The (Teaching) Role of Universities in the Diffusion of the Internet

Avi Goldfarb*
Rotman School of Management
University of Toronto
105 St. George St.
Toronto, ON M5S 3E6
CANADA
(416) 946-8604
agoldfarb@rotman.utoronto.ca
May 2004

Abstract

This paper provides evidence that students in the mid-1990s learned to use the Internet at university and then continued to use the Internet after graduation. They passed this knowledge on to other members of their households. Using the September 2001 CPS data from the US Census and panel data from A.C. Nielsen Canada, it shows that university attendance in the mid-1990s had a larger effect on Internet use than did university attendance in other periods. It also shows that people who live with students from the mid-1990s are more likely to be Internet users. These effects do not hold for the use of other technologies such as word processing and computer games. It explores the reasons behind this effect. It is not a merely a result of selection, occupation, or computer ownership. People who were students in the mid-1990s are more likely to use the Internet because they receive higher benefits from Internet applications, particularly from online communication. People who live with students from the mid-1990s are more likely to use the Internet because the overall costs of access are lower for them. (JEL Classification: L86, O33)

* Thanks to David Dunne and to Nielsen Canada for providing data, to seminar participants at the University of British Columbia and the University of Toronto, and to Shane Greenstein, Jihui Chen, Mara Lederman, and Maryann Feldman for helpful comments. The SSHRC Institute for the New Economy program provided funding.

1. Introduction

The role of educational institutions in teaching people about new technologies, while not well researched, is nontrivial. Universities likely played a role in encouraging the use of many technologies including laboratory equipment, software, and databases such as Lexis-Nexis; however, little empirical work has documented this role or tried to understand how it works. In this paper, I provide evidence that universities taught a generation of students how to use the Internet. These students then brought the technology into their homes after they left school. In addition to playing an important role in the invention of the Internet,[1] universities helped create demand for the technology. This may have been part of the reason that the Internet diffused so rapidly through American society.[2]

It is important to understand the causes of this rapid diffusion process. Information technology is often credited with the economic boom of the late 1990s.[3] Understanding the process of its diffusion will help provide insight into the process that led to rapid economic growth in the United States and elsewhere.

While it now may seem that the diffusion of the Internet was inevitable, the diffusion process took decades. Invented in the late 1960s, the Internet was used by few people outside of the research community in the early 1990s. Kenney (2001, pp. 6) writes, "When the WWW software was first released in 1992, the majority of adopters were in institutions, especially universities." In this paper, I show that universities played a role in creating demand for the technology outside the early adopters in the research community.

Based on the September 2001 Current Population Survey of the US Census, Figures 2 and 3 provide some preliminary motivating evidence for this role for universities in Internet diffusion. Figure 2

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[1] Numerous studies and books describe the role of universities in the invention of the network as it exists today (e.g. Ellsworth & Ellsworth 1997, Berners-Lee 1999, and Kenney 2001). The Internet browser was invented at the University of Illinois. The University of California at Berkeley was instrumental in connecting the Internet backbone to the west coast of the United States. Many Internet companies have been spun out of Stanford (e.g. Google), MIT (e.g. Akamai), and other schools.

[2] Figure 1 displays the growth of Internet access in the United States. In 1994, the technology was in few homes, but by September 2001 over half of all US households had Internet access.

shows that those who likely went to school in the mid-1990s (people born from 1971 to 1979 with a post-secondary education) are more likely to use the Internet than other groups. Furthermore, it shows that the increase due to education, controlling for age, is higher for this group than for others. Figure 3 shows that people who live with those who attended school in the mid-1990s are more likely to use the Internet than those who do not. Obviously, there are many possible reasons behind these summary statistics. In the analysis that follows, I add many controls and econometric tools to help determine the role of universities in Internet diffusion. The general pattern in these figures holds.

This paper is not the first to suggest universities play a role in technology development and diffusion. There is a long literature on the subject of technology spillovers from universities.[4] The role of educational institutions in the diffusion of technology has been most widely researched in agriculture.[5] According to Rogers (1995, pp. 358-9), land-grant universities in the United States were in many cases explicitly set up to teach farmers about the latest agricultural techniques. This paper is also not the first to find a link between education levels and technology adoption. It is well documented in the literature that higher education is correlated with adoption. Hoffman and Novak (2000) and National Telecommunications Information Administration (2000) show the raw correlations in national cross-sections. Bresnahan, Brynjolfsson, and Hitt (2002), Chun (2003), and Doms, Dunne, and Troske (1997) all find that information technology use by firms increases the demand for educated workers.

What is new in this paper is the demonstration that university attendance during the early years of the Internet is correlated with usage in later years.[6] In other words, I show that the marginal impact of

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[3] For example, see Oliner & Sichel (2000), Brynjolfsson & Hitt (2000), Baily & Lawrence (2001), Litan & Rivlin (2001), and the survey in Jalava & Pohjola (2002).

[4] Technology spillovers from universities are discussed in Acs, Audretsch, & Feldman (1992), Henderson, Jaffe, & Trajtenberg (1998), Jaffe (1989), Mansfield (1995), Zucker, Darby, & Brewer (1998), and many others. The Journal of Technology Transfer is partially dedicated to the movement of technology from university research to practical applications. Monjon & Waelbroeck (2003) discuss the roles of research collaboration between academia and business and of the publication of research results on technology diffusion. Bercovitz and Feldman (2004) discuss the influence of graduate schools on the propensity of graduates to participate in university-industry technology transfer.

[5] Rogers (1995) cites several studies in agriculture. A notable exception is Feller (e.g. 1993) who suggests using the agricultural transfer model in manufacturing. He gives a number of examples.

[6] Throughout this paper, I call an individual who continued using the Internet after graduation an "adopter". An individual who stops using the Internet becomes a "non-adopter". This is different from the standard language in the

university education in the mid-1990s on Internet use was much higher than in other periods. It is not just the level of education that leads to adoption, but the attendance (and presumed use of the technology) at the educational institution that leads to continued use of the technology many years into the future.

Furthermore, controlling for many factors I find that members of households with people who were students in the mid-1990s are more likely to be Internet users. In doing so, I provide a measurement for the magnitude of social learning in a narrow context: learning within the household. I show how students may have acted as change agents in facilitating technology diffusion. In this way, educational institutions may have had a role in technology diffusion beyond the direct transmission of knowledge to students.[7]

Most of the results are based on the September 2001 Computer and Internet Use Supplement to the Current Population Survey of the United States census. I show the results also hold on a second complementary data set from A.C. Nielsen Canada. The data sets are rich enough to allow modeling the decision to adopt Internet access simultaneously with the decisions to adopt Internet applications such as email, information search, and e-commerce. In this way, this paper explores the reasons that university attendance led to Internet use. In particular, I can determine if universities reduced barriers to adoption of the underlying technology or if universities increased benefits associated with particular applications.

The next section discusses the relevant literature. Section 3 presents the basic framework used in the paper. This is followed by a description of the data set used. Section 5 then shows that people who were students in the mid-1990s, and those who live with them, are particularly likely to adopt the Internet, even controlling for age, occupation, industry. This does not hold for other computing technologies such as word processing and computer games. In section 6, I explore the reasons behind these results. I find

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literature, but appropriate given the nature of the study. Almost all students would have used the Internet while attending university. What is interesting is adoption on a continuing basis.

[7] There is little evidence in the economics literature on the role of social learning in technology diffusion. One notable exception is Conley and Udry's (2003) study of the role of social learning in the diffusion of the pineapple in Ghana. Their study looks at social learning in the broader context of farm-to-farm. Following Manski (1993), they note that many studies of social learning suffer from an inability to identify actual communication. One way they overcome this problem is through a survey about communication networks. I overcome the problem by

that attendance at an educational institution in the mid-1990s increased the benefits of adopting Internet applications more than it reduced the overall costs of adoption. For people who live with students from the mid-1990s, however, the evidence supports the opposite conclusion. Section 7 concludes.

2. Relevant Literature: Diffusion, Universities, and Information Technology

This paper follows a long literature in economics exploring the causes of technology diffusion. Stoneman (2002) describes four main approaches to understanding diffusion: epidemic, probit (or rank), stock, and order approaches.[8] The earliest modeling tended to focus on epidemic effects (e.g. Griliches 1957). These models focus on learning and communication as the means through which technologies diffuse. The epidemic models suggest that by teaching people about a new technology, universities can play an important role in its diffusion.

The probit approach is also important for the current study. It suggests that there is heterogeneity in the costs and benefits of a technology within the population, implying that different people will adopt the technology at different times, and that some may never adopt. Ignoring the lessons of this approach would ignore important identification issues in determining the role of universities in adoption. The probit approach suggests that educated and younger people may be more likely to adopt technology and that any measured effect of university attendence on Internet use must control for such demographic factors. This approach consequently supplies the econometric framework used in this study.

Some theoretical models combine the ideas of the epidemic model on learning with a rank model on heterogeneity. For example, Bhattacharya, Chatterjee, and Samuelson (1986) explore the role of learning about innovations when the distribution of payoffs is unknown on technology adoption. Jensen (1982) also explores learning about the payoffs to adoption. In this paper, I also use a model that explores individual decision-making and its relation to a learning effect.

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narrowing the scope of investigation to household members. This intra-household diffusion (Stoneman 2002, p. 7-9) is another topic that has received little empirical exploration.

[8] Karshenas and Stoneman (1993) construct an empirical model to examine the importance of the various approaches.

The stock and order approaches are less relevant to this study. Both approaches typically deal with strategic adoption behavior by firms (e.g. Reinganum 1981 and Fudenberg and Tirole 1985); this is less relevant in the household adoption context.

This study is similar to Goolsbee and Klenow (2002) in that it explores the adoption of information technology with a large cross-sectional data set. Using a similar econometric framework to the one used in section 5 of this paper, they "find that local spillovers are important for household computer adoption" (p. 340). They argue that this effect is unlikely to be a result of unobserved local traits, local computer prices, local industry composition, peer pressure, or local schools. In examining local schools, they also explore the impact of educational institutions on technology adoption. They do not find these institutions to be particularly important. In contrast to their finding on elementary and high schools, I find that universities are important for Internet diffusion.[9]

This study also relates to the literature on the role of information technology in generating demand for skilled workers. Bresnahan, Brynjolfsson, and Hitt (2002), Chun (2003), and Doms, Dunne, and Troske (1997) all find that information technology increases demand for educated (or skilled) workers. In this paper, I examine the inverse role: the role of education in creating demand for information technology.

3. Basic Framework

As mentioned previously, Figures 2 and 3 show that people who were students in the mid-1990s, and those who live with them, are particularly likely to use the Internet. Table 1 lists eight different hypotheses, detailed below, that may explain this relationship. Hypotheses 1 through 4 explore whether the differences in Internet usage rates are a result of selection or factors peripheral to university teaching. A probit model of Internet adoption is developed in section 3.1 to test whether these hypotheses fully

[9] Using data from the same source, Goolsbee (2000) finds that local sales taxes play an important role in the adoption of electronic commerce. Other studies of Internet diffusion include Downes and Greenstein (2002) on universal access, Forman, Goldfarb, and Greenstein (2003) on urban/rural differences in Internet adoption by firms, and Parthasarathy and Bhattacherjee (1998) on post-adoption behavior.

explain differences in usage rates.[10] Hypotheses 5 through 8, on the other hand, examine why universities might drive future Internet usage. They are based on the argument that there is no reason to get Internet access without also using at least one of the many applications it enables, such as email, e-commerce, and information search. Since the decision to adopt these applications occurs simultaneously with the decision to adopt the Internet, any analysis of Internet adoption should simultaneously model the adoption of these various applications.[11] Section 3.2 describes a nested model of Internet use and adoption of various applications that allows for separate identification of the particular benefits that people who were students in the mid-1990s, and those who live with them, receive from Internet use.

3.1 Probit Model

Diffusion is a consequence of a number of individual-level adoption decisions. An individual adopts a technology if the benefits from adoption exceed the costs. Formally, individual *n* will adopt innovation *V* at time *t* if

$$NB_{Vnt}=B_{Vnt}-C_{Vnt}>0, \tag{1}$$

Where NB_{Vnt} is the net benefit of innovation *V* to individual *n* at time *t*, B_{Vnt} is the benefit to adopting *V*, and C_{Vnt} is the cost of adopting *V*.[12] In this section, I examine the overall propensity to adopt using a standard probit model of adoption. This model allows me to identify whether the differences in adoption rates are a function of selection, of computer ownership, or of a university-related role in changing net benefits independent of these factors. In section 3.2, I build a model that allows exploration of the university-related role.

[10] Stoneman's (2002, p. 33) survey calls this "the probit or rank approach", in line with his previous research on the subject (e.g. Karshenas and Stoneman (1993). David (1969) is an early example of this approach. An example of the probit approach applied to households is Stoneman and Battisti (2002) on unleaded gasoline.

[11] Applications provide the benefits of Internet use. Therefore, the overall decision to adopt controlling for application benefits is a cost-side decision. Possible costs include the step of connectivity (configuring the dial-up), comfort in dealing with technology support people, and understanding what to look for when choosing an ISP.

[12] Implicitly, the cost term, C, includes the opportunity cost of not adopting at some other time (Ireland and Stoneman 1986).

The probit model assumes that an individual will adopt a technology when equation (1) holds. Since benefits and costs cannot be separately identified and data is cross-sectional, covariates refer to the net benefit:

$$NB_{Vn}= B_{Vn}-C_{Vn} = S_n\gamma+L_n\delta+ Z_{Vn}\beta+\varepsilon_{Vn} \quad (2)$$

Here $S_n=1$ if individual n was a student in the mid-1990s and zero otherwise; $L_n=1$ if individual n lives with someone who was a student in the mid-1990s and zero otherwise; and Z_{Vn} is a vector of covariates relating to adoption of technology V by individual n. Using this framework, I explore hypotheses 1 through 4.

Hypothesis 1: People who were students in the mid-1990s, and those who live with them, use the Internet more because they are younger and more educated than the rest of the population. This hypothesis derives from the considerable evidence that younger, educated people are more likely to adopt new technologies in general and the Internet in particular (e.g. Rogers 1995, Hoffman and Novak 2000).

Hypothesis 2: People who were students in the mid-1990s, and those who live with them, use the Internet more because they are in occupations and industries that demand Internet skills. This hypothesis addresses the possibility that the occupations available to university graduates in this time period were disproportionately Internet-oriented. Therefore, they are more likely to use the Internet because of occupation-related factors independent of university influence. As mentioned earlier, Bresnahan, Brynjolfsson, and Hitt (2002), Chun (2003), and Doms, Dunne, and Troske (1997) all show that information technology use increases demand for educated workers. If information technology jobs were particularly prevelant in the late 1990s, then this could drive the result that education in this time period leads to technology adoption.

