent incremental sales.

It is also interesting to note the asymmetric affects of the price cuts on IBM Compatible vs. Apple sales. Under the baseline, the percentages of consumers predicted to buy IBM or Apple PCs by the end of wave 6 are 39.9% and 1.9%, respectively. With the 20% price cut (for both technologies) in wave 2, these figures increase to 42.7% and 2.6%. Thus, Apple sale increase 37% while IBM sales increase only 7%. This difference occurs in part because, in wave 2, Apple sale increase 100% while IBM sales increase 65%. But, in addition, the cannibalization of future sales is greater for IBM. In fact, the price cut slightly increases Apple sales in subsequent periods. This stems from the learning dynamics in the model. The substantial price cut in wave 2

[16] Recall that these figures are from a simulation of 2000 consumers, re-based to a population of N=281. That is why there are fractional numbers of consumers.

induces consumers to recognize it is a good period to buy. This encourages more search in period 2, so consumers learn more about Apple. Since prior uncertainty about Apple is greater, events that encourage more learning tend to favor Apple. This is discussed further in the next section.

VIII.3. How the Cost and Accuracy of Information Sources Affect Choice Behavior

In this section we examine how altering the cost and accuracy of the various information sources would alter choice behavior. Table 8 reports two experiments where search costs are reduced. In the top panel we reduce the cost of store visits, the most costly and most accurate information source, by 20%. This leads to an upward shift in the purchase hazard by roughly 1 to 2.5 points in all periods. In the baseline simulation (Table 4), 41.8% of consumers have bought by the end of wave 6, while under the experiment this increases to 48.1%.

In the bottom panel we reduce the cost of acquiring information through advertisements by 20%. Operationally, this might involve a manufacturer making its ads more readable or more easily accessible. This again leads to an acceleration of purchases, increasing the percentage of consumers who buy by the end of wave 6 to 46.0%. The effect is smaller than for store visits because reading advertisements is less expensive and provides less accurate information. Effects of reducing the costs of acquiring information from articles in general publications, articles in computer publications and word-of-mouth are similar, so we do not report them.

An interesting aspect of the experiments in Table 8 is that reducing the cost of acquiring information has a much more positive effect on Apple sales than on IBM sales. For instance, with a 20% decrease in the cost of acquiring information via a store visit, the percentage of consumers who buy an IBM or IBM compatible by the end of wave 12 increases from 77.5% to 78.7%, while the percent that buy an Apple increases from 4.1% to 6.2% (a 50% increase). However, the asymmetric positive effect for Apple is much less dramatic when we reduce the cost of gathering information via advertisements (which increases Apple sales from 4.1% to 4.7%), and the same is true for the other three information channels (not reported). This is presumably because these alternative channels are less costly and less accurate than store visits.

Table 9 reports a set of experiments where we increase the accuracy of the information sources. This again leads to an upward shift in the purchase hazard. Increasing the precision of information provided by store visits by 20% increases the percentage of consumers who buy by the end of wave 6 from 41.8% (baseline) to 49.6%. The percentage of consumers who buy by the end of wave 12 increases from 81.6% (baseline) to 85.3%. The effect on sales is again proportionately much greater for Apple than for IBM, with Apple sales by the end of wave 12 rising from 4.1% to 7.0%. Results for the other information sources are similar.

Thus, we find that making information more freely available, either by lowering the cost or increasing the accuracy of signals, favors the Apple platform. This occurs because consumers have much greater prior uncertainty with respect to the match quality of the Apple platform.

IX. Conclusion

We have estimated a dynamic model of how consumers learn about and choose between different brands of PCs, with an emphasis on the choice between the IBM Compatible and Apple/Macintosh technologies. Our work extends recent work on estimation of Bayesian learning models of consumer choice behavior in environments characterized by uncertainty about brand attributes. Specifically, while several authors have estimated models of passive learning about brand attributes, the present paper is, to our knowledge, the first attempt to estimate a model of active learning – i.e., a model in which consumers make optimal sequential decisions about how much information to gather prior to making a purchase.

Our work also makes two methodological contributions. Following the suggestion of Manski (2003), we collected data on consumer price expectations and used these data to model consumers' price expectation process. To our knowledge, this is the first time that a dynamic structural model has been estimated using such an approach in lieu of the typical rational expectations assumption.[17] Also, following the suggestion of McFadden (1989a), we incorporate stated brand quality information into our likelihood function, rather than modeling only revealed preference data (i.e., data on purchases and observed search behavior).

