THREE ESSAYS ON COMPUTER AND INTERNET USE AT HOME

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CHAPTER I

A DOUBLE-HURDLE MODEL OF COMPUTER AND INTERNET USE AT HOME IN THE UNITED STATES

1.1 Introduction

Individuals perform various economically significant activities at home using different household technologies, in which personal computers and the Internet have become a part in recent years. The Current Population Survey (CPS) has been collecting information on the diffusion and use of computer and the Internet (CI) in United States households since 1984. In addition to the employment-related information gathered each month by the CPS, the CPS Computer and Internet Use Supplements routinely gather data on computer or Internet access and uses from a relatively large number of respondents.[1] The surveys show that the adoption and use of these two technologies in United States households have been steadily increasing since the 1980s and 1990s. Home computer ownership grew from 8 percent in 1984 to 37 percent in 1994 and to 69 percent in 2003. The proportion of households with Internet access rose from 18 percent in 1997 to 62 percent in 2003 (Day et al, 2005).[2]

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[1]The Census Bureau, sponsored by the Bureau of Labor Statistics (BLS), conducts the surveys. The computer use data were gathered for the years 1984, 1989, 1993, 1997, 1998, 2000, 2001 and 2003, but the Internet data collection began from 1997. The data provide detailed information on the availability of computer at school, home, and work; reasons for and frequency of computer use at school, home, and work; and availability and use of Internet at school, home, and work.

[2] See Figure 1.1.

Among those who own computers, 68, 21 and 11 percent, respectively, have at least one, two or three computers or laptops at home. The majority (78%) of these computers are relatively new because they were bought after the year 2000 (Appendix A1-1). A Large fraction (84%) of computer owners use their home computers for various purposes: while 53 – 91% use them for connection to the Internet, for personal emails, to complete school assignment, for playing games and word processing, the others (31 – 39%) need their computers to work from home, for graphics and design, database management and for household records keeping (Appendix A1-2).

In 2003, slightly less than two-thirds of the households connect to the Internet via Dial-up (i.e., the slow speed Internet connection), mainly because they either do not need high speed internet (42%) or find it expensive (39%) (Appendix A1-3). On the other hand, only 36 percent use broadband technologies (i.e., Cable Modem and Digital Subscriber Line, DSL). In all instances, more than half of households with Internet access connect to the Internet at least once a day. Those who do not access the Internet from home (38%) use their work places, schools, other people's houses and public libraries to access the Internet. For those who are traveling, airports, hotels and Internet cafés serve as Internet access sites. However, the proportions of individuals who access the Internet at these places are relatively small. The most popular uses of Internet at home include email or instant messaging (42%), search for information about products and services (35%), obtaining news, weather and sports information (31%), purchasing products and services (23%) and playing games (21%) (Appendix A1-4).

As indicated above, home CI has been disseminating widely in United States households and is being used for various market and non-market activities. Technological advances are also making available for consumers ever-more complex gadgets to use in non-market work and play. Working or playing with these gadgets takes time, time that might alternatively be devoted to a different activity. For example, the time devoted to a home CI use is time not devoted to other activities. As a result, individuals face the problem of allocating their unpaid time to competing non-market activities.

Time allocation is best studied using time use data since these data provide detailed information on actual time use on a specific day, as opposed to the typical time use data obtained from traditional cross-sectional surveys. This study employs the American Time Use Survey (ATUS) to exploit the availability of information on how people in the United States spend their time on market work and various non-market household activities. The ATUS also provides valuable information on respondent and household characteristics. ATUS is a single-day time diary survey that has been conducted in U.S. annually since 2003. This study draws time use data from the 2006 survey on the actual minutes individuals spend using CI at home.

Time use data also have disadvantages as compared to other data sources. Time use data acquired on a single diary day contain a high percentage of zeros for many time use activities. For instance, in the 2006 ATUS data, nearly 85 percent of the respondents report zero minutes for CI use at home on the diary day, although we know from the CPS that there are computers in nearly 69 percent of the U.S. households.[3] These zero responses could arise from individuals' deliberate and random responses or the design of the survey. That is, the zero responses could come from non-ownership of a home computer or from individuals who own computers but did not use them on that single

[3] See Appendix A1-1.

diary day. The traditional approach for dealing with so-called zero-inflated data has been to use the standard *Tobit* model, originally formulated by Tobin (1958). However, this model is too restrictive as it assumes all the zeros to be the respondents' deliberate choices. Cragg's (1971) double-hurdle model overcomes this restrictive assumption. In this model, two hurdles must be crossed in order to report non-zero minutes of CI use. First, one decides whether to own a home CI, and then how many minutes to spend using it, once owned.

This research has two major contributions. The first contribution is that it provides information regarding the use of CI at home. In this vein, the study identifies different sets of factors that determine the decisions to own and the intensity of use of a home CI. The second contribution of the study relates to the choice of an estimation technique. To show that the double-hurdle model is indeed superior to other more commonly used censored models, the double-hurdle model is tested against the *Tobit* and Heckman's generalized *Tobit* models using likelihood ratio (LR) and Vuong tests, respectively. The tests reveal that, compared to these two models, the double-hurdle model is the best econometric specification to deal with the single-day diary data used in this study. This implies that the allocation of time for home CI use follows two distinct decision paths: the decision to acquire a home CI, and the decision on the intensity of use. The superiority of the double-hurdle model has implications for other research using time diary data.

The rest of the chapter proceeds as follows. Section 1.2 gives a detailed description of the data used in the econometric analyses. The third section reviews the underlying theoretical model and discusses the derivation of the time allocation model.

Estimation strategies of time use data and econometric specification issues are discussed in detail in the fourth section. The last two sections present the estimation results and the conclusions of the study.

1.2 Description of the Data

The main source of data for this study is the 2006 American Time Use Survey (ATUS). The U.S. Census Bureau, sponsored by the Bureau of Labor Statistics, has conducted this annual survey since its inception in 2003. The ATUS is a random subsample of respondents who have completed their final month of interviews for the Current Population Survey (CPS). Only one individual, who is at least 15 years of age, is chosen from each selected household and interviewed only one time about his or her time use for the previous 24 hours (BLS, 2007).

The ATUS collects time diary information from individuals in representative households on how people living in the United States spend their time in paid work and unpaid activities. It shows the different kinds of activities people are engaged in and the time they spend doing them, disaggregated by sex, age, educational attainment, labor force status, and other characteristics, as well as by weekday and weekend days (BLS, 2007). The ATUS, for example, provides information on the amount of time people spend in market work, childcare, adult care, housework, commuting, sleeping, volunteering, religious activities, socializing, exercising, using computers/Internet at home, and relaxing. The ATUS also collects information about where and with whom each activity is conducted, and whether the activities are performed for one's job or business.

The ATUS collects information regarding computer or Internet use as a by-product of time use categories related to other activities. For example, one activity included within the broader "umbrella" activity of household production is computer or Internet use. In total, CI use appears three times in the ATUS' complete activity lexicon. These three ways that CI use can be reported are: (a) household activities, (b) socializing, relaxing and leisure, and (c) volunteer activities. The first category includes the total minutes spent in using CI for household and personal e-mail and messages. The second category comprises CI uses for personal interest, excluding games.[4] For ease of presentation, the term leisure is used throughout the chapter for this group of activities. The third classification refers to the minutes reported in using CI for administrative and support activities related to volunteering.[5]

The 2006 ATUS consists of 12,943 households, however, the number of respondents that reported CI use at home on the diary day is much less than this figure. The numbers of those who reported the use of CI for the three time use variables of interest, namely, household, leisure and volunteer activities are only 912, 1193 and 111, respectively. In this chapter, to represent all the minutes spent in using CI by a single summary variable, a fourth variable (known as computer use time) is defined as the sum

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[4] Time spent playing games on the computer and over the Internet are included in the general category of "playing games" (rather than CI use) along with other board and card games and puzzles (ATUS Activity Lexicon 120307). Thus, minutes spent playing games on the CI cannot be disentangled from other game playing. Given the wide use of computers and Internet for playing games, this will understate the minutes reported for the activities categorized under "Socializing, Relaxing, and Leisure" (ATUS Activity Lexicon 120308).

[5] For specific examples on the activities given in (a), (b) and (c), refer to Appendix A2, ATUS Activity Lexicons 020904, 120308 and 150101, respectively.

of the minutes spent in the above described three time use categories. Using this aggregate measure, the total number of individuals reporting the use of CI at home becomes 1,954. This indicates that only 15 percent of the survey participants reported CI use at home on the diary day. The corresponding figure from the 2003 ATUS survey was 12 percent. These contrast with the approximately 58 and 47 percent of U.S. households who reported in 2003 not only owning but also using their computers for home activities and to connect to the Internet, respectively.[6] The ATUS reliance on a single diary day is one reason for such small CI use response rates. Designating many CI activities under other broad activity categories (most importantly, computer games) is the other major survey design problem in ATUS contributing to the generation of many zero responses.[7] For estimation purposes, this study relies on this aggregate measure of CI usage.

1.3 The Time Allocation Model

Individuals engage in a variety of economically significant market and nonmarket activities. Examples for nonmarket activities include food preparation, raising children and engagement in leisure. Technological advances have made available for consumers ever-more complex gadgets to use in nonmarket work and play. In addition, the rapid progress in microelectronics technology has facilitated the ownership and use of less

[6] The data gathered on computer or Internet use by the October supplement of the 2003 CPS indicate that out of the total 69.2% households who reported owning home computers, the proportion of those who actually use their computer and connect to the Internet from home are 83.7% and 61.5%, respectively (Appendix A1-1, A1-2 & A1-3).

[7] From the ATUS Activity Lexicon, it is possible to identify the activities that could either be partly performed using CI or are already identified as CI using activities, but reported under different categories. The following are some examples: 020901-02; 030201-03; 040505; 050401, 050403; 060101-02, 060301-02, 060401-02; 070101, 070104, 070201; 080201-02; 100103; 120307 and 120313.

costly personal computers and Internet at home for many households in the United States in the last 20 years (NSF, 2001). Working or playing with these gadgets takes time, time that might alternatively be devoted to different activities. For example, the time devoted to home CI use is time *not* devoted to other activities. As a result, individuals face the problem of allocating their unpaid time to competing nonmarket activities.

The time allocation decision of an individual can be viewed in terms of the structure of time. The finite nature of time requires individuals to make choices among various activities based on their perceived relative utilities. These choices can then be classified into groups. Traditionally, economists have designated two discontinuous structures for time, paid work and leisure, where leisure is typically defined residually. Unlike paid work, leisure contains a number of activities that cannot be easily defined in operational terms useful for analysis (Feldman and Hornik, 1981).

Traditional economic theory deals with the labor/leisure choice by treating leisure as a component of a utility function, where utility is assumed to depend only on the consumption of a composite good and leisure time (Gronau, 1980). Blundell and Meghir (1986) extended Gronau's model by adding a set of taste shifter observable factors in the utility function. Kooreman and Kapteyn (1987) further disaggregated the residual leisure time into a multiple of unpaid activities undertaken by individuals. Based on these modifications, a utility function can be written as:[8]

$$U = f(X,\ T_i; S) \qquad \text{for} \ \ i = 1, 2, \ldots\ldots, n \tag{1}$$

[8] As opposed to Gronau (1980), Kooreman and Kapteyn (1987) use a household with both male and female partners and subdivide leisure into the time spent by each partner on a number of activities. This study employs a single-person household model because ATUS collects information from a single respondent per household only.

This is a one-person, one-period model where X is consumption of a composite good, T_i is the time spent on the i_{th} unpaid activity, and $S = \{R, H, F\}$ denoting vectors of individual characteristics (R), household characteristics (H) and other factors (F), such as geographic location and the diary day that are assumed to influence the individual's time preferences (Kimmel and Connelly, 2007).[9]

An individual maximizes this utility function subject to the following two interrelated budget and time constraints: [10]

$$\sum_{k=1}^{m} X_k = A + w(T - \sum_{i=1}^{n} T_i) \quad \text{and} \quad T = T_m + \sum_{i=1}^{n} T_i \tag{2}$$

where X_k is the k_{th} consumption good, A is non-labor income, w is the fixed market wage rate, T_m is market work time, and T is total time available. Maximizing (1) with respect to the constraints stated under (2) yields the optimal consumer demand equations for consumption goods ($k = 1, 2, \ldots\ldots, m$) and for the various non-labor time allocations ($i = 1, 2, \ldots\ldots, n$) included in the model:

$$X_k^* = f_k(w, A; S) \qquad \text{and} \qquad T_i^* = f_i(w, A; S) \tag{3}$$

Equation (3) indicates that the optimal allocation of consumer goods and time for various activities depend on the price of time, w, and the set of taste shifter variables S.

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[9]NSF (2001) and Day et al (2005) also identify socioeconomic characteristics, demographic variables and family structure as important factors influencing the use of information technology (i.e., computer or Internet) at home.

[10]The budget constraint is derived by rearranging the expenditure equation $\sum_{k=1}^{m} P_k X_k + \sum_{i=1}^{n} wT_i \leq M \equiv A + wT$, which stipulates that total expenditure (M) on goods and leisure is at most equal to the sum of the labor and non-labor income. Here, price is normalized to 1. Because there is no price information in the ATUS, the survey can be treated as a cross-section and assume all respondents face the same price (Yen and Jensen, 1996).

Denoting all the factors that affect these optimal allocations by Z, equation (3) can be rewritten more compactly as:

$$X_k^* = f_k(Z) \qquad \text{and} \qquad T_i^* = f_i(Z) \tag{3'}$$

The time allocation this study focuses on is the sum of the three earlier-defined CI use activities: household, leisure and volunteer activities.

1.4 Estimation Strategies

1.4.1 Identification of Estimation Variables

Let the optimal leisure time in (3′) T_i^* be denoted by a vector specifying the allocation of time into n number of nonmarket activities, such as food preparation, household management, childcare, personal care, maintenance and repair, CI use, socializing and relaxing, and shopping: $T_i^* = (T_1, T_2, \ldots\ldots, T_j, \ldots\ldots\ldots, T_n)$. And let the time allocated for the use of CI at home be T_j. To estimate the impact of the explanatory variables described in equation (3) on the optimal allocations of time for CI use at home, the estimation version of the time demand equation (3′) can be written as:

$$T_j = \beta_0 + \beta_j' Z + \varepsilon_j \qquad \text{for} \quad j = 1, 2, \ldots, N \tag{4}$$

Here $j = 1, 2, \ldots\ldots, N$ represent the number of observations in the sample, and ε_j denote the error terms.[11] The vector of explanatory variables that can be expected to influence the amount of time an individual allocates for the use of CI at home are gathered in Z. As described earlier, these explanatory variables can be categorized into the following

[11]The distribution of the error terms and the various econometric specifications of the model in (4) will be discussed later.

broad groups: economic variables, respondent characteristics, household characteristics and spatial or location variables.

1.4.2 Description of Estimation Variables

1.4.2.1 Descriptive Statistics of Independent Variables

Descriptive statistics for the independent variables are presented in Table 1.1. As can be seen, approximately the same numbers of observations are drawn from the weekends and weekdays samples (6,457 and 6,486, respectively). In addition, no notable difference is observed in the mean values reported under these two groups.

Respondent characteristics: On average, the respondents are 46 years old with nearly 13 years of education. Nearly 55 percent of the respondents have some college education or better. The majority of the survey participants are females (57%). The nonwhite population constitutes nearly 18 percent of the sample. Non-citizens account for about 8 percent of the sample.

Household characteristics: Fifty-three percent of the respondents are living with their spouses or unmarried partners. While 50 percent of the households have children under the age of 9, only 47 percent report having children aged 10 to 17. On average, there is one other adult, other than the spouse, in the household and the average family size is about 3.

Location characteristics: The majority of the respondents (82%) are living in metropolitan areas. Respondents seem to be over-sampled from the south compared to other geographic regions due to survey design. However, there seems to be no variation in season sampling.

Economic characteristics: The factors in this category include hourly wage, family income and type of jobs. Since no hourly wages are reported for more than one-third of the respondents who are either unemployed or not in the labor force, an hourly wage is predicted for all observations.[12] Based on the predicated wage, three categories of wage measure (low, medium and high wages) are also constructed.[13] Hence, of the total observations considered for analysis, 64 percent are employed and earn an average hourly wage of about $16. More than two-thirds of the respondents are in the medium wage group. The majority (45%) of the respondents work in private institutions. The average annual family income for the sample individual is about $57,000.

1.4.2.2 Distribution of Minutes of Computer or Internet (CI) Use

The total minutes spent on CI use on the diary day is the dependent variable in this study. To examine the variations in the distribution of time spent on various activities, the total minutes of CI use is disaggregated based on some selected attributes believed relevant to time use decisions (such as days of the week, gender, marital status, parental and employment status and level of the hourly wage). Tables 1.2a and 1.2b, respectively, report the average minutes of CI use for the whole sample (including both

[12] For details of the computation of the predicted wage, see section 5.1.

[13] The three wage categories are constructed in the following way. Assuming a normal distribution, a medium wage can be defined as the mean predicted wage plus/minus one standard deviation. Since the mean predicted wage (in logs) is 2.76 (or $15.84 per hour) with standard deviation of 0.405 (or $1.50 per hour), the medium predicted wage will be in the range of 2.36 to 3.17 (or $10.59 to $23.81 per hour). Thus, any wage that lies above this range is designated as high and any wage that falls below the range is designated as low.

CI users and non-users) and for reporting cases only. Accordingly, the sample average for CI use at home is about 12 minute per day in both weekends and weekdays (Table 1.2a). The allocation of time for the three CI use activities does not seem to show big variations either. On average, an individual in the sample spends about 3, 9 and less than 1 minutes on household, leisure and volunteer activities, respectively, in any day of the week.

Variations in the number of minutes spent in using CI at home are observed among individuals who report CI use. In this case, an individual on average spends nearly 84 and 71 minutes per day using CI for different activities in weekends and weekdays, respectively. While individuals on average spend about 42 and 96 minutes per day during weekends using CI for household and leisure activities, respectively, the corresponding figures for the weekdays are 35 and 84 minutes per day. Table 1.2a also reports the cross tabulations of the average minutes of CI use by gender and employment status. In all cases, significant variations are observed among the specified categories in the average minutes of CI use. Note that the average minutes computed for volunteer activities seem to be larger than the minutes devoted to the other activities merely due to small reporting cases. Generally, minutes spent using the CI for both household activities and leisure are observed to be higher on weekends than weekdays, lower for females than males and higher for unemployed than employed individuals. In addition, the most common use of a CI is for leisure.

Finally, to examine the relationship between market wage levels and CI usage, the minutes spent in using CI are cross-tabulated against three wage levels: low, medium and high predicted wages (Table 1.3). The association between predicted wage and computer use seems to vary with marital status. For married respondents, the average minutes of computer use tends to be related negatively to the wage during the week and positively on the weekend. However, the opposite relationship exists for unmarried respondents. On the other hand, irrespective of the day of the week, unmarried respondents on average spend more minutes on CI use compared to married respondents.

1.4.2.3 Differences between CI Users and Non-users

A simple comparison of means is carried out in order to examine whether the use of CI is related to variations in individuals' allocation of time on both paid work and nonpaid activities. This comparison is based on the assumption that those who reported zero minutes for home CI use are non-users of this technology. For this purpose, two groups of activities are selected: activities that can be performed with or without using a CI and those not directly related to computer applications.[28] Government services, financial and banking services, shopping and job search are some examples for the first group of activities. Examples for the second group include the travel time associated with the above activities, physical exercises and leisure (excluding computer games). The comparisons of the average minutes spent by each group on the selected activities are presented in Table 1.4.

The comparisons reveal two important findings. First, individuals who reported zero minutes of home CI use are spending significantly more minutes on the majority of the services and activities as compared to their CI using counterparts. Second, the

[28]CI related activities are identified based on the various possible uses of CI reported by American households in the 2003 CPS October Supplement.

number of reporting cases for all the services and activities is much higher for this same group than for home CI users. In addition, both groups are spending statistically the same number of minutes on a few of the activities only: financial and banking services, purchase research, travel for government services, and travel for job search and interview. The statistically significant differences observed in the average minutes spent on the selected activities may imply that the use of CI at home could be one reason for the differences in the time allocations of the two groups of respondents. Those who reported the use of home CI seem to save some minutes from the activities and services on which their counterparts are spending on average more minutes.

Similarly, to see if there is any association between home CI use and hours worked, the average minutes reported by the two groups of respondents are compared. Those who use CI at home are observed to work about 1 hour less than their non-CI owning counterparts. The difference is also statistically significant. In addition, noticeable differences are observed between the average minutes spent in leisure activities and physical exercises. Although these two activities seem only remotely related to computer use, both groups of respondents seem to allocate different amount of time to these activities.

Finally, two tentative conclusions can be drawn from these simple comparisons of means. First, the individuals who report non-zero minutes of CI use at home seem to show statistically significant different time allocation behavior compared to those who report zero minutes of CI use. Second, the observed time allocation differences are not limited to the activities that can be performed using home CI. The differences also extend to the services and activities that are not directly related to CI use. Why such differences are observed between the two comparison groups is not evident but may be due to the manner that CI usage spills over onto other time uses.

1.4.3 Estimation Methods for Time Use Data

Time use data have peculiar characteristics that require special consideration when using them in regression analysis. Specifically, disproportionately high percentage of individuals report zero minutes of CI use on the single diary day. These characteristics may arise from the respondents' behavioral responses or the design of the time use survey. These unique characteristics may result in a high percentage of zeros reported for the various activities included in the time use surveys (Flood and Gråsjö, 1998; Schwierz, 2003). The same problem is also reported in labor supply and consumer expenditure surveys (Flood and Gråsjö, 1998). Specifically, because the ATUS collects just a single day's activities, many activities are likely to be reported by relatively few individuals on the diary date although a far larger percentage of the sample engages in the activities regularly. In addition to computer use, other activities likely to suffer from this single diary day problem include shopping and volunteering.[29]

For instance, in the 2006 ATUS data, the majority (85%) of the respondents report zero minutes for CI use at home on the diary day although, as mentioned earlier, approximately 69 percent report computer ownership (Appendix A1-1). The low usage can be explained in two ways. First, the individuals do not have a computer at home or the individuals own a computer but did not use it, for some random reason, on the diary

[29]In the 2006 ATUS, only 43.7 and 7.2% of the respondents report shopping and volunteering, respectively.

day. The zero values in the former case are related to the respondents' computer ownership decisions and are called behavioral zeros, while those in the latter case are termed as random zeros as they arise from random events.[30] Second, the design of the time use survey can also contribute to the generation of zero values due to the fact that the same time use questions are posed to all of the respondents without first asking questions regarding computer ownership.

The traditional approach to deal with a censored dependent variable has been to use the standard *Tobit* model, originally formulated by Tobin (1958). The model permits incorporation of all observations including those censored at zero, without considering the sources of the zeros. However, the *Tobit* model is criticized for failing to identify the zero observations generated by non-participating respondents. Consequently, applying the *Tobit* model imposes the assumption that the observed zeros are all the outcome of individuals' optimal choices, i.e., they can only arise if the individuals decide not to own a home CI. This amounts to saying that the zeros are arising from the characteristics of the individuals (Newman et al, 2003; Martínez-Espiñeira, 2006).

Heckman (1979) proposes a model that addresses the problem associated with the zero observations generated by non-participation decisions, arguing that an estimation on a selected subsample (i.e., censored estimation) results in sample selection bias. Heckman's model overcomes the selection bias by undertaking a two-step estimation procedure (known as *Heckit*). In this estimation, a full sample *Probit* estimation is followed by a sample-selection corrected estimation carried out on the selected subsample. While the first stage estimates the probability of observing a positive

[30]Carlin and Flood (1997) attribute the presence of too many zeros in the data either to censoring (behavioral or true zeros), or to faulty reporting, or other random effects (random zeros).

outcome (known as the selection or participation equation), the second estimates the level of participation conditional on observing positive values (known as the conditional equation) (Dow and Norton, 2003). This model formulation permits the possibility of using different explanatory variables in each of the two steps of estimation. As opposed to the *Tobit* model, Heckman's (1979) model considers the zero observations to arise mainly from respondents' self-selection. In other words, this means that all the zeros come from the respondents' deliberate choices on the day to which the data refer.

The Heckman model differs from the *Tobit* model in two ways. First, the Heckman model recognizes the process to be a two-stage decision, and second it permits the use of different sets of explanatory variables in each stage of estimation. Consequently, the Heckman model can be viewed as a generalized version of the *Tobit* model (also termed as the generalized *Tobit*).

Cragg (1971) modifies the *Tobit* model with his "double-hurdle" model that tackles the problem of many zeros in the survey data by disentangling econometrically the observed zeros into two types. The model assumes that two hurdles have to be passed to observe positive values. Stated in terms of acquisition of durable goods, first, one has to desire a positive amount, and second, there have to be favorable circumstances to realize this positive expenditure.[31] In terms of home CI use, this interpretation can be modified as follows. A non-zero home CI time can be observed if, first, a decision

[31] The studies that used the double-hurdle model in consumer demand models include Jones (1989, 1992) on tobacco expenditure, Newman et al (2003) on Irish household expenditure on prepared food, Fabiosa (2006) on wheat consumption in Indonesia, and Aristei et al (2007) on alcohol consumption in Italian households. The double-hurdle model has also been used in labor supply as well as other noneconomic statistical studies. Examples of uses of the double-hurdle model in the studies of labor supply are Blundell and Meghir (1987), Blundell et al (1998), and Carlin and Flood (1997). In other field of studies the double-hurdle is used in models of soil conservation (Gebremedhin and Swinton, 2002), in loan default analysis (Moffatt, 2005), in the examination of charitable giving in willingness to pay studies (Verdin-Johansson, 1999), and in effects of volunteering on social capital formation (Isham et al, 2006).

whether to acquire a home computer or to get connected to the Internet is made (the first-hurdle), and second, random circumstances permit usage on the diary day, given that the individual has access to CI use at home (the second-hurdle). In general, the first hurdle refers to the participation or ownership decision and the second to the level or intensity of use.

ATUS has no information on computer ownership but such information is not necessary for the model. In essence, the double-hurdle model treats the second stage as a *Tobit* (normally distributed) and looks for the number of zeros it expects out in the tail of the normally distributed minutes of CI use. The remaining zeros (i.e., those not belonging in the tail) are assumed to reflect non-ownership.[32]

The generalized *Tobit* (Heckman) and the double-hurdle models are similar in identifying the rules governing the discrete (zero or positive) outcomes. Both models recognize that these outcomes are determined by the selection and level of use decisions. They also permit the possibility of estimating the first- and second-stage equations using different sets of explanatory variables. However, the generalized *Tobit*, as opposed to the double-hurdle, assumes that there will be no zero observations in the second stage once the first-stage selection is passed. In contrast, the double-hurdle considers the possibility of zero realizations (outcomes) in the second-hurdle (via the assumed *Tobit*-like normal distribution) arising from the individuals' deliberate choices or random circumstances. This is the main difference between the two models.