I include age, education, occupation, and industry controls to see if the marginal effect of having been (living with) a student in the mid-1990s on the net benefit to Internet adoption is positive. If the marginal effect remains positive, then hypotheses 1 and 2 cannot be complete explanations for the relationship between Internet use and universities.

Hypothesis 3: People who were students in the mid-1990s, and those who live with them, use the Internet more because they are particularly technology-savvy. It is possible that even controlling for education, age, industry, and occupation, that the group of people being studied are naturally more technology-savvy than others. This idea is suggested by Goolsbee and Klenow (2002, p. 318) as an explanation for local spillovers.

Hypothesis 4: People who were students in the mid-1990s, and those who live with them, use the Internet more because students bought computers while in school and continue to own them. Consequently Internet use is less costly for them. This hypothesis addresses the possibility that universities did have an impact, but not because of anything taught at school. Universities may have had an impact because they encourage students to buy computers. If computer ownership is a major barrier to Internet usage, then the only effect universities may have is in encouraging computer ownership.

I address hypotheses 3 and 4 by examining usage of computing technologies that are not Internet related such as word processing.[13] If the marginal effect of having been (living with) a student in the mid-1990s on usage of other technologies is negligible, then these hypotheses can be rejected. If, however, the marginal effects compare to those for Internet access then hypotheses 3 and 4 are the most likely explanation for the differences in adoption rates shown in Figures 2 and 3.[14] Results of the probit regressions are presented in section 5, Tables 3 through 6, and Figures 5 through 7.

3.2 Full Nested Model

Educational institutions could have increased the benefits of Internet adoption. Students could have gained a network of other Internet users, thereby increasing the value of communications applications. Alternatively, students could have learned how to look for information effectively, thereby

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[13] Goolsbee and Klenow (2002) also compare Internet use with other software use. They find that Internet use influences local spillovers in computer adoption and that this is not the case for other software use. They argue that this suggests that the spillovers are likely a function of network effects.

[14] I focus on use of computing technologies rather than computer ownership because the direction of causality in computer ownership is ambiguous. Universities may increase computer ownership only because of Internet use. In

increasing the benefit to information applications. Formally, B_{Vn} may have risen. On the other hand, universities may have helped the technology diffuse by reducing the costs associated with diffusion. Before its widespread diffusion, the Internet was a difficult technology to sample. Individuals needed access to a computer with a modem as well as the programs that would allow them to access the Internet. Universities may have provided these requirements. They often forced students to use the Internet; meaning students had no choice but to try the technology.[15] They then might have learned that the technology was not as complex as it may have first appeared. By driving down the cost barriers to adoption, universities may have opened the way for students to use the Internet. Formally, C_{Vn} may have fallen.

The model used in this paper allows for the identification of the particular technologies adopted and their relative importance in the adoption decisions. The Internet, like many other technologies, has no value in itself. It is a platform for other technologies and only has value when combined with software applications. Consequently, the decision by a given individual to adopt the Internet will depend on the value that individual places on the various applications. In particular, an individual will adopt Internet technology if the benefits of adoption outweigh the costs. There are costs in adopting the core technology and in adopting the applications. For example, costs in adopting the core technology include getting a computer and a modem, learning how to access the Internet, signing up with an Internet service provider, and paying the access fee. Costs in adopting email include signing up for an account, learning how to use email, learning people's email addresses, and perhaps typing. Benefits, on the other hand, only accrue to the individual if they adopt applications. Just having Internet access will not generate utility. It is the use of applications like email, information access, and e-commerce that generates utility. Therefore, by determining whether the net benefit to Internet adoption is higher for students in the mid-1990s because of utility from applications or because of utility from the underlying technology, I can separately identify

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the data, computer ownership is higher for the relevant cohort. Since use of non-Internet computer applications is not higher, I interpret this to mean the increase in computer ownership is due to Internet use and not vice-versa.

[15] Rogers (1995) calls these the trialability and complexity barriers to adoption.

whether these students were more likely to adopt the Internet because of increased benefits or reduced costs. [16]

Jimeniz and Greenstein (1998) also examine the Internet as a nested diffusion process but in a different context. In a largely descriptive paper, they emphasize that Internet applications will only diffuse with the widespread adoption of personal computers and networking technologies. Gandal, Keane, and Rob (2000) estimate the relationship between hardware and software diffusion in the compact disc market. Like most other research on contingent products,[17] they focus on network externalities and the option value of adoption. I address a different question: given that Internet adoption will involve different applications for different people, what are the actual drivers of adoption?

To formalize these concepts, let $NB_{In}=B_{In}-C_{In}$ be the net benefit of using the Internet at all and let $NB_{an}=B_{an}-C_{an}$ be the net benefit of using particular application a (such as email, information search, or e-commerce). Individuals derive utility from the Internet only to the extent that they use applications. Therefore $\mathrm{B}_{\mathrm{In}} = \sum_{a \in A_n} NB_{an}$, where A_n is the set of all Internet applications used by individual n. Costs, however, may relate to the act of getting online. Consequently, I can separately identify B_I from C_I. This allows for separate measurement of the effect of universities on benefits and costs.[18]

In each period, individuals have a nested decision problem. They must decide whether to adopt the Internet, and if they adopt the Internet, they must decide which applications to adopt. Figure 4 shows

[16] I identify net benefits from application usage rather than from intensity of use. While the census did not ask questions about intensity of use, there is some evidence from the Nielsen data that application use is correlated with intensity. 62% of users of all three applications (e-commerce, e-information, and e-communication) use the Internet daily. 44% of users of two applications and 24% of users of just one application use the Internet daily. Furthermore, student in the mid-1990s who use the Internet are more likely than other Internet users to go online daily (59% vs. 51%). This data is not rich enough to conduct econometric analysis. While a conclusive result will only be possible with a comprehensive survey that asks about intensity of use, the descriptive evidence suggests that intensity of use is correlated with the number of applications used.

[17] The extensive research on the diffusion of contingent products in the marketing literature includes Bayus (1987) on CDs and Gupta, Jain, & Sawney (1999) on digital television. Peterson & Mahajan (1978) develop a contingent products Bass diffusion model.

[18] I cannot separate B_a from C_a. Therefore it is only at the level of the underlying technology, not at the application level, that I separate benefits from costs (e.g. physical costs, complexity, and trialability). Also, while I control for the most common application uses, it is possible that I miss some applications. Therefore the measured C_{In} includes benefits from uncommon applications.

this process. There are N households indexed by n and A applications indexed by a. The subscript for the Internet in general is I. The net benefit from adopting the Internet is then going to be

$$NB_{In} = \left[\sum_{a=1}^{A} \alpha_a \max(B_{an} - C_{an}, 0) \right] - C_{In} \tag{3}$$

where α_a is the weighting on the net benefit of application a. The net benefit from adopting a particular application a will be

$$NB_{an} = B_{an} - C_{an} \tag{4}$$

Since I am not able to distinguish benefits from costs at the application level, the net benefit of using a particular application is measured by

$$NB_{an} = X_{an}\beta + \varepsilon_{an} \tag{5}$$

where X_{an} is a k(a)xN matrix of covariates, β is the vector of coefficients and ε_{an} is the idiosyncratic error. X_{an} includes whether individual n was a student in the mid-1990s, whether individual n lives with someone who was a student in the mid-1990s, and a number of other covariates.

In order to reduce the computational burden of the model, I assume the household and time varying error term, ε_{an}, is distributed extreme value to give a logit specification on adoption probability:

$$\Pr(y_{an} = 1) = \frac{\exp(X_{an}\beta)}{1 + \exp(X_{an}\beta)} \tag{6}$$

where y_{an}=1 if individual n adopts application a, and y_{an}=0 otherwise.

The net benefit of adopting the Internet in general will be:

$$NB_{In} = X_{In}\beta + \varepsilon_{In} + \sum_{a \in \overline{A_n}} \alpha_a NB_{an} \tag{7}$$

where $\overline{A_n}$ is the set of applications that individual i uses. Again assuming the error term is extreme value, the probability of adopting the Internet is

$$\Pr(y_{In} = 1) = \frac{\exp(X_{In}\beta + \sum_{a \in \overline{A_n}} \alpha_a NB_{an})}{1 + \exp(X_{In}\beta + \sum_{a \in \overline{A_n}} \alpha_a NB_{an})} \tag{8}$$

The net benefit of the applications is only identified up to scale. As a result, the absolute value of α_a has no economic meaning. It re-weights the values in order to estimate the net benefit to Internet adoption from them. This is similar to an inclusive value in a nested logit regression.[19]

Estimating the likelihood function then becomes a matter of simultaneously estimating the net benefit of each individual application and the net benefit of adopting the Internet in general. The net benefit of Internet adoption will depend on how many applications are adopted. Below I give the joint probabilities of adopting the Internet and some applications:

$$\begin{aligned}
&\Pr(y_{In}=0, y_{an}=0, \forall a \in A) = \Pr(NB_{In}<0) \\
&\Pr(y_{In}=0, y_{an}=1 \text{ for any } a \in A) = 0 \\
&\Pr(y_{In}=1, y_{an}=0, \forall a \in A) = \Pr(NB_{In}\geq 0, NB_{an}<0, \forall a \in A) = \Pr(NB_{In}\geq 0)\prod_{a=1}^{A}\Pr(NB_{an}<0) \\
&\Pr(y_{In}=1, y_{an}=1, \forall a \in \overline{A}_n \subseteq A, y_{an}=0, \forall a \notin \overline{A}_n) = \Pr(X_{In}\beta+\varepsilon_{In}+\sum_{a\in\overline{A}_n}\alpha_a NB_{an}\geq 0, NB_{an}\geq 0, \forall a \in \overline{A}_n \subseteq A) \\
&\Rightarrow \Pr(y_{In}=1, y_{an}=1, \forall a \in \overline{A}_n \subseteq A, y_{an}=0, \forall a \notin \overline{A}_n)) = \Pr(X_{In}\beta+\varepsilon_{In}+\sum_{a\in\overline{A}}\alpha_a NB_{an}\geq 0)\prod_{a\in\overline{A}_n\subseteq A}\Pr(NB_{an}\geq 0)\prod_{a\notin\overline{A}_n\subseteq A}\Pr(NB_{an}<0)
\end{aligned} \tag{9}$$

The likelihood function is

$$L=\prod_{N=1}^{N}\left\{\begin{aligned}&\Pr(NB_{In}<0)^{1-y_{In}}\left(\Pr(NB_{In}\geq 0)\prod_{a=1}^{A}\Pr(NB_{an}<0)\right)^{y_{In}\prod_{a=1}^{A}(1-y_{an})} \\ &\cdot\prod_{all\,\overline{A}\subseteq A}\left(\Pr(X_{In}\beta+\varepsilon_{In}+\sum_{a\in\overline{A}}\alpha_a NB_{an}\geq 0)\prod_{a\in\overline{A}}\Pr(NB_{an}\geq 0)\prod_{a\notin\overline{A}}\Pr(NB_{an}<0)\right)^{y_{In}\prod_{a\in\overline{A}}y_{an}\prod_{a\notin\overline{A}}(1-y_{an})}\end{aligned}\right\} \tag{10}$$

The log likelihood function is then

$$\ln L=\sum_{n=1}^{N}\left\{\begin{aligned}&(1-y_{In})\ln\Pr(NB_{In}<0)+y_{In}\prod_{a=1}^{A}(1-y_{an})\left[\ln\Pr(NB_{In}\geq 0)+\sum_{a=1}^{A}\ln\Pr(NB_{an}<0)\right] \\ &+\sum_{all\,\overline{A}\subseteq A}\left(y_{In}\prod_{a\in\overline{A}}y_{an}\prod_{a\notin\overline{A}}(1-y_{an})\left[\ln\Pr(NB_{In}\geq 0)+\sum_{a\in\overline{A}}\ln\Pr(NB_{an}\geq 0)+\sum_{a\notin\overline{A}}\ln\Pr(NB_{an}<0)\right]\right)\end{aligned}\right\} \tag{11}$$

I focus on three main applications: e-commerce, e-information, and e-communication. Individuals are defined as using e-commerce if they claim to have made an online purchase of any kind that year. Individuals are defined as using e-information if they claim to have visited websites that contain information on news, entertainment, recipes, government services, or health. Individuals are

[19] Unlike a nested logit regression with a utility maximization model, α is not a probability measure. Therefore it

defined as using e-communication if they claim to have used the Internet for email or chat in the past year. To ensure the results are robust to specification, I show the results of one regression using e-finance and e-work/study and another regression using only e-finance.[20] There are certainly other applications but they are less commonly used. These are subsumed into the residual net benefit of using the base Internet technology.

This model allows me to test hypotheses 5 through 8.

Hypothesis 5: People who were students in the mid-1990s, and those who live with them, get a greater net benefit from the information available on the Internet. Universities may have taught students to be particularly skilled at accessing online information. Alternatively, universities may have showed people the benefits associated with online information search. In the language of Rogers (1995), the higher skill in accessing information is an increased "relative advantage" and the demonstration of benefits is increased "observability". They may then have transferred these skills to those who live with them.

Hypothesis 6: People who were students in the mid-1990s, and those who live with them, are more likely to purchase products online and do online banking. Universities may have taught students to be more trusting of Internet security and consequently are more willing to purchase products online. The opposite hypothesis is also a possibility: universities may have taught people to distrust Internet security. Students may then have transferred these attitudes to those who live with them.

Hypothesis 7: People who were students in the mid-1990s, and those who live with them, get a greater net benefit from online communication. People who attended universities in this time period may have a network of people they know from school who are also online. Since online communication is a technology that displays network effects, this would increase the benefit of the online communication.[21] The people they live with may also be connected to these networks (although this seems less likely). I cannot separately identify higher benefits from network effects from any other reason students may

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does not need to be between zero and one to be consistent with utility maximization.

[20] E-finance is defined by having used the Internet for banking or for stock trading. E-work/study is defined by having used the Internet for work or for school.

[21] For a discussion on network effects and email, see Shapiro & Varian (1999, p. 13).

receive a higher net benefit from email (such as comfort with electronic letters and familiarity through forced used during school).

Hypothesis 8: People who were students in the mid-1990s, and those who live with them, face lower costs to adoption than others. Universities may have showed that connecting to, and using, the Internet is not complicated. In Rogers' (1995) words, universities may have reduced "trialability" and "complexity" barriers to Internet adoption. These costs are separate from the costs of computer ownership discussed in hypothesis 4. Stoneman (2002, chapter 3) identified possible reasons as risk and uncertainty and learning-by-doing.

