Information Acquisition and Consumer Choice[*]

Preliminary Draft – INCOMPLETE – Comments sought!

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ABSTRACT

We specify and estimate a model of demand for new goods implementing Simon's idea that consumers may not know their entire choice set. The model is identified in data, like ours, in which there is information about both what consumers say about their choices and about their actual choices. Learning what consumers do not know about their choice set from what they say about their choices is difficult, but solvable. We apply our model to software upgrade demand in the era before automatic upgrading. We find that much of the consumer inertia in electronic markets around default changes arises from incomplete information about choice sets, not from high adjustment costs.

1. INTRODUCTION

We study the sources of consumer inertia around initial product choices in online markets. We build a model which lets us distinguish between two sources of inertia, adjustment costs net of the value of switching to a new product and incomplete information about the choice set. Measuring those demand forces is part of understanding the emergence of a number of modern market institutions, notably pay-for-referral institutions such as advertising-supported search and demander-choice-replacing institutions such as automatic upgrades.[1] Our approach

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[*] This version of the paper is preliminary in a number of senses. There are few citations, and we do not yet thank the many colleagues who have given us valuable comments.

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[1] There is a wide variety of such institutions. One dramatic change on the supply side is the emergence of a number of institutions by which sellers obtain product placement and/or consumer referrals. Advertising auctions

relies on having data on both what consumers do – actual demand – and what they say – self-reported demand. More importantly, we build a model that permits us to draw an inference about the demand role of what consumers know without assuming a close relationship between what they say and what they know.

In particular, we examine individual choice and information gathering by demanders in a technologically dynamic market. Technologically dynamic markets, in which newly-invented product varieties expand the choice set, present demanders with a Simon (1955) problem of learning their full choice set as well as a choice problem. We model this as a simple repeated two-stage problem for a rational consumer. In stage I of each period, the consumer either learns, or does not, the characteristics of any new products in the choice set. In stage II, the consumer decides on a product, with an adjustment cost if there is a product change.[2] The pace at which consumers take up a new version will be slower if either the arrival rate of information about the full choice set is slower or if more consumers, once informed, choose not to adopt the newest version. Our empirical goal is to tell those two sources of inertia apart.

More narrowly, we study upgrading to new versions of software in a context where the upgrades are free: Microsoft web browsers in the late 1990s. Studying upgrades in this early era, before software started insisting on upgrading itself, brings us a number of analytical advantages. First, the problem of knowing whether a new version has been introduced is a search problem

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are the most studied of these institutions: in them, advertisers typically pay for a referral, i.e., pay only if a consumer clicks on a link to their website (online) or runs her thumb over their ad (mobile). Other related institutions include "nagware," in which an old version of product asks to be updated, "soft" bundling in which a default choice of product B is presented to a consumer who has chosen product A, and collaborative filters which suggest products a consumer might like. These new institutions are (1) clearly intended to overcome frictions of some kind, despite the much-predicted explosion of "frictionless commerce" and (2) drive the private returns to technical progress online and in the rapidly growing mobile markets. Many high-tech industries have active corollary markets for "product placement" as a default choice. For example, consumers who buy a new computer typically are offered a number of products and services bundled with it, including try-to-buy software from antiviral to word processing, "free" software such as a browser or advertising-supported games, and internet service provider signups. The product placement is valuable; no economist will be surprised that software and services firms pay operating system (OS) suppliers or computer manufacturers for placement. Other industries have similar corollary markets. A consumer who buys an iPhone finds some apps on it and more made default through the app store (which you can be sure charges app developers for placement). These arrangements do not bind consumers to a particular choice in each of the related categories, but they do create a default choice. Many consumers take the default choice, and even continue to choose the same brand long after. A default choice lies somewhere in between having already chosen a particular product (so that search would be needed to find an alternative) and receiving an advertising message (so that search is cheaper for a particular product).

[2] While consumers have rational expectations about the rate of improvement of new varieties, limited attention means they do not necessarily know the realization of the improvement to their own utility from characteristics of a new variety. The consumers' initial choice before information acquisition may be determined either by a past choice or through a default or "opt out" choice being set for the consumer.

with a very simple structure, and we can hope to learn about consumers knowledge of their choice set from their answer to a simple and objective question, such as "are you using the newest version?" Second, studying free upgrades brings the problem of inertia to the foreground. These consumers were very slow to adopt the latest version, though quality was improving, rapidly at first, and the upgrade was free.[3] Our goal in this paper is to learn *why* consumers were so slow to adopt.

Empirically, we model consumers as heterogeneous both in the rate of information acquisition and in the net-of-cost benefits of new versions. We exploit a dataset that lets us distinguish between a Simon-esque interpretation – users who don't know their choice set – and a richly specified set of ordinary demand forces. The dataset is of a familiar and not all that uncommon form. Internet users filled out a survey questionnaire, and one of the questions they answered was "Are you using the newest version of your browser?" Because we linked the survey answers to the survey web log, we know the correct answer to that question. Like many papers in information economics, the key to our identifying assumptions is that we know something that the consumer may or may not know. In this case, we know it from something like an administrative record, i.e., the web log.

Another advantage of our particular context is that we have a great deal of information about consumer initial conditions and choice sets even though our sample is a repeated cross section. This advantage derives mostly from the well-documented distribution of Microsoft browsers with new personal computers (PCs) and by internet service providers (ISPs). Because of the importance of product placement in this "browser war" era, our problem has remarkably simple and clean initial conditions (IC). Our consumers were given an early version of Internet Explorer (IE) – the default version of the product – under conditions we can state precisely. We can then study their decision to opt-in to new, better versions. Because backward-looking

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[3] In earlier work, we showed that demand was inertial in two directions. Consumers were slow to upgrade to new versions, and tended to use the brand of browser that was given to them rather than to switch. Indeed, users tended to stay with both the brand of browser and the version of the brand that came with their computer or that was offered to them by their internet service provider (ISP). See Bresnahan and Yin (2005) and sources cited therein (both other scholarly studies and the business assessments of both browser firms of the era), which attribute inertia around defaults to "distribution convenience" but offer no deep insight into the reason consumers do the convenient thing of staying with the default. In this paper we drop the brand choice and go into the "why" of version choice inertia. The quantifications we undertook in the earlier paper suggest about the same degree of inertia in both the brand and version dimensions, but from the estimates in this paper we can't learn – yet – if the role if information is the same in both dimensions.

information about dates is incomplete, we will need to aggregate our model across multiple possible IC dates, but for each date we know with what product a consumer began, when they first had the opportunity to opt-in to the newest browser, and thus how long they have been at risk of learning about and possibly choosing to adopt the newest.

The core ideas behind our model can be seen in a simple diagram. The relationship between our model and a standard choice model can be seen in Figure 1. The (strongly Simon-esque) diagram shows the actual and known choice set of a hypothetical consumer. In fact, versions 1 through 3 have all been introduced into the market, but this consumer does not yet know of version 3, so we grey it out. This particular consumer, *i*, demands version 1, i.e. $x_i = x_1$. The product quality of version 3, x_3, might be high enough to induce this consumer to upgrade if she knew about it, but she doesn't.

Figure 1

Version 1	Version 2	Version 3
x_1	x_2	x_3

$x_i = x_1$

We endow each consumer, *i*, with two demand parameters, θ_i and Δ_i, where θ_i is the hazard that the consumer will learn of the true choice set.[4] By this we simply mean that each period (month in our application) the consumer in Figure 1 has probability θ_i of transitioning to knowing that version 3 exists, i.e., to redrawing Figure 1 with the third column no longer grayed out. In that eventuality, the consumer would consider adopting version 3, and Δ_i is the net cost of adoption.

We assume consumers have a dynamically optimum adoption policy and use the optimum in our estimates of demand. The main purpose of the demand model is to organize the comparative statics of the decision to adopt – which depend not only on θ_i and Δ_i, but also on the

[4] In one version of our model, we had consumers choose their rate of "search", i.e. the hazard function for learning the true state of the market, based on their cost of "search" effort. While this model is not literally identical to the one reported below, since the hazard function for learning would be higher if consumers expected a faster rate of improvement (as they should have in the early stages of our sample) it is practically identical and we don't report estimates of it.

consumer's IC, on the timing of when we observe the consumer, on the timing of browser releases, and on the improvements in product quality from one version to the next.

We make a more complex assumption about what consumers say. In our preferred specification, we assume a mixture model in which some consumers act as rational statisticians and try to answer the question "are you using the newest browser" the way a very dutiful economics graduate student would. Others answer in a more emotive, less rigorous way.

Either adjustment costs or consumer learning add dynamic elements to demand. New varieties may have lower demand (than they would have if both new and old varieties were presented to consumers on the same basis) either because consumers do not yet know about them, or because switching to them is costly. This raises the demand for product varieties which have already been chosen, creating an inertial effect. This will impact the rate of diffusion when a subset of consumers with high information-gathering and product-testing costs may optimally decide to become informed only slowly or when the adjustment costs to new versions are particularly high for them. That behavior will further slow the movement of demand to new options and away from existing ones.[5]

Both motives are plausible in technically dynamic markets, and we had no particular anticipation of what answer we would find. Technologically dynamic markets, in which newly-invented product varieties rapidly expand the choice set, clearly present demanders with an information acquisition problem as well as a choice problem. A consumer who has not recently investigated available product varieties will not know what choices are available; there may be (time) costs of investigating new product varieties to learn how much utility each will yield. Similarly, rapid change can increase the adjustment costs directly – e.g., by making new varieties larger and harder to download – or increase the salience of adjustment costs by limiting the period in which any particular new product will be used, shortening the payback period for a new variety.

We find that poor information about user choice sets explained most of the slow diffusion of new browsers in the late 1990s. We offer a present-tense interpretation of that result at the end.

[5] This possibility is well recognized in the literature on diffusion, which has long recognized the importance of information-spreading institutions such as agricultural extension services. See Griliches (1988), Hall (2004).

2. DATA

We employ individual level data on browser use from Georgia Institute of Technology's Graphics Visualization and Usability (GVU) Center's online surveys of web usage. These surveys were conducted biannually in April and October. We employ data from 7 waves of the survey (indexed by the variable *SURVEYS* as surveys 4-10) from October 1995 through October 1998.[6] The survey asked questions about the respondent's web browsing activity and demographics. Since the surveys were conducted online, web server logs recorded the operating system (OS) and browser used by the survey respondent. Detailed information about the survey and definitions for all variables from the survey and web server logs are listed in Appendix Table 1 and 2.

