Measuring the Digital Divide:

Structural Estimation of the Demand for Personal Computers

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<u>Abstract</u>

This paper estimates a structural model of demand for the personal computer (PC) in order to evaluate the drivers of the "Digital Divide." Taking advantage of a large dataset on household-level PC purchases, the econometric model incorporates dynamic optimization, observed and unobserved heterogeneity, and the presence of a (sunk) learning cost incurred by first-time purchasers. The model therefore provides estimates of the differences in the marginal value for quality across different demographic groups, different consumer types, and an estimate of the difference in costs faced by upgraders and those who have not yet purchased a PC. These estimates allow for counterfactual evaluation of how demand would shift in response to a change in the rate of PC quality improvement, and allows for an assessment of the impact of policies designed to close the Digital Divide, such as subsidies for first-time buyers. The main findings indicate that the marginal value of PC quality varies significantly across income, education, age, and household size – the value of an extra unit of quality (measured as 200 MHz) ranges from \$34 to \$392 in 1999 and \$0 to \$142 in 2001. The "learning" cost of buying a PC is estimated as \$2938 in 1999 and \$2234 in 2001. Further, PC owners are less sensitive to price and more sensitive to changes in the rate of PC quality improvement compared to non-owners. Finally, a short-term (one year only) subsidy of \$200 for first-time PC purchasers is estimated to increase non-owner demand (i.e. first time purchases) by approximately 60% while a long-term subsidy of the same magnitude will increase non-owner demand by approximately 10%. The evidence suggests that the Digital Divide results from the *interaction* between learning costs, persistent consumer heterogeneity and dynamic technological change in the personal computer industry.

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1. Introduction

The personal computer (PC) industry is a compelling topic of economic analysis for reasons beyond just its size (over $200 billion) and dynamism. Adoption (and repurchases) of PCs at the firm and household level has important effects on productivity and consumption. From the perspective of households, the adoption of a PC is a prerequisite to take advantage of powerful applications, ranging from education to searching for information about labor and financial markets, to more consumption-oriented activities such as digital photographic editing and interactive gaming.
In part because of the wide range of applications associated with PC adoption, policy makers have become increasingly concerned with the Digital Divide – the separation in opportunities between the owners of increasingly advanced PCs and those in the population who have not yet adopted.

The principal objective of this paper is to provide an empirical evaluation of the drivers of the Digital Divide. To do so, the paper incorporates both heterogeneity among consumers in terms of their valuation for personal computers and the presence of rapid (and sustained) technological progress within the PC industry. The interaction between consumer heterogeneity and technological dynamics has important empirical manifestations. Consider the differences between the first-time adoption of a PC versus the decision to upgrade from a prior generation. As can be seen in Table 1 (using household-level data which will be discussed more fully later in the paper), the probability of upgrading (purchasing a PC conditional on owning a PC already) is more than twice the probability of first-time adoption (20% versus 8% in 2001). From a revealed preference perspective, these data suggest that the marginal utility of an upgrade for many households is greater than the marginal utility of crossing the Digital Divide. Moreover, over time, the Digital Divide may widen as PC owners continue to upgrade their capabilities while those without a PC continue to put off the initial adoption decision.

In this paper, I construct a model of demand for the PC industry that can replicate the above empirical facts and remain consistent with an economic theory of durable goods purchases. The three main components of PC demand included in my model are heterogeneity, set-up (or learning) costs, and dynamics. As of this writing, no model of PC demand has yet incorporated all three of these components[2].

The first component is the presence of heterogeneity which impacts a household's propensity to buy a PC. Households differ across observable demographic variables such as income, education, age, and household size. Each of these characteristics has been identified as relevant for explaining differences in ownership rates nationally (NTIA, 2002, 2000, 1999). Households also differ in unobservable ways, such as a propensity for technology (i.e. some households are "techies"). As lovers of technology, techies strive to be on the technological frontier, and their buying patterns reflect this. Finally, households differ in their stock of PC holdings – some don't own a PC at all, and among those that do, the quality level of the PC holdings vary (a PC bought in 1995 is likely of much lower quality than one bought in 2000). Intuitively, households holding new, high quality computers will be, in general, less likely to purchase a new PC than those with old, low quality PCs, or those with no PC at all.

Second, learning costs account for the one-time fixed costs households incur when buying their first PC. Learning how to evaluate and use a PC's hardware, software, operating system, peripherals, etc. is a one-time cost of time and effort that is greatly reduced after the first purchase. Including this cost in the model provides a potential explanation why households already owning a PC purchase new PCs at a higher rate than those without one, since those who have not yet adopted face a high fixed cost of purchase.

Finally, the decision to adopt (or upgrade) a PC will depend on dynamics. As Rosenberg pithily suggested, "A decision to buy now may be, in effect, a decision to saddle oneself with a soon-to-be-obsolete technology."[3]. Households considering purchasing a new PC take into account future developments in the industry (i.e., quality improvements) and their expected future responses to those developments. A static model will have difficulty incorporating the possibility that a household experiencing a

[2] Two recent examples of PC demand models are Goolsbee and Klenow (2002) and Hendel (1999). In addition to several other differences, neither model is dynamic.
[3] He also noted that the rate of technological advancement of a product and the rate of adoption of that product can be very different, even negatively correlated.

net positive gain in utility from buying a PC in one period would wait to buy until the following period due to significant expected quality improvements in the PC[4].

Before describing my results, it's important to note the differences in descriptive and predictive power between this model and a static model such as the one used by Goolsbee and Klenow (2002), or Goolsbee (2001). First, the static models ignore the timing aspect of the purchasing decision. The expected likelihood of purchase for a given household may be miscalculated if deferred purchases due to better future options aren't taken into account. Second, static models are limited in their scope of analysis. A dynamic model can measure long-term elasticities for price and the rate of technological change, as well as the potential difference in impact between a short-term and long-term subsidy for first-time buyers; static models typically cannot.

I estimate a dynamic, discrete choice model incorporating (observed and unobserved) heterogeneity as well as learning costs using a rich household-level dataset covering PC adoption behavior in 1999 and 2001.[5] The estimates indicate that the marginal value for computer quality is positively related to income, the education of the head of household and household size, and negatively related to the age of the head of household. The marginal value of 200 MHz (my measure of a unit of quality) ranges from $34 to $392 in 1999 and $0 to $142 in 2001. Learning costs are estimated at $2938 in 1999 and $2234 in 2001. Further, techies (those who have a high valuation for cutting-edge technology) are estimated to comprise a significant, but declining, part of demand – falling from 27% to 8% between the two observation years.

These structural estimates allow counterfactual exercises in order to understand the impact of the rate of technological change and consumer heterogeneity on the Digital Divide. For example, the price elasticity for short-term and long-term price changes is higher for non-owners than owners (measured at 3.6 vs. 2.9 for short-term and 3.2 vs. 2.1 for long-term in 1999; 2.6 vs. 2.1 for short-term and 2.7 vs. 1.7 for long-term in 2001). As well, owners are estimated to be significantly more responsive than non-owners to

[4] Dynamics can also help explain the recent move to the low-end PC by households (beginning around 1997). Consider a household owning a "median" PC purchased in 1993 (i.e., the model costing approximately $2000) deciding what PC to purchase in 1997 (if any). The household may purchase the low-end PC while planning to purchase another in just two years because of anticipation of impending low (quality-adjusted) prices. This possibility in the PC market is built into a dynamic model but is missing in a static one.

[5] I focus exclusively on desktop PCs – the vast majority of PC purchases in the data set.

changes in the rate of technological progress. Specifically, if quality improvements change from doubling approximately every two years to doubling approximately every 1.5 years, owner demand falls by 6.4%, and non-owner demand falls by 4.2% in 1999; owner demand falls by 3.9%, and non-owner demand falls by .5% in 2001.

These estimates also allow us to evaluate the impact of potential policy changes to close the Digital Divide. For example, some have suggested that subsidies for first-time buyers may be an effective approach for narrowing the Divide. I consider the impact of two types of subsidy programs – (short-term) $200 subsidy which must be taken advantage of within one year, or the imposition of a permanent $200 subsidy. Because a subsidy with a limited time horizon has a more significant effect on the tradeoff between purchasing in the current period versus "waiting," I find that, whereas the permanent subsidy would only raise adoption by 10% in the first year, a short-term subsidy is estimated to raise the adoption rate by non-owners by more than 60%.

Of course, the estimates of any structural model depend ona number of assumptions, ranging from the discount rate to the functional form for utility to assumptions about the (expected) evolution of PC quality into the future. Interestingly, I find that while my core qualitative findings are robust across a variety of assumptions, incorporating dynamics into the PC purchasing decision is important. For example, not only does a model which incorporates dynamics and stock effects perform significantly better than a simple static model, but the estimates associated with a model which does not take account of stock effects are non-sensical. This suggests that accounting for stock effects is important for sensibly identifying the drivers of durable goods purchases when the vast majority of replacements are upgrades, not the result of the previous purchase wearing down or failing. Overall, by incorporating a detailed understanding of how PC purchasing decisions might vary across households and the importance of dynamic technical change, this paper offers a new perspective on the Digital Divide. In particular, the evidence suggests that the Digital Divide results from the *interaction* between learning costs, persistent consumer heterogeneity, and dynamic technological change in the personal computer industry.

The remainder of the paper is organized as follows. Section 2 describes the economics of personal computer purchases. Section 3 details an economic model of PC demand. Section 4 describes the data, and Section 5 presents the econometric model. Section 6 lists results and Section 7 concludes and suggests extensions.

2. The Economics of Personal Computer Purchases

As a high technology durable good with a well-defined architecture and a rapid but steady rate of technological progress, the PC serves as one of the great examples of diffusion over the past 200 years.

Diffusion theory points to the well-known sigmoid, or S-curve, to describe the standard process of adoption for a new durable good. We derive the curve by simply plotting ownership rates of the new product against time as in Graph 1. In the middle of this curve is the inflection point – this represents the time when adoption rates stop accelerating and begin to decelerate. For PCs in the United States, this inflection point almost certainly lies somewhere in the 1990s, 15% of American households owned a PC as of 1990 and 60% were PC owners by 2001 (NTIA, 2002).

When a new superior[6] product is introduced, the timing of adoption differs across households. A prominent explanation for this variation is household heterogeneity as described in a rank model of diffusion. Graph 2a illustrates how a basic rank model works. In the graph, households are distributed with different valuations for a new product. Over time, the price of the new product falls, so more consumers experience a net gain in purchasing the product as time passes. New adopters each period are those for whom the price just dropped below their valuation that period as highlighted in the graph.

For PCs, the prices have remained steady over the past decade [7], but the quality-adjusted prices have fallen dramatically[8]. If consumers have a valuation for PCs that is

[6] The PC is superior to the next best alternative along several dimensions – data storage, data processing, communication, etc.

[7] Prices have been predictably steady mainly due to high levels of competition among suppliers. The high level of competition since 1990 is attributable mainly to the open architecture of the PC beginning in the mid 1980s. The IBM PC (the dominant PC emerging from the 1980s) was "open" in that it used the technology of other firms, such as the microprocessor, operating system, software applications, and "plug-compatible" hardware, and in that "any user could add third-party hardware or software components" (Bresnahan and Greenstein, 1998).

[8] Even by 1980, the progress of the microprocessor already drew this comparison to the automobile industry by Computerworld magazine: "If the auto industry had done what the computer industry has done in the last 30 years, a Rolls-Royce would cost $2.50 and get 2,000,000 miles to the gallon" (Gordon, 1990).

increasing in quality but the rate of increase varies across the population, we'll see a similar phenomenon to that in Graph 2a. As quality increases over time, those with lower marginal values of quality for PCs will begin to adopt as illustrated in Graph 2b.

