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Consumer Adoption of Bandwidth Intensive Applications and Its Impacts on Broadband Adoption

Peter Helekiah Oburu

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CONSUMER ADOPTION OF BANDWIDTH INTENSIVE APPLICATIONS AND ITS IMPACTS ON BROADBAND ADOPTION

By

PETER HELEKIAH OBURU

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
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of
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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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ABSTRACT

CONSUMER ADOPTATION OF BANDWIDH INTENSIVE APPLICATIONS AND ITS IMPACTS ON BROADBAND ADOPTION

By

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This dissertation investigates the capacity required by an internet application in tandem with the network connection type (dial-up or broadband). An internet user's experience in accessing various types of applications with either high bandwidth or low bandwidth is examined in a consumer choice model of broadband adoption. A consumer implicitly values the time-saving benefits derived from a higher speed internet connection used to access a particular internet application, and compares those utility benefits to the higher price of high speed connection services in making the decision to shift to broadband or remain with a dial-up connection. We find that using broadband rather than dial-up to run bandwidth intensive applications presents considerable gains in the implicit value of time saved. Assuming that internet users are rational utility maximizing agents, a logit model is used to calculate the likelihood of broadband adoption as a function primarily of the nature/type of the internet applications ("elastic or inelastic"). While the empirical results are generally consistent with our hypothesis that consumers are more

likely to subscribe to broadband if they regularly run applications that are bandwidth intensive, the results vary somewhat by model specification, and are potentially sensitive to controlling for endogeneity. Correcting for endogeneity remains the major challenge in extending this research.

Research Question:

What is the relationship between consumer valuation of the net benefits of using bandwidth intensive applications and the adoption of broadband internet?

Hypothesis:

The less a consumer requires bandwidth intensive applications; the lower is the likelihood of switching from a low level bandwidth internet service like dial-up to a high level bandwidth internet type like broadband. While this relationship may appear obvious, it has not been systematically investigated or measured, nor has its importance in affecting lags in broadband adoption been adequately appreciated.

CHAPTER 1: INTRODUCTION

Overview

The last decade of the twentieth century witnessed the introduction and subsequent growth in broadband adoption. As the internet evolved, its content increased exponentially and web applications grew in prominence and capability. Each successive wave of client and web server technology upped the ante on the previous generation applications, increasing applications capability, integration and responsiveness. The magnitude of internet content design and proliferation of these different applications has led some researchers and practitioners alike to question whether the internet was designed to handle the amount of traffic it is experiencing today. Additionally, the increasing quantity of internet applications that require huge amounts of bandwidth to run efficiently exacerbates the problem of internet usage.

The increasing popularity of content variety within the internet has changed consumer behavior from the initial mindset that the internet was merely a means to access networked information, to the current emphasis on the quality of the information accessed. Therefore, the method for delivering increasingly varied internet content has become a central concern. For example a typical web page contains 15 to 20 kilobits (Kb) of information. By comparison, a web page with a video clip of one second duration contains more than 125 Kb of information, or close to 10 times the size of the typical/average web page. The quality of the typical web page, and that of the web page

containing the one-second video clip, will be different depending on the internet user's modem speed. The internet user's modem speed therefore places considerable restrictions on a content provider's ability to offer applications and services that require faster speeds in a manner perceived by the consumer (user) as being of high quality.

Speed and reliability are highly valued internet access attributes (Waldman & Savage, 2004). Anecdotal evidence suggests that faster internet connections are needed to address latency and reliability problems that have arisen from the growth of internet applications that require huge amounts of bandwidth to run efficiently. Unfortunately the demand for these applications has continued to outpace the ability of traditional internet connections such as dial-up internet to deliver qualitative content. This results in a frequently frustrating or disengaged user experience that has lead to dissatisfied internet consumers. This dissertation aims to show that the type of internet applications a consumer uses has been a significant factor in influencing the choice of bandwidth. Otherwise stated, a user places a relative value on their experience when consuming internet content. This relative value depends on the type of internet connection being used, the capacity or application being consumed, and the user's valuation of time.

Dissertation Question

The vast majority of users access the internet through computers that are connected to the internet via modems. These modems use one of two core methods to connect the user's computer to the internet–dial-up technology or broadband technology. Modems that make use of dial-up technology are commonly referred to as dial-up modems. These modems are classified as "slow" or "low-capacity modems" because the speed that they provide for a user to access the internet tends to be slow. On the other

hand, high-speed (i.e., high capacity) modems do not require dial-up. They enable a user's computer to connect directly to the internet without having to dial for a connection. These modems are normally referred to as broadband modems. It is this distinction that is responsible for the use of the terms "dial-up" and "broadband" respectively to classify the two leading present-day internet access methods employed by households in the United States.

The evolution of the internet has led to numerous applications. Each application requires a certain capacity for it to run effectively. This capacity is referenced herein as the bandwidth requirement. Since there are different applications we further distinguish the bandwidth requirement of these applications into two categories: bandwidth intensive applications (the applications that require significant capacity), and non-bandwidth intensive applications (the applications that require low capacity). Although bandwidth intensive applications can run on either a dialup (narrowband) or on a broadband connection, these applications are best serviced on broadband connections. We note that the capacity required by an application in tandem with network connection type (dial-up or broadband) affects the user's experience when consuming an internet application. In this process a consumer implicitly engages in a valuation of the benefits derived from the choice of the network type they make to access a particular internet application. And as will be shown, the benefit is the level of satisfaction they get from their choice.

Consequently the key research question is:

What is the relationship between consumer valuation of the net benefits of using bandwidth intensive applications and the adoption of broadband internet service?

It is important to first clarify the construct of the research question. Accessing an internet application involves what can be termed a demand side issue-the capacity (bandwidth) needed to access the application, and a supply side issue-the capacity provided by the internet connection (i.e., a dial-up or a broadband internet connection).

While an argument could be made that most internet applications can run on any internet connection, most applications are best utilized when the bandwidth provided by the network exceeds the bandwidth demanded by that application. To the end-user this is manifested in the time it takes to access the internet application. When the bandwidth demanded by the application is greater than the bandwidth supplied by the internet connection, the net result is that it takes a long time to access the application. This results in frustration and lower levels of satisfaction when accessing the internet application. By contrast, when the bandwidth demanded by the application is less than the bandwidth supplied by the internet connection, the net result is a short time to access the application and a more enjoyable consumer experience.

We examine an internet consumer's behavior as influenced by both types of internet applications (bandwidth-intensive vs. non bandwidth intensive) and the bandwidth level provided by the modem type (dial-up vs. broadband). If the greater use of bandwidth intensive applications leads to a greater demand for bandwidth delivery systems, the net benefits accruing from the use of bandwidth intensive applications will lead to an increase in the broadband subscriptions. That is, the more a consumer uses (or requires) bandwidth intensive applications, the greater the likelihood of switching from a

low bandwidth internet connection like dial-up to a high bandwidth connection like broadband.

Despite the rising number of home users who have adopted broadband, a substantial number still connect to the internet via dial-up. According to Nielsen/Netrating (a leader in internet media and market research) as of June 2005, 40.08 percent of internet households connected to the internet via dial-up and the remaining 59.92 percent connected via broadband connections.[1] These statistics underscore the persistently large number of dial-up users. Additionally several researchers have suggested that the rate of broadband uptake remains below initial expectations (Horrigan, 2005). Glassman (2001) stressed the role of broadband deployment (availability of broadband) in at least originally limiting broadband uptake (adoption), arguing that the "agonizingly slow deployment of broadband" (which he argued had in part a "political cause") despite the "technology for fast connections [being] well established, has led to "19 out of 20 U.S. families [being] stuck with poky dial-up modems." A fundamental argument made in this dissertation is that adoption of broadband is not merely a function of deployment or availability of broadband technology, but has more complex causes linked to consumer choice considerations.

Broadband Adoption: An Argument from the Consumer Perspective

In addressing this question, we begin with the premise that the adoption of broadband can be examined through the theory of consumer behavior. The premise is to examine how an internet consumer makes rational choices about their type of internet

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[1] Source of this Statistic is - http://www.websiteoptimization.com/bw/0509/: Retrieved October 27, 2007

connection (dial-up or broadband). The consumer treats the internet connection as a good among an array of other consumer options. Like any other good, it is subject to the principles that govern consumer choice. These involve choosing the best consumption bundle given a set of constraints. Therefore, we examine an internet consumer's behavior from the perspective of the internet application type and the bandwidth level.

A consumer chooses between paying more to have a higher/faster internet type to save time while consuming a particular internet application, or paying less for a lower/slower internet type resulting in a greater expenditure of time to access that same application. The consumer weighs the explicit out-of-pocket costs of access against the implicit time savings associated with a particular internet access method. If the benefits from the time savings using the faster internet type are greater than the incremental explicit expense of buying such speed, then a rational internet consumer would choose to pay more and switch to the higher/faster internet type. Hence the relevant costs are the explicit cost differential between the two bandwidth levels as well as the comparative values of time when using the different bandwidth speeds.

The contention here is that the full opportunity cost (explicit plus implicit) of using a faster internet connection when accessing bandwidth intensive applications is lower than the full opportunity cost of accessing such applications using a lower bandwidth connection. Thus, the more a consumer uses (or requires) bandwidth intensive applications, the greater the likelihood of switching from a low bandwidth internet connection like dial-up to a high bandwidth internet connection like broadband. Consequently the more users choose bandwidth intensive applications; the greater will be

broadband adoption. This argument seems logical, almost trivial. But the key question remains how to model this behavior, empirically test that hypothesis, and clarify the predictive strength of that relationship.

Prior Approaches to Explaining Broadband Adoption

Surprisingly, while this consumer perspective would seem fundamental to explaining broadband adoption, other approaches have dominated the debate on broadband adoption and the academic research. One reason seems to be the dominant belief that broadband adoption is best addressed at the macro-level without explicit reference to consumer choice theory. In general, three approaches have been used in studies that seek to explain and model broadband adoption.

The first set of studies examines state and local government policies required to leverage broadband adoption: (Wallsten, 2005; Bauer, Gai, Muth & Wildman, 2002; Gillett, Lehr & Osorio, 2003; Quast, 2005; A Nation of Laboratories. "Broadband Policy Experiments in the States," 2003). The second set examines broadband adoption from the perspective of a killer application: (Smith & Leung, 2002; Middleton, 2002; Heinzl, 2001; Luber, 2001). The third set of studies is the one that comes closest to employing a consumer perspective. This group of studies examines individuals' tolerance for slow connections: (Nah, 2004; Lightner & Bose, 1996; Galleta; Henry; McCoy, 2004; Barber, 2003). In the ensuing paragraphs we briefly describe each of these approaches and contrast them to the consumer approach utilized in this study. **Policy related approach**: This approach argues that policies adopted by states and local governments play a significant role in enhancing broadband deployment, which in turn stimulates

broadband demand. Wallsten (2005) summarizes these policies as: attempts to streamline rights-of-way laws and telecommunications unbundling regulations; subsidies; and direct municipal broadband provision. TechNet (2001) lists the three major areas in which state policies have a significant impact on broadband deployment. Firstly, state legislators and regulators are uniquely positioned to clear roadblocks and hurdles to broadband deployment. Secondly, state policies can create targeted, supply-side incentives for the deployment of broadband. Thirdly, state investment in offering of e-learning applications, health services and other e-government initiatives can play an important role in driving consumer demand for broadband. Bauer, et al., (2002) find that market forces are not sufficient to facilitate broadband deployment and because of that government broadband policies are important in synchronizing and aggregating the low level of existing broadband demand.

While this approach offers some explanation for broadband adoption rates, it is flawed in its fundamental underpinnings. It is built on the premise that broadband deployment (supply) translates directly into broadband adoption (demand). This is not necessarily so. Data from the FCC show that by December 2004, 95.4 percent of the zip codes in the United States had one or more high-speed providers. In addition 100 percent of the American population resides in a zip code with high-speed service when looking at areas with a population density of more than 3,147 persons per square mile. These statistics are evidence that there exists ubiquitous broadband deployment. But contrary to the argument presented by proponents of the policy approach, that broadband deployment is sufficient to stimulate demand and lead to broadband adoption, fewer than 29 percent of the 122 million households in the United State had adopted broadband as of December

2004 (Pew Internet, 2004). Favorable broadband policies therefore act as a catalyst that creates a suitable environment for broadband deployment but there is no evidence indicating that this deployment consequently stimulates demand thereby leading to higher broadband adoption.

In addition to this evidence that broadband deployment does not translate easily into broadband adoption (uptake), a more immediate problem for the public policy approach is that there is no consensus on what can be classified as the right/good policy. Tarpia and Ortiz (2006) argue that, since 2004 state level policies have been at loggerheads with those of the local governments and municipalities. This has led to legislation proposed at the state level to prevent local municipalities from developing or deploying some form of broadband infrastructure. Hence different questions continue to define the policy debate between the state and municipal levels. One of the key questions is whether municipal level initiatives will succeed or fail and whether the municipalities are making "right" policy decisions. This raises the obvious question: how can the proponents of the policy approach argue its merits if there is clear evidence of a lack of consensus among those practicing the approach?

The "Killer-Application" approach: A killer-application is defined as an application that will attain "must have" status and encourage non-users to become users. The application by its very nature is indispensable (C.A. Middleton, 2003). Proponents of the killer-approach approach simply believe that widespread adoption of broadband is dependent upon the development of such an application. They argue that the lack of an

identifiable killer application has been a leading barrier to broadband uptake (Heinzl, 2001; Carlyle, 2002; Lessig, 2002).

The starting point of this approach is that the killer-application will provide internet users such value as to increase their demand for bandwidth significantly thereby resulting in the widespread adoption of broadband. In addition there is a belief that the value realized from the killer-application will not only be limited to a few but it will be so evident for the masses that almost everyone will automatically subscribe to high bandwidth internet to run this application.

This approach is premised on the “must have” status that would influence consumer perceptions about the inherent value of the killer-application. There is no denying the force behind this argument; however, it also is far too simplified. For example how does one quantify the value gained from the use of a killer-application? Given the heterogeneity of the internet user-population, how does this perceived incremental value for one type of user translate to the masses?

An even more fundamental problem of this approach is that it is difficult to prove empirically that an application is a killer-application and that the application is responsible for an upsurge in broadband adoption. Broadband has been in use among the public for almost a decade and there has been extensive innovation in internet applications. Yet no killer-application has seemingly yet emerged. Businesses have steadily introduced new online services such as “You Tube,” “My Space,” “eBay,” etc., and research shows that users, especially in younger generations, are consuming more of these services. These applications have some of the attributes of a killer application yet

they are not so classified, nor have they contributed to a significant change in the rate of uptake of broadband adoption

Therefore, the killer-application argument as a way of explaining consumer behavior concerning broadband adoption remains, at best, questionable. This position is supported by (C.A. Middleton, 2003) who argues that broadband providers who understand their customers will recognize the value in providing peer-to-peer connectivity and opportunities for developing online communities rather than focusing their efforts solely on discovering the elusive killer application.[2] Horrigan and Rainie (2002) suggest that broadband uptake does not result from the discovery of the elusive killer-application. Instead, broadband growth will likely increase as more and more people gain experience, confidence, and trust in online content, and recognize the wealth of material that broadband access can offer a seasoned user.

Access-Tolerance approach: This approach seeks to determine appropriate response time goals for websites. It explores relationships between delay time and users' performance, attitudes and behavioral intentions. The premise is that internet users need a desired speed when accessing web pages and the lack of the desired speed leads to frustration for the internet user.[3] The benefit of this approach is that it confirms that there are desired speed thresholds beyond which consumers get frustrated with download times

[2] Miller states that demand for services will be driven by peer-to-peer networking and a desire for basic connectivity, rather than by a single provider controlled killer application. In addition network providers can increase demand for their services by providing users with applications that support the development of peer-to-peer community based networks and services.

[3] Paul Selvidge states that the number one complaint by internet users continues to be download speed or taking too long to load web pages. He references GVU website, 1998.

when accessing web applications. Secondly it measures this frustration at the consumer level thereby introducing consumer behavior. However it does not go far enough to determine what it takes for the consumer to change consumption habits. In other words, it does not identify the point at which a user will readily and deliberately terminate the existing low-speed access conduit (such as a dial-up modem) and replace it with a high-speed conduit (such as a broadband or cable modem).

A second limitation of this approach is that it does not account for variations in users' behavior propagated by both change in the context of use, and in the nature of the application being consumed by the users. There exists a wide diversity of applications, and consumer behavior will vary for each application depending on the context in which the consumer is using the application. For example, consumers may be more tolerant for a slow application when they are not under time pressure, but less so when they are facing tight deadlines. Therefore evaluating desired speeds in a controlled environment and extrapolating the results to the consumer's real life behavior is problematic. This puts into doubt the reliability of the results obtained via this method.

Somewhat similar to the "access tolerance" approach is the general focus on the speed of broadband connection. Evidence of this is the general advertisements by suppliers that the broadband speeds they offer are so much faster than dial-up connections (Blanc, 2000). The focus on speed creates a compounding dilemma. It places the consumer in the position of deciding whether a dial-up connection is "fast enough" without evaluating the more primary question of whether the speed the consumer currently has is sufficient for what they are doing on the internet. In addition

the focus on speed does not incorporate internet application usage. That omission is addressed in this study.

Motivation, Policy Significance and Contribution to Literature

After reviewing previous approaches and the extensive literature whose intent is to address why there is a lag in broadband adoption, it is evident that the relationship between the use of the various existing internet applications and the consumer's choice of the internet type (dial-up or broadband) with which to consume those applications has not been directly or empirically investigated. Consequently, one research goal is to analyze broadband adoption from a consumer-choice point of view.

What is the relationship between the net benefit of using bandwidth intensive applications and the adoption of broadband internet? We address this question by examining the difference in utility derived by a consumer when accessing bandwidth intensive internet applications via both broadband and dial-up internet types. The aim is to quantify the utility benefits derived by the consumer based on the level of bandwidth used to access an internet application. We then employ a Logit empirical analysis to model the likelihood of broadband internet choice. One practical result is to provide internet service providers with a viable method for making decisions about the marketing of broadband services and strategic plans for fostering broadband adoption.

Varian's Index Experiment project (Varian, 2002) is widely cited in the economic literature on broadband adoption because it models a consumer's bandwidth choice. The theoretical model presented here utilizes certain features of the Varian model, but addresses some limitations of that model in non-experimental settings. These limitations

include: (1) the difficulty in quantifying the utility of bits transferred to the internet user given that such data is not readily observable;[4] and (2) the valuation of time saving arising from bandwidth choice in a non-experimental setting. Hence, a second contribution of this research is the development of a theoretical model applicable to both experimental and non-experimental settings, including the calculation of the implicit value of time as a quantifiable measure of the benefits gained from the transition from a lower bandwidth to a higher bandwidth speed. This is demonstrated in Chapter 4 as an attempt to understand the point at which consumers make the transition from a slower internet connection method like dial-up to a faster method like broadband. This approach overcomes the inability of both the Killer application and tolerance methods to suggest a way of empirically validating what is required for a consumer to transition to broadband.

A third benefit of this approach is the analysis of data collected from actual use of the internet. Hence the results are easier to generalize and are of greater value to researchers and practitioners alike. In addition the empirical analysis expands the list of independent variables beyond the conventional socio-demographic variables to also include a number of application variables. We also address the weakness of past studies in interpreting Logit coefficients as Dummy independent variables using marginal effect estimates as opposed to discrete choice estimates. This is not commonly accounted for in the literature.

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[4] Varian in his model quantifies utility of bits transferred as a dollar value; hence he is able to employ a consumer surplus approach of subtracting both the explicit and implicit cost of the internet from the utility of bits transferred.

Finally, the literature currently focuses on broadband deployment and broadband adoption. As argued above, despite the widespread broadband deployment throughout the country, broadband adoption continues to seriously lag. When deciding on information systems to deploy broadband or to deliver broadband applications, a key determinant is the return on investment (ROI). ROI in this context measures the long-term probability of success of the information technology (IT) investment, be it broadband deployment or internet application delivery technology. However the success of any IT investment is primarily dependant on whether the IT technology applied is widely accepted by users so that it gets diffused within the population.

Presently there are no short-term financial, economic or mathematical models for measuring and quantifying broadband adoption in monetary terms, especially at the consumer level. Yet the long-term ROI for broadband infrastructure, deployment or application delivery is predicated on consumer level behavior. Thus the utility theory presented here is a first step in filling this void because it allows the quantification of the factors successfully diffusing applications at the consumer level. Thus our framework sheds light on the paradox between the widespread deployment of broadband and the lag in broadband adoption.

Key Terms

Broadband: There is much variation in the way broadband is defined[5]. In "*Falling through the Net: Toward Digital Inclusion,"* (National Telecommunications and Information Administration (NTIA), 2000) defines "broadband" to include digital

[5] See Sawyer, et al. (2003) -- the first paragraph of 'What if there is no killer application?' By Catherine Middleton.

subscriber lines (DSL), cable modems and such technologies as ISDN. The authors also note that these technologies may fall below the 200 kilobits per second definition used by the Federal Communications Commission. For example, DSL is often limited to transmission rates of 128 kbps in one direction and 256 kbps in the other. While this would not qualify for the FCC definition of "broadband," it would technically qualify DSL as a, "high-speed connection" by the FCC's standards. It is also important to note that each service provider arbitrarily sets DSL speed limits, so the infrastructure for DSL is capable of supporting speeds beyond what is typically offered to consumers in a DSL service plan

Dial-up: as defined by www.webopedia.com, an online dictionary and search engine for computer and internet technology definitions**, dial-up** refers to connecting a device to a network via a modem and a public telephone network. Dial-up access is really just like a phone connection, except that the parties at the two ends are computer devices rather than people. Because dial-up access uses normal telephone lines, the quality of the connection is not always good and data rates are limited. In the past, the maximum data rate with dial-up access was 56 Kbps (56,000 bits per second), but new technologies such as ISDN are providing faster rates shifting the previous maximum dial-up rate to 128 Kilobits per second (Kbps). In this dissertation the upper ceiling of dial-up transfer rates is 128 Kilobits per second; table 4 lists the classification of transfer rates that qualify in the dial-up category.

Broadband deployment: Broadband deployment refers to the percentage of U.S. households to which broadband service has been made available.

Broadband adoption: Broadband adoption is used to reference number of individuals or households that subscribe to broadband service. Broadband adoption is used interchangeably with broadband penetration. The term “penetration” is sometimes used to describe the percentage total households that subscribe to the service. In contrast, the term “take rate” attempts to measure the percentage of households that take the service where it actually has been deployed.

Quality of service (QoS): Quality of service is a very popular and overloaded term that is very often looked at from different perspectives by the networking and application-development communities (Network QoS Needs of Advanced Internet Applications, 2000). QoS is defined by “QoS Bandwidth Management” as the proficiency of a network element to furnish some degree of commitment for congenial network data delivery. In other words, QoS means, satisfying customer application requirements, providing a network that is transparent to its users. QoS does not generate bandwidth. Instead it only administers the bandwidth according to the application demands and network management settings.