There are several reasons why this data set is useful for studying the role of information about choice sets in the slow diffusion of new technologies. We observe several rounds of introduction of improved technologies, new versions of a browser. Automatic upgrading software was not yet in use at the time of our sample, so we observe the individual consumer's decision to opt-in to an upgrade. The survey gathers information about demand both by asking the consumer and by recording their employed choices directly to the web server logs, so we have data related to the consumer's knowledge state.

The respondents were sophisticated enough to have been on the Internet in the late 1990's, but we will limit our attention to the mainstream consumers within that population. Our sample consists of users running any version of the Internet Explorer (IE) browser and any version of Windows OS.[7] For these users, we have very good information about what browser was initially distributed to them before they faced the choice of opting-in to a new version. The restriction results in 5556 observations.

2.1. Web Server Log Dataset

Web servers record the "user-agent field," a code sent by a respondent's browser when the user goes to a web page. This field identifies the browser and OS of the user's computer so that

[6] While the surveys are not a panel, in a small number of cases the same individual responded to more than one wave. Since the incidence of repetition is small, we do not attempt to exploit the limited panel data structure.

[7] Extending our results to include browser brand choice awaits future work. By restricting the sample to one brand of browser, we avoid having to compare the quality of, or make assumptions about the rate of introduction of, competing brands. The treatment of initial conditions also grows more complicated. However, in earlier work we saw that the degree of overall consumer inertia in brand choice and in upgrading to new versions was similar, so we are optimistic that we can learn about the sources of the inertia in both dimensions.

web pages can be rendered in the appropriate way. We define dummies for the (major) OS being used: Windows 3.1 (including earlier versions), Windows 95, and Windows 98. Statistics on these variables are reported in Table 1. Similarly, we define dummies for the (major) version of IE being used and report on their prevalence in our sample in Table 2. Because of the timing of the surveys, our sample is dominated by IE 3 and 4 and by Windows 95.

Since we know the browser the user is running and the history of browser version introductions (see Appendix Table 2), we can define the dummy *NEWEST* = 1 if the user is running the newest (major) version of her browser on the date when she responds to the survey. We consider a "beta" version of the browser to be newest, rather than defining *NEWEST* according to which version is being distributed with a new computer. We adopt this definition because (1) we are studying opt-in and (2) half of total upgrades in our sample can occur before the distribution release date.[8] Only 27% of the sample updated to the newest version (Table 4).

2.2. Survey Responses Dataset

We employ a number of ordinary, self-described demographic or economic survey responses (*MALE*, *AGE*, *INCOME*) from the GVU survey. We also select regressors that capture cross-sectional variation in (1) users' interest and ability to process information about new technologies and (2) their demand (in the usual sense) for the newest technology. Their definitions and summary statistics are given in Table 4.

To control for particular expertise about browser technology, we include the dummy *OCCCOMP=1* if the occupation involves computers. Conversely, the date a respondent first got on the Internet (*ONWEBDATE)* controls for less knowledgeable "newbies" (people who just entered the market), while *PAYWORKDK=1* if the user does not know who pays for internet access or work pays.

USE and *HOURS* measure time spent on the web, reflecting the benefit of downloading the newest technology. The time costs of obtaining the newest browser version is measured by the log of internet access speed, *LSPEED*. We do not interpret these variables as exogenous determinants of technology demand, but rather as measures of cross-sectional variation in web demand and, therefore, demand for the newest web technology.

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[8] We have also estimated a version of the model using official "release to manufacturing" dates to define *NEWEST* and found little qualitative difference from our main results. The biggest difference quantitatively is that this model has a higher predicted probability of upgrading, not that it has a distinct breakdown between information and other causes.

2.3. Combined Web Server Log and Survey Datasets

In addition to the automatic recording of survey respondents' browser and OS by the web server logs, the survey redundantly asks the users whether their browser is the newest available of its brand and what OS they use. The survey also asks the respondents to indicate how confident they are in their answer (whether they are "certain" or "uncertain"). These answers give us the dependent variable *SAY,* which takes on the five values "yes, certain," "yes, uncertain," "don't know," "no, uncertain," and "no, certain."[9] See Appendix Table 3 for the specific wording and choices. See Table 7 for statistics on consumers' responses.

We compare the human to web server log answers to construct the dummy *RIGHT* = 1 if the human and web server log answers agree regarding whether the user is running the newest version of the browser. We code human/computer disagreements or the answer "don't know" as *RIGHT* = 0. Only 56% of the sample is right (Table 4) – the average user in our sample is doing only slightly better than flipping a coin.

A standard econometric approach would be to use the distinction between human and computer answers to "validate" survey responses, that is, to learn how much measurement error there is in the human responses compared to the computer responses.[10] Our approach is, in many ways, the reverse. We are instead going to use consumers' statements to draw an inference about what they *don't* know about demand. We emphasize that the consumer's statement and the administrative record correspond to distinct concepts: the consumer may not know the true state of the market.

The last column of Table 7, "Percent actually RIGHT," indicates that those who responded "Yes" are considerably less likely to be right than those who responded "No," suggesting the possibility of an "optimistic bias."[11] Table 7 also reveals that consumers who say they are "certain" are more likely to be *RIGHT,* regardless of their answer. This suggests some elements of accurate self-assessment in consumer's answers. The lessons we draw from this quick and descriptive examination of what consumers say are that (1) our model should provide for the

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[9] We treat the rare response "yes, and it is a beta version" as "yes, certain."

[10] A large literature in econometrics uses both survey research data and administrative records data, as we do, but for somewhat different purposes than ours. In this literature, "validation" is the label for learning how much measurement error there is in the survey data in order to design an econometric solution to the measurement error problem. See Bound et al. (2001) section 3.

[11] Indeed, users who answer that they are using the newest browser "and it is a pre-release/beta version" are less likely to be right than even uncertain users who answer no.

possibility of optimistic bias in attempting to isolate the part of consumers' answers which reveals their true mental state and (2) we should utilize not only the consumers' yes/no answers but also their degree of certainty in our model of what they say.

2.4. Missing Data

Survey respondents sometimes skip a question or answer "rather not say" in response to a specific question when the option is offered.[12] We include observations with missing regressors by adding a dummy for missing data. For example, *DAGE* is a dummy for the individuals for whom we do not know their age. The specific names of the dummies and the regressors for which these dummies are relevant are described in Appendix Table 3.

Some questions are not asked in some waves of the survey, so data may be missing for an entire year on a particular variable. We exclude such variables from consideration as regressors. One of our key dependent variables, what the users *SAY* about their demand behavior, is also missing because the question was not asked in a number of surveys. For those surveys, we do not predict *SAY*, and the likelihood contribution of an observation is the marginal probability of *NEWEST*.

3. FRAMEWORK

Assume there is a technology that is evolving over time. Consequently, new and better versions of the technology are released into the market over time. Consumers have heterogeneous demand for the technology, i.e., the utility of the technology net of cost varies across consumers. However, consumers are not perfectly informed about the release date of the new versions. Without observing the state of the world, they do not know for certain if the new version exists yet, nor how much more utility they would receive from the new version. Consumers thus face both an information acquisition problem and a product choice problem.

Consumers are heterogeneous in their probability of observing the state of the world. Some observe quite frequently, while others do not. This heterogeneity is driven, for example, by differences in consumers' occupations (some work daily with the technology and so are more likely to become informed about the existence of a new version).

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[12] Even for the same question, the ability to respond with "rather not say" can change from survey to survey. See Appendix Table 3.

If the consumer observes the state of the world AND observes that a newer version of the technology exists, the consumer can then chose to upgrade to the newest version of the technology. Otherwise, the consumer stays with her current version of the technology. Although the new version is assumed to provide greater utility than the previous versions, the consumer may choose to remain with her current version if the disutility from adoption costs associated with the new version is too large.

In this setting, there are two potential reasons why a consumer may not adopt the newest version of a technology. First, if the consumer is informed of their full choice set, the utility of the newest version may not exceed the adoption costs. Second, a consumer simply may not be informed of the existence of a new version of the technology. These two reasons have different implications for how policy and market institutions would affect consumer welfare.

The shape of the aggregate diffusion path for a new technology is thus determined by the distribution in the consumer population of the (net) costs of adopting the new technology, which we will call Δ and the rate at which consumers become informed, which we will call θ. An econometrician seeking to distinguish between these two reasons cannot simply look at the pattern of diffusion of the newest technology: there could be considerable delay before adoption either because many consumers, i, have high Δ_i (low net benefits of adoption) or, alternatively, because many consumers have low θ_i (low information arrival rates).[13] The econometrician needs some information that reveals the consumer's knowledge of her choice set in order to compare adoption rates by informed and uninformed consumers. This will identify the importance of information about the state of the world (specifically, the existence of a new version of a technology) relative to adoption costs for the diffusion of the technology.

3.1. Model Overview

We propose a model and a corresponding dataset which allows us to separately identify and quantify the role of information and adoption costs on delayed diffusion of a new technology. The center of our estimation strategy is that we employ two dependent variables to measure adoption costs (the consumer's demand for elements in the choice set) and information (the consumer's knowledge of her choice set). The first dependent variable is a traditional

[13] This is a familiar observation in the economics of diffusion of new technologies. See, e.g. "Innovation and Diffusion," by Bronwyn H. Hall, in Fagerberg, J., D. Mowery, and R. R. Nelson (eds.), Handbook of Innovation, Oxford University Press, 2004.

diffusion variable called *NEWEST*, and it is an indicator of whether a consumer has upgraded to the newest version at time t ($NEWEST_{it}$=1 if consumer i has the newest version at time t). The second dependent variable is called SAY_{it}, and it is a statement by the consumer about whether she has the newest version at time t. Like our dataset, many modern computer generated datasets create a variable like *NEWEST* automatically; constructing a variable like *SAY* requires administering a survey to consumers by researchers or business people.

To use these two dependent variables, we need a working model both of what people *do*, i.e. a dynamic demand model, and of what people *say*. To understand the key modeling steps in our approach, first consider a dream dataset in which (a) consumers' actual choices are automatically recorded over time, (b) consumers are asked every period whether they are using the newest version of the technology, and (c) all consumers answer that question in a way which reveals their exact knowledge state.