Heterogeneity in valuation of quality is one part of the theory behind the diffusion of PCs; however, another kind of heterogeneity also plays a significant role – stock. Since the value of a new PC is increasing over time, we have an aspect of the diffusion process distinct from that described in Graph 2a, multiple purchases. With an average turnover rate between 3 and 5 years, we see a large fraction of new PC purchases made by households already owning a PC as shown in Table 1. If we view multiple purchases as replacement decisions, a household already owning a PC will buy a new PC if the difference of value between a new PC and the one already owned is greater than the price of the new PC. If two households are identical except that one owns a low quality PC and the other owns a high quality PC, we'll likely see a period where the one with the low quality PC will re-adopt while the one with the high quality PC will stick with the one it already has.

Accounting for stock heterogeneity in explaining adoption and replacements is especially important if first-time adoption involves some level of fixed cost. First-time buyers of PCs must delve into a technological world of hardware, software, operating systems, and likely the Internet. For many, the first attempt at learning and working with these entities is costly. This cost plays a role in the adoption decision for a first-time buyer but drops to zero for those making a repeat purchase.

If we only incorporate the heterogeneity described above in a theoretical model of diffusion for a durable good such as the PC, we would treat all households as simply waiting until their value of a new PC (net learning costs and the value of a currently owned PC, if applicable) is higher than the price and then making a purchase. This ignores a key component of the dynamic "buy/wait" decision – expectations. The quality of PCs in the form of better processors[9], memory storage, peripheral devices, etc., has increased at a predictable rate for years now. Regarding adoption of durable goods with rapid technological progress, Rosenberg (1976) explains it well: "A decision to buy now

[9] Improvements of integrated circuits have followed Moore's Law. Moore's Law is the bold claim made in 1965 that the complexity of integrated circuits would double every two years. It was later revised to a doubling every 18 months.

may be, in effect, a decision to saddle oneself with a soon-to-be-obsolete technology." As a result, households must compare the net gain from buying a PC today to the net gain from waiting and buying a PC next period.

In summary, a model of adoption and replacement for PCs must include heterogeneity in marginal values of quality, heterogeneity in PC holdings (stock), fixed costs of first-time adoption, and the dynamic nature of the adoption decision (expectations).

3. An Economic Model of PC Demand

The Model

The model of adoption and replacement of PCs as described above is a dynamic model of PC demand. The previous section described the key factors in adoption and replacement; this section formally details these factors in a simple economic model and considers several hypotheses that such a model allows us to test.

We have a set of households, *I*, indexed by *i*[10]. Define one period of time to be a year, and let the per-period utility function for a given PC look as follows:

(1) $$u(z, q_{jt}, p_t(z, q_{jt}))$$

where: z is a vector of household characteristics.

q_{jt} is the quality level of the PC *j* at time *t*.

$p_t(z, q_{jt})$ is the price paid for PC *j* at time *t*.

The price is an increasing function of quality. The vector *z* accounts for heterogeneity across households in the population. Price also is a function of household characteristics, *z*, since *z* captures whether the household already owned a PC of quality *q* entering the period, which would set the price of owning that PC at zero. Otherwise, the

[10] For ease of exposure, this subscript will be omitted except when it is directly relevant.

household has to pay the market price for a PC of quality q. The utility function is decreasing in price and increasing in quality, but the rate of increase depends on household characteristics, z.

This model includes several dimensions of heterogeneity. First, it includes differences in income levels. The National Telecommunications and Information Association (NTIA) reports that, in 2000, only 15.1% of households earning less than $15,000 per year owned a PC compared to 88.3% of those earning $75,000 or more. Second, it includes differences in education. The NTIA reports that in 1998, 68.7% of Americans with a B.A. or more owned a PC compared to 7.9% of those with only an elementary school education[11]. Third, it includes age differences. In 1998, households headed by someone aged 35-44 years had the highest PC ownership rate at 54.9% while those headed by someone 55 or older had an ownership rate of 25.8%. Fourth, it includes differences in household size. Finally, it considers differences in technological savvy. This last measurement simply accounts for the fact that some households have a strong proficiency and liking of technology (techies) while others are averse to it (non-techies).

The above per-period utility function accounts for heterogeneity in stock holdings in a simple way. If, entering period t, a household i already owns a PC of quality q, its utility from that PC in period t is $u(z,q,0)$ [12]. If a household doesn't own a PC of quality q entering period t, its utility from a PC of quality q is $u(z,q,p_t(z,q))$.

The model includes learning, or set-up, costs in the above utility formulation in the following way. Let the per-period utility function be separated into two parts:

$$(2) \qquad u(z,q,p(z,q)) = a(z,q,p(z,q)) - c * I(q>0, "noPC" \in z)$$

Part of the household characteristics captured in z is whether that household purchased a PC in a prior period. In the above formulation, $I(.)$ is the identity function equaling 1 when the household purchases a PC never having owned one previously and 0 otherwise. So, c represents a constant fixed cost for buying a first PC.

[11] This comparison wasn't available for PCs in the 2000 report.

[12] Note that $p(z,q)=0$ if the household enters the period already owning the PC of quality q.

The households each have J_t PCs available from which to choose in any given period *t*. The size of the choice set, J_t, is at least two (it must include buy/don't buy), and is larger than two when we include more than one choice of computer for the household to purchase. In this model, the number of choices each period is set to be the same each period[13], $J = 4$. The household can choose "no PC" ($j = 1$), the low quality PC ($j = 2$), the median quality PC ($j = 3$), or the high quality PC ($j = 4$). Following the notation of Keane and Wolpin, the decision process is defined as $d_j(t) = 1$ if PC *j* is chosen in period *t*, and $d_j(t) = 0$ otherwise. These decisions are mutually exclusive, so we have $\sum_{j=1}^{J} d_j(t) = 1$ for all *t*. This yields a general per-period utility function of:

$$(3) \qquad \sum_{j=1}^{J} u(z, q_{jt}, p_t(z, q_{jt})) * d_j(t)$$

If their life spans were only one period, households would simply choose the option yielding the highest per-period utility among the four. However, households exist for much longer than one period and take into account improvements in the choice set in subsequent periods along with the possibility of replacement purchases in the future when making decisions in the present.

In this model, households are infinitely-lived entities,[14] and a state of the world, *s(t)*, for household *i* in period *t* is: the set of household characteristics *z* (which includes the PC already owned entering period *t*) and the PCs available to purchase in period *t*. It is assumed that there is no depreciation of the product over time since almost all PC

[13] The actual choice sets individuals will face each period will differ among individuals and over time since the choice set will depend on the PC you already own and the PCs available each period. However, the number of choices will remain fixed at 4. Note that PC characteristics depend explicitly on time since choice *j* in time *t* does not have the same characteristics as choice *j* in time *t+k*.

[14] Note that I'm not using a finite horizon as in Keane and Wolpin since my data is not conducive for this. The timing of the decision relative to the terminal period is relevant for the finite horizon model but such timing is difficult to evaluate with my data. Probably the best way to attempt to do this would be to use age as a measure of horizon length; however, this can still prove problematic since forecasts much beyond 6 years become difficult to envision in such a dynamic industry. Thus, if we allow a "cap" to exist on forecast length, an infinite horizon model actually makes more sense due to the fact that it is capable of "containing" all plausible finite horizon models one might find appropriate. I discuss the cap in the Results section.

replacements are made because the PC has fallen technologically behind, not because it broke down[15]. Regarding the evolution of the state of the world, we assume:

(**A1a**) The state of the world is a Markov process. That is:

$$\Pr(s(t+1) \mid \{d_j(t)\}_{j=1}^{J}, s(t), \{d_j(t-1)\}_{j=1}^{J}, s(t-1), \ldots) = w(s(t+1) \mid \{d_j(t)\}_{j=1}^{J}, s(t)).$$

(A1b) The probabilities of states of the world are deterministic. That is:

$w(s(t+1) \mid \{d_j(t)\}_{j=1}^{J}, s(t)) = 1$ for exactly one value of *s(t+1)* and 0 for all others for each conditioned event, $(\{d_j(t)\}_{j=1}^{J}, s(t))$.

The first part of the assumption states that determining the state of the world tomorrow only requires knowing the state of the world today. The second part implies all households know the path of evolution for the choice set for all periods. While this aspect of the assumption is quite strong, it is appropriate for the PC industry where the choices of PCs have been consistently predictable for at least a decade.

With the above definition of a state of the world along with a zero depreciation rate, we define a household's present value of utility as follows:

$$(4) \qquad V(s(t)) = \sup_{\Pi} E\{\textstyle\sum_{\tau=t}^{\infty} \delta^{\tau-t} \sum_{j\in J} u(z, q_{jt}, p_t(z, q_{jt})) * d_j(\tau) \mid s(t)\}$$

where: Π is an infinite sequence of decision vectors = $(\{d_j(t)\}, \{d_j(t+1)\}, \ldots)$.

$E\{.\}$ is the expectation operator.

δ is the constant discount rate.

Given A1a and A1b, we solve for V using Bellman's equation:

$$(5) \qquad V(s(t)) = \max_{\{d_j(t)\}_{j=1}^{J} \in \{0,1\}} [\textstyle\sum_{j\in J} u(z, q_{jt}, p_t(z, q_{jt})) * d_j(t) + \delta E[V(s(t), d_j(t))]]$$

[15] However, one can consider a "one hoss shay" model that allows for a very special kind of deterioration. I discuss this in the Extensions section.

where: $E[V(s(t),d_j(t))]$ is *V(s(t+1))* and *s(t+1)* is the state such that

$$w(s(t+1)\,|\,\{d_j(t)\}_{j=1}^{J},s(t))=1\,.$$

The present value of utility, *V(s(t))*, is the sum of discounted utility for a household entering period *t* with the state of the world *s(t)* taking into account the deterministic evolution of the state space and optimizing behavior in all future periods.

Households make their decisions each period based on *V*, not on *u*. That is, decisions are optimal in the long run since they take into account future developments in the industry and future decisions of the household[16]

Hypotheses

A model with the properties listed above is able to test many interesting hypotheses for the PC industry, some of which are unapproachable for a static model. At its early stages, new purchases certainly were driving the demand for the PC market. However, now that the PC is entering the latter portion of the sigmoid curve, it's likely no longer the case that the majority of buyers are first-time buyers. This leads to our first hypothesis:

Hypothesis 1: *The majority of new PC purchases now are made by repeat purchasers.*

The model also identifies which demographic groups are dominating PC purchases. Reduced form analyses (such as those by the NTIA) suggest four observable variables (income, education, age, and household size) are correlated with PC purchases but are unable to demonstrate their importance in one joint dynamic analysis. With this in mind, we formulate a second hypothesis.

[16] A common criticism of such a model as described here is that no household actually goes through the process of solving such a complicated expression when making a PC purchase; however, Rust (1988) makes an excellent point in this regard: "The agent may not literally solve the control problem in the sense of consciously performing the calculations involved, much the way a good pool player exploits the laws of physics without being consciously aware of these principles" (Rust, 1988). This comment reflects a similar logic used by Friedman regarding prices.

Hypothesis 2: *Income, education, age, and household size are correlated with PC valuation (and therefore are correlated with the propensity to buy a PC in a given period). Further, the correlations for income, education, and household size are positive while the correlation for age is negative.*

The technologically savvy, or techies, are defined above as those who find extra value in being on the technological frontier. These are the purchasers we often see buying the high quality PC with a high turnover rate. In the early years of the PC market, techies likely were the drivers of PC demand. Now that the PC has penetrated the majority of American households, the relative importance of techie demand certainly has diminished. Regarding the role in demand of techies, the model allows us to test the following hypothesis.