Throughput: This is the amount of data transferred from one place to another or processed in a specific amount of time.

CHAPTER 2: REVIEW OF LITERATURE

In this chapter we discuss the previous literature that addresses, directly or indirectly, the issue of broadband adoption, or develops economic methods that have been adapted to this dissertation.

Product Adoption Models

An argument could be made for the use of diffusion models to address why the rate of broadband adoption is lagging. The use of this methodology would be supported because of its prior use in similar cases to forecast different product life cycles. These cases include the adoption of the following products: IBM mainframe computers (V. Mahajan & Muller, 1996), mobile phones (Botelho & Ligia Costa Pointo, 2004) and residential high-speed internet services technology (Vanston, 2002). As to whether this methodology remains the sole best approach warrants review, especially in light of the different methodology that is employed in this study, i.e., the consumer choice methodology. The ensuing paragraphs discuss the origins of diffusion models and the different models employed when addressing product adoption using this methodology. In addition, the application and limitations of using diffusion modeling in the study of broadband adoption is presented. The models discussed include a general diffusion model and two additional specific models: the Bass diffusion model and the logistic growth S-shaped curve model.

Adoption refers to the commitment to and continued use of a new product, while a product is defined as anything offered to a market to satisfy a want or a need. Robertson, et al., (2007) state that the established route to the modeling of innovative

new-product penetration/adoption throughout the early stages of the product lifecycle relies on diffusion models. Diffusion can therefore be defined as the process through which the innovation "*is communicated through certain channels over time among members of a social system*" (Rogers, 1995, 4th edition).

V. Mahajan and Muller (1979) have stated that the objective of a diffusion model is to present the spread over time of an innovation among a given set of prospective adopters. The use of a diffusion model depicts the successive increases in the number of adopters and predicts the continued development of a diffusion process already in progress. Robertson, et al., (2007) state that diffusion models provide an estimate of the hazard rate-which is defined as the probability that an innovation will be adopted at a particular time by a particular individual within a given social system, providing that the individual has not yet adopted the system.

Origins of Diffusion

Rogers (1976) points out that there are several origins of diffusion models:

- British and German-Austrian schools of diffusion in anthropology.
- French sociologist, (Tarde, 1903). Tarde proposed the S shaped diffusion curve and emphasized the role of opinion leaders in the imitation process.
- In the 1960's diffusion gained prominence emerging as an individual body of knowledge with its own concepts and generalizations.

Since its origin, diffusion has been applied to a number of disciplines, anthropology, sociology, medical sociology, education, geography, politics, industrial economy, communication and marketing.

Structure of diffusion models

The general structure of a diffusion model considers a situation in which each purchase refers to the sale of one unit of a durable product. According to (V. Mahajan & Muller, 1979) the market is divided into 3 segments.

Segment 1: Refers to the untapped market; these are consumers who do not know that an innovation exists at time t or consumers who are not considered possible consumers of the innovation at time t.

Segment 2: Refers to the effective potential market; these are consumers who have moved from segment 1 and who are now potential consumers of that innovation at time t.

Segment 3: Refers to the current market; these are consumers who have bought the innovation at time t.

Modeling diffusion

Ruiz Condz (2005) states that a diffusion function is usually defined as the solution $y = y(t)$ of a differential equation $\frac{dy}{dt} = f(y,t)$, where y defines how the diffusion process evolves over time and f defines the shape of the diffusion curve. From

a number of papers, (V. Mahajan & Schoeman, 1977; Kalish & Sen, 1986 ; V. Mahajan, Mullar & Bass, 1993), the basic diffusion model can summarized as follows;

(1) $n(t) = \dfrac{dN(t)}{dt} = g(t)\left[M - N(t)\right]$

Where:

$N(t) = \int_{to}^{t} n(t)dt$, $n(t)$ = number of adopters at time t, $N(t)$ = cumulative number of adopters at time t, M = potential number of adopters at time t, $g(t)$ = parameter of diffusion/rate of adoption /individual probability of adoption /probability that a random adopter adopts at time t.

$g(t)$ = is also known as the conversion parameter, or the transfer parameter of a potential adopter to an effective adopter. The innovation literature has represented $g(t)$ as a linear function of $N(t)$

(2) $g(t) = a + bN(t)$

Where:

a = external influence is determined by: i) the intrinsic value for individuals to innovate, and ii) external communication. Bass (1969) refers to the external influence as innovation.

b = internal influence, referring to personal contact with previous adopters. Bass 1969 refers to the internal influence as imitators.

Substituting $g(t)$ from equation (2) into equation (1) we get

$$(3) \qquad n(t) = \frac{dN(t)}{dt} = a + bN(t)\left[M - N(t)\right]$$

From equation (3), when internal influence $b = 0$ we can determine the external (innovators) influence diffusion model:

$$(4) \qquad n(t) = \frac{dN(t)}{dt} = a\left[M - N(t)\right]$$

From equation (3) when internal influence $a = 0$ we can determine the internal (imitators) influence diffusion model:

$$(5) \qquad n(t) = \frac{dN(t)}{dt} = bN(t)\left[M - N(t)\right]$$

Bass diffusion model

Bass (1969) published a paper, "A new product growth for model consumer durables" that became the foundation of a lot of modern marketing research. In his paper Bass developed the Bass diffusion model that explained the process of product adoption of durable goods. Parker (1994) states that the Bass model is the most parsimonious aggregated model developed in the diffusion literature.

Mathematically the central idea of the Bass model is that the conditional probability of a person adopting a product at time *t*, given that the individual has not yet adopted it is a linear function of previous adopters.

The Bass model can be represented as follows:

(6) $$\frac{f(t)}{1-F(t)} = p + qF(t)$$

Where:

$f(t)$ = the probability of adoption at time t

$F(t)$ = the cumulative distribution function

$1-F(t)$ = the number of people who have not yet adopted

$\frac{f(t)}{1-F(t)}$ = conditional probability of a person adopting at time t given that a person has not yet adopted

$p + qF(t)$ = Linear function of previous adopters

p = a parameter of innovation, and q = a parameter of imitation

But from the general structure of diffusion models we saw that

$n(t)$ = number of adopters at time t.

$N(t)$ = cumulative number of adopters at time t.

M = potential number of adopters at time t.

Therefore the number of adopters at time *t* is the product of the number of potential adopters and the probability of adopters at time *t*.

(7a) $$n(t) = Mf(t)$$

(7b) $$\Rightarrow f(t) = \frac{n(t)}{M}$$

Likewise if we do not include *t*, the cumulative adopters are the product of the potential adopters and the cumulative distribution function.

(8a) $$N(t) = MF(t)$$

(8b) $$\Rightarrow F(t) = \frac{N(t)}{M}$$

The Bass model represented by equation (6) now becomes:

(9) $$f(t) = [p + qF(t)][1 - F(t)]$$

Incorporating equations (7b) and (8b)

(10) $$n(t) = \left[p + q\frac{N(t)}{M}\right][1 - N(t)]$$

The number of people who have not adopted at time is given by $[M - N(t)]$ and the total number of adopters in time *t+1* is $p * [M - N(t)]$. Also the cumulative adopters $N(t)$ will interact with those who have not adopted $[M - N(t)]$. From regression analysis we know that interactions are represented by the product of the variables, therefore the

total number of interactions is given by $N(t) * [M - N(t)]$. Of these interactions,

$\frac{q}{M}$ result in imitation. The total number of imitators at time *t+1* is given

by $\frac{q}{M} * N(t) * [M - N(t)]$.

Hence the total sales at time *t+1* is given by:

$$S_{(t+1)} = p * [M - N(t)] + \frac{q}{M} * N(t) * [M - N(t)] \tag{11}$$

$$S_{(t+1)} = pM + [q - p]N(t) - \frac{q}{M} * N(t)^2 \tag{12a}$$

This can be represented as follows:

$$S_{(t+1)} = a + bN(t) + cN(t)^2 \tag{12b}$$

Where $a = pM$, $b = [q - p]$ and $c = \frac{q}{M}$

Equation (12b) shows that the Bass model provides a blanket measure of the diffusion of an innovation.

Application of the Bass diffusion model to the study of broadband adoption

Table 1 depicts bi-annual residential and small business adoption of broadband in the United States for the period December 2000 to June 2005. Using the Bass model (equation 12b) we can forecast the sales of broadband adoption Broadband adoption in the United States.

Table 1: Residential and Small Business Adoption of Broadband in the United States

Time Period	Sales	Cumulative Sales	Cumulative Sales Squared
Dec-00	5,097,136	5,097,136	25,980,795,402,496
Jun-01	7,743,902	12,841,038	164,892,256,917,444
Dec-01	10,993,973	23,835,011	568,107,749,370,121
Jun-02	13,877,745	37,712,756	1,422,251,965,115,540
Dec-02	17,252,537	54,965,293	3,021,183,434,575,850
Jun-03	20,503,570	75,468,863	5,695,549,282,512,770
Dec-03	25,800,072	101,268,935	10,255,397,196,034,200
Jun-04	29,900,121	131,169,056	17,205,321,378,014,800
Dec-04	35,055,768	166,224,824	27,630,692,168,224,800
Jun-05	42,214,903	208,439,727	43,447,119,791,834,500

Source of data: Federal Communications Commission (FCC)

By running a simple OLS regression on equation (12b), $Y = a + bN(t) + cN(t)^2$ to determine the total number of broadband sales on the next period i.e., $S_{(t+1)}$ we can find that:

$$Y = 4{,}583{,}687.9 + 0.2497065N(t) - 4.091E - 10N(t)^2$$

$$\frac{dY}{dN} = 0.2497065 - 8.18E - 10N(t)$$

$$N = \frac{0.2497065}{8.18E - 10}$$

$N = 3.05E + 08$ Y now becomes

$Y = 4{,}583{,}687.9 + 0.2497065(3.05E+08) - 4.091E-10(3.05E+08)^2$

$Y = 80{,}793{,}819.71$.

Therefore using the Bass model, the total number of forecasted broadband adopters by June 2005 (the next period after December 2004) in Table 1 is 80,793,819. This far exceeds the actual number of 42,214,903 reported by the FCC for that next time period. This result demonstrates the limitations of applying the Bass diffusion model to forecasting broadband adoption.

Diffusion models using the S-shape diffusion curve

As noted in earlier that, French sociologist (Tarde, 1903) proposed the "S shaped" diffusion curve. Several studies have been conducted with this diffusion methodology suggesting that the diffusion of new products normally reflects an S-shaped function. The most common function used to depict this S-shape is a logistic function, chosen because it is simple to fit. Therefore, we attempt to fit an S shaped (logistic) curve to broadband adoption data from the FCC for the eleven periods of semi-annual data for the period December 2000 to December 2005 (Table 2 data plus two more observations).

The logistic growth curve is defined as $y_t = \alpha / 1 + e^{-(\beta - \lambda t)}$, where y_t is state level broadband adoption expressed as a percentage of the state population, and α is the ceiling or equilibrium value of broadband (i.e., the carrying capacity or saturation level, which is the cap of broadband adoption as t = time goes to infinity. β is the constant of integration which positions the curve on the time scale. γ is the growth coefficient. Several features of the logistic function are of interest: It is asymptotic to 0 and α , and

symmetric around the inflection point. The point of inflection gives the point in time after which the growth rate of diffusion declines. In other words, after the inflection point the number of new users/customers is decreasing. The time period of inflection is given by $-\beta/\gamma$, which is the root of the second derivative of the diffusion curve. Another important quality of the diffusion curve is that the rate of growth is proportional to the growth already achieved and to the distance from the ceiling/ carrying capacity.

Using a non-linear least squares approach, the first step is to fit overall broadband adoption data for the period December 2000 to December 2005 to the following model $y_t = \alpha / 1 + e^{-(\beta - \lambda t)} + \varepsilon_t$ to determine if broadband adoption by users follows an S-shaped logistic curve. The model's estimation results are shown in Table 2.

Table 2: Non-Linear Least Squares estimates for Semi-annual data, December 2000 – December 2005

Dependent Variable: Overall Broadband Adoption

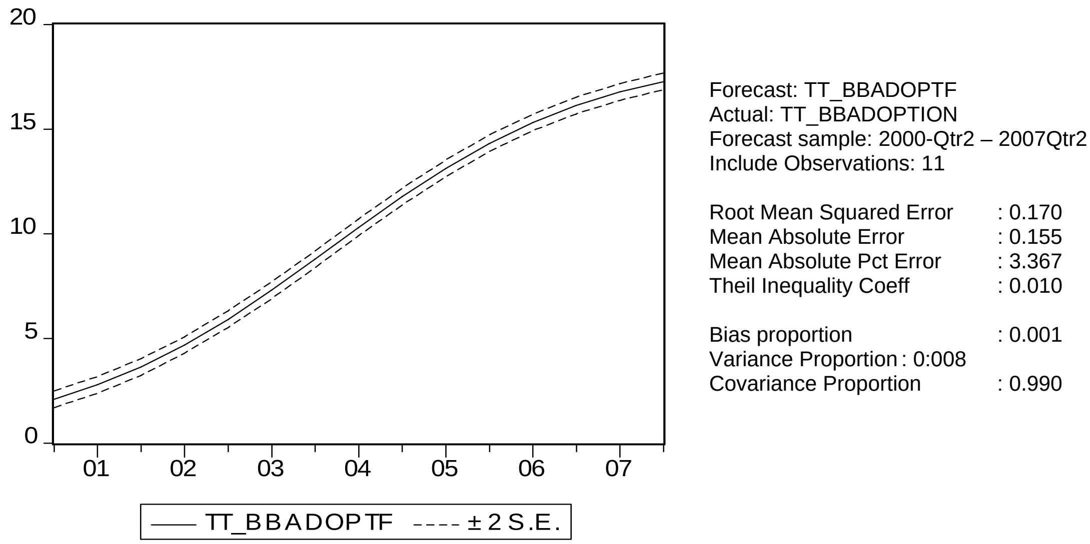
	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\alpha}$	18.713	0.875	21.393	0
$\hat{\beta}$	-2.075	0.043	-48.420	0
$\hat{\gamma}$	0.325	0.016	20.516	0

Included observations: 11

The second step is to determine if the adoption pattern follows an S-shaped diffusion curve. We forecast existing data by adding to our sample range the four semi-annual periods July 2006 to December 2007. Therefore, the data for the model is from

December 2000 to December 2007. The results reflect an S-shaped forecasted trend as depicted in Figure 1.

Figure 1



The final step is to determine if adoption rates have slowed down. The inflection point occurs at 6.37 periods ($-\beta / \gamma$). Therefore the point of inflection using December 2000 as the base year will be seven periods, which is June 2004. Since we have already passed the inflection point the results provide evidence that the broadband adoption rate has slowed down.

While this suggests some support for the S-shaped diffusion methodology inasmuch as it is consistent with the rate of broadband adoption, it does not explain why the rate is at a specific level. By using a consumer adoption approach, we address this limitation.

Limitations of studying broadband through product diffusion methodologies

The use of diffusion models to study broadband adoption has several important limitations. An empirical weakness was the large discrepancy between the Bass diffusion

model forecasted June 2005 adoption rate and the actual number. A more conceptual limitation of diffusion models is their inability to account for the reasons why individuals adopt a product; instead viewing adoption merely in terms of the cumulative sales or distribution pathways of a product from the point of market entry to the time the market becomes saturated. Bottomly and Fildes (1998) state that aggregate models of innovation diffusion do not capitalize on valuable consumer adoption dynamics.

Consumer adoption dynamics are addressed in this dissertation by focusing on the relationship between a consumer's use of bandwidth intensive applications and the adoption of broadband internet. Hence a major weakness of the diffusion model approach is directly addressed herein by analyzing broadband adoption from a consumer utility maximizing perspective.

A practical limitation to empirically applying either the Bass model or the S-shaped diffusion model to broadband adoption in the United States is the relatively limited amount of historical data available since the introduction of broadband. The alternative approach suggested here is not immune to data limitations, but is better adapted to confronting those limitations.

The role of individual choice

A central focus of microeconomics is consumer theory, focusing on decisions by utility-maximizing agents. Hauser and Urban (1979) state that modeling and measuring how consumers form preferences for products or services is critical to the understanding of consumer behavior. They also state that considerable research has been applied to the task of determining how consumers combine perceptions of product attributes into preferences.

Utility theory provides a framework for modeling rational choice with the assumption that the consumer acts to maximize his or her utility or satisfaction subject to constraints.

The fundamental tenet of utility theory is that agents assess the choices available to them so that they can maximize the utility obtained from the consumption of a mix of goods and services. Hence the agents choose the mix of goods that provides them with the greatest utility, implying of course that rational decision-making should also be applicable to the adoption of broadband technology.

Utility theory is part of the larger debate on what determines the value of a good or service. When looking at the history of this value theory debate, four distinct schools of thought can be distinguished. The oldest of these is the evaluation of utility from a monetary perspective. The use of monetary expenditures was mainly a means of determining the value of a good by presenting a way of ranking the preferences chosen by the consumer. Bernoulli proposed that the utility of money could be best measured by using the logarithm of the number of units of money, leading to the Bernoullian

assumption about diminishing marginal utility of wealth. The dominant focus was on monetary expenditure with no regard for the time-based factors that influence the choice of the goods. Hence in this approach the value of a good was strictly interpreted as the monetary value ascribed to the good.

Another school of thought was linked to classical economists like David Ricardo, who argued that the value of a product was determined by its production costs. With this approach there was less emphasis on time, especially on the consumption side. The use of labor in this approach acts as a surrogate to measure time. However time refers to the time required producing the good; hence it is a supply side notion. As shown in the ensuing sections, this concept of time has no effect on a consumer's determination of the value of broadband versus dialup internet access.

However with the emergence of the marginal utility school of thought, with founders like Jevons, Menger and Walras, there was a shift toward the subjective valuation of a good, in particular the marginal utility of the last unit consumed, as the key determinant of a product's value. This approach serves as a foundation for evaluating the effects of time on determining choice. Specifically, it can be used to study individual behavior regarding the adoption and diffusion of an innovation, including the impact of consumer choice on broadband diffusion. Fortunately, a key limitation of this approach, i.e., how to quantify utility, was addressed by neo-classical economists like John Hicks, who substituted ordinal utility for the concept of measurable marginal utility. Ordinal utility provides a way of measuring utility with an interval scale, and this standard approach is adopted here.

Time Allocation Models

Time played a role in classic consumer and producer theories of value, but generally not an explicit one. When considering consumer decisions regarding broadband adoption, the time it took to generate or produce internet content is not important. What matters instead is the time required to access the content in order to consume it and put it to use. The ensuing paragraphs discuss extensions of classical consumption theory to more explicitly consider the role of time as a critical constraint affecting optimal consumer choice.

According to Carlstein and Thrift (1978), George Soule was the first to deal extensively with time-allocation issue. Soule argued that economists had failed to develop an extensive theory dealing with time as a scarce resource and that "economic theorists had not absorbed the concept of time into their basic thinking." (Soule, 1955). He questioned whether the market system could be relied upon to allocate time to uses best fitted to satisfy human needs.

The role of time in utility maximization received special emphasis starting in 1965 with the seminal paper by Gary Becker "A Theory of the Economics of Time," (Becker, 1965). This paper introduced the cost of time systematically into decisions about non-work activities. Becker makes use of the idea developed by (Cairncross, 1958) that households are analogous to a small factory. The household manufactures what Becker calls "basic commodities" which create utility as they are consumed. In this context, "friendship," "career satisfaction," or "becoming informed" could be considered as commodities (although these were certainly not identified in the original simplified

examples used by Becker, focusing on sleep or watching movies), and browsing the internet is one way to become informed. It could even be considered a commodity in its own right. The household production function involves combining market goods and time into the production of these ultimately consumable commodities. While one can write the Becker optimization problem using a direct utility function defined over commodities Z_j, Z_k, the optimization problem can also be written using a kind of indirect utility function defined over the inputs X (a vector of market goods and services) and total time T:

$$\underset{X,T}{Max}\, u(X,T)$$

Subject to two constraints; a budget constraint and a time constraint:

$$\sum_i P_i X_i \leq I_f + wT_w$$
$$\sum_i T_i + T_w = T$$

Where, I_f is income not derived from working time (e.g., financial investments or inheritance), T_w is time spent working , P_i is the price of the i_{th} market good X_i, w is the applicable market wage, and total time is divided between working or applying it to the production of commodities, T_i. The two constraints can be combined into one yielding the famous Becker "full income constraint" by which full income is the total time available valued at the market wage, with this time being "spent" either on the purchase of market goods to be used in the production of ultimate commodities or in the utilization of time in the household production of such commodities, valued at the opportunity cost of time, the wage rate.

$$\sum_i P_i X_i + T_i w = I_f + wT$$

Becker's work is of considerable importance as a pioneering attempt to deal with the problem of time allocation, and it yields valuable insight into the issues involved in the decision to adopt broadband.

DeSerpa (1971) developed a model similar to Becker's by including both goods and time as arguments in the utility function. However DeSerpa extends Becker's model by adding a set of time constraints defined as linear functions between the time it takes to consume the market commodity and the amount of the market commodities consumed. The technological constraint for a basic commodity is given by $a_i Q_i \leq T_i$ where a_i in the time consumption constraint, which can be interpreted as the minimum amount of time required to consumer one unit of good Q_i .

DeSerpa's optimization problem can be written as:

$$\underset{X,T,T_w}{Max}\, u(X, T, T_w)$$

Subject to:

$$\sum_i P_i X_i \leq I_f + wT_w$$
$$\sum_i T_i + T_w = T$$
$$a_i Q_i \leq T_i$$

Further extensions of the allocation of time literature include (Evans, 1972; Kraan, 1994; Bates, 1987). What is evident in these studies is the need to incorporate the

value a consumer places on the time it takes to perform household activities. The important role played by time in the utility maximizing agent's decisions is exploited in this study of the adoption of broadband.

Limitations of Becker's approach in empirical modeling

Any explicit attempt to express Becker's time allocation model in terms of econometric equations can be difficult, in part because his original threefold classification of commodities is too simplified. But any commodity classification scheme is just for illustrative purposes and, as suggested above, the definition of commodities can be expanded to fit many purposes.

A more fundamental problem is that the distinction between "basic commodities" that enter direct utility functions and "goods" that serve as inputs into household production functions is not always clear. Also, some goods related activities such as eating a piece of chocolate require only trivial allocations of time. Conversely some time intensive activities such as meditation do not require any goods inputs. While these problems are not insurmountable, we limit the use of Becker's insights to the critical role played by time allocation without expressly estimating a Becker household production model.

Varian's bandwidth consumer choice model

Rather than attempt to adapt the Becker model explicitly to our problem, Varian provides a more directly applicable approach. He conducted "Index Project" experiments and presented a model of consumer choice between different levels of bandwidth. This model emphasizes that there is a subjective cost involved in the consumer's bandwidth

choice. This subjective cost is determined by the user and is based on the time each user takes to access the internet via various bandwidth speeds utilized in the experiment.