Our analysis has shed light on how consumer choice behavior is influenced by both forward-looking price expectations and the process of learning about quality. A key finding is that estimates of <u>dynamic</u> price elasticities of demand – i.e., demand elasticities that account for how a price change today alters expectations of future price changes – exceed estimates that ignore the expectations effect by roughly 50%.

[17] There has been prior work using data on expectations to predict choice behavior in choice models that are static, or that can be interpreted as reduced form approximations to the optimal decision rules from dynamic models. Examples include Delevande (2003), who models how expected effectiveness of different birth control methods affects choice of method, and Lochner (2003), who models how expected apprehension probabilities affect decisions to engage in criminal activity.

This occurs because our estimated expectations formation process implies that consumers expect mean reversion in price changes. That is, if there is an exceptionally large price cut today, consumers expect a price rebound tomorrow. This enhances the incentive to buy now.

Our findings highlight the more general point that estimates of demand elasticities from static models, or estimates from dynamic models that make incorrect expectational assumptions, can be quite misleading. To the extent that demand elasticities are sensitive to how consumers form price expectations, it becomes important to collect data on expectations to learn more about how they are formed.

Finally, while our work has focused specifically on the PC market and on the choice between Apple and IBM compatible technologies, the modeling approach we develop here should be useful for studying a wide range of high-tech, high-involvement durable goods markets where active learning about different technologies is important.

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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	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

Price Process Parameters			**Utility Parameters (continued)**		
Price Process Coefficents			No Purchase Utility Coefficients		
θ_0	0.041	(0.012)	Constant	3.917	(1.258)
θ_1	1.239	(0.163)	Ownership of Computer	0.149	(0.061)
θ_2	-0.958	(0.194)	Experience	0.009	(0.049)
σ_ν	0.088	(0.013)	Age	0.644	(0.278)
			Education	-0.019	(0.089)
Measurement Error Std. Dev.			Gender	0.543	(0.245)
σ_π	0.076	(0.043)	Income	-0.294	(0.124)
Utility Parameters			**Information Search Process Parameters**		
Price Coefficent	0.478	(0.193)	Prior Std.Dev. of Quality Perception		
			IBM	0.927	(0.160)
Risk Aversion Coefficient	1.000	-	Apple	2.071	(0.350)
Discount Factor	0.995	-	Variability of Information		
			Store Visit	1.977	(0.659)
Utility Weight			Ads and Articles	4.741	(1.976)
Constant	1.000	-	Word of Mouth	3.128	(1.325)
Experience	0.479	(0.238)			
Age	0.207	(0.103)	Information Costs		
Education	-0.734	(0.257)	Store Visits	1.415	(0.123)
Gender	0.639	(0.283)	General Articles	0.642	(0.088)
Income	-0.670	(0.399)	Computer Articles	1.137	(0.175)
			Advertising	0.379	(0.052)
Quality Coefficients			Word of Mouth	0.318	(0.057)
Mean Quality(IBM)[a]	0.891	(0.397)			
Mean Quality(Apple)[a]	-0.891	-	**Quality Perception Interval Coefficients**		
Mean Quality(IBM)[b]	-0.275	(0.125)	IBM-Left	-1.741	(0.267)
Mean Quality(Apple)[b]	0.275	-	IBM-Right	2.867	(0.419)
			Apple-Left	-3.217	(0.569)
Latent Class Probabilities			Apple-Right	2.433	(0.388)
1st Latent Class	0.879	(0.155)			
2nd Latent Class	0.121	-			

[a] 1st Latent Class
[b] 2nd Latent Class

Note. Values enclosed in parentheses represent standard errors.

TABLE 4

Sample Frequencies vs. Model Simulation: Purchase Behavior

Sample frequencies

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	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

Attrition Adjusted Sample Frequencies

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	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	261	240	19	2	91.8	7.3	0.8
4	240	213	26	1	88.6	10.9	0.5
5	213	191	22	0	89.5	10.5	0.0
6	191	162	27	2	85.0	14.2	0.8
Total	281	162	113	6	57.7	40.2	2.1