I explore hypotheses 5 through 8 using the variables on whether people were students in the mid-1990s and on whether people live with a student from the mid-1990s in each nest. For example, if being a student in the mid-1990s is a significant predictor of adoption of e-communication in the model then I assert that hypothesis 7 holds for this group. If, on the other hand, living with someone who was a student in the mid-1990s is not a significant predictor of adoption of e-commerce then I assert that hypothesis 6 does not hold for this group. Hypothesis 8 holds if the coefficients are significant for adoption of the underlying technology controlling for a number of applications. Results of the nested model are presented in section 6 and table 7.

4. Data

4.1 Data Sets Used

Most of the results are based on the September 2001 Computer and Internet Use Supplement to the Current Population Survey (CPS) of United States Census.[22] These results are complemented by similar regressions on the December 1998 Computer and Internet Use Supplement and on the *Internet Planner* panel survey conducted by A.C. Nielsen Canada from 1995 to 2000.

The September 2001 CPS supplement contains information about the computer and Internet habits of a representative sample of 142,667 Americans. In particular, it contains information on demographics, Internet access, Internet application usage, and whether two respondents live in the same household. Unlike the other CPS supplements, the September 2001 supplement contains information on the use of non-Internet computer applications including word processing and desktop publishing, spreadsheets and databases, computer games, and programs for managing household records. This data allows me to explore whether the results in the study relate to computer use in general or to the Internet in particular. I focus on this supplement mainly because it is the most recent data available; however, the information on non-Internet computer applications makes it especially attractive. The primary weakness of the CPS data for this study is that it is cross-sectional. Consequently, I cannot exactly identify individuals who were students during the mid-1990s. I have to approximate this based on education and age.

The *Internet Planner* Survey, conducted by A.C. Nielsen on Canadian Internet usage and repeated annually from 1995 to 2000, does not suffer from this weakness. Due to the panel nature of the study, I can identify individuals who were students in the mid-1990s and then examine their Internet habits in later years. The raw sample consists of 12,100 individuals in Nielsen's Homescan® panel. Respondents completed the survey using a hand-held computing response system to scan a bar-coded questionnaire. There are 5,519 individuals with data for 2000.

The Nielsen data set, however, has two main weaknesses. The first weakness is the flip side of the main strength. To be identified as a student during the mid-1990s and remain in the data set in 2000, individuals must be in the data set for more than one year. However, to be in the data set in multiple years, individuals cannot have changed residences. Second, they must be the self-identified head of the household. This makes for an unusual population, one that is less mobile and older than the general population. These weaknesses are especially relevant in examining the role of universities as students and young professionals are particularly transient and much less likely to be the head of a household than the general population. This is one of the reasons I focus on the CPS data rather than the Nielsen data. Still,

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[22] Kuhn and Skuterud (2004) also use the CPS Computer and Internet Use Supplements. They explore the effect of Internet job search on unemployment duration.

the weaknesses of the CPS and Nielsen data sets are in many ways opposite. Therefore, I conclude that if the same results hold in both then the results are likely independent of the weaknesses.

4.2 Variable Definitions

Internet use is defined in response to straightforward questions such as "Do you use the Internet at any location?" (CPS Sept. 2001 question). All surveys ask whether the respondent used a number of applications over the past year including email, chat, purchase, information (of various kinds), and free entertainment. I divide these into three broad categories: e-communication (email and chat), e-commerce (purchase), and e-information (information and free entertainment). The CPS survey also asks about school use, work use, job search, online banking, and online stock trading. I group the school use, work use, and job search together as e-work/study; and I group online banking and online stock trading together as e-finance. Most results in the nested model focus on e-communication, e-commerce, and e-information because the computational burden of including five applications is large, e-finance is not as widely used as other applications, and e-work/study is a vague category that likely encompasses the other categories such as e-communication. Table 2 shows summary statistics. In the 2001 CPS supplement, 54% of respondents had connected to the Internet, 21% used e-commerce, 47% used e-information, 45% used e-communication, 10% used e-finance, and 33% used the Internet for work or school.

The main independent variable of interest is whether the individual respondent was a student during the mid-1990s, the time period I hypothesize to be key to the diffusion of the Internet through universities. In the Nielsen data, this group of people is easy to identify. *Student 1995-97* is equal to one if the person was a student in 1995, 1996, or 1997. *Student 1995-99* is defined similarly. In the CPS data, however, I use an approximation to define whether an individual was a student in the relevant time period. I proxy this group as those individuals who attended college or university and were aged 18 to 22 at some point from 1993 to 1997. In other words, all individuals born between 1971 and 1979 who have a college or university education are included in this group. All regressions also include whether the individual has a college or university education and whether the individual was born between 1971 and

1979, creating a difference-in-difference identification of the effect of university attendance. The interaction variable therefore identifies whether the effect of postsecondary education on Internet use was particularly strong for the cohort that went to college or university in the mid-1990s. Table 2 shows that 6.4% of CPS respondents were born between 1971 and 1979 and have a college or university education.

The CPS data contain household level information. I include a variable for whether respondents live with somebody who was a student in the mid-1990s (and are not such former students themselves). 4.7% of respondents fit in this category. Many regressions also include controls for whether there is someone born from 1971 to 1979 in the household and whether there is someone with a post-secondary education in the household. This data allows me to investigate indirect transmission of the technology from the university to the general public through informal communication networks. These networks are difficult to identify. Chevalier and Mayzlin (2003) discuss the difficulties researchers face in measuring word-of-mouth effects. The data allow me to estimate the size of a particular type of word-of-mouth effect.

The CPS data also allow controls for race, income group, citizenship, metropolitan area, state, occupation, industry, employment status, gender, age, marital status, and whether the individual is currently enrolled in postsecondary education (*Current student*).[23] In most regressions with the CPS data, I include the variable *Child* which is equal to one if the individual is sixteen years old or younger. I choose this cut-off age as there are very few people in this age group who have any postsecondary education (16 total).

The Nielsen data allow controls for income group, metropolitan area, region, gender, age, number of other Internet users in the sample who live nearby (in the same Forward Sortation Area), and whether the individual is currently enrolled in postsecondary education (*Current student*).

The next two sections analyze this data. In Section 5, I show that college or university attendance had a particularly large effect on Internet use by people who attended school in the mid-1990s. I

[23] Occupations and industries are listed in the appendix.

eliminate Hypotheses 1 through 4 of Table 1 as complete explanations for this effect. In Section 6, I examine the reasons behind this effect with particular reference to Hypotheses 5 through 8.

5. Internet Adoption

5.1 Students in the Mid-1990s Became Leaders in Internet Adoption

Tables 3a and 3b show the coefficients and marginal effects, respectively, of the core results. These tables should be interpreted as a difference-in-difference. The coefficient on *Born 1971-79 and has postsecondary education* (in the first row) shows that post-secondary education has a particularly large effect on people in this age cohort. Model (1) presents the main regression; model (2) allows for a discrete jump in the effect of age for those born after 1979; model (3) controls for the characteristics of other household members; model (4) divides education into narrow categories; model (5) drops occupation and industry fixed effects; and model (6) drops children from the regression. The results do not change much regression to regression, although the marginal effect of having a postsecondary education for those in the cohort born from 1971 to 1979 varies between 2.0% and 5.2%.[24]

The models support Hypotheses 1 and 2; however, these are not complete explanations for the impact of school attendance in this time period. Hypothesis 1 states that people who were students in the mid-1990s are more likely to use the Internet because they are young and educated. The coefficients on age and education support this. Hypothesis 2 states that people who were students in the mid-1990s are more likely to use the Internet because they are in occupations and industries that demand Internet skills. The higher marginal effect on *Born 1971-79 and has postsecondary education* in model (5) relative to model (1) supports this. These hypotheses, however, only provide a partial explanation. The coefficient in the first row is always significantly positive.

[24] These marginal effects are based on the average levels of the covariates. For example, 44% of people without a postsecondary education who were born from 1971-79 adopt the Internet. Column (1) of Table 3b shows the marginal effect of postsecondary education to be 23% and the additional effect of education for the cohort born 1971-79 to be 2.5%. Therefore the probability of adoption for someone born 1971-79 with a post-secondary education will be 69.5%, all else equal. Since actual adoption rates are 83%, the remaining 13.5% must be due to other factors such as occupation, marital status, citizenship, etc.

Figure 5 splits the sample by age cohort using a spline. The exact coefficients are presented in Appendix Table A.1. Rather than assuming age and education have a constant effect for all age cohorts besides those born from 1971-79, this table presents different age and education effects for those born after 1979, those born 1960-70, those born 1950-59, those born 1940-49, those born 1930-39, those born 1920-29, and those born before 1920. The main results do not change from Table 3. The effect of education on Internet adoption for people born from 1971-79 is roughly 2% higher than for people born from 1960-70. Figure 5 illustrates marginal effect of postsecondary education by age cohort. It is highest for those born from 1971-79.

Figure 6 presents the marginal effects of education in a similar regression, where a separate coefficient is estimated for each age and for each interaction term of age and postsecondary education. The group highlighted by the box (age 22-30 in 2001) is the cohort of people that was born between 1971 and 1979. The marginal effect of education for this group is clearly higher than for the groups that immediately preceded and followed it. Above age 70, the marginal effects should be interpreted with caution due to large standard errors (there are few adopters and few who are educated in each year).

Table 4 shows that the result is robust to different definitions of the cohort that attended school in the mid-1990s, but does not extend to the cohort that would have left school before 1993.

Tables 5 and 6 present results using different data sets. Table 5 uses data from A.C. Nielsen Canada's *Internet Planner*. The advantage of this data set is that people who were students in the mid-1990s (1995-97) are accurately identified due to the panel nature of the data. The overall results do not change; however the marginal effect of going to university in the mid-1990s is more than 8%. This effect may be larger because people who attended school in the relevant period are more accurately identified. On the other hand, it may also be due to weaker demographic controls or the unusual characteristics of students in this data set.[25] Table 6 shows that the general results hold with the 1998 CPS Computer and Internet Use Supplement data.

[25] As mentioned earlier, all member of this data set are household heads who did not change residences.

Many of the other results are likely familiar to readers who have studied technology adoption (see for example Jimeniz and Greenstein 1998, Compaine 2001, and Clemente 1997). Young, wealthy, educated city dwellers are most likely to adopt the technology. The results also point to a large drop in the digital divide in education over time: the youngest cohorts don't experience it.

In summary, the effect of postsecondary education is especially important for the group that attended university in the mid-1990s. This effect is only partially explained by age, education, occupation, and industry controls.

5.2 Students in the Mid-1990s Transmitted Their Knowledge to People Living with Them

The teaching role of universities in the diffusion of the Internet goes beyond direct transmission to students. The regressions described above also show that adults living with people who were students during the relevant time period are more likely to use the Internet. For example in Table 3, row 2 shows the effect of having someone who was a student between 1993 and 1997 in the household. This secondary effect is nearly as large as the primary effect in model (1). In model (3), which controls separately for having someone born between 1971 and 1979 and for having someone with a postsecondary education in the household, the extra effect of having someone who has a postsecondary education and was born between 1971 and 1979 is especially large (close to 15%). In each model, the coefficient on having someone who likely attended university in the mid-1990s is positive and significant. In some cases, this indirect effect of universities on adoption is larger than the direct effect on former students.

Column 5 of table 3 suggests that Hypothesis 2 does not hold for people living with someone who attended university in the mid-1990s. While occupation and industry controls appear to reduce the direct relationship between university attendance during this period and Internet use, they do not appear to reduce the indirect effect of living with someone who attended university during this period.

5.3 Students in the Mid-1990s Were Not Leaders in Adopting Other Computer Technologies

The results presented in sections 5.1 and 5.2 do not apply to uses of computer technologies that are not Internet related. Figure 7 presents model (1) of Table 3 employing the usage of five different computer technologies as dependent variables: Internet use (“connect to the Internet”), “Do word processing or desktop publishing” at home or work, “Use spreadsheets or databases” at home or work, “Play games on the computer” at home, and “Use home computer to manage household records or finances”. Appendix Table A.2 presents the coefficients. What is striking about this figure is that there is no significant relationship between attendance at university in the mid-1990s and use of computer applications that are not Internet related. There is also no significant relationship between living with someone who attended university in the mid-1990s and use of computer applications that are not Internet related. Furthermore, the direct and indirect effects of university attendance in the mid-1990s are of a much larger magnitude than are the effects on other computer applications. Figure 7 suggests rejection of Hypotheses 3 and 4. Since people who attended university in the mid-1990s and those who live with them are not more likely than others to adopt computing technologies besides the Internet, it is unlikely that they are particularly technology-savvy (Hypothesis 3). Furthermore, Hypothesis 4, which states that the main effect of universities was to bring computers into these homes, is inconsistent with the finding that other uses of computers are not higher for these groups.

6. Separating Costs and Benefits of Internet Adoption

Table 7 presents the results of the nested diffusion regressions. The “Use Internet” rows show the results of coefficients on the propensity to adopt the Internet in general, controlling for benefits related to known application use. The application-specific rows show the coefficients on propensity to adopt each application. The variables of interest are labeled “Former student” and “Former student in HH”. The other variables in the regressions serve as controls. Table 7a shows results using only e-commerce, e-information, and e-communication. Models (1) and (2) show different specifications of the model using the 2001 CPS Supplement; model (3) includes controls for household composition; and model (4) shows results with the Nielsen data for 2000. In Table 7b, model (5) includes e-finance and e-work/study in addition to the applications used in Table 7a; model (6) includes e-finance but not e-work/study. The main qualitative results change little model-to-model.

The first ("Use Internet") row shows that, in all models, students in the mid-1990s are no more likely to use the Internet than others, controlling for application use. It is application net benefits that appear to drive the high probability of Internet use among this group. E-communication benefits are particularly important. Having been a student in the mid-1990s has a significant and positive effect on e-communication adoption in all models. This may be a result of building a network of people online while at school, or of somehow learning about the ease of online communication. These reasons cannot be separately identified with this data and methodology.

The results on the other applications are mixed. For e-commerce, the effect is positive and significant only when both marital status and employment status controls are included. Furthermore, the result is negative (though not significant) in the Nielsen data. For e-finance, the results are significant in model (5) but not model (6), although the coefficients are of similar magnitude. The results also suggest universities did not enable particularly large benefits to using e-information. The coefficient is only significantly positive in one of the six models, and then only at the 90% confidence level. It is negative (and insignificant) in two models.

Those who live with people who were students in the mid-1990s, however, are more likely to adopt the underlying technology than others, even controlling for application use. The coefficients on overall Internet use for this group (controlling for applications) are always significantly positive, while the coefficients for the applications are mixed. In general, however, no application stands out as giving this group a particularly large net benefit of use.