The difference between the two models can best be illustrated using the following example on computer use. According to the Heckman model, only non-computer owning

[32] Many thanks to Professor Christine Moser for the econometrics insight.

respondents can report zero minutes of computer use. The model implies that individuals owning a home computer do not report zero values at all.[33] On the other hand, the double-hurdle model assumes that zero values can be reported in both decision stages. The zeros reported in the first-stage arise from non-ownership and those in the second stage come from non-computer use due to the respondents' deliberate decisions or random circumstances. In this regard, the double-hurdle model can be considered as an improvement both on the standard *Tobit* and generalized *Tobit* (Heckman) models.[34]

From the review of the literature, it appears that the double-hurdle model is not extensively used in studies that employ time diary data.[35] In contrast, the standard *Tobit* is the most favored estimation method in time use studies. The following are examples for the studies that employ the standard *Tobit* estimations on time diary data. Kalenkoski et al (2005) investigate how parents' time spent in child care is affected by marital status and other demographic characteristics. Kimmel and Connelly (2007) examine whether mothers' time spent with their children is household production or leisure time, and Sayer et al (2004) analyze factors influencing mothers' and fathers' time investment in their children.

1.4.4 Econometric Specifications

The purpose of this study is to investigate the factors that determine the minutes spent in using CI using the double-hurdle estimation technique. As a robustness check,

[33] This implication is drawn from the assumptions used in Heckman two-stage estimation (see Heckman, 1979, p. 157).

[34] Also known as *Tobit* type I and *Tobit* type II models, respectively (Flood and Gråsjö, 1998, 2001).

[35] Most of the studies cited above use survey data rather than time diary data.

the estimated parameters are compared to the corresponding standard and generalized *Tobit* estimations. Furthermore, likelihood ratio (LR) and Vuong tests, respectively, are conducted to check whether the double-hurdle estimation is indeed superior to the standard and generalized *Tobit* models. This section presents the econometric models for the above three estimation techniques.

1.4.4.1 The Standard *Tobit*

The standard *Tobit* model is specified as:

$$t_i^* = X_i^{'}\beta + \varepsilon_i \qquad with \quad \varepsilon_i \sim N(0, \sigma^2) \quad and \quad i = 1, \dots, n \tag{5a}$$

$$t_i = \begin{cases} t_i^* & if \quad t_i^* > 0 \\ 0 & if \quad t_i^* \leq 0 \end{cases} \tag{5b}$$

where t_i^* is a latent endogenous variable representing individual $i's$ desired level of minutes devoted to using CI, and t_i is the corresponding actual (observed) number of minutes.[36] X_i is a set of individual characteristics that explain both ownership and level of CI use, and β is the corresponding vector of parameters to be estimated. In this model, ε_i is assumed a homoskedastic, normally distributed error term. Equation (5b) states that the observed number of minutes become positive continuous values if only positive number of minutes are desired, but zero otherwise. Note that since there is no negative number of minutes, the censoring could be placed at zero without any loss of generality. This shows that the observed 0's on t_i can mean either a "true" 0 (i.e., due to the

[36] Heckman (1979) defines the latent variable as a variable that may or may not be directly observable.

individual's deliberate choice) or censored 0 (i.e., those caused by data collection method).[37]

The standard *Tobit* model is estimated via maximum likelihood methods with the following log likelihood function:

$$LL = \sum_{0} ln\left[1 - \Phi\left(\frac{X_i'\beta}{\sigma}\right)\right] + \sum_{+} ln\left[\frac{1}{\sigma}\varphi\left(\frac{t_i - X_i'\beta}{\sigma}\right)\right] \qquad (6)$$

where the "0" under the summation sign indicates summation over the zero observations in the sample ($t_i = 0$) and "+" indicates summation over positive observations ($t_i > 0$). $\Phi(\cdot)$ and $\varphi(\cdot)$ are the standard normal distribution and density functions (*cdf* and *pdf*), respectively.

1.4.4.2 The Generalized *Tobit*

As discussed before, to overcome the sample selection bias arising from estimations carried out using only the observed positive values of the dependent variable, Heckman (1979) proposed a two-step estimation method. Using the model to the case at hand, the first step refers to the participation (or computer ownership) decision and the second to the level of usage decision. Based on these specifications, the standard *Tobit* can be modified following Heckman (1979), and Flood and Gråsjö (1998, 2001) as:

(a) Ownership decision:

Index equation $$d_i^* = X_{1i}' \beta_1 + u_i, \qquad u_i \sim N(0,1) \qquad (7a)$$

Threshold index equation $$d_i = \begin{cases} 1 & if \quad d_i^* > 0 \\ 0 & if \quad d_i^* \leq 0 \end{cases} \qquad (7b)$$

[37] The latter refers to the 0's arising from the single-day diary survey.

(b) Level of usage decision:

CI time equation $$t_i^* = X_{2i}^{'}\beta_2 + v_i, \qquad v_i \sim N(0, \sigma^2) \tag{7c}$$

Threshold CI time equation $$t_i = \begin{cases} t_i^* & if \quad d_i = 1 \\ 0 & if \quad d_i = 0 \end{cases} \tag{7d}$$

In this specification, separate sets of factors are assumed to influence the decisions to own a home CI versus the actual minutes spent in using it, once it is owned. Hence, X_{1i} and X_{2i} are vectors of explanatory variables that affect these two-stage decisions, respectively. Both variables are also assumed to be uncorrelated with their respective error terms u_i and v_i. β_1 and β_2 are the corresponding vectors of parameters. While d_i^* is a latent index variable that denotes binary censoring, d_i is the observed value representing the individual's participation decision (i.e., if 1 it means the respondent is reporting a positive number of minutes ($d_i^* > 0$), else 0). Hence, the actual observed number of minutes t_i equals the unobserved latent value t_i^* only when a positive number of minutes is reported; otherwise, it takes the value 0 (equation 7d). In this specification, the error terms are assumed to be normally and independently distributed, implying that there is no dependence between the ownership and level of use decisions (i.e., the two decisions are made independently).[38]

The log-likelihood function[39] for this specification is (Flood and Gråsjö[40], 1998; Aristei et al, 2007):

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[38] In such a case, the error terms in (7a) and (7c) can be alternatively represented as $\binom{u_i}{v_i} \sim N\left[\binom{0}{0}, \begin{pmatrix} 1 & 0 \\ 0 & \sigma^2 \end{pmatrix}\right]$.

[39] Instead of using maximum likelihood estimation, Heckman (1979) suggests a two-step method (known as *Heckit*). This requires estimating first the indicator equation (7a) using a *Probit* model and then computing the inverse Mill's ratio based the coefficient estimates $\left[\lambda_i(-X_{1i}^{'}\widetilde{\beta_1}) = \varphi(X_{1i}^{'}\widetilde{\beta_1})/\Phi(X_{1i}^{'}\widetilde{\beta_1})\right]$. Finally, the CI time equation (7c) can be estimated using $\lambda_i(\cdot)$ as an additional right-hand-side variable.

[40] The authors also suggest the software Limdep to estimate this log likelihood function.

$$LL = \sum_{0} ln[1-\Phi\,(X_{1i}'\beta_1)] + \sum_{+} \ln\left[\Phi(\,X_{1i}'\beta_1)\frac{1}{\sigma}\varphi\left(\frac{t_i - X_{2i}'\beta_2}{\sigma}\right)\right] \tag{8}$$

Notice that this specification is for the case where the error terms in (7a) and (7c) are assumed independent.

1.4.4.3 The Double-Hurdle Model

In this specification, an individual has to overcome two hurdles in order to report a positive number of minutes for home CI use. The first hurdle relates to whether or not the individual owns a home computer or has access to the Internet, and the second relates to the intensity of use by those who own a CI at home.[41] The indicator (ownership) and usage (CI time) equations of the double-hurdle model resemble those of the generalized *Tobit* model. Hence, a slight modification of the threshold CI time equation (7d) gives the double-hurdle model:[42]

(a) Ownership decision:

Index equation $$d_i^* = X_{1i}'\,\beta_1 + u_i, \qquad u_i \sim N(0,1) \tag{9a}$$

Threshold index equation $$d_i = \begin{cases} 1 & if \;\; d_i^* > 0 \\ 0 & if \;\; d_i^* \leq 0 \end{cases} \tag{9b}$$

(b) Level of usage decision:

CI time equation $$t_i^* = X_{2i}'\,\beta_2 + v_i, \qquad v_i \sim N(0,\,\sigma^2) \tag{9c}$$

Threshold CI time equation $$t_i = \begin{cases} t_i^* & if \;\; d_i = 1 \; and \; t_i^* > 0 \\ 0 & else \end{cases} \tag{9d}$$

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[41]Here the assumption is that individuals reporting positive minutes for a CI use at home are indirectly reporting the presence of a computer at home and access to the Internet from home. Because ATUS selects only one respondent from a household, the one reporting the use of CI might not necessarily be the owner. However, in this study the respondent is assumed to be the owner of the home CI.

[42]Note however that Cragg (1971) formulates the double-hurdle model by modifying the standard *Tobit* model.

This indicates that the observed number of minutes t_i is zero either when there is censoring at zero ($t_i^* \leq 0$) or if there is faulty reporting, or due to some random circumstance on the diary day. Rewriting Equation (9) more elaborately can help show explicitly the processes involved in observing zero values (Jones, 1992):

$$\begin{aligned} t_i = t_i^* = X_{2i}' \beta_2 + v_i \quad & \text{if} \quad X_{1i}' \beta_1 + u_i > 0 \ \text{and} \ X_{2i}' \beta_2 + v_i > 0 \\ = 0 \quad & \text{if} \quad X_{1i}' \beta_1 + u_i > 0 \ \text{and} \ X_{2i}' \beta_2 + v_i \leq 0 \\ & \text{or} \quad X_{1i}' \beta_1 + u_i \leq 0 \ \text{and} \ X_{2i}' \beta_2 + v_i > 0 \\ & \text{or} \quad X_{1i}' \beta_1 + u_i \leq 0 \ \text{and} \ X_{2i}' \beta_2 + v_i \leq 0 \end{aligned}$$

Hence, positive minutes of CI use is observed if only an individual owns a home CI and he/she uses it (the first condition). On the other hand, a zero value is observed if an individual owns a CI but did not use it on the diary day (second equation), or he/she does not own a CI and hence does not report any positive minutes of usage (last equation). The third condition indicates the possibility of reporting non-zero minutes of usage by a non-owner of a PC, denoting a faulty report. Note that the second equation underlines the basic difference between the generalized Tobit and the double-hurdle models.

Assuming the error terms in (9a) and (9c) are independent, the stochastic specification can be written as:

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & \sigma^2 \end{pmatrix}\right] \qquad (9e)$$

The double-hurdle model with independent error terms can be estimated by the following log-likelihood function (Moffatt, 2005; Aristei et al, 2007):[43]

[43]Jones (1992) was the first to derive the likelihood function.

$$LL = \sum_{0} ln\left[1 - \phi(X'_{1i}\beta_1)\, \Phi\left(\frac{X'_{2i}\beta_2}{\sigma}\right)\right] + \sum_{+} ln\left[\phi(X'_{1i}\beta_1)\, \frac{1}{\sigma}\varphi\left(\frac{t_i - X'_{2i}\beta_2}{\sigma}\right)\right] \quad (10)$$

The first term on the right-hand side corresponds to the contribution of all the observations with an observed zero. It indicates that the zero observations result from the ownership decisions as well as the usage decisions. This contrasts with the generalized *Tobit* model that assumes all the zeros are generated only by non-ownership decision. Comparing the first term of equation (8) to that of equation (10) reveals that the additional term $\Phi\left(\frac{X'_{2i}\beta_2}{\sigma}\right)$ depicts the contribution of the double-hurdle model. This term captures the possibility of observing zero values in the second stage decision, indicating that this second stage is represented like a *Tobit* model.

The second term in equation (10) accounts for the contribution of all the observations with non-zero minutes. The probability in the second term is the product of the conditional probability distribution and density function coming from the censoring rule and observing non-zero values, respectively (Fabiosa, 2006). For the case at hand, the former denotes the probability of passing the ownership hurdle, and the latter indicates the density of observing non-zero minutes of CI use.

Furthermore, under the assumption of independence between the two error terms, the log-likelihood function of the double-hurdle model is equivalent to the sum of the log-likelihoods of a truncated regression model and a univariate *Probit* model (Martínez-Espiñeira, 2006; Aristei et al, 2007). Consequently, the log-likelihood function of the double-hurdle model can be maximized, without loss of information, by maximizing the two components separately: the *Probit* model (over all observations) followed by a truncated regression on the non-zero observations (Jones, 1989).[44] This study estimates the log-likelihood function using a simplified model variation that assumes the error terms of the two hurdles are independent, homoskedastic and normally distributed. This might not be the best specification and I will pursue the estimation of the model with the correction for these error specifications in future research.[45]

1.5 Model Specification and Estimation Results

This section presents the estimation results of the standard *Tobit*, generalized *Tobit* and double-hurdle models.[46] First, the issue of equation specification and variable identification is discussed. Secondly, a log-likelihood ratio (LR) and Vuong tests are used to choose the appropriate model from these three specifications. Finally, results from the selected model are presented in detail and contrasted briefly with results from the other models.

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[44] Many studies seem to choose this approach mainly because there is no statistical software to handle the estimation of the double-hurdle model. Some researchers provide custom-built commands in *Limdep* and *Gauss* (Jones, 1992) and *Stata* (Moffatt, 2005; Fennema and Sinning, 2007). This study estimates the log-likelihood function of the double-hurdle model relying on user-written programs in the Stata software.

[45] See Appendix A4.

[46] The standard *Tobit* model is incorporated in many computer packages and it can be estimated easily. Additionally, the generalized *Tobit* model can be estimated by maximum likelihood. However, the double-hurdle estimation is not yet incorporated in the standard statistical software (Flood and Gråsjö, 1998; Schwierz, 2003). In this study, the three models are estimated by maximum likelihood method. For the double-hurdle model, user-written programs are used. These programs were written for Stata by Julian Fennema and are available at: **http://www.sml.hw.uk/somjaf/Stata/**.

1.5.1 Equation Specification and Identification

The selection of regressors for the standard *Tobit* model is straightforward. All variables that are assumed to influence the allocation of time for home CI use are included based on variables used in other time allocation studies. However, the choice of explanatory variables for the ownership and level of use equations for the generalized *Tobit* and double-hurdle models is more complex. There is no clear theoretical guidance regarding equation specifications for these two models. In the existing research, the selection of explanatory variables appears to be somewhat arbitrary (Newman et al, 2003; Aristei et al, 2007). One approach is to include non-economic variables in the sample selection equation (Jones, 1992; Yen and Jensen, 1996; Newman et al, 2003; Yen, 2005; Moffatt, 2005; Aristei et al, 2007).

In this study, with only a few exceptions, the same set of explanatory variables are included in the first and second stage equations based on the notion that comparison across models would be easier if all the models use the same variables in both stages. The explanatory variables are selected from the list of factors identified in other studies as relevant in explaining the two-step decisions. Accordingly, a set of economic and non-economic variables are included in the CI time equations of both the generalized *Tobit* and double-hurdle models as determinants of the ownership of a home CI and the actual minutes devoted to using it. However, the weekday and season variables are excluded from the first-stage equations assuming that they are less likely to have any impact on the probability of owning a home CI. Specifically, the first-stage decisions are identified with the following variables: age, female dummy, race, citizenship, marital status, number of children, location variables, and economic variables. In the second-stage equation, weekday and season variables are included in addition to the above variables. The economic variables involve a measure of hourly wage. However, since not all respondents report hourly wages, calculating the predicted wage becomes necessary.

Calculation of the predicted wage: Nearly 36% of the respondents in the 2006 ATUS data are either unemployed or not in the labor force.[47] Thus, no hourly wages are reported (or can be constructed using earnings and work hours) for this group of respondents. Excluding such observations from the regression analysis creates a sample selection problem, resulting in biased parameter estimates. In addition, the non-zero reported hourly wages could also be measured with error or considered endogenous. To address these problems, a sample-selection-corrected hourly wage is computed for all observations using Heckman's two-step consistent estimator (or *Heckit correction*). The predicted wage is in natural logs and is used to construct three categories of wage measures: low, medium and high predicted wage dummies. Assuming a normal distribution, the dummy for medium wage is defined as the mean predicted wage plus/minus one standard deviation. Thus, any wage that lies above this range is designated as high and any wage that falls below the range is designated as low. The variables included in the selection equation and the outcome equation (first and second step estimations) and the overall prediction results are reported in Appendix A3.[48]

[47] 4.08% are unemployed and 32.18% are not in the labor force.

[48] The choice of the variables to be included in these two equations are made in such a way that the resulting mean predicted wage would be comparable to the observed mean log wage.

1.5.2 Estimation Results

The estimation results presented in this section emphasize the two main goals of the study: learning about the various factors that influence the decisions to own and use CI at home, and selecting the best model for analyzing these choices using a single-day time diary data.

The dependent variable in this study is total minutes spent using CI at home. This censored variable is modeled using three alternative specifications: the standard *Tobit*, generalized *Tobit* and double-hurdle models. As discussed before, the double-hurdle model nests the standard *Tobit* model and is considered an improvement over the generalized Tobit specification. Hence, the question at hand is whether the double-hurdle model is the most appropriate specification to analyze the determinants of time allocated for CI use. To this end, first, each of the three models is estimated and the results are briefly compared. In order to account for the differences in the parameters, the maximum likelihood coefficients of the three models are summarized and reported in Appendix A5. Second, statistical tests are carried out to pick the best model. The test results are presented in Table 1.5. Third, the results from the econometrically preferred model are discussed.

1.5.3 Model Selection Tests

Comparison of the parameters across the three estimation techniques reveals that very few of the coefficients have conflicting (opposite) signs. Most of these conflicting signs are observed in the second-hurdle of the generalized *Tobit* and in either part of the double-hurdle model. There is also similarity in the significance level of the parameters across the models. In particular, almost all the coefficient estimates in the standard *Tobit* and the first-hurdle of the generalized *Tobit* specifications are significant at 10 or better significance levels. In addition, these estimates have the same significance levels in the majority of the cases.

In contrast, the double-hurdle model estimates show a remarkable difference with the other specifications in terms of significance levels. Only approximately half of the variables in either hurdle are significant, and at higher significance levels than the estimates in the other specifications. The differences observed in both signs and significance levels among these estimation techniques are probably due to the way these specifications treat the zero observations in the sample. As discussed before, the standard *Tobit* incorporates all observations, including those censored at zero, in the estimation without considering the sources of the zeros. In the generalized *Tobit* specification, the zero observations are treated differently. The model permits running regressions first on the entire sample (including the zero observations) and then on the selected non-zero sample. The explicit assumption here is that all the zero minutes in the sample emanate from non-ownership of home CI. However, the double-hurdle model differs from the other specifications in its assumption that the zero minutes may result from non-ownership of CI or from owning CI but reporting zero minutes for various reasons.

To select the model that best identifies the determinants of home CI use, two model specification tests are carried out in the following manner. First, the double-hurdle model is tested against the standard *Tobit* specification, and then the double-hurdle model is tested against the generalized *Tobit* model. The results for these two model specification tests are presented in Table 1.5. Since the standard *Tobit* specification is nested within the double-hurdle model, a LR test can be used to distinguish between these specifications. The LR test of the double-hurdle model against the standard *Tobit* model strongly rejects the latter specification. This is evidence suggesting the existence of two separate decision-making stages in which individuals make independent decisions regarding ownership and CI usage at home.[35] In this case, the standard *Tobit* model is shown to be restrictive in the sense that it does not make any distinction between the two stages of decision-making. The rejection of the standard *Tobit* model shows further that not all the zero minutes for home CI use can be considered as corner solutions (i.e., deliberate choices made by individuals).

To test the double-hurdle model against the generalized *Tobit*, a Vuong test is applied because the generalized *Tobit* model is not nested within the double-hurdle. When the double-hurdle model is tested against the generalized *Tobit*, the Vuong test rejects the latter.[36] The rejection of the generalized *Tobit* model in favor of the double-hurdle model implies that all the observed zero minutes are not due to non-ownership of CI alone, as explicitly assumed by the generalized Tobit model. Finally, based on the results of these two tests, one can conclude that the double-hurdle model is the best specification to model individuals' decisions regarding ownership and use of home CI.

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[35]The conceptual framework Venkatesh et al (1985) propose for technology adoption (including computers) in the households supports this result. The authors argue that the technology adoption process has two steps: first, a household decides to acquire a technology based on its perceived needs, and second, once acquired, the household determines the amount of time to be spent and the tradeoffs to be established.

[36] The Vuong test (due to Vuong, 1989) is a test for hypothesis of model equivalence for nonnested models (Clarke, 2007).

1.5.4 Detailed Discussion of Results from the Double-Hurdle Model

As shown above, the independent double-hurdle model is found to be the best specification to identify the determinants of CI ownership and use at home using a single-day time diary data.[37] Hence, the maximum likelihood (ML) parameter estimates of the double-hurdle model are used to analyze the impacts of the explanatory variables included in the estimation. The double-hurdle model is estimated by maximizing the log-likelihood function in equation (10). The results are presented in Table 1.6. The coefficients in the first hurdle indicate how a given variable affects the likelihood (probability) of owning a home CI. The results in the second hurdle denote how a variable influences the level of usage (i.e., the number of minutes devoted to CI use) given that a decision has been made to own a home CI.

A general view of the results shows the following notable differences in the parameter estimates of the variables in the ownership and level of use equations. The majority of the variables appearing in both equations have opposite effects in terms of both sign and level of significance. In particular, except the variables age, being a noncitizen, number of children aged 0 and 9, the three regions and family income, the rest have opposite signs in the ownership and level of use equations. Being female and nonwhite, marital status, number of children aged 10 to 17, residence in metropolitan area, wage and job types have coefficients that change signs. These indicate that the listed variables have different effects on the home CI ownership decision and the level of use

[37] Focus is now only on the sign and statistical significance of the coefficients of the double-hurdle model. At this point, the marginal effects could not be computed, as the existing statistical packages do not support the user-written programs used to estimate the double-hurdle model. In general, since the signs of the marginal effects remain the same as the signs of the coefficients (Greene, 2000), the qualitative analyses of the explanatory variables will not be affected all.

decision. Turning to the discussion of specific parameter estimates, factors that significantly increase the probability of ownership and the level of use are presented below.

Respondent characteristics: The variables listed under this category determine both the probability of ownership and the level of use of a home CI. While increase in age and being nonwhite significantly lower the probability of owning a home CI, the level of education raises the intensity of CI use.[38] Age is observed to affect negatively individuals' decisions to both own CI and allocate time to CI use, although the latter is not statistically significant. This implies that older individuals are less likely to own a home CI. The allocation of time for home CI use is also observed to increase with each level of education. The female dummy has opposite effects on the ownership and level of use decisions. While being female increases the probability of owning a home CI, it also negatively affects the rate of CI use at home. This implies that, compared to males, females are more likely to own CI at home, but they spend less time using it. These opposite effects probably arise from the fact that females, compared to males, are more likely to both have access to CI at their work places and be engaged in time-consuming household chores and childcare activities at home. While the first is likely to induce them to acquire CI for home use, the second might create a time constraint for using CI at home.

On the other hand, although being nonwhite significantly reduces the probability of ownership, this variable does not affect the level of usage. This means that significant differences are observed between whites and nonwhites in the acquisition of CI, but both

[38]The education variable was removed from the ownership equation to facilitate convergence.

groups do not show substantial differences in using these technologies at home. The implication of this result is that there may be other factors, relating to differences in individual characteristics, which lead to variation in CI ownership among these racial groups.

Household characteristics: The household composition variables seem to have more significant effects on the intensity of a home CI use rather than on ownership. For instance, having younger children in the household affects more significantly how many minutes one spends in using CI at home. This implies that individuals who have younger children spend more time on childcare activities than using CI at home. However, the negative impacts of having children on one's use of home CI eventually diminishes as the children get older. In contrast, the presence of teenagers in the household enhances the probability of ownership probably due to their interest in using CI. On the other hand, the presence of a spouse or unmarried partner in the household is found to significantly increase the probability of owning a home CI. This may sound more like an income effect since the presence of another adult increases the probability of earning more family income. However, marital status has an opposite effect when it comes to the level of CI use at home. Individuals living with partners spend fewer minutes in using CI at home than those living alone. This may be more evident in households that own a single home computer, in which case the possibility of sharing the CI among couples or partners is likely to reduce the amount of minutes each spends using it.[39]

Location and season characteristics: The location variables are used in the estimation to capture the variation that might exist in the availability of computers and

[39] Recall that the majority of households (68%) own a single home computer (see Appendix A1-1).

computer accessories, and the Internet infrastructure in different regions of the United States. The estimation results show that individuals living in metropolitan areas spend more minutes using home CI compared to their counterparts in nonmetropolitan areas. Only individuals living in the Midwest have a significantly higher probability of owning a home CI as opposed to those living in the South (the excluded region). Moreover, CI usage is observed to be significantly higher during the weekdays than the weekends and in the winter than in the summer (the excluded category). In the latter case, individuals use their home CI more intensely during the winter season probably because they stay inside at home more in the winter than they do in the summer.

Economic characteristics: As discussed before in connection with equation specification, some studies suggest using economic variables to identify the second hurdle only.[40] In this study, the same variables are included in both hurdles because no exclusions are necessary for identification and there is no theoretical justification for including variables in one hurdle that are excluded in the other. Among the economic variables used, annual family income and a medium hourly wage dummy variable significantly increase the probability of owning a home CI. These results may reflect the impacts of rising wages and income in increasing individuals' purchasing power or changing their tastes or preferences for CI use.

On the other hand, the predicted wage (in logs) is related negatively to the allocation of time for CI use at home. Compared to low wage earners (the excluded

[40]Since there is no theoretical guidance as to which variable to include in each hurdle, an attempt was made to include economic variables in both hurdles during estimation. However, the maximum likelihood estimation fails to converge with this broadened specification, particularly whenever these variables are included in the first hurdle (ownership equation) together with the education variable. The results reported here are obtained by excluding education from the first hurdle.

category), medium and high wage earning individuals spend less time on home CI. This may be explained in terms of the opportunity cost of time. The higher the hourly wage, the less would be individuals' willingness to spend more minutes on their home CI, an unpaid activity. In addition, compared to self-employed individuals (the excluded category), those working in government and private institutions spend fewer minutes in home CI use. This may be due to the fact that these groups of individuals have access to CI at their working places so that they have a reduced tendency to use their own CI at home.

1.6 Summary and Conclusions

This study employs time use data to analyze individuals' choices regarding the time allocated to computer or Internet (CI) usage at home. The study has two major contributions. The first contribution is that it provides information regarding the use of CI at home. In this vein, the study identifies different sets of factors that determine the decisions to own and the intensity of use of a home CI. The second contribution of the study relates to the choice of estimation technique. The study shows that the double-hurdle model, compared to the standard and generalized *Tobit* models, is the best econometric specification to identify the determinants of computer or Internet use at home using time diary data.

The study uses the 2006 American Time Use Survey (ATUS) and measures CI use at home in minutes on the 24-hour diary day. The double-hurdle estimation results show that the use of a home CI follows two distinct decisions: the decision to acquire CI and the decision concerning intensity of use. The estimation results also reveal that the probability of owning a home CI is higher for females, for individuals living with their spouses or partners and have teenage children, for those residing in the Midwest and earning higher family income. In contrast, age, being nonwhite, and having small children (age 0 to 2) are observed to significantly reduce the probability of owning CI at home.