Varian's model defines the utility function in terms of currency[6]; hence the net utility from bits transferred is the utility less the cost. These costs consist of the subjective implicit cost and the explicit cost of chosen bandwidth *b*, where b is defined as bits transferred by unit of time, or $b = x/t$. Therefore net utility is represented as:

$u(x) - [ct + p(b^*)]$ for $f\left(u, x, ct, p(b^*)\right) > 0$.

Where:

$u(x)$ is consumer utility as a function of bits transferred x, ct is the subject cost and $p(b^*)$ is the explicit cost of chosen bandwidth. The consumer's maximization problem becomes

$$(3) \qquad \max_{x>0} u(x) - [ct + p(b^*)]$$

Since bandwidth was defined as bits per unit of time, we can solve for time to be, $t = x/b$, and equation (3) becomes

$$\max_{x>0} u(x) - [c\frac{x}{b} + p(b^*)]$$

The internet consumer maximizes the utility of bits transferred when;

---

6 The utility functions which describe how sensitive users are to changes in the quality of service (QoS) while using the internet, can be viewed as the amount of money an internet user is willing to pay for certain QoS guarantees (DaSilva, 2000).

$$(4) \qquad \frac{\partial u(x)}{\partial x} = \left[\frac{c}{b}\right]$$

Equation (4) provides an important decision-rule that shows what is necessary to maximize the utility of bits transferred.

Varian's behavioral model presents some disadvantages, especially the difficulty of translating some of the assumptions from the experimental setting into a more general framework applicable to non-experimental research. From Varian's model one can determine how many bits are required to maximize consumer utility from the choice of a given level of bandwidth. However, the number of bits transferred is not a readily tangible consideration for consumers when deciding to subscribe to broadband as opposed to dial-up internet.

The internet consumer's decision to subscribe to a higher level of bandwidth (e.g., broadband) as opposed to a lower level of bandwidth (e.g., dial-up) requires an estimation of the time gains from higher bandwidth along with their subjective value of time. This decision is the focus of our model, in which the internet user evaluates the competing considerations of saving money by remaining with the lower bandwidth versus saving time by choosing a higher/faster bandwidth.[7] Chapter 3 expands upon specific features of the Varian approach that we can adapt into a theoretical model appropriate for addressing our research question.

[7] Since moving to a higher bandwidth level always costs more in explicit fees, staying at the existing lower bandwidth level creates an explicit cost savings.

CHAPTER 3: THEORETICAL FRAMEWORK

We posit that two key factors contribute to the utility that a consumer derives from internet use. The first is the type of internet connection, as measured by bandwidth, which a consumer uses to access the internet. The second factor is the type (or nature) of internet application being accessed by the consumer. Therefore, in this chapter we present a theoretical framework of consumer adoption of internet connections as a function, in part, of internet applications.

Type of Internet Connection

The type of internet connection refers to the speed at which a user is connected to the internet as determined by the connection device such as a dial-up modem or a broadband modem. The speed is measured in the modem's bandwidth. Bandwidth in today's terms describes the network speed which is measured in bits per second or bytes (characters) per second. The general assumption is that for a given application, higher levels of bandwidth lead to a more satisfying internet use experience by the consumer. This is because the consumer is able to access, download and consume a specific internet application without being subjected to long periods of idle waiting as the application gets downloaded, and executed by the computer. Lower level of bandwidth may cause a frustrating usage experience for the consumer owing to the lengthy time it takes for the application to be downloaded and executed.

Type of Internet Application

An internet application is any well defined software product or service that the consumer uses when connecting to the internet. Examples include emails, instant messaging, file transfer software, and portals, among others. All internet applications can be broadly classified into two categories; elastic applications and inelastic applications. These two types of applications respond differently to varying levels of bandwidth.

Elastic applications are those applications that can tolerate significant variations in throughput and delay without considerably affecting the applications quality. Examples of elastic applications include traditional data transfer applications like file transfer, email and some http traffic (simple or basic websites). Because of their nature, these types of applications are more adaptive to bandwidth fluctuations. From a user's perspective, what is common to all elastic applications is their ability to transfer data in a short time; this is because these applications adjust to available bandwidth as they are transmitted through the network.

Inelastic applications (also called real-time applications) are comparatively intolerant to delay, delay variance, throughput variance and errors. This is because they usually support some kind of "Quality of Service" (QoS) sensitive media like voice or remote control commands. Examples of inelastic applications include audio and video streaming applications. From a user's perspective, what is common to all inelastic applications is that they do not transfer data in a short time, because these applications do not easily adjust to available bandwidth when they are transmitted through the network.

Table 3: summarizes some popular elastic and inelastic internet applications based on their bandwidth and timing requirements.

Table 3: Reliability, bandwidth, and timing requirements of some popular and emerging internet applications

Application	Bandwidth	Time sensitive?
File Transfer	Elastic	No
Electronic Mail	Elastic	No
Web Documents	Elastic	No
Financial Applications	Elastic	Yes and No
Real-Time Audio/Video	Inelastic Audio: Few Kbps to 1Mbps Video: 10's Kbps to 5 Mbps	Yes: 100's of msec
Stored Audio/Video	Inelastic Same as interactive audio/video	Yes: few seconds
Interactive Games	Inelastic Few Kbps to 10's Kbps	Yes: 100's msecs

Source: http://userpages.umbc.edu/~dgorin1/451/OSI7/dcomm/client_server.htm
Retrieved on 12/01/2007

Consumer Utility when using Internet applications

DaSilva (2000) suggests that utility functions of internet users should describe the sensitivity of users to changes in the quality of service (QoS). In our analysis we view QoS as comprising the user's perception of the level of satisfactory performance by the internet access point (i.e., the internet type that the user employs to connect to the internet) in availing and executing internet-based applications. QoS, in this context encompasses the entire consumption experience from the point at which the user initiates the transaction to access/download the application, to the point at which the user has

finished using the application. Utility can be viewed as the amount of money an internet user is willing to pay for certain QoS guarantees.

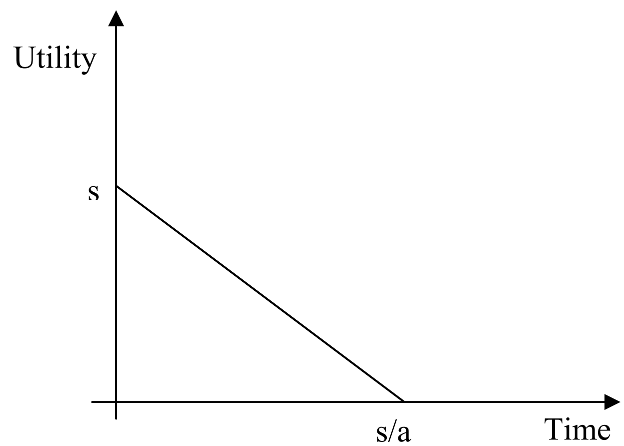
Utility functions are therefore capable of showing an application's degree of adaptability with respect to bandwidth (Lee, 1995; Naghshineh et al., 1997; Campbell, 1997). For example, inelastic applications require high levels of bandwidth, and are therefore classified as bandwidth intensive applications. When these applications are accessed at low bandwidth levels, the result is a halting (start-stop) behavior characterized by extremely long idle-times as the application is executing. This translates into an unsatisfactory (or a less than optimal) experience for the consumer.

The utility value is therefore a function of the amount of time it takes to access the internet application. The time needed to access a given internet application will vary as the level of bandwidth changes. The longer it takes to access a given application the less satisfied a user is likely to be. Therefore the utility value of accessing any application is a negative function of the time required, as represented by Figure 2 (adopted from Gambiroza & Knightly, 2006).

Figure 2

$Utility = s - at$

Where s=internet user's happiness when transfer is infinitely fast
t=is the transfer time
a=rate at which satisfaction decreases with time



This suggests that the different utility values as mapped into a utility function represent the different levels of satisfaction experienced when accessing a chosen internet application using different levels of bandwidth. Since the level of bandwidth encompasses a time component, the utility function becomes a mapping of time based on (a) the level of bandwidth and (b) the elasticity of the application.

When an internet user accesses a given internet application, utility is derived as a function of the bandwidth at which the user accesses the internet and the elasticity of the application being utilized. A mapping of the different utility values derived from accessing a given application (which we hold constant) using different bandwidths, represents a utility function for bandwidth usage.

Elasticity: Reconciling Economics Elasticity and Internet Application Elasticity

Before demonstrating how consumer utility from different internet applications is influenced by the level of bandwidth, it is useful to reconcile the categorization of applications based on their elasticity to the economics concept of elasticity.

Elasticity in general terms is a measure of responsiveness. The notion of responsiveness of y to x means that a change in x causes people to react by changing their behavior toward y, and elasticity is used to measure the magnitude of that reaction. The classification of internet applications as elastic or inelastic is based on how those applications respond to changes in the level of available bandwidth. The term elastic was first introduced in the networking research community by (Shenker, 1995). Shenkar called applications that adjust to their sending rates according to available bandwidth as elastic applications, and applications that do not change their sending rates according to available bandwidth as inelastic applications. Yuksel and Kalyanaraman (2005) note that this interpretation of elasticity by Shenkar is the same as "adaptiveness," i.e., an application is elastic if it adapts to the rate that bits are transferred depending on network conditions. An application is inelastic if it does not.

The following discussion uses the familiar concept of the price elasticity of demand to illustrate its similarity to the internet concept of elasticity. To an economist, any elasticity is a particular measure of responsiveness defined as the percentage change in the dependent variable divided by the percentage change in an independent variable. Thus, the "own" price elasticity of demand (one of many elasticities of demand) is the responsiveness of the quantity demanded of some product to changes in its price, defined

specifically as the percentage change in the quantity demanded divided by the percentage change in price. After some simple manipulation of this percentage change definition, the expression for this price elasticity can be restated as follows:

$$(1) \qquad \eta_{X(p)} = \frac{dX(p)}{dp}\frac{p}{X(p)}$$

Where p the price of the good, $X(p)$ is the quantity demand of a good and $\eta_{X(p)}$ is the price elasticity of demand.

The own price elasticity of demand is always considered to be negative, and when defined as absolute values , there are three cases as depicted by the functional form $L_{\eta_{X(p)}}$:

$$(1a) \qquad L_{\eta_{X(p)}} = \begin{cases} elastic, & \left|\eta_{X(p)}\right| > 1 \\ unit\ elastic, & \left|\eta_{X(p)}\right| = 1 \\ inelastic, & \left|\eta_{X(p)}\right| < 1 \end{cases}$$

Let x be the bits transferred when a consumer is using an internet application from a given level of bandwidth b. The concept of elasticity, conventionally used to analyze quantity demanded sensitivity to price as explained above, can also be applied to internet applications. Specifically, it applies to how internet applications respond to available bandwidth. Consequently, internet applications commonly termed elastic applications exhibit more sensitivity to changes in bandwidth. Inelastic applications are less sensitive to changes in bandwidth. Therefore we can refine the elasticity equation provided in (1) above to reflect how adaptive applications are to changes in bandwidth. The elasticity of applications with respect to their bandwidth (or the "bandwidth elasticity

of applications") can formally be depicted in equation (2), where x(b) is bits transferred as a function of the level of bandwidth b:

$$(2) \qquad \eta_{x(b)} = \frac{dx(b)}{db}\frac{b}{x(b)}$$

Where $\eta_{x(b)}$ is the elasticity of application with respect to bandwidth, i.e., the applications adaptiveness to changes in available bandwidth. Let $u(x)$be the internet user's utility from bits transferred from a chosen level of bandwidth$b$, where b is contained in the set of all available bandwidths. Therefore the "bandwidth elasticity of applications" affects $u(x)$.

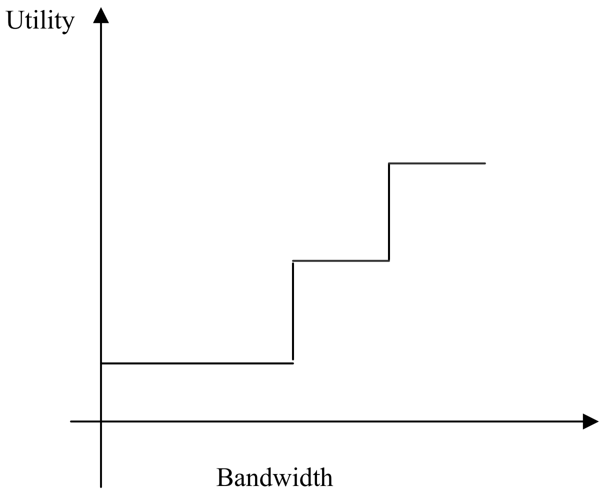
In conventional demand theory, price elasticity is depicted by $\eta_{X(p)}$ and defined as the responsiveness of quantity demanded to price. However in the functional form $\eta_{x(b)}$ in equation (2) elasticity is defined as the adaptiveness of the application to bandwidth. It is this latter definition of elasticity that we use, firstly to classify internet applications, and secondly, as we develop a testable model of optimal broadband choice.

Suggested Framework

As defined in the preceding section, inelastic applications such as audio and video streaming applications are less sensitive to bandwidth changes. This behavior of inelastic applications with regards to bandwidth can be modeled as a step function because user utility remains unchanged until there is a significant change in bandwidth. Figure 3 represents the total utility of inelastic applications at varying levels of bandwidth.

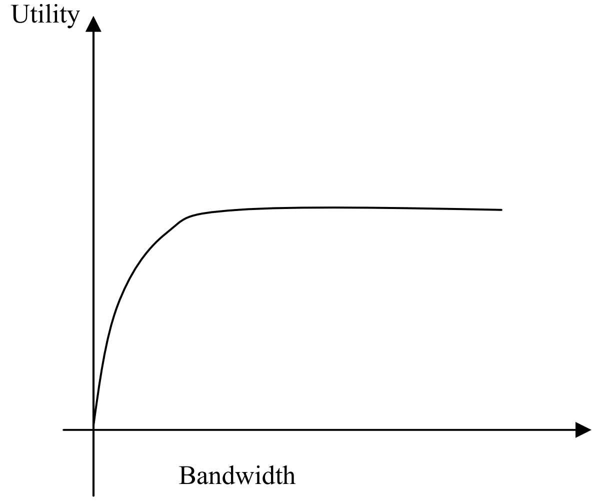
On the other hand, elastic applications such as traditional data transfer applications like email and some http traffic are more sensitive to changes in bandwidth. Therefore, even a small increase in the bandwidth level leads to an almost instantaneous increase in utility until the maximum utility threshold is achieved, at which point further increases in bandwidth yield no increases in utility and the application can be called "perfectly elastic." Therefore these applications can be represented by an increasing, strictly concave (decreasing marginal improvement) utility function, until marginal utility ultimately becomes zero (see Figure 4).

Figure 4



Inelastic applications

Figure 3



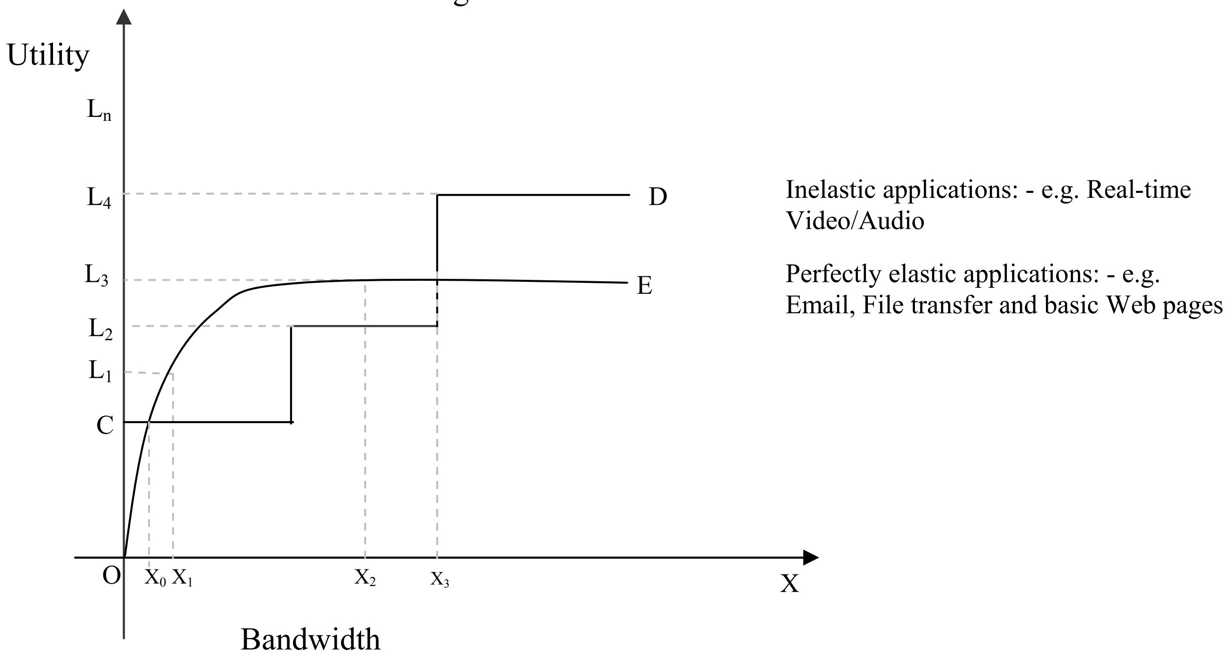
Perfectly elastic applications

Now, let us develop a framework that depicts bandwidth-allocation effects on utility, so as to directly link bandwidth choice to internet user utility. For purposes of clarity we show the behavior of elastic and inelastic applications in one graph-Figure 5. In this exposition the X-axis depicts the bandwidth level of an internet subscriber. The Y-axis depicts the various values of utility of either an elastic or inelastic application. The Y-axis therefore represents a quantized utility-axis divided into a range of increasing utility levels from O to L_n (the utility scale is unimportant in this discussion but serves mainly to rank the different levels of utility that can be attained).

Now suppose that in our framework there are two groups of home internet users, Group A and Group B. Group A subscribe to OX_1 level of bandwidth and Group B subscribe to OX_2 level of bandwidth ($OX_1<OX_2$). Due to heterogeneity of internet use, internet users in both groups access both elastic and inelastic applications. Users who

access perfectly elastic applications (beyond x_2) face a utility function OE, whereas users accessing inelastic applications face the step utility function CD.

Figure 5



Let the first scenario represent the access of perfectly elastic applications. In this scenario the users in Group A (those accessing the applications at bandwidth level OX_1) derive OL_1 level of utility from their bandwidth level. For users in Group B (accessing the same application at a higher level of bandwidth OX_2) the level of utility they receive is OL_3. It is clear that internet users in Group B receive a higher level of utility ($OL_3 > OL_1$) when accessing perfectly elastic applications, than their counterparts in Group A. Therefore accessing perfectly elastic internet applications at higher levels of bandwidth is associated with higher levels of utility, at least until the point of zero marginal returns on utility is reached.

In a second scenario, assume the same groups of users are accessing an inelastic application at the two already predefined levels of bandwidth subscriptions. The utility derived by users in group A is OC, while that derived by member is group B is OL_2. Again higher bandwidth-subscription levels lead to higher levels of utility. Therefore this demonstrates that subscribers to higher bandwidths receive higher levels of utility when accessing either inelastic or elastic internet applications (at least up to the OX_2 bandwidth level for elastic applications).

Consider a third scenario where one group of subscribers, say group A, use a specific level of bandwidth subscription in this case OX_1 to access both elastic and inelastic applications. The utility that they derive for accessing the elastic application is OL_1 and the utility they derive from accessing the inelastic application is OC. Clearly utility OL_1 is greater than OC because of the attributes associated with inelastic applications (i.e., inelastic applications are less sensitive to changes in bandwidth), rather than due to the bandwidth subscription level itself. Of course, for bandwidth levels above $OX_{3\,,}$ only inelastic applications yield higher utility, since elastic applications ceased benefiting from additional bandwidth capacity beyond the lower bandwidth level X_2, while the utility from inelastic applications makes the discontinuous jump to the highest utility level shown in Figure 5 as a result of the bandwidth level finally reaching that critical threshold capacity.

The previous examples have shown that different level of bandwidth OX_1 and OX_2 yield varying levels of utility depending on the type of application one uses (with higher levels of utility resulting from the use of elastic rather than inelastic applications in

that range), as does bandwidth level OX_3 which represents the bandwidth level at which the utility levels for elastic vs. inelastic applications reverse. Note also that below bandwidth level OX_0, this reversal of utility levels as a function of elastic and inelastic applications also applies.

As argued previously, the additional total utility attained from higher bandwidth is a result of the shorter time required when accessing web applications of either type (elastic or inelastic).[8] This also explains why a user who "mistakenly" purchases excess bandwidth for the type of applications intended, such as using beyond the OX_2 level of bandwidth when no inelastic applications are envisioned, receives no additional utility since there is really no further time saving applicable beyond that bandwidth from the sole use of elastic applications. Correspondingly, accessing applications of either type using lower bandwidth yields a lower level of utility (although discontinuously regarding inelastic applications, and only for bandwidths < OX_2 for elastic applications).

As suggested earlier, a utility function can be mapped revealing the utility from time saved as a function of the bandwidth level, or in an alternative form, as the utility from time saved as a function of the elasticity of the application. Scenario 1 and 2 demonstrates the former version, with utility generally increasing as function of bandwidth (although not continuously in the case of inelastic applications, and not

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[8] The shorter time used in accessing an application leads to a more satisfying experience for an internet user. Satisfying used in this context refers to the users' happiness or fulfillment.

Paul Selvidge (2003), in his experiment examining tolerance for online delays finds that Dial-up users wait longer than Cable User when accessing the internet.

Selvidge, *et al.*, (2002), "The world wide wait: effects of delays on user performance", find that frustration was affected by longer delay times, with 60 and 30 second delays being rated as significantly more frustrating than 1 second delays.

Selvidge's (1999) study shows that there is no difference in users' frustration levels between 1-second and 20-second delay, but a difference (with 1-second delay) was observed at the 30-second delay.

beyond some maximum bandwidth level in the case of elastic applications). Scenario 3 and the related variations demonstrate the later, with the utility from time savings being higher for elastic applications being higher for broadband levels >OX_0 and <OX_3 in the case of the relationships illustrated in Figure 5.

We observe that the utility functions illustrated in our framework are limited because they do not capture the specific time frames over which an application can respond to available bandwidth. However, we can infer that the difference in utility levels shown on the utility axis is the result of the differences in the time required for accessing different applications using a range of available bandwidths. To further justify this inference we can point to a previous study such as (Campbell, 2000) , who illustrates the example of a utility curve with five critical utility levels corresponding to a mean-opinion-score measure (obtained via subjective testing) when downloading a video quality application. These results show that various bandwidth levels yield different and measurable download times, which in turn yield different utility levels.