Hypothesis 3: *Techies are now an inconsequential component of PC demand.*

The above three hypotheses focus on the drivers of demand. On a deeper level, the model is able to measure price elasticity regarding long-term and short-term price changes as well the response of demand to changes in the rate of quality improvements. Further, we can consider differences in demand response to price changes and quality acceleration (or deceleration) between PC owners and non-owners. This leads to the next hypotheses.

Hypothesis 4: *Non-owners are more sensitive to price (short-term and long-term) than PC owners.*

Hypothesis 5: *PC owners are more sensitive to the rate of technological change than non-owners.*

Finally, this PC model can be used as a tool for policy analysis. While the purpose of this study is not to assess how to close the Digital Divide for PCs, it provides a new perspective on the effect of at least one potential instrument for closure – subsidies for new purchasers. To this end, we consider one final hypothesis.

Hypothesis 6: *Subsidies are an effective tool for increasing first-time PC purchases.*

With an appropriate data set and econometric model, we can address each of the above hypotheses empirically.

4. Data

Data Descriptions and Sources

The data for this analysis comes from Forrester Research, Inc. The firm privately collects large amounts of micro-level data that academic economists are only beginning to utilize[17]. Forrester collects approximately 100,000 household surveys each year. They ask questions about technological purchases, preferences, and attitudes. The survey provides information on the household's most recent desktop[18] PC purchase, such as price paid, when it was purchased, hardware specifications, brand, operating system, etc. Furthermore, the survey provides general household information such as income and family size. The survey response rate is typically between 58% and 68%, and the demographic distribution of the respondents is close to that of the nation as a whole[19].

Table 2 gives an overview of the demographic distribution of respondents in each data set (1998-99 and 2000-01). Households are distinguished along six dimensions: age of head of household, size of household, income, education of head of household, marital status, and market size. Since all the variables listed are either qualitative or measured in ranges, counts and percentages are used to illustrate each distribution.

[17] Goolsbee & Klenow (2002) being one notable exception.
[18] The data includes information on laptops as well; however, due to the significant differences between the desktop and laptop characteristics and the very low presence of laptop purchases compared to desktops, I didn't include laptops in this analysis.
[19] The sample does have a higher proportion of wealthy and educated households than the nation on the whole, but since these are observed variables, this fact alone won't bias the results.

So far, this information is insufficient for a replacement model since knowledge of a household's most recent PC purchase doesn't say anything about what that PC replaced. Therefore, we need at least two surveys from a household to garner any information about its replacement decision. Fortunately, Forrester surveys a number of households several times. The data has information on households who responded to the survey for 1998 and 1999 and households who responded to the survey in 2000 and 2001. Due to a change in data providers, there is no known overlap in the 1999 and 2000 surveys[20]. Overall, there are approximately 29,000 respondents for both 1998 and 1999 and 19,000 for both 2000 and 2001.

Using the overlapping data sets, for every household in the data set, we can see for one period whether a PC purchase is made and the PC stock of the household going into that period. For example, in the '98&'99 data, for a given household, we know from the '98 survey what PC the household owned going into 1999. Then, from the '99 survey, we can see if the most recent PC purchase changed from '98 to '99. If it did, assuming no reporting error, the most recent PC purchased in the '99 survey was purchased in 1999 and replaced the most recent PC purchase listed in the '98 survey. If there was no change, the household did not purchase a PC in 1999 and stuck with whatever it listed in the '98 survey.

The most notable shortcoming of the data is its inability to pin down the specifics of the PC purchased last by a household. The survey gathers information on the brand, processor (but only generally, such as Pentium III), operating system, hardware options, and such, but it doesn't allow us to directly see the processor speed and memory specifications. In the analysis that follows, we're interested in household choices with regard to "computing power," which boils down to choices mainly over specifics such as processor speed (MHz). While we don't observe these specifications, we do observe the price paid and the year of purchase. These observations allow us to make rough estimates as to what line of PC the household purchased (high, middle, or low). For example, if a household reports that it paid $2500 for a PC in 1995, we can infer that it likely had a processor of approximately 100 MHz. While this is a rough approximation,

[20] This is an unfortunate loss of data; however, for a potential analysis combining these data sets, it gives us confidence that there is little overlap between the '98&'99 households and the '00&'01 households - strong support for inter-temporal independence of error terms in a combined model.

the fact that the model only calls for coarse groupings of PCs makes it much less restricted than it seems.

Data from PC World Magazine allows us to make inferences about PC specifications from price and year of purchase. Data was collected back to 1992 using magazines from each year from 1992 to 2003. With this, we can build a list of prices matched with year and specifications. In each year, the cut-off between specifications for low, middle, and high end PCs is reasonably clear. I use a simple regression to establish the average price charged each year for the low, middle, and high quality PC, and then I also use these average prices to categorize the PC purchased in a given period if a purchase is made.

Table 3 gives an overview of the quality levels of PC holdings for each of the data sets. While the cut-offs to distinguish between low, middle and high quality each year in the model aren't exactly $1000 and $2000, these are more intuitive for a first glance and do well to provide a general picture of the distribution of PC holdings going into the respective years of 1999 and 2001 (the actual cut-offs are detailed in Table A1). From Table 3 we see there is a wide distribution in price paid and vintage of the PC holdings across households, indicating significant variation in the quality of PC holdings[21].

In summary, for each household and for one period, the Forrester Data along with price lists from PC World give us: the PC purchased in that period (or "no purchase"), the PC owned at the beginning of that period (or "no PC"), the price paid for the PC purchased in that period, and many demographic variables.

Preliminary Analysis

[21] One note of caution is in order for this table: the market share of low-end PCs increased in 1997, which corresponds to 2 year-old PCs for the 1999 data set and 4 year -old PCs for the 2001 data set. However, especially for the 2001 data set, the holdings of low-end PCs from 1997 are underrepresented since these are the PCs replaced more quickly – thus, many households who purchased a low-end PC in 1997 will have replaced it before 2001, meaning they'll report this new PC as their current holding with no reference to the 1997 purchase.

Before moving on to the results of the full model, some preliminary analysis motivates the consideration of heterogeneity in household characteristics and stock. Also, it paints a more lucid picture of the full details of the data set.

Table 3 combined with Graph 3 and Graph 4 demonstrates the importance of stock effects for PC purchasing behavior. As mentioned above, Table 3 shows there is a large amount of variation in quality of PC holdings entering 1999 and 2001. Graph 3 provides a summary of the vintages of PC stock holdings for new PC purchasers in 1999 and 2001. In this graph, we see that the majority (approx. 50% in 1999 and 60% in 2001) of new PC purchases were made by households already owning a PC aged three years or younger. Graph 4 uses my translations of price and year of purchase into quality levels[22] to measure the quality level of stock holdings (instead of just age) and then measures the probability of a replacement purchase in 1999 and 2001 for each of these levels. In this graph, we see the highest replacement rates among the lowest quality PCs as we would expect[23]. Overall, we see high turnover rates for PCs, variety in the quality level of PC holdings, and significant differences in the propensity to purchase a new PC across stock quality levels.

Tables 4a and 4b give a comprehensive summary of the variation in participation rates in the PC market across several demographic groups. We see that PC ownership is generally negatively correlated with the age of head of household (although roughly the same for under 35 and 35-49 groupings) and positively correlated with household size, income, the education of head of household, marital status, and market size[24]. Further, especially along the lines of the age of head of household, household size, income, and the education of head of household, we see these correlations also holding for new PC purchasing rates.

[22] For example, PC 7 corresponds to the top PC in 1996, the median PC in 1997, and the lowest PC in 1998.

[23] We do see a slight surge in replacement rates for PC 11 vs. PC 10 in 2001 and PC 9 vs. PC 8 in 1999. This may seem unusual since it essentially implies that those buying the highest level PC are replacing it the very next year. However, many of these households are likely the techies who want to be on the cutting edge of technology at all times. In fact, approximately half of these consumers buy at the high end again to replace their high end PC.

[24] As detailed in the Results section, I don't use measures of marital status and MSA in the formal model since the reduced-form correlations were weak and because they're both suspect of endogeneity problems.

The similarity in correlations between PC ownership and new PC purchases also implies that the segments of the population with higher PC ownership rates are the ones buying the majority of the new PCs. Tables 4a and 4b capture this more explicitly by breaking down the new PC purchasing rate for each subgroup of each demographic category into the new PC purchasing rate for those owning a PC and the new PC purchasing rate for those not owning a PC. For virtually every subgroup, we see a large gap in the rate of new purchases between PC owners and non-owners, affirming that the higher propensity to purchase a new PC as illustrated in Table 1 holds across demographic groups.

5. The Econometric Model

With a theoretical model and data set in hand, the task remains to estimate this model econometrically. A dynamic stochastic discrete choice (DSDC) model is the appropriate framework for this estimation process.

In general, DSDC models for durable goods solve out structural parameters for agents optimizing in expected value a discounted lifetime objective function (maximization of utility in this case). The agents choose an optimal sequence of decisions, and upon observing the agents and their choices, the parameters of the model are estimated (usually through maximum likelihood). These models widely have been acclaimed as the appropriate devices for describing consumer behavior in many markets, but they almost always have proven challenging or even unworkable due to large integrations required to solve them. However, the past twenty years have seen a great deal of progress in solution techniques using full solution and non-full solution methods[25] [26](see Rust, 1987, Pakes, 1987, Hotz and Miller, 1993, Hotz, Miller, Sanders, Smith, 1994). The model below follows Rust ('87 & '88) – a full solution model.

[25] See Eckstein and Wolpin ('89) for a good early survey.

[26] Topics studied in the literature include: job search (Wolpin, '87 and Miller, '84), patent renewal (Pakes, '86), bus engine replacement (Rust, '87), retirement (Berkovec and Stern, '91), fertility (Wolpin, '84), labor force participation (Eckstein and Wolpin, '86), electric heating and central air-conditioning equipment (Fernandez, '00), harvesting of timber (Provencher, '95), and shutting down nuclear power plants (Rothwell and Rust, '97).

The economic model described above is a deterministic one. That is, if we know *s(t)* for all *t* for a given household, we know exactly what decision that household will make every period. However, from the econometrician's perspective, we won't see every component of *z*, so the decision won't appear deterministic due to lack of information.

Beyond not knowing all components of *z*, we don't know the discount rate, δ, and we don't know the functional form of $u(.)$. Each of these issues is addressed below in reverse order.

The functional form for $u(.)$ must be assumed. Rust ('88) shows that $u(.)$ is non-parametrically unidentified in an econometric model, so any functional form for $u(.)$ is an assumption. For the remainder of this section, I assume that $u(.)$ is linear in its arguments. Specifically:

(6) $u(z, q_{jt}, p_t(z, q_{jt})) =$

$$[1 \;\; z_1 \;\; z_2 \;\; z_3 \;\; z_4 \;\; q_{jt} \;\; q_{jt}z_1 \;\; q_{jt}z_2 \;\; q_{jt}z_3 \;\; q_{jt}z_4 \;\; I(q_{jt} = top_t) \; -p(z_6, q_{jt}) \; -I(q_{jt} > 0, z_5 = 0)\;]*\theta$$

where: z_1 measures income.

z_2 measures education.

z_3 measures age.

z_4 measures household size.

z_5 equals zero if no PC had been purchased prior to period *t* and one otherwise[27].

z_6 is the quality level of the PC purchased most recently.