On the other hand, the factors that positively influence the allocation of time for home CI use are: the level of education, and residing in the metropolitan area and in the Midwest. A number of variables are also negatively associated with the total minutes devoted to home CI use. These include being female, living with one's spouse or partner, having younger children, and working in government and private institutions. In addition, individuals earning medium to high income are observed to spend fewer minutes in using CI at home compared to low wage earning individuals. Some variables, such as gender, marital status, number of children age 0 to 2, and individuals' medium predicted wage affect both the ownership and level of use decisions.

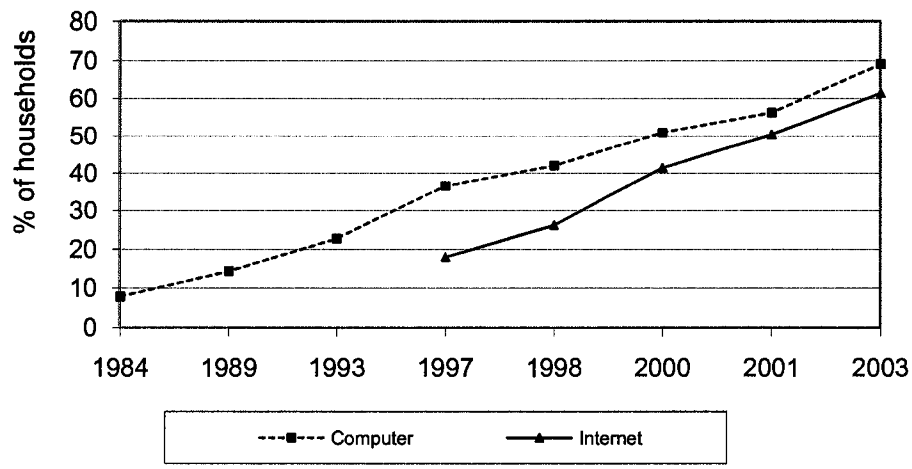
In general, the study shows that the majority of the variables under investigation affect the level of usage rather than the probability of CI ownership. This implies that the time allocation decision is central in the use of these technologies at home. Based on this observation, it may be possible to draw a preliminarily conclusion that the ownership decision is probably dominated by the level of use decision. This calls for further study to address the issue of dependence (with CI usage dominating the ownership decisions), relaxing the assumption of error "independence" used in this study. In addition, the following are other possible extensions for future studies:

(i) Increasing the sample size by using more than one year of ATUS data;

(ii) Working on error correction specifications.

In conclusion, to show that the double-hurdle model is indeed superior to other more commonly used censored models, the double-hurdle model is tested against the standard *Tobit* and generalized *Tobit* models using likelihood ratio (LR) and Vuong tests, respectively. The tests reveal that, compared to these two models, the double-hurdle model is the best econometric specification to deal with the single-day diary data used in the study of CI time use. This implies that the double-hurdle model is perhaps the most important contribution as it carries implications for many other time use research applications, which involve activities with many zeros in the data, most like CI use, and commonly estimated by the *Tobit* model. Examples for such activities include volunteering and shopping. The study also demonstrates the importance of employing a more sophisticated econometric technique, like the double-hurdle model, in time use researches.

Figure 1.1: Computer and Internet Access at Home



Note: CPS started collecting Internet access data in 1997
Source: CPS 1984, 1989, 1993, 1997, 1998, 2000, 2001, 2003

Table 1.1: Descriptive Statistics

Variables	Weekends		Weekdays	
	Mean	Std. Dev	Mean	Std. Dev
Respondent characteristics				
Age	45.49	17.77	46.03	17.74
Female	0.58	0.49	0.57	0.50
Education (years)	13.32	3.30	13.39	3.17
High school graduate or below (reference)	45.5	0.50	44.1	0.50
Some college or associate degree	25.8	0.44	27.4	0.45
Bachelor's degree or above	28.7	0.45	28.4	0.45
Nonwhite	0.17	0.38	0.18	0.39
Non-citizen	0.08	0.27	0.07	0.26
Household characteristics				
Spouse or unmarried partner present*	0.53	0.50	0.53	0.50
No. of children age 0 to 2	0.14	0.40	0.13	0.39
No. of children age 3 to 5	0.15	0.41	0.14	0.40
No. of children age 6 to 9	0.21	0.49	0.21	0.49
No. of children age 10 to 12	0.17	0.42	0.16	0.42
No. of children age 13 to 17	0.30	0.60	0.30	0.61
Location and season characteristics				
Metropolitan area	0.82	0.39	0.81	0.39
Northeast	0.17	0.38	0.17	0.38
Midwest	0.25	0.43	0.24	0.43
South (reference group)	0.36	0.48	0.36	0.48
West	0.22	0.41	0.22	0.41
Summer (reference group)	0.24	0.43	0.23	0.42
Fall	0.25	0.43	0.24	0.43
Winter	0.26	0.44	0.26	0.44
Spring	0.26	0.44	0.28	0.45
Economic characteristics				
Log of predicted wage	2.76	0.41	2.77	0.40
High wage (dummy)	15.5	0.36	14.3	0.35
Medium wage (dummy)	68.0	0.47	69.7	0.50
Low wage (reference group dummy)	16.7	0.37	15.6	0.36
Household income ('000)	57.2	47.7	56.9	41.1
Government job	11.1	0.31	11.1	0.31
Private job	45.9	0.50	44.7	0.50
Self-employed (reference group)	7.4	0.26	7.3	0.26
Sample size	**6457**		**6486**	

*Those living with their spouses are 50.4%.

Table 1.2a: Average Minutes Spent per Day in Using CI (including zeros)

Category	Total minutes of CI use	Household activities	Relaxing, socializing and leisure	Voluntary activities
Weekends	11.61 (42.12) 6457	2.49 (13.88) 6457	8.55 (37.91) 6457	0.56 (9.93) 6457
Weekdays	11.60 (42.50) 6486	2.88 (14.27) 6486	7.99 (37.76) 6486	0.72 1(2.16) 6486
Female	10.00 (37.88) 7427	2.72 (13.47) 7427	6.43 (32.14) 7427	0.85 (13.12) 7427
Male	13.76 (47.54) 5516	2.64 (14.86) 5516	10.74 (44.25) 5516	0.37 (7.60) 5516
Employed	10.29 (38.22) 8250	2.20 (11.54) 8250	7.61 (35.08) 8250	0.48 (8.72) 8250
Not employed	13.92 (48.59) 4693	3.55 (17.65) 4693	9.44 (42.22) 4693	0.93 (14.36) 4693

Notes: The average minutes of CI use are computed for the whole sample (including CI users and non-users).
Numbers in each cell denote the mean, standard deviation and number of observations.

Table 1.2b: Average Minutes Spent per Day in Using CI (excluding zeros)

Category	Total minutes of CI use	Household activities	Relaxing, socializing and leisure	Voluntary activities†
Weekends	83.92 (82.24) 893	42.38 (39.83) 380	95.50 (88.12) 578	79.11 (88.21) 46
Weekdays	70.90 (82.72) 1061	35.14 (36.78) 532	84.28 (92.83) 615	72.32 (98.64) 65
Female	69.70 (76.44) 1066	36.37 (34.67) 556	81.38 (83.55) 587	84.07 (100.76) 75
Male	85.44 (89.00) 888	40.95 (43.11) 356	97.79 (96.54) 606	56.53 (76.43) 36
Employed	69.21 (75.86) 1226	32.47 (31.37) 559	83.11 (84.74) 755	60.00 (77.57) 66
Unemployed	89.72 (91.80) 728	47.17 (45.71) 353	101.11 (99.26) 438	97.33 (111.36) 45

Notes: The average minutes of CI use are computed for the reporting cases (CI users) only. Numbers in each cell denote the mean, standard deviation and number of observations.

†Average minutes computed for these activities are larger than the other activities due to small reporting cases.

Table 1.3: Average Minutes of CI Use by Level of Wage, Marital Status and Day of the Week†

		Predicted wage		
		Low	Medium	High
Weekends, Married/spouse present	Total computer use	69.29 (60.99) 7	77.98 (73.78) 261	74.09 (68.02) 148
	Household activities	28.33 (27.54) 3	36.24 (32.20) 105	38.87 (34.00) 75
	Relaxing, socializing and leisure	85.00 (64.03) 4	88.72 (75.73) 174	75.68 (64.85) 88
Weekends, Not married/no spouse present	Total computer use	100.89 (96.76) 146	87.05 (92.88) 264	81.01 (57.53) 67
	Household activities	65.76 (62.41) 51	40.09 (34.71) 115	43.06 (36.63) 31
	Relaxing, socializing and leisure	106.15 (103.49) 105	107.13 (104.11) 166	93.49 (57.11) 41
Weekdays, Married/spouse present	Total computer use	68.00 (50.70) 5	59.74 (68.51) 404	55.18 (59.59) 130
	Household activities	33.33 (25.17) 3	28.59 (22.27) 210	30.62 (34.28) 66
	Relaxing, socializing and leisure	120.00 (0.0001) 2	72.97 (80.17) 226	60.00 (56.67) 69
Weekdays, Not married/no spouse present	Total computer use	75.83 (68.11) 136	85.57 (100.30) 304	88.48 (113.47) 82
	Household activities	51.43 (56.43) 56	42.67 (45.39) 150	27.45 (20.02) 47
	Relaxing, socializing and leisure	80.14 (68.98) 92	101.34 (111.40) 176	115.00 (131.68) 50

Notes: The average minutes reported for the low-wage group appear to be larger mainly because the number of observations is very small in the majority of the cases. Numbers in each cell denote the mean, standard deviation and number of observations.

†Average minutes of computer use for volunteer activities are excluded from the analysis due to small number of observations.

Table 1.4: Average Minutes Spent on Various Activities and Services†

Number of Minutes	Respondents who reported CI use			Respondents who did not report CI use			Differences‡
	Mean	Std. Dev	Obs	Mean	Std. Dev	Obs	
Computer or Internet use	76.85	82.74	1954	-	-	-	-
Government services	31.67	28.39	9	65.60	68.45	52	-2.53*
Travel: government services	21.56	28.45	9	29.89	25.81	46	-0.82
Civic obligation	12.50	3.54	2	85.04	111.22	24	-3.18**
Travel: civic obligation	10.00	0.00	2	29.89	38.68	19	-2.24*
Financial and banking services	11.41	13.14	85	13.52	17.85	283	-1.19
Grocery shopping	29.97	28.38	582	32.92	31.59	2823	-2.24*
Travel : grocery shopping	20.88	15.71	349	24.59	24.05	1753	-3.64**
Nongrocery shopping	60.45	65.53	604	72.05	75.71	2986	-3.86**
Travel: nongrocery shopping	32.15	39.28	734	36.94	46.07	3592	-2.92**
Purchase research	82.60	79.59	5	40.00	16.69	8	1.18
Job search and interview	85.55	97.43	31	130.83	134.13	87	-2.00*
Travel: job search and interview	64.08	104.77	13	57.58	70.52	45	0.21
Leisure without computer use	255.48	168.12	1889	299.73	200.38	10485	-10.21**
Physical activities	91.95	89.54	434	104.58	100.44	1737	-2.56*
Paid work	367.77	211.64	731	434.82	198.14	4108	-7.97**

† All the reported minutes, except those in the first row, are for non-CI uses.
‡ t-statistic for the differences between the mean minutes reported by CI users and non-users.
* significant at 5%, ** significant at 1% for the difference in means.

Table 1.5: Specification Tests

Model	Type of test	Test value†	Decision
Standard *Tobit* vs independent double-hurdle	LR	111.08 (19) [0.005]	Reject *Tobit*
Independent Double-hurdle vs. Generalized *Tobit*	Vuong	34.04*	Reject generalized *Tobit*

†For the LR test statistic, the degrees of freedom of the χ^2 statistic and the corresponding p-values are reported in round and square brackets, respectively.

Table 1.6: Maximum Likelihood Estimation of the Double-Hurdle Model: Total Minutes of CI Use

	Double-Hurdle			
Variable	1st Hurdle		2nd Hurdle	
Respondent characteristics				
Age	-0.030	(5.29)***	-0.453	(0.96)
Some college/assoc deg			45.670	(7.65)***
Bachelor's deg/above			69.245	(9.90)***
Female	0.429	(2.79)***	-23.431	(2.48)**
Nonwhite	-0.737	(3.73)***	11.226	(0.62)
Noncitizen	-0.315	(0.86)	-22.921	(1.41)
Household characteristics				
Married & spouse or partner present	0.321	(1.69)*	-18.539	(1.84)*
Children age 0 to 2	-0.453	(1.91)*	-18.994	(2.35)**
Children age 3 to 5	-0.256	(1.22)	-11.180	(1.51)
Children age 6 to 9	-0.010	(0.05)	-11.836	(2.14)**
Children age 10 to 12	0.011	(0.04)	-6.629	(1.01)
Children age 13 to 17	0.525	(1.68)*	-3.744	(0.74)
Location and season characteristics				
Urban	-0.116	(0.45)	18.760	(2.23)**
Northeast	0.344	(1.54)	1.216	(0.14)
Midwest	0.393	(2.01)**	6.009	(0.72)
West	0.173	(0.88)	10.183	(1.25)
Weekdays			11.053	(2.73)***
Spring			1.806	(0.30)
Fall			-0.790	(0.13)
Winter			11.950	(1.99)**
Economics characteristics				
Family income	0.182	(2.57)**	1.740	(0.85)
High wage (dummy)	4.094	(1.02)	-87.388	(2.83)***
Medium wage (dummy)	1.635	(3.43)***	-71.140	(3.77)***
Government job	0.460	(1.07)	-39.867	(4.02)***
Private job	0.054	(0.29)	-39.885	(5.33)***
Constant	0.073	(0.14)	-57.862	(1.51)
No. of observations	12943			

Absolute value of z statistics in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
Note: The level of education variables are omitted from the first hurdles due to lack of convergence during estimation.

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Appendix A1-1: Computer Ownership at Home (CPS October 2003)

		% Reporting
Have computer/laptop at home		69.2
Own	1	67.7
	2	21.4
	3 or more	10.9
Newest bought (year):		
	2003	20.2
	2002	22.7
	2001	19.1
	2000	15.6
	1999	8.4
	1998	6.0
	Before 1998	8.2

Appendix A1-2: Computer Use at Home (CPS October 2003)

	% Reporting
Use computer at home	83.7
For: Internet connection (personal)	90.6
e-mail (personal)	72.3
School assignment	74.8
Playing games (without Internet)	58.9
Word processing or desktop publishing	53.4
Work from home	38.8
Graphics (images, photo, etc.)	37.8
Database/spreadsheet	31.9
Managing household records/finance	31.2

Appendix A1-3: Internet Connectivity at Home (CPS October 2003)

		% Reporting
Connected from home		61.5
Device for connection:	Home PC	93.2
	Laptop	5.7
	TV-based Internet	0.76
	Mobile	0.15
	PDA	0.08
	Game Machine	0.02
	Other means	0.19
Connection type:		
	Dial-up	62.6
	DSL (digital subscriber line)	14.5
	Cable modem	21.6
	Fixed wireless connection	0.38
	Others	0.97
Why not use high-speed Internet?		
	Don't need/not interested	41.5
	Too expensive	39.4
	Not available in the area	11.8
	Others	7.3
Last year's frequency of use:		
	At least once/day	53.8
	At least once/week, not every day	33.5
	At least once/month, not every week	7.8
	Less than once/month	4.9
Why not have Internet at home?		
	Too high costs	27.1
	Don't need/not interested	35.1
	No computer	23.5
	Lack of skill	3.7
	Others	10.6
Non-owners access Internet at:		
	Work place	18.3
	School	11.6
	Someone else's house	6.3
	Public library	5.7
	Airport, hotel, etc	2.5
	Internet café/coffee shop	0.85

Appendix A1-4: Current Use of Internet at Home (CPS October 2003)

	% Reporting
Email or instant messaging	42.0
Search info about products and services	35.3
Get news, weather or sports info	30.8
Purchasing products and services	23.2
Playing game	21.3
Search info about health services or practices	18.0
Search info about government services or agencies	15.2
Complete school assignment	12.7
Online banking	11.7
Download federal, state or local government forms	11.3
Listening to radio or viewing TV or movie	10.2
Submit federal, state or local government forms	7.9
Search for a job	7.8
Read online job ads, or search online job listings	7.2
Search info about potential employers	5.4
Submitting resume or application to employer	4.3
Post resume on a job listing site or with a service	3.0
Trade stocks, bonds or mutual funds	2.8
Taking online course	2.7
For telephone calls	1.6

Appendix A2: Variables for which Minutes Spent in Using CI can be Reported in ATUS

American Time Use Survey Activity Lexicon: 2006

Major Categories 1st - tier	2nd - tier	3rd - tier	Examples

02 Household Activities

09 Household Management

04 Household and personal e-mail and messages

Reading e-mail (personal or household)
Instant messaging (personal)
Sending e-mail (personal or household)
Reading/sending e-mail, not specified
Checking e-mail (personal or household)
Cleaning out e-mail inbox (personal or household)

12 Socializing, Relaxing, and Leisure

03 Relaxing and Leisure

08 Computer use for leisure (except games)

Computer use, unspecified
Computer use, leisure (personal interest)
Surfing the internet (personal interest)
Downloading files, music, pictures (personal interest)
Surfing the web (personal interest)
Participating in a chat room (personal interest)
Burning CDs (personal interest)
Designing/updating website (personal interest)
Browsing on the internet (personal interest)

15 Volunteer Activities

01 Administrative and Support Activities

01 Computer use

Writing/sending e-mail (volunteer)
Checking e-mail (volunteer)
Designing website for volunteer organization
Computer use, unspecified (volunteer)
Surfing the internet (volunteer)

Appendix A3: Estimation of the Predicted Wage

Variable	Labor force participation equation	Wage equation
Age	0.133 (26.41)***	0.052 (7.63)***
Age squared	-0.002 (28.19)***	-0.001 (5.79)***
Education	0.154 (5.97)***	0.083 (21.93)***
Female	-0.192 (7.23)***	-0.190 (10.81)***
Nonwhite	-0.035 (1.00)	-0.100 (4.82)***
Noncitizen	0.080 (1.56)	-0.095 (3.21)***
Urban	0.030 (0.87)	0.178 (8.29)***
Education squared	-0.001 (1.20)	
Age*Education	-0.002 (5.78)***	
No. of children age 0 to 2	-0.248 (7.48)***	
No. of children age 3 to 5	-0.176 (5.51)***	
No. of children age 6 to 9	-0.075 (2.83)***	
No. of children age 10 to 12	-0.094 (3.00)***	
Family income	0.000021 (5.72)***	
Constant	-3.202 (15.00)***	0.465 (2.38)**
No. of observations	11193	11193
Absolute value of z statistics in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%		

Appendix A4: Error Specification Issues in the Double-Hurdle Model

The main issue in this paper is specifying the use of CI at home in terms of the framework of the double-hurdle model. As discussed in the text, the double-hurdle model involves two distinct decisions: the participation decision (whether to own a home CI) and the level of participation (the extent of use of CI). The type of association between these decisions and the specifications of the error terms determine the likelihood function to be estimated. Hence, if an individual makes both decisions separately, the two decisions are modeled independently; or if both decisions are made simultaneously, they are modeled jointly; or if one decision is made first and affects the other one, they are modeled sequentially (Martínez-Espiñeira, 2006). The resulting models are called the *independence*, the *dependence* and the *dominance* models, respectively. In addition, in limited dependent variable models, the likelihood functions are derived based on the assumptions of normality and homoskedasticity of the error terms. When either assumption is violated, the corresponding maximum likelihood (ML) estimates become inconsistent (Amemiya and Powell, 1981; Arabmazar and Schmidt 1981, 1982).

This paper does not address each of these specification issues. Instead, the study uses the double-hurdle model derived based on the assumptions of independent ownership and usage decisions (i.e., independent error terms) and homoskedastic and normally distributed error terms. Dealing with these error specification issues will be an area of extension in future studies.

Appendix A5: Maximum Likelihood Estimation of *Tobit*, Generalized *Tobit* and Double-Hurdle Models: Total Minutes of CI Use

Variable	*Tobit*	Generalized *Tobit*		Double-Hurdle	
		1st Hurdle	2nd Hurdle	1st Hurdle	2nd Hurdle
Age	-1.898 (11.90)***	-0.013 (12.09)***	-0.007 (0.03)	-0.030 (5.29)***	-0.453 (0.96)
Some college or Assoc degree	45.779 (7.80)***	0.336 (8.63)***	-9.859 (1.32)		45.670 (7.65)***
Bachelor's degree or above	71.393 (10.18)***	0.516 (11.14)***	-11.698 (1.17)		69.245 (9.90)***
Female	-14.476 (3.27)***	-0.061 (2.04)**	-16.359 (4.05)***	0.429 (2.79)***	-23.431 (2.48)**
Nonwhite	-14.212 (2.49)**	-0.129 (3.36)***	12.743 (2.28)**	-0.737 (3.73)***	11.226 (0.62)
Noncitizen	-32.351 (3.57)***	-0.222 (3.67)***	-0.174 (0.02)	-0.315 (0.86)	-22.921 (1.41)
Married & spouse/ partner present	-13.090 (2.66)***	-0.067 (2.02)**	-11.085 (2.44)**	0.321 (1.69)*	-18.539 (1.84)*
No. of children age 0 to 2	-33.780 (5.49)***	-0.213 (5.23)***	-7.756 (1.22)	-0.453 (1.91)*	-18.994 (2.35)**
No. of children age 3 to 5	-19.690 (3.44)***	-0.123 (3.26)***	-6.735 (1.24)	-0.256 (1.22)	-11.180 (1.51)
No. of children age 6 to 9	-14.444 (3.16)***	-0.092 (3.01)***	-2.720 (0.63)	-0.010 (0.05)	-11.836 (2.14)**
No. of children age 10 to 12	-8.130 (1.58)	-0.038 (1.12)	-7.377 (1.63)	0.011 (0.04)	-6.629 (1.01)
No. of children age 13 to 17	9.260 (2.50)**	0.069 (2.79)***	-2.662 (0.77)	0.525 (1.68)*	-3.744 (0.74)
Urban	15.543 (2.64)***	0.111 (2.81)***	0.868 (0.15)	-0.116 (0.45)	18.760 (2.23)**
Northeast	10.062 (1.65)*	0.066 (1.61)	0.499 (0.09)	0.344 (1.54)	1.216 (0.14)
Midwest	15.820 (2.89)***	0.076 (2.09)**	10.953 (2.19)**	0.393 (2.01)**	6.009 (0.72)
West	16.135 (2.87)***	0.083 (2.20)**	8.852 (1.76)*	0.173 (0.88)	10.183 (1.25)
Weekdays	11.473 (2.76)***		-13.082 (3.55)***		11.459 (2.73)***
Spring	2.579 (0.43)		-4.197 (0.80)		1.806 (0.30)
Fall	2.121 (0.35)		-6.164 (1.14)		-0.790 (0.13)
winter	11.979 (2.03)**		2.199 (0.42)		11.950 (1.99)**

Appendix A 5 – Continued

Variable	*Tobit*	Generalized *Tobit*		Double-Hurdle	
		1st Hurdle	2nd Hurdle	1st Hurdle	2nd Hurdle
Family income	5.655 (4.17)***	0.051 (5.62)***	-3.977 (2.93)***	0.182 (2.57)**	1.740 (0.85)
High wage	10.245 (0.92)	0.041 (0.55)	7.233 (0.69)	4.094 (1.02)	-87.388 (2.83)***
Medium wage	7.503 (0.94)	0.035 (0.66)	4.606 (0.56)	1.635 (3.43)***	-71.140 (3.77)***
Government job	-35.440 (4.96)***	-0.206 (4.33)***	-21.292 (3.11)***	0.460 (1.07)	-39.867 (4.02)***
Private job	-40.988 (8.49)***	-0.256 (7.96)***	-16.611 (2.94)***	0.054 (0.29)	-39.885 (5.33)***
Constant	-116.292 (9.51)***	-0.735 (9.89)***	124.700 (4.63)***	0.073 (0.14)	-57.862 (1.51)
Observations	12943	12943		12943	

Absolute value of t statistics in parentheses for *Tobit* and generalized *Tobit* models.
Absolute value of z statistics in parentheses for double-hurdle model.
* significant at 10%; ** significant at 5%; *** significant at 1%
Note: Education variables are omitted from the first hurdle to facilitate convergence.

CHAPTER II

IMPACTS OF COMPUTER AND INTERNET USE AT HOME ON THE ALLOCATION OF TIME

2.1 Introduction

Individuals allocate their time across competing activities. Many time allocation studies examine the allocation of time among market work, household production and leisure. The first is a paid activity while the other two are unpaid tasks. Household production activities may involve combining market purchased goods and individuals' time in order to produce a variety of economically significant household consumption goods and services or "commodities" (Becker, 1965; Gronau, 1980). Examples of household production activities include preparing food, cleaning the house, shopping, childcare and care of other family members, maintaining the house and yard, mending and laundry (Ramey and Francis, 2006). Individuals perform these and other activities using various household appliances, known as *household goods*.[6]

Technological advances in the home sector, particularly following the onset of electricity, have brought a host of new household goods into private homes (Greenwood and Seshadri, 2005). Since these home technologies result in the simplification and mechanization of housework, they are called *time-saving* household goods. The electric stove, iron, washing machines and dryers, dishwasher, microwave oven and food processor are some examples of *time-saving* household goods (Greenwood and

[6] Becker (1965) and Greenwood and Seshadri (2005) call them capital goods.

Vandenbroucke, 2005). Housework is also greatly simplified by a variety of other innovations, such as vacuum cleaners, central heating, refrigerators, freezers, blenders and many smaller devices, and the availability of pre-packaged meals, wash-and-wear fabrics as well as the expansion of supermarkets and fast-food restaurants (Caplow et al, 2001).

On the other hand, technology is constantly producing new entertainment goods that eventually become sources of new activities for the household. Examples for this group include radio, board games, television and the videocassette recorder. These goods are *time-using* by their nature and are called *leisure goods* (Greenwood and Vandenbroucke, 2005). According to these authors, some goods, such as the telephone and personal computers could be both *time-saving* and *time-using* based on how they are used in private homes. Then, the question one should ask is, What is happening to the allocation of time in the face of all these innovations?

Some studies have been conducted to investigate the impacts of advances in technology both at marketplace and home production on the allocation of time (e.g., Greenwood and Seshadri, 2005; Greenwood and Vanderbroucke, 2005). There seems to be consensus regarding the fall in market work over time following an increase in workplace productivity. However, whether the use of labor-saving goods at home has resulted in producing time shifts in housework and leisure is an open question. That is, studies produce mixed results regarding the time shifts in housework and leisure.

Greenwood and Seshadri (2005) argue that improvements in household goods freed up a tremendous amount of women's labor so that the participation of married women in the labor force rose from 4 percent in 1890 to 49 percent in 1980. As a result, housework time dropped drastically from 58 to 18 hours per week between 1975 and 1900. Aguiar and Hurst (2007) find a dramatic increase in leisure between 1965 and 2003. These authors show that leisure for men increased by nearly 6 to 9 hours per week due to a decline in market work hours, and for women by about 4 to 8 hours per week because of a fall in housework hours. Greenwood and Vandenbroucke (2005) document the fall in market work from 70 to 41 hours per week between 1830 and 2002. They also show that the proportion of women who spent more than 4 hours per day engaged in unpaid household work fell from 87 percent to 14 percent between 1924 and 1999. In a study that employs time diary data, Robinson and Godbye (1999) show that market work time decreased and leisure time increased in the United States between 1965 and 1995. The implication of all these studies is that housework has been falling and leisure rising over time.