Theoretical Model

In the prior section we presented a diagrammatic framework depicting the difference in utility between different levels of bandwidth. The internet consumer's choice of the level of bandwidth can be modeled using a behavioral model different from the one presented by (Varian, 2002). In this section we present a theoretical model using a "representative agent" model, meaning that the utility of one internet user is representative of all users, assuming all users are identical.

Continuing with the same notation in equation (2) x denotes the bits transferred from a chosen level of bandwidth b.[9] Internet consumers get utility $U(x)$ from bits transferred. There is an associated cost of time taken to transfer the bits to the internet user. This cost has two components, the first of which is the subjective cost of time (c).[10] In our previous analysis we demonstrated that there was a difference in utility when using higher/faster bandwidth (OX_2) in comparison to slower/lower speed bandwidth (OX_1). This difference was the result of time gains from the use of the higher level of bandwidth. The value an individual places on the time savings is what we refer to as the internet user's subjective cost of time.

The second component is the explicit dollar cost of bandwidth chosen $p(b)$ (where b is the chosen level of bandwidth) this cost is known a priori to the consumer. It is important to note that in our model the explicit cost of the chosen level of bandwidth is a flat rate normally charged monthly to the user. This is different from Varian's use of an explicit cost accessed to the consumer based on usage. The difference in our case is that the explicit cost becomes $p(b)$, for $p(b) > 0$, whereas in the Varian case this cost depends on the time one spends on the internet, hence its representation as $p(b)t$.

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[9] Remember the definition of Bandwidth presented earlier: Bandwidth in today's terms describes Network Speed as measured in bits per second or Bytes (characters) per second.

[10] Varian in his model also represents the users subjective cost of time with the same notation c.

The associated cost of the time taken to transfer the bits to the internet user is the internet user's subjective cost of time plus the explicit cost of the chosen level of bandwidth. This can be represented as $\left[ct + p(b)\right]$.

In Varian's behavioral model he assumes that the internet user's utility function $u(x)$ can be expressed in monetary terms. The net utility from bits transferred is the utility from bits transferred less the cost, which consists of the subjective cost and the explicit cost of time. This net utility can be represented as $u(x) - [ct + p(b)t]$. Varian's treatment of $u(x)$ in monetary terms could be justified by (DaSilva, 2000), who argues that utility functions describing the sensitivity of users to changes in the quality of internet service (QoS) can be viewed as measuring the amount of money a user is willing to pay for certain QoS guarantees. The limitation is that while utility is ordinal and not cardinal, $u(x)$ to Varian is measurable because respondents reveal their willingness to pay for the various levels of bandwidth chosen. However this information is not available in a non- experimental setting.

Let R be the consumer's income which is also the maximum a consumer is willing to pay for a given level of bandwidth. The consumer's budget constraint becomes $R - \left[ct + p(b)\right]$.

The consumer maximizes utility subject to the budget constraint, as given by equation [1] and equation [1'].

[1] $\max u(x)$

[1'] *subject to* $R - [ct + p(b)]$

Solving for the optimal bandwidth $b*$

[2] $L = u(x) - \lambda\,[R - [ct + p(b)]]$ max $w.r.t\ x, b, \lambda$

Since bandwidth is by definition bits per unit time $t = \dfrac{x}{b}$ equation [2] becomes

[2'] $L = u(x) - \lambda\left[R - \left[c\dfrac{x}{b} + p(b)\right]\right]$

F.O.C

[3] $\dfrac{\partial L}{\partial b} = u'(x) * \dfrac{\partial x}{\partial b} - \dfrac{cx}{b^2} + p'(b) = 0$

[4] $\dfrac{\partial L}{\partial x} = u'(x) - \dfrac{c}{b} = 0$

[5] $\dfrac{\partial L}{\partial b} = R - [ct + p(b)] = 0$

Dividing Equation [3] and [4]

[6] $\dfrac{\partial x}{\partial b} = \dfrac{cx - b^2 p'(b)}{bc}$

Let $\dfrac{\partial x}{\partial b} = x'(b)$

Equation [6] then becomes

[6’] $x'(b)bc = cx - b^2 p'(b) \quad \equiv \quad [p'(b)]b^2 + x'(b)cb - cx = 0$

Since $p(b) \equiv$ total cost of chosen bandwidth $p'(b) > 0$

Let $p(b) = a + db \quad \Rightarrow \quad p'(b) = d$

Also $b = \frac{x}{t} \quad \Rightarrow \quad x = bt \quad \Rightarrow \quad x'(b) = t$

Substituting for $p'(b)$ and $x'(b)$ in equation [6’]

[7] $[d]b^2 + [tc]b - cx = 0$

[8] $b^* = \frac{-tc \pm \sqrt{tc + 4acx}}{2d}$

Since $b^* > 0$ equation [8] can only take the following form

[8’] $b^* = \frac{-tc + \left[t^2c^2 + 4acx\right]^{\frac{1}{2}}}{2d}$

What is of interest to us is the comparison between the optimal bandwidth b^* for inelastic application and by contrast for elastic applications. From the definition of the type of internet applications and the earlier depicted framework of elastic and inelastic application, the time taken to access inelastic applications is larger than the time taken to access elastic applications. From this we can deduce that $\left[t^2c^2 + 4acx\right]^{\frac{1}{2}} > tc$ in equation [8’].

$$Therefore \left\{ b_{inelastic}* = \frac{-t_{inelastic}c + \left[t_{inelastic}{}^{2}c^{2} + 4acx \right]^{\frac{1}{2}}}{2d} \right\} > \left\{ b_{elastic}* = \frac{-t_{elastic}c + \left[t_{elastic}{}^{2}c^{2} + 4acx \right]^{\frac{1}{2}}}{2d} \right\}$$

From our solution we can conclude that the optimal bandwidth $b_{inelastic}*$ is higher for inelastic applications compared to the optimal bandwidth $b_{elastic}*$ for elastic applications.

In the empirical testing of economic models it is of course important to hold other things constant when interpreting the effect of a specific variable. We present two methods of validating the theoretical model. Obtaining similar results in both analyses confirms that the utility derived from time saving is a good indicator as to whether or not people adopt broadband. The first approach is presented in chapter 4. By focusing on bandwidth as the sole determinant of a consumer's decision to choose either dial-up or broadband, we demonstrate that time savings can be used as a predictor of the type of internet connection a consumers choose.

On the other hand, the decision to consume a given type of internet connection is influenced by the many other goods that the household consumes. Therefore the analysis of the consumer's choice of internet connection must control for the basket of goods consumed by a household. Therefore the second approach, presented in chapter 5, uses an empirical model that evaluates the impact of time savings as seen through the type of applications used as a predictor of the choice of internet connection. This provides additional empirical validation of the theoretical model.

CHAPTER 4: IMPLICIT VALUE OF TIME SAVED BY THE TRANSITION FROM A DIAL-UP TO BROADBAND

In order to validate the role played by time savings in the consumer's choice of internet connection, we argue that time saved is primarily determined by the type of internet application that a user is trying to access. The utility gains resulting from the timesaving are influenced by the bandwidth (bandwidth of the type of connection, and bandwidth consumed by the internet application).

The important role played by bandwidth is confirmed by studies designed specifically to test the user's tolerance to "latency" while downloading internet applications (Nah, 2004; Lightner & Bose, 1996; Galleta, et al., 2004; Barber, 2003). These studies were also referenced in Chapter 1 when discussing the "access tolerance approach," and measure the thresholds of acceptable download times of various internet applications. Table 4 presents some of these findings related to a typical user's tolerable waiting time for a web page download. The results reported in the table demonstrate that there is frustration or satisfaction depending on the time required to download a web page, confirming that users react strongly to delays regardless of the context in which the applications is being accessed. This is an indication that bandwidth level is likely to be a sufficiently significant determinant of consumer behavior to warrant initially focusing upon it independent of other factors.

Table 4: Summary of User Tolerable Waiting Time for Web Page Downloads

Study	Finding
Ramsey, Barbesi and Preece (1998)	Delay of 41 seconds is suggested as the cut-off for long delays' based on users perceptions.
Selvidge (1999)	Delay of 30 seconds is suggested as the cut-off based on users' performance and frustration level
Nielsen (1993, 1995, 1996)	Delay of 15 second is tolerable in the web context
Hoxmeier and DiCesare (2000)[1]	Delay of 12 seconds cause satisfaction to decrease
Gallatta, Henry, McCoy and Polak	Delay of 4 seconds causes performance and behavioral intentions to stabilize whereas attitudes remain unchanged after delay exceeds 8 seconds

Table adopted from Nah (2004) "A study on tolerable waiting time: how long are Web users willing to wait?"
[1] Hoxmeier andDiCesare (2000) employed a simulated web environment and subjects were engaged in an information retrieval search task using download delays of 0, 3,9 and 12 seconds. The results supported a significant relationship between satisfaction and delay, with satisfaction being highest in the 0-second delay condition.

Also, Varian's index experiment, in a paper widely cited in the economic literature of broadband adoption, uses a model of consumer choice of bandwidth, further justifying our focus upon bandwidth.

In the theoretical framework presented in Chapter 3, we demonstrated that internet consumers who use a higher level of bandwidth (for example broadband) will receive a higher level of utility when accessing either elastic or inelastic applications due to the resulting timesaving when compared to using lower bandwidth levels (see Figure 3 in Chapter 3). The decision to transition from a dial-up speed to a broadband speed depends critically on the individual's value of the time saved, as well as on the cost of purchasing this faster connection speed. It is critical therefore to be able to empirically

measure this tradeoff between the value of time saved and the higher price of speedier connectivity.

While the explicit cost involved in the choice of a particular bandwidth level is known *a priori* because it is a publicly quoted price, the timesaving benefits from higher bandwidth speeds can be difficult for the internet user to quantify. What is required is an evaluation of the time saved by the choice of bandwidth type along with the subjective value of time

This chapter addresses these information requirements by adapting an empirical estimation technique from (Cooper, 2000). This model can be used to quantify the subjective cost (value) of time saved by the transition from dial-up to broadband. This methodological approach to the implicit value of time stems from the integration of two areas of prior research: internet congestion models, and studies that measure the implicit value of life. Internet congestion models look at various pricing schemes that have been employed to control internet congestion. These schemes are based on the idea that users have to pay a price to obtain some bandwidth. Such models derive theoretical demand schedules based on the obvious assumption that people value faster transmission speeds and that people are willing to trade off higher purchasing costs for faster transmission. By contrast, studies that determine the implicit value of life do so by measuring how much a person is willing to pay for the reduction of the risk of death by some quantifiable amount, and comparing that with the price of the good or service that reduces that risk.[11]

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[11] Dardis (1980) states that this approach is favored by many economists on the ground that it incorporates the preferences of individuals toward risk.

Variables Used in the Empirical Estimation of the Implicit Value of Time Saved between different Bandwidth Levels

Amount of Information Accessed Monthly

A very important component of the implicit value of time model is the amount of information accessed over a certain period of time by an individual. In our analysis we use monthly information. According to Nielsen/Net rating (See Table 5) the average home internet user in 2006 spent approximately 32 hours 53 minutes per month on the internet at home. The difficulty we face in our analysis is finding out how much information was accessed in kilobytes during that period (monthly internet use in kilobytes). This information is not readily available, but using prior research we can infer an approximate value to enable us to conduct the analysis. In 2000 the average user accessed 60,000 kilobytes (60 megabytes) of information a month (Odlyzko, 2000). In that year, according to Nielsen/Net rating, the average internet user spent 9 hours and 41 minutes per month on the internet.

Based on the average time spent on the internet, coupled with the quantity of information accessed in the year 2000, we make some necessary assumptions to be able to approximate the average amount of information accessed per month in 2006 by the average internet user.

Table 5 presents the November 2006 monthly statistics of the average monthly web user according to Nielsen/NetRating. The amount of information accessed per hour

for the average user in the year 2000 was 6,196 kilobytes per hour.[12] At this rate, the amount of information accessed for 32 hours 53 minutes, which is the time spent by an average internet user in 2006 (see table 5), would be 203,752 kbm. For simplicity, we assume that the average monthly information measured in kilobytes per month (kbm) in 2006 has increased at the same rate as the amount of time spent per month on the internet has increased from 2000 to 2006, which is threefold. So the current average monthly user access average is 180,000 kbm.[13]

Table 5: Monthly Average Usage of a Home User

Sessions/Visits Per Person	35
Domains Visited Per Person	64
PC Time Per Person (minutes)	32:53:44
Duration of a Web Page Viewed	0:00:48

Another issue that needs to be considered when quantifying the monthly kilobytes of information accessed by a user is the heterogeneity that exists among internet users, especially with regards to the duration per session and the frequency of internet use. To account for this heterogeneity we classify internet users into three groups: heavy,

[12] Average amount of information accessed per month/average time spent on the internet per month. [(60,000 kbm)/(9 hour 41 minutes)]

[13] The amount of time spent on the internet at home has increased threefold during the period 2000 to 2006. This is based in the average amount of time spent on the internet per day, Juniper communications states that the average amount to time spent on the internet per day in 2000 was 70 minutes, Stanford Center for the Quantitative Study of Society states that the average amount of time spent on the internet per day in 2005 was 176 minutes. With this increase coupled with the evolution and introduction of numerous internet applications that require greater bandwidth, it is logical to assume that the amount of information accessed monthly on the internet had increased from the 60,000 kilobytes accessed in 2000.

medium/average, and light users. For purposes of our analysis we assume that the heavy user accesses 240,000 kbm of information; the medium user accesses 180,000 kbm of information a month; and the light user accesses 120,000 kbps of information a month. This is the same approach presented by (Cooper, 2000) and our assumption of the three level of users is consistent with levels presented by Cooper. It is also important to note that the accuracy of the amount of information accessed per month by either type of user should not matter in our analysis because the overall objective of our analysis is to determine the relative value people place on their time saved.

Connection Types, Speeds and Prices

Table 6 presents the various internet access speeds and prices for internet connectivity. The type of internet service and estimated throughput price is derived from the data transfer rate conversion table from the following website, http://www.scotsnewsletter.com/best_of/dtrct.htm. The data listed in the table is a comprehensive reference point and it is corroborated with other web sources to ensure its accuracy. The prices corresponding to various types of internet services are compiled from various relevant websites.

Table 6: Types of Internet Connections, Download Speeds and their Corresponding Prices

Connection Type		**Connection Type Speeds**	**Download Speed for various Internet connection types**	
Typical Service Level	*Classification*	*kilobits per second (kbps)*	*Estimated Ideal Throughput*	*Cost*
"28.8K" Analog Modem	Narrowband	28.8-kbps	22.4-kbps	$10
"33.6K" Analog Modem		33.6-kbps	26.4-kbps	$10
"56K" Analog Modem		53.3-kbps	41.6-kbps	$10
1-channel ISDN		64-kbps	49.6-kbps	$10
2-channel ISDN / IDSL		128-kbps	100-kbps	$15
Fractional T-1	Broadband	256-kbps	200-kbps	$24
384 S-DSL		384-kbps	300-kbps	$39
Satellite		400-kbps	312-kbps	$99
Fractional T-1		512-kbps	400-kbps	$45
Cable / DSL		768-kbps	600-kbps	$45
1-Mbps / Cable / DSL		1,000-kbps	784-kbps	$60
T-1 / Cable / DSL		1,544-kbps	1208-kbps	$70

The speed of any internet connection is not the same as the download speed experienced by the end user. The former speed is the maximum speed at which a specific internet connection can be achieved if the end user is not experiencing any network related problems, or if the network is void of congestion related issues. Whereas the latter speed, also called the estimated throughput, factors in the various network conditions. This means that the estimated download speed of various internet connections (listed as the estimated throughput) could be lower than the connection type speed.

Empirical Estimation of the Implicit Value of Time Saved between Different Bandwidth Levels

To measure the implicit value of time saved over the internet, we compute the ratio of the explicit cost differential between the two choices of internet service to the corresponding difference in the rate of download time between the two choices. The result of this computation provides a value that can in turn be used to deduce the demand for internet usage of a specific bandwidth level. The next step involves comparing the different values placed on various bandwidth levels against the time saving based on any respective choice. This comparison provides the basis of the cost-benefit decision in determining the tradeoff between time-saved from higher connectivity and the higher prices associated with higher bandwidth.

The value model we use to estimate the implicit value of a user's time is represented as follows (this model is adopted from (Cooper, 2000))

$$Value = \left[\frac{\left(\left| \cos t(a) - \cos t(b) \right| \right)}{\left[\frac{\left| \left(\frac{kbm}{volume(a)} \right) - \left(\frac{kbm}{volume(b)} \right) \right|}{3600} \right]} \right]$$

Where:

-*Value* = the implicit value of time saved

-*cost (a)* = the cost of faster internet connection type

-cost (b) = the cost of slower internet connection

-volume (a) = the effective transmission rate (estimated throughput) of the faster internet connection

-volume (b) = the effective transmission rate (estimated throughput) of the slower internet connection

-kbm = kilobytes per month

-3600 = how many seconds there are in an hour (it translates the data into hours instead of seconds)

Now consider an average (medium) internet user who is faced with a choice between two internet types; a 64kbps modem *(dial-up modem)* and a cable modem (broadband modem). The cable modem has a transfer speed of 600-kbps *(volume (a))* and the 64 kbps dialup modem has a transfer speed of 49.6-kbps (*volume (b))*. The cable modem costs $45 *(cost (a))* per month and the 64 kbps dialup modem has a cost of $10 *(cost (b))* per month. The explicit difference in cost is $35 per month. The time saved in a month accessing the 180,000 kilobytes of information using the cable modem as opposed to the 64 kbps dialup modem is 0.92 hours (55.2 minutes) per month.[14] The time

14 Time saved in a month is calculated by the denominator of the implicit value model

$$\left[\frac{\left|\frac{kbm}{Volume(a)} - \frac{kbm}{Volume(b)}\right|}{3600}\right]$$

saved indicates the nominal amount of time saved by switching from the slower modem (e.g., dial-up) to faster modems (e.g., broadband).

If an internet user who is currently using a 64 kbps dialup modem wants to switch to a cable modem, they will save 0.92 hours per month in internet usage time. In addition the explicit cost to make the switch would be $35 per month (the cost differential between the cable modem and the 64 kbps modem). The implicit value of time saved by this choice is given by the ratio of cost savings to monthly time saved, which is $35.51 per hour. The implicit value of time saved is the dollar amount that expresses the minimum amount a person must value their saved time in order to justify making a switch from the slower modem to a faster modem. Therefore the 64kbps user must value each hour of his/her time at a dollar rate of at least $35.51 to justify the switch to cable modem. As long as the individual values time at a value lower than this, he/she will not switch to cable modem.

The argument presented here is an attempt to measure the utility gained from the time saved by choosing the faster modems over the slower modems. After the quantification of this increase in utility from the time that is saved, the issue becomes how to determine whether an internet user will make a switch from a slow to faster internet connection based on the additional utility value presented as a dollar amount.

While the purpose of this exercise is to empirically measure the tradeoff between time saved and higher connectivity prices, the difficulty is in quantifying each user's value of time. The economic literature has used an individual's earnings as an indicator of how they value time. The argument has been that the wage of an individual is the

reservation price of how much they are willing to accept to work instead of engaging in leisure or other activities during that time. Using an individual's wage as the gauge for the value of their time, if an internet user in our example earned a wage of $15 an hour from the workforce, then the move from the dial-up connection of 64 kbps to the broadband connection from the cable modem would not make sense. This is because the value of their time (on an hourly basis) is less than the dollar value of the utility gain they experience by making the switch from the slower modem to the faster internet modem.

If the user's wage earned from the workforce on the other hand were $45 an hour, then the switch would make sense. This is because the value of their time is greater than the implicit value they would gain by making the transition, meaning they have a relatively high value of their time, and it then makes sense to switch to the broadband connection. Tables 7, 8 & 9 presents similar calculations of time saved and the corresponding implicit value of time saved by choosing cable modem over other internet type connections for light users, average/medium and heavy users.

Therefore internet consumers sacrifice the dollars they would save if they remained at an existing level of bandwidth for the time they gain by choosing an internet type with higher speed. The decision to make the tradeoff between the type of internet speed and the time gained depends on how they value the gains in time received from the internet type with faster speed. By using the implicit value model, we are able to associate a value to the time saved when a particular internet-connection type is chosen.

The larger the implicit value of time saved the more likely a consumer will choose to move from a lower to a faster internet speed connection. If an internet user who

accesses average/ medium monthly content is currently subscribing to a 28.8 kbps modem and chooses to subscribe to a cable modem, the implicit value of time saved from that choice is $16.28 per hour. If another internet user currently subscribing to a 256 kbps DSL lite modem chooses to subscribe to a cable modem, the implicit value of time saved from the choice is $126. A user will perceive it to be more valuable to switch from a 256 kbps lite modem to a cable modem than from a 28.8 kbps modem to cable modem.

Table 7: Comparison of the Choice between Various Internet Speeds and Cable Modem - For a Light User

Initial modem (Slower modem)	**New modem (Faster modem)**	**Difference in Cost between Slower and Faster Modem**	**Time Saved per month by switching to the faster modem from the slower modem**	**Implicit Value of Time saved in $**
28.8 kbps modem	Cable Modem	35.0	1.43	24.43
56 kbps modem	Cable Modem	35.0	0.75	46.93
64 kbps modem	Cable Modem	35.0	0.62	56.77
128 kbps modem	Cable Modem	30.0	0.28	108.00
256 kbps DSL lite	Cable Modem	21.0	0.11	189.00

Table 8: Comparison of the choice between Various Internet Speeds and Cable Modem- For an Average/Medium User

Initial modem (Slower modem)	**New modem (Faster modem)**	**Difference in Cost between Slower and Faster Modem**	**Time Saved per month by switching to the faster modem from the slower modem**	**Implicit Value of Time saved in $**
28.8 kbps modem	Cable Modem	35.0	2.15	16.29
56 kbps modem	Cable Modem	35.0	1.12	31.29
64 kbps modem	Cable Modem	35.0	0.92	37.85
128 kbps modem	Cable Modem	30.0	0.42	72.00
256 kbps DSL lite	Cable Modem	21.0	0.17	126.00

Table 9: Comparison of the choice between Various Internet Speeds and Cable Modem- For a Heavy User

Initial modem (Slower modem)	**New modem (Faster modem)**	**Difference in Cost between Slower and Faster Modem**	**Time Saved per month by switching to the faster modem from the slower modem**	**Implicit Value of Time saved in $**
28.8 kbps modem	Cable Modem	35.0	2.87	12.22
56 kbps modem	Cable Modem	35.0	1.49	23.47
64 kbps modem	Cable Modem	35.0	1.23	28.39
128 kbps modem	Cable Modem	30.0	0.56	54.00
256 kbps DSL lite	Cable Modem	21.0	0.22	94.50

CHAPTER 5: EXPLAINING BANDWIDTH CHOICE: THE EMPIRICAL MODEL AND RESULTS

In Chapter 4 we demonstrated that a consumer uses the implicit value of time saved to assess the gross benefits from different internet capacities, and compares those to the additional cost of purchasing larger capacity. The larger the implicit value of time saved the more likely a consumer is to choose to move from lower to a faster internet connection. In Chapter 3 we demonstrated that the choice of internet bandwidth was dependent on the type of applications the consumer accesses while on the internet. Therefore the empirical consumer choice model predicts that the type of internet connection chosen is determined by the net benefits of time saved resulting from the capacity of bandwidth and the applications accessed with that bandwidth. Of course, any internet choice model must account for other factors affecting consumption at the household level, including education, age and income, and the price paid for internet service is important in determining the net benefits of generating additional time savings from expanded bandwidth.