As long as the econometrician can observe what version of technology the consumer is using at each time t and can observe the release dates of each new version, $NEWEST_t$ is easy to construct for all periods. As a result, we could identify exactly when a consumer adopted a new version. But how do we know whether a non-adopter did not know about the new version or, instead, knew about it and decided against adopting? In our dream dataset, each consumer's answer to the question "Are you using the newest version of the technology?" is easy to interpret. A consumer answers "yes" only if she means "I observed the state of the world this period, and then I chose to adopt the newest version," or "I saw that I already have the newest version." She says "no" only to mean "I observed the state of the world this period, and although I saw that a newer version existed, I chose not to adopt, because the net utility did not exceed that of my current version." Finally, she says "I don't know" only if (recall, this is a dream) she didn't observe this period. With this information, one could divide non-adopters into the uninformed and the unwilling-to-adopt, and then pin down the distribution of Δ_i and θ_i. That is, diffusion could be divided into its learning and choosing elements.

Our data differs from this ideal panel data in two ways. First, we do not observe consumers at each time t. We observe several cross-sections of consumers at survey times $t=S$. This means that we cannot observe exactly when a consumer upgraded to a newer version. We only know that it occurred sometime between S and the release date of the newer version, time $t=R$. Similarly, a consumer may have observed the state of the market at any time between her initial period t_0 and S. We build a dynamic programming model of the consumer's path of observation and upgrades and accumulating hazard for *NEWEST* from R to S.

Second, no survey can hope, realistically, to direct all consumers to answer a question (especially one to which they do not know the answer) in a way which reveals their exact knowledge state (see the literature on surveys and elicitation of consumer preferences and beliefs).[14] We construct a model in which a consumer who gives a better answer, e.g. a consumer who answers the question correctly, is more likely to be a well-informed consumer. However, our model is much more cautious than the one that would work in our dream dataset; in particular, we do not make the assumption that *any* consumer answers in a way which fully reveals their information. Instead, we assume that a subset of consumers answers the question as a rational statistician while another subset of consumers answers in a way which is *not* related to their information type. Our rational statistician (RS) model is very restrictive, and we draw information about consumers' information types only to the extent that their answers correspond to the RS model.

Our empirical model addresses our data constraints so that we can identify the difference between information and transaction cost reasons for delayed diffusion of new browser versions.

3.2. Dynamic Model of Technology Demand

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[14] The experimental economics literature since Becker, DeGroot and Marschak (1964) has emphasized the importance of incentive-compatible elicitation of preferences and probabilities. Many experiments have linked consumer statements in surveys to incentive-compatible actions in the surveys. Glaeser et al. (2000) has shown that there can be a complex relationship among (1) self-reported beliefs, (2) self-reported past actions, (3) tastes (as revealed by actual behavior) and beliefs (as revealed by actual behavior).

A large number of studies, most in cognitive psychology but some in other social sciences, illuminate the problem of modeling the relationship between what a consumer knows and says. This is a complex area, but some knowledge decays with time, and consumers are particularly bad at remembering the precise date of long ago events. Consumers are better at recall of major events than of minor ones. These empirical regularities are relevant to our estimation because the question of whether a consumer has the newest browser involves recalling when they got their browser, typically not an important event, after different amounts of time have elapsed.

A considerable literature, almost all outside economics, considers consumers' tendency to report, in some circumstances, what they would like to be true or what they would like to be perceived as true by others. In our context, this could plausibly lead to a tendency to say "newest" or even "certain newest" without regard to their actual knowledge.

"Measuring utility by a single-response sequential method," GM Becker, MH DeGroot, J Marschak - Behavioral Science, 1964, pp. 226-232.

Edward L. Glaeser, David I. Laibson, José A. Scheinkman, and Christine L. Soutter, "Measuring Trust," The Quarterly Journal of Economics (2000) 115(3): 811-846.

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We model a consumer's optimal demand decision over time in this section. Step 1 is the consumer's environment. Step 2 is the consumer's information and her optimizing decision over whether to opt-in to new versions of the technology she observes.

The evolution of technology over time is characterized by a scalar time-series process

$$X_t = X_{t-1} + s_t \varepsilon_t, \qquad (1)$$

where $s_t \in \{0,1\}$, the version-introduction dummy, follows a Markov chain and $\varepsilon_t > 0$, the product quality improvement, has an i.i.d. distribution with positive support.

Each consumer i is infinitely-lived and discounts utility from future periods by factor ρ. At the beginning of period t, consumer i is using technology x_{it}, acquired at some earlier time period. Since the consumer may not have the latest technology, $x_{it} \leq X_t$. Consumer i begins at time t_{0i} with technology x_{it0}. Consumers are heterogeneous in initial conditions (IC), varying in t_{0i}, in x_{it0}, and by not always having $x_{it0} = X_t$.

Consumers are heterogeneous in their ability to observe realizations of the aggregate technology process X_t. Specifically, consumer i observes the current level X_t only with probability θ_i in period t. All consumers, however, form statistically correct expectations about unobserved X_t. Consumers are also heterogeneous in their cost of adopting the newest technology. If the consumer observes, she can decide to pay an adoption cost $\Delta_i > 0$ and download the newest version, setting $x_{it+1} = X_t$. Otherwise, if the consumer does not observe, or if the consumer observes but decides not to adopt, the consumer's technology does not change, i.e. $x_{it+1} = x_{it}$. Consumers are not heterogeneous in flow utility, $u(\ )$, i.e. a consumer with technology x receives flow utility $u(x)$.

Denote the outcome of the probabilistic observation opportunity in period t by $\Theta_{it} \in \{0,1\}$,with $\Pr(\Theta_{it} = 1 | \Theta_{it-1} = 0) = \theta_i$ for all t. The consumer's only decision each period is whether or not to download the newest version conditional on $\Theta_{it} = 1$. Let this decision be $d_{it} \in \{0,1\}$. We can thus write the complete life-time optimization problem of consumer i as

$$\max_{\{d_{it}\}} \sum_{t=0}^{\infty} \rho^t \mathrm{E}_{t_0} \{(1-\Theta_{it})u(x_{it}) + \Theta_{it}[d_{it}(u(X_t)-\Delta_i) + (1-d_{it})u(x_{it})]\} \qquad (2)$$

subject to the transition constraint for the individual consumer

$$x_{it+1} = (1-\Theta_{it})x_{it} + \Theta_{it}\left(d_{it}X_t + (1-d_{it})x_{it}\right), \qquad (3)$$

and to the aggregate (market) technology transition (1) and IC (t_{0i}, x_{it0}).

To calculate the expectation operator in (2), we assume that all consumers know their own type θ_i, Δ_i, and the distributions of s_t and ε_t. Hence the expectation operator in equation 2 implies a rational expectation over the evolution of future technology levels and own observation and adoption opportunities, given time t_0 information.

We assume the per-period utility function $u(\ )$ has $u'(x)>0$ and $u''(x)<0$. This is important for the long-run stationarity of the problem. Note that the average level of technology improvements $E(\varepsilon_t)$ is constant based on the specification in Equation 1.[15] For our implementation, however, the relevant range of the state space is an intermediate stage in which adopting the next version is most likely beneficial to consumers.

We use dynamic programming to solve for the optimal adoption behavior conditional on consumer type ($\theta_i.\ \Delta_i$) and IC (t_{0i}, x_{it0}).

Our first dependent variable is *NEWEST* at the time we observe the consumer, S. If $X_s > x_{ti0}$, the consumer can only have the newest technology by opting-in. In that case, the newest technology must have been introduced at a time R such that $S \geq R > t_{0i}$ and the consumer's opt-in interval is [R, S]. This means that if the user becomes informed at any time in that interval, she may choose to obtain the newest version. *NEWEST* is a compound event whenever $R<S$ because the choice may occur at any point in the opt-in interval.

The full (numerical) solution to the demand model lets us calculate the probability that a user whom we observe at time S demands the newest version of the technology. To do this, we condition on the realization of X.[16] Let $R \leq S$ be the earliest date at which $X_R = X_S$. We calculate the pdf of the event that i's most recent observation was at time t, $m_{it}=\{\Theta_{it} = 1\ \&\ \Theta_{it'} = 0$ for $t<t' \leq S\}$, and call it $f_m(t, \theta)$.[17] We calculate

$$\Pr(NEWEST_i |\ \theta_i, \Delta_i, S, R, t_0, x_{it0}) = \Sigma_{t=R\ldots S} \Pr(d_{it} |\ \theta_i.\ \Delta_i, t_{0i}, x_{it0})\ f_m(t, \theta_i). \quad (1)$$

We will often use a survivor (cumulative hazard) interpretation of this probability in which θ_i is the hazard for consumer i becoming informed and $\Pr(d_{it} |\ \theta_i.\ \Delta_i, t_{0i}, x_{it0})$ is the hazard for adopting an available technology conditional on becoming informed. Note that this depends on θ_i as well as Δ_i because we derive it from a consumers' dynamic optimum, so that the

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[15] Decreasing marginal utility, in combination with a strictly positive and constant cost of adoption $\Delta_i > 0$, then implies that after a certain date the expected utility gain from adopting the next version will be less than the adoption cost. This is realistic when applied to a narrow category of technology such as web browsers.

[16] We must condition on the realization of X even to define the dependent variable *NEWEST*. More importantly, as with any serious study in the economics of information, it is essential that we know something the consumers do not, i.e. the realization of the X process.

[17] By a recursion, we see $f_m(S)= \theta$, $f_m(S\text{-}1)= (1\text{-}\ \theta)\ \theta$ and so on.

likelihood of becoming informed again in the future affects the consumers' decision to download conditional on observing today.

An example may illustrate how we use the model to calculate the probability that $NEWEST_{\mathrm{i}}$=1. Suppose a user gets her computer at time 1, with version X_1 installed as the default. A new version of the technology, X_2, is introduced at time 5, and we observe the user at time 6. So this example has $S=6 > R=5 > t_{i0}=1$. The opt-in interval is $[R, S]=[5,6]$. To calculate the probability, we condition on the event that the opt-in interval begins at time 5 and that the technological level of the newest technology is X_2. Consumers whose latest observation occurs before the opt-in interval cannot have the latest technology, so we can calculate the Pr(*NEWEST*) as follows:

Figure 2

Period	Hazard for Getting Informed	Hazard for Obtaining | Informed	Probability of Obtaining *NEWEST*
5	θ_i	$D_5=\Pr(d_5=1)$	$\theta_i D_5$
6	θ_i	$D_6=\Pr(d_6=1)$	$(1- D_5\theta_i)\theta_i D_6$
Pr(*NEWEST*)			$\theta_i D_5+(1- D_5\theta_i)\theta_i D_6$

In the example, calculating the probability that a user has adopted by time S is simply a matter of accumulating the hazard for adoption at each of the two dates in the opt-in interval. Of course, to calculate $D_5=\Pr(d_{i5}|\ \theta_i.\ \Delta_i, t_{0i}, x_{it0})$ we need to solve the consumer's dynamic optimum.