Model Simulation - Baseline

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	265.1	13.3	2.6	94.3	4.7	0.9
2	265.1	246.6	17.3	1.2	93.0	6.5	0.5
3	246.6	226.1	19.8	0.6	91.7	8.0	0.3
4	226.1	204.5	21.2	0.4	90.5	9.4	0.2
5	204.5	183.5	20.9	0.2	89.7	10.2	0.1
6	183.5	163.6	19.7	0.2	89.2	10.7	0.1
Out of Sample							
7	163.6	142.4	19.5	1.8	87.0	11.9	1.1
8	142.4	120.7	20.3	1.4	84.8	14.2	1.0
9	120.7	100.9	18.7	1.1	83.6	15.5	0.9
10	100.9	81.1	19.0	0.9	80.3	18.8	0.8
11	81.1	64.8	15.6	0.6	80.0	19.3	0.8
12	64.8	51.8	12.6	0.5	79.9	19.4	0.8
First 6	281	163.6	112.1	5.2	58.2	39.9	1.9
Total	281	51.8	217.8	11.5	18.4	77.5	4.1

TABLE 5

Sample Frequencies vs. Model Simulation: Search Behavior

Sample Frequencies

		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	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

Attrition Adjusted Sample Frequencies

		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	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	261	87	107	92	140	144	33.5	41.2	35.5	53.9	55.5
4	240	91	103	98	143	137	38.1	43.1	41.1	59.9	57.4
5	213	60	84	69	101	123	28.4	39.5	32.7	47.5	58.0
6	191	55	79	65	93	120	29.2	41.7	34.2	49.2	63.3
Total	1467	589	653	570	828	975	40.1	44.5	38.9	56.4	66.5

Model Simulation - Baseline

		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	281	170	164	139	189	231	60.5	58.4	49.5	67.3	82.2
2	265	88	103	81	155	179	33.2	38.9	30.6	58.5	67.5
3	247	71	92	83	129	126	28.7	37.2	33.6	52.2	51.0
4	226	83	84	78	125	123	36.7	37.2	34.5	55.3	54.4
5	205	51	72	57	89	106	24.9	35.1	27.8	43.4	51.7
6	184	47	65	55	81	109	25.5	35.3	29.9	44.0	59.2
Out of Sample											
7	164	42	59	46	70	98	25.6	36.0	28.0	42.7	59.8
8	143	35	47	40	58	76	24.5	32.9	28.0	40.6	53.1
9	122	29	39	34	46	62	23.8	32.0	27.9	37.7	50.8
10	102	24	36	27	41	50	23.5	35.3	26.5	40.2	49.0
11	82	19	27	23	31	40	23.2	32.9	28.0	37.8	48.8
12	65	16	21	19	26	32	24.6	32.3	29.2	40.0	49.2
First 6	1408	510	580	493	768	874	36.2	41.2	35.0	54.5	62.1
Total	2086	675	809	682	1040	1232	32.4	38.8	32.7	49.9	59.1

TABLE 6

Simulated Effects of Changing Price Expectations and Raising Search Costs

A. Consumers Expect No Downward Trend in Prices

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	263.7	14.4	2.8	93.8	5.1	1.0
2	263.7	241.5	20.1	2.2	91.6	7.6	0.8
3	241.5	217.2	22.9	1.3	90.0	9.5	0.5
4	217.2	193.6	22.8	0.8	89.1	10.5	0.4
5	193.6	171.2	21.9	0.5	88.4	11.3	0.3
6	171.2	150.9	20.0	0.3	88.1	11.7	0.2
Out of Sample							
7	150.9	131.4	18.1	1.4	87.1	12.0	1.0
8	131.4	111.2	19.0	1.1	84.6	14.5	0.9
9	111.2	92.2	17.7	1.3	82.9	15.9	1.2
10	92.2	75.8	15.8	0.7	82.2	17.1	0.7
11	75.8	62.1	13.1	0.5	82.0	17.3	0.7
12	62.1	50.9	10.9	0.3	81.9	17.5	0.6
First 6	281	150.9	122.2	7.9	53.7	43.5	2.8
Total	281	50.9	216.7	13.4	18.1	77.1	4.8