In summary, Table 7 suggests that people who were students in the mid-1990s gained tools that were complementary to Internet use. The high benefit of online communication suggests that the key direct role universities played in encouraging Internet usage was a network of other Internet users. Universities also played an indirect role. These former students then brought Internet use into their homes, reducing the underlying cost of adoption for those who lived with them. There are many possible explanations for this. Perhaps with a household member to show them how to use it, the complexity barrier was reduced. Alternatively, seeing the benefits of Internet use to a household member may have reduced observability or trialability barriers. Or maybe having a household member go through the process of setting up the wires reduced physical barriers to access. Choosing between these explanations is beyond the scope of this study.

7. Discussion and Conclusions

The correlation between university education and Internet adoption for those who attended university in the mid-1990s is much higher than for other cohorts. Furthermore, this relationship is driven by increased benefits of online applications, particularly online communication. This may be due to network effects, the effective teaching of email at universities, or some other underlying factor. The evidence on within-household transmission of the technology provides preliminary evidence that these students helped bridge the gap between the research community that had used the Internet until the mid-1990s and the rest of the population. This likely helped the technology to "cross the chasm" that Moore (1999) describes as the difficult process of diffusing a technology beyond early adopters and into the early majority segment of the population.

These results suggest that in addition to creating knowledge and educating the workforce, universities provide a conduit for new innovations to diffuse into society. This role links the other roles of universities together. The Internet is an example of disseminating research through teaching rather than through publications or industry relationships.

The role of higher education in diffusing technology has important implications for the digital divide and inequality.[26] Rogers (1995, pp. 125) asserts that "we often find that the diffusion of

[26] See Compaine (2001) for a detailed discussion on this topic

innovations widens the socioeconomic gap between the higher and lower status segments of a system." This gap will be exacerbated if an important mechanism of diffusion is the university.[27]

Many companies already appear to recognize the role of universities in teaching technology. For example, in 2001 Microsoft donated several million dollars to the University of Waterloo. As part of the agreement, the university agreed to start teaching Microsoft's C# programming language instead of Sun Microsystems' Java. Even though both parties were criticized widely in the Canadian media for the transaction, Microsoft likely hoped that University of Waterloo students would take the technology learned at school with them to their workplaces after they graduated (Restivo 2001). Similarly, Apple has a history since the late 1970s of generously donating its technology to the education system. Apple founder Steven Jobs has acknowledged that these donations were partly aimed at getting former students to demand Apple computers once they entered the workforce (Kheit 2003).

Marketers of other technologies should ask whether their products could be effectively integrated in a classroom setting. If a new technology can significantly increase the effectiveness of classroom teaching (e.g., through better communication or more effective learning techniques) then managers have an incentive to subsidize adoption of the technology in the classroom. Still, the negative press Microsoft received for its donation to the University of Waterloo shows that caution needs to be used in forcing students to adopt a new technology. A new technology in the classroom should not replace a competitor's equally valuable technology. The new technology needs to be both genuinely novel and useful.

Many questions about this third role of universities remain unanswered but are beyond the scope of this study. Did universities play a key role in diffusing other technologies? How important was the diffusion of the Internet through universities to economic growth in the 1990s? What are the most effective ways to diffuse technology through universities? Answering these questions will lead to a better understanding of the various roles universities play in the economy.

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[27] Preliminary evidence, however, suggests that in the case of the Internet the divide between the educated and uneducated will disappear over time. University education does not appear to be highly correlated with Internet use

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Appendix: Data Description

The 46 occupation fixed effects are from the CPS definitions of PRDTOCC1. They are defined as follows:

Administrators and Officials; Public Administration; Other Executive, Administrators, and Managers; Management Related Occupations; Engineers; Mathematical and Computer Scientists; Natural Scientists; Health Diagnosing Occupations; Health Assessment and Treating Occupations; Teachers, College and University; Teachers, Except College and University; Lawyers and Judges; Other Professional Specialty Occupations; Health Technologists and Technicians; Engineering and Science Technicians; Technicians, Except Health, Engineering and Science; Supervisors and Proprietors; Sales Occupations; Sales Representatives, Finance, and Business Service; Sales Representatives, Commodities, Except Retail; Sales Workers, Retail and Personal Services; Sales Related Occupations; Supervisors-Administrative Support; Computer Equipment Operators; Secretaries, Stenographers, and Typists; Financial Records, Processing Occupations; Mail and Message Distributing; Other Administrative Support Occupations, Including Clerical; Private Household Service Occupations; Protective Service Occupations; Food Service Occupations; Health Service Occupations; Cleaning and Building Service Occupations; Personal Service Occupations; Mechanics and Repairs; Construction Trades; Other Precision Production Occupations; Machine Operators and Tenders, Except Precision; Fabricators, Assemblers, Inspectors, and Samplers; Motor Vehicle Operators; Other Transportation Occupations and Material Moving; Construction Laborer; Freight, Stock, and Material Handlers; Other Handlers, Equipment Cleaners, and Laborers; Farm Operators and Managers; Farm Workers and Related Occupations; Forestry and Fishing Occupations; Armed Forces last job, currently unemployed; Armed Forces.

The 52 industry fixed effects are from the CPS definitions of PRDTIND1. They are defined as follows:

Agricultural Service; Other Agriculture; Mining; Construction;
Manufacturing (Durable Goods): Lumber and Wood Products, Except Furniture; Furniture and Fixtures; Stone Clay, Glass, and Concrete Product, Primary Metals, Fabricated Metal; Not Specified Metal Industries; Machinery, Except Electrical; Electrical Machinery, Equipment, and Supplies; Motor Vehicles and Equipment; Aircraft and Parts; Other Transportation Equipment; Professional and Photographic Equipment, and Watches; Toys, Amusements, and Sporting Goods; Miscellaneous and Not Specified Manufacturing Industries;
Manufacturing (Nondurable Goods): Food and Kindred Products; Tobacco Manufactures; Textile Mill Products; Apparel and Other Finished Textile Products; Paper and Allied Products; Printing, Publishing and Allied Industries; Chemicals and Allied Products; Petroleum and Coal Products; Rubber and Miscellaneous Plastics Products; Leather and Leather Products;
Transportation; Communications; Utilities and Sanitary Services; Wholesale Trade; Eating and Drinking Places; Other Retail Trade; Banking and Other Finance; Insurance and Real Estate; Private Household Services; Business Services; Repair Services; Personal Services, Except Private Household; Entertainment and Recreation Services; Hospitals; Health Services, Except Hospitals; Educational Services; Social Services; Other Professional Services; Forestry and Fisheries; Justice, Public Order and Safety; Administration of Human Resource Programs; National Security and Internet Affairs; Other Public Administration; Armed Forces last job, currently unemployed, Armed Forces.

Table 1: Competing hypotheses for why people who were students in the mid-1990s, and those who live with them, are more likely than others to use the Internet

Hypothesis	Source of evidence
1. They are younger and more educated.	Age and education controls.
2. They are in occupations and industries that demand Internet skills.	Occupation and industry controls.
3. They are particularly technology-savvy.	Comparison to similar technologies such as word processing and computer games.
4. They bought computers while in school and continue to own them. Consequently Internet use is less costly for them.	Comparison to similar technologies such as word processing and computer games.
5. They get a greater net benefit from the information available on the Internet.	See if the benefits to online information are particularly strong for these groups.
6.They are more likely to purchase products online and do online banking.	See if the benefits of online purchasing (e-commerce) are particularly strong for these groups.
7. They get a greater net benefit from online communication.	See if the communication benefits of the Internet are particularly strong for these groups.
8.They face lower costs to adoption than others.	See if the net benefits to Internet use are particularly strong for these groups, controlling for the net benefits of applications.

Table 2: Summary Statistics

	US Census CPS September 2001 Supplement data N=142,667		Nielsen data in 2000 N=5,519	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Born 1971-79 with postsecondary education	0.0639	0.245	0.0123	0.110
Born 1971-79 (Age 18-22 from 1993-97)	0.112	0.315	0.0205	0.142
Current student	0.0808	0.272	0.014	0.121
Born 1971-79 with postsec. education lives in the household	0.0468	0.211		
Someone born 1971-79 lives in the household	0.0779	0.268		
Someone with a post-sec. educ. lives in the household	0.281	0.449		
"Connect to the Internet" (home or work)	0.540	0.498	0.621	0.485
Use e-commerce (purchase products or services)	0.206	0.404	0.246	0.431
Use e-information (search, news, entertainment, etc.)	0.467	0.499	0.513	0.500
Use e-communication (email, instant messaging, chat)	0.448	0.497	0.550	0.497
Use e-finance (banking, stock trading)	0.0963	0.295		
Use e-work/study	0.328	0.470		
"Do word processing or desktop publishing" (home or work)	0.356	0.479		
"Use spreadsheets or databases" (home or work)	0.225	0.417		
"Play games on the computer" (home)	0.338	0.473		
"Use home computer to manage household records or finances"	0.115	0.320		
Computer in household	0.644	0.479	0.552	0.497
Income <US$20K	0.159	0.366		
Income US$20K-US$60K	0.394	0.489		
Income >US$60K	0.208	0.406		
US citizen	0.944	0.230		
Metropolitan area	0.755	0.430		
Employed	0.493	0.500		
Unemployed	0.0230	0.150		
Age	36.16	22.31	51.52	13.76
Child (16 and under)	0.247	0.431		
Female	0.516	0.500	0.500	0.500
Post-secondary education	0.382	0.486	0.519	0.500
High school diploma	0.247	0.431	0.136	0.343
Some college or university	0.141	0.348	0.209	0.406
College or university graduate	0.240	0.427	0.310	0.463
US Midwest	0.251	0.433		
US south	0.287	0.452		
US west	0.248	0.432		
White	0.841	0.366		
Black	0.104	0.305		
Married	0.434	0.496		
Never married	0.208	0.406		
Income C$30,000-C$69,999			0.486	0.500
Income >=C$70,000			0.210	0.407
Canadian west			0.351	0.477
Ontario			0.249	0.433
Quebec			0.280	0.449
Other users in FSA			6.53	4.93
# years in sample 95-99			3.45	1.47
Student 1995-97			0.0286	0.167
Student 1995-99			0.0466	0.211

Table 3a: Factors Driving Internet Use
(Probit coefficients—Standard errors in parentheses)

Dependent variable is "Connect to the Internet" (home or work)	Model (1)	Model (2)	Model (3)	Model (4)	No occupation or industry fixed effects (5)	Only people 17 & older included (6)
Born 1971-79 and has postsecondary education^	0.0674	0.0522	0.135	0.0856	0.119	0.0841
	(0.0259)**	(0.0261)*	(0.0261)**	(0.0261)**	(0.0251)**	(0.0261)**
In household with someone born 71-79 & educated	0.0668	0.0709	0.388	0.0545	0.0661	0.0461
	(0.0188)**	(0.0188)**	(0.0217)**	(0.0189)**	(0.0182)**	(0.0190)*
Born 1971-79	-0.0279	-0.00185	-0.167	-0.0526	-0.0639	-0.188
	(0.0190)	(0.0208)	(0.0195)**	(0.0192)**	(0.0186)**	(0.0193)**
Age	-0.0134	-0.0128	-0.0150	-0.01400751	-0.0127	-0.0245
	(0.000331)**	(0.000393)**	(0.000337)**	(0.000334)**	(0.000324)**	(0.000396)**
Postsecondary education	0.612	0.629	0.687		0.802	0.612
	(0.0104)**	(0.0108)**	(0.0112)**		(0.00964)**	(0.0106)**
Child	0.0602	0.101	-0.00154	0.307	0.148	
	(0.0206)**	(0.0251)**	(0.0209)	(0.0225)**	(0.0202)**	
Household income <US$20K#	-0.437	-0.435	-0.365	-0.409	-0.493	-0.442
	(0.0128)**	(0.0129)**	(0.0132)**	(0.0130)**	(0.0126)**	(0.0155)**
Household income US$20K-US$60K#	-0.0296	-0.0294	-0.00709	-0.0248	-0.0511	-0.0242
	(0.00957)**	(0.00957)**	(0.00966)	(0.00961)**	(0.00932)**	(0.0113)*
Household income >US$60K#	0.374	0.373	0.326	0.365	0.427	0.424
	(0.0120)**	(0.0120)**	(0.0121)**	(0.0120)**	(0.0116)**	(0.0149)**
Student	0.971	0.965	0.308	1.05	0.964	0.710
	(0.0187)**	(0.0195)**	(0.00478)**	(0.0189)**	(0.0185)**	(0.0231)**
Employed##	0.281	0.281	0.284	0.278	0.603	0.230
	(0.0413)**	(0.0413)**	(0.0415)**	(0.0416)**	(0.0103)**	(0.0446)**
Unemployed##	0.202	0.196	0.194	0.211	0.442	0.131
	(0.0455)**	(0.0455)**	(0.0457)**	(0.0457)**	(0.0257)**	(0.0493)**
US citizen	0.391	0.390	0.355	0.351	0.517	0.526
	(0.0177)**	(0.0177)**	(0.0179)**	(0.0181)**	(0.0167)**	(0.0195)**
Female	0.0411	0.0427	0.0403	0.0353	0.12224389	0.0182
	(0.00837)**	(0.00838)**	(0.00843)**	(0.00841)**	(0.00750)**	(0.0107)+
Married###	0.266	0.269	0.260	0.240	0.258	0.184
	(0.0118)**	(0.0119)**	(0.0118)**	(0.0119)**	(0.0114)**	(0.0127)**
Never married###	0.140	0.134	0.119	0.122	0.0992	-0.0679
	(0.0150)**	(0.0151)**	(0.0151)**	(0.0151)**	(0.0145)**	(0.0168)**
White####	0.0556	0.0550	0.0512	0.0671	0.0521	0.0662
	(0.0180)**	(0.0180)**	(0.0181)**	(0.0181)**	(0.0162)**	(0.0222)**
Black####	-0.287	-0.288	-0.2847	-0.270	-0.320	-0.370
	(0.0216)**	(0.0216)**	(0.0217)**	(0.0217)**	(0.0195)**	(0.0268)**
Metropolitan area	0.0538	0.0541	0.0492	0.0507	0.0398	0.0990
	(0.0101)**	(0.0101)**	(0.0102)**	(0.0102)**	(0.00874)**	(0.0122)**
Born 1980-84		0.100				
		(0.0260)**				
Born 1980-84 and has postsecondary education		-0.197				
		(0.0393)**				
High school diploma##				0.425		
				(0.0145)**		
Some college or university##				0.778		
				(0.0167)**		
College or university graduate ##				1.06		
				(0.0165)**		
Someone born 1971-79 lives in the household			-0.527			
			(0.0130)**			
Someone with postsec. educ. lives in the household			0.243			
			(0.0105)**			
N	142,667	142,667	142,667	142,667	142,667	107,361
Log likelihood	-73,754	-73,739	-72,535	-73,121	-77,098	-49.966

+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include a constant and state, industry, and occupation fixed effects.
^I sometimes refer to this group as "Former Students" in the text. They are in the age cohort that attended university from 1993-97.
#Base=refused to answer; ##Base=out of labor force; ###Base=widowed, divorced, or separated; ####Base=Other