This chapter presents an empirical model consistent with the theoretical model that is capable of testing these propositions. We begin by describing the data used, followed by a description of the empirical estimation model and the empirical results. The robustness of the empirical results was validated using four survey datasets, requiring those results to be reported and discussed individually for each survey.

Data

Data obtained from four different surveys are used in the empirical analysis. The surveys contain cross sectional data of internet users among individuals 18 years and

older in United States households. The Princeton Survey Research Associates International (PSRAI) administered the surveys for the Pew Internet and American life project (PI&ALP)[15]. Random digit samples of telephone numbers were used to select the survey samples in the respective time periods. The survey samples were designed to reflect national propensities and to be unbiased. The four surveys are the most recent available from the PI&ALP and are listed in Table 5.1a.

Table 10: List of Surveys used in the Empirical Analysis

Survey Title	**Period in which survey was conducted**	**Sample Size**
Daily Tracking Survey November 2003	Nov 18 – Dec 15, 2003	1,400
February 2004 Tracking Survey	Feb 3 – Mar 1, 2004	2,204
January 2005 Daily Tracking Survey	Jan 13 – Feb 9, 2005	2,201
November/December 2005 Daily Tracking Survey	Nov 29 – Dec 31, 2005	3,011

Telephone interviews have known biases resulting from the problem of non-responsiveness. Participation tends to vary for different subgroups of a population, and responses from subgroups are also likely to vary across questions of substantive interest.[16] To compensate for these known biases, PSRAI constructed a weighting system for each sample. The weight variables in each survey are constructed from the Census Bureau's Annual Social Economic Supplement (CBAES) available during the relevant survey time period. The CBAES analysis produces population parameters for the demographic characteristics of adults aged 18 or older living in households that have a telephone. PSRAI compared the parameters with the sample characteristics of each

[15] PI&ALP is a non-profit research center studying the social effects of the internet on Americans.

[16] This point is noted in the methodology sections of the different respective survey questionnaires.

survey to construct the respective sample weights by using an iterative technique that simultaneously balances the distribution of all weighting parameters.

Each of the four surveys was designed to generate the following extensive information at the household level: the type of internet connection subscribed to by that household; the applications used during an internet session; the highest level of education attained; frequency of internet use; total months of internet use; the price paid for internet access; total household income; age of respondent and other relevant variables. All questions in the surveys offered as possible answers: “Don’t Know” and “Refused,” and a large number of respondents selected these options. Therefore the sample is limited to only those respondents who answered the question about what mode they used to access the internet at home (the critical dependent variable for the empirical analysis). Details of this are explained in the next section, which provides a formal description of the dependent variable.

The surveys ask respondents about the applications they use during an internet session, and these applications can be classified as either elastic or inelastic based on our earlier analysis (Chapter 3). It is important to note that subsequent surveys following the daily tracking survey of November 2003 report more application variables since they included more application related questions. Table 11 lists the various applications asked about in the surveys, and their respective elasticity classification.

Table 11: Internet Applications and their classification by Elasticity

Applications	Classification
Email	Elastic
Instant Message	Elastic
Chat	Elastic
Other Weblog	Elastic
Download Music	Inelastic
Download Video	Inelastic
Browse for News	Inelastic
Share Files Online	Inelastic
General Browsing	Inelastic
Direction Searching	Inelastic
E Commerce	Inelastic
E Trading	Inelastic
Map Searches	Inelastic
Own Weblog	Inelastic
Online Auction	Inelastic
Product Search	Inelastic
Search for Sports Info.	Inelastic
Charity Giving	Inelastic
Online Banking	Inelastic
View Images	Inelastic
Online Gaming	Inelastic
Do work related at home	Inelastic
Take Online Classes	Inelastic

The classification of applications by their elasticity is vital for testing the empirical model because inelastic applications are bandwidth intensive whereas elastic applications are not. The type of internet connection combined with the applications used determines the degree of satisfaction or frustration during an internet session. The type of application used is therefore a proxy for the level of user satisfaction when accessing the application via a specific type of internet connection.

Dependant Variable

The dependent variable is the type of internet connection subscribed to by the household, hereafter termed broadband status (level of bandwidth), defined as a binary

variable. The dependent variable therefore takes a dichotomous form: = *1 if a household uses a broadband internet connection type, or 0 if otherwise.* Subscription to connection type is determined from the question asking individuals about the mode they use to access the internet at home. A dial-up internet connection is identified by only one category called "dial-up telephone line." However, a broadband connection type is identified via the following options: a DSL enabled phone line, a cable modem, a wireless connection (either land based or satellite), or a T-1 fiber optic connection.

Figures 6 – 9 show the univariate distributions of internet access types (broadband or dialup) for respondents in the four different surveys.

Figure 6

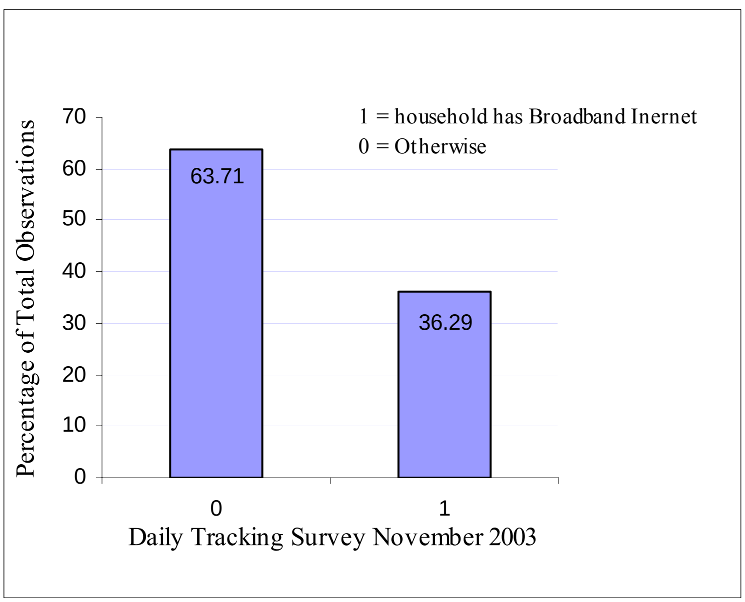


Figure 7

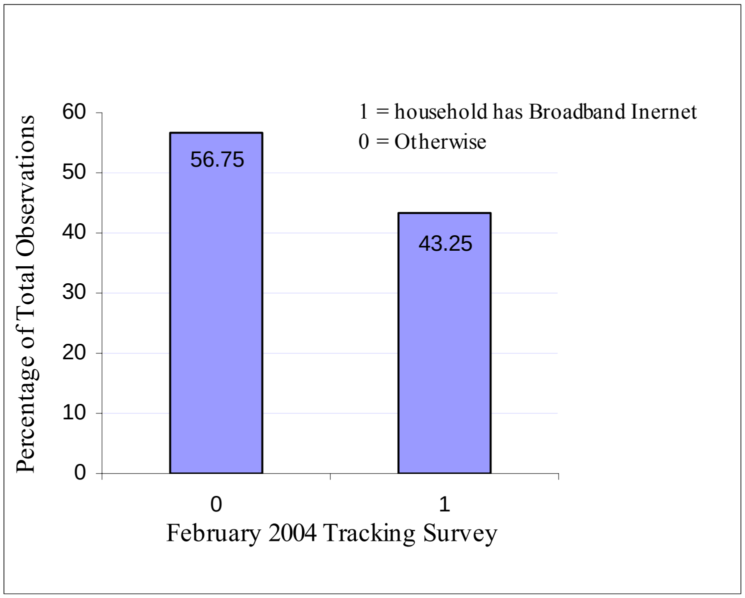


Figure 8

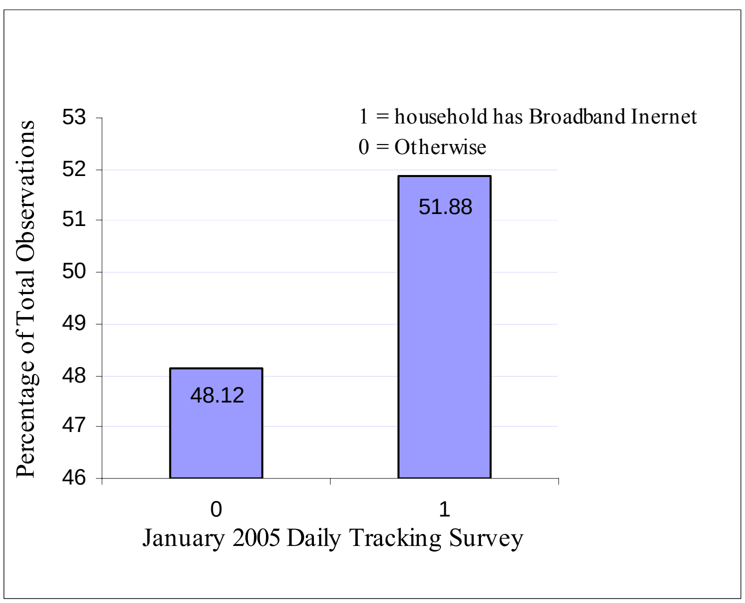
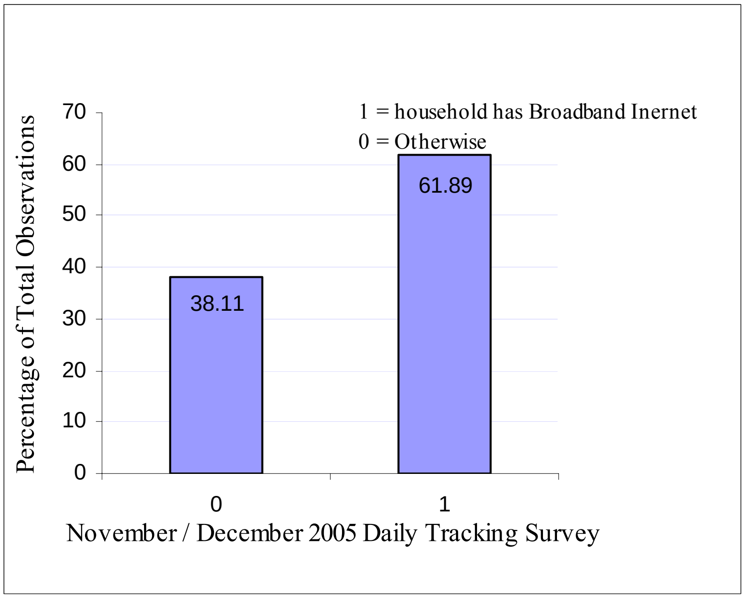


Figure 9



Explanatory variables

The criteria used by (Hoag, 1997) in constructing the explanatory variables are incorporated into this model. Using a survey instrument, Hoag classifies internet usage variables into two groups: consumption related variables and satisfaction related variables. This approach is consistent with the argument that the type of connection used to access internet applications determines the satisfaction level of the user.

Consumption variables measure four key areas: (i) the amount of time spent online; (ii) how many parts or number of internet applications are accessed when individuals go online; (iii) the intensity of internet use; and (iv) the time and money spent on other media (newspaper, magazines, TV, home video, and telephone).

Consistent with (Hoag, 1997) approach, we construct independent variables that can be classified as consumption variables. The variables designed to capture the amount

of time spent online (the first measure of consumption) include: the total months of internet use, the amount of time spent on the internet yesterday, and the frequency of internet use (captured in the question asking how often a respondent uses the internet at home.

We are not able to construct variables that can capture the second measure of consumption (i.e., how many parts or number of internet applications are accessed when individuals go online), because there is no question in any of the four surveys that measures such a variable. To capture the third measure of consumption (i.e., the intensity of internet use) we use the "frequency of internet use" variable.

Hoag (1997) compares the expected frequency of adoption of a "part" of the internet (Email, Web, Usenet, FTP, IRC/MUD, Internet telephony/ videoconferencing) to the observed frequency by modem speed. She then generates the likelihood of using a particular medium to access an internet application, and draws conclusions about internet user satisfaction based on the results. In a similar fashion, to measure the internet user's satisfaction we construct several binary variables based on the usage of internet applications. These internet applications are proxy measures of the internet user's satisfaction. Chapter 3 noted that each application could be classified based on its elasticity. This classification in turn indicates which type of bandwidth is preferable to run the application efficiently. For example, if an inelastic application that requires fast bandwidth (broadband) because it is bandwidth intensive is running on low bandwidth, the user is more likely to be frustrated because of the time required to access the application, leading to a low level of satisfaction. A more detailed description of various

scenarios facing an internet user running either elastic or inelastic applications was presented in the theoretical framework in Chapter 3. This chapter also established that the internet connection type combined with the applications used determine if a user becomes satisfied or frustrated during an internet session.

Internet users face various levels of frustration when they use bandwidth intensive applications (inelastic applications) on a low level of bandwidth connection like dial-up. Our hypothesis is that the use of bandwidth intensive applications increases the probability of adopting a broadband internet connection at the household level. This hypothesis is based on the fact that users of bandwidth intensive applications are more likely to subscribe to broadband at the household level in order to overcome the frustration of accessing these applications using low-level bandwidth capacity modems like dialup.

Our use of application variables is also supported by the argument presented by the General Accounting Office (GAO, 2006), which states that in addition to household characteristics, the availability of internet applications and internet content that cannot easily be accessible through a dial-up connection, coupled with the degree to which consumers are aware of the value of the available applications, contributes to a household’s decision to adopt broadband. Among the examples given by the GAO of applications that could lead to broadband adoption are gaming, VOIP (voice over internet protocol), music and video downloads.

Another justification for the inclusion of the application variables in our model is (Waldman & Savage, 2004), who present a detailed overview from various literatures

about internet applications and their content as they relate to the type of internet connection subscribed to.

In addition to the consumption and satisfaction related variables we include other independent variables relevant to the empirical model that may not be classified as either consumption or satisfaction type variables. These variables include: the levels of education, the price of internet access, total household income and age. The education variable is a categorical variable that accounts for the effect of education on a household adopting broadband. We construct four dummy grouping from the education variable with the base category being the individuals who have a technical or vocational certificate as the highest level of education attained. Our hypothesis is that the more educated an individual, the more likely they are to subscribe to broadband for household usage. This is because more educated people are more exposed to newer forms of technology, including bandwidth intensive internet applications. Also more educated people would most likely engage in research related activities, which are by nature bandwidth intensive. Both income and age are continuous variables. Income is constructed by using the median income of the income group indicated by respondents. Regarding age, the hypothesis is that older people are slower adopters of newer technology so they will lag when it comes to adopting the new bandwidth intensive applications.

The use of these variables (income, price paid for internet, education, age) is consistent with the previous literature on internet or broadband adoption and usage. For example, the GAO in its May 2006 report on broadband deployment in the United States

uses those variables and many more: income, education, age, the presence of children in household, racial composition of household, the occupation of heads of the household, the number of people in the household, whether household resides in an urban, suburban or rural location, number of companies providing broadband service in the area and whether the state in which the respondent resides imposes a tax on internet service. Other studies use similar household characteristics to determine which of the characteristics influence the adoption of broadband at the household level.[17] Chaudhuri, Horrigan and Flamm (2004) use education as one of the socio-demographic variable in modeling the probability of having access to the internet at home. Waldman and Savage (2004) list education as a measure of socio-economic disadvantage for some households that affects the type of internet access to which they subscribe. Kridel, Rapport and Taylor (1999) use price in their logit model to determine the probability of access to the internet.

Table 12 describes the variables used in our empirical analysis for all the four surveys, and Table 13 presents the sample statistics of the variables for each of the four surveys.

[17] See Scott Wallsten, Broadband Penetration: An Empirical Analysis of State and Federal Policies (Washington, D.C.: AEI-Brookings Joint Center for Regulatory Studies, 2005); Scott J. Savage amd Donald M. Waldman, "United States Demand for Internet Access," Review of Network Economics, Vol 3, no. 2 (2004) 228-247; Debra J. Aron and David E. Burnstein, "Broadband Adoption in the United States: An Empirical Analysis"(paper presented at the 31st Annual Telecommunications Policy Research Conference, Arlington Va., 2003), Gary Madden & Michael "Residential broadband subscription demand: an econometric analysis of Australian choice experiment data", Applied Economics, 1997, 29, 1073-1078.

Table 12: Variable Definitions

Variables	Classification	Variable Description
Dependent Variable		
Household Broadband Status		
Independent Variables		
Email	Elastic	=1 if respondent uses the internet to send or to receive email, =0 Otherwise
Instant Message	Elastic	=1 if respondent uses the internet for Instant Messaging, =0 Otherwise
Chat	Elastic	=1 if respondent uses the internet to Chat, =0 Otherwise
Other Weblog	Elastic	=1 if respondent uses the internet to participate on other peoples Logs, =0 Otherwise
Download Music	Inelastic	=1 if respondent uses the internet to Download Music, =0 Otherwise
Download Video	Inelastic	=1 if respondent uses the internet to Download Videos, =0 Otherwise
Browse for News	Inelastic	=1 if respondent uses the internet to Browse for News, =0 Otherwise
Share Files Online	Inelastic	=1 if respondent uses the internet to Share Files Online, =0 Otherwise
General Browsing	Inelastic	=1 if respondent uses the internet to do General Browsing, =0 Otherwise
Directory Searching	Inelastic	=1 if respondent uses the internet to Search for Directions, =0 Otherwise
E_commerce	Inelastic	=1 if respondent uses the internet for E_Commerce, =0 Otherwise
E_Trading	Inelastic	=1 if respondent uses the internet for E_Trading, =0 Otherwise
Map Searches	Inelastic	=1 if respondent uses the internet for Map Searching, =0 Otherwise
Own Weblog	Inelastic	=1 if respondent uses the internet for managing their own Web Log, =0 Otherwise
Online Auction	Inelastic	=1 if respondent uses the internet to participate on Online Autions, =0 Otherwise
Product Search	Inelastic	=1 if respondent uses the internet to perform Product Searches, =0 Otherwise
Search for Sports Info.	Inelastic	=1 if respondent uses the internet to Search for Sport Information, =0 Otherwise
Charity Giving	Inelastic	=1 if respondent uses the internet for Charity Giving, =0 Otherwise
Online Banking	Inelastic	=1 if respondent uses the internet to do Online Banking, =0 Otherwise
View Images	Inelastic	=1 if respondent uses the internet to View Images, =0 Otherwise
Online Gaming	Inelastic	=1 if respondent uses the internet to Play Online Games, =0 Otherwise
Do work related @ home	Inelastic	=1 if respondent uses the internet to Do wok Related Stuff at home, =0 Otherwise
Take Online Classes	Inelastic	=1 if respondent uses the internet to Take Online Classes, =0 Otherwise
Wireless Connection	Inelastic	=1 if respondent connects to the Internet through a Wireless Connection, =0 Otherwise
Several Times A Day	Freq. of Use	=1 if respondent uses the internet, several times a day, =0 otherwise
3 to 5 times a week	Freq. of Use	=1 if respondent uses the internet, about once a day or 3-5 days a week, =0 otherwise
Once a Day*	Freq. of Use	=1 if respondent uses the internet, once a day, =0 otherwise
Less Frequently	Freq. of Use	=1 if respondent uses the internet, about 1-2 days a week or every few weeks, =0 otherwise
Less Often	Freq. of Use	=1 if respondent uses the internet, Less Ofen, =0 otherwise
Less Than 8th Grade	Education	=1 if respondent attained Grade 8 as the highest level of Education, =0 otherwise
HighSch	Education	=1 if respondent attained High School as the highest level of Education, =0 otherwise
Tech or Vocational*	Education	=1 if respondent attained Technical or Vocational training as the highest level of Education, =0 otherwise
Colgrad	Education	=1 if respondent attained a college degree of higher as the highest level of Education, =0 otherwise

Time on Int. Y_L15	Intensity of Use	=1 if Time Spent on the Internet Yesterday is less than 15 minutes , =0 Otherwise
Time on Int. Y_G15L1hr	Intensity of Use	=1 if Time Spent on the Internet Yesterday is between 15 minutes and 1 hour, =0 Otherwise
Time on Int. Y_Btwn 1hr&3hrs*	Intensity of Use	=1 if Time Spent on the Internet Yesterday is greater than 1 hour but less than 3 hours, =0 Otherwise
Time on Int. Y_G3hrL4hr	Intensity of Use	=1 if Time Spent on the Internet Yesterday is greater than 3 hours but less than 4 hours, =0 Otherwise
Time on Int. Y_G4hr	Intensity of Use	=1 if Time Spent on the Internet Yesterday is greater than 4 hours , =0 Otherwise
Age		Age
Income		Total Household Income
Price Paid for Internet		Monthly Price paid for Internet
Months of Internet Use		Months of Internet Use
Weight Variable		
Weight		

*Represents Base Group within the Category

Table 13: Descriptive Statistics of Survey-1 (S1), Survey-2 (S2), Survey-3 (S3), and Survey-4 (S4)