In short, we use the solution to the optimizing model to calculate the probability of the event $x_{iS}=X_s$.[18] We create a function that yields this probability; it depends on the date and the initial conditions and the user's type.[19] We call this function $\Pr(NEWEST_{\mathrm{i}}\ |\ (\theta_i.\ \Delta_i, t_{0i}, x_{it0})$.

[18] Each of these events in which a user obtains the latest technology at time t can also be a compound event when the history is longer than in our example. In particular, the user can have obtained a version of the technology in between x_{i0} and X_n. It is also possible that the user has observed at earlier times than she downloads (either before or after t_{1N}) but this does not create a compound event as earlier observations are superseded by the latest observation under our information assumptions.

[19] The solution to the optimization problem for the user depends on the realizations of the dates of introductions of all improvements before S and also on the extent of those improvements. We calculate the probability conditioning on those introductions. Since the date S and the IC determine the history of introductions, we do not include it as a separate conditioning event in $\Pr(x_{iS} = X_S|\text{events})$.

3.3. Model of Survey Responses

We as econometricians know whether each consumer has the newest version of the technology. Given the information-processing problem just described, a consumer need not know the correct answer. We now model a consumer's answer to the question "Do you have the newest version of the technology?" to sharpen our inference about their information-processing type, θ_i.

An obvious intuition is that consumers who know their choice set are more likely to answer this question correctly than consumers who do not know their choice set. One simple model – not obviously correct, but easy to interpret – thus posits that consumers with higher θ are better informed and thus more likely to answer the question correctly. We estimate a version of this model, specifying a simple descriptive model of *RIGHT* as a function of θ and other causes. To be specific, we model

$$\Pr(RIGHT_i \mid NEWEST_i)=\text{logit}(Z_R\beta_R) \quad (2)$$

where Z_R includes θ_i and $NEWEST_i$. The benefit of this model is that the inclusion of θ_i in the model for *RIGHT* imposes a cross-equation restriction which permits separate identification of econometric models of θ_i and of Δ_i.

That simple and obvious model has two kinds of problems. First, it assumes that all consumers answer the question as best they can using an economist's rational-statistician frame of reference. The empirical literature on consumer information reporting is not encouraging for making this assumption about all consumers. Second, it does not adequately account for the possibility that a well- but not perfectly-informed consumer could give the wrong answer. For example, if $R=S$, thoughtful consumers who observed last period might answer "yes." Such consumers are wrong, but, conditional on their information set, have given a very good answer. Our solution to these two problems is to construct a model (1) with heterogeneity in how consumers answer and (2) that carefully specifies the relationship between what a rational-statistician consumer knows and what she says.

3.3.1. Rational-statistician (RS) consumer types

Let Q be the set of responses a consumer can choose in response to "Are you using the latest version?" In our application, Q={"yes, certain," "yes, uncertain," "no, certain," "no, uncertain," "don't know"}.

An RS consumer gives the best possible answer to the question given her information at the time of the survey, S. Denote the consumer's information set at time t as $\mathcal{I}_{it}$. What the consumer says at time S, $\acute{\eta}_{iS} \in Q$, is the outcome of a decision rule that maps her information into the answer set, $\acute{\eta}_{iS}=\acute{\eta}(\mathcal{I}_{it})$. The RS-consumer bases her answer on the objective probability that her technology is the newest version at the time of survey, i.e. $\pi_{is} = \Pr(x_{iS}=X_s \mid \mathcal{I}_{iS})$. We use a simple model based on two thresholds, $q_2<q_1<.5$.

We assume that the RS consumer uses the same model in calculating $\Pr(x_{iS}=X_s \mid \mathcal{I}_{it})$ as in the demand model but permit consumers to be uncertain in their recall of dates.[20] Begin with a consumer who most recently observed at time m. If a consumer observed and did not adopt, i.e.

if $m \geq t_{0i}$ & $X_m > x_{iS}$, then $\pi_{is} = \Pr(x_{iS}=X_s \mid \mathcal{I}_{iS})=0$. (3)

This is a restriction between the RS model and the demand model based on the assumption that a consumer who has decided not to adopt (knowing their choice set at that time) recalls the decision. If a consumer observed and has the newest version (whether adopting at time m or earlier), then they use the Markov chain model with introduction probability p_i to calculate the probability. The consumer calculates if $m \geq t_{0i}$ & $X_m=x_{im+1}$, then $\pi_{is} = \Pr(x_{iS}=X_s \mid \mathcal{I}_{iS})=p_i^{(S-m)}$ where we assume that p_i is distributed BETA(α_q, β_q). Thus we calculate

$$\pi_{is}(m,\alpha_q,\beta_q) = E[\Pr(x_{iS}=X_s \mid \mathcal{I}_{iS})=p_i^{(S-m)} \mid \alpha_q, \beta_q] \quad (4)$$

Figure 3

Consumer Response $\acute{\eta}_{iS}$	Thresholds Partition Probability
Yes, certain	$\pi_{is}>1-q_2$
Yes, uncertain	$1-q_2>\pi_{is}>1-q_1$
Don't know	$1-q_1>\pi_{is}>q_1$
No, uncertain	$q_2< \pi_{is} <q_1$
No, certain	$\pi_{is} <q_2$

Finally, we need to make an assumption about the information set of a consumer who has never observed, i.e., make an assumption about the information set at t_{0i}. Neither economic theory nor anything else is helpful here, so we consider a variety of assumptions about $\pi_{it0}=\Pr(x_{it0}=X_{t0} \mid \mathcal{I}_{ito})$, including (a) the consumer is informed of the state of the market at t_{0i} and

[20] {Cite to survey research literature on date recall.}

(b) the consumer is certain that they have the newest version at t_{0i}. These differ importantly when consumers IC involve getting an older version at t_{0i}.

The econometrician does not know when the consumer last observed, but the consumer does (i.e. $\mathcal{I}_{iS}$ contains m_{iS}). Recall that $f_m(m, \theta)$ is the pdf of m, We calculate

$$\Pr(\acute{\eta}_{iS} \mid \theta_i, \alpha_q, \beta_q, q_2, S,R,t_{0i}) = (1\text{-}\ f_m(t_{0i}, \theta_i)\ )\pi_{it0} + \Sigma_{t=R\ldots S}\ f_m(m, \theta_i)\ \pi_{is}(m,\alpha_q, \beta_q) \qquad (5)$$

Thus we see that the same distribution over time, driven by θ, mixes the model for adoption (1) and the RS model for what consumers say (7). These restrictions are what lead the joint estimation of the demand model and the RS model to identify θ.

3.3.2. Descriptive (DE) consumer types

Some consumers may answer the question without attempting to remember when they last observed and working out the statistics. We construct a simple model of what (in Q) these descriptive (DE) consumers say. Scholars in other disciplines have determined that many consumers have a bias toward positive answers, particularly men, and that many consumers have a bias toward certainty, particularly men. So we model Q for these consumers as a bivariate logit:

$$\begin{aligned} &\text{PrY=Pr(Yes)=logit}(\ \alpha_0+\ \alpha_M MALE), \\ &\text{PrC=Pr(Certain)= logit}(\ \alpha_{c0}+\ \alpha_{c1}+\alpha_{cM} MALE); \qquad (6) \\ &\text{PrD=Pr(Don't Know)=1- logit}(\ \alpha_{c0}+\alpha_{cM} MALE) \end{aligned}$$

Finally, we model the probability that a particular user is an RS or a DE. Our simplest model is an independent mixture model, in which Pr(DE)=λ.

4. ECONOMETRIC ESTIMATION

We now turn to econometric estimation of our models. The structure of our estimation is presented in Figure 5. First, we specify which deep parameters we assume fixed and which ones are functions of observables. Second, we solve the problems raised by incomplete sample information about IC.

4.1.1. Deep parameters as function of observables

We do not actually observe θ_i or Δ_i but instead have an econometric model of them that depends on covariates, z, and parameters β=(β_θ, β_Δ). Let the observable data about consumer i be z_i and assume an econometric model such that the distribution of θ_i, Δ_i is $G(\theta_i, \Delta_i \mid z_i, \beta)$.

The per-period observation hazard θ_i is naturally bounded on the interval [0,1], and, from both the perspective of a user and the econometrician, future observation events are random as long as θ_i is in the interior. Accordingly, we model θ_i as a deterministic function of user characteristics:

$$\theta_i = [1+\exp(-z_i\,\beta_\theta)]^{-1} \qquad (7)$$

We include regressors, listed in Table 8, which we suspect might be particularly likely to capture consumer heterogeneity in information about software.

Demand in the ordinary sense in our model consists both of the flow utility *u(x)* and the one-time adjustment cost. Since *u(x)* does not depend on *i*, we model Δ_i as capturing variety in the taste for new technology as well as literal download cost. Thus we include not only user characteristics that predict download cost (such as modem speed) but also characteristics that predict value in use (such as hours spent on the web.) These are listed in Table 8. We let the range of Δ_i be $[0, \Delta_{max}]$ so that at one extreme it is always optimal to download, never optimal at the other. Finally, we reverse signs so that β_Δ will have the sign of demand, not of cost, and write

$$\Delta_i = \Delta_{max}\,[1+\exp(z_i\,\beta_\Delta)]^{-1} + \varepsilon_i, \qquad (8)$$

where ε_i is distributed type 1 extreme value. While the agent knows Δ_i, we can observe only z_i, not ε_i.

A number of elements of the demand model are assigned constants rather than estimated. Details are in Appendix Table 4. We assign values to the utility X_t of each new version, and a function for *u( )*. To some degree, this is a normalization, since we permit consumers to be heterogeneous in the costs of adopting. However, it does impose a restriction on the demand behavior of consumers considering IE3 vs. IE2 because we only let Δ_i vary across individuals, not across individuals and versions.

We treat the level of technology X_t as an index, and rather than estimate it, assign a separate value for each version of each brand of browser using data and a variation on regressions in Bresnahan & Yin (2005).[21]

4.1.2. Ranges of Initial Conditions (IC)

We only observe consumers on their survey date, but have three kinds of information about their IC: (1) respondents answer a question about when they first used the Internet, (2) the

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[21] Essentially, using a different, aggregate dataset, that paper regresses the logit of the market share of the newest version of a browser within its brand on a version dummy, the time since introduction of the newest version, and various controls for the distribution of browsers. The coefficients on the version dummy dummies form our estimate of X_t.

respondent's OS gives us some information about when they got their current computer, and (3) IE was not available for every OS at the same date. This information gives us a *range* of possible IC dates and states for each user. We sum the likelihood over this range using a weighting scheme that reflects outside information about the relative likelihood of different dates and, in specifications estimated but not reported in this version, also reflects concerns about the relative quality of different IC information. We call the range of dates T_{0i}, with $t_{0i} \in T_{0i}$, and the initial demand states x_{it0}. We first discuss how we determine T_{0i} and then discuss how we deal with the uncertainty within the range and how we determine IC demand states.