In contrast, Ramey and Francis (2006) argue that despite the fall in market work and improvements in household technologies, there is no change in housework and leisure time over the last 105 years. The authors arrive at this conclusion by employing a new measure that counts the entire population and accounts all the possible non-leisure uses of time. On the other hand, Ramey (2008), in his new estimates for home production in the U.S. during the 20th century, contends that per capita time spent in housework per week shows a slight increase over the century if the entire population is taken into account. However, when disaggregated by sex and age, the results show that for prime-age women weekly housework time fell by 6 hours from 1900 to 1965 and by another 12 hours from 1965 to 2005, while that of prime-aged men rose by 13 hours from

1900 to 2005.[7] Mokyr (2000) argues that despite the diffusion of presumably labor-saving household goods, housewives' home production time did not decrease as much as expected since 1880, and may have in fact increased for long periods of time. According to Mokyr, this occurs because the time saving impact resulting from the diffusion of household goods is offset by the increase in the volume of housework following the diffusion of knowledge about the causes and transmission mechanisms of infectious diseases. What is commonly observed in these studies is that individuals, particularly women, continue to spend more time in home production despite the wide spread availability and use of time-saving household goods.

This study revisits the time allocation issue from a different perspective. As mentioned above, home computers and the Internet serve as both *time-saving* household goods and *time-using* leisure goods. While the first frees up time by enhancing the efficiency of time in the home production, the second leads to the consumption of more time. These make computers and the Internet different from the household goods discussed above, which mainly are *time-saving* household goods. As a result, predicting the net effect of these technologies on an individual's time allocation decisions becomes more difficult. Hence, using a representative individual's preference function, this study investigates whether the use of a computer and the Internet (CI) at home produces any time displacement effects on the allocation of time for market work, housework and leisure. That is, the study develops a theoretical model that incorporates CI use in an individual's utility function in order to examine whether the role home computers and the Internet play as household goods and leisure goods leads to time reallocation.

[7] Ramey's (2008) uses the term prime-age for individuals ages 18-64.

The rest of the chapter is organized as follows. Section 2 presents the conceptual framework on which the study is based. The theoretical model is developed and discussed in section 3. In section 4, the estimation results are presented. The last section provides the summary and conclusions of the study.

2.2 Conceptual Framework and Methodological Approach

Computers and the Internet are now becoming more and more part of household goods in many United States households. Technological advances in microelectronics, network infrastructure and telecommunication systems are responsible for making personal computers and Internet available to the public at affordable prices since the early 1980s and 1990s. In the United States, information on computer and Internet uses at home has been collected in various Supplements to the Current Population Survey (CPS) beginning from 1984 and 1997, respectively.[8] These surveys show that the trend of computer and Internet ownership at home has been increasing steadily over time. While the proportion of households with a computer grew from nearly 8 percent in 1984 to about 69 percent in 2003, the proportion of those who access the Internet from home rose from 18 percent in 1997 to nearly 62 percent in 2003 (Day et al, 2005).

The main motivation of this study is to study the impact that such a rapid increase of the use of these technologies is likely to produce on individuals' allocation of time. The study is based on the conceptual framework that using a computer and the Internet at home changes the existing patterns of individuals' time allocation (Venkatesh et al, 1985). This is based on the assumption that widely spread use of a computer and the

[8] See U.S. Census Bureau (2003). The following surveys contain information on computer and Internet use at home: CPS 1984, 1989, 1993, 1997, 2000, 2001 and 2003.

Internet at home may create new lines of activities for individuals living in households with access to these technologies. The CPS Computer and Internet Use Supplements indicate that computer and Internet are being used at home for various activities. Some of the most popular uses of these technologies at home include word processing, database management, household record keeping, graphics, completing school assignments, email or instant messaging, playing games, getting news and sports information, online banking and shopping, downloading and submitting government forms, and searching for a job. As these activities can be either time-saving or time-using, the overall impact of using computer and the Internet at home would be a shift in the existing pattern of time uses and emergence of a new pattern for time allocation. Regarding the determination of the direction of the resulting time shifts, the study advances the following two arguments.

Argument 1: Computer and Internet as time-saving household goods

With the increase in the ownership and use of computers and the Internet in many households, individuals are more likely to use them to carry out some household activities. This argument is based on the fact that the use of home CI enables individuals to complete some household activities (such as shopping, paying bills, using government services, etc.) more conveniently and faster without leaving the comfort of their homes and save time in the process. Good examples for this case are the traveling time saved from shopping, using government services and paying bills online. In addition, using a high-speed Internet, individuals can also carry out their Internet-based activities in the shortest time possible and save more household time. Having more freed up time, in turn, would give individuals the opportunity to either explore new utility-maximizing non-labor time uses or spend more time on existing market and leisure activities. One possible outcome of this argument would be that home CI use results in reallocating time away from home production and into either market work or leisure activities, or both.

Argument 2: Computer and Internet as time-using leisure goods

In this case, individuals are assumed to use home computer or the Internet dominantly for pure entertainment purposes. With the introduction of new computer- and Internet-based games and accessibility of sound and visual entertainment (e.g., music and movies), individuals are likely to spend more time using computers or the Internet. Since spending more time in one activity necessitates spending less in another, this is likely to reduce the time allocated for housework or market work, or both. If this argument holds, the outcome would be a shift in the time use from other activities into CI-related leisure activities.

From the above two arguments, it can be inferred that using a home computer and the Internet is likely to produce time displacing impacts not only on the allocation of time for housework and leisure, but also on the supply of paid work hours. Therefore, the major goal of the study is investigating the possible impacts of the use of home CI on the allocation of time. In this regard, the study employs two methodological approaches. First, the impacts of CI use on an individual's allocation of time are analyzed theoretically. This is accomplished by modeling CI use in a representative individual's utility function. The theoretical foundations developed by Becker (1965, 1976) and a number of studies that followed (e.g., Wales and Woodland, 1977; Gronau, 1977, 1980; Graham and Green, 1984; Kooreman and Kapteyn, 1987; Greenwood and

Vandenbroucke, 2005) serve as the basis for the modeling.[9] Second, the predictions of the theoretical model are tested using data from the 2003 ATUS and the 2003 CPS computer and Internet use Supplement.[10]

2.3 A Model of Computer or Internet (CI) Use

The first part of this section deals with the development of a theoretical model that incorporates CI use at home. The second part analyzes the predications of the model via comparative static analyses. The final part discusses the implications of the theoretical model in comparison with the predications of the standard labor supply theory.

2.3.1 Modeling Computer and Internet (CI) Use in a Utility Function

Consider a representative individual with a utility function:[11]

$$U = U(X, L, \tau) \tag{1}$$

This is a non-negative, non-decreasing and quasi-concave utility function.[12] $U(X, L, \tau)$ denotes utility from the consumption of all goods X (market and nonmarket), leisure L

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[9] Becker (1965, 1976) revised the traditional theory of the allocation of time by incorporating household produced commodities in the household utility function. The other authors developed various versions of household production models based on Becker's formulations and introduced different approaches of testing them.

[10] Both datasets are obtained from U.S. Bureau of Labor Statistics, Washington, D.C.

[11] This utility model extends on the basic labor supply theory by introducing an additional argument (τ). For the details on the traditional model see, for example, Gronau 1977, 1980; Graham and Green, 1984; Kooreman and Kapteyn, 1987; Solberg and Wong, 1991.

[12] That is, none of the variables generate disutility and the utility function is increasing in each of its arguments (i.e., $U_X, U_L, U_\tau > 0$) at a decreasing rate (i.e., $U_{XX}, U_{LL}, U_{\tau\tau} < 0$).

and computer and Internet (CI) services τ. Consumption goods are either purchased in the market X_m or produced at home X_h (both measured in the same units):

$$X = X_m + X_h \tag{2}$$

Goods are produced at home using market purchased inputs z_h and an individual's time t_h. In other words, t_h is the time spent in the production of various home produced goods and services (cooking, cleaning, childcare and so on).[13] For simplicity, suppressing the market purchased inputs, the home production function can be written in terms of time inputs alone as (Solberg and Wong, 1991, Palmquist et al, 2007):[14]

$$X_h = h(t_h) \tag{3}$$

CI services are produced with the production function

$$\tau = f(\kappa, t_c) \tag{4}$$

In this expression, κ can be considered as the level or type of CI technology an individual is using at home (i.e., the processing power of a home computer and/or the

[13] In addition, the utility function is assumed to be separable as shown below. Substituting (2) in (1), the utility function can be rewritten as $U = U(X_m, X_h, L, \tau) \equiv U(t_m, t_h, L, t_c)$. The last expression is obtained by approximating the amount of goods and services consumed by the amount of time used to acquire or produce them. That is, one has to work for t_m hours to be able to purchase X_m, and spend t_h and t_c hours at home to produce X_h and τ. Then, $U = U(t_m, t_h, L, t_c)$ can be assumed separable in the branches 1, 2, 3 and 4 if it can be written as $U = U\left(V^1(t_m), V^2(t_h), V^3(L), V^4(t_c)\right)$. Each branch represents the allocation of time for different set of activities that generate utility. The following are the activities in each branch. Branch 1: market work (job 1, job 2, ...). Branch 2: home production (food preparation, cleaning, washing, caregiving,......). Branch 3: leisure (sleeping, reading, grooming,....); Branch 4: CI use (record keeping, financial management, email, browsing, surfing the web,....). Given the total available time $T = 1$, first the individual allocates time to each branch, and then optimally spends each allocation on the activities in its branch, independent of the allocation of time in other branches. This implies that the marginal rate of substitution between any two activities in any two branches cannot be affected by an activity in any other branch (*strong separability* assumption). For example, the marginal rate of substitution between a certain market activity (say, time spent in job 1) and a given housework activity (say, time spent in cleaning) is independent of the allocation of time for any of the leisure activities (say, reading): $\frac{\partial}{\partial L_1}\left(\frac{\partial U/\partial t_{m1}}{\partial U/\partial t_{h1}}\right) = 0$. However, the allocation of time to any activity could change through reallocation of time between branches (Strotz 1957; 1959).

[14] Suppressing the market purchased inputs from the home production function is justified by the difficulties in measuring these inputs and separating X_m from X_h (Gronau, 1980).

speed of Internet connection). Hence, CI services are produced by using κ for t_c units of time.[15] The production functions in Equations (3) and (4) have the standard property of decreasing marginal productivity,

$$h_{t_h} > 0, f_k > 0, f_{t_c} > 0 \quad \text{and} \quad h_{t_h t_h} < 0, f_{kk} < 0, f_{t_c t_c} < 0.$$

The money cost of using CI at home consists of initial or fixed cost κ_0 required to purchase a computer or to get connected to the Internet, and a unit price r paid for using it:[16]

$$C = \kappa_0 + r\kappa \tag{5}$$

Let the total time, normalized to unity, be divided into market work t_m, leisure L, home production t_h, and CI use t_c (note that CI use is partially leisure and partially home production):

$$t_m + L + t_h + t_c = 1 \tag{6}$$

Taking the market purchased good as a numeraire, the budget constraint can be written as:

$$X_m + \kappa_0 + r\kappa = Y + wt_m \tag{7}$$

where w is the market wage rate and Y is non-labor income.[17] Combining the time and budget constraints gives a single constraining function in terms of the numeraire good:

[15] Becker (1965) assumes that households combine goods and time to produce commodities.

[16] Here the assumption is that κ is indivisible and generates a flow of services for which an individual pays a unit price r for the services used. The usage price r can also be envisaged as the rental rate on capital (considering computer or Internet technology as a capital good).

[17] The budget constrain can be alternatively written, equating total expenditure to total income, as $X_m + \kappa_0 + r\kappa = Y + w(1 - t_c - t_h - L) \Rightarrow X_m + \kappa_0 + r\kappa + w(t_c + t_h + L) = Y + w$.

$$X_m = (Y - \kappa_0) + w(1 - t_c - t_h - L) - r\kappa$$

and

$$\begin{aligned} X &= X_m + X_h \\ &= (Y - \kappa_0) + w(1 - t_c - t_h - L) - r\kappa + h(t_h) \end{aligned} \tag{8}$$

Then, an individual selects the allocation of time (t_c, t_h, L) and the type of CI technology (κ) to maximize utility (1) subject to constraint (8):[18]

$$S(w, r, \kappa_0, Y) = \max_{t_c,\, t_h,\, \kappa,\, L} U\left\{\underbrace{(Y - \kappa_0) + w\left(1 - t_c - t_h - L\right) - r\kappa + h(t_h)}_{X}, L, \underbrace{f(\kappa, t_c)}_{\tau}\right\} \tag{9}$$

The first order conditions governing the time allocations and expenditure are:

$$\frac{\partial S}{\partial t_c} = -wU_X + f_{t_c}U_\tau = 0 \tag{10a}$$

$$\frac{\partial S}{\partial t_h} = [-w + h'(t_h)]\, U_X = 0 \tag{10b}$$

$$\frac{\partial S}{\partial \kappa} = -rU_X + f_\kappa U_\tau = 0 \tag{10c}$$

$$\frac{\partial S}{\partial L} = -wU_X + U_L = 0 \tag{10d}$$

Interpretations of the FOCs:

All the first order conditions, except (10b), can be interpreted in terms of the marginal costs and marginal benefits associated with allocating an extra unit of time for leisure or computer use, following Greenwood and Seshadri (2005) and Greenwood and Vandenbroucke (2005). Accordingly, (10a) states that an extra unit of time in CI increases the production of computer services by the marginal product of computer time

[18] Note that the constrained utility maximization is transformed into unconstrained one by substitution. The utility function in (9) is of the form $U = U(t_c, t_h, \kappa, L; w, r, \kappa_0, Y)$.

(f_{t_c}). Multiplying this by the marginal utility of computer services (U_τ) yields the total marginal benefit generated in utility terms. At the optimal point, this MB equals its total MC, the forgone utility from consumption (wU_X) due to a reduction in market work. The constraint in (10c) specifies that the MB obtained from using computer services (given in utility terms as the product of the MU of computer services U_τ and the marginal product of computer use f_κ) equals the associated MC (the forgone utility from consumption, given as MU from consumption multiplied by unit price of computer use, $-rU_X$). In (10d) an individual allocates time for leisure up to the point where the marginal benefit gained from the extra unit of leisure (denoted by the marginal utility of leisure, U_L) equals the corresponding marginal cost expressed in terms of the forgone utility from consumption (wU_X).

Alternatively, by combining (10a) and (10c), the optimal expenditure pattern can be expressed in terms of the marginal rate of substitution between consumption goods X and CI services τ :

$$\frac{U_X}{U_\tau} = \frac{f_{t_C}}{w} = \frac{f_\kappa}{r} \quad \Rightarrow \quad \frac{f_{t_C}}{f_\kappa} = \frac{w}{r} \quad \Rightarrow \quad MRS_{X,\tau} = \frac{w}{r}$$

The constraint in (10b) describes the decision rule for allocating time for market work and home production. Time is allocated between these two competing uses based on the condition that the marginal productivity of time in home production is at least equal to the prevailing market wage rate:

$$h'(t_h) = w\,.$$

That is, the marginal productivity of work at home should be high enough to compensate for the forgone market wage. If the marginal productivity of time in home production is less than the market wage rate, an individual will shift the allocation of time to market work, and vice versa. At the optimal allocation, the marginal product of work at home equals the wage rate.

The FOCs in (10a) – (10d) represent four equations in four decision variables (t_c, t_h, κ, L) and four exogenous variables (w, r, κ_0, Y). If the *Jacobian* determinant is nonzero, i.e.,

$$J = \left| \frac{\partial S_j}{\partial(t_c, t_h, \kappa, L)} \right| \neq 0$$

where $j = t_c, t_h, \kappa, L$ and S_j denotes each FOC in (10a) – (10d), then the variables (t_c, t_h, κ, L) can be expressed as explicit functions of (w, r, κ_0, Y) at and around any point that satisfies the FOCs (Silberberg, 1990).[19] This means that the FOCs can be solved for the explicit choice functions:

$$\begin{aligned} t_c &= t_c^*(w, r, \kappa_0, Y) \\ t_h &= t_h^*(w, r, \kappa_0, Y) \\ \kappa &= \kappa^*(w, r, \kappa_0, Y) \\ L &= L^*(w, r, \kappa_0, Y) \end{aligned} \tag{11a}$$

These give the optimal allocations of time for CI use (t_c), housework (t_h) and leisure (L), and the optimal choice of the type of CI technology (κ) in terms of the exogenous variables (w, r, κ_0, Y). Using the relation in (6), the optimal time allocation

[19] The *Jacobian* determinant can be used to test for functional relationships. If $J = 0$, the equations in the FOC are said to be functionally dependent such that no explicit solutions can be found for the endogenous variables. When $J \neq 0$, the explanatory variables in the FOCs are mutually independent and hence yield explicit solutions.

for market work will be:

$$t_m^* = 1 - t_c^* - t_h^* - L^* \quad \text{such that} \quad t_m = t_m^*(w,\ r,\ \kappa_0,\ Y) \tag{11b}$$

The *sufficient* second-order conditions for maximum are that the principal minors of the matrix of second partials (known as the *Hessian*) alternate in sign.[20]

2.3.2 Comparative Static Analyses

Assuming that all goods and services are normal, the changes in the optimal allocations of time and the choice of CI technology $(t_c^*,\ t_h^*,\ L^*,\ \kappa^*)$ with respect to changes in the exogenous variables $(w, r,\ \kappa_0, Y)$ are analyzed below. These are accomplished by first substituting the optimal solutions in (11a) back into the FOCs and obtaining the identities:

$$-wU_X\left((Y-\kappa_0)+w(1-t_c^*-t_h^*-L^*)-r\kappa^*+h(t_h^*)\right)+f_{t_c}(\kappa^*,t_c^*)\,U_\tau\left(f(\kappa^*,t_c^*)\right)\equiv 0 \tag{10a$'$}$$

$$[-w+h'(t_h^*)]\,U_X\left((Y-\kappa_0)+w(1-t_c^*-t_h^*-L^*)-r\kappa^*+h(t_h^*)\right)\equiv 0 \tag{10b$'$}$$

$$-rU_X\left((Y-\kappa_0)+w(1-t_c^*-t_h^*-L^*)-r\kappa^*+h(t_h^*)\right)+f_\kappa(\kappa^*,t_c^*)\,U_\tau\left(f(\kappa^*,t_c^*)\right)\equiv 0 \tag{10c$'$}$$

$$-wU_X\left((Y-\kappa_0)+w(1-t_c^*-t_h^*-L^*)-r\kappa^*+h(t_h^*)\right)+U_L\left(L^*\right)\equiv 0 \tag{10d$'$}$$

---

[20] Taking the direct and cross-partials of the FOCs in (10a) – (10d), the *Hessian* determinant can be constructed as:

$$|H| = \begin{vmatrix} S_{t_ct_c} & S_{t_ct_h} & S_{t_c\kappa} & S_{t_cL} \\ S_{t_ht_c} & S_{t_ht_h} & S_{t_h\kappa} & S_{t_hL} \\ S_{\kappa t_c} & S_{\kappa t_h} & S_{\kappa\kappa} & S_{\kappa L} \\ S_{Lt_c} & S_{Lt_h} & S_{L\kappa} & S_{LL} \end{vmatrix}.$$

Utility to be maximized at the optimal allocations given by (11a), the principal minors should alternate in sign:

$$|H_1| = S_{t_ct_c} < 0,\quad |H_2| = \begin{vmatrix} S_{t_ct_c} & S_{t_ct_h} \\ S_{t_ht_c} & S_{t_ht_h} \end{vmatrix} > 0,\quad |H_3| = \begin{vmatrix} S_{t_ct_c} & S_{t_ct_h} & S_{t_c\kappa} \\ S_{t_ht_c} & S_{t_ht_h} & S_{t_h\kappa} \\ S_{\kappa t_c} & S_{\kappa t_h} & S_{\kappa\kappa} \end{vmatrix} < 0 \quad \text{and} \quad |H_4| = |H| > 0.$$

Then, to find the responses of the system to a change in a given variable, say w, differentiate these identities with respect to w. The resulting system of equations can be solved by Cramer's rule. For ease of understanding the processes involved, each comparative static analysis is illustrated using a change in market wage. For the rest of the cases, the details are suppressed for the sake of brevity.

2.3.2.1 Effects of a Change in the Market Wage

The effects of a change in the market wage rate on the optimal allocations of time and the choice of computer/Internet type can be shown by differentiating (10a′) – (10d′) with respect to w:

$$
\begin{aligned}
&(w^2U_{XX} + f_{t_c t_c}U_\tau + f_{t_c}^2 U_{\tau\tau})\frac{\partial t_c}{\partial w} - w(-w+\mathrm{h}'(\mathrm{t_h}))\mathrm{U_{XX}}\frac{\partial t_h}{\partial w} + (wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau})\frac{\partial \kappa}{\partial w} \\
&\qquad + w^2U_{XX}\frac{\partial L}{\partial w} \equiv U_X + w(1-t_c-t_h-L)U_{XX} \\[2ex]
&-w(-w+\mathrm{h}'(\mathrm{t_h}))\mathrm{U_{XX}}\frac{\partial t_c}{\partial w} + \left(h''(t_h)U_X + \left(-w+h'(t_h)\right)^2 U_{XX}\right)\frac{\partial t_h}{\partial w} - r(-w+\mathrm{h}'(\mathrm{t_h}))\mathrm{U_{XX}}\frac{\partial \kappa}{\partial w} \\
&\qquad - w(-w+\mathrm{h}'(\mathrm{t_h}))\mathrm{U_{XX}}\frac{\partial L}{\partial w} \equiv U_X - (-w+h'(t_h)(1-t_c-t_h-L)\, U_{XX} \\[2ex]
&(rwU_{XX} + f_{\kappa t_c}U_\tau + f_\kappa f_{t_c}U_{\tau\tau})\frac{\partial t_c}{\partial w} - r(-w+\mathrm{h}'(\mathrm{t_h}))\mathrm{U_{XX}}\frac{\partial t_h}{\partial w} + (r^2U_{XX} + f_{\kappa\kappa}U_\tau + f_\kappa^2 U_{\tau\tau})\frac{\partial \kappa}{\partial w} \\
&\qquad + rwU_{XX}\frac{\partial L}{\partial w} \equiv r(1-t_c-t_h-L)U_{XX} \\[2ex]
&w^2U_{XX}\frac{\partial t_c}{\partial w} - w(-w+\mathrm{h}'\ (\mathrm{t_h}))\mathrm{U_{XX}}\frac{\partial t_h}{\partial w} + wr\mathrm{U_{XX}}\frac{\partial \kappa}{\partial w} + (w^2\mathrm{U_{XX}} + U_{LL})\frac{\partial L}{\partial w} = U_X + w(1-t_c-t_h-L)U_{XX}
\end{aligned}
\tag{12}
$$

The above system of equations can be rewriting in matrix form as:

$$\begin{pmatrix} w^2U_{XX}+f_{t_ct_c}U_\tau+f_{t_c}^2U_{\tau\tau} & -w(-w+h'(t_h))U_{XX} & wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX} \\ -w(-w+h'(t_h))U_{XX} & h''(t_h)U_X+\left(-w+h'(t_h)\right)^2U_{XX} & -r(-w+h'(t_h))U_{XX} & -w(-w+h'(t_h))U_{XX} \\ rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau} & -r(-w+h'(t_h))U_{XX} & r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau} & wrU_{XX} \\ w^2U_{XX} & -w(-w+h'(t_h))U_{XX} & wrU_{XX} & w^2U_{XX}+U_{LL} \end{pmatrix}\begin{pmatrix} \partial t_c/\partial w \\ \partial t_h/\partial w \\ \partial\kappa/\partial w \\ \partial L/\partial w \end{pmatrix} \quad (13a)$$

$$= \begin{pmatrix} U_X+w(1-t_c-t_h-L)U_{XX} \\ U_X-(-w+h'(t_h))\,(1-t_c-t_h-L)U_{XX} \\ r(1-t_c-t_h-L)U_{XX} \\ U_X+w(1-t_c-t_h-L)U_{XX} \end{pmatrix}$$

The LHS term is the same as the Hessian matrix (i.e., the second partials of the FOCs). By the sufficient second-order conditions, the Hessian determinant has the sign $(-1)^n$ for a maximum. Hence, $|H_4|=|H|>0$. The comparative static computations can be simplified further by using the FOC given in (10b)(i.e., $-w+h'(t_h)=0$). Substituting this in (13) and using $z_1=w(1-t_c-t_h-L)$ and $z_2=r(1-t_c-t_h-L)$:

$$\begin{pmatrix} w^2U_{XX}+f_{t_ct_c}U_\tau+f_{t_c}^2U_{\tau\tau} & 0 & wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX} \\ 0 & h''(t_h)U_X & 0 & 0 \\ rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau} & 0 & r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau} & wrU_{XX} \\ w^2U_{XX} & 0 & wrU_{XX} & w^2U_{XX}+U_{LL} \end{pmatrix}\begin{pmatrix} \partial t_c/\partial w \\ \partial t_h/\partial w \\ \partial\kappa/\partial w \\ \partial L/\partial w \end{pmatrix} = \begin{pmatrix} U_X+z_1U_{XX} \\ U_X \\ z_2U_{XX} \\ U_X+z_1U_{XX} \end{pmatrix} \quad (13b)$$

Again, (13b) can be simplified further by denoting the terms appearing as elements of the coefficient matrix by $n_{ij}, i, j=1,\ldots,4$, and those of the constant vector by $c_j, j=1,\ldots,4$.

$$\begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix}\begin{pmatrix} \partial t_c/\partial w \\ \partial t_h/\partial w \\ \partial\kappa/\partial w \\ \partial L/\partial w \end{pmatrix} = \begin{pmatrix} \underline{c}_1 \\ c_2 \\ c_3 \\ \underline{c}_4 \end{pmatrix} \quad (14)$$

Note that all the nonzero n_{ij}'s have negative signs except where $n_{13} = n_{31}$ which involve terms with mixed signs. For example, $n_{11} < 0$ because $w^2 \overbrace{U_{XX}}^{-} + \overbrace{f_{t_c t_c}}^{-} \overbrace{U_{\tau}}^{+} + f_{t_c}^2 \overbrace{U_{\tau\tau}}^{-} < 0$. For n_{13}, the marginal product of time spent in using computer/Internet at home is assumed to increase in κ (i.e., $f_{t_c \kappa} > 0$) so that $wr \overbrace{U_{XX}}^{-} + \overbrace{f_{t_c \kappa}}^{+} \overbrace{U_{\tau}}^{+} + \overbrace{f_{t_c} f_{\kappa}}^{+} \overbrace{U_{\tau\tau}}^{-} \gtrless 0$. Similarly, $n_{31} \gtrless 0$ since $f_{\kappa t_c} > 0$. ikewise, $c_1 = c_4$ could be either negative or positive depending on the relative magnitudes of U_X *and* U_{XX}, but $c_2 > 0$ *and* $c_3 < 0$.[21]

The impacts of the change in market wage on the optimal allocations of time and the choice of computer/Internet type is determined by using Cramer's rule.