B. Increase Search Cost 60%

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	266.3	13.3	1.4	94.8	4.7	0.5
2	266.3	248.0	17.3	1.0	93.1	6.5	0.4
3	248.0	228.2	19.1	0.7	92.0	7.7	0.3
4	228.2	209.3	18.5	0.4	91.7	8.1	0.2
5	209.3	190.8	18.3	0.2	91.1	8.7	0.1
6	190.8	172.8	18.0	0.1	90.5	9.4	0.0
Out of Sample							
7	172.8	154.4	17.5	0.9	89.4	10.1	0.5
8	154.4	135.7	17.9	0.8	87.9	11.6	0.5
9	135.7	117.6	17.5	0.7	86.6	12.9	0.5
10	117.6	100.8	16.3	0.5	85.7	13.8	0.5
11	100.8	86.4	14.0	0.4	85.7	13.9	0.4
12	86.4	74.0	12.2	0.3	85.6	14.1	0.3
First 6	281	172.8	104.5	3.7	61.5	37.2	1.3
Total	281	74.0	199.8	7.3	26.3	71.1	2.6

TABLE 7

Price Cut Simulations

A. 20% Price Decline in Wave 2 - Total Effect

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	265.1	13.3	2.6	94.3	4.7	0.9
2	265.1	234.2	28.4	2.5	88.3	10.7	1.0
3	234.2	214.4	18.8	1.0	91.6	8.0	0.4
4	214.4	192.8	21.1	0.6	89.9	9.8	0.3
5	192.8	172.6	19.8	0.4	89.5	10.3	0.2
6	172.6	153.7	18.7	0.2	89.1	10.8	0.1
Out of Sample							
7	153.7	133.4	18.5	1.8	86.8	12.0	1.2
8	133.4	112.8	19.3	1.4	84.5	14.4	1.1
9	112.8	93.9	17.8	1.1	83.2	15.8	1.0
10	93.9	75.0	18.1	0.8	79.9	19.2	0.9
11	75.0	59.5	14.9	0.6	79.4	19.8	0.8
12	59.5	47.1	11.9	0.5	79.1	20.1	0.8
First 6	281	153.7	120.0	7.3	54.7	42.7	2.6
Total	281	47.1	220.4	13.5	16.8	78.4	4.8

B. 20% Price Decline in Wave 2 - Expected Future Price Changes Held Fixed

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	265.1	13.3	2.6	94.3	4.7	0.9
2	265.1	237.9	25.1	2.0	89.8	9.5	0.8
3	237.9	218.2	19.1	0.6	91.7	8.0	0.3
4	218.2	197.0	20.7	0.6	90.3	9.5	0.3
5	197.0	176.7	20.1	0.2	89.7	10.2	0.1
6	176.7	157.5	19.0	0.2	89.2	10.7	0.1
Out of Sample							
7	157.5	137.1	18.8	1.7	87.0	11.9	1.1
8	137.1	116.2	19.6	1.3	84.8	14.3	1.0
9	116.2	97.1	18.1	1.0	83.5	15.6	0.9
10	97.1	77.9	18.3	0.8	80.3	18.9	0.9
11	77.9	62.2	15.1	0.6	79.8	19.4	0.8
12	62.2	49.6	12.1	0.5	79.7	19.5	0.8
First 6	281	157.5	117.3	6.2	56.1	41.7	2.2
Total	281	49.6	219.2	12.2	17.6	78.0	4.3

TABLE 8

Simulated Effects of Decreasing Search Costs

A. 20% Decrease in the Cost of a Store Visit

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	258.1	18.2	4.7	91.8	6.5	1.7
2	258.1	233.9	21.4	2.7	90.6	8.3	1.0
3	233.9	209.6	22.7	1.6	89.6	9.7	0.7
4	209.6	187.4	21.3	1.0	89.4	10.1	0.5
5	187.4	165.6	21.2	0.6	88.4	11.3	0.3
6	165.6	145.8	19.3	0.5	88.1	11.7	0.3
Out of Sample							
7	145.8	125.1	18.9	1.9	85.8	12.9	1.3
8	125.1	104.8	18.8	1.5	83.8	15.0	1.2
9	104.8	86.1	17.5	1.2	82.1	16.7	1.1
10	86.1	68.8	16.4	0.9	79.9	19.0	1.1
11	68.8	54.6	13.6	0.7	79.3	19.7	1.0
12	54.6	42.4	11.7	0.4	77.7	21.5	0.8
First 6	281	145.8	124.1	11.0	51.9	44.2	3.9
Total	281	42.4	221.0	17.6	15.1	78.7	6.2