Our model is a model of opt-in to the newest version of application software. The user opts-in by upgrading to the newest version from whatever earlier version was running on their computer. Accordingly, the conceptually correct IC are the first use of any version – that is, the date and version of that first use -- of the software on the user's current computer. The applications software IC occur when the user buys a new computer with the software on it or gets on the web and receives a copy of the software from their ISP. We make a fundamental assumption that those events are exogenous. Perhaps more to the point, we do not treat the consumer's as "choosing" the browser that came with their computer or from their ISP; we model only their decision to opt-in to newer versions.

4.1.2.1. Definition of IC dates

Respondents were asked, "How long have you been on the Internet?" and given several time intervals from which to choose (see Table 3). We subtract the beginning and end of this range from the survey date to get a range of dates, T_{Ri}. In our study period of rapid Internet growth, these first-use times are typically quite recent. We also know the range of dates, T_{Ai}, when some version of the software was available for user i's OS up to and including S.[22] The early bound on T_{0i} is defined as (1) the earliest date in T_{Ri} or (2) the earliest date in $T_{Ai} \supseteq T_{0i}$, whichever is *latest*.

With those details in place we can say that the early bound on T_0 is defined as (1) the earliest date in T_{Ri} OR (2) the earliest date in T_{Ai}, whichever is <u>latest</u>. The later bound on T_{0i} is more complex. Even if a user first got on the Internet long ago, they may have bought a

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[22] To avoid the proliferation of notation, we end T_{Ai} at the survey date S: this is just the assumption that all IC are at or before S. If the user is running Win95, T_{Ai} begins with the introduction date of IE1 (also the introduction date of Win95); if Win3.1, with the introduction date of IE2 for Win3.1, if Win98, with the introduction date of Win98.

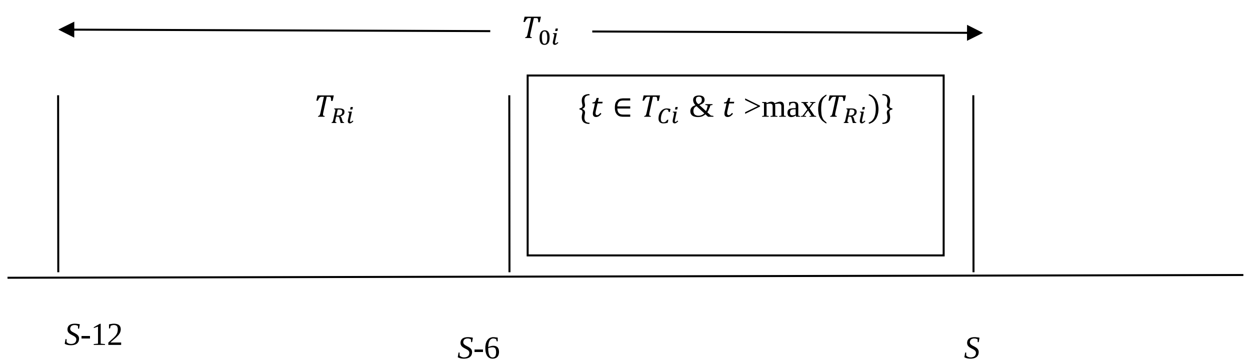
computer more recently and thus have new IC. We infer a range of dates at which *i* might have bought their computer, T_{Ci}, from the range of dates when i's current OS was the newest OS. Then $T_{Ai} \cap T_{Ci}$ is the range of dates at which buying a new computer would have led to getting a new browser version. We consider only the subset of these dates which are after max(T_{Ri}). Taking this into account, our definition of the range of dates which might be IC is

$$T_{0i} = T_{Ai} \cap \{T_{Ri} \cup [T_{Ci} \cap \{t > \max(T_{Ri})]\}.$$

The logic can be easily seen in this example drawn from our data. We observe a user at *S* running the newest OS, which has been in the marketplace and has had the software available for at least a year. The user's T_{Ri} is [*S*-12, *S*-7], i.e., they report they got on the web between six months and a year ago. However, since they might have bought a new computer in the last six months, the information available to us does not rule out IC in [*S*-6, *S*]. Thus T_{0i} is, as shown in Figure 4, the union of these two ranges of date, [*S*-12, *S*]. It is obvious in the example and easy to show generally that this leads to a contiguous list of dates.

The example shows the caution in our definition of T_{0i}. It includes all the different IC times that are not explicitly ruled out by a fact in the data. The mean length of the IC interval (i.e., max(T_{0i})- min(T_{0i})) is reported in Table 5.

Figure 4



We show, in a specification reported in Table 9, that even if the only information about IC we use is $t_{0i} \in T_{0i}$, we can estimate the parameters of our model with considerable precision. That is because even though there are many users for whom we have only an IC date range, there is still tremendous variation across individuals in IC. We have some individuals where we know their IC are in the last few months (for example, those who are surveyed early on) and others where we know their IC are long ago; for others we are certain that they did not get the newest version of the software at their IC. Statistics on the IC are reported in Table 5

4.1.2.2.Weighting within IC date range

We consider two weighting schemes that assign different probabilities, w_t, to dates $t \in T_{0i}$. These let us construct the predicted probability that the user has the newest browser as

$$\sum_{t\in T_{0i}} w_t \sum_{t\in T_{0i}} w_t \Pr(N|t = t_0 NEWEST_i|t = t_{0i}. \qquad (9)$$

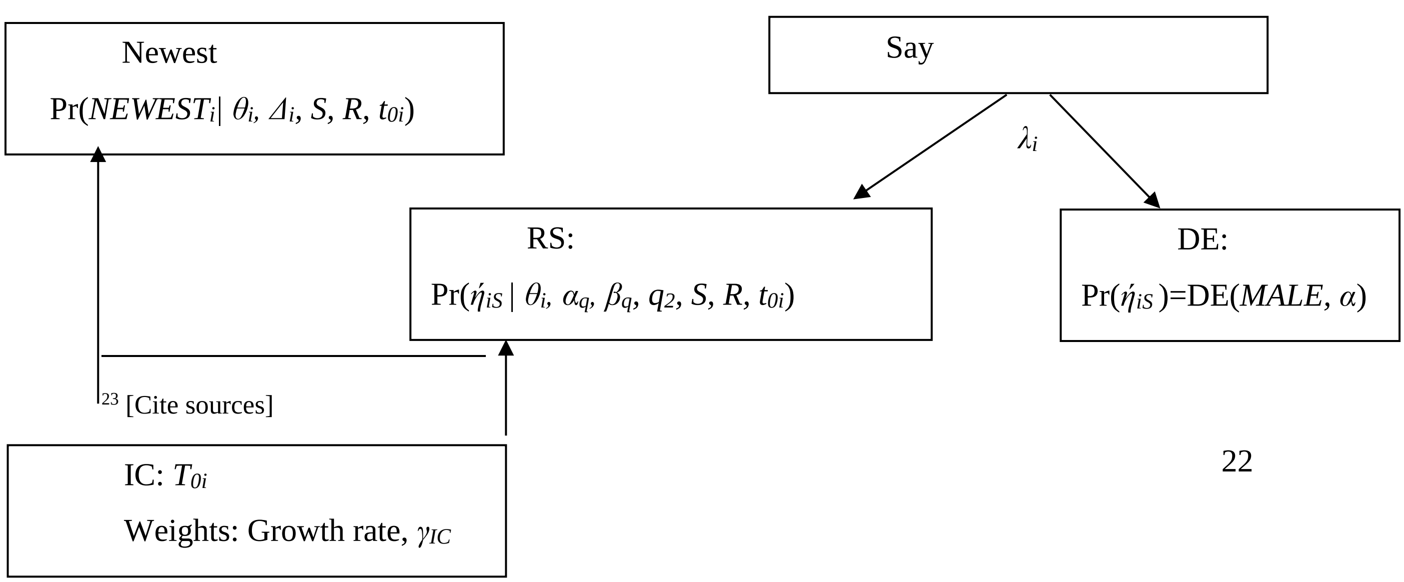
The first weighting scheme is used in all of our specifications. It assigns higher weights to more recent dates, using information on the growth rate of PC demand and of Internet usage.[23] This is a nontrivial element of our main specification, as both PC demand and Internet usage grew at about 1% per *month* in our period.

Our second weighting scheme arises only in cases like that shown in Figure 4 above, where the range of IC dates includes both the user's self-reported Internet start time and a possible later computer purchase time. In specifications not yet reported in this version, we add a parameter, γ_{rt}, which is the probability that the user has correctly reported their IC dates. We put γ_{rt} weight on the subset of T_{0i} which is in T_{Ri} and 1-γ_{rt} on the rest.

4.1.2.1.IC demand states

Once we have defined the list of times at which the IC could have occurred, we associate the browser version that would have been given to the user with a new computer or a new ISP signup at each date. This is based on the distribution release dates shown in Table 2. We also associate each date with an initial expectation about the state of the market.

Figure 5 Model Structure



[23] [Cite sources]

4.1.3. The special case of Pr(*NEWEST*=1)

In some cases, a consumer will have gotten the newest technology at their IC and need not opt-in to adopt it. In our application, these are a subset of the cases in which $R<t_{i0}$, since the dates at which OEMs and ISPs could distribute the newest browser to consumers typically came after the dates at which consumers could download it. We include such cases, assigning Pr($NEWEST_i$ | (θ_i. Δ_i, t_{0i}, x_{it0}) =1. These cases do not influence our estimates via prediction of *NEWEST* because for them Pr(Pr($NEWEST_i$ | …) is a trivial function of parameters. However, these users may be well or badly informed about their choice set, contributing to our estimates of information parameters.

5. RESULTS

5.1. Descriptive Results

As a threshold matter, we note that the rate of diffusion in our sample is low. Table 6 shows the mean of *NEWEST* to be .27, so a considerable majority of browser users have not downloaded the newest version. *PCTCOVER* also shows that just over 10% of our users would have *NEWEST* without downloading (i.e., at their IC), so the actual rate of opting in is even lower. Finally, the table shows that users whose IC is before *R*, have, on average, about 5.8 months to opt-in. If under 20% of consumers are opting-in after just less than 6 months on average after release of a new browser version, then there is some inertia around IC.