(1a) Effect of a wage change on CI time

From (14), Cramer's rule gives:

$$\frac{\partial t_c}{\partial w} = \frac{\begin{vmatrix} \underline{c}_1 & 0 & \underline{n}_{13} & n_{14} \\ c_2 & n_{22} & 0 & 0 \\ c_3 & 0 & n_{33} & n_{34} \\ \underline{c}_4 & 0 & n_{43} & n_{44} \end{vmatrix}}{H}$$

Expanding the numerator along the cofactor of column 2,

$$\frac{\partial t_c}{\partial w} = \frac{a_{22} \begin{vmatrix} \underline{c}_1 & \underline{n}_{13} & n_{14} \\ c_3 & n_{33} & n_{34} \\ \underline{c}_4 & n_{43} & n_{44} \end{vmatrix}}{H} = \frac{n_{22}\left\{ \left[\underline{c}_1 n_{33} n_{44} + \underline{n}_{13} n_{34} c_4 + n_{14} n_{43} c_3\right] - \left[n_{14} n_{33} \underline{c}_4 + n_{34} n_{43} \underline{c}_1 + n_{44} c_3 \underline{n}_{13}\right]\right\}}{H} \qquad (15a)$$

[21] A bar under the letter denotes terms with mixed signs.

The sign of the LHS term depends on the signs of the terms in the numerator. After a series of mathematical manipulations, the RHS terms can be signed as: [22]

$$\frac{\partial t_c}{\partial w}=\frac{\left[\underbrace{\left(\overbrace{f_{t_c\kappa}U_\tau n_{34}}^{-}-\overbrace{n_{14}n_{33}}^{+}-\overbrace{n_{34}n_{43}}^{+}\right)\overbrace{n_{22}U_X}^{-}}_{+}+\underbrace{\left(\overbrace{n_{33}n_{44}}^{+}+wr\overbrace{U_{XX}n_{34}}^{+}+\overbrace{f_{t_c}f_\kappa U_{\tau\tau}n_{34}}^{+}\right)\overbrace{n_{22}z_1U_{XX}}^{+}}_{+}+\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{14}n_{43}c_3}^{-}-\overbrace{n_{44}c_3f_{t_c\kappa}U_\tau}^{+}\right)}_{+}\right]}{\underbrace{H}_{+}}+$$

$$\frac{\left[\underbrace{\left(\overbrace{n_{33}n_{44}}^{+}+wr\overbrace{U_{XX}n_{34}}^{+}+\overbrace{f_{t_c}f_\kappa U_{\tau\tau}n_{34}}^{+}\right)\overbrace{n_{22}U_x}^{-}}_{-}+\underbrace{\left(\overbrace{f_{t_c\kappa}U_\tau n_{34}}^{-}-\overbrace{n_{14}n_{33}}^{+}-\overbrace{n_{34}n_{43}}^{+}\right)\overbrace{n_{22}z_1U_{xx}}^{+}}_{-}+\underbrace{\overbrace{n_{22}n_{44}c_3}^{-}\left(-wr\overbrace{U_{XX}}^{-}-\overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}\right)}_{-}\right]}{\underbrace{H}_{+}}\ \substack{\geq\\<}\ 0 \tag{15b}$$

The allocation of time for CI use at home could increase or decrease following a change in the market wage depending upon the net impact of the substitution and income effects induced by the change in the market wage. To show the substitution and income effects, (15b) can be rewritten as:

$$\frac{\partial t_c}{\partial w}=\frac{[Positive\ term]}{H}+\frac{[\text{Negative term}]}{\text{H}}\ \substack{\geq\\<}\ 0 \tag{15c}$$

Then, the RHS expressions can be interpreted as follows.

(i) $\frac{\partial t_c}{\partial w}=\frac{[Negative\ term]}{H}<0$

This condition indicates that when the wage rises the time allocated for CI use declines, denoting the substitution effect of a wage change. Here the intuition is that as the wage increases, the opportunity cost of using time for nonmarket work rises so that an individual tends to spend less time on CI use at home and instead increase market work.

[22] See (1a) in Appendix A1 for the details.

(ii) $\dfrac{dt_c}{dw} = \dfrac{[Positive\ term]}{H} > 0$

This denotes the income effect of a wage change, in which CI time increases with the rise in market wage. The intuition that can be drawn from this condition is that when the wage rises, an individual will feel wealthier and hence can afford to spend more time on non-market activities (CI use in this case), cutting back on market work.

Then, the net effect of the wage change on the allocation of time for CI use depends on the relative sizes of these opposite effects. In other words, one tends to allocate more time for CI use if only the income effect is strong enough to induce one to forgo market work. When the substitution effect is dominant, an individual will have more of an incentive to substitute home CI use time for market work.

(1b) Effect of a wage change on home production time

Equation (14) gives:

$$\frac{\partial t_h}{\partial w} = \frac{\begin{vmatrix} n_{11} & \underline{c}_1 & \underline{n}_{13} & n_{14} \\ 0 & c_2 & 0 & 0 \\ \underline{n}_{31} & c_3 & n_{33} & n_{34} \\ n_{41} & \underline{c}_4 & n_{43} & n_{44} \end{vmatrix}}{H}$$

Expanding the numerator along the cofactor of row 2,

$$\frac{\partial t_h}{\partial w} = \frac{c_2 \begin{vmatrix} n_{11} & \underline{n}_{13} & n_{14} \\ \underline{n}_{31} & n_{33} & n_{34} \\ n_{41} & n_{43} & n_{44} \end{vmatrix}}{H} = \frac{c_2\left\{ \left[n_{11}n_{33}n_{44} + \underline{n}_{13}n_{34}n_{41} + n_{14}n_{43}\underline{n}_{31}\right] - \left[n_{14}n_{33}n_{41} + n_{34}n_{43}n_{11} + n_{44}\underline{n}_{31}\underline{n}_{13}\right] \right\}}{H} \quad (16a)$$

Signing the terms:[23]

$$\frac{dt_h}{dw} = \frac{\overbrace{c_2}^{+}\left[\underbrace{\overbrace{n_{11}n_{33}n_{44}}^{-}}_{-} + \underbrace{\left(\overbrace{wrU_{XX}}^{-} + \overbrace{f_{t_c}f_{\kappa}U_{\tau\tau}}^{-}\right)\left(\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}n_{43}}^{+}\right)}_{-}\right]}{\underbrace{H}_{+}} \tag{16b}$$

$$+ \frac{\overbrace{c_2}^{+}\left[\underbrace{\overbrace{f_{t_c\kappa}U_{\tau}}^{+}\left(\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}n_{43}}^{+}\right)}_{+} - \underbrace{\left(\overbrace{n_{14}n_{33}n_{41}}^{-} + \overbrace{n_{34}n_{43}n_{11}}^{-} + \overbrace{n_{44}n_{31}n_{13}}^{-}\right)}_{+}\right]}{H} \gtrless 0$$

Equation (16b) can also be expressed in terms of the substitution and income effects of the change in wage as:

$$\frac{\partial t_h}{\partial w} = \frac{[Negative\ term]}{H} + \frac{[\text{Positive term}]}{\text{H}} \gtrless 0 \tag{16c}$$

Accordingly, if an increase in the wage generates a higher substitution effect $\left(\frac{dt_h}{dw} = \frac{[Negative\ term]}{\text{H}} < 0\right)$ compared to its income effect $\left(\frac{dt_h}{dw} = \frac{[Positive\ term]}{\text{H}} > 0\right)$, one tends to shift time from home production to market work. However, if the income effect is dominant, more time will be allocated for housework following the rise in the wage. This is consistent with the assertion of the optimal time allocation condition stated in (10b).

(1c) Effect of a wage change on the choice of CI technology

As described by the FOC in (10c), the optimal choice of the type of CI technology is governed by the equilibrium condition $-rU_X + f_{\kappa}U_{\tau} = 0$. The effect of a change in market wage on the optimal choice of CI technology can be shown by using (14):

[23] See (1b) in Appendix A1 for the details.

$$\frac{\partial \kappa}{\partial w} = \frac{\begin{vmatrix} n_{11} & 0 & \underline{c}_1 & n_{14} \\ 0 & n_{22} & c_2 & 0 \\ \underline{n}_{31} & 0 & c_3 & n_{34} \\ n_{41} & 0 & \underline{c}_4 & n_{44} \end{vmatrix}}{H}$$

Expanding the numerator along the cofactor of column 2,

$$\frac{\partial \kappa}{\partial w} = \frac{n_{22}\begin{vmatrix} n_{11} & \underline{c}_1 & n_{14} \\ \underline{n}_{31} & c_3 & n_{34} \\ n_{41} & \underline{c}_4 & n_{44} \end{vmatrix}}{H} = \frac{n_{22}\left\{\left[n_{11}c_3n_{44} + \underline{c}_1n_{34}n_{41} + n_{14}\underline{c}_4\underline{n}_{31}\right] - \left[n_{14}c_3n_{41} + n_{34}\underline{c}_4n_{11} + n_{44}\underline{n}_{31}\underline{c}_1\right]\right\}}{H} \quad (17a)$$

After rearranging (17a) can be signed as:[24]

$$\begin{aligned}
\frac{d\kappa}{dw} = {} & \frac{\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{11}c_3n_{44}}^{-} + \left(\underbrace{-\overbrace{n_{34}n_{11}}^{+} + \overbrace{n_{14}f_{t_c\kappa}U_\tau}^{-} \overbrace{-n_{44}}^{+}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})}_{-}\right)\overbrace{U_X}^{+}\right)}_{+}}{\underbrace{H}_{+}} \\
& + \frac{\underbrace{\overbrace{n_{22}}^{-}\left(\underbrace{\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}}^{-}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}) - \overbrace{n_{44}f_{t_c\kappa}U_\tau}^{-}}_{+}\right)z_1\overbrace{U_{XX}}^{-}}_{+}}{H} \\
& + \frac{\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{-n_{14}c_3n_{41}}^{+} + \left(\underbrace{\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}}^{-}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}) - \overbrace{n_{44}f_{t_c\kappa}U_\tau}^{+}}_{+}\right)\overbrace{U_X}^{+}\right)}_{-}}{\underbrace{H}_{+}} \\
& + \frac{\underbrace{\overbrace{n_{22}}^{-}\left(\underbrace{-\overbrace{n_{34}n_{11}}^{-} + \overbrace{n_{14}f_{t_c\kappa}U_\tau}^{-} \overbrace{-n_{44}}^{+}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})}_{-}\right)z_1\overbrace{U_{XX}}^{-}}_{-}}{H} \gtrless 0 \qquad (17b)
\end{aligned}$$

By rewriting (17b) the effect of the change in wage on the choice of CI type can be shown in terms of the substitution and income effects:

[24] See (1c) in Appendix A1 for the details.

$$\frac{\partial \kappa}{\partial w} = \frac{[\textit{Positive term}]}{H} + \frac{[\text{Negative term}]}{\text{H}} \ \substack{\geq \\ <} \ 0 \qquad (17c)$$

Equation (17c) is interpreted as follows.

(i) $\frac{\partial \kappa}{\partial w} = \frac{[\textit{Negative term}]}{H} < 0$

This shows a fall in κ following a rise in the market wage. Since κ denotes the type of CI technology, a fall in κ means a tendency not to purchase a computer with a higher operating capacity (or choosing not to have a high speed Internet) when market wages rise. This negative impact of the wage on κ could also be considered as the indirect impact of the substitution effect of the wage on the allocation of time for CI use. As discussed above in (1a), the substitution effect involves allocating time away from CI use and into market work. This may imply less interest in high-technology CI and hence a fall in κ.[25]

(ii) $\frac{\partial \kappa}{\partial w} = \frac{[\textit{Positive term}]}{H} > 0$

This comparative static condition indicates the tendency of an individual to choose a high-technology CI when the market wage rises. The implication is that a high wage earning individual is more likely to adopt the latest technology.

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[25] An alternative explanation could be the fact that high income earning individuals may have better access to the latest computers and high-speed Internet at their work places so that they settle for low-technology CI at home. Complementing the work place high-technology CI with the low one at home could be a rational decision for this group of individuals.

(1d) Effect of a wage change on leisure

Solving (14) for $\partial L/\partial w$ gives:

$$\frac{\partial L}{\partial w}=\frac{\begin{vmatrix} n_{11} & 0 & \underline{n}_{13} & \underline{c}_1 \\ 0 & n_{22} & 0 & c_2 \\ \underline{n}_{31} & 0 & n_{33} & c_3 \\ n_{41} & 0 & n_{43} & \underline{c}_4 \end{vmatrix}}{H}$$

Expanding the numerator along the cofactor of column 2,

$$\frac{\partial L}{\partial w}=\frac{n_{22}\begin{vmatrix} n_{11} & \underline{n}_{13} & \underline{c}_1 \\ \underline{n}_{31} & n_{33} & c_3 \\ n_{41} & n_{43} & \underline{c}_4 \end{vmatrix}}{H}=\frac{n_{22}\left\{\left[n_{11}n_{33}\underline{c}_4+\underline{n}_{13}c_3n_{41}+\underline{c}_1n_{43}\underline{n}_{31}\right]-\left[\underline{c}_1n_{33}n_{41}+c_3n_{43}n_{11}+\underline{c}_4\underline{n}_{31}\underline{n}_{13}\right]\right\}}{H}$$

(18a)

Rearranging and signing give,[26]

$$\frac{dL}{dw}=\frac{\left[\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{43}f_{t_c\kappa}U_\tau}^{-}-\overbrace{n_{33}n_{41}}^{+}-\overbrace{\underline{n}_{31}\underline{n}_{13}}^{+}\right)\overbrace{U_X}^{+}}_{+}+\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{11}n_{33}}^{+}+\overbrace{n_{43}}^{-}(wr\overbrace{U_{XX}}^{-}+\overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\right)z_1\overbrace{U_{XX}}^{-}}_{+}+\underbrace{\overbrace{n_{22}}^{-}\left((wr\overbrace{U_{XX}}^{-}+\overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\overbrace{c_3n_{41}}^{+}+\overbrace{c_3n_{43}n_{11}}^{-}\right)}_{+}\right]}{\underbrace{H}_{+}}$$

$$+\frac{\left[\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{11}n_{33}}^{+}+\overbrace{n_{43}}^{-}(wr\overbrace{U_{XX}}^{-}+\overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\right)\overbrace{U_X}^{+}}_{-}+\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{43}f_{t_c\kappa}U_\tau}^{-}-\overbrace{n_{33}n_{41}}^{+}-\overbrace{\underline{n}_{31}\underline{n}_{13}}^{+}\right)z_1\overbrace{U_{XX}}^{-}}_{-}+\underbrace{\overbrace{n_{22}}^{-}\overbrace{f_{t_c\kappa}U_\tau}^{+}\overbrace{c_3n_{41}}^{+}}_{-}\right]}{\underbrace{H}_{+}}\gtrless 0$$

(18b)

Rewriting (18b) gives,

$$\frac{\partial L}{\partial w}=\frac{[Positive\ term]}{H}+\frac{[\text{Negative term}]}{\text{H}}\gtrless 0 \qquad (18c)$$

A change in the market wage produces similar effects on leisure as in the case of the allocation of time for CI use and housework. While the substitution effect tends to

[26] See (1d) in Appendix A1 for the details.

decrease leisure (by increasing market work), the income effect counteracts this by inducing an individual to allocate more time for leisure. Ultimately, the net effect of a change in the wage on leisure depends on the relative sizes of the substitution and income effects. If the income effect $\left(\frac{\partial L}{\partial w} = \frac{[Positive\ term]}{H} > 0\right)$ dominates the substitution effect $\left(\frac{\partial L}{\partial w} = \frac{[Negative\ term]}{H} < 0\right)$, the allocation of time for leisure increases, and vice versa.

In sum, from the preceding discussions it can be concluded that the effects of a change in market wage on the optimal time allocations and the choice of CI technology depend mainly on the relative strengths of the substitution and income effects generated by a change in the wage. The following summarizes the impacts of the change in market wage on the four choice variables:

(i) Substitution effect of w: $\uparrow w \;\Rightarrow\; \uparrow t_m \;\Rightarrow\; \downarrow (L, t_h, t_c)$ and $\downarrow \kappa$

(ii) Income effect of w: $\uparrow w \;\Rightarrow\; \downarrow t_m \;\Rightarrow\; \uparrow (L, t_h, t_c)$ and $\uparrow \kappa$

2.3.2.2 Effects of an Advance in CI Technology

Rapid technological progress in computer and computer peripherals has led to continued quality improvements and decline in production costs. As a result, prices have dropped at a rate of 25 percent per year since 1977 (Greenwood and Kopecky, 2007). This shows clearly that an advance in technology reduces the initial or fixed costs of CI use (κ_0). Moreover, it can also be inferred that the unit cost of CI use (r) is also declining over time following advances in computer hardware and software developments and Internet technologies.[27] Hence, undertaking comparative static analyses in terms of the decreases in r and κ_0 can be used to capture the impacts of the change in technology on the optimal allocations stated in (11a).

Differentiate the identities in (10a$'$) – (10d$'$) with respect to r and κ_0, and simplifying give:[28]

$$\begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c/\partial r \\ \partial t_h/\partial r \\ \partial \kappa/\partial r \\ \partial L/\partial r \end{pmatrix} = \begin{pmatrix} d_1 \\ 0 \\ d_3 \\ d_4 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c/\partial \kappa_0 \\ \partial t_h/\partial \kappa_0 \\ \partial \kappa/\partial \kappa_0 \\ \partial L/\partial \kappa_0 \end{pmatrix} = \begin{pmatrix} e_1 \\ 0 \\ e_3 \\ e_4 \end{pmatrix} \qquad (19)$$

where the nonzero d_j's and e_j's are all positive.

Since the coefficient matrices in (19) are equivalent and the constant vectors have the same sign, both equations yield similar comparative static results when viewed in terms of sign. That is, the changes in unit price and initial cost of computer use affect the equilibrium allocations likely in different magnitudes but in the same direction. These indicate that an advance in technology has the same effect on the equilibrium allocations in either of the channels.[29] Hence, the impacts of both r and κ_0 can be analyzed with the following more compact notation:

[27] Usage fees may be higher in absolute terms, but if viewed in terms of the lower connection time required when using the latest technologies (as these lower the opportunity cost of time), the per unit payment could be lower.

[28] See Appendix A2, equations (A2-1) to (A2-4).

[29] Note that advance in technology reduces both unit and fixed costs of computer use (i.e., $\uparrow tech \Rightarrow \downarrow (r, \kappa_0)$).

$$\begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c / \partial \theta \\ \partial t_h / \partial \theta \\ \partial \kappa / \partial \theta \\ \partial L / \partial \theta \end{pmatrix} = \begin{pmatrix} g_1 \\ 0 \\ g_3 \\ g_4 \end{pmatrix} \tag{20}$$

where $\theta = r, \kappa_0$, $g_j = d_j, e_j$ for all $j = 1,...,4$, and the nonzero g_j's are positive. Then, the direction of impact of the advance in technology on optimal allocations of time and choice of CI technology can be analyzed using Cramer's rule.

(2a) Effects of declines in r and κ_0 on CI time

An advance in technology is observed to produce mixed effects on the equilibrium allocation of CI time. The comparative static results indicate that the optimal time allocated for home CI use could either rise or fall with the advance in technology.[30]

$$\frac{\partial t_c}{\partial \theta} \gtreqless 0 \quad \begin{cases} \dfrac{\partial t_c}{\partial r} \gtreqless 0 \Rightarrow \dfrac{\partial t_c}{\partial r} > 0 \quad or \quad \dfrac{\partial t_c}{\partial r} < 0 \\[2ex] \dfrac{\partial t_c}{\partial \kappa_0} \gtreqless 0 \Rightarrow \dfrac{\partial t_c}{\partial \kappa_0} > 0 \quad or \quad \dfrac{\partial t_c}{\partial \kappa_0} < 0 \end{cases} \tag{21}$$

There are two possible ways of interpreting the conditions contained in (21).

(i) $\dfrac{\partial t_c}{\partial r} > 0$ and $\dfrac{\partial t_c}{\partial \kappa_0} > 0$

These indicate that as both unit price and initial cost of CI use fall following the advance in technology, an individual tends to spend less time using CI at home (i.e. $\downarrow r \Rightarrow \downarrow t_c$ and $\downarrow \kappa_0 \Rightarrow \downarrow t_c$). This means that, in addition to lowering the unit price and initial cost of usage, the advance in technology makes CI use more efficient. As a result, individuals

[30] See Appendix A2, equation (A2-6).

will be able to perform their CI related activities in less time. In this case, CI can be considered as "time-saving goods."

(ii) $\frac{\partial t_c}{\partial r} < 0$ and $\frac{\partial t_c}{\partial \kappa_0} < 0$

These conditions reveal that the technology induced fall in the unit price and initial cost of CI use results in raising the allocation of time for CI use (*i.e.*, $\downarrow (r, \kappa_0) \Rightarrow \uparrow \mathrm{t_c}$). This result is consistent with the law of demand, indicating that one tends to spend more time in using a home CI when the costs associated with usage fall. For instance, in addition to making home computers more user-friendly, an advance in technology is making available various computer- and web-based games and entertainment media. These are likely to enhance the allocation of time for CI use. In this case, CI can be considered as "time-using leisure goods."

The overall effect of an advance in technology may depend on each individual's valuation of CI use at home. If CI is more of a time-saving necessity good for an individual, rather than being a leisure good, t_c is likely to fall following the advance in technology (i.e., a fall in r and κ_0). On the other hand, for an individual who mainly uses CI as a leisure good, t_c will most likely increase with the advance in technology.

(2b) Effects of declines in r and κ_0 on home production time

An advance in technology is observed to produce no direct impact on the optimal allocation of time for housework ($\partial t_h / \partial \theta = 0$).[31] Irrespective of the fall in the unit price

[31] See Appendix A2, equation (A2-7).

and initial cost of CI use, home production time remains unchanged. This result is likely to arise when individuals are using their home CI more for leisure than as a capital good that can be used in the home production process. Based on this result, it can be concluded that CI use at home is unlikely to produce any displacement effect on home production time so long as it is used as a leisure good.

(2c) Effects of declines in r and κ_0 on the choice of CI technology

The comparative static analyses do not produce a clear result as to what an individual's technology choices would be when faced with a fall in unit price and initial cost of CI usage.[32]

$$\frac{\partial \kappa}{\partial \theta} \gtreqless 0 \quad \begin{cases} \dfrac{\partial \kappa}{\partial r} \gtreqless 0 \Rightarrow \dfrac{\partial \kappa}{\partial r} > 0 \quad or \quad \dfrac{\partial \kappa}{\partial r} < 0 \\ \\ \dfrac{\partial \kappa}{\partial \kappa_0} \gtreqless 0 \Rightarrow \dfrac{\partial \kappa}{\partial \kappa_0} > 0 \quad or \quad \dfrac{\partial \kappa}{\partial \kappa_0} < 0 \end{cases} \tag{22}$$

Two possible interpretations of these conditions are:

(i) $\dfrac{\partial \kappa}{\partial r} > 0 \quad and \quad \dfrac{\partial \kappa}{\partial \kappa_0} > 0$

These results show that individuals tend to choose low-technology CI when unit price and initial cost of CI use fall. This seems to be counter-intuitive and something that is unlikely to occur for a normal good as it contradicts demand theory. However, such result holds only theoretically for either *Giffen* or *Veblen* goods.[33] Nevertheless, both

[32] See (2c) in Appendix A2 for the details.

[33] Most commonly cited examples for *Giffen* goods are inferior quality staple foods, while exclusive, high-status or prestige goods, such as expensive wines, perfumes, diamonds and luxury cars are examples for *Veblen* goods. The Veblen effect, named after Thorstein Veblen who first wrote about conspicuous consumption and status-seeking in 1899, states that individuals' preferences for prestige goods are

computer and the Internet are not likely to be goods that fall in either of these special groups.

(ii) $\frac{\partial \kappa}{\partial r} < 0 \quad or \quad \frac{\partial \kappa}{\partial \kappa_0} < 0$

Consistent with demand theory, a fall in the unit price and initial cost of CI use leads to the choice of high-technology CI (*i.e.*, $\downarrow (r, \kappa_0) \Rightarrow \uparrow \kappa$). That is, the lower the cost of usage the higher is the demand for the latest computers and high-speed Internet.

(2d) Effects of declines in r and κ_0 on leisure

The equilibrium allocation of time for leisure is seen to either increase or decrease with unit price and initial cost of computer use.

$$\frac{\partial L}{\partial \theta} \gtreqless 0 \quad \begin{cases} \frac{\partial L}{\partial r} \gtreqless 0 \quad \Rightarrow \quad \frac{\partial L}{\partial r} > 0 \quad or \quad \frac{\partial L}{\partial r} < 0 \\ \\ \frac{\partial L}{\partial \kappa_0} \gtreqless 0 \quad \Rightarrow \quad \frac{\partial L}{\partial \kappa_0} > 0 \quad or \quad \frac{\partial L}{\partial \kappa_0} < 0 \end{cases} \tag{23}$$

The channel through which an advance in technology affects leisure can be traced using the time constraint in (6) and based on the "time-saving" and "time-using" aspects of CI use described in section (2a) above.

(i) $\frac{\partial L}{\partial r} > 0 \quad and \quad \frac{\partial L}{\partial \kappa_0} > 0$

Under these conditions, the fall in r and κ_0 decreases leisure. Since $t_m = 1 - t_c - t_h - L$, if an advance in technology increases t_c (i.e., CI is more of a time-using leisure good) and

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assumed to decrease when their prices fall, and vice versa. Two most recent studies on *Veblen* goods are Eaton and Eswaran (2005) and Charles et al (2007).

keeps t_h constant, it is the fall in L that translates into an increase in t_c.[34] This shows the reallocation of time out of leisure and into CI use. In other words, an advance in technology displaces time from leisure to CI use.

(ii) $\frac{\partial L}{\partial r} < 0 \quad or \quad \frac{\partial L}{\partial \kappa_0} < 0$

From these comparative static results it can be seen that leisure increases with the fall in r and κ_0. In this case, the rise in L comes from the fall in t_c. As discussed above, t_c falls when the advance in technology makes t_c more efficient (i.e., CI is more of a time-saving good). As a result, time is "freed up" from CI use and reallocated to leisure.

In summary, an advance in technology results in reducing the unit price and initial cost of CI use. The comparative static predictions of the model with respect to these two variables indicate that an advance in technology has mixed impacts on the allocation of time and choice of CI technology. These mixed impacts can be traced through the following four channels.[35]

Channel 1: $\downarrow (r, \kappa_0) \Rightarrow \downarrow t_c, \downarrow L, \bar{t}_h \Rightarrow \uparrow t_m$ (Displacement effect: reallocation of time from CI use and leisure to market work.)

Channel 2: $\downarrow (r, \kappa_0) \Rightarrow \uparrow t_c, \uparrow L, \bar{t}_h \Rightarrow \downarrow t_m$ (Displacement effect: reallocation of time from market work to CI use and leisure.)