$I(q_{jt} = top_t)$ is the identity function equaling 1 if the PC with quality level q_{jt} is the high quality PC that period and 0 otherwise.

$I(q_{jt} > 0, z_5 = 0)$ is the identity function equaling 1 if buying a PC with quality level q_{jt} is the household's first PC and 0 otherwise.

[27] Note that the z's are vectors of dummy variables in the econometric model since we have categorical data.

θ is a column vector of parameters to be estimated[28].

The third last entry in θ is a measure of extra value from being on the "cutting edge" of technology for PCs – this is an increase in utility for the techies (a random coefficient described below). The second last entry in θ is the marginal utility of money, and the last entry in θ is the measure of the learning cost.

In the econometric model, the discount rate is theoretically identified, but difficult to pin down in practice (as described by Rust ('87) and Keane and Wolpin ('94)). The discount rate is assumed to be .9 for the remainder of this section; the robustness of this assumption along with the importance of a positive discount rate (dynamic vs. static) is tested in the Results section.

The components listed in the vector *z* above certainly aren't all the relevant household characteristics for PC valuation. Therefore, we can't deterministically know what choice a given household will make just based on *z*. To account for unknown "shocks" to the value of each choice, a random variable, η_{jt}, is included for each choice *j* in each period *t*. In doing so, the per-period utility function is now the following:

(7) $$U(z, q_{jt}, p_t(z, q_{jt}), \eta_{jt})$$

Further, the measure of technological savvy, or of being a techie, is unobservable. I account for this by allowing the coefficient on $I(q_{jt} = top_t)$, say θ_{top}, to take on two values, θ_{top}^H for techie and θ_{top}^L for non-techie, and p is the probability of being a techie for the population (i.e., $\Pr(\theta_q = \theta_q^H) = p$). Finally, I make a standard assumption that $\theta_{top}^L = 0$, so there is no extra utility from having the top PC (in addition to the value from its quality) for the non-techies.

With the above specifications, the value function now looks as follows:

(8) $$V_\theta(s(t)) = \sup_\Pi E\{\sum_{\tau=t}^{\infty} \delta^{\tau-t} \sum_{j\in J} U(z, q_{jt}, p_t(z, q_{jt}), \eta_{jt}) * d_j(\tau) \mid s(t), \eta_t, \theta\}$$

[28] Note that there is no loss of generality by not including interaction terms with price.

recall: Π is an infinite sequence of decision vectors = $(d_j(t), d_j(t+1), \ldots)$.

z is a vector of household characteristics described above.

q_{jt} is the quality level of the PC *j* at time *t*.

$p_t(z, q_{jt})$ is the price paid for PC *j* at time *t*.

η_t is a vector of utility shocks for each of the available PCs in period *t*.

θ is a vector of unknown parameters of the model.

s(t) is the set of household characteristics *z* (which includes the PC already owned entering period *t*) and the PCs available to purchase in period *t*.

At this point, I make three assumptions crucial for the solution process:

Assumption 2a (A2a): The joint stochastic process is a controlled Markov process. That is:

$$\Pr\{s(t+1), \eta_{t+1} \mid \{d_j(t)\}_{j=1}^{J}, s(t), \eta_t, \{d_j(t-1)\}_{j=1}^{J}, s(t-1), \eta_{t-1}, \ldots\} = w(s(t+1), \eta_{t+1} \mid \{d_j(t)\}_{j=1}^{J}, s(t), \eta_t, \theta)$$

Assumption 3 (A3): *U*(.) is additively separable:

$$U(z, q_{jt}, p_t(z, q_{jt}), \eta_\tau) = u(z, q_{jt}, p_t(z, q_{jt})) + m(\eta_\tau)$$

Assumption 4 (A4): Conditional Independence (CI). That is, the transition density of the controlled process $\{s(t), \eta_t\}$ factors as:

$$w(s(t+1), \eta_{t+1} \mid s(t), \eta_t, \{d_j(t)\}_{j=1}^{J}, \theta) = a(\eta_{t+1} \mid s(t+1), \theta) * b(s(t+1) \mid s(t), \{d_j(t)\}_{j=1}^{J}, \theta)$$

Assumption 2b (A2b): $b(s(t+1) \mid s(t), \{d_j(t)\}_{j=1}^{J}, \theta)$ equals one for exactly one value of *s(t+1)* and 0 for all other values for each conditioned event, $(s(t), \{d_j(t)\}_{j=1}^{J}, \theta)$.

Assumption 2a extends A1a from the model section above. The problem is a standard Markov decision process regarding both the state of the world and the random shocks. The state space and random shock tomorrow depend only on this year's state space and this year's shock – once we know what happened this year, the state of the world and random shocks prior to this year provide no additional information toward predicting tomorrow's realizations. Further, Assumption 2b replicates A1b – all households know the state of the world in period *t+1* once they know the state of the world in period *t*. This again implies that households know the evolution of the choice set in all subsequent periods.

Assumption 3 is self-explanatory, and from this point forward, I assume $m(\eta_t) = \eta_t$. Assumption 4 is the crucial conditional independence assumption. It implies that *q* and *z* are sufficient statistics for η; therefore, we can think of the random shocks as conditionally independent. Also, CI implies that the evolution of *q* doesn't depend on η[29][30].

With these assumptions, we can solve for the value function using well-known results from dynamic programming. Define $V_\theta(s(t))$ as the value function; then it is the unique solution to Bellman's equation:

$$(9) \qquad V_\theta(s(t)) = \max_{\{d_j(t)\}_{j=1}^{J} \in \{0,1\}} [\sum_{j \in J} U(z, q_{jt}, p_t(z, q_{jt}), \eta_{jt}) * d_j(t) + \delta E[V_\theta(s(t), d_j(t))]]$$

where:

$$(10) \qquad E[V_\theta(s(t), d_j(t))] = \int_S \int_\eta V_\theta(y) p(dy, d\eta \mid s(t), \eta_t, d_j(t), \theta)^{31} =$$

$$P * \int_\eta V_\theta(y) p(dy, d\eta \mid s(t), \eta_t, d_j(t), \theta)$$

where: *P* is transition matrix consisting of only zeros and ones.

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[29] The assumption of a deterministically evolving state space makes the second aspect of the conditional independence assumption trivially satisfied.
[30] This assumption is crucial for the solution technique described later to be manageable.
[31] Note that this integration will be over the realizations of the "shock" terms, η, and the possible set of PCs from which to choose. The integration over the shock terms is quite common but defining the probabilities for the possible new PC selections could be troublesome (but not impossible), which gives yet another reason why an assumption of deterministic evolution in this area is useful.

Recall from A2b that the state space is assumed to evolve deterministically, which explains why the transition matrix P has the form described above[32][33].

The number of states in the state space is infinite if the quality of new choices always increases with time and time extends to infinity. This makes the Bellman equation unworkable, so I assume the state space remains constant after a certain "cap" period set at 7 years into the future. The robustness of this assumption is tested in the Results section.

Price is assumed to be exogenous; it is completely determined by the quality level of the PC and whether the PC was bought in a previous period (price is zero if the PC was purchased in a previous period). This implies no unobserved quality. To justify this, I run a simple regression of price on observable quality in Table A2 and find observable quality explains 88% of the variation in price.

Recall that the choice set consists of four elements each period. Every period the price for these PCs stays the same (the choice of no new PC, $j = 1$, has price 0 every period), but the quality of the PCs at each price is improving over time. If we have the high quality PC priced at $3000, this represents a PC with 300 MHz of speed in 1997 while this represents a PC with 700 MHz of speed in 2000. The peculiar aspect of this choice set is that, while nominally the choice set remains the same each period, {1,2,3,4}, the PC implied by each choice changes over time.

I've broken the price component into discrete levels[34], and the other observed attributes of the PC are already in discrete form (e.g., MHz, my measure of quality, is in discrete form); this ensures that the space of PC choices is discrete.

Finally, I assume the error terms, η, have the type I extreme-value distribution, so they have unique mode at 0 and mean of .577.

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[32] The assumed path of technological evolution is detailed in the Appendix, Table A1.

[33] In Rust's and many others' more general models, they must estimate another set of parameters which play a role in the stochastic evolution of the state space. For example, in Rust's model of bus engines, the state space (mileage for an engine) evolved stochastically depending on whether the engine was replaced each period (i.e., the number of miles the bus is driven each period isn't deterministic). Technically, I can imagine the choices of computers evolving in a similar way since people can't know for certain what the available choices will be in future periods. However, assuming a deterministic evolution of the entire state space isn't too much of a stretch since consumer attributes obviously won't change, the PC purchased is clearly known, and the PCs from which to choose have been predictable over the past decade.

[34] Note here that there's no a priori obvious way to set the bounds for the price ranges. We'll simply choose natural boundary points (nice round numbers like 500, 1000, etc.) that coincide with average prices for the PC choices each period.

Now, the optimal choice in a given period assuming optimal choices in the future is:

(11) $$f(z,q_t,\eta,\theta)=\arg\max_{d\in\{1,2,3,4\}}[u(z,q_{dt},p_t(z,q_{dt}),\theta)+\eta_{dt}+\delta E[V_\theta(s(t),d)]]$$

Simply put, the agent each period is choosing which PC of the four possible choices yields the highest current period payoff plus discounted payoffs in the future assuming she will make optimal choices from tomorrow onward.

The data sample consists of a large number of households, N[35]. We observe each household for one period, and during this period, we see the household's attributes, the PC they own entering the current period[36], the PCs from which they can choose in the current period, and the choice they make in the current period[37]. From the assumptions above, the conditional probability of observing a choice of PC, say a, is the following:

(12)

$$\Pr(a\mid s(t),\theta)=$$

$$p*\frac{\exp\{u(z,q_{at},p(z,q_{at}),\theta^H)+\delta E[V_{\theta^H}(s(t),a)]\}}{\sum_{j\in\{1,2,3,4\}}\exp\{u(z,q_{jt},p(z,q_{jt}),\theta^H)+\delta E[V_{\theta^H}(s(t),j)]\}}+(1-p)*\frac{\exp\{u(z,q_{at},p(z,q_{at}),\theta^L)+\delta E[V_{\theta^L}(s(t),a)]\}}{\sum_{j\in\{1,2,3,4\}}\exp\{u(z,q_{jt},p(z,q_{jt}),\theta^L)+\delta E[V_{\theta^L}(s(t),j)]\}}$$

where: θ^H is the parameter vector where $\theta_{top}=\theta^H_{top}$

θ^L is the parameter vector where $\theta_{top}=\theta^L_{top}=0$.

[35] For this study, N can be 19,000, 29,000, or it can be 48,000 when the data sets are combined.
[36] This is inferred from the price paid and the year purchased as described in the Data section.
[37] We observe the purchasing behavior of each household all the way back to their most recent PC purchase since the survey asks what the last purchase was and when it was made; however, incorporating this whole string of choices for each household would bias our results as those who waited the longest between purchases would be weighted too heavily in the likelihood function. For example, if, in 1998, we have one family's most recent purchase in 1998 (thus, they replaced this period) and another's most recent purchase in 1994, then we would have just one observation for the 1998 purchasers while we would have four for the 1994 purchasers (they didn't purchase in 1995, 1996, 1997, and 1998). The family that waited longer for a new purchase would have more impact on the likelihood function.