Can the inertia be explained by information? The same table shows that only just over half of users, 56%, are *RIGHT*. This encourages the view that consumers are badly informed. The last two rows of the table show that consumers who are *RIGHT* are much more likely (66%) to have downloaded *NEWEST* than those who are not *RIGHT* (7%). Many economists would conclude at this point, saying that consumer ignorance must provide much of the answer. However, what if many consumers answer “yes” to this question without deep thought? The dependence between *RIGHT* and *NEWEST* would follow mechanically. This cautionary interpretation is consistent with Table 7, which shows that those who say they have the newest are significantly less likely to be *RIGHT* than those who say they do not.

5.2. Structural Results

In Table 10 we present estimates of a model using the structure in equations (9), (8), and (6). The estimates for the two models of what consumers say (RS and DE) are shown in the right panel of Table 10. The DE model estimates are as one would expect from the bias literature. The average user tends to say "yes" (men do so more) and the average user tends to be certain (men, more so).

The RS estimates have the structure we have imposed. The threshold for certainty, q_2=0.0046 is quite close to π_{is}=1 or 0, suggesting that RS types would not casually indicate any response with certainty. The threshold for "don't know," q_1=0.46, is also close to π_{is}=.5. The average consumer responds as if the hazard for version introductions is .58, somewhat slower than the true hazard.

At the bottom of Table 10 we compare predicted values from the RS and DE models to the actual data from Table 7. It is easy to see here where the restricted RS model has trouble predicting. It particularly underpredicts "yes, certain" and overpredicts "no, certain," a response we impose if a consumer has observed the state of the market and not downloaded. Imposing symmetry and orderedness is clearly not consistent with the behavior of most consumers. It is not surprising that the estimated mixture weight on the DE model is 0.85.

We next consider the relative importance of information vs. ordinary demand in determining the pace of diffusion. The hazard for adopting in a particular period is $\theta_i \Pr(d_{it} | \theta_i. \Delta_i, t_{0i}, x_{it0})$ which we abbreviate as $\theta_i H_{it}(\,)$, the product of two hazards. While there are a number of different ways to decide which of these is "more important" in explaining the low rate of diffusion, a simple calculations seems to work for our estimates. We first note that if $\theta_i H_{it}(\,)$ were a constant, h, then h=.130 would predict the sample mean of *NEWEST*. The estimated mean of θ_i is .295, and the estimated mean of $H_{it}(\,)$ is .571, suggesting that any calculation is going to assign more of the slow diffusion to information.

Since θ_i enters not only as the hazard for becoming informed, but as one determinant of $H_{it}(\,)$, the (dynamically-optimal) probability of downloading, several different definitions of the relative importance of information are possible. These do not differ much.[24]

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[24] Those two estimates of the relative importance of information diverge because θ_i and $H_{it}(\,)$ covary. So we examine changes in the predicted mean of newest, $(\overline{NEWEST})(\theta,\Delta) \equiv \Sigma_i \Pr(NEWEST_i | \theta_i, \Delta_i, S, R, {}_t0_i, x_{it0})$ that would arise if (a) θ_i=1 and (b) $\Delta_i=-\infty$ so that $H_{it}(\,)$=1. $(\overline{NEWEST})(1,\hat{\Delta})-(\overline{\mathrm{NEWEST}})(\hat{\theta},\hat{\Delta})$ measures how much faster users would adopt if information were immediately available, and $(\overline{NEWEST})(\hat{\theta},-\infty)-(\overline{NEWEST})(\hat{\theta},\hat{\Delta})$ measures how much faster they would adopt if they always select the newest they know of. If we were to instead define a marginal "contribution of information" we would consider letting $H_{it}(\,)$ vary with θ_i, in computing the predicted values. In general, $\Pr(d_{it} | \theta_i. \Delta_i, t_{0i}, x_{it0})$ is decreasing in θ_i, because a low-θ_i consumer considering skipping a version expects to wait a long time for the next version. This would tend to reduce the marginal

5.3. A model in which *RIGHT* reflects better information

In Table 9 we present joint estimates of equation (9), our demand model, and (2), the simple descriptive model in which those who have higher θ_i are more likely to be *RIGHT*. This model is semi-structural in that it continues to use our demand model but identifies information vs. ordinary demand without any requirement that consumers be rational statisticians. Identification follows from the idea that consumers who are better information processors are more likely to be *RIGHT*. In this table, all regressors that were included above in either θ_i, Δ_i are included in both – no exclusion restrictions. The point of this table, then, is to show that demand in the ordinary sense can be separately identified from information without any exclusion restrictions.

Looking first at demand in the ordinary sense (Δ_i), we note that few coefficients are estimated precisely. The consumer's modem speed variables (*DSPEED* and *LSPEED*) are the exception, and these coefficients tells us that, as we would expect, a consumer who has a faster modem, or who does not know the modem speed (for example, because they get Internet connection services at work or at a university) has a lower download cost.

Now looking at the consumers' hazard for observing the state of the market, θ_i, we note that most of the coefficients are estimated reasonably precisely. Looking at the precisely-estimated coefficients, we see that consumers tend to become informed about new versions if they use the Internet more, if they work in the computer industry, if they are men, if they are younger, or if they manage their own internet connection instead of having it done for them at work. This looks like a model of information processing. The same was true in the structural model in Table 10, but there we imposed exclusion restrictions on which z's predict Δ_i vs θ_i.

The model does a good job of predicting *NEWEST,* and a less good job of predicting *RIGHT*. The equation for *RIGHT* is reported to the right of the table. The model appears to be doing what we asked, as the coefficient on θ_i suggests that those users with higher θ_i tend to be more *RIGHT*. So, too, are users who have the *NEWEST,* which we interpret as this model's treatment of excess optimism.

Looking now at information/ordinary demand breakdown at the bottom of the table, we see that this model, too, reports information as the key determinant of demand. The mean of θ_i is

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contribution of better information to more rapid diffusion. As we can see in Table 7, however, these effects are small. They also do not impact the "total" calculations reported in text.

far smaller than the mean of $H_{it}(\ )$, meaning once again that most of the slow diffusion is attributed to poor information. Why? This model has no restrictive treatment of who is an informed person, nor does it restrict the regressors permitted to predict Δ_i vs θ_i. The finding that information about the choice set is more important seems robust.

Indeed, information is much more important in this model than in the structural model just reported.[25] This difference in results is easy to understand. The structural model restricts the role of θ_i (in what consumers say) to only RS consumers. Since this restriction binds quite tightly, and since there is no comparable restriction on Δ_i, maximum likelihood on the demand model substitutes out of using θ_i into Δ_i to predict *NEWEST*. In the present model, we relax the restriction played by θ_i in what consumers say and it thus ends up predicting a larger portion of what they do.

We find that, in both a restricted model and a less restricted one, information about the choice set is the primary explanation of slow diffusion. To be sure, a few variables which predict demand in the usual sense (the speed of a consumer's modem, which is the main cost variable, and the hours of internet use) have statistically significant effects, but demand in the usual sense comes in as a distant second economically to information about the choice set. When we do not restrict the specification, consumer characteristic (z) appear to enter demand not through the ordinary channel of trading off the costs and benefits of downloading and installing the latest browser, but rather through variation in the consumer's information gathering.

6. CONCLUSION

We have reported two broad empirical findings about the sources of consumer inertia in the browser market. The first is methodological: we were able to distinguish between consumers' not knowing their full choice set and other sources of inertia by combining information about what consumers say and what they do. Perhaps surprisingly, this works only because a subset of consumers are rational in what they say. Alternative models, designed to be less than rigorous about discounting the irrational statements of consumers, provide a higher estimate of the importance of incomplete consumer information. We are encouraged by our success in a simple problem – product upgrades without brand choice – to consider more

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[25] The result that the variation in *NEWEST* explained by variation in θ_i is far larger than that explained by variation in Δ_i also provides an intuitive explanation of why we are better able to estimate the coefficients in θ_i.

difficult consumer problems with potentially incomplete choice set information. The ability to discern when information processing is central to the distinction between opt-in and opt-out is more generally important, and we will continue to investigate it.

Our second finding is substantive. The consumers we study, browser users in the late 1990s, exhibit considerable inertia in their software demand. The primary cause of the inertia, larger than all other causes together, is consumers' incomplete information about their choice sets.

We think this finding about demand partly explains two large changes in supply in electronic markets since the early days studied here. In our study era, consumers opt-in to the upgrade. Today, consumers of most software packages are confronted with an automatic upgrading system. They may either opt-in or opt-out of this system. Most use the system and thus do not have an opportunity to choose any particular product upgrade. Automatic upgrades economize on consumers' costs of becoming informed. However, there is no presumption of efficiency: suppliers will select the same policy about upgrades as that which would have been chosen by consumers only if consumers' and suppliers' interests in upgrades are aligned.

Second, large scale electronic markets have emerged to "nudge" particular products into consumers' choice sets. These take on a number of very different forms. Amazon, a retailer, recommends that consumers consider products similar to ones they have searched for or bought, increasing sales for itself and product suppliers. Google and Bing auction off the right to be presented for consideration to consumers who have searched for particular terms. Applications running on mobile phones or tablets similarly sell the attention of consumers. Markets to "nudge" can only emerge when consumers will react to learning that something is in their choice set. Much of the private return to technical progress in the 21st century has been created in these "nudge" markets. Here, too, any efficiency conclusion turns not on the motivations of the nudged (incomplete information) but on the motivations of the nudger (making a profitable or an efficient sale).

Whether efficient or not, these two sets of efforts -- to get in consumers' choice sets and to become the incumbent product and manage customers' demand for future versions – are here to stay. Efforts to sell consumers' attention have made it scarcer by crowding it not only with electronic products, but with media, games, and ordinary products.

It is worth pointing out that this growth is consistent only with our finding about information, not with the alternative explanations that, say, the browsers we study were hard to download or install. Today's consumers face many more choices on the online world and in the mobile world than the users we study. If the important blockage to rapid and widespread adoption of new technologies were technological, we should expect technical progress to improve it. In our example, if the important reason for the slow diffusion of new browsers was time-consuming downloads (slow modems) or difficult installations we should expect technical resources to speed up downloads and/or to make installations easier, as, indeed, occurred. So if that were the blockage, the problem we examine in this paper should be, by now, going away. If, however, the important blockage is that mass market users are incompletely informed, we should expect the problem to continue to get worse. There are more and more applications, and consumer attention is drawn to more and more diverse topics, as the online world moves to being the mobile world. Despite efforts to give consumers better and better opportunities to become informed through search or through social networks, the problem of incomplete information is growing secularly. We forecast that the importance of a wide variety of novel supply institutions, many with a default or demand-steering flavor, will grow. Such institutions today are providing much of the mechanism for "monetizing" consumer-oriented technical progress in the online and mobile worlds today; understanding them is one part of understanding the extremely rapid technical progress seen in consumer-oriented networks today.