Table 3b: Factors Driving Internet Use
(Marginal effects—Standard errors in parentheses)

Dependent variable is "Connect to the Internet" (home or work)	Model (1)	Model (2)	Model (3)	Model (4)	No occupation or industry fixed effects (5)	Only people 17 & older included (6)
Born 1971-79 and has	0.0264	0.0205	0.0524	0.0335	0.0466	0.0322
postsecondary education^	(0.0101)**	(0.0102)*	(0.0100)**	(0.0101)**	(0.00972)**	(0.00990)**
In household with someone	0.0262	0.0278	0.146	0.0214	0.0260	0.0177
born 71-79 & educated	(0.00732)**	(0.00733)**	(0.00758)**	(0.00738)**	(0.00712)**	(0.00728)*
Born 1971-79	-0.0110	-0.000727	-0.0662	-0.0208	-0.0253	-0.0735
	(0.00750)	(0.00817)	(0.00777)**	(0.00760)**	(0.00738)**	(0.00763)**
Age	-0.00526	-0.00505	-0.00592	-0.00552	-0.00501	-0.00949
	(0.000130)**	(0.000155)**	(0.000133)**	(0.000132)**	(0.000128)**	(0.000154)**
Postsecondary education	0.234	0.240	0.261		0.304	0.234
	(0.00379)**	(0.00394)**	(0.00402)**		(0.00340)**	(0.00393)**
Child	0.0236	0.0395	-0.000607	0.118	0.0581	
	(0.00806)**	(0.00976)**	(0.00823)	(0.00847)**	(0.00788)**	
Household income	-0.173	-0.172	-0.145	-0.162	-0.1953	-0.174
<US$20K[#]	(0.00502)**	(0.00502)**	(0.00518)**	(0.00508)**	(0.00483)**	(0.00611)**
Household income	-0.0116	-0.0116	-0.00279	-0.00976	-0.0202	-0.00939
US$20K-US$60K[#]	(0.00377)**	(0.00377)**	(0.00380)	(0.00379)**	(0.00369)**	(0.00438)*
Household income	0.143	0.143	0.125	0.140	0.163	0.157
>US$60K[#]	(0.00439)**	(0.00439)**	(0.00449)**	(0.00442)**	(0.00422)**	(0.00516)**
Student	0.320	0.319	0.870	0.339	0.324	0.240
	(0.00453)**	(0.00475)**	(0.0196)**	(0.00433)**	(0.00464)**	(0.00631)**
Employed[##]	0.110	0.110	0.111	0.109	0.235	0.0897
	(0.0161)**	(0.0161)**	(0.0162)**	(0.0162)**	(0.00391)**	(0.0174)**
Unemployed[##]	0.0777	0.0756	0.0748	0.0813	0.165	0.0500
	(0.0170)**	(0.0170)**	(0.0172)**	(0.0171)**	(0.00878)**	(0.0184)**
US citizen	0.155	0.155	0.141	0.139	0.203	0.207
	(0.00691)**	(0.00691)**	(0.00703)**	(0.00711)**	(0.00629)**	(0.00755)**
Female	0.0162	0.0168	0.0159	0.0139	0.0483	0.00705
	(0.00329)**	(0.00330)**	(0.00332)**	(0.00331)**	(0.00296)**	(0.00414)+
Married[###]	0.104	0.105	0.102	0.0939	0.102	0.0713
	(0.00456)**	(0.00460)**	(0.00458)**	(0.00461)**	(0.00446)**	(0.00494)**
Never married[###]	0.0547	0.0521	0.0465	0.0476	0.0390	-0.0264
	(0.00579)**	(0.00585)**	(0.00585)**	(0.00586)**	(0.00569)**	(0.00654)**
White[####]	0.0219	0.0217	0.0202	0.0265	0.0206	0.0258
	(0.00711)**	(0.00711)**	(0.00716)**	(0.00716)**	(0.00643)**	(0.00869)**
Black[####]	-0.114	-0.114	-0.113	-0.107	-0.127	-0.146
	(0.00856)**	(0.00856)**	(0.00862)**	(0.00862)**	(0.00770)**	(0.0106)**
Metropolitan area	0.0212	0.0213	0.0194	0.0200	0.0157	0.0385
	(0.00400)**	(0.00400)**	(0.00403)**	(0.00402)**	(0.00346)**	(0.00477)**
Born 1980-84		0.0391				
		(0.0100)**				
Born 1980-84 and has		-0.0781				
postsecondary education		(0.0157)**				
High school diploma[##]				0.163		
				(0.00531)**		
Some college or				0.276		
university[##]				(0.00504)**		
College or university				0.370		
graduate [##]				(0.00479)**		
Someone born 1971-79			-0.208			
lives in the household			(0.00497)**			
Someone with postsec. educ.			0.0944			
lives in the household			(0.00404)**			
N	142,667	142,667	142,667	142,667	142,667	107,361
Log likelihood	-73,754	-73,739	-72,535	-73,121	-77,098	-49.966

+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include a constant and state, industry, and occupation fixed effects.
^I sometimes refer to this group as "Former Students" in the text. They are in the age cohort that attended university from 1993-97.
[#]Base=refused to answer; [##]Base=out of labor force; [###]Base=widowed, divorced, or separated; [####]Base=Other

Table 4: Comparison of different definitions of the key age cohort
(Standard errors in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)
	Born 1971-79	Born 1972-76	Born 1974-77	Born 1970-79	Born 1960-67	Born 1960-70
COEFFICIENTS						
In key age cohort and has postsecondary education	0.135	0.0964	0.117	0.0874	-0.00959	0.0302
	(0.0261)**	(0.0291)**	(0.0373)**	(0.0246)**	(0.0247)	(0.0224)
In key age cohort	-0.167	-0.122	-0.100	-0.0757	0.135	0.119
	(0.0195)**	(0.0212)**	(0.0264)**	(0.0184)**	(0.0175)**	(0.0161)**
MARGINAL EFFECTS						
In key age cohort and has postsecondary education	0.0524	0.0377	0.0455	0.0342	-0.00378	0.0119
	(0.0100)**	(0.0112)**	(0.0144)**	(0.00955)**	(0.00975)	(0.00878)
In key age cohort	-0.0662	-0.0482	-0.0397	-0.0299	0.0525	0.0466
	(0.00777)**	(0.00845)**	(0.0105)**	(0.00731)**	(0.00672)**	(0.006225)**
N	142,667	142,667	142,667	142,667	142,667	142,667
Log likelihood	-72,535	-72,700	-72,904	-72,705	-73,318	-73,288

+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include a constant and state, industry, and occupation fixed effects. Regressions also include the variables: Age, Postsecondary Education, Child, Household Income <US$20K, Household Income US$20K-US$60K, Household Income >US$60K, student, employed, unemployed, US Citizen, Female, Married, Never Married, White, Black, Someone born in cohort lives in the household, Someone with postsecondary education lives in the household, and Metropolitan Area.

Table 5: Probit Regressions using the Nielsen data

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Year=2000$ Coefficients	Year=2000$ Marginal Effects	Year=2000$ Coefficients	Year=2000$ Marginal Effects	Year=2000$ Coefficients	Year=1998$$ Coefficients
Student 1995-97	0.235	0.0835			0.232	0.319
	(0.116)*	(0.0387)*			(0.116)*	(0.0882)**
Student 1995-99			0.316	0.110		
			(0.0953)**	(0.0305)**		
Number of other users in FSA	0.0135	0.00501	0.0133	0.00495	0.0135	0.0166
	(0.00387)**	(0.00144)**	(0.00388)**	(0.00144)**	(0.00387)**	(0.00416)**
Current student	0.545	0.176	0.476	0.157	0.535	0.430
	(0.208)**	(0.0551)**	(0.213)*	(0.0598)**	(0.208)*	(0.131)**
Personal income C$30-C$69K#	0.402	0.148	0.406	0.150	0.404	0.401
	(0.0422)**	(0.0154)**	(0.0423)**	(0.0154)**	(0.0422)**	(0.0387)**
Personal income > C$70K#	0.938	0.298	0.945	0.299	0.940	0.84
	(0.0585)**	(0.0147)**	(0.0586)**	(0.0147)**	(0.0585)**	(0.0497)**
Postsecondary education	0.451	0.167	0.449	0.166	0.661	0.441
	(0.0379)**	(0.0139)**	(0.0379)**	(0.0139)**	(0.147)**	(0.0355)**
Age	-0.470	-0.175	-0.463	-0.172	-0.434	-0.266
	(0.0261)**	(0.00973)**	(0.0263)**	(0.00979)**	(0.0354)**	(0.0182)**
Age*Post-secondary educ.					-0.0744	
					(0.0505)	
Canadian west##	0.271	0.0990	0.269	0.0983	0.270	0.0497
	(0.0612)**	(0.0219)**	(0.0613)**	(0.0219)**	(0.0612)**	(0.0571)
Ontario##	0.323	0.116	0.325	0.116	0.321	0.127
	(0.0662)**	(0.0227)**	(0.0663)**	(0.0227)**	(0.0662)**	(0.0596)*
Quebec##	0.0188	0.00698	0.0197	0.00733	0.0191	-0.199
	(0.0633)	(0.0235)	(0.0634)	(0.0235)	(0.0633)	(0.0602)**
Female	-0.0441	-0.0164	-0.0424	-0.0158	-0.0432	-0.0790
	(0.0376)	(0.0140)	(0.0376)	(0.0140)	(0.0376)	(0.0339)*
Constant	0.880		0.790		0.777	-0.0498
	(0.105)**		(0.125)**		(0.125)**	(0.0877)
N	5,519	5,519	5,519	5,519	5,519	6,356
Log likelihood	-3,074	-3,074	-3,082	-3,082	-3,081	-3,881

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

$includes dummy variables on whether have data on the individuals for 1995, 1996, 1997, 1998, and 1999.

$$includes dummy variables on whether have data on the individuals for 1995, 1996, and 1997.

#Base=income<C$30K; ##Base=Atlantic Canada

Table 6: Comparison with 1998 CPS Data
(Probit coefficients—Standard errors in parentheses)

	(1)	(2)	(3)	(4)
Dependent variable is "Connect to the Internet" (home or work)	2001 CPS Data Coefficients	2001 CPS Data Marginal Effects	1998 CPS Data Coefficients	1998 CPS Data Marginal Effects
Born 1971-79 and has postsecondary education^	0.0674	0.0264	0.0878	0.0317
	(0.0259)**	(0.0101)**	(0.0275)**	(0.0101)**
In household with someone born 71-79 & educated	0.0668	0.0262	0.299	0.111
	(0.0188)**	(0.00732)**	(0.0164)**	(0.00639)**
Born 1971-79	-0.0279	-0.0110	-0.161	-0.0553
	(0.0190)	(0.00750)	(0.0215)**	(0.00711)**
Age	-0.0134	-0.00526	-0.0110	-0.00389
	(0.000331)**	(0.000130)**	(0.000379)**	(0.000134)**
Postsecondary education	0.612	0.234	0.485	0.177
	(0.0104)**	(0.00379)**	(0.0113)**	(0.00417)**
Child	0.0602	0.0236	0.427	0.156
	(0.0206)**	(0.00806)**	(0.0257)**	(0.00952)**
Household income <US$20K#	-0.437	-0.173	-0.0586	-0.0206
	(0.0128)**	(0.00502)**	(0.0153)**	(0.00535)**
Household income US$20K-US$60K#	-0.0296	-0.0116	0.406	0.146
	(0.00957)**	(0.00377)**	(0.0125)**	(0.00450)**
Household income >US$60K#	0.374	0.143	0.926	0.348
	(0.0120)**	(0.00439)**	(0.0137)**	(0.00507)**
Student	0.971	0.320	0.607	0.234
	(0.0187)**	(0.00453)**	(0.0277)**	(0.0110)**
Employed##	0.281	0.110	-0.523	-0.194
	(0.0413)**	(0.0161)**	(0.0242)**	(0.00919)**
Unemployed##	0.202	0.0777	-0.484	-0.149
	(0.0455)**	(0.0170)**	(0.0371)**	(0.00944)**
US citizen	0.391	0.155	0.0484	0.0170
	(0.0177)**	(0.00691)**	(0.0196)*	(0.00679)*
Female	0.0411	0.0162	0.0652	0.0232
	(0.00837)**	(0.00329)**	(0.00887)**	(0.00315)**
Married###	0.266	0.104	0.0967	0.0340
	(0.0118)**	(0.00456)**	(0.0138)**	(0.00482)**
Never married###	0.140	0.0547	0.281	0.103
	(0.0150)**	(0.00579)**	(0.0176)**	(0.00665)**
White####	0.0556	0.0219	0.721	0.227
	(0.0180)**	(0.00711)**	(0.0155)**	(0.00412)**
Black####	-0.287	-0.114	0.277	0.103
	(0.0216)**	(0.00856)**	(0.0208)**	(0.00802)**
Metropolitan area	0.0538	0.0212	0.0869	0.0305
	(0.0101)**	(0.00400)**	(0.0108)**	(0.00375)**
N	142,667	142,667	135,977	135,977
Log likelihood	-73,754	-73,754	-66,993	-66,993

+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include a constant and state, industry, and occupation fixed effects.
^I sometimes refer to this group as "Former Students" in the text. They are in the age cohort that attended university from 1993-97.
#Base=refused to answer; ##Base=out of labor force; ###Base=widowed, divorced, or separated; ####Base=Other

Table 7a: Nested Diffusion Regressions (Standard errors in parentheses)