Variables	**Classification**	**Obs**				**Mean**				**Std. Dev.**				**Min**				**Max**			
		S1	**S2**	**S3**	**S4**	**S1**	**S2**	**S3**	**S4**	**S1**	**S2**	**S3**	**S4**	**S1**	**S2**	**S3**	**S4**	**S1**	**S2**	**S3**	**S4**
Household Broadband Status		1,174	1,214	1,249	1,661	0.363	0.432	0.519	0.6189	0.481	0.496	0.5	0.4858	0	0	0	0	1	1	1	1
Weight		2,013	2,204	2,201	3,011	1.733	1.816	1.909	2.0201	0.599	0.686	0.786	0.8199	1	1	1	1	3.1	3.5	3.9	4
Email	Elastic	1,355	1,366	1,448	1,927	0.924	0.917	0.919	0.917	0.265	0.276	0.273	0.276	0	0	0	0	1	1	1	1
Instant Message	Elastic		1,369	1,447	1,928		0.373	0.376	0.3449		0.484	0.485	0.4755		0	0	0		1	1	1
Chat	Elastic			1,447				0.149				0.356				0				1	
Other Weblog	Elastic		1,351	1,425			0.168	0.219			0.374	0.414			0	0			1	1	
Download Music	Inelastic	1,354	1,369		1,930	0.134	0.156		0.2109	0.34	0.363		0.408	0	0		0	1	1		1
Download Video	Inelastic	1,353	1,367		1,927	0.127	0.135		0.1645	0.333	0.342		0.3708	0	0		0	1	1		1
Browse for News	Inelastic		1,368	1,449	1,926		0.708	0.722	0.6838		0.455	0.448	0.4651		0	0	0		1	1	1
Share Files Online	Inelastic	1,353	1,367			0.2	0.215			0.4	0.411			0	0			1	1		
General Browsing	Inelastic	1,350			1,927	0.827			0.6305	0.378			0.4828	0			0	1			1
Directory Searching	Inelastic		1,369		1,921		0.846		0.9115		0.361		0.2841		0		0		1		1
E_commerce	Inelastic		1,371				0.648				0.478				0				1		
E_Trading	Inelastic		1,370				0.126				0.331				0				1		
Map Searches	Inelastic		1,369				0.543				0.498				0				1		
Own Weblog	Inelastic		1,356	1,445			0.049	0.075			0.215	0.263			0	0			1	1	
Online Auction	Inelastic		1,368	1,448			0.227	0.238			0.419	0.426			0	0			1	1	
Product Search	Inelastic		1,366	1,449			0.791	0.79			0.406	0.408			0	0			1	1	
Search for Sports Info.	Inelastic		1,368				0.42				0.494				0				1		
Charity Giving	Inelastic			1,447				0.113				0.317				0				1	
Online Banking	Inelastic			1,448	1,922			0.411	0.4214			0.492	0.4939			0	0			1	1
View Images	Inelastic			1,445				0.15				0.357				0				1	
Online Gaming	Inelastic																				
Do work related @ home	Inelastic		1,369	1,448	1,923		0.512	0.506	0.5065		0.5	0.5	0.5001		0	0	0		1	1	1
Take Online Classes	Inelastic				1,931				0.1088				0.3114				0				1
Wireless Connection	Inelastic		1,351				0.163				0.369				0				1		
Several Times A Day	Freq. of Use	1,195	1,235	641	1,708	0.259	0.287	0.281	0.1885	0.438	0.452	0.45	0.3912	0	0	0	0	1	1	1	1
3 to 5 times a week	Freq. of Use	1,195	1,235	641	1,708	0.223	0.202	0.176	0.2816	0.416	0.402	0.381	0.4499	0	0	0	0	1	1	1	1
Less Frequently	Freq. of Use	1,195	1,235	641	1,708	0.206	0.218	0.218	0.2119	0.404	0.413	0.413	0.4088	0	0	0	0	1	1	1	1
Less Often	Freq. of Use	1,195	1,235	641	1,708	0.03	0.03	0.047	0.041	0.171	0.171	0.211	0.1983	0	0	0	0	1	1	1	1
Less Than 8th Grade	Education	2,006	2,181	2,185	2,972	0.017	0.031	0.026	0.0249	0.131	0.173	0.158	0.1558	0	0	0	0	1	1	1	1
HighSch	Education	2,006	2,181	2,185	2,972	0.347	0.398	0.379	0.4149	0.476	0.49	0.485	0.4928	0	0	0	0	1	1	1	1
Colgrad	Education	2,006	2,181	2,185	2,972	0.357	0.302	0.315	0.3183	0.479	0.459	0.465	0.4659	0	0	0	0	1	1	1	1
Time on Int. Y_L15	Intensity of Use			412	1,200			0.087	0.0742			0.283	0.2622			0	0			1	1
Time on Int. Y_G15L1hr	Intensity of Use			412	1,200			0.07	0.4758			0.256	0.4996			0	0			1	1
Time on Int. Y_G3hrL4hr	Intensity of Use			412	1,200			0.505	0.0708			0.501	0.2567			0	0			1	1
Time on Int. Y_G4hr	Intensity of Use			412	1,200			0.107	0.1433			0.309	0.3506			0	0			1	1
Time on Int. Y_L15	Intensity of Use			412	1,200			0.087	0.0742			0.283	0.2622			0	0			1	1
Age		1,966	2,119	2,131	2,927	47.011	48.487	49.963	50.806	17.108	17.619	17.954	18.194	18	18	18	18	93	97	93	95
Income		1,651	1,712	1,724	2,244	52.121	48.906	50.196	52.914	30.732	30.418	31.721	31.863	5	5	5	5	100	100	100	100
Price Paid for Internet			1,241		1,931		138.5		48.771		306.26		33.996		0		1		999		99
Months of Internet Use		1,358	1,371	713	1,931	88.601	91.432	109.7	92.103	135.12	144.09	150.58	54.084	1	0	1	0	1188	1188	1188	636

Survey-1 (S1)=Daily Tracking Survey Nov 2003, Survey-2 (S2)=Daily Tracking Survey Feb 2004, Survey-3 (S3)=Jan 2005 Daily Tracking Survey, and Survey-4 (S4)=Nov/Dec 2005 Daily Tracking Survey

The Empirical Estimation Strategy

When contemplating the use of a particular internet application, a person makes the choice to either pay more for a faster internet connection to save time, or pays less for a slower internet connection and spends more time to access the same application. If the argument were correct that the use of bandwidth intensive applications increases the demand for bandwidth delivery systems, it would be sufficient to argue that the use of bandwidth intensive applications will lead to an increase in broadband subscription. This would also mean that the more a consumer uses (or requires) bandwidth intensive applications, the greater the likelihood of him/her switching from a low level bandwidth internet type like dial-up to a high level bandwidth internet type like broadband.

Therefore, the objective of the empirical estimation is to determine if (and the extent to which) the use of bandwidth intensive applications influences the household choice of internet connection type, while controlling for household consumption variables.

We assume that internet users are rational and aware of the loss of utility they face with low speed (dial-up) modems when accessing bandwidth intensive applications. For this reason they choose to subscribe to high-speed bandwidth modems when accessing bandwidth intensive applications. This simple argument was further substantiated by the model presented in Chapter 3, which found that the optimal bandwidth required for inelastic applications is greater than the optimal bandwidth required for elastic applications. In addition, the General Accounting Office (GAO, 2006) states that households will purchase or adopt broadband service only if the value

(or utility) that members of the household receive from the service exceeds the price of the service. The implicit value of time is clearly important (see Chapter 4) in determining if a user will make the shift to faster access bandwidth, and it has been argued that the types of internet applications accessed can be viewed as a proxies for the implicit value of time for the user.

Using neoclassical consumer theory (McFadden, 1974, 1981) relates the probability of making a choice to a set of behavioral rules. Since a consumer's choice is a reflection of their preferences interacting with the constraints they face, we posit that the probability of choosing a broadband internet connection type is determined by a set of behavioral rules. In our model these are captured by (a) the consumption and application variables, with the latter linked closely to consumer satisfaction, and (b) the household socio-demographic variables defined in the preceding section.

A binary logit model (also referred to as a logistic model) is used to estimate the probability of choosing to subscribe to broadband at the household level. Logistic regression has been widely used in the consumer choice and consumer adoption literature. The robustness of the logit model coupled with its desirable statistical properties makes it appropriate for this analysis. Furthermore it has also been used in some studies specific to the adoption of broadband, e.g., in (Flam & Chaudhuri, 2007; Ida & Kuroda, 2006; Savage, Madden, & Simpson, 2002; Madden, 1997). In order to implement the model the dependent variable *Broadband Status* is dichotomous and is defined as follows: = 1 if a household uses a broadband internet connection type or, = 0 if otherwise. Various independent variables that influence broadband choice are used to

determine the impact of bandwidth intensive applications on broadband choice, while controlling for other factors that influence household consumption.

Our general logit model assumes that p_i (the probability that the household subscribes to broadband internet) takes the following form:

(5.1) P_i (Have broadband at home) $= F(X_i\beta)$

where, i (i = $1,..,n$) refers to the i-th household,

P_i = the probability that the household subscribes to broadband internet service given the independent variables X_{ij}.

$$X_i\beta = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik}$$

is a linear combination of the independent variables.

Since we use four surveys in the empirical analysis *(See Table 5.1a)*, T is used to represent a particular survey.

We define the empirical model with the following general latent form;

(5.2) $y_{iT}{}^* = X_{iT}\beta_T + u_{iT}$

where T=1,..,4 denote four survey y_{iT}* periods. y_{iT}* is not observed and can be considered to be the net benefit to a household from a particular internet choice.

$$y_{iT} = \textit{household subscribes to broadband internet} = 1 \textit{ if } y^*_{iT} > 0$$
$$y_{iT} = \textit{household does not subscribe to broadband internet} = 0 \textit{ if } y^*_{iT} \leq 0$$

In addition to the conventional socio-demographic variables of age and household income, we introduce internet application variables as critical determinants of broadband choice. In so doing we extend and broaden existing models on broadband adoption. This also extends past research by accounting for the limitation of interpreting logit coefficients for dummy independent variables using marginal effect estimates as opposed to rightfully using discrete choice estimates in their interpretation. This is not commonly accounted for in the literature. The marginal effect estimate measures the partial impact of changes in the corresponding variable on the likelihood of a household subscribing to broadband internet type, all other factors held constant,[18] whereas the discrete change indicates how much the predicted probabilities will change when we increase a variable x_k by δ from the baseline i.e., from x_k to $x_k + \delta$, holding all other variables at given values.[19] Unless δ approaches zero i.e., it is infinitely small, the discrete change and marginal change are not the same. The discrete change therefore becomes useful when we interpret the coefficients of dummy variables and when we wish to focus on the predicted probability changes for a particular range of an independent variable.

[18] Marginal changes are computed by taking the first partial derivative with respect to corresponding independent variables. $\frac{\partial \Lambda(X\beta)}{\partial x_k} = \frac{e^{X\beta}}{1+e^{X\beta}}\beta_k = \Lambda(X\beta)[1-\Lambda(X\beta)]\beta_k$. The marginal effects vary depending o the values of the independent variables. In our empirical analysis the mean values of x_k are used.

[19] The δ represents a range of value changes, such as from 0 to 1. In various literature additional value changes are reported i.e., from minimum to maximum, from -1/2 from baseline to ½ and from -1/2 standard deviation from the baseline to ½ standard deviation.

Our specifications are designed to test the hypothesis that if internet users access bandwidth intensive applications, they are more likely to purchase broadband connection services due to the utility benefits from the time saved with higher bandwidth connection speeds. The equation specifications control for the following: the frequency of internet use, the education level attained, duration of time spent online during a typical internet session (also referred to as the intensity of internet use), age, total household income, price of internet access and months of internet use.

If the inelastic application (bandwidth intensive application) coefficients are statistically significant with a positive sign, this is evidence consistent with the hypothesis that the utilization of bandwidth intensive applications increases the likelihood of subscribing to broadband service. Because this empirical model includes application variables that have not been tested in previous literature, it is especially important to ensure that the proposed empirical model is defensible, i.e., a model that has :(1) the correct functional form, and (2) includes all relevant and no irrelevant independent variables. Otherwise, specification error may result.[20]

To address this concern we present different specifications when analyzing each survey. With each survey, one specification is the unrestricted model, which includes the

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[20] Scott Menard, in *"Applied Logistic Regression" (pp 67- 69)* outlines the effects of Specification Error. Misspecification may result in biased logistic regression coefficients, coefficients that are systematically over estimated or underestimated.

Including one or more irrelevant variables has the effect of increasing the standard error of the parameter estimates, which reduces the efficiency of the estimates, without biasing the coefficients. Whereas omitting relevant variables from the equation in the logistic regression results in biased coefficients for the independent variables, to the extent that the omitted variable is correlated with the independent variables in the logistic regression. Berry and Feldman (1985) state that the direction of the bias depends on the parameter for the excluded variable, the direction of the effect of the excluded variable on the dependent variable, and the direction of the relationship between excluded and included variables.

complete set of independent variables. By contrast, the restricted specification version allows us to test if the excluded variables matter simultaneously. To do this we employ the likelihood ratio test to compare if the unrestricted and the restricted models are significantly different. The Likelihood Ratio [LR] test can be explained as follows:

$$LR[q] = \{[-2LL(constrained \text{ model}, i = k - q)] - [-2LL(constrained \text{ model}, i = k)]\},$$

where the LR has a chi-square distribution with q degrees of freedom, with q=1 or more omitted variables.

Before examining the results of the different specifications in each of the four surveys, it is important to highlight the general difficulty in determining the goodness of fit in any logistic model. This is because the logistic regression lacks an analog to the Ordinary Least Squares (OLS) R^2 statistic.

To aid in the evaluation of the performance of the logistic regressions, several pseudo-R^2 statistics have been proposed: (Hagle, Mitchell, 1992 ; Menard, 2000; Veall, Zimmerman, 1996) . Menard (2000) states that in terms of the analogy between the -2LL (log likelihood multiplied by -2) statistic reported for the logistic regression and the SSR/SST (sums of squares) for OLS regression, the most natural choice is the likelihood ratio R^2 ; see also (McFadden,1974; Argesti, 1990; Demaris, 1992; Homer, Lemeshow, 2000). Therefore, several studies that use logistic analysis report McFadden's Adjusted Pseudo- R^2.

Further evidence of the lack of consensus on the best reported goodness of fit measure is that numerous studies prefer the McElvey and Zavoina R^2 statistic as the most

conducive in terms of its comparability across different types of empirical models. DeMaris (2002) finds the McElvey and Zavoina R^2 statistic to be the best at estimating explained variance in a study comparing eight R^2 analogues.[21]

Empirical Results and Implications

The following sections present the empirical results for the various specifications used to analyze each of the four different surveys. The empirical results for each of the surveys are presented individually in the following sections.

Empirical Results for survey-1 (S1): The Daily Tracking Survey November 2003

Using the daily tracking survey from November 2003, we estimate four specifications for the proposed general logit model (equation 5.2). The maximum likelihood estimates for the different specifications with their robust standard errors in parenthesis are shown in Table 14. The estimated coefficients of the logit equation

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21 For this reason, we report both the McElvey and Zavoina's R2 statistic and the McFadden's Adjusted Pseudo R2 statistic as the measures of the goodness of fit for the logistic models employed in the various empirical specifications. The formal representation of the McElvey and Zavoina's R2 is $R^2_{MZ} = \dfrac{\sum_{i=1}^{N}(\hat{y}_i - \overline{\hat{y}_i})^2}{N + \sum_{i=1}^{N}(\hat{y}_i - \overline{\hat{y}_i})^2}$; where $\hat{y}_i = X_i^{'}\hat{\beta}$ and $\overline{\hat{y}_i} = \sum_{i=1}^{N}\hat{y}_i / N$, and the McFadden's Adjusted Pseudo - $R^2 = 1 - \left(\dfrac{\ln \hat{L} - K}{\ln L_0}\right)$; where $\ln[L_0]$ is the maximized value of the log-likelihood function computed with only the constant term, and $\ln\left[\hat{L}\right]$ is the maximized value of the log-likelihood function for the model.

indicate the direction of change for an individual who subscribes to broadband at the household level.

The specification 1 restrictions include the frequency of internet use variables, the education variables, and the age variable. The specification 2 restrictions are the frequency of internet use variables and the age variable. Specification 3 restrictions include the age variable only, while specification 4 is the unrestricted model. The results for the R^2 statistic proposed by (McElvey and Zaviona, 1981) shows that our model fits relatively well for specifications 3 and 4. The R^2 for those specifications are 0.221 and 0.225 respectively. It is worth noting that there is an increase in the R^2 statistic as you move from specification 1 to specification 4. This can be explained by the restrictions placed on specifications 1, 2 and 3, which resulted in those specifications having a significantly poorer fit than specification 4, the unrestricted model. The likelihood ratio test statistic between the restricted specifications and the unrestricted specification 4 shows that specification 4 is the preferred specification in table 14. A detailed review of the likelihood ratio test between specifications for this survey is presented in Appendix A.

Table 14: Maximum Likelihood Estimates for the Daily Tracking Survey November 2003

Dependant variable Y=1 if household subscribes to broadband internet,=0 otherwise

VARIABLES	VARIABLES CLASSIFICATION	COEFFICIENTS			
		Spec 1	Spec 2	Spec 3	Spec 4
Constant		**-1.533***	**-1.422***	**-0.868****	**-0.169**
		(0.357)	*(0.376)*	*(0.394)*	*(0.454)*
Email	Elastic	**0.561**	**0.492**	**0.102**	**0.036**
		(0.351)	*(0.355)*	*(0.350)*	*(0.358)*
Download Music	Inelastic	**0.594***	**0.656***	**0.595***	**0.482****
		(0.200)	*(0.202)*	*(0.205)*	*(0.213)*
Download Video	Inelastic	**0.590***	**0.597***	**0.459****	**0.406****
		(0.200)	*(0.201)*	*(0.200)*	*(0.204)*
Share Files Online	Inelastic	**0.204**	**0.189**	**0.006**	**0.008**
		(0.169)	*(0.171)*	*(0.178)*	*(0.178)*
General Browsing	Inelastic	**0.246**	**0.164**	**0.117**	**0.198**
		(0.196)	*(0.199)*	*(0.201)*	*(0.205)*
Several Times a day	Freq. of Use			**0.720***	**0.760***
				(0.177)	*(0.180)*
3 to 5 times a week	Freq. of Use			**-0.395****	**-0.397****
				(0.195)	*(0.198)*
Less Frequently	Freq. of Use			**-0.849***	**-0.911***
				(0.219)	*(0.225)*
Less Often	Freq. of Use			**-1.493***	**-1.547***
				(0.578)	*(0.578)*
HighSch	Education		**-0.228**	**-0.141**	**-0.12**
			(0.189)	*(0.197)*	*(0.202)*
Colgrad	Education		**0.211**	**0.154**	**0.224**
			(0.151)	*(0.159)*	*(0.161)*
Age					**-0.018***
					(0.005)
Number of Observations		1,156	1,154	1,150	1,128
χ^2 test of significance of the Regression		39.00*	44.48*	109.46*	123.68*
Estimated Value of the log-liklihood		-733.53	-728.27	-686.29	-661.63
McElvey and Zavoina R^2 Statistic		0.083	0.097	0.221	0.255
McFadden's Adjused Psuedo-R^2					

Robust standard errors are in parentheses
*** significant at 10%, ** significant at 5%; * significant at 1%

The parameter estimates for two of the four bandwidth intensive applications used in the model i.e., “Download Video” and “Download Music” are significant at the one percent level of significance. These results are robust under all the specifications shown in Table 14. The results are consistent with the hypothesis that individuals who utilize applications that are bandwidth intensive (inelastic) are more likely to subscribe to

broadband internet connection services at home compared to individuals who do not use these applications. The parameter estimates of the other two inelastic applications "Sharing files" and "General browsing" are not statistically significant. This is contrary to the hypothesis. A possible explanation for these results is that the classification of internet use into the "General Browsing" category is too broad and may not be limited to web sites that are only bandwidth intensive. While this argument is primarily anecdotal, it is plausible inasmuch as at the time of the survey in 2003, many websites did not have extensive bandwidth intensive content. In later periods there is a wider variety of application categories showing that websites tended to offer more bandwidth intensive content (see the upcoming sections that reports the results of the other three surveys).[22]

The negative sign of the age variable indicates that the older a person, the lower the likelihood for that household to subscribe to broadband internet services. This finding is consistent with the hypothesis that older internet users will most likely not see the benefit of using broadband because they do not engage in extensive bandwidth intensive applications. Therefore the additional explicit cost associated with a broadband subscription would not be a warranted expense for these individuals. It was also noted that older people do not engage in bandwidth intensive applications because they typically are late adopters of new innovations.

The results also show that the frequency of internet browsing by an individual has an effect on the likelihood of broadband adoption. Individuals who browse the internet "Several times a day" compared to individuals who browse once a day (this being the

[22] As mentioned in Chapter 1that, as the internet evolved its content increased exponentially and web applications grew in prominence. This is evident with the increase in applications that respondents are asked about in surveys subsequent to the "Daily Tracking Survey November 2003."

base group for the frequency of internet use variable) have an increased likelihood of broadband subscription at the household level. Similarly individuals who browse either "between 3 and 5 days per week" or less frequently, i.e., "1 or 2 times weekly" have a lower likelihood of subscribing to broadband compared to households who browse once a day. The negative coefficient estimates confirm these results. These results are also robust for all specifications and confirm the stated hypothesis that an increase in the frequency of internet use will increase the likelihood of household broadband subscription.

The marginal effects, discrete changes, and elasticities of the logit model for specification 4 are shown in Table 15. The discrete change results show that individuals who "Download Music" have a probability of subscribing to broadband that is 0.11 times greater than their counterparts who do not download music. Individuals who "Download Videos" have a probability of subscribing to broadband that is 0.09 times greater than their counterparts who do not download music on the internet.

For individuals who browse the internet several times a day, the discrete changes results show that they have a probability of subscribing to broadband that is 0.18 times greater than individuals who browse the internet only once per day. The results also show that individuals who browse the internet less frequently have a 0.18 times lower probability of subscribing to broadband than their counterparts who browse the internet once a day. As for the age variable, the marginal effect results demonstrate that an increase in age by ten years (for example) reduces an individual's probability of subscribing to broadband by 0.04 times.

Table 15: Marginal Effects, Discrete changes and Elasticities for the Daily Tracking Survey November 2003

VARIABLES	VARIABLES CLASSIFICATION	Marginal Effects	Discrete Changes	Elasticities
Email	Elastic	**0.008**	*0.008*	**0.022**
		0.080		*0.221*
Download Music	Inelastic	**0.113****	*0.114***	**0.052****
		0.052		*0.023*
Download Videos	Inelastic	**0.095***	*0.095**	**0.039****
		0.049		*0.020*
Sharing_Files	Inelastic	**0.002**	*0.002*	**0.001**
		0.040		*0.025*
General_Browsing	Inelastic	**0.044**	*0.044*	**0.107**
		0.044		*0.111*
Several Times a day	Freq. of Use	**0.179***	*0.179**	**0.126***
		0.043		*0.030*
3 to 5 times a week	Freq of Use	**-0.086****	*-0.086***	**-0.060****
		0.041		*0.030*
Less Frequently	Freq of Use	**-0.185***	*-0.185**	**-0.126***
		0.040		*0.032*
Less often	Freq of Use	**-0.250***	*-0.025**	**-0.029***
		0.057		*0.109*
HghSch	Education	**-0.027**	*-0.027*	**-0.024**
		0.045		*0.04*
Colgrad	Education	**0.051**	*0.051*	**0.055**
		0.037		*0.04*
Age		**-0.004***		**-0.048***
		0.001		*0.133*

Standard errors are reported in the second row

Empirical Results for Survey-2 (S2): February 2004 Tracking Survey

This section reports the results of the logit model (equation 5.2) using the second survey: February 2004 Tracking Survey. The approach we use to analyze this second survey is similar to the approach used to analyze the first survey. Therefore, the results presented in this section will follow a similar format as those presented for the first survey in the preceding. The empirical results of this survey are reported in Table 16. The table also reports the number of observations, a χ^2 test of significance of the regression, the McElvey and Zavoina R^2 Statistic, and the McFadden's Adjusted Pseudo R^2.

The results include four specifications. Specification 1 restricts the following variables: the frequency of internet use, education, age, months of internet use, and price paid for the internet. Specification 2 restricts the frequency of internet use variables, the age, months of internet use, and the variable for the price paid for the internet. Specification 3 restricts the age, months of internet use, and the price paid for internet service. Specification 4 is the unrestricted model.