[34] Note here that t_m is not part of the comparative statics and hence is not directly affected by r and κ_0. In order to explain the case at hand, it may be plausible to assume the indirect effect on t_m to be zero (i.e., t_m is constant).

[35] The impacts are traced using the time constraint equation, $t_m = 1 - t_c - t_h - L$. Note that the comparative static results showed no impact on the optimal allocation of time for housework so that t_h is held constant, $\bar{t}_h$.

Channel 3: $\downarrow (r, \kappa_0) \Rightarrow \downarrow t_c, \uparrow L, \bar{t}_h \Rightarrow \uparrow t_m$ (Time "freed up" from CI use can be reallocated to leisure and/or market work.)

Channel 4: $\downarrow (r, \kappa_0) \Rightarrow \uparrow t_c, \downarrow L, \bar{t}_h \Rightarrow \uparrow t_m$ (Displacement effect: reallocation of time from leisure to CI use and/or market work.)[36]

2.3.2.3 Effects of a Change in Non-Labor Income on the Choice Variables

The standard labor supply theory assumes that non-labor income has opposite effects on the allocation of time for market work and leisure. Accordingly, an increase in non-labor income expands the budget constraint so that individuals enjoy more leisure and consumption, which implies a reduction in market work. This section completes the comparative static analyses by examining how the optimal time allocations for CI use, home production and leisure and the choice of CI technology vary with the change in non-labor income. These can be done by differentiating the identities in (10a′) – (10d′) with respect to Y. Rearranging and simplifying yields:

$$\begin{pmatrix} w^2U_{XX} + f_{t_ct_c}U_\tau + f_{t_c}^2U_{\tau\tau} & 0 & wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX} \\ 0 & h''(t_h)U_X & 0 & 0 \\ rwU_{XX} + f_{\kappa t_c}U_\tau + f_\kappa f_{t_c}U_{\tau\tau} & 0 & r^2U_{XX} + f_{\kappa\kappa}U_\tau + f_\kappa^2U_{\tau\tau} & wrU_{XX} \\ w^2U_{XX} & 0 & wr\mathrm{U}_{\mathrm{XX}} & w^2\mathrm{U}_{\mathrm{XX}} + U_{LL} \end{pmatrix} \begin{pmatrix} \partial t_c / \partial Y \\ \partial t_h / \partial Y \\ \partial \kappa / \partial Y \\ \partial L / \partial Y \end{pmatrix} = \begin{pmatrix} wU_{XX} \\ 0 \\ rU_{XX} \\ wU_{XX} \end{pmatrix} \qquad (24a)$$

[36] Channel 3 and 4 may result in not changing t_m.

This can be written more compactly as,

$$\begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c / \partial Y \\ \partial t_h / \partial Y \\ \partial \kappa / \partial Y \\ \partial L / \partial Y \end{pmatrix} = \begin{pmatrix} s_1 \\ 0 \\ s_3 \\ s_4 \end{pmatrix} \tag{24b}$$

where the nonzero s_j's are negative. Then, the effects of the change in non-labor income on each of the four choice variables can be examined using Cramer's rule.

The comparative statics indicate that the change in non-labor income affects all the choice variables, except housework time, either positively or negatively:[37]

$$\frac{\partial t_c}{\partial Y} \gtrless 0, \quad \frac{\partial t_h}{\partial Y} = 0, \quad \frac{\partial \kappa}{\partial Y} \gtrless 0 \quad \text{and} \quad \frac{\partial L}{\partial Y} \gtrless 0 \tag{25}$$

These give two sets of results. First, as was the case for unit price and initial cost of CI use, here also non-labor income has no direct impact on the optimal allocation of time for housework. Second, an increase in non-labor income could either increase or decrease the equilibrium levels of CI time, leisure and choice of CI technology through its impacts on the utility function. However, imposing the simplifying assumption that all goods and services are normal reduces the comparative statics in (25) to strictly positive inequalities:

$$\frac{\partial t_c}{\partial Y} > 0, \quad \frac{\partial L}{\partial Y} > 0 \quad \text{and} \quad \frac{\partial \kappa}{\partial Y} > 0.$$

These conditions indicate that as non-labor income rises, allocation of time for both CI use and leisure also rise, and an individual tends to choose high-technology CI. When viewed in terms of the time constraint (6), the increase in minutes of CI use and leisure becomes more apparent since the increase in both variables comes at the expense

[37] See Appendix A3, equations (A3-1 to A3-4).

of a decrease in market work only, as housework time remains unaffected by the change in non-labor income. Note that a decrease in market work with a rise in non-labor income is one of the predictions of the standard labor supply theory. In addition, higher non-labor income may induce individuals to choose a more advanced CI technology. These results are intuitively appealing compared to the interpretations that can be drawn if the alternative strictly negative inequalities are considered:

$$\frac{\partial t_c}{\partial Y} < 0, \quad \frac{\partial L}{\partial Y} < 0 \quad \text{and} \quad \frac{\partial \kappa}{\partial Y} < 0.$$

Here the first two conditions indicate a decrease in the allocation of time for unpaid activities (i.e., computer use and leisure), hence an increase in market work, when non-labor income rises. This would imply that both CI use and leisure are inferior goods. Furthermore, as shown by the third condition, a rise in non-labor income would lead to the choice of an old CI technology. This also amounts to saying that the services derived from the use of CI technology are not normal goods or services. Nevertheless, neither CI use and leisure nor CI technology belong to the category of inferior goods.

To conclude, a change in non-labor income has either positive or negative effects on the optimal allocations of CI time and leisure. It is observed to produce the same impact on the choice of the type of CI technology as well. While the positive impacts appear to be consistent with standard economic theory, the negative impacts are non-plausible mainly because such results can hold only if either the goods themselves or the services derived from using them are not normal goods. Finally, dropping the counter-intuitive negative impacts, the superseding comparative static result of the change in non-labor income can be summarized as follows:

$$\uparrow Y \Rightarrow \uparrow t_c, \uparrow L, \bar{t}_h \Rightarrow \downarrow t_m.$$

These indicate that when non-labor income increases more time is allocated for non-paid activities, resulting in the fall of market work. However, the allocation of time for housework remains constant when non-labor income changes.

2.3.3 Discussion of the Implications of the Theoretical Model

This study attempts to analyze the impacts of CI use at home on an individual's allocation of time for various activities. The issues involved are analyzed by modeling CI use in a representative individual's preference function. However, the comparative static predictions are ambiguous about the impacts of changes in the exogenous variables on the choice variables. This section examines whether there is any theoretical justification for such mixed results. This can be undertaken by rewriting the basic model of the study in terms of the standard labor supply model.

Equation (1) represents the level of utility that can be attained by consuming X amount of consumer goods (market purchased or home produced), L amount of leisure and τ level of services derived from using CI. Collecting goods and services to one side, the utility function can be expressed equivalently as,

$$U(X, L, \tau) \equiv U(X_m + X_h + \tau, \quad L) \equiv U(X_m + X_h + \tau, \quad 1 - t_m - t_h - t_c) \tag{26a}$$

The last term on the right-hand-side is derived from the time constraint in (6) and shows that leisure is the residual of all the hours spent on market work, home production and CI use. Using the assumption that total consumption expenditure on goods and services equals total income from market work and non-labor sources, this utility function can also be written in terms of total income as,[38]

$$U(X_m + X_h + \tau, \quad 1 - t_m - t_h - t_c) \equiv U(Y + wt_m, \quad 1 - t_m - t_h - t_c) \tag{26b}$$

For the purpose of using two-dimensional exposition and to conform to the labor supply model, assume only two categories of time allocations: time for paid work and unpaid activities.[39] Accordingly, rewriting (6) gives $t_u = 1 - t_m$, where the time spent on unpaid activities is $t_u = t_c + t_h + L$.[40] Incorporating this in the above utility function yields,

$$U(Y + wt_m, \quad 1 - t_m - t_h - t_c) \equiv U(Y + wt_m, \quad 1 - t_m) \tag{26c}$$

The leisure-consumption (or income) tradeoff in the standard labor supply model can be modified to fit the case at hand. Here the issue is choosing between more income (or consumption) and enjoying more unpaid activities. In other words, the choice is between allocating more hours for either paid work or unpaid activities. The budget lines in the figures below specify these as choices available for an individual. The optimal allocation of time is determined based on the individual's tastes or preferences depicted by Equation (26c) and the budget constraint. Let the point of tangency between the utility function and the budget line at E_0 represent the equilibrium allocation of time for market work and unpaid activities (i.e., t_m^* and t_u^*, where $t_u^* = t_c^* + t_h^* + L^*$). Further,

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38 This assumption is based on the budget constraint in (7) $X_m + X_h + \kappa_0 + r\kappa = Y + wt_m$. However, X_h was suppressed in (7) for simplicity.

39 In the standard labor supply theory, the leisure-labor (or consumption) dichotomy is employed.

40 Notice that leisure is part of the unpaid activities. Though not directly pursued in this study, the paid vs. unpaid hours dichotomy can also be used in light of the argument that part of the time devoted for housework and CI use can also generate utility.

assume that these values correspond to the optimal allocations obtained from the optimization problem in (9). Then, the ambiguous comparative static predictions about the effects of a change in each of the exogenous variables on the time allocation variables under consideration can be explained in light of the general predictions of labor supply theory.

Effects of an increase in market wage:

The standard labor supply model predicts that an increase in the market wage has an ambiguous effect, mainly due to the offsetting substitution and income effects induced by the change in wage (e.g., Gronau, 1977). This directly corresponds to what is observed in the comparative static results as shown in Figures 2.1 and 2.2. If the hourly wage increases from w to w', the budget line pivots upward. This results in increasing the total income of the individual, leading to a higher level of utility (i.e., a shift from U to U'). At the new optimal level, the allocation of time for unpaid activities may increase or decrease depending on the relative magnitudes of the income and substitution effects. If the income effect (movement from E_1 to E_2) dominates the substitution effect (movement from E_0 to E_1), the optimal allocation of time for unpaid activities increases (Figure 2.1). Since $t_u^* = t_c^* + t_h^* + L$, this implies an increase in at least one or all of them following a rise in the market wage.[41] That is, when the hourly wage increases, individuals reallocate their time away from market work and into either CI use, or housework, or leisure. On the other hand, in the case where the substitution effect

[41] Note that $\partial t_u^*/\partial w > 0 \Rightarrow \partial t_u^*/\partial w = \partial/\partial w(t_c^* + t_h^* + L^*) > 0$ so that at least one of them is increasing with market wage in a way that offsets the decrease in others, if any. Likewise, $\partial t_u^*/\partial w < 0$ denotes a fall in either of these time variables.

outweighs the income effect, more hours would be allocated for paid work than for the unpaid activities (Figure 2.2). Thus, it can be concluded that the comparative static predictions obtained in section 2.3.2 are consistent with the predictions of standard labor supply theory.

Effects of an increase in non-labor income:

In Figure 2.3, a parallel shift of the budget line from Y to Y' depicts an increase in non-labor income. Consequently, an individual would be able to attain a higher level of utility denoted by U'. The question, then, is finding the new optimal allocations of time (or the new tangency point) resulting from the increase in the non-labor income. The comparative static predictions discussed in the preceding section become unambiguous about the effect of an increase in non-labor income on the allocations of time for CI and leisure when the counter-intuitive results are dropped. In addition, a rise in non-labor income is found to have no impact on household production time.

On the other hand, the standard labor supply theory, which is modeled as a leisure-consumption choice, predicts that an individual chooses more leisure over hours of market work when non-labor income increases.[42] For the case at hand, this translates into choosing to allocate more time for unpaid activities at the expense of market work (i.e., $\partial t_u^* / \partial Y > 0$). This can be indicated by a movement in the northeast direction from E_0 to E_1. That is, with a rise in non-labor income, an individual is more likely to choose to work fewer hours and devote more time to unpaid activities. Since $\partial / \partial Y \left(t_c^* + t_h^* + L^* \right) > 0$ and $\partial t_h^* / \partial Y = 0$, the overall effect of a rise in non-labor income

[42] This prediction is based on the assumption that leisure is a normal good. It further assumes that given enough non-labor income, an individual may also choose not to work at all, allowing the possibility for a corner solution.

would be increasing the amount of minutes allocated for CI use or leisure or both.[43] The underlying assumption here is that CI use and leisure are normal goods.

Effects of a decrease in fixed cost and unit price of CI use:

The impacts of the changes in fixed cost and unit price of CI use on the optimal allocations of time can be analyzed based on either the theoretical or the empirical evidence available in the literature. Fixed costs of working are not explicitly included in traditional time allocation theory.[44] The effects of fixed costs are studied as an extension to the basic theory with an emphasis on labor force participation. Some of the studies that consider the impacts of fixed costs on hours of work include Hanoch (1976), Cogan (1980) and Hausman (1980). These studies generally indicate that incorporating fixed costs in the standard model changes the results implied by the standard labor supply model. Accordingly, for those who are working, fixed costs reduce non-labor income so that the budget line shifts downward by the amount of the fixed costs, resulting in increasing the hours of work (or decreasing leisure if it is a normal good). Fixed cost also affect the initial labor force participation decision by raising the reservation wage.

Although not fixed costs of working, the model in this study incorporates fixed cost of CI use (κ_0). Hence, the impact of a fall in κ_0 due to a technological advance on the optimal allocations of time for market and non-market activities can be explained analogous to the effects of fixed costs in the studies cited above. As can be seen in the budget constraint (7), a decrease in κ_0 means a rise in the total money income

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[43]Note that this conclusion is made by fine-tuning the comparative static results in terms of the theoretical predictions of the standard labor supply model.

[44] Examples for fixed money costs of working include work clothes, transportation (bus fare, purchase of a second vehicle, etc.) and childcare.

available.[45] Since such a change in income can be indicated by an upward parallel shift of the budget line, the impact will be the same as the one observed before for an exogenous increase in non-labor income (Figure 2.3). That is, a fall in fixed cost of CI use decreases the hours of market work and increases the allocation of time for unpaid activities, if all the unpaid activities are normal goods.[46]

Traditional theory of labor supply implies that an increase in the price of consumption goods simultaneously shifts and pivots the budget line upwards.[47] Likewise, the fall in the unit price of CI use due to technological improvements raises both the level and slope of the budget line as it increases the non-labor income and the market wage rate.[48] Such simultaneous rise in the level and slope of the budget line is likely to produce the combined effects of an increase in non-labor income and market wage. Consequently, disentangling the net impact of a fall in unit price of CI use on the allocation of time becomes difficult. As discussed above, while a rise in non-labor income increases the allocation of time for unpaid activities (Figure 2.3), the rise in market wage could either increase or decrease it depending on the relative sizes of the substitution and income effects of wage (Figures 2.1 and 2.2). Therefore, the direction of impact of a decrease in the unit price of CI use on the allocation of time for market work and unpaid activities could go either way (i.e., $\partial t_m^*/\partial r \gtreqless 0$ and $\partial/\partial r(t_c^* + t_h^* + L^* \gtreqless 0)$.

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[45] Rewriting the budget constraint in (7) gives $X_m + r\kappa = Y - \kappa_0 + wt_m$. This indicates that a fall in κ_0 leads to a rise in the right-hand-side expression.

[46] In terms of the comparative static results, this means $\partial t_m^*/\partial\kappa_0 < 0$ and $\partial/\partial\kappa_0\left(t_c^* + t_h^* + L^*\right) > 0$. Since $\partial t_h^*/\partial\kappa_0 = 0$, the overall effect of the fall in fixed cost is decreasing the allocation of time for market work and increasing that of CI use and leisure.

[47] Following Hausman (1980), the standard model $PX = Y + wt_m$ can be rearranged to give $X = Y/P + (w/P)t_m$. This shows that if price falls, the real values of both non-labor income and market wage rise so that the budget line simultaneously shifts and pivots upward.

[48] Rewriting the expression in footnote (36) yields $\frac{X_m}{r} + \kappa = \frac{Y - \kappa_0}{r} + \frac{w}{r}t_m$. The terms in the right-hand-side show that a fall in r results in increasing the intercept and slope of the budget line.

Finally, from the discussions in this section, it can be concluded that (1) all the comparative static predictions fail to provide the net impacts of changes in the exogenous variables on the choice variables under investigation; and (2) the attempt made to identify the directions of impact based on the predictions of the standard labor supply theory does not also seem to help much since some of the comparative statics could not be accurately signed. Consequently, determining the net effects of changes in the exogenous variables becomes an empirical issue. The next section presents the results of the empirical investigation.

2.4 Empirical Approach

2.4.1 Identification of Estimation Equations and Variables

To empirically estimate the impacts of the variables of the model (i.e., w, r, κ_0, Y) on the equilibrium allocations of time for market work (t_m), housework (t_h), CI use (t_c) and leisure (t_l) as well as on the choice of CI technology (κ), the optimal values in (11a) and (11b) can be rewritten as,

$$\begin{aligned} t_i &= f(w, r, \kappa_0, Y; z_1, ..., z_m) \quad for \quad i = m, h, c, l \\ \kappa &= g(w, r, \kappa_0, Y; z_1, ..., z_m) \end{aligned} \tag{27}$$

where $(z_1, ..., z_m)$ denote a set of demographic, socioeconomic, location and other variables that might reasonably be expected to influence the choice variables.[49] Equation (27) can also be written in testable form as,

[49]Here t_i for $i = m, h, c, l$ denotes minutes spent on market work, housework, CI use and leisure, respectively. Note that the notation used to represent leisure in the theoretical models (L) is changed here to t_l in the interest of writing a single equation for all the time allocation variables.

$$
\begin{aligned}
t_{ij} &= \alpha_0 + \alpha_j^{\prime} R + u_j \\
\kappa_j &= \gamma_0 + \gamma_j^{\prime} R + v_j
\end{aligned}
\tag{28}
$$

where $R = (w, r, \kappa_0, Y; z_1, ..., z_n)$ represents the randomly distributed explanatory variables, $j = 1, 2, ..., n$, is number of observations, and $i = m, h, c, l$ as defined above. u_j and v_j are random error terms that are uncorrelated across observations, and also unrelated by construction across equations.[50] As a result, each equation in (28) can be estimated one at a time by Ordinary Least Squares (OLS) without any loss of efficiency.

The estimation data for equation (28) are drawn from two sources: the 2003 American Time Use Survey (ATUS) and the October 2003 CPS Computer and Internet Use Supplement.[51] Both surveys are sponsored by the Bureau of Labor Statistics and collected by the Census Bureau. The ATUS measures the amount of time Americans spend doing various activities, which could be broadly categorized as paid work and unpaid activities. In addition to the labor-related information gathered each month by the CPS, the October 2003 Supplement collects data, among others, on computer and Internet access and uses.[52]

For estimation purpose, a new dataset is generated by merging the above two surveys. While the ATUS data provide the number of minutes individuals spent on

[50] The errors are unrelated by construction because of the assumption of separable utility function in (1), where the allocation of time for one branch of activity (say, market work) is assumed to be independent of the allocation of time for any other branches (say, leisure). This implies that the demand equations in (28) are independent. Alternatively, one may argue that since the errors may include factors that are common to all the equations in (28), the errors link the equations giving rise to a Seemingly Unrelated Regression (SUR) model, which should be estimated by Generalized Least Squares (GLS) method. However, according to Greene (2000), there will be no gain in efficiency by using GLS instead of OLS if the equations (a) are actually unrelated and (b) have identical explanatory variables even if related.

[51] This study employs the 2003 surveys since the 2007 CPS Computer and Internet Use Supplement has not been released yet.

[52] CPS gathered computer and Internet use data for the years 1984, 1989, 1993, 1997, 1998, 2000, 2001 and 2003. The data provide detailed information on the availability of computer at school, home, and work; reasons for and frequency of computer use at school, home, and work; and the availability and use of Internet at school, home, and work.

various time use variables of the model, the CPS data are used to draw detailed information on both individuals and households' access to computer and Internet at home. Furthermore, both surveys provide similar information on other individual and household characteristics and labor force related issues. The 2003 ATUS and CPS October Supplement contain 20,720 and 156,941 observations, respectively. However, the size of the final merged sample is only 5,188. A sizable proportion of observations were lost mainly due to the design of the two surveys and use of very restrictive merging criteria.[53]

Appendix A4 gives the definition and description of the four time use dependent variables. It also indicates the ATUS codes for these variables. Each of the time use variables entering the estimation denote the total minutes that respondents spent on a number of activities that can be categorized under each of these four time use variables. For instance, the variable computer time is defined as the total time spent on three broad categories of activities using CI: household, leisure (including socializing and relaxing) and volunteer activities. The total time for market work, housework and leisure are also defined in a similar fashion.

[53]Based on the linking procedure outlined in ATUS Guide, the ATUS and CPS files are linked using the information on the ATUS-CPS file. The ATUS sample is selected from a subset of households that have completed their eighth and final month interviews for the CPS and the survey is conducted 2 to 5 months after the CPS. These make linking a single year's ATUS to 14 months of CPS files possible. Consequently, the 2003 ATUS can be linked to CPS interviews conducted from August 2002 to October 2003 using the following linking variables in both surveys: HRHHID, PULINENO, HRMONTH, HRYEAR4, and HRSERSUF. For the case at hand, the October 2003 CPS is merged to the 2003 ATUS. The sample size of the merged file is only 5,188 due to two reasons. First, since ATUS draws its sample from CPS's 8th round sample, out of the total 156,941 observations in the October 2003 CPS, only 20,253 are candidates for inclusion in the 2003 ATUS. Secondly, in addition to the above linking variables, HUHHNUM (household number) and gender are used as merging criteria in order to pick the same person from the two surveys. These are selected as the best merging criteria after many attempts with other merging conditions. For the details on the linking procedure, see BLS (2007).

As shown in equation (27), $\kappa = g(w, r, \kappa_0, Y; z_1,...,z_m)$ is one of the estimation equations. Since no direct measures are available for κ, κ_0 and r in either of the surveys, an attempt is made to develop proxies for each variable. The dependent variable, the type of CI technology (κ), is defined as a dummy variable taking a value of 1 for individuals who own CI at home and/or report a positive minutes of CI use, and 0 otherwise. Although this definition does not show the types of CI technology being used at home (e.g., the home computer's processor capacity, speed and storage space, or whether the type of Internet connection is high or low speed), it captures the preferences of individuals to the CI technology given the variables that influence their decisions.

Here the unit price of CI use (r) is akin to monthly Internet usage fees. In the absence of data on prices, the unit price of CI use is defined in terms of the number of Internet service providers (ISPs) operating in a given state. This helps capture the state-level variation in the price of the Internet. The underlying assumption here is that the higher the number of ISPs in a given state, the lower will be the price they charge for the Internet services being provided. The n-firm Cournot model is used to derive the competitive equilibrium price.[54] Assume n identical Cournot firms with an inverse demand function $P = a - bq$, where P and q are price and quantity of Internet services, respectively, and a and b are parameters of the model. Then, the Cournot competition equilibrium price becomes,

$$P = \frac{a + mn}{n + 1} \tag{29a}$$

where m is the ISP's marginal cost of production. Taking $a = 0 \ and \ m = 1$ for ease of computations reduces the equilibrium price to,

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[54] I thank Donald Alexander (Department of Economics, WMU) for suggesting this.

$$P = \frac{n}{n+1}. \tag{29b}$$

Equation (29b) is used to compute state-level proxy prices for Internet services using the number of ISPs in each state.[55]

On the other hand, there is no appropriate proxy measure for the initial cost of CI use (κ_0) and hence it is not included in any of the regressions.[56] The data for the other explanatory variables (i.e., w, Y; $z_1,\ldots,z_m$) are drawn from the merged data set. The natural log of the predicted wage represents the market wage rate. The predicted wage is computed for the whole sample in order to incorporate the non-employed respondents in the estimation. Excluding unemployed respondents or those out of the labor force from the regression analysis creates a sample selection bias. In addition, the non-zero reported hourly wages could also be measured with error or considered endogenous. These problems are solved by estimating a sample-selection-corrected hourly wage for all observations using Heckman's two-step consistent estimator (or *Heckit correction*).

Non-labor income (Y) is used in the theoretical model as an explanatory variable. However, both surveys (CPS and ATUS) report the combined (labor and non-labor) income of all the family members during the last 12 months prior to the survey year. Since there is no way of disentangling the non-labor income (Y) from the reported family income, family income is used as a proxy measure for non-labor income in the estimation. Furthermore, the commonly used individual characteristics (e.g., age, education, gender, race and employment status), household characteristics (e.g., marital

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[55] The data for the number of ISPs in each state are obtained from U.S. Federal Communications Commission (FCC) Statistical Reports, Local Telephone Competition and Broadband Development at http://www.fcc.gov.

[56] The initial cost of CI use (κ_0) could be the price of a computer or the connection fee for the Internet. However, no data are available for either of these variables.

status and number of children), and location and season variables are included in the estimation as additional explanatory variables.

2.4.2 Descriptive Statistics

Tables 2.1 and 2.2 present the descriptive statistics for both the dependent and independent variables. For description purposes, the sample is classified into CI users and non-CI users in order to examine whether there are any significant behavioral differences in the allocation of time for the different activities. The same classification may also be used to see if the two groups differ in their individual and household characteristics. While all who own a home computer, access the Internet from home, and/or report a positive minutes of CI use are classified as CI users, those who do not meet any of these criteria are categorized as non-CI users. In general, as depicted in both tables, statistically significant differences are observed between the two groups of respondents in the majority of the variables under consideration.

CI users on average allocate significantly more time to market work and household production, but less time to leisure, than the non-CI users. Compared to their counterparts, CI users tend to be younger, more educated, earn a higher hourly wage and annual income, live with their spouses or unmarried partners, have more children, and dwell in urban areas. In contrast, compared to the CI users, the non-CI users group is composed of significantly large proportions of women, nonwhites, noncitizens, and individuals who have a high school or lower education.

2.4.3 Estimation Results

As discussed earlier, the comparative static results are unable to unambiguously predict the direction of impacts of the basic variables of the model (i.e., w, r, κ_0, Y) on the dependent variables.[57] The implications of the theoretical model are tested with observed data to identify the net effects of the changes in these variables and other variables of interest. This is done by estimating Equation (28). Since three of the dependent time use variables, except leisure, involve many zero responses, they are estimated using the *Tobit* model, while leisure is estimated by the Ordinary Least Squares (OLS) method. Moreover, the choice of CI technology is estimated using a *Probit* model as it is defined as a binary choice variable.

Appendix A5 reports the full estimation results. However, the discussion in this section is focused mainly on the three basic exogenous variables of the model ($w,\ r,\ Y$). The net impacts of these variables on the dependent variables are summarized in Table 2.3. It should be noted that the magnitudes of the actual effects are not always significant. Therefore, Table 2.3 is used primarily to sign the indeterminate comparative static results discussed in section 2.3.2.

Market wage:

Other things being equal, an increase in the market wage rate is observed to significantly increase the allocation of time for CI use, market work and housework, but it decreases the minutes spent in leisure activities. That is, an increase in the wage

[57] The comparative static results can be generalized by $\frac{\partial t_i}{\partial \Omega} \gtrless 0$ and $\frac{\partial \kappa}{\partial \Omega} \gtrless 0$, for $i = m,h,c,l$ and $\Omega = (w, r, \kappa_0, Y)$.

displaces time from leisure. In terms of the results of the theoretical model, the income effect of the market wage seems to dominate the substitution effect in cases where time is allocated for CI use, market work and home production. The substitution effect is particularly strong for the allocation of time for leisure activities. On the other hand, the rise in market wage markedly increases the probability of acquiring CI for home use.