Nest	Variable	(1)	(2)	(3)	(4)-Nielsen (2000)^^
Use Internet	Former student^	-0.00529 (0.116)	-0.0993 (0.0939)**	0.0289 (0.108)	0.359 (0.221)
	Former student in HH^	0.0431 (0.00795)**	0.127 (0.0117)**	0.620 (0.0810)**	
	Student	1.03 (0.0521)**	1.14 (0.0116)**	1.04 (0.0525)**	0.00214 (0.221)
	Born 1971-79	-0.336 (0.0765)**	-0.0504 (0.00925)**	-0.321 (0.0813)**	
	Postsec. education	0.715 (0.0397)**	0.813 (0.00418)**	0.876 (0.0360)**	0.699 (0.174)**
	Age	-0.0230 (0.000626)**	-0.0148 (3.15E-05)**	-0.0189 (0.000586)**	-0.0517 (0.00634)**
	HH inc. <US$20K#	-0.518 (0.0365)**	-0.492 (0.00344)**	-0.404 (0.0377)**	
	HH inc. US$20-60K#	-0.0155 (0.0161)	0.0161 (0.000199)**	0.0334 (0.0210)	0.125 (0.194)
	HH inc. >US$60K#	0.364 (0.0364)**	0.377 (0.0134)**	0.261 (0.0387)**	0.925 (0.253)**
	Child		0.520 (0.00101)**	0.412 (0.0193)**	
	Born 1971-79 in HH			-0.763 (0.0425)**	
	Postsec educ. in HH			0.250 (0.0201)**	
	E-commerce	-5.40 (0.522)**	-7.57 (0.957)**	-7.80 (0.923)**	-86.4 (35.46)**
	E-information	592.1 (5.75)**	658.0 (3.21)**	638.7 (2.02)**	95.53 (1.42)**
	E-communication	879.0 (7.16)**	11,934 (3.12)**	1,368.4 (2.61)**	28.85 (4.75)**
Use E-Commerce	Former student^	-0.000743 (0.0501)	0.199 (0.0436)**	0.252 (0.0495)**	-0.234 (0.205)
	Former student in HH^	0.135 (0.0327)**	0.0399 (0.0302)	0.255 (0.0467)**	
	Student	0.222 (0.0268)**	-0.0997 (0.0256)**	-0.113 (0.0303)**	0.0242 (0.247)
	Born 1971-79	0.548 (0.0425)**	0.0792 (0.0356)*	0.00973 (0.0436)	
	Postsec. education	0.801 (0.0194)**	0.604 (0.0108)**	0.635 (0.0221)**	0.333 (0.0730)**
	Age	0.0158 (0.000566)**	-0.000881 (0.000288)**	-0.00119 (0.000649)+	-0.00950 (0.00254)**
	HH inc. <US$20K#	-0.354 (0.0346)**	-0.347 (0.0338)**	-0.331 (0.0334)**	
	HH inc. US$20-60K#	-0.109 (0.0203)**	-0.0985 (0.00665)**	-0.0950 (0.0130)**	0.521 (0.0966)**
	HH inc. >US$60K#	0.402 (0.0212)**	0.420 (0.0121)**	0.413 (0.0192)**	0.702 (0.0942)**
	Employed##	0.600 (0.0185)**	0.212 (0.00957)**	0.215 (0.0113)**	
	Unemployed##	0.552 (0.0527)**	0.152 (0.0486)**	0.153 (0.0512)**	
	Married###		0.245 (0.00844)**	0.242 (0.0223)**	
	Never married###		0.175 (0.0186)**	0.169 (0.0272)**	
	Child		-1.37 (0.0275)**	-1.40 (0.0361)**	
	Born 1971-79 in HH			-0.276 (0.0400)**	
	Postsec educ. in HH			0.0869 (0.0260)**	
Use E-Information	Former student^	-0.0262 (0.0711)	0.106 (0.0556)+	0.125 (0.0775)	-0.253 (0.228)
	Former student in HH^	0.119 (0.0420)**	0.0480 (0.0507)	0.132 (0.0613)*	
	Student	0.295 (0.0239)**	0.162 (0.0248)**	0.151 (0.0331)**	-0.292 (0.281)
	Born 1971-79	0.588 (0.0454)**	0.191 (0.0410)**	0.162 (0.0601)**	
	Postsec. education	0.652 (0.0258)**	0.504 (0.0239)**	0.524 (0.0283)**	0.0253 (0.0933)
	Age	0.00792 (0.000653)**	-0.00657 (0.000482)**	-0.00677 (0.000705)**	-0.00521 (0.00359)
	HH inc. <US$20K#	-0.246 (0.0379)**	-0.248 (0.0319)**	-0.232 (0.0368)**	
	HH inc. US$20-60K#	0.0145 (0.0240)	0.0116 (0.0126)	0.0159 (0.0241)	0.297 (0.110)**
	HH inc. >US$60K#	0.270 (0.0237)**	0.281 (0.0170)**	0.274 (0.0291)**	0.465 (0.132)**
	Female	-0.316 (0.0199)**			-0.0155 (0.0880)
	Metropolitan area	-0.0801 (0.0200)**	-0.0637 (0.0179)**	-0.0639 (0.0213)**	
	White		0.264 (0.00422)**	0.260 (0.0232)**	
	Child		-0.769 (0.0137)**	-0.783 (0.0318)**	
	Born 1971-79 in HH			-0.119 (0.0393)**	
	Postsec educ. in HH			0.0528 (0.0272)+	
Use E-Communication	Former student^	0.250 (0.0629)**	0.389 (0.0570)**	0.409 (0.0634)**	0.559 (0.308)+
	Former student in HH^	0.167 (0.0245)**	0.0621 (0.0443)	0.138 (0.0398)**	
	Student	0.970 (0.0253)**	0.850 (0.0246)**	0.822 (0.0334)**	0.524 (0.410)
	Born 1971-79	0.476 (0.0435)**	0.0805 (0.0430)+	0.0361 (0.0453)	
	Postsec. education	0.715 (0.0218)**	0.549 (0.00883)**	0.564 (0.0261)**	0.168 (0.107)
	Age	0.0250 (0.000540)**	0.0106 (1.64E-05)**	0.00955 (0.000502)**	0.0113 (0.00435)**
	HH inc. <US$20K#	-0.201 (0.0150)**	-0.305 (0.00694)**	-0.221 (0.0114)**	
	HH inc. US$20-60K#	-0.156 (0.0177)**	-0.166 (0.0110)**	-0.163 (0.0195)**	0.434 (0.130)**
	HH inc. >US$60K#	0.303 (0.0164)**	0.334 (0.0207)**	0.326 (0.0233)**	0.675 (0.155)**
	US citizen	0.0430 (0.0255)+	0.0737 (0.00202)**	0.132 (0.0142)**	
	White	0.227 (0.0131)**			
	Female		0.148 (0.0150)**	0.144 (0.00745)**	-0.0721 (0.108)
	Child		-0.791 (0.00578)**	-0.805 (0.00274)**	
	Born 1971-79 in HH			-0.107 (0.00257)**	
	Postsec educ. in HH			0.0286 (0.0178)	
	Log likelihood	-123,754	-122,731	-122,518	5,483.1
	N	142,667	142,667	142,667	5,519

+ significant at 10%; * significant at 5%; ** significant at 1%; ^Former student means born 1971-79 and has post-secondary education; ^^For Nielsen data Income is C$30-69K and >=C$70K with base of <C$30K, "Former student" means student at some point from 1995-97.
#Base=refused to answer; ##Base=out of labor force; ###Base=widowed, divorced, or separated; all nests of each regression include a constant

Table 7b: Nested Diffusion Regressions (Standard errors in parentheses, N=142,667)

Nest	Variable	(5)	(6)
Use Internet	Former student^	-0.150 (0.134)	0.147 (0.102)
	Former student in household^	0.175 (0.0846)*	0.0847 (0.0140)**
	Student	0.407 (0.0843)**	0.943 (0.0116)**
	Born 1971-79	-0.0661 (0.0755)	-0.513 (0.00793)**
	Postsecondary education	0.585 (0.0457)**	0.647 (0.00602)**
	Age	-0.0165 (0.000514)**	-0.0260 (0.00374)**
	Household inc. <US$20K[#]	-0.674 (0.0385)**	-0.551 (0.00735)**
	Household inc. US$20-60K[#]	-0.0919 (0.000123)**	-0.0395 (0.000608)**
	Household inc. >US$60K[#]	0.346 (0.0397)**	0.302 (0.0102)**
	Child	-0.0256 (0.000321)**	-0.0864 (0.00114)**
	Constant	-2.91 (0.00653)**	-1.85 (0.000227)**
	E-commerce	-12.93 (1.92)**	-7.42 (1.05)**
	E-information	23,784 (0.342)**	83.59 (2.31)**
	E-communication	39,653 (0.121)**	144.7 (1.70)**
	E-finance	-53,138 (0.545)**	-65.02 (0.521)**
	E-work/study	130,157 (0.153)**	
Use E-Commerce	Former student^	0.209 (0.0497)**	0.197 (0.225)
	Former student in household^	0.0729 (0.0326)*	0.0507 (0.372)
	Student	-0.103 (0.0324)**	-0.189 (0.157)
	Born 1971-79	0.0783 (0.0436)+	0.0699 (0.0146)
	Postsecondary education	0.602 (0.0198)**	0.612 (0.148)**
	Age	-0.000762 (0.000712)	-0.00243 (0.00116)*
	Household inc. <US$20K[#]	-0.352 (0.0342)**	-0.364 (-0.158)*
	Household inc. US$20-60K[#]	-0.100 (0.0187)**	-0.0981 (0.0489)*
	Household inc. >US$60K[#]	0.424 (0.0202)**	0.425 (0.0550)**
	Employed[##]	0.219 (0.0214)**	
	Unemployed[##]	0.151 (0.0535)**	
	Married[###]	0.230 (0.0244)**	0.254 (0.0735)**
	Never Married[###]	0.174 (0.0297)**	0.192 (0.116)+
	Child	-1.37 (0.0423)**	-1.55 (0.169)**
	Constant	-1.02 (0.0453)**	-0.797 (0.149)**
Use E-Information	Former student^	0.107 (0.0711)	0.125 (0.102)
	Former student in household^	0.0379 (0.0445)	0.0177 (0.383)
	Student	0.161 (0.0321)**	0.162 (0.120)
	Born 1971-79	0.191 (0.0510)**	0.179 (0.126)
	Postsecondary education	0.497 (0.0256)**	0.494 (0.0749)**
	Age	-0.00607 (0.000746)**	-0.00655 (0.00118)**
	Household inc. <US$20K[#]	-0.279 (0.0335)**	-0.226 (0.198)
	Household inc. US$20-60K[#]	0.00767 (0.0226)	0.0186 (0.0795)
	Household inc. >US$60K[#]	0.292 (0.0267)**	0.271 (0.180)
	US citizen		-0.328 (0.0954)
	Metropolitan area	-0.0856 (0.0204)**	0.267 (0.123)*
	Child	-0.769 (0.0317)**	-0.793 (0.0963)**
	Constant	2.00 (0.0421)**	1.91 (0.0875)**
	Log likelihood	-197,027	-154,371
Use E-Communication	Former student^	0.388 (0.0630)**	0.395 (0.179)*
	Former student in household^	0.0606 (0.0434)	0.0464 (0.588)
	Student	0.848 (0.0319)**	0.863 (0.126)**
	Born 1971-79	0.0784 (0.0467)+	0.0874 (0.0974)
	Postsecondary education	0.550 (0.0246)**	0.543 (0.0610)**
	Age	0.0105 (0.000702)**	0.0111 (0.00280)**
	Household inc. <US$20K[#]	-0.305 (0.0205)**	-0.340 (0.0716)**
	Household inc. US$20-60K[#]	-0.166 (0.0216)**	-0.162 (-0.0683)*
	Household inc. >US$60K[#]	0.335 (0.0258)**	0.331 (0.0817)**
	Child	-0.789 (0.0289)**	-0.795 (0.109)**
	Constant	1.06 (0.0336)**	1.05 (0.0975)**
	Female	0.148 (0.0161)**	0.0622 (0.0489)
	White		0.0194 (0.0324)
Use E-Finance	Former student^	0.229 (0.0622)***	0.227 (0.155)
	Former student in household^	0.00223 (0.0379)	0.000134 (0.719)
	Student	-0.714 (0.0404)***	-0.601 (0.0770)**
	Born 1971-79	0.0585 (0.0567)	0.0844 (0.0407)*
	Postsecondary education	0.681 (0.0251)***	0.668 (0.129)**
	Age	-0.00582 (0.000764)***	-0.00407 (0.00155)**
	Household inc. <US$20K[#]	-0.364 (0.0463)***	-0.331 (0.210)
	Household inc. US$20-60K[#]	-0.157 (0.0240)***	-0.155 (0.142)
	Household inc. >US$60K[#]	0.391 (0.0248)***	0.383 (0.0762)**
	Employed[##]		0.227 (0.0759)**
	Unemployed[##]		0.105 (0.239)
	US citizen	-0.321 (0.0405)***	
	Child	-3.62 (0.114)***	-3.41 (0.301)**
	Constant	-1.22 (0.0509)***	-1.79 (0.0957)**
Use E-Work/Study	Former student^	0.338 (0.0273)***	
	Former student in household^	0.00362 (0.00359)	
	Student	0.914 (0.0235)***	
	Born 1971-79	-5.48E-05 (0.000501)	
	Postsecondary education	0.458 (0.0118)***	
	Age	-1.64E-06 (8.64E-06)	
	Household inc. <US$20K[#]	-8.03E-06 (0.000262)	
	Household inc. US$20-60K[#]	5.84E-06 (0.000187)	
	Household inc. >US$60K[#]	0.223 (0.0147)***	
	White	-0.0390 (0.000362)***	
	Child	0.409 (0.0142)***	
	Constant	0.0392 (0.000523)***	

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

^Former student means born 1971-79 and has post-secondary education.