The McElvey and Zavoina R^2 statistic shows that all the specifications perform relatively well, but with specifications 3 and 4 yielding the best fit. The R^2 statistics for those specifications are 0.366 and 0.391 respectively. The results of the likelihood ratio tests between the restricted and the unrestricted specifications demonstrates that the restrictions placed on specifications 1, 2 and 3 resulted in them having a significantly poorer fit in comparison to the unrestricted specification 4. These results show that specification 4 is the preferred specification in table 16. Again, a detailed review of the likelihood ratio test between specifications for this survey is presented in Appendix A.

Table 16: Maximum Likelihood Estimates for the February 2004 Daily Tracking Survey

Dependant variable Y=1 if household subscribes to broadband internet,=0 otherwise

VARIABLES	VARIABLES CLASSIFICATION	COEFFICIENTS			
		Spec 1	Spec 2	Spec 3	Spec 4
Constant		-1.609*	-1.448*	-0.897**	-0.485
		(0.351)	*(0.369)*	*(0.401)*	*(0.502)*
Email	Elastic	0.072	0.059	-0.101	0.06
		(0.318)	*(0.328)*	*(0.323)*	*(0.332)*
Instant Message	Elastic	0.183	0.226	0.102	0.037
		(0.148)	*(0.150)*	*(0.158)*	*(0.162)*
Other Weblog	Elastic	0.024	0.01	-0.033	0.002
		(0.204)	*(0.208)*	*(0.217)*	*(0.222)*
Download Music	Inelastic	-0.071	-0.06	-0.024	-0.122
		(0.212)	*(0.213)*	*(0.220)*	*(0.232)*
Download Video	Inelastic	0.528**	0.529**	0.387***	0.432***
		(0.218)	*(0.218)*	*(0.222)*	*(0.230)*
Browse for News	Inelastic	-0.017	-0.055	-0.161	-0.122
		(0.168)	*(0.170)*	*(0.170)*	*(0.176)*
Share Files Online	Inelastic	0.333***	0.325***	0.285	0.296
		(0.182)	*(0.184)*	*(0.188)*	*(0.190)*
Directory Search	Inelastic	0.406***	0.391***	0.371***	0.427***
		(0.217)	*(0.220)*	*(0.221)*	*(0.236)*
E_Commerce	Inelastic	0.331**	0.326***	0.265	0.254
		(0.166)	*(0.166)*	*(0.170)*	*(0.175)*
E_Trading	Inelastic	0.357***	0.294	0.141	0.141
		(0.204)	*(0.208)*	*(0.218)*	*(0.219)*
Map Searches	Inelastic	0.307**	0.273***	0.201	0.141
		(0.153)	*(0.155)*	*(0.158)*	*(0.163)*
Own Weblog	Inelastic	-0.462	-0.393	-0.484	-0.622
		(0.330)	*(0.338)*	*(0.363)*	*(0.380)*
Online Auction	Inelastic	0.217	0.214	0.135	0.07
		(0.172)	*(0.172)*	*(0.176)*	*(0.182)*
Product Search	Inelastic	-0.294	-0.327***	-0.335***	-0.371***
		(0.187)	*(0.188)*	*(0.190)*	*(0.195)*
Search for Sports Info	Inelastic	0.201	0.222	0.222	0.165
		(0.145)	*(0.145)*	*(0.151)*	*(0.157)*
Do work related @ home	Inelastic	0.287**	0.209	0.257	0.257
		(0.146)	*(0.153)*	*(0.160)*	*(0.168)*
Wireless Connection	Inelastic	1.355*	1.331*	1.309*	1.242*
		(0.208)	*(0.209)*	*(0.219)*	*(0.228)*
Several Times A Day	Freq. of Use			0.677*	0.686*
				(0.194)	*(0.198)*
3 to 5 times a week	Freq of Use			-0.671*	-0.694*
				(0.209)	*(0.218)*
Less Frequently	Freq of Use			-0.466**	-0.545**
				(0.211)	*(0.217)*
Less Often	Freq of Use			-0.328	-0.467
				(0.420)	*(0.451)*
HighSch	Education		-0.332***	-0.371**	-0.414**
			(0.182)	*(0.185)*	*(0.192)*
Colgrad	Education		0.132	0.026	0.023
			(0.169)	*(0.177)*	*(0.182)*
Age					-0.014**
					(0.006)
Price Paid for Internet					0.001**
					0.000
Months of Internet Use					0.001
					(0.001)
Number of Observations		1,148	1,140	1,138	1,103
χ^2 test of significance of the Regression		117.16*	125.17*	166.32*	171.75*
Estimated Value of the log-likelihood		-700.99	-693.237	-665.12	-635.80
McElvey and Zavoina R^2 Statistic		0.288	0.298	0.366	0.391

Robust standard errors are in parentheses

*** significant at 10%, ** significant at 5%; * significant at 1%

The results also show that the estimated coefficients for the bandwidth intensive applications “Download Video,” “Share Files Online,” “Directory Search,” “E-Commerce,” “E-Trading,” “Map Searches,” and “Product Search” are statistically significant and positively signed. These parameter estimates indicate that engaging in these bandwidth intensive applications increases the likelihood of broadband subscription at the household level. The results are robust and consistent with our hypothesis.

It is noteworthy that the parameter estimate results for the internet application “Share Files Online” from this survey mark a change from the results from the first survey analyzed – the daily tracking survey November 2003. In that prior analysis (reported in Table 14) the parameter estimates of the application “Share Files Online” were not significant. This result may speak to the uptake of broadband being a gradual process that involves education of the public. The wider use of certain internet applications, in this case the sharing of files over the internet, leads to the production of web content that allows the use of those applications. The net result is that internet users realize that they need a broadband type connection to access those applications with minimal levels of frustration. In that regard one could argue that in 2003, when the first survey was conducted, the use of the internet application “Share files online” was at its infancy. By February 2004 the demand for this application had grown due to the development of web content that could be shared online.

The age of a person again has an impact on the likelihood of broadband adoption, with the results showing that the older a person, the lower the likelihood of broadband subscription. This result is consistent with the prior finding from the analysis of the November 2003 daily tracking survey presented in table 14. Also similar to the earlier

findings are the results of the frequency of internet use variable. These results show that individuals who browse the internet "several times a day" have a higher likelihood of broadband subscription compared to households who browse the internet once a day (the base group for this category). Similarly, individuals who browse the internet less often, either "between 3 and 5 days per week," or even less frequently, i.e., "1 or 2 times weekly" have a lower likelihood of subscribing to the broadband compared to households who browse the internet once a day (the base group for this category). These results are robust and are consistent with our hypothesis.

Our results also show that individuals who pay more for internet service are more likely to subscribe to broadband. This result seems to contradict the usual downward sloping demand curve presumption. However, the various types of internet connection options (which is the key consumption good in this case) have different attributes. Therefore the parameter estimate for the "Price Paid for Internet" variable, which is positive, must be interpreted in the context of the attribute qualities associated with the different internet access types, such that the price is likely to be a strong proxy for product quality. The (Lancaster, 1966) approach to consumer theory links household utility to a set of intrinsic properties (attributes) of the goods being consumed. Different goods (or inputs) contain different relative (fixed) proportions of the various intrinsic attributes (or joint outputs). The way equation 5.2 is specified, the different attributes from the different internet types are grouped together. This specification masks the individual internet connection differences, and these differences are important in determining the likelihood of broadband adoption at the household level.

Table 17 shows the marginal effects, discrete results, and elasticities of specification 4 (shown in Table 16).

Table 17: Marginal Effects, Discrete changes and Elasticities for the February 2005 Daily Tracking Survey

VARIABLES	VARIABLES CLASSIFICATION	Marginal Effects	Discrete Changes	Elasticities
Email	Elastic	**0.015** 0.081	**0.015**	**0.032** *0.179*
Instant Message	Elastic	**0.009** 0.043	**0.009**	**0.009** *0.037*
Other Weblog	Elastic	**0.0005** 0.054	**0.0004**	**0.0002** *0.021*
Download Music	Inelastic	**-0.030** 0.056	**-0.030**	**-0.012** *0.024*
Download Video	Inelastic	**0.107***** 0.057	**0.107**	**0.038***** *0.020*
Browse for News	Inelastic	**-0.030** 0.043	**-0.030**	**-0.050** *0.073*
Share Files Online	Inelastic	**0.073** 0.047	**0.073**	**0.038** *0.024*
Directory Search	Inelastic	**0.101***** 0.054	**0.102**	**0.211***** *0.117*
E_Commerce	Inelastic	**0.062** 0.042	**0.062**	**0.100** *0.069*
E_Trading	Inelastic	**0.035** 0.054	**0.035**	**0.010** *0.016*
Map Searches	Inelastic	**0.034** 0.040	**0.035**	**0.045** *0.052*
Own Weblog	Inelastic	**-0.143** 0.079	**-0.144**	**-0.018** *0.011*
Online Auction	Inelastic	**0.017** 0.045	**0.017**	**0.010** *0.026*
Product Search	Inelastic	**-0.092***** 0.048	**-0.092**	**-0.171***** *0.090*
Search for Sports Info	Inelastic	**0.041** 0.038	**0.041**	**0.042** *0.040*
Do work related @ home	Inelastic	**0.063** 0.041	**0.063**	**0.076** *0.049*
Wireless Connection	Inelastic	**0.300*** 0.050	**0.299**	**0.122*** *0.022*
Several Times A Day	Freq. of Use	**0.169*** *0.049*	**0.169**	**0.106*** *0.031*
3 to 5 times a week	Freq of Use	**-0.162*** *0.047*	**-0.164**	**-0.082*** *0.026*
Less Frequently	Freq of Use	**-0.129**** *0.049*	**-0.130**	**-0.071**** *0.029*
Less Often	Freq of Use	**-0.109** *0.099*	**-0.110**	**-0.008** *0.008*
HighSch	Education	**-0.099**** *0.046*	**-0.100**	**-0.062**** *0.028*
Colgrad	Education	**0.006** *0.045*	**0.006**	**0.005** *0.037*
Age		**-0.004**** *0.001*		**-0.337**** *0.132*
Price Paid for Internet		**0.0002** *0.000006*		**0.047**** *0.019*
Months of Internet Use		**0.0002** *0.001*		**0.034** *0.033*

Standard errors are reported in the second row

The discrete change results show that individuals who engaged in either downloading music or directory searches have a probability of subscribing to broadband

that is about 0.1 times greater than their counterparts who do not engage in those applications. The result of the discrete changes for the "Product Search" inelastic application is contrary to our expectation. The results indicate that individuals engaging in this activity are less likely, by a probability of 0.09, to subscribe to broadband than their counterparts who do not engage in product searches.

Individuals who browse the internet several times a day have a probability of subscribing to broadband that is 0.17 times greater than individuals who browse the internet once a day. The results also show that individuals who browse the internet less frequently have a 0.13 times lower probability of subscribing to broadband than their counterparts who browse the internet once a day. Also, as expected, an increase in age of ten years (for example) decreases an individual's probability of subscribing to broadband by 0.04 times.

The marginal effects results for the price variable demonstrate that an increase in price by one dollar increases the probability of broadband adoption. However, this increase in the probability of adoption is very minute i.e., 0.0002. We repeat the empirical analysis to discover the marginal effect of increasing the price variable by 10 dollars. Such an increase increases the probability of broadband adoption by a very minimal amount i.e., by 0.001. This suggests that internet users at the time of this survey were very insensitive to price changes. This can be confirmed by the results showing the price elasticity of broadband demand as 0.047, indicating that there is a 0.047 percentage increase in the probability of adopting broadband given a 1 percent increase in the price of broadband.

Empirical Results for survey-3 (S3): January 2005 Daily Tracking Survey

The results presented in this section stem from an analysis that is again analogous to the ones conducted for the first two surveys. The importance of conducting similar analysis across different surveys is that each survey is conducted in a different year and presents a wider range of internet application options due to the rapid development of new internet applications that were lacking in the previous surveys. Using different survey time periods is important for testing the robustness of the core hypothesis.

Table 18 shows the empirical results for five different specifications of the logit model (equation 5.2) applied to the January 2005 Daily Tracking Survey. The table reports the results of several random-effects logistic regressions where the dependent variable takes the value of 1 if the household subscribes to broadband internet service. This table also reports the number of observations, a χ^2 test of significance of the regression, the McElvey and Zavoina R^2 Statistic and the McFadden's Adjusted Pseudo R^2. Certain variables were restricted from specification 1, and 2. When these variables are introduced into specification 3, 4 and 5, the number of observations used for the maximum likelihood estimation in specifications 3, 4 and 5 drops to 368, 368 and 303 respectively. This is because the variables introduced in the unrestricted model had limited observations.

Specification 1 restricts the frequency of use, education and the intensity of use as well as the age, income and months of internet use variables. Specification 2 restricts the frequency of use and intensity of use dummy variables, as well as the age, months of internet use and income variables. Specification 3 restricts the frequency of use variables as well as the age, months of internet use and income variables. Specification 4 restricts

the age, months of internet use and income variables; and specification 5 is the unrestricted model. The McElvey and Zavoina R^2 statistic shows that all our specifications perform relatively well, however specification 4 and 5 give us the best fit. The R^2 statistics for those specifications are 0.429 and 0.544 respectively. As done previously, a detailed review of the likelihood ratio test between specifications for this survey is presented in Appendix A.

Table 18: Maximum Likelihood Estimates for the January 2005 Daily Tracking Survey

Dependant variable Y=1 if household subscribes to broadband internet,=0 otherwise

VARIABLES CLASSIFICATION	VARIABLES CLASSIFICATION	COEFFICIENTS				
		Spec: 1	Spec: 2	Spec: 3	Spec: 4	Spec: 5
Constant		**-0.791***	**-0.551*****	**-0.129**	**-0.027**	**-0.019**
		(0.291)	*(0.317)*	*(0.910)*	*(0.889)*	*(1.291)*
Email	Elastic	**-0.001**	**-0.106**	**-0.402**	**-0.554**	**-0.706**
		(0.287)	*(0.289)*	*(0.827)*	*(0.750)*	*(1.181)*
Instant Message	Elastic	**0.175**	**0.21**	**-0.11**	**-0.386**	**-0.591*****
		(0.141)	*(0.144)*	*(0.260)*	*(0.272)*	*(0.321)*
Chat	Elastic	**-0.096**	**-0.061**	**-0.428**	**-0.605**	**-0.4**
		(0.191)	*(0.193)*	*(0.357)*	*(0.370)*	*(0.449)*
Other Weblog	Elastic	**0.235**	**0.215**	**0.46**	**0.384**	**0.199**
		(0.171)	*(0.172)*	*(0.314)*	*(0.324)*	*(0.387)*
Browse for News	Inelastic	**0.102**	**0.073**	**0.398**	**0.449**	**0.303**
		(0.160)	*(0.161)*	*(0.326)*	*(0.354)*	*(0.391)*
Own Weblog	Inelastic	**0.045**	**0.068**	**-0.04**	**-0.137**	**0.101**
		(0.272)	*(0.274)*	*(0.484)*	*(0.503)*	*(0.582)*
Online Auction	Inelastic	**0.492***	**0.499***	**0.465*****	**0.359**	**0.121**
		(0.163)	*(0.164)*	*(0.277)*	*(0.283)*	*(0.318)*
Product Search	Inelastic	**-0.014**	**-0.053**	**0.083**	**-0.065**	**-0.199**
		(0.182)	*(0.182)*	*(0.366)*	*(0.435)*	*(0.547)*
Charity Giving	Inelastic	**0.736***	**0.692***	**0.761****	**0.635*****	**0.63**
		(0.235)	*(0.236)*	*(0.383)*	*(0.385)*	*(0.447)*
Online Banking	Inelastic	**0.663***	**0.630***	**0.847***	**0.891***	**1.068***
		(0.138)	*(0.138)*	*(0.259)*	*(0.282)*	*(0.331)*
View Images	Inelastic	**0.112**	**0.1**	**-0.118**	**0.045**	**-0.092**
		(0.194)	*(0.194)*	*(0.356)*	*(0.394)*	*(0.419)*
Do work related @ home	Inelastic	**0.355****	**0.317****	**0.093**	**0.177**	**-0.084**
		(0.141)	*(0.145)*	*(0.285)*	*(0.296)*	*(0.354)*
Several Times A Day	Freq. of Use				**0.701****	**0.638*****
					(0.326)	*(0.371)*
3 to 5 times a week	Freq. of Use				**-1.333***	**-1.368***
					(0.425)	*(0.468)*
Less Frequently	Freq of Use				**-0.974****	**-1.053****
					(0.403)	*(0.463)*
Less Often	Freq of Use				**-0.316**	**0.662**
					(1.104)	*(1.857)*
Less Than 8th Grade	Education		**-1.007**			
			(1.265)			
HighSch	Education		**-0.281**			
			(0.174)			
Colgrad	Education		**0.066**			
			(0.163)			
Time on Int. Y_L15	Intensity of Use			**-0.415**	**0.221**	**1.121*****
				(0.510)	*(0.550)*	*(0.626)*
Time on Int. Y_G15L1hr	Intensity of Use			**-0.22**	**0.252**	**0.236**
				(0.311)	*(0.340)*	*(0.385)*
Time on Int. Y_G3hrL4hr	Intensity of Use			**0.631**	**0.787**	**1.133**
				(0.644)	*(0.732)*	*(0.815)*
Time on Int. Y_G4hr	Intensity of Use			**-0.384**	**-0.091**	**-0.239**
				(0.497)	*(0.504)*	*(0.563)*
Age						**-0.023*****
						(0.012)
Income						**0.019***
						(0.005)
Months of Internet Use						**0.004**
						(0.004)
Observations		1,211	1,207	368	368	303
χ^2 test of significance of the Regression		86.38*	87.89*	34.29*	54.03*	49.72*
Estimated Value of the log-likelihood		-778.09	-773.22	-221.30	-205.698	-157.368
McElvey and Zavoina R^2 Statistic		0.214	0.221	0.281	0.162	0.532
McFadden's Adjused Psuedo-R^2		0.056	0.056	0.030	0.077	0.106

Robust standard errors are in parentheses

*** significant at 10%, ** significant at 5%; * significant at 1%

The results show that individuals who utilize the bandwidth intensive internet applications “Online Auction,” “Charity Giving,” and “Online Banking” are likely to subscribe to broadband. The result of the online auction application in this survey is different from the result of the same application in the previous survey (S2). This result suggests that when an application is in its infancy, it may not yet contain sufficiently complex content to induce users to subscribe to broadband connections in order to avoid the frustration associated with accessing that new application using a dialup connection.

Similar to the results of the previous surveys, age lowers the likelihood that a household will subscribe to broadband service. The results also show that households that browse the internet “several times a day” have a higher likelihood of broadband subscription compared to households browsing only “once a day” (the base group for this category). Similarly households that browse the internet on fewer occasions, either “between 3 and 5 days a week” or “less frequently i.e., 1 or 2 times weekly” have a lower likelihood of subscribing to broadband compared to households that browse the internet once a day, as revealed by the negative coefficient estimates. The results for the income variable are consistent with expectations and show that an increase in household income increases the likelihood of broadband subscription.

Specifications 3, 4 and 5 introduce a set of dummy variables for the “time spent on the internet yesterday.” The question on the time spent on the internet was not included in previous surveys, hence this is the first time we introduce it in our analysis. “Time spent on the internet yesterday,” is used as a proxy for how much time respondents spent online on a typical day. None of the results from the variables in this group show any significance.

Table 19 shows the marginal effects, discrete changes, and elasticities for specification 5. The discrete changes in Table 19 show that individuals that engage in the inelastic application "Online Banking" have a probability that is 0.21 times greater of subscribing to broadband than their counterparts who do not engage in online banking. The results of discrete changes of the frequency of use variable are similar to the results of the previous surveys 1 and 2. The results confirm that the more frequently individuals use the internet, the greater the probability of subscribing to broadband connection services. The implied income elasticity of broadband service is 0.139, indicating that there is a 0.139 percentage increase in the probability of adopting broadband given a 1.0 percent increase in income.

Table 19: Marginal Effect and Discrete changes for the January 2005 Daily Tracking Survey

VARIABLES	VARIABLE CLASSIFICATION	Marginal Effects	Elasticities	Discrete Changes
Email	Elastic	**-0.123**	**-0.207**	**-0.099**
		0.190	*0.368*	
Instant Message	Elastic	**-0.128*** **	**-0.088*** **	**-0.110**
		0.074	*0.052*	
Chat	Elastic	**-0.120**	**-0.036**	**-0.105**
		0.113	*0.033*	
Other Weblog	Elastic	**0.041**	**0.016**	**0.035**
		0.088	*0.034*	
Browse for News	Inelastic	**0.085**	**0.105**	**0.074**
		0.094	*0.114*	
Own Weblog	Inelastic	**0.021**	**0.004**	**0.018**
		0.131	*0.023*	
Online Auction	Inelastic	**0.016**	**0.010**	**0.013**
		0.072	*0.044*	
Product Search	Inelastic	**-0.050**	**-0.070**	**-0.042**
		0.116	*0.167*	
Charity Giving	Inelastic	**0.122**	**0.035**	**0.101**
		0.087	*0.027*	
Online Banking	Inelastic	**0.247***	**0.210***	**0.214**
		0.073	*0.065*	
View Images	Inelastic	**-0.034**	**-0.010**	**-0.029**
		0.097	*0.029*	
Do work related @ home	Inelastic	**-0.042**	**-0.042**	**-0.035**
		0.082	*0.083*	
Several Times A Day	Freq. of Use	**0.152*** **	**0.091*** **	**0.127**
		0.075	*0.047*	
3 to 5 times a week	Freq. of Use	**-0.331***	**-0.063***	**-0.312**
		0.109	*0.023*	
Less Frequently	Freq of Use	**-0.256** **	**-0.046** **	**-0.235**
		0.112	*0.021*	
Less Often	Freq of Use	**0.070**	**0.001**	**0.058**
		0.379	*0.008*	
Time on Int. Y_L15	Intensity of Use	0.194	0.024	0.156
		0.089	*0.014*	
Time on Int. Y_G15L1hr	Intensity of Use	**0.028**	**0.023**	**0.023**
		0.087	*0.070*	
Time on Int. Y_G3hrL4hr	Intensity of Use	**0.190**	**0.028**	**0.193**
		0.125	*0.023*	
Time on Int. Y_G4hr	Intensity of Use	**-0.074**	**-0.011**	**-0.064**
		0.137	*0.020*	
Age		**-0.006**	**-0.365**	
		0.003	*0.173*	
Income		**0.004**	**0.384**	
		0.001	*0.123*	
Months of Internet Use		**0.001**	**0.139**	
		0.001	*0.151*	

Standard errors are reported in the second row

Empirical Results for survey-4 (S4): November/December 2005 Daily Tracking Survey

This section presents the final logit analysis of equation 5.2 using the fourth survey (S4) - November/December 2005 Daily Tracking Survey. Table 20 reports five specifications of the model. The table also reports the results of several random-effects logistic regressions where the dependent variable takes the value of 1 if the household subscribes to broadband. Again, the table reports the number of observations, a χ^2 test of significance of the regression, the McElvey and Zavoina R^2 Statistic and the McFadden's Adjusted Pseudo R^2.