Family income:

This is a proxy measure for individuals' non-labor income used in the theoretical model. Family income affects the allocation of time in the same way as the market wage, with only two exceptions: family income fails to influence significantly the minutes spent in using CI and home production. Both market wage and family income turn out to have the same effect possibly because family income is composed of earnings from both paid and unpaid activities. Generally, since the change in income has significant but opposite impacts only on total leisure and market work, it can be concluded that when income rises individuals tend to cut back on leisure and reallocate their time to market work.[58] Furthermore, the probability of owning a home CI also increases significantly with a rise in family income.

Unit price of Internet use:

This variable has a substantial negative effect only on one time variable: the allocation of time for home production. That is, individuals show a tendency to reallocate their time away from home production and into Internet use, total leisure and

[58] Recall that all the minutes in a day are modeled in the four time uses so that more time in one time use means less time in at least one of them (see the time constraint equation (6) and Table 2.1).

market work when usage fees rise. However, the increase in the number of minutes in the latter three time uses is not large enough to be statistically significant. In addition, the probability of owning CI at home tends to decline with the rise in user fees. This seems to be consistent with the theory of demand. The declining tendency in CI ownership may be due to the response of those who do not already own CI at home. This group of individuals may respond by not buying a computer or getting Internet connection when the price of CI use rises. Nevertheless, the change in the price of CI use is unlikely to be considered a strong hindrance to the acquisition of CI for home use as its impact is insignificant. In contrast, individuals who already have these technologies at home may have a tendency to continue using them in spite of the rise in user prices, as demonstrated by the positive, but insignificant, marginal coefficient of CI use time (see Appendix A5).

Other explanatory variables:

A number of explanatory variables that are expected to influence the allocation of time and choice of CI technology are included in the estimation. These include variables relating to individual and household characteristics, job types and geographic locations.[59] Following is a brief description of some of the variables that significantly affect the choice variables under consideration.

The older an individual, the less will be the time allocated for CI use and market work, *ceteris paribus*. However, leisure and housework increase with age. Education seems to displace time from housework and market work and enhance the allocation of more minutes on CI use and leisure. Compared to males, women allocate less time to leisure and market work and more time for housework and CI use. Living with a spouse

[59] See Appendix A5 for the detailed estimation results.

or partner and having children significantly increase the amount of time spent in home production and reduces the amount of minutes one spends on market work, leisure and CI use. As opposed to self-employed individuals, those working in government and private institutions spend less time on home CI use, leisure and housework and more time on their jobs.

Respondents are observed to spend significantly more time on CI use and market work but less time on leisure and housework on weekdays than weekends. Finally, individuals with a university education, living with their spouses or partners, and who reside in the western part of the country are more likely to own CI at home compared to their respective counterparts. In contrast, age and being nonwhite and noncitizen of the United States markedly decrease the likelihood of owning CI technology at home.

2.5 Summary and Conclusions

The main aim of this study is to investigate using a theoretical framework how CI use in the United States households affects individuals' allocation of time. The study is based on the conceptual framework that the use of CI technology at home changes the existing patterns of individuals' time allocation behavior. The issues involved are addressed using three approaches. First, CI use is modeled in a representative individual's preference function and analytically examined to see how the parameters of the model affect the choice variables under consideration. Second, an attempt is made to find a theoretical justification for the indeterminate signs of the comparative static results obtained in the first part of the analyses. This is done by rewriting the basic model of the study in terms of the standard labor supply model. Third, the implications of the theoretical model are tested using empirical data.

Optimization of the utility function with respect to the budget and time constraints yields four time allocation variables (i.e., CI use, housework, leisure and market work) and one variable relating to choice of CI technology. The optimal allocations of these choice variables are found to be dependent upon the market wage rate, initial or fixed cost of CI use, unit price of CI use and non-labor income. Comparative static analyses are carried out to examine how the equilibrium allocations change with each of these parameters. However, the comparative static predictions of the model fail to provide many unambiguous effects. In most instances, the comparative static results are composed of both positive and negative expressions. These imply that the net impacts of the change in the exogenous variables depend on the relative magnitudes of the positive and negative impacts they produce on the choice variables. For instance, the net effect of an increase in market wage on the four optimal time allocations depends on the relative sizes of the substitution and income effects produced by the rise in wage. In the case where the income effect dominates the substitution effect, the time allocations increase, and decrease otherwise.

These mixed comparative static results are corroborated with the predictions of the standard labor supply theory. The theoretical construction of the model verifies that while market wage and unit price of CI use change the slope of the budget line, non-labor income and initial cost of CI use affect the level of the budget line. Consequently, the size of the impact of each of these exogenous variables on the choice variables depends on the relative position of the utility function after the change *vis-à-vis* that before the change.

Empirical estimations are employed in order to gain some insight about the indeterminate signs of the comparative static predictions regarding the impacts of change in the exogenous variables(i.e., market wage, unit price of CI use, and non-labor income) on the optimal allocations of the choice variables (i.e., time for CI use, leisure, market work and housework, and choice of CI technology). The following are summaries of the empirical results.

The income effect of the market wage is found to dominate the substitution effect in cases where time is allocated for CI use and home production. So when market wage rises, individuals tend to spend more minutes on CI use and home production. The substitution effect is particularly strong for the allocation of time for market work and leisure activities. In this case, the tendency is to cut back on minutes spent in leisure activities and increase market work when market wage rises. In addition, individuals become more likely to own CI at home when their market wage increases. Family income, a variable used as a proxy measure of non-labor income, also affects the allocation of time in the same way as market wage, with only one exception. It tends to increase the minutes spent in using CI and housework, but the influence is not statistically significant in both cases. A strong positive association is observed between the choice of the CI technology and an increase in family income. Generally, when market wage and family income rise, individuals tend to cut back on leisure and reallocate time to market work, housework and CI use.

The unit price of CI use has a strong negative impact only on the allocation of time for home production. That is, though the impact is not considerably strong, individuals show a tendency to reallocate their time away from housework and into CI use, leisure and market work when usage fee rises. On the other hand, an increase in the usage fee tends to lower individuals' probability of owning a home CI, but the effect is not statistically significant.

To conclude, the possible impacts of CI use at home on individuals' allocation of time are analyzed primarily using comparative static analyses. Since the predictions of these analyses are indeterminate, an attempt is made to harmonize them with the predictions of the standard labor supply model. Furthermore, empirical estimations are used to determine the net effect of the change in the exogenous variables on the choice variables under investigation.

Figure 2.1: The Income Effect of a Wage Increase Outweighing the Substitution Effect

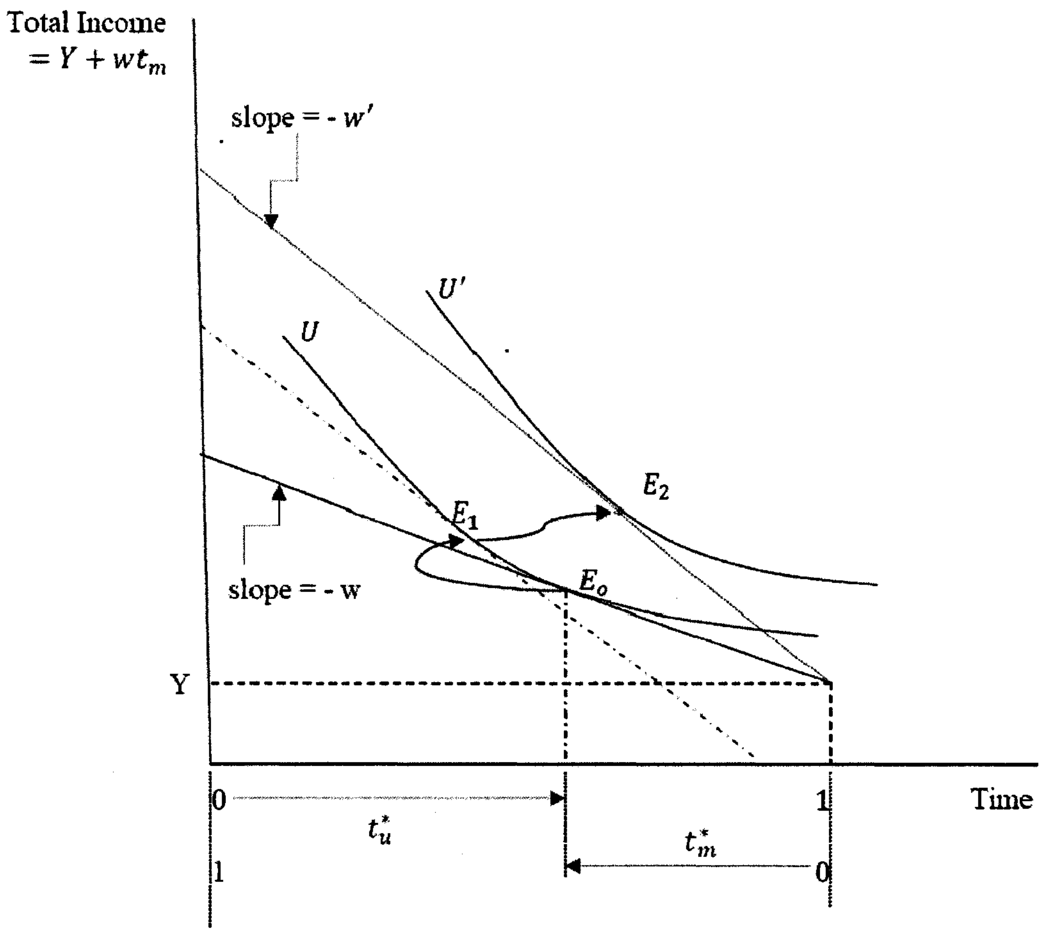

Figure 2.2: The Substitution Effect of a Wage Increase Outweighing the Income Effect

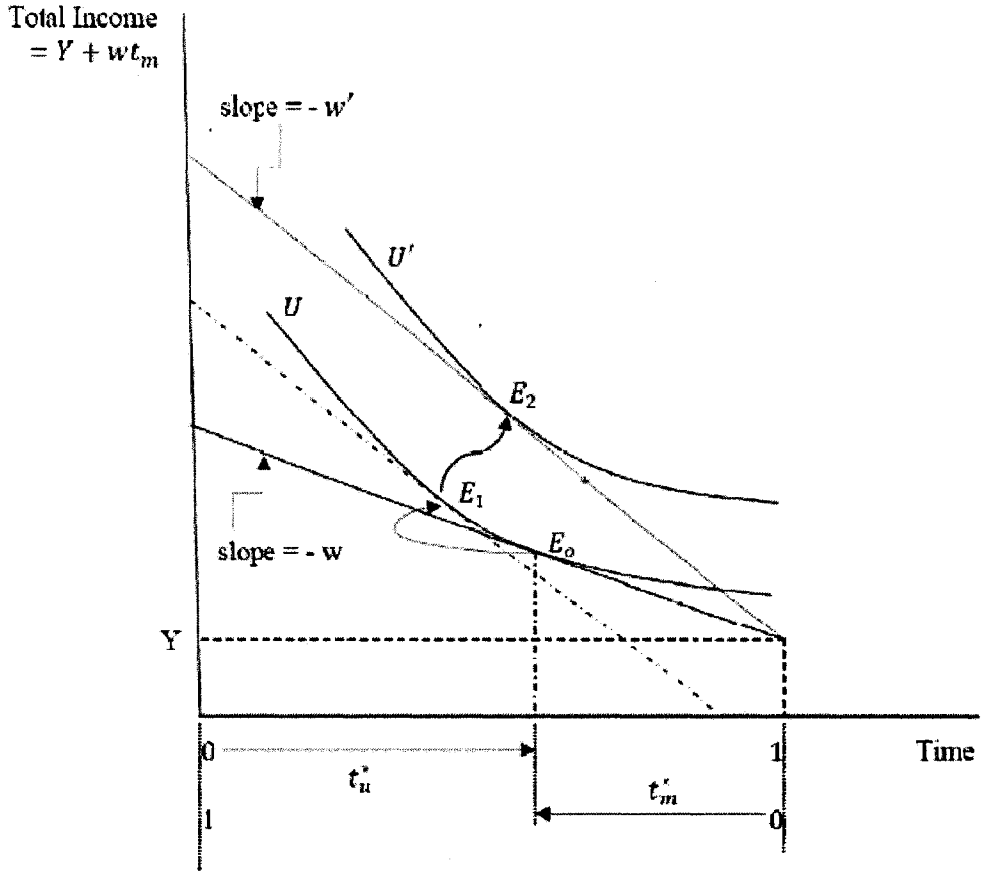

Figure 2.3: The Effect of an Increase in Non-Labor Income

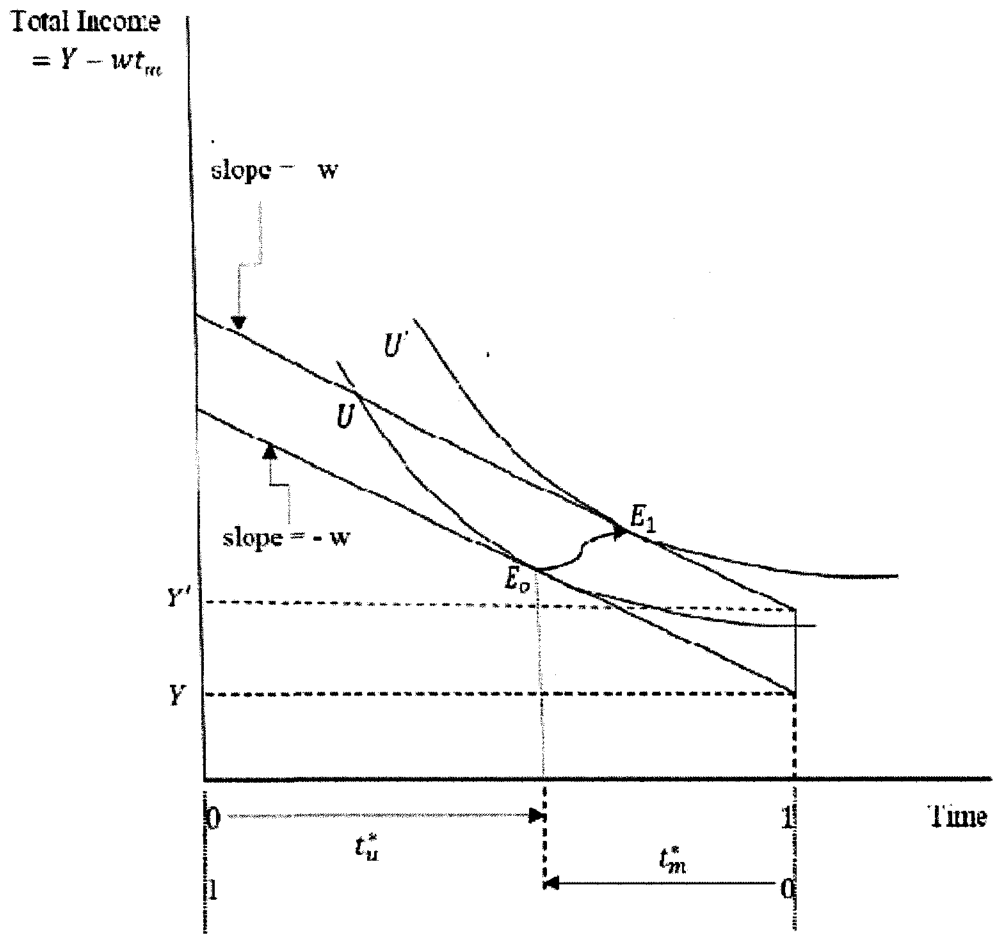

Table 2.1: Descriptive Statistics for the Time Use Dependent Variables

Average minutes spent on .... per day	CI Users		Non-CI Users		Differences£
	Mean	Std. dev	Mean	Std. dev	
CI use (total)€	14.26	46.16	0	0	-
CI use for household activities	3.20	18.25	0	0	-
CI use for Leisure activities	10.13	39.79	0	0	-
CI use for volunteer activities	0.93	11.85	0	0	-
Market work (total)@	191.03	268.95	161.97	253.18	3.66**
Main and other jobs†	180.18	265.46	153.20	249.10	3.45**
Work related activities	0.66	9.69	0.49	9.65	0.56
Other income generating activities	1.62	25.52	0.65	12.57	1.82*
Job search and interviewing	1.75	20.01	1.16	15.08	1.14
Education for degree†	6.83	51.84	6.46	48.83	0.24
Housework (total)	252.37	203.09	236.56	206.87	2.49**
Household activities†	133.39	147.46	127.00	144.72	1.42
Care giving†	60.83	105.87	54.88	113.47	1.73*
Shopping (grocery and nongrocery) †	47.72	81.24	44.74	78.52	1.22
Professional and personal care services†	10.43	39.14	9.94	38.67	0.41
Leisure activities (total)	970.32	251.38	1027.30	262.17	-7.14**
Sleeping	511.83	120.39	527.23	135.57	-3.80**
Personal care†	45.22	56.68	50.68	65.35	-2.81**
Eating and drinking†	78.59	64.49	72.50	63.24	3.10**
Socializing, relaxing and leisure†	282.19	197.37	329.60	230.75	-6.94**
Participating in sports, exercises and recreation†	21.09	68.92	15.59	56.54	2.96**
Attending sporting/recreational events†	3.25	28.09	4.12	39.36	-0.77
Religious and spiritual activities†	14.74	51.50	15.76	55.37	-0.61
Volunteer activities†	12.29	58.80	10.14	58.17	1.20
Education for personal interest†	1.14	16.16	1.68	15.59	-1.12
Average total minutes reported‡	1427.95 minutes		1425.83 minutes		
Year the newest CI purchased (median)	2001		-		
Number of observations	3718		1470		

£ The t statistics for the difference between the mean minutes reported by CI users and nonusers.
€ The average minutes for reporting cases are 78.53 (n = 675) for total CI use, and 41.56 (n = 286), 89.64 (n = 420) and 84.73 (n = 41) minutes for household, leisure and volunteer activities, respectively.
@ The mean for total market work is only about 3 hours mainly because the majority of the respondents did not report market work time. For reporting cases, however, the mean is 7.52 (n = 1574) and 7.53 (n = 527) hours for CI users and non-users, respectively.
† These variables include minutes of the related travel time.
‡ The average reported minutes are less than the total 1440 minutes available in a 24-hours day.
* Significant at 5%, **significant at 1% for the difference in means.

Table 2.2: Descriptive Statistics for the Independent Variables

Variables	CI Users		Non-CI Users		
	Mean	Std. dev	Mean	Std. dev	Differences£
Log of predicated wage	2.79	0.38	2.60	0.42	15.82**
Household income ('0000s)	54.79	27.79	38.13	27.55	19.58**
Age	47	15.17	50	17.21	-5.60**
Education (years)	14.1	2.96	12.7	3.14	14.83**
High school graduate or below	0.36	0.48	0.53	0.50	-11.58**
Some college or associate degree	0.29	0.45	0.29	0.45	0.14
Bachelor's degree or above	0.35	0.48	0.18	0.38	13.69**
Female	0.54	0.50	0.61	0.49	-4.41**
Nonwhite	0.12	0.32	0.20	0.40	-6.98**
Noncitizen	0.05	0.12	0.07	0.26	-3.48**
Government job	0.12	0.33	0.10	0.30	2.12*
Private job	0.48	0.50	0.43	0.49	3.52**
Self-employed	0.08	0.27	0.05	0.22	4.40**
Live with spouse or unmarried partner	0.69	0.46	0.50	0.50	12.27**
No. of children age 0 to 2	0.13	0.38	0.12	0.37	0.45
No. of children age 3 to 5	0.16	0.41	0.13	0.37	2.52**
No. of children age 6 to 9	0.23	0.51	0.19	0.47	2.71**
No. of children age 10 to 12	0.17	0.42	0.14	0.41	1.70
No. of children age 13 to 17	0.24	053	0.18	048	3.47**
Urban	0.82	0.38	0.77	0.42	4.07**
Northeast	0.20	0.40	0.19	0.39	0.80
Midwest	0.26	0.44	0.26	0.44	-0.16
West	0.23	0.42	0.17	0.38	4.80**
South	0.32	0.46	0.38	0.49	-4.40**
Weekdays	0.50	0.50	0.46	0.50	2.30*
Summer	0.25	0.43	0.24	0.43	0.53
Spring	0.23	0.42	0.23	0.42	0.02
Fall	0.25	0.43	0.25	0.43	0.44
Winter	0.26	0.44	0.27	0.45	-0.96
Number of observations	3718			1470	

£ The t-statistics for the difference between the mean values reported by CI users and nonusers.
* Significant at 5%, **significant at 1% for the difference in means.

Table 2.3: Summary of the Net Effects of the Basic Explanatory Variables on the Choice Variables

	CI use time	Total leisure	Market work time	Housewor k time	Choice of CI technology‡
Market wage	+	−	+	+	+
Family income ('000)	⊕	−	+	⊕	+
Unit price of Internet use	⊕	⊕	⊕	−	⊖

Note: + and − denote significant positive and negative impacts, while ⊕ and ⊖ show insignificant impacts, respectively.
‡ A dummy variable taking a value of 1 for individuals who reported owning and/or using CI at home, and 0 else.

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Appendix A1: Signing the Impacts of the Change in Market Wage Rate

(1a) Effect of wage on computer/Internet time

From (15a), $\quad sign\left\{\dfrac{\partial t_c}{\partial w}\right\} = sign\,\{terms\ in\ numerator\}$

Since $\underline{c}_1 = \underline{c}_4$ and $\underline{n}_{13} = \underline{n}_{31}$ and both contain terms with mixed signs, first factor them out and then substitute their corresponding values:

$$
\begin{aligned}
& n_{22}\{\,[\underline{c}_1(n_{33}n_{44} + \underline{n}_{13}n_{34}) + n_{14}n_{43}c_3] - [(n_{14}n_{33} + n_{34}n_{43})\underline{c}_1 + n_{44}c_3\underline{n}_{13}]\,\} \\
&\quad = n_{22}\{\underline{c}_1(n_{33}n_{44} + \underline{n}_{13}n_{34} - n_{14}n_{33} - n_{34}n_{43}) + (n_{14}n_{43}c_3 - n_{44}c_3\underline{n}_{13})\} \\
&\quad = n_{22}(U_X + z_1U_{XX})[n_{33}n_{44} + (wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau})n_{34} - n_{14}n_{33} - n_{34}n_{43}] + n_{22}[n_{14}n_{43}c_3 - n_{44}c_3(wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau})] \\
&\quad = [(f_{t_c\kappa}U_\tau n_{34} - n_{14}n_{33} - n_{34}n_{43})n_{22}U_X + (n_{33}n_{44} + wrU_{XX}n_{34} + f_{t_c}f_\kappa U_{\tau\tau}n_{34})n_{22}z_1U_{XX} + n_{22}(n_{14}n_{43}c_3 - n_{44}c_3f_{t_c\kappa}U_\tau)] \\
&\qquad\quad + [(n_{33}n_{44} + wrU_{XX}n_{34} + f_{t_c}f_\kappa U_{\tau\tau}n_{34})n_{22}U_x + (f_{t_c\kappa}U_\tau n_{34} - n_{14}n_{33} - n_{34}n_{43})n_{22}z_1U_{xx} - n_{22}n_{44}c_3(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau})]
\end{aligned}
$$

Signing the terms,

$$
\frac{\partial t_c}{\partial w} = \frac{\left[\underbrace{\left(\overbrace{f_{t_c\kappa}U_\tau n_{34}}^{-} - \overbrace{n_{14}n_{33}}^{+} - \overbrace{n_{34}n_{43}}^{+}\right)\overbrace{n_{22}U_X}^{-}}_{+} + \underbrace{\left(\overbrace{n_{33}n_{44}}^{+} + \overbrace{wrU_{XX}n_{34}}^{+} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}n_{34}}^{+}\right)\overbrace{n_{22}z_1U_{XX}}^{+}}_{+} + \underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{14}n_{43}c_3}^{-} - \overbrace{n_{44}c_3f_{t_c\kappa}U_\tau}^{+}\right)}_{+}\right]}{\underbrace{H}_{+}}
$$

$$
+\frac{\left[\underbrace{\left(\overbrace{n_{33}n_{44}}^{+} + \overbrace{wrU_{XX}n_{34}}^{+} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}n_{34}}^{+}\right)\overbrace{n_{22}U_x}^{-}}_{-} + \underbrace{\left(\overbrace{f_{t_c\kappa}U_\tau n_{34}}^{-} - \overbrace{n_{14}n_{33}}^{+} - \overbrace{n_{34}n_{43}}^{+}\right)\overbrace{n_{22}z_1U_{xx}}^{+}}_{-} + \underbrace{\overbrace{n_{22}n_{44}c_3}^{-}\left(-\,wr\overbrace{U_{XX}}^{-} - \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}\right)}_{-}\right]}{\underbrace{H}_{+}} \gtrless 0
$$

$$\frac{\partial t_c}{\partial w} = \frac{[\textit{Positive term}]}{H} + \frac{[\text{Negative term}]}{\text{H}} \gtrless 0$$

(1b) Effect of wage on home production time

From (16a), $$sign\left\{\frac{\partial t_h}{\partial w}\right\} = sign\,\{terms\ in\ numerator\}$$

Factoring out the terms with mixed signs (i.e., $\underline{n}_{13} = \underline{n}_{31}$) and substitution yields:

$$\begin{aligned}
&c_2\left\{\left[n_{11}n_{33}n_{44} + \underline{n}_{13}n_{34}n_{41} + n_{14}n_{43}\underline{n}_{31}\right] - \left[n_{14}n_{33}n_{41} + n_{34}n_{43}n_{11} + n_{44}\underline{n}_{31}\underline{n}_{13}\right]\right\}\\
&= c_2\left[n_{11}n_{33}n_{44} + \underline{n}_{13}\left(n_{34}n_{41} + n_{14}n_{43}\right)\right] - c_2\left[n_{14}n_{33}n_{41} + n_{34}n_{43}n_{11} + n_{44}\underline{n}_{31}\underline{n}_{13}\right]\\
&= c_2\left[n_{11}n_{33}n_{44} + \left(wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau}\right)\left(n_{34}n_{41} + n_{14}n_{43}\right)\right] - c_2\left[n_{14}n_{33}n_{41} + n_{34}n_{43}n_{11} + n_{44}\underline{n}_{31}\underline{n}_{13}\right]\\
&= c_2\left[n_{11}n_{33}n_{44} + \left(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}\right)\left(n_{34}n_{41} + n_{14}n_{43}\right)\right] + c_2\left[f_{t_c\kappa}U_\tau\left(n_{34}n_{41} + n_{14}n_{43}\right) - \left(n_{14}n_{33}n_{41} + n_{34}n_{43}n_{11} + n_{44}\underline{n}_{31}\underline{n}_{13}\right)\right]
\end{aligned}$$