Clearly, the coefficients on covariates that are constant for all choices (coefficients on 1, z_1, z_2, z_3, z_4) aren't identified in this model since they represent a "base" level of utility each household receives regardless of their choice, and this model only can identify differences among the choices. All other components of θ are identified under the structural assumptions. Variation in quality, price, and demographic characteristics allows us to identify the marginal utility of quality across demographic groups as well as the marginal utility of money. Also, variation in PC ownership (own/don't own) allows us to identify the "learning cost" of buying a PC for the first time, (the last component of θ). Finally, we're able to disentangle *p* from θ_{top}^{H} due to the assumed structure of the error term and because of their differing relationships in the per-period utility function and the $E[V_\theta(s(t), d_j(t))]$ term.

Now, with many thousands of observations, we are able to estimate the identified variables with reasonably high confidence.

Solution Overview

While the economics of dynamic discrete choice models is straight-forward, solving these models can be a challenge. For the solution process, several papers in the literature resort to "non-full-solution" methods where the authors avoid fully solving the contraction mapping (Hotz and Miller, 1993; Hotz, Miller, Sanders, and Smith, 1994). As this model follows the approach taken by Rust, it calls for a full-solution method where no simplification for the contraction mapping is used. The three key assumptions in the model which simplify it enough to allow for full-solution techniques are: a) the utility function is additively separable in the unobservables, b) the unobservables are conditionally independent, c) the unobservables have a type I extremum distribution.

In general, the solution process combines an "inner" fixed-point algorithm with an "outer" hill-climbing algorithm. Starting with an arbitrary guess for θ (the parameters of interest), we solve for the function $E[V_\theta(s(t), d_j(t))]$ - the fixed point of a contraction mapping determined by the Bellman equation. This is the inner part of the algorithm. Once we have $E[V_\theta(s(t), d_j(t))]$, we evaluate the likelihood function, and make another guess for θ. The next guess for θ is made using the downhill simplex method[38] by Nelder and Mead. This method requires no derivatives and generally finds global maxima of likelihood functions better than the quasi-Newton method used by Rust[39]. The sequential guesses for θ comprise the outer portion of the algorithm.

In summary, I used the simplex method to find my estimate for θ due to its superior performance in finding a global maximum, but I used Rust's techniques for deriving variances when estimating standard errors. This is because, regardless of the method used, the inference established in Rust (1988) still applies. In short, we have the standard result that $\sqrt{N}(\theta^M - \theta^*)$ converges weakly to $N(0, -H(\theta^*)^{-1})$ where θ^M is our estimate for the true θ, θ^*, and:

$H(\theta^*) = -E\{[\partial \log P(d_t \mid s(t), \theta^*) / \partial\theta][\partial \log P(d_t \mid s(t), \theta^*) / \partial\theta']\}$ (Theorem 4.2 from Rust).

The reader interested in the full details of the solution algorithm can find them in a separate Appendix B available upon request from the author.

6. Results

The Dynamic Model

The covariates in the estimated models include: MHz, price , income, education, age, household size, an identity function indicating whether the PC was the top quality PC of the observation year, and an identity function indicating whether the household was without a PC entering the observation year and purchased a PC in the observation year. I didn't include other quality measures such as RAM and ROM since they are both highly correlated with MHz, and the technological path of advancement for MHz does well in approximating the advancement in PC quality. Income, education, age, and household size are treated as qualitative variables, with cut-offs identical to the ones used in Table 2. I excluded marital status and location because both are likely endogenous,

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[38] This is commonly referred to as the "amoeba" algorithm.
[39] Each method can only claim to find local maxima, but the amoeba algorithm performs a "wider" search.

and they appeared to have a significantly smaller impact on PC decisions from the preliminary analysis.

Tables 5a and 5b list parameter estimates for the dynamic model with a discount rate of .9 along with estimates for a static model and one without stock effects. Since the dynamic model was the best fit for the data, I'll discuss the results and implications from that model and postpone comparisons across model specifications until the next subsection.

For both 1999 and 2001, we see that observed heterogeneity does explain at least part of the variation in PC valuations across households. Marginal value for quality is increasing in income, education, and household size, and decreasing in age. Specifically, households with the highest marginal values for PC quality in both years are those with an income over $100,000, education level of at least a college degree, age under 35, and household size of 3 or more. For these households, the value of an additional 200 MHz is $392 and $142 for 1999 and 2001, respectively [40]. Households with the lowest marginal values for PC quality in both years are those with an income under $20,000, education level less than a high school diploma, age over 60, and household size of 1. For these households, the value of an additional 200 MHz is $34 and $0[41] respectively[42]. Finally, first-purchase fixed costs are significant. They are $2938 and $2234 for 1999 and 2001, respectively.

From the above results, we can accept Hypothesis 2. Further, the model not only verifies the qualitative relationship between the demographic variables and PC purchases, but it quantifies this relationship as well.

The remainder of this subsection analyzes demand and demand elasticity. In general, we calculate demand as:

$$(13) \quad \sum_{s(t)\in S(t)} N_{s(t)} \sum_{a=2}^{4} \Pr(a \mid s(t))$$

[40] Note that marginal values are calculated by taking the sum of the relevant coefficients, dividing by the marginal utility of money, and multiplying by 100 (since price was divided by 100 in solving the model).
[41] The actual value is slightly less than 0. Since it doesn't significantly differ from zero and a negative marginal value isn't sensible, I've rounded it to 0.
[42] The cost of 200 MHz in 1999 was approximately between $250 and $450 and in 2001 was between $100 and $200.

where: $N_{s(t)}$ is the number of households in state s(t)

In what follows, $N_{s(t)}$ is determined by the makeup of the data set[43]; the results in this subsection can be extended to populations with differing demographic proportions by modifying $N_{s(t)}$ appropriately.

Regarding Hypothesis 1, we use (13) to calculate: $\frac{D_{owners}}{D_{non-owners}}$. This value is 3.73 in 1999 and 10.13 in 2001. These numbers indicate that repeat purchases already exceeded new purchases in 1999, and they've grown to approximately 90% of all household PC purchases by 2001. From this and the results in Table 1, we can accept Hypothesis 1.

We calculate the proportion of demand attributable to the techie population in a similar way. Specifically, we find the ratio of demand by techies to total demand: $\frac{D_{techie}}{D_{total}}$. In calculating this value, we find that techies make up 27% of demand in 1999 and 8% of demand in 2001. The results in Tables 5a and 5b indicate that the increase in value from owning the highest quality PC for techies stayed virtually constant between the two years (approximately \$1600 - \$1800), but the proportion of households behaving like techies declined. This significant drop in the proportion of techies from 1999 to 2001 is likely partially due to the recession in 2001. Overall, these numbers indicate techies still are a notable component of PC demand, especially since high quality PCs usually have the highest margins resulting in higher profits for suppliers. It follows that Hypothesis 3 is false – techies do still matter in demand analysis for PCs.

Regarding price elasticity, the dynamic model allows consideration of demand response to short-run and long-run changes in price. From Table 6a, for 1999, we see that a short-run 10% decline in prices results in a 36% increase in demand for non-owners and a 29% increase in demand for owners; and in 2001, a short-run 10% decline in prices results in a 26% increase in demand for non-owners and a 21% increase in demand for owners. A long-run 10% decline in prices results in a 32% increase in

[43] As a result, the estimates for demand are likely biased upward for the American population as a whole since the average income of the data set is higher than that of the country.

demand for non-owners and a 21% increase in demand for owners for 1999; and for 2001, a long-run 10% decline in prices results in a 27% increase in demand for non-owners and a 17% increase in demand for owners. As expected, long-run changes in price have a smaller impact on present demand than short-run changes. The difference between demand response to long-term and short-term price changes highlights the value of incorporating dynamics into the analysis. Further, these results indicate that non-owners are generally more price sensitive; therefore, we accept Hypothesis 4.

Regarding changes in the rate of technological advancement, I've measured the response of demand to an increase in the rate of quality improvement from doubling just under every two years to doubling just under every 1.5 years[44]. Further, since the rate of technical change typically won't fluctuate in the short term, I considerthe response of demand to the technological acceleration beginning one year in the future and continuing. From Table 6b, if quality increases are expected to accelerate one year in the future, demand for non-owners falls by 4.2%, and demand for owners falls by 6.4% in 1999; this same expectation causes demand for non-owners to fall by .5%, and demand for owners to fall by 3.9% in 2001. If the acceleration is expected more than one year into the future, demand response is almost negligible. From these numbers, we see that the dynamic model is able to capture forward-looking behavior of the households – if the PCs over the next few years are going to be much better than the options in the present year, waiting to buy becomes a more appealing option. Further, we see that owners are more sensitive to changes in the rate of technological advancement than non-owners leading us to accept Hypothesis 5.

This model also allows us to analyze public policy designed to increase PC ownership. One possible tool to achieve this end is a subsidy. Table 7 shows the changes in demand for non-owners corresponding to short-term and long-term subsidy plans for first-time purchases. As we would expect from a dynamic model, short-term subsidies induce the largest short-term change in non-owner demand[45] since forward-

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[44] Specifically, if quality doubles every 2 years, we can write the general formula as $q = 2^{t/2} q_0$ where q_0 is the initial quality level. To accelerate the process in my model, I multiply quality by $2^{3t/10}$. Since the rate of doubling of quality was just under 2 years, this adjustment makes the rate of doubling fall just under 1.5 years.

[45] The demand for owners is obviously unaffected by these subsidies.

looking households recognize that the present year is the only chance to capitalize on the lower prices. Specifically, we see that a short-term subsidy of $100 increases demand for non-owners by nearly 30% for both years, and a short-term subsidy of $200 increases demand for non-owners by over 60% for both years. In the long-term, these subsidies increase demand by only approximately 5% and 10% respectively for both years. Again, the incorporation of dynamics in the model allows us to account for the forward-looking behavior of households evident in their strong response to a short-term subsidy. Further, these results indicate that implementable subsidies for first-time purchasers may have a significant effect on increasing PC ownership. This provides some support for Hypothesis 6.

Finally, these estimates allow firms with sufficient information on the makeup of consumers in a market to better assess PC demand in that market. Even if the data on PC ownership only differentiates between owners and non-owners, the firm can form a reasonable expectation as to that market's response to a change in product and/or price.

Model Comparison

In addition to parameter estimates for the dynamic stock model, Tables 5a and 5b give the parameter estimates for a myopic stock model (discount rate = 0) and a model without stock effects[46]. We can compare the dynamic replacement model directly with the myopic replacement model using the standard likelihood ratio test since the myopic model simply restricts the discount rate to be zero[47]. The likelihood ratio statistic is 182 for 1999 and 64 for 2001, both significant at the one percent level. This indicates that the dynamic model is a significantly better fit for the data than the static one[48].

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[46] Note that the discount rate is irrelevant in a no stock effects model. A model with no stock effects and a discount rate greater than zero means that each period, the purchase from last period has no impact on utility – the good is not viewed as durable beyond one period by the consumer. Therefore, decisions today have no impact on utility in the future resulting in myopic behavior equivalent to that observed when the discount rate is equal to zero.

[47] This isn't the precise value of the likelihood ratio test since I didn't allow the discount rate to vary in the dynamic model. However, this does serve as a lower bound since the likelihood function would only improve if the discount rate was allowed to vary.

[48] One conceptual reason for this is the following. Consider two households with identical stock holdings – one with a high marginal valuation for computing power and one with low marginal valuation for computing power. In the data, it may well be the case that both households purchased the low end PC for

The qualitative effect of each covariate on utility is the same for both the dynamic and myopic models, but they differ quantitatively. In particular, the static model overemphasizes heterogeneity in marginal values for quality and underestimates the learning cost parameter. Further, the static model underestimates price elasticity for both years. For the myopic model of 2001, a short-term[49] 10% decrease in price results in a 22% increase in demand for non-owners and a 17% increase in demand for owners; these estimates are below those of 26% and 21% respectively for the dynamic model that year. We see similar comparisons for 1999. These measurements show the dynamic model's ability to account for households buying earlier to capitalize on lower prices that will only last for one period, behavior the static model is unable to capture.