[#]Base=refused to answer; [##]Base=out of labor force; [###]Base=widowed, divorced, or separated

Appendix Table A.1: Spline regression results
(Standard errors in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Born 1971-79 and has	0.708	0.249	0.845	0.288	0.820	0.281
postsecondary education^	(0.0242)**	(0.00706)**	(0.0244)**	(0.00648)**	(0.0244)**	(0.00660)**
Born 1980-89 and has	0.271	0.103	0.439	0.163		
postsecondary education	(0.0353)**	(0.0129)**	(0.0359)**	(0.0121)**		
Born 1980-84 and has					0.532	0.194
postsecondary education					(0.0383)**	(0.0122)**
Born 1960-70 and has	0.637	0.230	0.719	0.256	0.700	0.250
postsecondary education^^	(0.0199)**	(0.00623)**	(0.0203)**	(0.00607)**	(0.0202)**	(0.00613)**
Born 1950-59 and has	0.576	0.210	0.674	0.241	0.654	0.236
postsecondary education	(0.0202)**	(0.00655)**	(0.0207)**	(0.00637)**	(0.0207)**	(0.00644)**
Born 1940-49 and has	0.624	0.224	0.727	0.255	0.711	0.251
postsecondary education	(0.0231)**	(0.00714)**	(0.0235)**	(0.00681)**	(0.0236)**	(0.00689)**
Born 1930-39 and has	0.689	0.241	0.780	0.267	0.767	0.263
postsecondary education	(0.0284)**	(0.00818)**	(0.0287)**	(0.00772)**	(0.0287)**	(0.00781)**
Born 1920-29 and has	0.674	0.236	0.755	0.259	0.741	0.256
postsecondary education	(0.0366)**	(0.0106)**	(0.0368)**	(0.00998)**	(0.0368)**	(0.0101)**
Born before 1920 and has	0.476	0.175	0.560	0.202	0.540	0.196
postsecondary education	(0.0724)**	(0.0237)**	(0.0725)**	(0.0226)**	(0.0726)**	(0.0229)**
Born 1971-79	1.53	0.441	1.45	0.429	1.24	0.391
	(0.0515)**	(0.00825)**	(0.0518)**	(0.00898)**	(0.0519)**	(0.0108)**
Born 1980-89	2.12	0.533	2.09	0.531		
	(0.0497)**	(0.00549)**	(0.0501)**	(0.00568)**		
Born 1980-84					1.57	0.428
					(0.0531)**	(0.00690)**
Born 1990-2001	1.174	0.388	1.18	0.392		
	(0.0488)**	(0.0120)**	(0.0494)**	(0.0121)**		
Child					1.54	0.495
					(0.0491)**	(0.0112)**
Born 1960-70	1.43	0.443	1.44	0.447	1.32	0.421
	(0.0505)**	(0.0102)**	(0.0507)**	(0.0102)**	(0.0508)**	(0.0112)**
Born 1950-59	1.26	0.405	1.26	0.406	1.16	0.382
	(0.0506)**	(0.0113)**	(0.0509)**	(0.0114)**	(0.0509)**	(0.0123)**
Born 1940-49	0.991	0.332	0.996	0.334	0.909	0.311
	(0.0511)**	(0.0129)**	(0.0513)**	(0.0130)**	(0.0514)**	(0.0138)**
Born 1930-39	0.667	0.238	0.664	0.237	0.609	0.220
	(0.0516)**	(0.0157)**	(0.0517)**	(0.0158)**	(0.0519)**	(0.0164)**
Born 1920-29	0.318	0.121	0.319	0.121	0.290	0.111
	(0.0542)**	(0.0196)**	(0.0544)**	(0.0197)**	(0.0545)**	(0.0199)**
In household with someone	0.0430	0.0169	0.253	0.0972	0.372	0.140
born 71-79 & educated	(0.0189)*	(0.00739)*	(0.0219)**	(0.00812)**	(0.0218)**	(0.00770)**
Someone born 1971-79			-0.405	-0.160	-0.514	-0.203
lives in the household			(0.0133)**	(0.00521)**	(0.0130)**	(0.00497)**
Someone with postsec.			0.288	0.112	0.241	0.0938
educ. lives in the household			(0.0108)**	(0.00411)**	(0.0106)**	(0.00409)**
N	142,667	142,667	142,667	142,667	142,667	142,667
Likelihood	-70,925	-70,925	-69,994	-69,994	-71,641	-71,641

+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include a constant and state, industry, and occupation fixed effects. In this table I have omitted coefficients for Household Income <US$20K, Household Inc. US$20K-US$60K, Household Income >US$60K, student, employed, unemployed, US Citizen, Female, Married, Never Married, White, Black, and Metropolitan Area. The base age cohort is the cohort born before 1920.
^I sometimes refer to this group as "Former Students" in the text. They are in the age cohort that attended university from 1993-97.
^^This is significantly different from the first row with 95% confidence for columns 1 & 2 and 99% confidence for columns 3 to 6.

Appendix Table A.2a: Comparison of usage of different computing technologies
(Probit coefficients—Standard errors in parentheses)

	(1)	(2)	(3)	(4)	(5)
	"Connect to the Internet" (home or work)	"Do word processing or desktop publishing" (home or work)	"Use spreadsheets or databases" (home or work)	"Play games on the computer" (home)	"Use home computer to manage household records or finances"
Born 1971-79 and has postsecondary education^	0.0674	0.0206	0.0219	0.0197	0.0363
	(0.0259)**	(0.0257)	(0.0271)	(0.0240)	(0.0309)
In household with someone born 71-79 & educated	0.0668	-0.0111	-0.0111	-0.0130	-0.0784
	(0.0188)**	(0.0182)	(0.0187)	(0.0174)	(0.0209)**
Born 1971-79	-0.0279	-0.0486	-0.000119	-0.0628	-0.0438
	(0.0190)	(0.0210)*	(0.0230)	(0.0195)**	(0.0273)
Age	-0.0134	-0.00805	-0.00653	-0.0128	-0.00876
	(0.000331)**	(0.000340)**	(0.000405)**	(0.000326)**	(0.000462)**
Postsecondary education	0.612	0.581	0.508	0.198	0.499
	(0.0104)**	(0.0105)**	(0.0114)**	(0.0103)**	(0.0126)**
Child	0.0602	0.159	-0.648	0.391	-1.41
	(0.0206)**	(0.0203)**	(0.0256)**	(0.0196)**	(0.0412)**
Household Income <US$20K#	-0.437	-0.448	-0.331	-0.447	-0.297
	(0.0128)**	(0.0144)**	(0.0182)**	(0.0132)**	(0.0210)**
Household Inc. US$20K-US$60K#	-0.0296	-0.0731	-0.0640	0.0121	-0.0142
	(0.00957)**	(0.00988)**	(0.0116)**	(0.00934)	(0.0130)
Household Income >US$60K#	0.374	0.327	0.196	0.201	0.210
	(0.0120)**	(0.0114)**	(0.0129)**	(0.0108)**	(0.0141)**
Student	0.971	0.811	0.603	0.470	-0.0566
	(0.0187)**	(0.0171)**	(0.0191)**	(0.0163)**	(0.0247)*
Employed##	0.281	0.419	0.658	0.0331	0.0908
	(0.0413)**	(0.0401)**	(0.0463)**	(0.0384)	(0.0537)+
Unemployed##	0.202	0.176	0.0938	0.117	0.0550
	(0.0455)**	(0.0449)**	(0.0524)+	(0.0427)**	(0.0602)
US Citizen	0.391	0.227	0.204	0.387	0.209
	(0.0177)**	(0.0191)**	(0.0221)**	(0.0184)**	(0.0248)**
Female	0.0411	0.166	0.00181	-0.0614	-0.0234
	(0.00837)**	(0.00862)**	(0.0104)	(0.00798)**	(0.0115)*
Married###	0.266	0.164	0.238	0.155	0.255
	(0.0118)**	(0.0122)**	(0.0136)**	(0.0118)**	(0.0153)**
Never Married###	0.140	0.0909	0.145	0.0573	-0.106
	(0.0150)**	(0.0152)**	(0.0170)**	(0.0146)**	(0.0199)**
White####	0.0556	0.0851	0.0317	0.0997	0.116
	(0.0180)**	(0.0186)**	(0.0223)	(0.0175)**	(0.0251)**
Black####	-0.287	-0.184	-0.131	-0.220	-0.0904
	(0.0216)**	(0.0228)**	(0.0276)**	(0.0213)**	(0.0317)**
Metropolitan Area	0.0538	0.0466	0.0635	0.0246	0.0564
	(0.0101)**	(0.0105)**	(0.0125)**	(0.00976)*	(0.0139)**
N	142,667	142,667	142,667	142,667	142,667
Likelihood	-73,754	-69,313	-49,669	-81,665	-40,190

+ significant at 10%; * significant at 5%; ** significant at 1%
All regressions include a constant and state, industry, and occupation fixed effects.
^I sometimes refer to this group as "Former Students" in the text. They are in the age cohort that attended university from 1993-97.
#Base=refused to answer; ##Base=out of labor force; ###Base=widowed, divorced, or separated; ####Base=Other

Appendix Table A.2b: Comparison of usage of different computing technologies
(Marginal Effects—standard errors in parentheses)

	(1)	(2)	(3)	(4)	(5)
	"Connect to the Internet" (home or work)	"Do word processing or desktop publishing" (home or work)	"Use spreadsheets or databases" (home or work)	"Play games on the computer" (home)	"Use home computer to manage household records or finances"
Born 1971-79 and has postsecondary education^	0.0264	0.00740	0.00474	0.00703	0.00425
	(0.0101)**	(0.00926)	(0.00592)	(0.00860)	(0.00370)
In household with someone born 71-79 & educated	0.0262	-0.00398	-0.00236	-0.00462	-0.00846
	(0.00732)**	(0.00649)	(0.00397)	(0.00615)	(0.00213)**
Born 1971-79	-0.0110	-0.0172	-0.0000254	-0.0221	-0.00487
	(0.00750)	(0.00738)*	(0.00492)	(0.00678)**	(0.00295)+
Age	-0.00526	-0.00288	-0.00140	-0.00454	-0.00100
	(0.000130)**	(0.000122)**	(0.0000875)**	(0.000115)**	(0.0000542)**
Postsecondary education	0.234	0.212	0.116	0.0710	0.0633
	(0.00379)**	(0.00383)**	(0.00280)**	(0.00371)**	(0.00190)**
Child	0.0236	0.0580	-0.115	0.144	-0.105
	(0.00806)**	(0.00750)**	(0.00365)**	(0.00744)**	(0.00189)**
Household Income <US$20K#	-0.173	-0.147	-0.0622	-0.146	-0.0290
	(0.00502)**	(0.00422)**	(0.00294)**	(0.00383)**	(0.00174)**
Household Inc. US$20K-US$60K#	-0.0116	-0.0261	-0.0136	0.00431	-0.00162
	(0.00377)**	(0.00351)**	(0.00245)**	(0.00333)	(0.00148)
Household Income >US$60K#	0.143	0.121	0.0447	0.0732	0.0265
	(0.00439)**	(0.00435)**	(0.00313)**	(0.00403)**	(0.00196)**
Student	0.320	0.3121	0.165	0.179	-0.00622
	(0.00453)**	(0.00649)**	(0.00621)**	(0.00643)**	(0.00262)*
Employed##	0.110	0.149	0.142	0.0118	0.0104
	(0.0161)**	(0.0142)**	(0.0101)**	(0.0137)	(0.00615)+
Unemployed##	0.0777	0.0654	0.0211	0.0425	0.00654
	(0.0170)**	(0.0171)**	(0.0123)+	(0.0159)**	(0.00745)
US Citizen	0.155	0.0769	0.0393	0.125	0.0206
	(0.00691)**	(0.00609)**	(0.00382)**	(0.00522)**	(0.00209)**
Female	0.0162	0.0595	0.000387	-0.0219	-0.00268
	(0.00329)**	(0.00307)**	(0.00224)	(0.00284)**	(0.00132)*
Married###	0.104	0.0590	0.0519	0.0555	0.0301
	(0.00456)**	(0.00439)**	(0.00301)**	(0.00422)**	(0.00189)**
Never Married###	0.0547	0.0329	0.0325	0.0205	-0.0116
	(0.00579)**	(0.00557)**	(0.00396)**	(0.00528)**	(0.00207)**
White####	0.0219	0.0301	0.00671	0.0349	0.0124
	(0.00711)**	(0.00645)**	(0.00466)	(0.00600)**	(0.00253)**
Black####	-0.114	-0.0635	-0.0265	-0.0747	-0.00975
	(0.00856)**	(0.00753)**	(0.00523)**	(0.00685)**	(0.00323)**
Metropolitan Area	0.0212	0.0166	0.0133	0.00873	0.00629
	(0.00400)**	(0.00373)**	(0.00257)**	(0.00345)*	(0.00152)**
N	142,667	142,667	142,667	142,667	142,667
Likelihood	-73,754	-69,313	-49,669	-81,665	-40,190

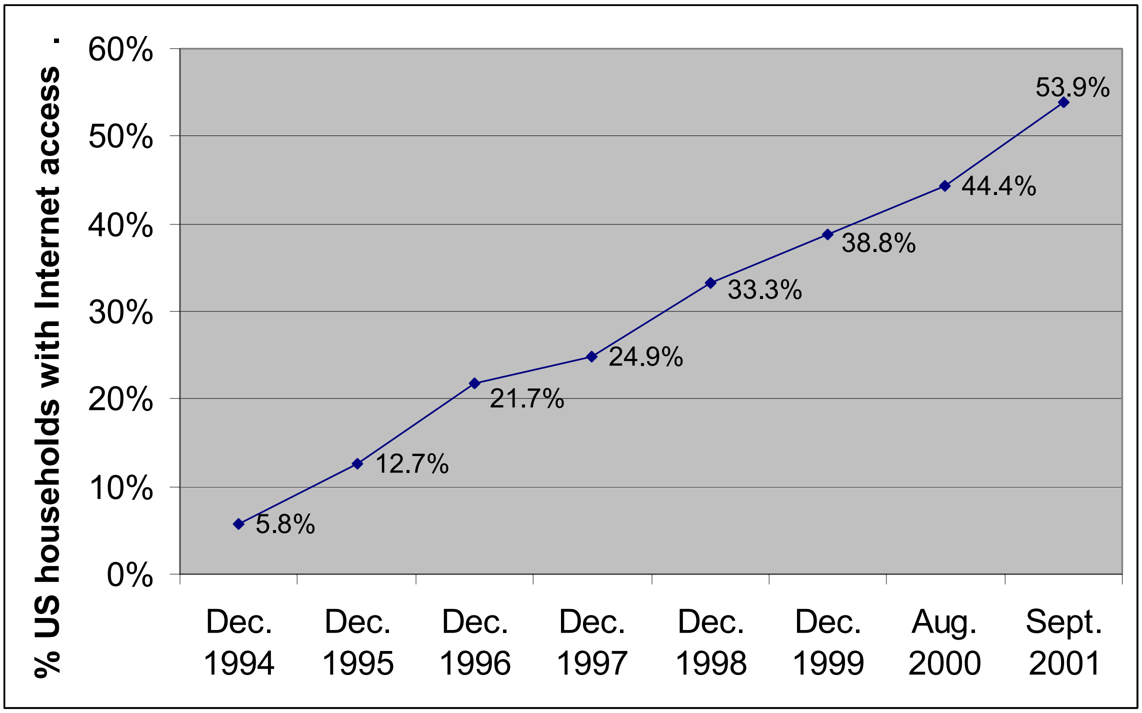
+ significant at 10%; * significant at 5%; ** significant at 1%

All regressions include a constant and state, industry, and occupation fixed effects.

^I sometimes refer to this group as "Former Students" in the text. They are in the age cohort that attended university from 1993-97.

#Base=refused to answer; ##Base=out of labor force; ###Base=widowed, divorced, or separated; ####Base=Other

Figure 1: Percentage of US Households with Internet Access 1994-2001



Source: Up to 1999 from Saloner & Spence (2002) citing U.S. Internet Council, "State of the Internet: USIC's Report on Use and Threats in 1999" citing Forrester Reports; 2000 and 2001 from National Telecommunications Information Administration (2002). The National Telecommunications Information Administration (2002) reports Dec. 1998 access as 32.7%.