Specification 1 restricts the following variables: frequency of use, education, intensity of use, age, months of internet use, income and the price paid for internet variable. Specification 2 restricts the intensity of use, the frequency of use, age, months of internet use, income and the price paid for internet variable. Specification 3 restricts the frequency of use dummy variables as well as the age, months of internet use, income and price paid for internet service. Specification 4 restricts the, age, months of internet use, income and the price paid for internet service. Specification 5 is the unrestricted model.

Using the R^2 statistic proposed by (McElvey & Zaviona, 1981), specifications 3, 4 and 5 seem to fit well. The R^2 statistics for the various specifications are as follows: specification 3 has an R^2 statistic of 0.206; specification 4 has an R^2 statistic of 0.271; and specification 5 has an R^2 statistic of 0.520.

We perform the likelihood ratio tests between pairs of specifications in a similar fashion to the analysis conducted in the previous surveys. The aim of the test is to find out if the variables removed from each of the restricted specifications, when comparing between a pair of the nested models, are simultaneously equal to zero i.e., whether restricting this variable(s) has any effect. The likelihood ratio test is conducted by defining the restricted models as the null hypothesis and the unrestricted model as the alternative hypothesis. Again, a detailed review of the likelihood ratio test between specifications for this survey is presented in Appendix A.

The maximum likelihood estimates for the January 2005 Daily tracking survey are shown in table 20.

Table 20: Maximum Likelihood Estimates for the November/ December 2005 Daily Tracking Survey

Dependent variable is the Choice of Broadband Internet at the household level

VARIABLES CLASSIFICATION	VARIABLES CLASSIFICATION	COEFFICIENTS				
		Spec: 1	Spec: 2	Spec: 3	Spec: 4	Spec: 5
Constant		**-0.600***** *(0.309)*	**-0.538** *(0.330)*	**0.311** *(0.378)*	**0.768** *(0.656)*	**-0.823** *(0.889)*
Email	Elastic	**-0.049** *(0.244)*	**-0.08** *(0.248)*	**-0.433** *(0.265)*	**-1.096**** *(0.500)*	**-0.555** *(0.502)*
Instant Message	Elastic	**-0.117** *(0.125)*	**-0.098** *(0.126)*	**-0.254***** *(0.131)*	**-0.198** *(0.169)*	**-0.221** *(0.198)*
Download Music	Inelastic	**0.389**** *(0.162)*	**0.404**** *(0.164)*	**0.352**** *(0.170)*	**0.228** *(0.215)*	**0.032** *(0.244)*
Download Video	Inelastic	**0.184** *(0.174)*	**0.151** *(0.176)*	**0.073** *(0.181)*	**0.292** *(0.236)*	**0.332** *(0.283)*
Browse for News	Inelastic	**0.264**** *(0.131)*	**0.249***** *(0.133)*	**0.213** *(0.138)*	**0.025** *(0.185)*	**0.067** *(0.232)*
General Browsing	Inelastic	**0.249***** *(0.129)*	**0.295**** *(0.132)*	**0.159** *(0.137)*	**0.313***** *(0.172)*	**0.415**** *(0.207)*
Directory Search	Inelastic	**0.345** *(0.243)*	**0.323** *(0.245)*	**0.301** *(0.267)*	**0.502** *(0.411)*	**0.739** *(0.543)*
Online Banking	Inelastic	**0.600*** *(0.121)*	**0.554*** *(0.122)*	**0.344*** *(0.128)*	**0.500*** *(0.158)*	**0.506*** *(0.181)*
Online Gaming	Inelastic	**-0.023** *(0.134)*	**0.019** *(0.136)*	**-0.096** *(0.138)*	**0.052** *(0.176)*	**-0.036** *(0.208)*
Do work Related @ home	Inelastic	**0.326*** *(0.122)*	**0.258**** *(0.128)*	**0.260**** *(0.131)*	**0.166** *(0.171)*	**-0.198** *(0.213)*
Take Online Classes	Inelastic	**0.474**** *(0.198)*	**0.416**** *(0.201)*	**0.386***** *(0.201)*	**0.303** *(0.251)*	**0.217** *(0.276)*
Several Times a day	Freq of Use			**0.621*** *(0.171)*	**0.588*** *(0.197)*	**0.636*** *(0.236)*
3 to 5 days a week	Freq of Use			**-0.193** *(0.168)*	**-0.175** *(0.214)*	**-0.048** *(0.260)*
Less Frequently	Freq of Use			**-0.816*** *(0.169)*	**-0.595**** *(0.247)*	**-0.542***** *(0.301)*
Browse often	Freq of Use			**-1.381*** *(0.357)*	**-2.040*** *(0.758)*	**-3.648*** *(1.044)*
Less than 8th Grade	Education		**-0.884** *(0.969)*	**-1.313** *(1.077)*	**-1.079** *(0.965)*	**-1.964**** *(0.906)*
HighSch	Education		**-0.196** *(0.152)*	**-0.198** *(0.159)*	**-0.294** *(0.215)*	**-0.459***** *(0.263)*
Colgrad	Education		**0.243***** *(0.141)*	**0.125** *(0.146)*	**0.208** *(0.179)*	**0.158** *(0.212)*
Time on Int. Y_L15	Intensity of Use				**-0.265** *(0.332)*	**-0.239** *(0.428)*
Time on Int. Y_G15L1hr	Intensity of Use				**0.077** *(0.191)*	**0.175** *(0.232)*
Time on Int. Y_G3hrL4hr	Intensity of Use				**-0.445** *(0.327)*	**-0.12** *(0.372)*
Time on Int. Y_G4hr	Intensity of Use				**0.196** *(0.278)*	**0.495** *(0.325)*
Age						**-0.021*** *(0.007)*
Months of Internet Use						**0** *(0.002)*
Income						**0.012*** *(0.004)*
Price Paid for Internet						**0.027*** *(0.005)*
Observations		1,632	1,617	1,611	1,090	878
χ^2 test of significance of the Regression		86.38*	87.89*	34.29*	54.03*	49.72*
Estimated Value of the log-likelihood		-778.09	-773.22	-221.30	-205.698	-157.368
McElvey and Zavoina R^2 Statistic		0.214	0.221	0.281	0.162	0.532
McFadden's Adjusted Psuedo-R^2		0.056	0.056	0.030	0.077	0.106

Robust standard errors are in parentheses

*** significant at 10%, ** significant at 5%; * significant at 1%

The results show that individuals who perform the following bandwidth intensive internet applications are more likely to subscribe to broadband at home: download music, browse for news, general browsing, online banking, do work related activities at home, and take online classes. The coefficient estimates are positive for each of these applications. But only the results for online banking and general browsing are robust across the different specifications. The results also show that individuals who primarily use non-bandwidth intensive applications such as email and instant messaging, are less likely to subscribe to broadband connection services in the household.

As before, older age lowers the likelihood that a household will subscribe to broadband. Also the frequency with which an individual browses the internet has an impact on the internet access decision. Individuals who browse the internet "several times a day" have a higher likelihood of subscribing to broadband compared to households browsing only once a day (the base group for this category). Similarly households who browse the internet on fewer occasions, either "between 3 and 5 days a week," or "less frequently i.e., 1 or 2 times weekly" have a lower likelihood of subscribing to broadband compared to households who browse once a day (the base group for this category), as shown by the negative coefficient estimates for those variables. These results concur with the findings of the maximum likelihood estimates from the surveys presented in the previous sections.

The results also show that an increase in income in the household as well as an increase in the price paid for the internet service both increase the likelihood of adopting broadband. The results for the price variable are again contrary to expectation, and are similar to the findings from the February 2004 tracking survey presented in table 16. As

argued previously, the positive coefficient for the price paid for internet variable must be interpreted in the context of the attribute qualities obtained from any particular internet connection service.

Table 21 shows the marginal effects and discrete results of specification 5 of the logit model applied to the November/ December 2005 Daily Tracking Survey

Table 21: Marginal Effect and Discrete changes for the November/December 2005 Daily Tracking Survey

Variables	VARIABLES CLASSIFICATION	Marginal Effects	Discrete Changes	Elasticities
Email	Elastic	**-0.0984**	**-0.085**	**-0.108**
		0.061		0.104
Instant Message	Elastic	**-0.0391**	**-0.04**	**-0.023**
		0.034		0.018
Download Music	Inelastic	**0.0056**	**0.006**	**0.000**
		0.040		0.016
Download Video	Inelastic	**0.0589**	**0.056**	**0.016**
		0.042		0.014
Browse for News	Inelastic	**0.0119**	**0.012**	**0.002**
		0.039		0.040
General Browsing	Inelastic	**0.0736**	**0.077**	**0.069**
		0.038		0.033
Directory Search	Inelastic	**0.1311**	**0.154**	**0.105**
		0.115		0.113
Online Banking	Inelastic	**0.0897**	**0.091**	**0.067**
		0.032		0.023
Online Gaming	Inelastic	**-0.0064**	**-0.006**	**0.000**
		0.035		0.015
Do work Related @ home	Inelastic	**-0.0351**	**-0.035**	**-0.021**
		0.034		0.027
Take Online Classes	Inelastic	**0.0385**	**0.037**	**0.007**
		0.042		0.008
Several Times a day	Freq of Use	**0.1127**	**0.108**	**0.058**
		0.038		0.020
3 to 5 days a week	Freq of Use	**-0.0084**	**-0.009**	**0.001**
		0.043		0.010
Less Frequently	Freq of Use	**-0.0961**	**-0.107**	**-0.013**
		0.061		0.007
Browse often	Freq of Use	**-0.6468**	**-0.693**	**-0.007**
		0.092		0.002
Less than 8th Grade	Education	**-0.3482**	**-0.45**	**-0.003**
		0.206		0.001
HighSch	Education	**-0.0814**	**-0.087**	**-0.023**
		0.049		0.014
Colgrad	Education	**0.028**	**0.028**	**0.011**
		0.035		0.019
Time on Int. Y_L15	Intensity of Use	**-0.0424**	**-0.045**	**-0.001**
		0.076		0.005
Time on Int. Y_G15L1hr	Intensity of Use	**0.0311**	**0.031**	**0.014**
		0.038		0.023
Time on Int. Y_G3hrL4hr	Intensity of Use	**-0.0212**	**-0.022**	**-0.002**
		0.067		0.006
Time on Int. Y_G4hr	Intensity of Use	**0.0877**	**0.08**	**0.016**
		0.045		0.011
Age		**-0.0037**	**-0.002**	**-0.192**
		0.001		0.057
Months of Internet Use		**0.0022**	**0.003**	**0.015**
		0.000		0.015
Income		**0.0047**	**0.007**	**0.176**
		0.001		0.051
Price Paid for Internet		**0.0001**	**0.0001**	**0.252**
		0.001		0.043

Standard errors are reported in the second row

The discrete changes in Table 21 show that individuals who utilize the inelastic application online banking have a probability of adopting broadband that is 0.09 times greater than their counterparts who do not engage in online banking. The results of discrete changes in the frequency of use variable are similar to the results of the previous surveys 1, 2 and 3. The results confirm that the more frequently individuals use the internet, the greater the probability of subscribing to broadband internet services.

The discrete changes show that the education level of an individual has an effect on the probability of broadband subscription at the household level. Individuals who had an education below the 8^{th} grade level have a probability of subscribing to broadband that is 0.45 lower than households where individuals have attained technical or vocational training as their highest level of education. The difference in the probability is lower for individuals who have high school education as the highest level of education attained. These individuals have a probability of subscribing to broadband that is 0.08 lower than the probability of individuals who have attained technical or vocational training. Individuals who engaged in general browsing have a probability of subscribing to broadband that is 0.07 times greater than their counterparts who do not engage in this application.

Individuals who browse the internet several times a day have a probability of subscribing to broadband that is 0.11 times greater than the probability for individuals who browse the internet once a day.

The results in this case generate a very low income elasticity of broadband adoption of 0.0047. This indicates that there is only a 0.0047 percentage change in the probability of adopting broadband for a 1.0 percent increase in income. The price

elasticity of demand results reveal that a 1.0 percent increase in internet price increases the probability of broadband adoption by a very minimal amount i.e., by 0.001. Therefore, while any positive elasticity for an own price variable is enigmatic (although explained above as a proxy for the quality of the attributes obtained), this positive own price elasticity is very low.

CHAPTER 6: CONCLUSIONS

This research has addressed several important issues regarding consumer utilization of bandwidth intensive applications and its impact on broadband adoption. We explored the capacity required by an application in tandem with the network connection type (dial-up or broadband) and how that affects the users experience when consuming an internet application. We then examined this experience and explained how a consumer implicitly engages in the valuation of the benefits derived by the choice of the internet connection type they choose to access a particular internet application.

While it may be surprising, this perspective of examining and explaining broadband adoption from a consumer decision-making (consumer-choice) point of view is not common, and hence provides an analytical improvement over most past treatments. Secondly, a theoretical model was developed that is applicable to both an experimental and a non-experimental setting using the implicit value of time calculation as a quantifiable measure of the gross benefits gained in the transition from a lower bandwidth speed to a higher bandwidth speed. In addition, it has been demonstrated that time saved as a result of the bandwidth used to access the internet can determine the type of internet connection a consumer chooses.

Finally, using household survey data, the empirical analysis in chapter 5 validated the theoretical model presented earlier in chapter 3. The results from the empirical analysis showed that certain bandwidth intensive internet applications do increase the likelihood of broadband adoption at the household level. Therefore the type of internet

applications a consumer uses is a significant factor in influencing the choice of internet connection. The results show that the approach of looking at broadband adoption through the lens of the internet user's consumption of internet applications is one that warrants serious consideration in policy making. For example, in order to increase lagging broadband adoption rates, policy makers should focus on creating incentives that will promote the development of bandwidth intensive applications. Current polices promoted by many state and local governments have focused primarily on expanding the deployment of broadband infrastructure under the assumption that broadband adoption will simply follow broadband deployment. But this strategy has not seemed to generate significant additional incremental uptake in broadband adoption rates in those jurisdictions. This is evident from the statistic presented in chapter 1 from the FCC, that despite the country being 95.4 percent broadband deployed as of December 2004 it is still lagging in the uptake of broadband. The results of this research, therefore, present a compelling reason for addressing the issue of broadband adoption through the perspective of the consumer's use of internet applications.

One limitation of our analysis is the challenge of identifying adequate instrumental variables that could address the potential endogeneity that may exist in the internet application variables used in our model. This limitation arose because we used survey data that did not include questions that could have been used as instruments for the potential endogenous variables. For example, it is important to try to determine whether broadband service was adopted for some reason prior to an individual being aware of the full range of available applications, and then finding that high speed access

made the use of, say, on-line banking services more feasible and convenient, on-line banking became one of the major high bandwidth applications used by the household. Future research that adopts this methodology of addressing broadband adoption by looking at adoption of bandwidth intensive applications should be sensitive to this concern about the direction of the causality implicit in the empirical results that have been reported. One way to address this challenge would be to include questions in the survey questionnaire that could be used as instruments when conducting the empirical analysis. While some information is available in the survey about characteristics such as the existence of children in the household that might serve as plausible instruments for determining the likelihood of adopting broadband prior to a household utilizing the range of internet applications investigated herein, the empirical model framework necessary to test the hypotheses in this study is inappropriate for addressing the endogeneity issue via such instruments. Hence, this extension must remain on the agenda for further research.

Appendix A:

Likelihood Ratio tests of for the various specifications for Survey-1 (S1): The Daily Tracking Survey November 2003

The likelihood ratio test between the nested versions of the models is necessary to discover if the variables excluded are simultaneously equal to zero i.e., whether the exclusion of these variables has any effect in our model. The restricted model in this case is defined as the null hypothesis and the unrestricted model as the alternative hypothesis. Table A1 summarizes the hypothesis for the likelihood ratio tests.

Table A1: Hypothesis for the likelihood ratio tests for the Daily Tracking Survey November 2003

Null hypothesis	Alternative hypothesis			
	Spec 1	Spec 2	Spec 3	Spec 4
Spec 1		$B_{30}=\beta_{31}=0$		
Spec 2			$B_{25}=\beta_{26}=\beta_{27}=\beta_{28}=0$	
Spec 3				$B_{39}=0$
Spec 4				

Our results are as follows: the chi-square statistic for the likelihood ratio test for specification 1 nested in specification 2 $(\beta_{30} = \beta_{31} = 0)$ is 8.08 and is statistically significant at the 1 percent level. The comparison of specification 2 nested in specification 3 $(\beta_{25} = \beta_{26} = \beta_{27} = \beta_{28} = 0)$ yields a chi-square of 80.02, which is also statistically significant at the 1 percent level. The chi-square statistic of specification 3 nested in specification 4 $(\beta_{39} = 0)$equals 12.46 and is also significant at the 1 percent level. From these results it is evident that the restriction of the dummy variables,

education and frequency of use as well as the age variable from specification 1, 2 and 3 resulted in those specifications having a significantly poorer fit, and therefore those variables should be included in the final model as in the case of the unrestricted model (specification 4). In addition to the likelihood ratio test between the various specifications, none of the specifications showed any sign of multicollinearity when tested. Therefore, the unrestricted model specification 4 is our preferred specification for the general logistic model (equation 5.2) for analyzing the "daily tracking survey November 2003."

Likelihood Ratio tests of for the various specifications for Survey-2 (S2): The February 2004 tracking survey

Table A2 summarizes the hypothesis for the various likelihood ratio tests performed between the nested versions of the model. The restricted model is defined as the Null hypothesis and the unrestricted model as the alternative hypothesis:

Table A2: Hypothesis for the likelihood ratio tests for the February 2004 tracking survey

Null hypothesis	Alternative hypothesis			
	Spec 1	Spec 2	Spec 3	Spec 4
Spec 1		$B_{31}=\beta_{32}=0$		
Spec 2			$\beta_{25}=\beta_{26}=\beta_{27}=\beta_{28}=0$	
Spec 3				$B_{39}=\beta_{41}=\beta_{42}=0$
Spec 4				

The chi-square statistic for the likelihood ratio test for specification 1 nested in specification 2 $(\beta_{31} = \beta_{32} = 0)$ is 7.00 and it is statistically significant at the 5 percent

level of significance. Based on this we discard specification 1 and continue investigating the remaining specifications. The comparison of specification 2 nested in specification 3 $(\beta_{25} = \beta_{26} = \beta_{27} = \beta_{28} = 0)$ yields a chi- square value of 52.72, which is statistically significant at the 1 percent level. Similarly we discard specification 2 and proceed to evaluate the remaining specifications 3 and 4. The chi-square statistic of specification 3 nested in specification 4 $(\beta_{39} = \beta_{41} = \beta_{42} = 0)$ equals 56.63 and is also significant at the 1 percent level of significance. The results from likelihood ratio tests demonstrates that the restriction of the education and the frequency of internet use dummy variables as well as the age, "Months of Internet Use" and "Price paid for Internet" variables from specification 1, 2 and 3 resulted in those specifications having a significantly poorer fit, and hence the variables should be included in the final model as is the case in the unrestricted model, specification 4.

Likelihood Ratio tests of for the various specifications for Survey-3 (S3): January 2005 Daily Tracking Survey

Table A3
Hypothesis for the likelihood ratio tests for the January 2005 Daily Tracking survey

Null hypothesis	Alternative hypothesis				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
Spec 1		$\beta_{30}=\beta_{31}=\beta_{33}=0$	$\beta_{34}=\beta_{35}=\beta_{37}=\beta_{38}=0$		
Spec 2					
Spec 3				$\beta_{25}=\beta_{26}=\beta_{28}=\beta_{29}=0$	
Spec 4					$B_{39}=\beta_{40}=\beta_{42}=0$
Spec 5					

The chi-square statistic for the likelihood ratio test for specification 1 nested in specification 2 $(\beta_{30} = \beta_{31} = \beta_{33} = 0)$ is 4.10 and is not significant. This indicates that the education dummy variables added in specification 2 are not statistically significantly different from zero. We then proceed to compare specification 1 nested in specification 3 $(\beta_{34} = \beta_{35} = \beta_{37} = \beta_{38} = 0)$. The chi-square statistic equals 8.34 and is statistically significant at the 10 percent level. We discard specification 2 and proceed to evaluate the remaining specifications 3 and 4. The chi-square statistic of specification 3 nested in specification 4 $(\beta_{25} = \beta_{26} = \beta_{28} = \beta_{29} = 0)$ equals 28.66 and is statistically significant at the 1 percent level. Our final comparison involves specification 4 nested in specification 5, the unrestricted specification $(\beta_{39} = \beta_{40} = \beta_{42} = 0)$. The results yield a chi-square statistic of 15.06, which is significant at the 1 percent level of significance. The results from likelihood ratio tests of the comparison of various specifications demonstrates that

the restriction of the amount of intensity of use and the frequency of use dummy variables, as well as the age, months of internet use and income variables from specification 1, 3 and 4 resulted in those specifications having a significantly poorer fit. Hence, the variables should be included in the final model as is the case in the unrestricted model, specification 5.

Likelihood Ratio tests of for the various specifications for Survey-4 (S4): The January 2005 Daily Tracking Survey

Table A4 summarizes the hypothesis for the likelihood ratio tests performed between the nested versions of the model for the November/December 2005 Daily Tracking survey:

Table A4
Hypothesis for the likelihood ratio tests for the November/December 2005 Daily Tracking survey

Null hypothesis	Alternative hypothesis				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
Spec 1		$\beta_{30}=\beta_{31}=\beta_{33}=0$			
Spec 2			$\beta_{25}=\beta_{26}=\beta_{28}=\beta_{29}=0$		
Spec 3				$\beta_{34}=\beta_{35}=\beta_{37}=\beta_{38}=0$	
Spec 4					$\beta_{39}=\beta_{40}=\beta_{41}=\beta_{42}=0$
Spec 5					

The chi-square statistic for the likelihood ratio test for the comparison of specification 2 against specification 1 is 11.86 and it is significant at the 1 percent level. The comparison of specification 3 against specification 2 yields a chi-square of 83.91 and

is statistically significant at the 1 percent level. The comparison of specification 4 against specification 3 yields a chi-square of 713.08, which is also statistically significant at the 1 percent level. The final comparison involves specification 5, the unrestricted specification against specification 4. The chi-square statistic of the likelihood ratio test is 358.93, which is significant at the 1 percent level of significance.

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Peter's main areas of research and interest include microeconomics with a focus of consumer behavior as well as public finance. He has worked as an Analyst for several companies including Cox Communications, AT&T Telecommunications and Choice Point Inc., focusing on statistical analysis of factors affecting consumer decisions. He currently works as a Statistical Consultant for a multi-national marketing company and his responsibilities include developing predictive models of consumer behavior.