Regarding the importance of stock effects, assuming that the PC being replaced is unimportant amounts to assuming everyone gets the same base utility from "no purchase" each period. In no way can we directly test a dynamic model with stock effects against a model without stock effects; however, the estimates for the model without stock effects make very little economic sense. A zero marginal utility of money[50] along with negative marginal values for all groups is enough to cast serious doubt that this model is able to capture the behavior of these households at all. Ultimately, this isn't a surprising result since we can hardly believe that households owning PCs make PC purchasing decisions ignoring the fact that they already own one.

Finally, the dynamic stock model, static stock model, and no stock model all assume that households have four choices each period. I consider a simpler version of these models where households face only two choices each period, buy or don't buy. By

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the observation year. The low valuation household does so because it doesn't want to spend the money for extra power and is content with the low end PC; however the high valuation household does so because it plans to purchase another cheap PC in just a couple years. Even after accounting for the PC the household already owns, a static model will be unable to account for the possibility that a high marginal valuation household would choose the low end PC, whereas this possibility is built into the dynamic model. A counterargument would contend that the high valuation household would replace at a faster rate, so a static model could account for this by taking into account the age of the PC replaced. However, this wouldn't necessarily work since we could easily have a situation where a high valuation household would buy the median PC at large intervals for a period of time and then as technology advances, move to buying the cheap PC more frequently without any fundamental change in preferences. Thus, a static model might observe a household with a seemingly low turnover rate purchase a low end PC and interpret the household as a low valuation household.

[49] We can only compare results for the short-term price decline since the myopic model can't tell the difference between a short-term and long-term price decline.

[50] The model actually estimates a slightly negative marginal utility of money, but I constrained this parameter to be positive and report the results with this constraint implemented.

including extra detail about the purchases each year, we get more accurate measurements of the parameters as indicated in Table 8a. As in the comparison to the static model, the results are similar qualitatively but differ quantitatively. Most notably, we have distinct differences in the measure of the marginal utility of money, and the 2 choice model is unable to identify the presence of techies with any level of precision[51].

Robustness Tests

By using a structural model, the results can be dependent on any subset of the assumptions we've made to ensure the tractability of the model. We can easily test the robustness of two of these assumptions. Namely, we've assumed the discount rate is .9 and the horizon length is seven years. Regarding the discount rate, I made estimates for both years for various levels of δ, and none made a significant improvement over those corresponding to $\delta = 9$. Regarding the horizon length, Table 7b lists results for horizon lengths of 6 and 8 years. From the table, we see that the estimates differ trivially across horizon lengths ranging from 6 to 8 years.

7. Conclusions and Extensions

The model presented here accounts for many of the major components in households' PC purchasing decisions – heterogeneity (observed, unobserved, and stock), learning costs, and dynamics. The estimates from the econometric model indicate that each of these components is an important determinant of PC demand. By building a more complete model of demand for PCs, we are able to make some measurements more accurately (such as price elasticity, variation in marginal values, etc.) and make some measurements that weren't previously possible (the impact of a change in the rate of technological advancement). We also can attempt to address policy issues, such as closing the Digital Divide, in a more sophisticated way.

[51] Techies aren't completely unidentified since they would be those who like having a new PC each year, but the data set isn't rich enough to pin down this behavior with such a coarse model.

The determinants of demand emphasized in this study apply to the demand of many other durable goods. Heterogeneity, set-up costs, and dynamics (or some subset of the three) are important for measuring the demand for any durable good that involves a fixed cost for first-time adoption, whose quality improves over time, and for which the marginal value of quality differs across households.

A planned extension to this analysis is to incorporate time inconsistency into the model used here. Many studies dating all the way back to Strotz (1956) have pointed out the existence of time inconsistent behavior in many walks of life. Since the decision to purchase a PC directly involves a consideration of future costs and benefits, the method for computing the present value of these costs and benefits is important.

Regarding the modeling of the choice process, I plan to use a nested logit instead of a multinomial logit to account for a two-stage process of buying a PC; that is, first decide whether to buy, and if the decision is to buy, which PC should be purchased.

I can also extend the model by treating PCs as a one hoss shay. In the model above, there is no deterioration. Treating the PC as a one hoss shay means treating it as a product with either 0% or 100% deterioration over time – nothing in between. This assumption is viable since PCs typically are either in working order or crashed to the point of being unusable[52].

Finally, I can extend this model by accounting for more states. As always, computing time is an issue with this type of model, so efficiency in the number of states is crucial. However, the results certainly will be more accurate when more information from the data set is included. This data set is very rich with detail, so a large expansion of the state space is possible; and with the rapid pace of advancement in computing speed, I will continually be able to process more information in the model in a reasonable amount of computing time.

[52] One can imagine interior deterioration rates as clutter may slow the run time, etc.

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TABLES

Table 1

Frequency of new PC purchases for those entering 1999 and 2001 with and without a PC

	1999 Households				2001 Households			
	Did not purchase new PC in observation year	Purchased new PC in observation year	Total	Frequency of new PC purchase	Did not purchase new PC in observation year	Purchased new PC in observation year	Total	Frequency of new PC purchase
No PC entering observation year	9534	1246	10780	***.1156***	3792	347	4139	***.0838***
Owned PC entering observation year	13752	4047	17799	***.2274***	11885	2909	14794	***.1966***
Total	23286	5293	28579	.1852	15677	3256	18933	.1720

Table 2

Descriptive Statistics for demographic characteristics of survey respondents for 1999 and 2001

		1999		2001	
Category	**Subgroup**	**Count**	**% of Sample**	**Count**	**% of Sample**
Age of Head of Household	Under 35	4096	14.33	2166	11.44
	35-49	10762	37.66	6732	35.56
	50-59	6865	24.02	4721	24.94
	60+	6856	23.99	5314	28.07
Household Size	1 member	3909	13.68	2899	15.31
	2 members	12372	43.29	8342	44.06
	3+ members	12298	43.03	7692	40.63
Household Income	< $20k	2787	9.75	2600	13.73
	$20k-$35k	3276	11.46	2985	15.77
	$35k-$60k	7615	26.65	4080	21.55
	$60k-$100k	10516	36.80	5833	30.81
	$100k+	4385	15.34	3435	18.14
Education of Head of Household	Less than high school	2450	8.57	1651	8.72
	High school degree	7888	27.60	5165	27.28
	Some college	5923	20.73	3849	20.33
	College degree+	12318	43.10	8268	43.67
Marital Status	Not married	6322	22.12	4847	25.71
	Married	22257	77.88	14008	74.29
Market size[53]	Rural/small town	5032	17.61	3495	18.46
	Small city	5568	8.75	2685	14.18
	Medium city	9847	45.19	3866	20.42
	Large city	8132	28.45	8887	46.94

[53] Measured as size of metropolitan statistical area (MSA). Specifically, rural/small town is < 50,000 for 1999 and < 100,000 for 2001; small city is 50,000-.5mil for 1999 and 100,000-.5mil for 2001; medium city is .5 mil-2.5mil for 1999 and .5mil-2mil for 2001; large city is 2.5mil+ for 1999 and 2mil+ for 2001.

Table 3

Descriptive statistics for PC ownership entering observation years

Sample is limited to only those owning a PC entering the observation year

			1999			2001		
PC ownership	Age of PC	Price Paid	Count	% of PC owners	% of age group	Count	% of PC owners	% of age group
Own PC			17799	100		14794	100	
	> 5 years		1838	10.33		1382	9.34	
		< $1k	448	2.52	24.37	437	2.95	31.62
		$1k-$2k	909	5.11	49.46	609	4.12	44.07
		$2k+	481	2.70	26.17	336	2.27	24.31
	5 years		1166	6.55		893	6.04	
		< $1k	126	.71	10.81	203	1.37	22.73
		$1k-$2k	624	3.51	53.52	401	2.71	44.90
		$2k+	416	2.34	35.68	289	1.95	32.36
	4 years		1973	11.08		1509	10.20	
		< $1k	198	1.11	10.04	326	2.20	21.60
		$1k-$2k	982	5.52	49.77	751	5.08	49.77
		$2k+	793	4.46	40.19	432	2.92	28.63
	3 years		3445	19.36		3473	23.48	
		< $1k	430	2.42	12.48	926	6.26	26.66
		$1k-$2k	1754	9.85	50.91	1874	12.67	53.96
		$2k+	1261	7.08	36.60	673	4.55	19.38
	2 years		4581	25.74		4098	27.70	
		< $1k	668	3.75	14.58	1308	8.84	31.92
		$1k-$2k	2343	13.16	51.15	2141	14.47	52.24
		$2k+	1570	8.82	34.27	649	4.39	15.84
	1 year		4796	26.95		3439	23.25	
		< $1k	906	5.09	18.89	1134	7.67	32.97
		$1k-$2k	2460	13.82	51.29	1589	10.74	46.21
		$2k+	1460	8.20	30.44	716	4.84	20.82

Table 4a

PC ownership and purchasing rates by demographic groupings

Category	Subgroup	% of subgroup owning PC entering 1999	% of subgroup buying new PC in 1999	% of PC owners in subgroup buying new PC in 1999	% of non-PC owners in subgroup buying new PC in 1999
Full Sample		62.28	18.52	22.74	11.56
Age of Head of Household	Under 35	70.73	21.46	22.71	18.43
	35-49	71.44	21.44	23.52	16.23
	50-59	64.33	19.34	23.19	12.41
	60+	40.81	11.36	19.91	5.47
Household Size	1 member	52.49	15.50	22.42	7.86
	2 members	56.14	16.81	22.13	10.01
	3+members	71.56	21.20	23.29	15.93
Household Income	< $20k	19.45	5.99	19.56	2.72
	$20k-$35k	44.60	13.34	20.12	7.88
	$35k-$60k	63.48	18.50	21.00	14.17
	$60k-$100k	71.26	20.64	22.23	16.68
	$100k+	79.09	25.31	27.85	15.70
Education of Head of Household	Less than high school	25.96	8.73	18.55	5.29
	High school degree	47.78	14.63	19.66	10.03
	Some college	67.77	20.65	23.74	14.14
	College degree+	76.15	21.94	23.84	15.90
Marital Status	Not married	55.46	17.08	23.05	9.66
	Married	64.22	18.93	22.66	12.23
Market size[54]	Rural/small town	53.95	15.88	20.74	10.19
	Small city	62.81	19.36	23.19	12.89
	Medium city	64.07	19.15	23.62	11.19
	Large city	64.90	18.81	22.41	12.16

[54] Measured as size of metropolitan statistical area (MSA). Specifically, rural/small town is < 50,000 for 1999 and < 100,000 for 2001; small city is 50,000-.5mil for 1999 and 100,000-.5mil for 2001; medium city is .5 mil-2.5mil for 1999 and .5mil-2mil for 2001; large city is 2.5mil+ for 1999 and 2mil+ for 2001.