Table 1 Observed OS and their market periods (n=5556)

OS	Windows 3.1	Windows 95	Windows 98
Market Period	Through 7/95	8/95—7/98	after 8/98
% of Sample	.045	.902	.052

Table 2 Major Microsoft browser versions in our analysis (n=5556)

Version	IE1	IE2	IE3	IE4	IE5
Definition	includes 1.x	includes 2.x	includes 3.x	includes 4.x	includes 5.x
% of Sample	.062	.051	.536	.346	.004

Table 3 *Ynet*: User-recalled time on the internet (n=5556)

Time	Percent
0 - 6 months	12.31%
6 months - 1 year	14.58%
1 – 3 years	44.06%
4 – 6 years	22.03%
Over 7 years	7.02%
Total	100.00%

Table 4 Descriptive Statistics of Data in Estimation sample n: 5556 (except as noted)

	Mean	Std Dev	Minimum	Maximum
NEWEST[1]	0.27160	0.44482	0	1
RIGHT[2]	0.56154	0.49628	0	1
AWIN98	0.052556	0.22317	0	1
SURVEY	7.70644	1.70065	4.	10.
USE[3]	1.14483	0.89117	0	2.52000
HOURS[4]	0.15400	0.1193	.5	0.50000
DHOURS[5]	0.081353	0.27340	0	1
LSPEED[6]	3.945025	1.528081	1.94591	11.96582
DSPEED	0.0445	0.20613	0	1
MALE	0.71220	0.45278	0	1
AGE[7]	0.3664	0.1302	.02	0.83
DAGE	0.013499	0.11541	0	1
INCOME[8]	0.6065	0.3967	.05	5.
DINCOME	0.13301	0.33962	0	1
ONWEBDATE[9]	0123.3	8.26	105	139
PAYWORKDK	0.25198	0.43419	0	1
OCCCOMP	0.27178	0.44492	0	1

[1] The dummy *NEWEST* = 1 when the browser identified in the user-agent field is the newest available as of the survey date on the respondent's OS (also identified from the user-agent field) based on the introduction dates in Appendix Table 2.

[2] The dummy *RIGHT* = 1 if *NEWEST* = 1 and the consumer gave any of the three "yes" answers listed in Table 7, or if *NEWEST*=0 and the consumer gave either of the two "no" answers listed there. This definition treats "don't know" as uninformed and puts it in the same class as an incorrect response. Sample size: 2933

[3] Units: times/month. Sample size: 5104.

[4] Units: hours/week. Sample size: 5104

[5] We include a dummy for each continuous regressor if the consumer does not answer the question, and give it a name Dz. Thus DHOURS is a dummy for no data on HOURS. It also controls for no data on USE.

[6] Log of modem and internet access speeds measured in kbaud, which the respondent selects from a menu of rated access speeds.

Sample size: 5309

[7] Units: years/100, sample size: 5481

[8] Units: ranges scaled 1-5 sample size: 4817

[9] This is equal to the survey date minus the midpoint of the range of dates selected by the user in answer to the question, "How long have you been on the Internet?"

Units: days/100.

Table 5 Initial Conditions (IC) Statistics (n=5556)

Variable	Mean	Std. Dev.	Min	Max
S (Survey date)	Aug 1997	310.47*	Oct 1995	Oct 1998
Lag from t_{0i} to *S*[1]	9.49	5.91	0.00	30.43
On web before t_{0i}[2]	0.361	0.480	0.000	1.000
IC Interval				
min(T_{0i})	Feb 1996	302.72*	Sep1995	Sep 1998
max(T_{0i})	Jul 1997	308.29*	Oct1995	Oct 1998
T_{0i} length[3]	17.66	11.29	0	36

*Standard Deviations are measured in days

Table 6 Dependent Variables Statistics for Descriptive Statistics Analysis

Variable	Mean
NEWEST[4]	0.272
RIGHT[5]	0.562
PCTCOVER[6]	0.106
Opt-in period[7]	5.83
NEWEST | *RIGHT*	0.660
NEWEST | not *RIGHT*	0.074

[1] In months, measured from center of T_{0i} to *S*.

[2] Dummy: = 1 if *last* reported on web date is (weakly) before earliest date in T_{0i}.

[3] Max(T_{0i}) - min(T_{0i}), in months.

[4] *NEWEST* is a dummy that is one when the browser identified in the user-agent field is the newest one available as of the survey date on the user's OS (also identified from the user-agent field) based on the introduction dates in Appendix Table 2.

[5] *RIGHT* is 1 if *NEWEST*=1 and the consumer gave any of the three "yes" answers listed in Table 7 or if *NEWEST*=0 and the consumer gave either of the two "no" answers listed there. Note this definition treats "don't know" as uninformed, and puts in the same class as an incorrect response.

[6] *PCTCOVER* is the likelihood that a user got *NEWEST* at their initial conditions. Calculated as the (unweighted) mean across the months in T_{0i} of the dummy $t_0 \geq R'$.

[7] The opt-in period is the number of months S-R' .

Table 7 Consumer Statements (*SAY)* and *RIGHT* (2,933 respondents)

Possible response to "Do you think you are using the most up-to-date version of your browser?"		
	Frequency	Percent Actually *RIGHT*
Yes, I am quite certain	.5742	.5540
Yes, and it is a pre-release/beta version	.0147	.5349
Yes, but I am not so certain	.1643	.2697
No, I think I am using an older version	.0603	.8079
No, I am definitely using an older version	.1558	.9147
Don't know	.0307	(NA)
All	1.00	.5615

Table 8 Included Regressors (Preferred Specification)

β_θ	β_Δ
CONSTANT	*CONSTANT*
ONWEBP[1]	*DSPEED*
OCCOMP	*LSPEED*
PAYWKDK	*DHOURS*
	HOURS
	DAGE
	AGE
	INCNS
	INC
	MALE

[1] See Appendix Table 3 for survey questions underlying these variables. ONWEBP is (days on the web since the beginning of the self-reported interval in Ynet)/10,000. OCCOMP is OccComp, self-reported profession is computers or computer consulting. PAYWDK is the sum of PayWork and PayDK, i.e. a dummy for people uninformed about their internet costs either because their employer pays or because they say they don't know who pays.

Table 9 Estimates of Model with *RIGHT*

	Δ_i		θ_i			RIGHT	
	Est	SE	Est	SE		Est	SE
CONST	-0.906	0.629	-1.855	0.402	*CONST*	7.074	0.723
DHOURS	0.521	0.307	-0.142	0.236	*AWIN98*	-1.354	0.233
HOURS	0.743	0.728	0.491	0.642	*SURVEY*	-0.811	0.078
USE	0.120	0.106	0.225	0.109	θ_i	0.669	0.192
PAYWORK	0.097	0.199	-0.713	0.212	$NEWEST_i$	2.719	0.124
DSPEED	1.965	0.709	-1.242	0.500			
LSPEED	0.459	0.190	-0.102	0.043			
OCCCOMP	0.247	0.171	0.265	0.174			
MALE	0.023	0.185	0.827	0.266			
DAGE	1.613	1.217	-1.329	0.654			
AGE	-0.360	0.541	-1.290	0.600			
DINC	-0.031	0.217	0.122	0.230			
INC	0.184	0.228	-0.206	0.201			

Obs=5556 for *NEWEST*, 2933 for *RIGHT*
Ln(likelihood)=- 5222.969

For the columns headed Δ_i, and θ_i, what is presented are the estimates of β and their estimated standard errors. For *RIGHT*, which has a new set of row labels, the columns are the probit estimates and their standard errors.

Predictions:

avg. Pr(*NEWEST)*	0.543	for users who have *NEWEST*
avg. Pr(*NEWEST*)	0.329	for users who don't have *NEWEST*
avg. Pr(*RIGHT*)	0.753	for users with *RIGHT=1*
avg. Pr(*RIGHT*)	0.681	for users with *RIGHT=0*

Demand Breakdown:

Mean of $H_{it}()$ .963 Mean of $H_{it}()*\theta_i$ .130

Table 10 Estimates of Structural Model Parameters

	Est	SE		Est	SE
β_θ			RS Model		
CONSTANT	3.45575	0.1725	q_1	.46	.0116
ONWEBP	-3.52681	0.1348	q_2/q_1	.01	.6513
OCCOMP	0.42981	0.1320	*mean(p)*	.58	.9982
PAYWKDK	-0.36118	0.1273			
			DE Model		
Mean(θ_i)	.295		Yes		
			Constant	1.79669	
β_Δ			*Male*	-0.02599	
CONSTANT	-1.29077	0.5406	Certain		
DSPEED	0.47005	0.5605	*Constant*	-2.87040	
LSPEED	-0.10657	0.1016	*C2*	-1.13045	
DHOURS	0.58107	0.2677	*Male*	2.37841	
HOURS	-3.50724	0.9882			
DAGE	-0.47825	0.7159	Pr(DE)	.85249	
AGE	2.01000	0.4915			
INCNS	0.96495	0.2200			
INC	0.32595	0.2507			
MALE	-1.24024	0.6483			

Obs=5556 for *NEWEST*, 2933 for *RIGHT*.
Ln(likelihood)= -3240.35

Actual and Predicted *SAY*

	yc	yu	nu	nc	dk
Actual data	0.589	0.164	0.060	0.156	0.031
RS	0.208	0.103	0.251	0.410	0.029
DE	0.652	0.176	0.030	0.112	0.030

Table 11 Probability Derivatives for Hazard (based on model in Table 9)

Person	$\partial\theta_i\ H(\Delta_i,\ \theta_i)\ /\partial z$	$\partial H((\Delta_i,\ \theta_i)/\ \partial z$
	Unconditional Hazard for *NEWEST*	Conditional adoption hazard
DHOURS	0.009	-0.013
HOURS	-0.050	0.049
USE	-0.019	0.021
PAYWORK	0.029	-0.054
DSPEED	0.035	-0.079
LSPEED	0.007	-0.009
OCCCOMP	-0.023	0.025
MALE	-0.102	0.083
DAGE	0.035	-0.082
AGE	0.035	-0.081
DINC	-0.009	0.011
INC	0.012	-0.018

7. Appendix

Appendix Table 1 Variable Definitions from Web Server Log

Variable	Definition
who	unique identifier
IE	Dummy for choice of Internet Explorer
v	Numerical value (1-5) of version of browser used
Amac	Dummy for operating system (OS) used, according to agent file: Mac = 1
Awin31	Dummy for OS used, according to agent file: Windows 3.1 = 1
Awin95	Dummy for OS used, according to agent file: Windows 95 = 1
Awin98	Dummy for OS used, according to agent file: Windows 98 = 1

Appendix Table 2 Introduction (beta) date for each browser on each OS

	Windows 3.1	Windows 95	Windows 98
IE1		Aug. 1995	
IE2	April 1996	Dec. 1995	
IE3	Dec. 1996	Aug. 1996	
IE4	Feb. 1998	Oct. 1997	Aug. 1998
IE5	March 1999	March 1999	March 1999

Appendix Table 3 Variable Definitions from GVU Survey
Superscripts on variable names indicate survey numbers in which question was asked. No superscript indicates that the question was asked in surveys 4-10.