Figure 2: Internet use by education and age cohort

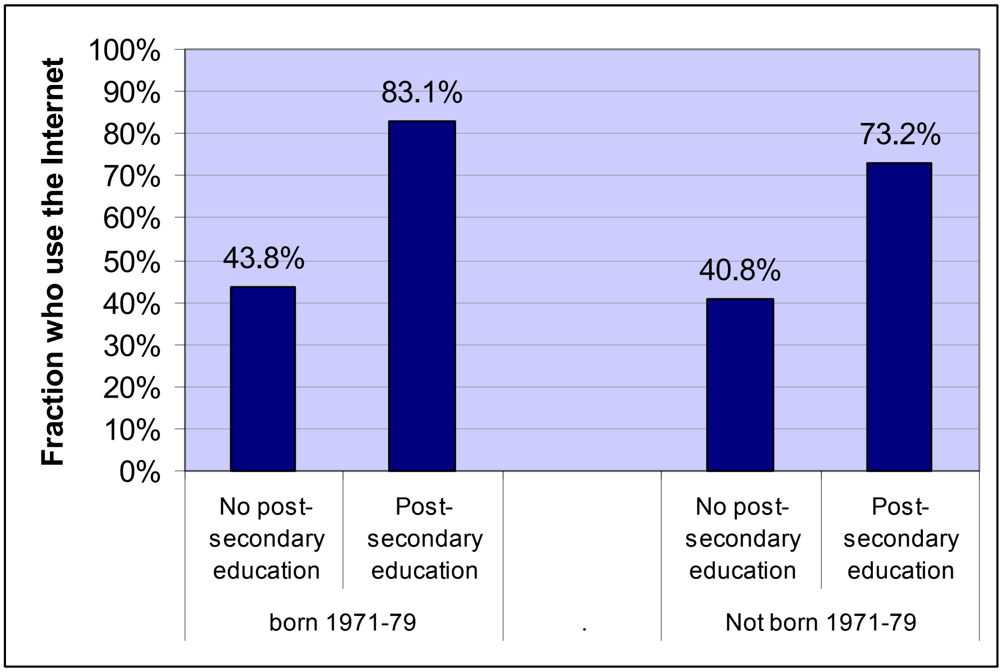


Figure 3: Internet use for those who were not likely to be students from 1993-97

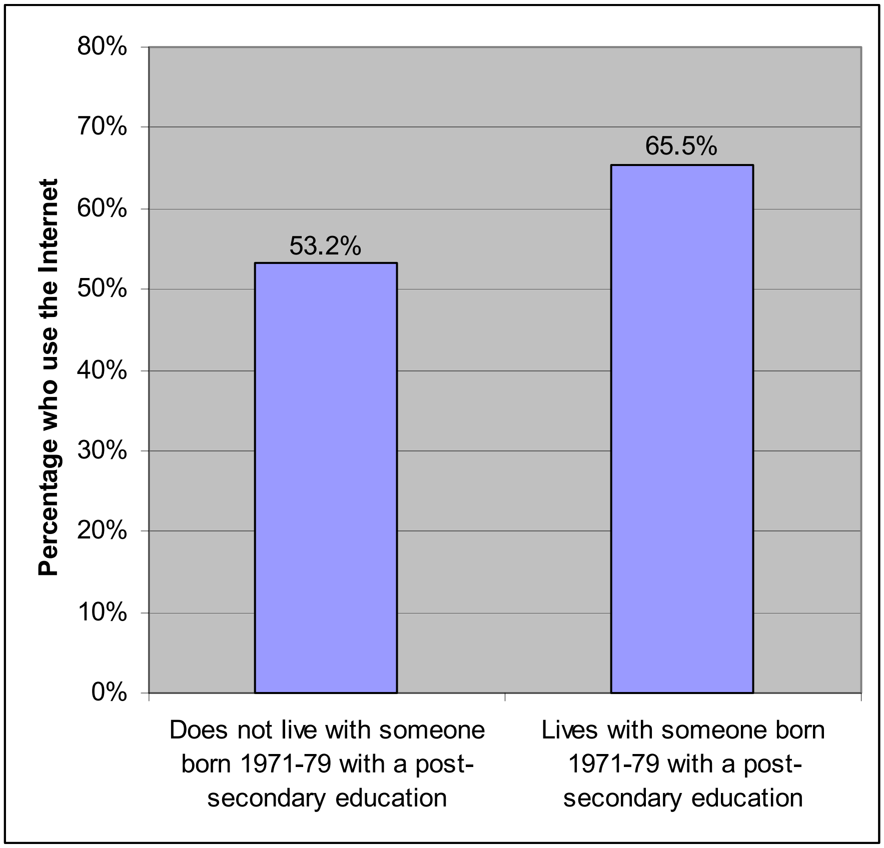


Figure 4: Internet adoption as a nested decision process

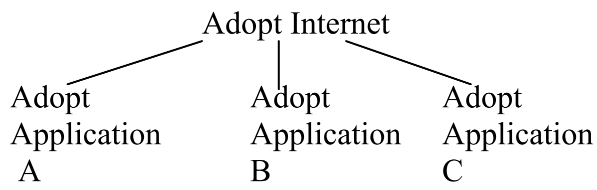


Figure 5: Marginal Impact of Education on Internet Use by Age Cohort

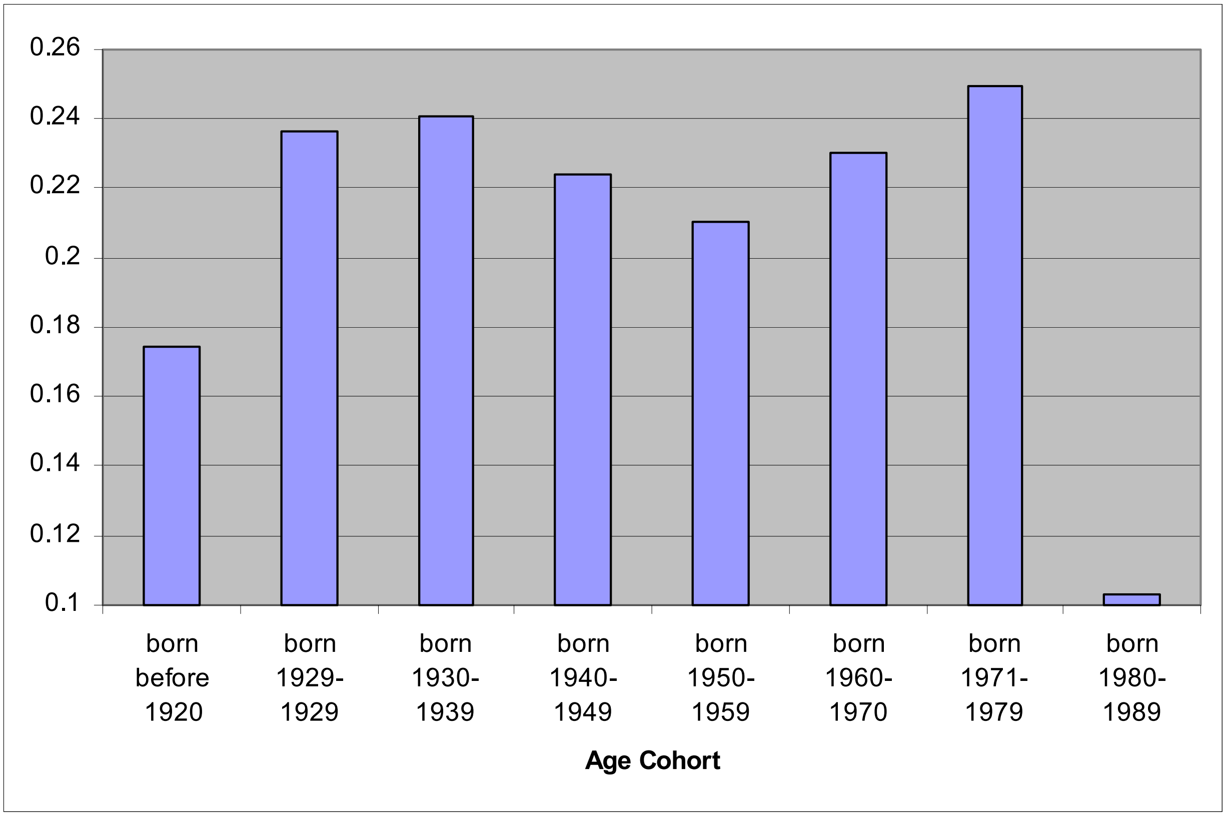


Figure 6: Marginal Effect of Education by Age
Regression has separate covariates for each age and the interaction of post-secondary education with each age

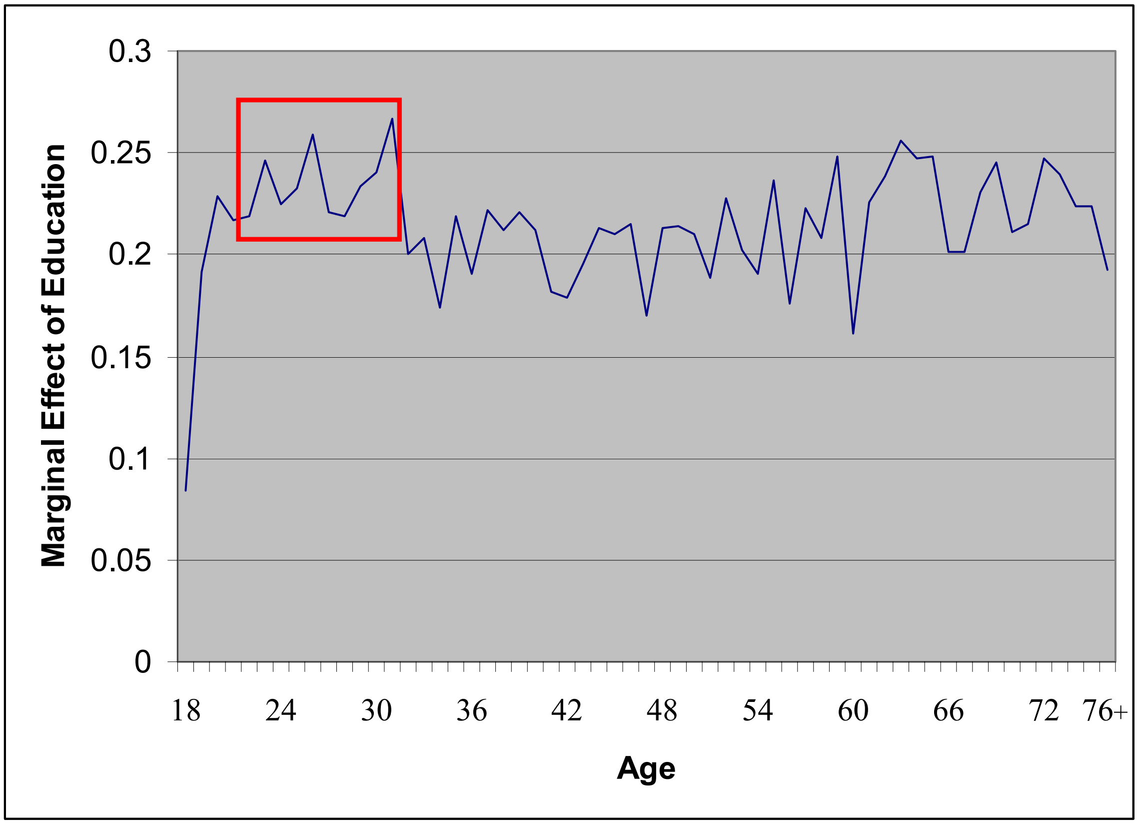
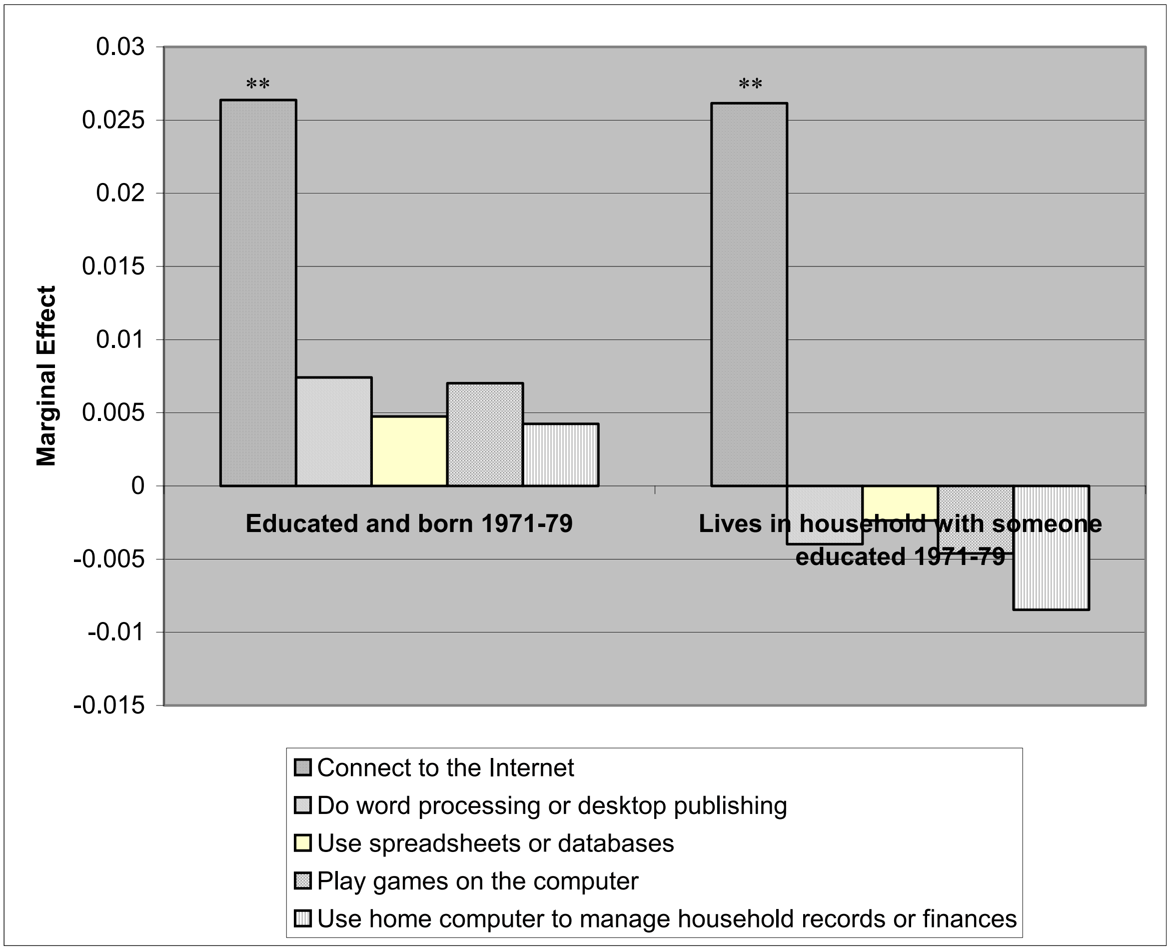


Figure 7: Internet use is different from other computer applications



*significantly greater than zero with 99% confidence. No other values are significantly different from zero with 90% confidence.