Table 4b

PC ownership and purchasing rates by demographic groupings for 2001

Category	Subgroup	% of subgroup owning PC entering 2001	% of subgroup buying new PC in 2001	% of PC owners in subgroup buying new PC in 2001	% of non-PC owners in subgroup buying new PC in 2001
Full Sample		78.14	17.20	19.66	8.38
Age of Head of Household	Under 35	79.41	19.58	20.70	15.25
	35-49	84.40	20.83	22.30	12.86
	50-59	82.65	18.28	20.17	9.28
	60+	65.68	10.67	14.30	3.73
Household Size	1 member	61.75	12.52	17.54	4.42
	2 members	78.00	15.37	17.37	8.28
	3+members	84.46	20.94	22.55	12.22
Household Income	< $20k	44.54	9.00	14.85	4.30
	$20k-$35k	68.54	12.53	14.76	7.67
	$35k-$60k	82.25	15.71	16.90	10.22
	$60k-$100k	88.10	20.09	21.17	12.10
	$100k+	90.10	24.31	25.20	16.18
Education of Head of Household	Less than high school	42.94	8.36	14.10	4.03
	High school degree	71.27	13.15	15.54	7.21
	Some college	80.83	16.99	18.77	9.49
	College degree+	88.21	21.59	22.67	13.54
Marital Status	Not married	63.63	13.78	18.19	6.07
	Married	83.21	18.42	20.08	10.20
Market size[55]	Rural/small town	73.36	15.48	18.17	8.06
	Small city	78.25	18.21	20.66	9.42
	Medium city	78.76	17.33	19.64	8.77
	Large city	79.71	17.51	19.92	8.04

[55] Measured as size of metropolitan statistical area (MSA). Specifically, rural/small town is < 50,000 for 1999 and < 100,000 for 2001; small city is 50,000-.5mil for 1999 and 100,000-.5mil for 2001; medium city is .5 mil-2.5mil for 1999 and .5mil-2mil for 2001; large city is 2.5mil+ for 1999 and 2mil+ for 2001.

Table 5a

Parameter estimates for dynamic, myopic, and no stock models with linear utility function, and seven year forecasting for 1998-99 data set[56]

	Stock model		Myopic stock model		No stock model	
Covariate[57]	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
MHz	.4059***	.04336	.1599	.11168	-2.8558	.22821
Low/Med. Wealth*MHz	.2133***	.03576	.4721***	.08472	.5024	.06846
Med. Wealth*MHz	.3373***	.03274	.7018***	.07626	.6681	.06168
Med./High Wealth*MHz	.4201***	.03412	.8323***	.07699	.7244	.06196
High Wealth*MHz	.6041***	.04004	1.1083***	.08626	.8998	.06768
H.S. Education*MHz	.0737**	.03175	.1967***	.06599	.2617	.05580
Some College*MHz	.1868***	.03430	.3916***	.06880	.4366	.05755
College/Post College*MHz	.2263***	.03382	.4315***	.06715	.4131	.05604
Age(35-49)*MHz	-.0289	.02714	-.0246	.04391	.0058	.03362
Age(50-59)*MHz	-.1015***	.02932	-.1319***	.04833	-.0630	.03700
Age(60+)*MHz	-.2898***	.03026	-.4264***	.05264	-.2873	.04095
FamSize(2)*MHz	.0622**	.02639	.0842*	.04861	.0445	.03799
FamSize(3+)*MHz	.0863***	.02730	.1073**	.04917	.0673	.03818
Top PC	5.3537***	.08933	5.1256***	.19115	4.8867	.25610
Probability of techie	.1154***	.00583	.1250***	.01236	.1126	.01354
Marginal Utility of Money	.3374***	.00303	.3107***	.00427	0	.02749
PC Learning Cost	9.9124***	.10560	1.5144***	.05120	.6881	.03975
Likelihood	-19411		-19502		-19546	

[56] MHz was divided by 200 and Price was divided by 100.

[57] *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table 5b

Parameter estimates for dynamic, myopic, and "no stock" models with linear utility function, and seven year forecasting for 2000-01 data set[58]

	Stock model		Myopic stock model		No stock model	
Covariate[59]	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
MHz	.0933***	.01820	-.0737	.05457	-.9333	.05677
Low/Med. Wealth*MHz	.0141	.00967	.0691**	.03400	.0470	.02510
Med. Wealth*MHz	.0273***	.01105	.1208***	.03199	.0677	.02326
Med./High Wealth*MHz	.0904***	.01430	.2339***	.03250	.1305	.02321
High Wealth*MHz	.2022***	.01835	.3826***	.03565	.2149	.02532
H.S. Education*MHz	.0063	.00962	.0450	.03622	.0506	.02675
Some College*MHz	.0368***	.01312	.1445***	.03744	.1157	.02735
College/Post College*MHz	.0807***	.01471	.1970***	.03770	.1500	.02737
Age(35-49)*MHz	-.0053	.01475	.0018	.02446	.0126	.01706
Age(50-59)*MHz	-.0392**	.01561	-.0492*	.02670	-.0171	.01828
Age(60+)*MHz	-.0947***	.01481	-.1985***	.02870	-.1017	.01968
FamSize(2)*MHz	.0126	.00877	.0188	.02612	.0209	.01790
FamSize(3+)*MHz	.0531***	.01166	.1168***	.02677	.0766	.01838
Top PC	5.5477***	.37040	6.2532***	.33124	4.4910	.40413
Probability of techie	.0362***	.00708	.0324***	.00394	.0790	.02095
Marginal Utility of Money	.3030***	.00460	.2771***	.00579	0	.01511
PC Learning Cost	6.7701***	.24808	1.3433***	.07247	.8320	.06292
Likelihood	-12608		-12640		-12097	

[58] MHz was divided by 200 and Price was divided by 100.

[59] *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table 6a

Price elasticity comparisons for owners and non-owners

	1999			2001		
	Non-owner price elasticity	Owner price elasticity	Total price elasticity	Non-owner price elasticity	Owner price elasticity	Total price elasticity
Short-term 10% price decline	3.6221	2.6962	2.8920	2.5515	2.0502	2.0952
Long-term 10% price decline	3.2307	2.0636	2.3103	2.6533	1.6582	1.7476

Table 6b

Demand response to a change in the rate of quality increase from a doubling nearly every 2 years to a doubling nearly every 1.5 years

	1999			2001		
	% change in demand for non-owners	% change in demand for owners	Total % change in demand	% change in demand for non-owners	% change in demand for owners	Total % change in demand
Technology acceleration beginning in one year	-4.2%	-6.4%	-6%	-.5%	-3.9%	-3.6%
Technology acceleration beginning in two years	-1.4%	-.5%	-1.2%	≈ 0% [60]	≈ 0%	≈ 0%
Technology acceleration beginning in three years+	≈ 0%	≈ 0%	≈ 0%	≈ 0%	≈ 0%	≈ 0%

[60] ≈ 0% implies an absolute percentage change less than one and is only used if this is the case for all three entries corresponding to a given scenario.

Table 7

Predictions in the percentage change by subsidy level for short-term and long-term subsidies provided to households buying a PC for the first time

		1999	2001
		% change in demand for non-owners	% change in demand for non-owners
Short-term Subsidy	$100	29.38%	27.94%
	$200	65.04%	61.76%
Long-term Subsidy	$100	4.98%	5.83%
	$200	10.15%	11.93%

Table 8a

Robustness analysis:

Results for stock model when choice set is limited to buy/don't buy each period

	1999		2001	
	Full Model	**2 choice model**	**Full model**	**2 choice model**
Covariate[61]	Estimate	Estimate	Estimate	Estimate
MHz	.4059***	.2004***	.0933***	.1084***
Low/Med. Wealth*MHz	.2133***	.0897***	.0141	.0212**
Med. Wealth*MHz	.3373***	.1685***	.0273***	.0287***
Med./High Wealth*MHz	.4201***	.2073***	.0904***	.0618***
High Wealth*MHz	.6041***	.2927***	.2022***	.1278***
H.S. Education*MHz	.0737**	.0117	.0063	.0057
Some College*MHz	.1868***	.0850***	.0368***	.0327***
College/Post College*MHz	.2263***	.0940***	.0807***	.0564***
Age(35-49)*MHz	-.0289	-.0424*	-.0053	-.0203
Age(50-59)*MHz	-.1015***	-.0987***	-.0392**	-.0585***
Age(60+)*MHz	-.2898***	-.2010***	-.0947***	-.1093***
FamSize(2)*MHz	.0622**	.0073	.0126	.0097
FamSize(3+)*MHz	.0863***	.0432***	.0531***	.0452***
Top PC	5.3537***	.0231	5.5477***	.0116
Probability of techie	.1154***	.1369	.0362***	.2030
Marginal Utility of Money	.3374***	.1680***	.3030***	.1779***
PC Learning Cost	9.9124***	4.7146***	6.7701***	4.9896***

[61] *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level.

Table 8b

Robustness analysis:

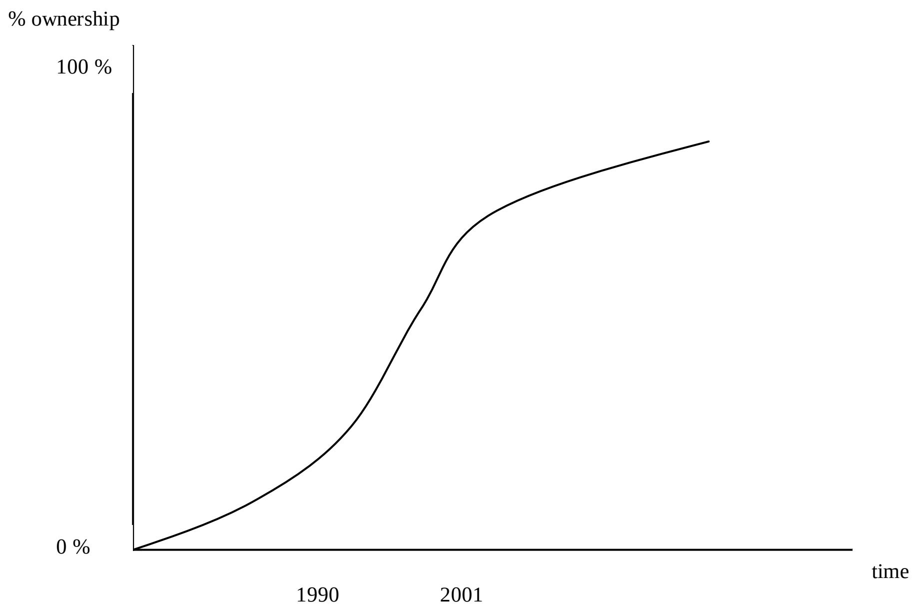
Results for stock model for variations in length of horizon

	1999			2001		
	Discount Rate = .9 Horizon: 7 years	Discount Rate = .9 Horizon: 8 years	Discount Rate = .9 Horizon: 6 years	Discount Rate = .9 Horizon: 7 years	Discount Rate = .9 Horizon: 8 years	Discount Rate = .9 Horizon: 6 years
Covariate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
MHz	.4059	.0376	.0359	.0933	.0925	.0943
Low/Med. Wealth*MHz	.2133	.2096	.2100	.0141	.0147	.0138
Med. Wealth*MHz	.3373	.3351	.3360	.0273	.0273	.0261
Med./High Wealth*MHz	.4201	.4202	.4203	.0904	.0908	.0910
High Wealth*MHz	.6041	.6152	.6167	.2022	.2023	.2023
H.S. Education*MHz	.0737	.0709	.0709	.0063	.0064	.0058
Some College*MHz	.1868	.1829	.1833	.0368	.0366	.0366
College/Post College*MHz	.2263	.2205	.2213	.0807	.0806	.0803
Age(35-49)*MHz	-.0289	-.0316	-.0306	-.0053	-.0050	-.0054
Age(50-59)*MHz	-.1015	-.1075	-.1077	-.0392	-.0392	-.0394
Age(60+)*MHz	-.2898	-.2885	-.2895	-.0947	-.0949	-.0940
FamSize(2)*MHz	.0622	.0614	.0621	.0126	.0125	.0127
FamSize(3+)*MHz	.0863	.0857	.0863	.0531	.0525	.0529
Top PC	5.3537	5.2404	5.2380	5.5477	5.5473	5.5471
Probability of techie	.1154	.1233	.1235	.0362	.0363	.0362
Marginal Utility of Money	.3374	.3348	.3349	.3030	.3029	.3035
PC Learning Cost	9.9124	9.4507	9.4384	6.7701	6.7696	6.7684
Likelihood	-19411	-19408	-19408	-12608	-12608	-12608