Variable	Definition
who	unique identifier
Survey	Survey number
S	Date of survey
Age$^{4\text{-}8}$	"What is your age?" Numerical value entered by respondent or "Rather not say" (not an option in survey 4)
Age$^{9\text{-}10}$	"What is your age?" Checkboxes for 5 year intervals and "Rather not say"
Dage	Dummy=1 for "Rather not say" age
Male	"What is your sex?" Dummy for sex: male = 1
White	"How would you classify your race?" Dummy for race: white = 1
Asian	"How would you classify your race?" Dummy for race: asian = 1
Black	"How would you classify your race?" Dummy for race: black = 1
Raceot	"How would you classify your race?" Dummy for race: hispanic, latino, indigenous, native, multi, spanish, other = 1
Racens	"How would you classify your race?" Dummy for race: not say, na = 1
Educ11	"Please indicate the highest level of education achieved." Dummy for education: grammar = 1
EducHS	"Please indicate the highest level of education achieved." Dummy for education: HS, special, abitur, voctech = 1
EducSC	"Please indicate the highest level of education achieved." Dummy for education: some college, some = 1
EducC	"Please indicate the highest level of education achieved." Dummy for education: college = 1
EducPG	"Please indicate the highest level of education achieved." Dummy for education: masters, professional, doctoral = 1
EducOT	"Please indicate the highest level of education achieved." Dummy for education: other = 1
Income	"Please indicate your current household income." (in thousands of dollars) Checkboxes for $10-$15 intervals and "Rather not say"
Dincome	Dummy for "Rather not say" income
Ynet	"How long have you been using the internet?" Checkboxes for intervals
USA	"Where are you located?" Dummy for location: USA=1
EUR	"Where are you located?" Dummy for location: Europe=1
LocOT	"Where are you located?" Dummy for location: Africa, Antarctica, Asia, Canada, Central America, Mexico, Middle East, Oceania, South America, West Indies = 1

Dos	"What is your primary computing platform?" Dummy for platform: dos = 1
NT	"What is your primary computing platform?" Dummy for platform: nt = 1
Win	"What is your primary computing platform?" Dummy for platform: Windows = 1
Win95	"What is your primary computing platform?" Dummy for platform: Windows 95 = 1
Mac	"What is your primary computing platform?" Dummy for platform: Mac = 1
Win98[10]	"What is your primary computing platform?" Dummy for platform: Windows 98 = 1
PlatDK	"What is your primary computing platform?" Dummy for platform: don't know = 1
PlatOT	"What is your primary computing platform?" Dummy for platform: unix, pc_unix, os2, vt100, next step, vms, t, webtv, other = 1
OccComp[10]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: support, consultant = 1
OccComp[4-9]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: computer = 1
OccProf[10]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: trained professional = 1
OccProf[4-9]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: professional = 1
OccMgmt[10]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: upper management, middle management, junior management = 1
OccMgmt[4-9]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: management = 1
OccOT[10]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: student, researcher, skilled labor, self employed, administrator, temporary, other = 1
OccOT[4-9]	"Which of the following categories best describes your primary occupation?" Dummy for occupation: education, other = 1
AccessW[5-10]	"What is the primary place you access the WWW from?" Dummy for place of access: work, primarily work = 1
AccessH[5-10]	"What is the primary place you access the WWW from?" Dummy for place of access: home, primarily home, friend = 1
AccessP[8-10]	"What is the primary place you access the WWW from?" Dummy for place of access: public = 1
AccessOT[5-10]	"What is the primary place you access the WWW from?" Dummy for place of access: distributed, school, other, na = 1
PaySelf[4-8,10]	"Who pays for your internet access?" Dummy for payer: self, parents = 1
PayWork[4-8,10]	"Who pays for your internet access?" Dummy for payer: work, school, other = 1
PayDK[4-8,10]	"Who pays for your internet access?" Dummy for payer: don't know = 1
Eng[5-10]	"What is your native/first language?" Dummy for language: English = 1
LangOT[5-10]	"What is your native/first language?" Dummy for language: all other languages = 1
Marr	"What is your current marital status?" Dummy for marital status: married = 1
Single	"What is your current marital status?" Dummy for marital status: single = 1

Marrot	“What is your current marital status?” Dummy for marital status: divorced, separated, widowed, other, not say = 1
IEPref[4-6,8-10]	“What online service do you currently subscribe to?” Dummy for online services: aol, att, compuserve, delphi, ibm, mindspring, msn, netcom, prodigy = 1
OnlineOT[4-6,8-10]	“What online service do you currently subscribe to?” Dummy for online services: ambert, europeonline, genie, pipeline, t-online, other, other_local, other_national, web-based e-mail = 1
OnlineDK[4-6,8-10]	“What online service do you currently subscribe to?” Dummy for online services: don’t know, none = 1
Netsc[5-10]	“Which browser do you expect to be your primary browser in 12 months?” Dummy for browser: netscape communicator, netscape navigator = 1
Micro[5-10]	“Which browser do you expect to be your primary browser in 12 months?” Dummy for browser: aol, Microsoft = 1
BrowseOT[5-10]	“Which browser do you expect to be your primary browser in 12 months?” Dummy for browser: hotjava, lotus, lynx, netcom, netcruiser, psi, spry, other = 1
Speed	“Which of the following connection speeds do you primarily use to connect to the internet?” (in kbaud) Checkboxes for finite speeds and unsure
Dspeed	Dummy for speed unsure
Use	“On average, how often do you use your WWW browser?” Checkboxes for varying time intervals
Duse	Dummy for missing answer to Use
Hours	“On average, how many hours a week do you use your WWW browser?” Checkboxes for varying time intervals
Dhours	Dummy for missing answer to hours
Say[8-9]	“Do you think you are using the most up-to-date version of your browser?” Checkboxes for responses (“Yes, I am quite certain,” “Yes, and it is a pre-release/beta version,” “Yes, but I am not so certain,” “No, I think I am using an older version,” “No, I am definitely using an older version,” “Don’t know”)
Say[10]	“For your primary browser, do you think you are using the most up-to-date version?” Checkboxes for responses (“Yes, I am quite certain,” “Yes, and it is a pre-release/beta version,” “Yes, but I am not so certain,” “No, I think I am using an older version,” “No, I am definitely using an older version,” “Don’t know”)

Appendix Table 4 Assumed Constants

Constant or Parameter	Definition	Value	Source
ρ	Consumer discount	.95	standard
Δ_{max}	Maximum Adoption cost	10	Upper Bound. Calculated using optimization model.
x_t, X_t	Quality of new version	2*v	Estimates of Bresnahan & Yin (2005)
$u(\ )$	Consumer flow utility		Assumed
p	Transition matrix for s (product introduction)	$\begin{bmatrix} .9 & .1 \\ 1 & 0 \end{bmatrix}$	Assumed structure, estimates from historical new version introductions

7.1. Appendix 2: Consumer's Decision Problem.

The consumer's problem can be characterized by dynamic programming. In this appendix, we show how we solve it, dropping all subscripts i for clarity.

At each date t, there are two phases to the consumer's decision problem. First, the consumer gets to observe the current technology level with probability θ. A consumer who observes can additionally decide to choose the current version by paying a cost of Δ. This cost Δ can be spread out over several periods of usage, so the condition for choosing the new technology is not the same as $u(X_t)- \Delta > u(x_t)$ but instead depends on the dynamic program.

We begin by defining all of the state variables of the problem. At time t, the consumer is using version x_t. The consumer most recently observed at time τ_t, and we record the observations they made at that time as $\tilde{x}_t$, $\tilde{s}_t$.

Let the value function at the beginning of the period (before potentially observing) be given by $W(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t)$. It is easiest to work backwards by defining two value functions, called $V^O(x_t, s_t, X_t)$ for the case of observation, and $V^N(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t)$ for the case of non-observation. The arguments of $V^O(x_t, s_t, X_t)$ are the technological level of the consumer's existing choice and the release status and technological level as of time t – which have been observed by the consumer. The arguments of $V^N(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t)$ are the same as of W() because the consumer's information set does not change.

The case of non-observation is simple. The consumer's information state does not change and the consumer keeps using the same product as before. Thus

$$V^N(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t)=u(x_t)+\rho W(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t+1) \qquad \text{(A10)}$$

where ρ is the consumer's discount factor.

The case of observation involves choice by the consumer and, whether the choice is of the newest technology or not, an updated information state. That is, $\tilde{x} = X_t$ because the consumer has observed it (and similarly for $\tilde{s}_t$). In particular, we have

$$V^O(x_t, s_t, X_t)=\max\{u(x_t)+\rho W(x_t, X_t, s_t, 0),\ u(X_t)-\Delta +\rho W(X_t, X_t, s_t, 0)\} \qquad \text{(A11)}$$

The consumer's decision to chose X_t is called d_t and is given by

$$d_t=1 \text{ iff } u(x_t)+\rho W(x_t, X_t, s_t, 0) < u(X_t)-\Delta +\rho W(X_t, X_t, s_t, 0) \qquad \text{(A12)}$$

We can now write out W() based on the likelihood that the consumer becomes informed and the distribution of the information should she get it, which is

$$W(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t)=(1- \theta)\, V^N(x_t, \tilde{x}_t, \tilde{s}_t, \tau_t)+ \theta E[V^O(x_t, s_t, X_t)|\, \tilde{x}_t, \tilde{s}_t, \tau_t] \qquad \text{(A13)}$$

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