B. 20% Decrease in the Cost of Gathering Information from Advertising

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	261.4	15.6	3.9	93.0	5.6	1.4
2	261.4	239.5	20.1	1.8	91.6	7.7	0.7
3	239.5	216.2	22.4	0.9	90.3	9.4	0.4
4	216.2	194.5	21.1	0.5	90.0	9.8	0.2
5	194.5	172.2	22.0	0.3	88.5	11.3	0.2
6	172.2	151.8	20.2	0.2	88.1	11.7	0.1
Out of Sample							
7	151.8	130.8	19.4	1.6	86.1	12.8	1.1
8	130.8	110.0	19.5	1.3	84.1	14.9	1.0
9	110.0	91.5	17.6	1.0	83.1	16.0	0.9
10	91.5	73.5	17.2	0.8	80.3	18.8	0.8
11	73.5	58.9	14.0	0.6	80.2	19.0	0.8
12	58.9	47.3	11.2	0.4	80.3	19.0	0.7
First 6	281	151.8	121.5	7.7	54.0	43.2	2.7
Total	281	47.3	220.4	13.3	16.8	78.4	4.7

TABLE 9

Simulated Effects of Making Information Sources More Accurate

A. Store Visit - 20% Increase in Precision

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	256.7	18.7	5.6	91.4	6.6	2.0
2	256.7	231.5	21.7	3.5	90.2	8.5	1.4
3	231.5	206.9	22.9	1.7	89.4	9.9	0.7
4	206.9	183.3	22.6	1.0	88.6	10.9	0.5
5	183.3	161.4	21.2	0.7	88.1	11.5	0.4
6	161.4	141.7	19.2	0.5	87.8	11.9	0.3
Out of Sample							
7	141.7	121.1	18.7	1.9	85.4	13.2	1.3
8	121.1	101.0	18.6	1.5	83.4	15.3	1.2
9	101.0	83.3	16.5	1.2	82.5	16.4	1.2
10	83.3	66.2	16.1	0.9	79.5	19.4	1.1
11	66.2	52.4	13.2	0.7	79.1	19.9	1.0
12	52.4	41.4	10.6	0.4	79.0	20.2	0.8
First 6	281	141.7	126.2	13.1	50.4	44.9	4.7
Total	281	41.4	219.9	19.7	14.7	78.3	7.0

B. Advertising, Articles in General and Computer Publications - 20% Increase in Precision

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	256.3	18.0	6.7	91.2	6.4	2.4
2	256.3	230.2	22.5	3.6	89.8	8.8	1.4
3	230.2	204.3	24.2	1.7	88.7	10.5	0.7
4	204.3	179.4	23.9	1.0	87.8	11.7	0.5
5	179.4	156.7	22.0	0.6	87.4	12.3	0.3
6	156.7	136.5	19.8	0.4	87.1	12.6	0.3
Out of Sample							
7	136.5	116.3	18.5	1.7	85.2	13.6	1.2
8	116.3	96.8	18.2	1.3	83.3	15.6	1.1
9	96.8	78.6	17.2	1.0	81.2	17.7	1.1
10	78.6	62.3	15.6	0.8	79.2	19.8	1.0
11	62.3	49.2	12.5	0.6	79.0	20.1	0.9
12	49.2	38.2	10.5	0.5	77.6	21.4	1.1
First 6	281	136.5	130.5	14.0	48.6	46.4	5.0
Total	281	38.2	222.9	19.9	13.6	79.3	7.1

C. Word-of-Mouth - 20% Increase in Precision

		Number of Purchases			Percentage of Purchases		
Wave	Sample Size	No Purchase	IBM	Apple	No Purchase	IBM	Apple
1	281.0	261.3	15.2	4.5	93.0	5.4	1.6
2	261.3	235.4	23.5	2.5	90.1	9.0	1.0
3	235.4	209.9	24.4	1.1	89.2	10.4	0.5
4	209.9	185.8	23.5	0.6	88.5	11.2	0.3
5	185.8	163.1	22.3	0.4	87.8	12.0	0.2
6	163.1	142.3	20.6	0.2	87.2	12.6	0.1
Out of Sample							
7	142.3	121.5	19.3	1.5	85.4	13.6	1.0
8	121.5	101.5	18.9	1.1	83.5	15.5	0.9
9	101.5	84.0	16.6	0.9	82.7	16.4	0.9
10	84.0	68.1	15.3	0.7	81.0	18.2	0.8
11	68.1	55.0	12.5	0.5	80.8	18.4	0.7
12	55.0	44.6	10.0	0.4	81.1	18.2	0.7
First 6	281	142.3	129.5	9.2	50.6	46.1	3.3
Total	281	44.6	222.1	14.3	15.9	79.0	5.1