Graph 1

The S-curve for diffusion of a durable good:

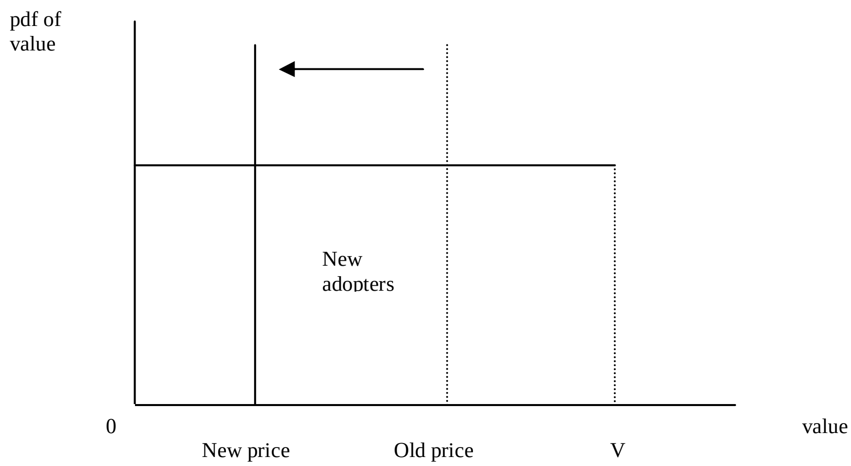
Percentage of ownership in the population graphed against time



Graph 2a

The standard rank model of diffusion:

Households values are uniformly distributed in [0,V], and buyers are those for whom value-price > 0



Graph 2b

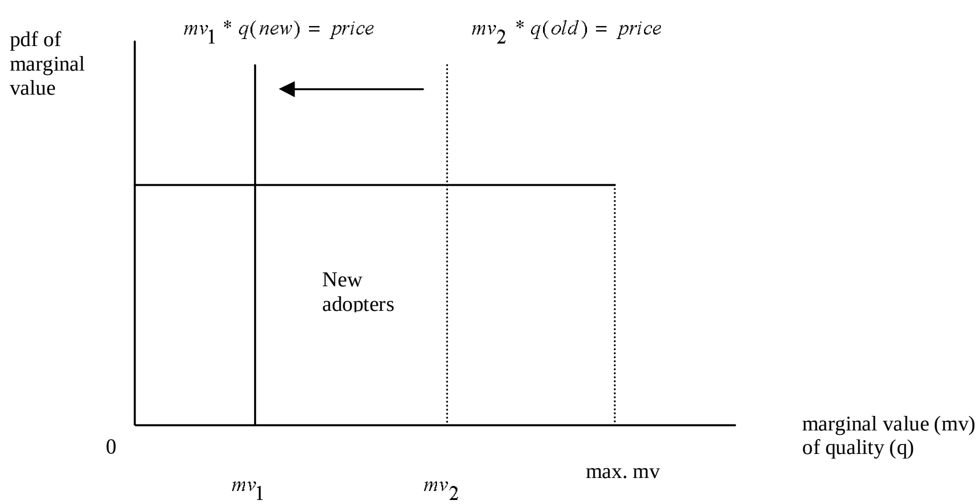
Rank model of diffusion for PCs:

Price is constant and households are uniformly distributed over marginal values of quality.

Assuming marginal value for each household is constant, buyers are those

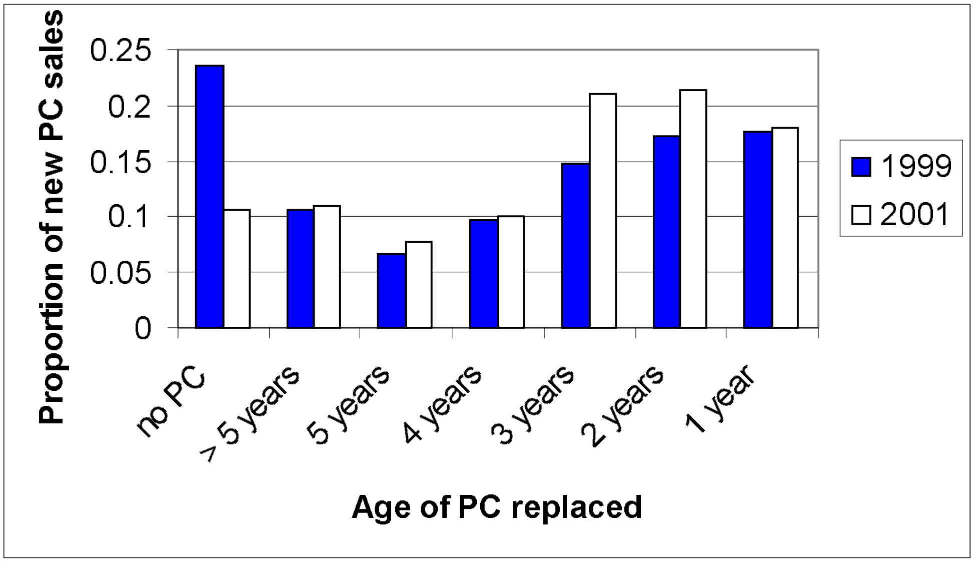
for whom (marginal value)*quality > price.

q(new) > q(old)



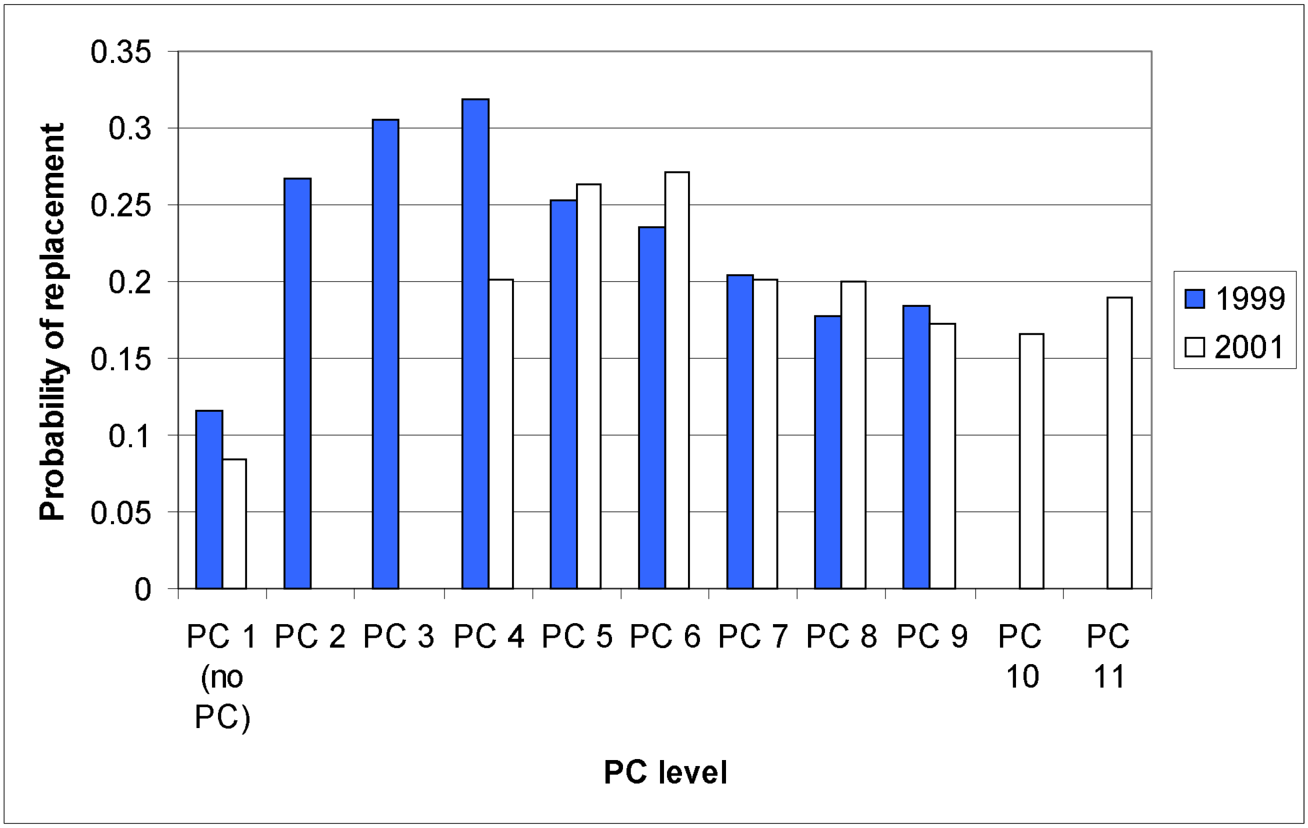
Graph 3

Proportions of new PC sales across vintages of PC holdings for 1999 & 2001



Graph 4

Replacement rates across "levels"[62] of PCs owned entering observation year



[62] Levels determine the power level of the PC as measured by the year and price paid for the PC owned by the household. For example, PC 7 corresponds to the top PC in 1996, the median PC in 1997, and the lowest PC in 1998.

APPENDIX

Table A1

Estimated and forecasted evolution of quality and price for PCs[63]

Year	Quality Level	Processor Speed	Price
	Low	25	1200
1993	Middle	33	1800
	High	50	2500
	Low	33	1200
1994	Middle	50	1800
	High	75	2500
	Low	50	1200
1995	Middle	75	2000
	High	100	2700
	Low	75	1400
1996	Middle	100	2100
	High	166	2800
	Low	100	1000
1997	Middle	166	1600
	High	200	2300
	Low	166	700
1998	Middle	200	1200
	High	300	2300
	Low	200	500
1999	Middle	300	1500
	High	500	2400
	Low	300	600
2000	Middle	500	1300
	High	800	2400
	Low	500	600

[63] Processor speed is measured in megahertz and price is measure in dollars.

2001	Middle	800	1300
	High	1500	2400
	Low	800	600
2002	Middle	1500	1300
	High	2400	2400
	Low	1500	600
2003	Middle	2400	1300
	High	3300	2400
	Low	2400	600
2004	Middle	3300	1300
	High	5000	2400
	Low	3300	600
2005	Middle	5000	1300
	High	8000	2400
	Low	5000	600
2006	Middle	8000	1300
	High	13000	2400
	Low	8000	600
2007	Middle	13000	1300
	High	20000	2400
	Low	13000	600
2008	Middle	20000	1300
	High	32000	2400
	Low	20000	600
2009	Middle	32000	1300
	High	50000	2400

Table A2

Natural log of price regressed on time and natural log of quality (measured as MHz) [64]

R square	**.8813**	
Observations	27	
Coefficient	***Estimate***	***t-stat***
Intercept	4.015	13.403
Time	-0.512	-13.339
Ln(MHz)	1.166	12.459

[64] The regression comes from taking the natural log of the assumed model of: $P = \theta_1 * e^{\theta_2 * t} * Q^{\theta_3}$. Note that we fail to reject $\theta_3 = 1$.