Signing terms,

$$\frac{\partial t_h}{\partial w} = \frac{\overbrace{c_2}^{+}\left[\underbrace{\overbrace{n_{11}n_{33}n_{44}}^{-}}_{-} + \underbrace{\left(\overbrace{wrU_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}\right)\left(\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}n_{43}}^{+}\right)}_{-}\right] + \overbrace{c_2}^{+}\left[\underbrace{\overbrace{f_{t_c\kappa}U_\tau}^{+}\left(\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}n_{43}}^{+}\right)}_{+} \underbrace{- \left(\overbrace{n_{14}n_{33}n_{41}}^{-} + \overbrace{n_{34}n_{43}n_{11}}^{-} + \overbrace{n_{44}\underline{n}_{31}\underline{n}_{13}}^{-}\right)}_{+}\right]}{\underbrace{H}_{+}} \gtrless 0$$

$$\frac{\partial t_h}{\partial w} = \frac{[\textit{Negative term}]}{H} + \frac{[\text{Positive term}]}{\text{H}} \gtrless 0$$

(1c) Effect of wage on the choice of computer/Internet technology

From (17a) $\quad sign\left\{\frac{\partial\kappa}{\partial w}\right\} = sign\left\{terms\ in\ numerator\right\}$

$$n_{22}\left\{\left[n_{11}c_3n_{44} + \underline{c}_1n_{34}n_{41} + n_{14}\underline{c}_4\underline{n}_{31}\right] - \left[n_{14}c_3n_{41} + n_{34}\underline{c}_4n_{11} + n_{44}\underline{n}_{31}\underline{c}_1\right]\right\}$$
$$= n_{22}\left\{n_{11}c_3n_{44} - n_{14}c_3n_{41} + \underline{c}_1\left(n_{34}n_{41} - n_{34}n_{11}\right) + \underline{c}_1\underline{n}_{31}\left(n_{14} - n_{44}\right)\right\}$$
$$= \left[n_{22}\left(n_{11}c_3n_{44} - n_{14}c_3n_{41}\right) + n_{22}\left(U_X + z_1U_{XX}\right)\left(n_{34}n_{41} - n_{34}n_{11}\right)\right] + \left[n_{22}\left(U_X + z_1U_{XX}\right)\left(wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau}\right)\left(n_{14} - n_{44}\right)\right]$$
$$= \left\{\left[n_{22}\left(n_{11}c_3n_{44} + (-n_{34}n_{11})U_X + (n_{34}n_{41})z_1U_{XX}\right)\right] + \left[n_{22}\left(n_{14}f_{t_c\kappa}U_\tau - n_{44}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau})\right)U_X + n_{22}\left(n_{14}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}) - n_{44}f_{t_c\kappa}U_\tau\right)z_1U_{XX}\right]\right\}$$
$$+ \left\{\left[n_{22}\left(-n_{14}c_3n_{41} + (n_{34}n_{41})U_X + (-n_{34}n_{11})z_1U_{XX}\right)\right] + \left[n_{22}\left(n_{14}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}) - n_{44}f_{t_c\kappa}U_\tau\right)U_X + n_{22}\left(n_{14}f_{t_c\kappa}U_\tau - n_{44}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau})\right)z_1U_{XX}\right]\right\}$$
$$= \left[n_{22}\left(n_{11}c_3n_{44} + \left(-n_{34}n_{11} + n_{14}f_{t_c\kappa}U_\tau - n_{44}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau})\right)U_X\right) + n_{22}\left(n_{34}n_{41} + n_{14}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}) - n_{44}f_{t_c\kappa}U_\tau\right)z_1U_{XX}\right]$$
$$+ \left[n_{22}\left(-n_{14}c_3n_{41} + \left(n_{34}n_{41} + n_{14}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}) - n_{44}f_{t_c\kappa}U_\tau\right)U_X\right) + n_{22}\left(-n_{34}n_{11} + n_{14}f_{t_c\kappa}U_\tau - n_{44}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau})\right)z_1U_{XX}\right]$$

Signing the terms,

$$\frac{\partial\kappa}{\partial w} = \frac{\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{11}c_3n_{44}}^{-} + \underbrace{\left(\overbrace{-n_{34}n_{11}}^{+} + \overbrace{n_{14}f_{t_c\kappa}U_\tau}^{-} \overbrace{-n_{44}}^{+}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\right)}_{-}\overbrace{U_X}^{+}\right)}_{+} + \underbrace{\overbrace{n_{22}}^{-}\left(\underbrace{\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}}^{-}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}) - \overbrace{n_{44}f_{t_c\kappa}U_\tau}^{-}}_{+}\right)z_1\overbrace{U_{XX}}^{-}}_{+}}{\underbrace{H}_{+}}$$

$$+ \frac{\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{-n_{14}c_3n_{41}}^{+} + \underbrace{\left(\overbrace{n_{34}n_{41}}^{+} + \overbrace{n_{14}}^{-}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-}) - \overbrace{n_{44}f_{t_c\kappa}U_\tau}^{+}\right)}_{+}\overbrace{U_X}^{+}\right)}_{-} + \underbrace{\overbrace{n_{22}}^{-}\left(\underbrace{\overbrace{-n_{34}n_{11}}^{-} + \overbrace{n_{14}f_{t_c\kappa}U_\tau}^{-} \overbrace{-n_{44}}^{+}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})}_{-}\right)z_1\overbrace{U_{XX}}^{-}}_{-}}{\underbrace{H}_{+}} \gtrless 0$$

$$\frac{\partial\kappa}{\partial w} = \frac{[Negative\ term]}{H} + \frac{[\text{Positive term}]}{\text{H}} \gtrless 0$$

(1d) Effect of wage on leisure

From (18a) $\quad sign\left\{\dfrac{\partial L}{\partial w}\right\} = sign\ \{terms\ in\ numerator\}$

Note that $\underline{n}_{31}\underline{n}_{13} > 0$ and does not need expansion. Factor out and make substitution only for $\underline{c}_1$ or $\underline{c}_4$ (since $\underline{c}_1 = \underline{c}_4$).

$$
\begin{aligned}
& n_{22}\{[n_{11}n_{33}\underline{c}_4 + \underline{n}_{13}c_3n_{41} + \underline{c}_1 n_{43}\underline{n}_{31}] - [\underline{c}_1 n_{33}n_{41} + c_3 n_{43}n_{11} + \underline{c}_4\underline{n}_{31}\underline{n}_{13}]\} \\
&= n_{22}\{[\underline{c}_1(n_{11}n_{33} + n_{43}\underline{n}_{31} - n_{33}n_{41} - \underline{n}_{31}\underline{n}_{13}) + \underline{n}_{13}c_3n_{41} + c_3n_{43}n_{11}]\} \\
&= n_{22}[(U_X + z_1U_{XX})(n_{11}n_{33} + n_{43}(wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau}) - n_{33}n_{41} - \underline{n}_{31}\underline{n}_{13})] + n_{22}[(wrU_{XX} + f_{t_c\kappa}U_\tau + f_{t_c}f_\kappa U_{\tau\tau})c_3n_{41} + c_3n_{43}n_{11}] \\
&= [n_{22}(n_{43}f_{t_c\kappa}U_\tau - n_{33}n_{41} - \underline{n}_{31}\underline{n}_{13})U_X + n_{22}(n_{11}n_{33} + n_{43}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}))z_1U_{XX} + n_{22}((wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau})c_3n_{41} + c_3n_{43}n_{11})] \\
&+ [n_{22}(n_{11}n_{33} + n_{43}(wrU_{XX} + f_{t_c}f_\kappa U_{\tau\tau}))U_X + n_{22}(n_{43}f_{t_c\kappa}U_\tau - n_{33}n_{41} - \underline{n}_{31}\underline{n}_{13})z_1U_{XX} + n_{22}f_{t_c\kappa}U_\tau c_3n_{41}]
\end{aligned}
$$

Signing the terms,

$$
\frac{\partial L}{\partial w} = \frac{\left[\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{43}f_{t_c\kappa}U_\tau}^{-} - \overbrace{n_{33}n_{41}}^{+} - \overbrace{\underline{n}_{31}\underline{n}_{13}}^{+}\right)\overbrace{U_X}^{+}}_{+} + \underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{11}n_{33}}^{+} + \overbrace{n_{43}}^{-}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\right)\overbrace{z_1U_{XX}}^{-}}_{+} + \underbrace{\overbrace{n_{22}}^{-}\left((wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\overbrace{c_3n_{41}}^{+} + \overbrace{c_3n_{43}n_{11}}^{-}\right)}_{+}\right]}{\underbrace{H}_{+}}
$$

$$
+ \frac{\left[\underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{11}n_{33}}^{+} + \overbrace{n_{43}}^{-}(wr\overbrace{U_{XX}}^{-} + \overbrace{f_{t_c}f_\kappa U_{\tau\tau}}^{-})\right)\overbrace{U_X}^{+}}_{-} + \underbrace{\overbrace{n_{22}}^{-}\left(\overbrace{n_{43}f_{t_c\kappa}U_\tau}^{-} - \overbrace{n_{33}n_{41}}^{+} - \overbrace{\underline{n}_{31}\underline{n}_{13}}^{+}\right)\overbrace{z_1U_{XX}}^{-}}_{-} + \underbrace{\overbrace{n_{22}}^{-}\overbrace{f_{t_c\kappa}U_\tau}^{+}\overbrace{c_3n_{41}}^{+}}_{-}\right]}{\underbrace{H}_{+}} \gtrless 0
$$

$$
\frac{\partial L}{\partial w} = \frac{[Positive\ term]}{H} + \frac{[\text{Negative term}]}{\text{H}} \gtrless 0
$$

Appendix A2: Signing the Impacts of Advance in Technology (i.e., Changes in Unit Price r and Initial/Fixed Cost κ_0)

Differentiate the identities in (10a$'$) – (10d$'$) with respect to r gives:

$$\begin{aligned}
&\left(w^2U_{XX}+f_{t_c t_c}U_\tau+f_{t_c}^2U_{\tau\tau}\right)\frac{\partial t_c}{\partial r}-w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\frac{\partial t_h}{\partial r}+\left(wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau}\right)\frac{\partial\kappa}{\partial r}+w^2U_{XX}\frac{\partial L}{\partial r}\equiv-w\kappa U_{XX}\\
&-w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\frac{\partial t_c}{\partial r}+\left(h''(t_h)U_X+\left(-w+h'(t_h)\right)^2U_{XX}\right)\frac{\partial t_h}{\partial r}-r\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\frac{\partial\kappa}{\partial r}-w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\frac{\partial L}{\partial r}\equiv\kappa\left(-w+h'(t_h)\right)U_{XX}\\
&\left(rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau}\right)\frac{\partial t_c}{\partial r}-r\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\frac{\partial t_h}{\partial r}+\left(r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau}\right)\frac{\partial\kappa}{\partial r}+rwU_{XX}\frac{\partial L}{\partial r}\equiv U_X-r\kappa U_{XX}\\
&w^2U_{XX}\frac{\partial t_c}{\partial r}-w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\frac{\partial t_h}{\partial r}+wr\mathrm{U_{XX}}\frac{\partial\kappa}{\partial r}+\left(w^2\mathrm{U_{XX}}+U_{LL}\right)\frac{\partial L}{\partial r}\equiv-w\kappa U_{XX}
\end{aligned}\qquad\text{(A2-1)}$$

The above system of equations can be rewritten in matrix form as:

$$\begin{pmatrix}
w^2U_{XX}+f_{t_c t_c}U_\tau+f_{t_c}^2U_{\tau\tau} & -w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}} & wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX}\\
-w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}} & h''(t_h)U_X+\left(-w+h'(t_h)\right)^2U_{XX} & -r\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}} & -w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}}\\
rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau} & -r\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}} & r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau} & wrU_{XX}\\
w^2U_{XX} & -w\left(-w+\mathrm{h}'(\mathrm{t_h})\right)\mathrm{U_{XX}} & wr\mathrm{U_{XX}} & w^2\mathrm{U_{XX}}+U_{LL}
\end{pmatrix}
\begin{pmatrix}\partial t_c/\partial r\\ \partial t_h/\partial r\\ \partial\kappa/\partial r\\ \partial L/\partial r\end{pmatrix}
=\begin{pmatrix}-w\kappa U_{XX}\\ \kappa\left(-w+h'(t_h)\right)U_{XX}\\ U_X-r\kappa U_{XX}\\ -w\kappa U_{XX}\end{pmatrix}\qquad\text{(A2-2a)}$$

Simplifying (A2-2a) using , $-w+\mathrm{h}'(\mathrm{t_h})=0$ (from FOC),

$$\begin{pmatrix}
w^2U_{XX}+f_{t_c t_c}U_\tau+f_{t_c}^2U_{\tau\tau} & 0 & wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX}\\
0 & h''(t_h)U_X & 0 & 0\\
rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau} & 0 & r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau} & wrU_{XX}\\
w^2U_{XX} & 0 & wr\mathrm{U_{XX}} & w^2\mathrm{U_{XX}}+U_{LL}
\end{pmatrix}
\begin{pmatrix}\partial t_c/\partial r\\ \partial t_h/\partial r\\ \partial\kappa/\partial r\\ \partial L/\partial r\end{pmatrix}
=\begin{pmatrix}-w\kappa U_{XX}\\ 0\\ U_X-r\kappa U_{XX}\\ -w\kappa U_{XX}\end{pmatrix}\qquad\text{(A2-2b)}$$

Similarly, differentiating the identities given in (10a$'$) – (10d$'$) with respect to κ_0, rearranging in matrix form and simplifying using $-w+h'(t_h)=0$ yield,

$$\begin{pmatrix} w^2U_{XX}+f_{t_ct_c}U_\tau+f_{t_c}^2U_{\tau\tau} & -w(-w+h'(t_h))U_{XX} & wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX} \\ -w(-w+h'(t_h))U_{XX} & h''(t_h)U_X+(-w+h'(t_h))^2U_{XX} & -r(-w+h'(t_h))U_{XX} & -w(-w+h'(t_h))U_{XX} \\ rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau} & -r(-w+h'(t_h))U_{XX} & r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau} & wrU_{XX} \\ w^2U_{XX} & -w(-w+h'(t_h))U_{XX} & wrU_{XX} & w^2U_{XX}+U_{LL} \end{pmatrix} \begin{pmatrix} \partial t_c/\partial\kappa_0 \\ \partial t_h/\partial\kappa_0 \\ \partial\kappa/\partial\kappa_0 \\ \partial L/\partial\kappa_0 \end{pmatrix} = \begin{pmatrix} -wU_{XX} \\ (-w+h'(t_h))U_{XX} \\ -rU_{XX} \\ -wU_{XX} \end{pmatrix} \quad \text{(A2-3a)}$$

$$\begin{pmatrix} w^2U_{XX}+f_{t_ct_c}U_\tau+f_{t_c}^2U_{\tau\tau} & 0 & wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau} & w^2U_{XX} \\ 0 & h''(t_h)U_X & 0 & 0 \\ rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau} & 0 & r^2U_{XX}+f_{\kappa\kappa}U_\tau+f_\kappa^2U_{\tau\tau} & wrU_{XX} \\ w^2U_{XX} & 0 & wrU_{XX} & w^2U_{XX}+U_{LL} \end{pmatrix} \begin{pmatrix} \partial t_c/\partial\kappa_0 \\ \partial t_h/\partial\kappa_0 \\ \partial\kappa/\partial\kappa_0 \\ \partial L/\partial\kappa_0 \end{pmatrix} = \begin{pmatrix} -wU_{XX} \\ 0 \\ -rU_{XX} \\ -wU_{XX} \end{pmatrix} \quad \text{(A2-3b)}$$

Note that the coefficient matrices in (A2-2b) and (A2-3b) are equivalent so that their elements can be denoted by n_{ij} (with a bar at the bottom if a term has mixed signs).

$$\begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c/\partial r \\ \partial t_h/\partial r \\ \partial\kappa/\partial r \\ \partial L/\partial r \end{pmatrix} = \begin{pmatrix} d_1 \\ 0 \\ d_3 \\ d_4 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c/\partial\kappa_0 \\ \partial t_h/\partial\kappa_0 \\ \partial\kappa/\partial\kappa_0 \\ \partial L/\partial\kappa_0 \end{pmatrix} = \begin{pmatrix} e_1 \\ 0 \\ e_3 \\ e_4 \end{pmatrix} \quad \text{(A2-4)}$$

where the nonzero d_j's and e_j's are all positive.

Since the coefficient matrices in (A2-4) are identical and the constant vectors have the same sign, the directions of impact of r and κ_0 can be analyzed using θ to denote both variables.[1]

$$\begin{pmatrix} n_{11} & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & n_{34} \\ n_{41} & 0 & n_{43} & n_{44} \end{pmatrix} \begin{pmatrix} \partial t_c / \partial \theta \\ \partial t_h / \partial \theta \\ \partial \kappa / \partial \theta \\ \partial L / \partial \theta \end{pmatrix} = \begin{pmatrix} g_1 \\ 0 \\ g_3 \\ g_4 \end{pmatrix} \tag{A2-5}$$

where $\theta = r, \kappa_0$, $g_j = d_j, e_j$ for all $j = 1,\ldots,4$, and the nonzero g_j's are positive.

(2a) Effects of θ on computer/Internet time

$$\frac{\partial t_c}{\partial \theta} = \frac{\begin{vmatrix} g_1 & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ g_3 & 0 & n_{33} & n_{34} \\ g_4 & 0 & n_{43} & n_{44} \end{vmatrix}}{H} = \frac{n_{22}\begin{vmatrix} g_1 & \underline{n}_{13} & n_{14} \\ g_3 & n_{33} & n_{34} \\ g_4 & n_{43} & n_{44} \end{vmatrix}}{H} = \frac{n_{22}\left\{ \left[g_1 n_{33} n_{44} + \underline{n}_{13} n_{34} g_4 + n_{14} n_{43} g_3 \right] - \left[n_{14} n_{33} g_4 + n_{34} n_{43} g_1 + n_{44} g_3 \underline{n}_{13} \right] \right\}}{H}$$

$$sign\left\{\frac{\partial t_c}{\partial \theta}\right\} = sign\left\{terms\ in\ numerator\right\}$$

Rewriting the terms in the numerator yields,

[1] Note that advance in technology reduces both unit and fixed costs of computer use (i.e., $\uparrow tech \Rightarrow \downarrow (r, \kappa_0)$).

$$
\begin{aligned}
&n_{22}\{[g_1 n_{33} n_{44} + \underline{n}_{13} n_{34} g_4 + n_{14} n_{43} g_3] - [n_{14} n_{33} g_4 + n_{34} n_{43} g_1 + n_{44} g_3 \underline{n}_{13}]\} \\
&\quad = n_{22}\{g_1 n_{33} n_{44} + n_{14} n_{43} g_3 + \underline{n}_{13}(n_{34} g_4 - n_{44} g_3) - n_{14} n_{33} g_4 - n_{34} n_{43} g_1\} \\
&\quad = n_{22}\{g_1 n_{33} n_{44} + n_{14} n_{43} g_3 + (wrU_{XX} + f_{\iota_c \kappa} U_\tau + f_{\iota_c} f_\kappa U_{\tau\tau})(n_{34} g_4 - n_{44} g_3) - n_{14} n_{33} g_4 - n_{34} n_{43} g_1\} \\
&\quad = n_{22}[(wrU_{XX} + f_{\iota_c} f_\kappa U_{\tau\tau})(-n_{44} g_3) + f_{\iota_c \kappa} U_\tau (n_{34} g_4) - n_{14} n_{33} g_4 - n_{34} n_{43} g_1] \\
&\qquad\quad + n_{22}[g_1 n_{33} n_{44} + n_{14} n_{43} g_3 + (wrU_{XX} + f_{\iota_c} f_\kappa U_{\tau\tau})(n_{34} g_4) + f_{\iota_c \kappa} U_\tau (-n_{44} g_3)]
\end{aligned}
$$

Signing the terms,

$$
\frac{\partial t_c}{\partial \theta} = \frac{\overbrace{\underbrace{\overbrace{n_{22}}^{-}\left[\left(\overbrace{wrU_{XX} + f_{\iota_c} f_\kappa U_{\tau\tau}}^{-}\right)\overbrace{(-n_{44} g_3)}^{+} + \overbrace{f_{\iota_c \kappa} U_\tau (n_{34} g_4)}^{-} \overbrace{- n_{14} n_{33} g_4 - n_{34} n_{43} g_1}^{-}\right]}_{+}}{}}{\underbrace{H}_{+}}
+ \frac{\overbrace{n_{22}}^{-}\left[\overbrace{g_1 n_{33} n_{44} + n_{14} n_{43} g_3}^{+} + \left(\overbrace{wrU_{XX} + f_{\iota_c} f_\kappa U_{\tau\tau}}^{-}\right)\left(\overbrace{n_{34} g_4}^{-}\right) + \overbrace{f_{\iota_c \kappa} U_\tau (-n_{44} g_3)}^{+}\right]}{\underbrace{H}_{+}} \gtrless 0
$$

$$
\frac{\partial t_c}{\partial \theta} = \frac{[\textit{Positive term}]}{H} + \frac{[\text{Negative term}]}{\text{H}} \gtrless 0 \quad \begin{cases} \dfrac{\partial t_c}{\partial r} \gtrless 0 \\[2ex] \dfrac{\partial t_c}{\partial \kappa_0} \gtrless 0 \end{cases} \tag{A2-6}
$$

(2b) Effects of θ on home production time

From (A2-5),

$$\frac{\partial t_h}{\partial \theta}=\frac{\begin{vmatrix} n_{11} & g_1 & \underline{n}_{13} & n_{14} \\ 0 & 0 & 0 & 0 \\ \underline{n}_{31} & g_3 & n_{33} & n_{34} \\ n_{41} & g_4 & n_{43} & n_{44} \end{vmatrix}}{H}=0 \qquad \Rightarrow \qquad \frac{\partial t_h}{\partial \theta}=0 \quad \begin{cases} \dfrac{\partial t_h}{\partial r}=0 \\ \dfrac{\partial t_h}{\partial \kappa_0}=0 \end{cases} \qquad \text{(A2-7)}$$

(2c) Effects of θ on the choice of computer/Internet technology

$$\frac{\partial \kappa}{\partial \theta}=\frac{\begin{vmatrix} n_{11} & 0 & g_1 & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & g_3 & n_{34} \\ n_{41} & 0 & g_4 & n_{44} \end{vmatrix}}{H}=\frac{n_{22}\begin{vmatrix} n_{11} & g_1 & n_{14} \\ \underline{n}_{31} & g_3 & n_{34} \\ n_{41} & g_4 & n_{44} \end{vmatrix}}{H}=\frac{n_{22}\left\{\left[n_{11}g_3n_{44}+g_1n_{34}n_{41}+n_{14}g_4\underline{n}_{31}\right]-\left[n_{14}g_3n_{41}+n_{34}g_4n_{11}+n_{44}\underline{n}_{31}g_1\right]\right\}}{H}$$

$$sign\left\{\frac{\partial \kappa}{\partial \theta}\right\}=sign\left\{terms\ in\ numerator\right\}$$

$$\begin{aligned}
&n_{22}\left\{\left[n_{11}g_3n_{44}+g_1n_{34}n_{41}+n_{14}g_4\underline{n}_{31}\right]-\left[n_{14}g_3n_{41}+n_{34}g_4n_{11}+n_{44}\underline{n}_{31}g_1\right]\right\} \\
&\quad=n_{22}\left\{n_{11}g_3n_{44}+g_1n_{34}n_{41}+\underline{n}_{31}\left(n_{14}g_4-n_{44}g_1\right)-n_{14}g_3n_{41}-n_{34}g_4n_{11}\right\} \\
&\quad=n_{22}\left\{n_{11}g_3n_{44}+g_1n_{34}n_{41}+\left(rwU_{XX}+f_{\kappa t_c}U_\tau+f_\kappa f_{t_c}U_{\tau\tau}\right)\left(n_{14}g_4-n_{44}g_1\right)-n_{14}g_3n_{41}-n_{34}g_4n_{11}\right\} \\
&\quad=n_{22}\left[\left(rwU_{XX}+f_\kappa f_{t_c}U_{\tau\tau}\right)\left(-n_{44}g_1\right)+f_{\kappa t_c}U_\tau\left(n_{14}g_4\right)-n_{14}g_3n_{41}-n_{34}g_4n_{11}\right] \\
&\qquad+n_{22}\left[n_{11}g_3n_{44}+g_1n_{34}n_{41}+\left(rwU_{XX}+f_\kappa f_{t_c}U_{\tau\tau}\right)\left(n_{14}g_4\right)+f_{\kappa t_c}U_\tau\left(-n_{44}g_1\right)\right]
\end{aligned}$$

Signing the terms,

$$\frac{\partial \kappa}{\partial \theta}=\frac{\underbrace{\overbrace{n_{22}}^{-}\left[\left(\overbrace{rwU_{XX}+f_{\kappa}f_{t_c}U_{\tau\tau}}^{-}\right)\left(\overbrace{-n_{44}g_{1}}^{+}\right)+\overbrace{f_{\kappa t_c}U_{\tau}\left(n_{14}g_{4}\right)}^{-}\overbrace{-n_{14}g_{3}n_{41}-n_{34}g_{4}n_{11}}^{-}\right]}_{+}}{\underbrace{H}_{+}}$$

$$+\frac{\underbrace{\overbrace{n_{22}}^{-}\left[\overbrace{n_{11}g_{3}n_{44}+g_{1}n_{34}n_{41}}^{+}+\left(\overbrace{rwU_{XX}+f_{\kappa}f_{t_c}U_{\tau\tau}}^{-}\right)\left(\overbrace{n_{14}g_{4}}^{-}\right)+\overbrace{f_{\kappa t_c}U_{\tau}\left(-n_{44}g_{1}\right)}^{+}\right]}_{-}}{\underbrace{H}_{+}}\ \substack{\geq \\ <}\ 0$$

$$\frac{\partial \kappa}{\partial \theta}=\frac{[Positive]}{H}+\frac{[\text{Negative}]}{\text{H}}\ \substack{\geq \\ <}\ 0\ \begin{cases}\dfrac{\partial \kappa}{\partial r}\ \substack{\geq \\ <}\ 0\\[2ex]\dfrac{\partial \kappa}{\partial \kappa_{0}}\ \substack{\geq \\ <}\ 0\end{cases}\tag{A2-8}$$

(2d) Effects of θ on leisure

$$\frac{\partial L}{\partial \theta}=\frac{\begin{vmatrix} n_{11} & 0 & \underline{n}_{13} & g_{1}\\ 0 & n_{22} & 0 & 0\\ \underline{n}_{31} & 0 & n_{33} & g_{3}\\ n_{41} & 0 & n_{43} & g_{4}\end{vmatrix}}{H}=\frac{n_{22}\begin{vmatrix} n_{11} & \underline{n}_{13} & g_{1}\\ \underline{n}_{31} & n_{33} & g_{3}\\ n_{41} & n_{43} & g_{4}\end{vmatrix}}{H}=\frac{n_{22}\left\{\left[n_{11}n_{33}g_{4}+\underline{n}_{13}g_{3}n_{41}+g_{1}n_{43}\underline{n}_{31}\right]-\left[g_{1}n_{33}n_{41}+g_{3}n_{43}n_{11}+g_{4}\underline{n}_{31}\underline{n}_{13}\right]\right\}}{H}$$

$$sign\left\{\frac{\partial L}{\partial \theta}\right\}=sign\ \{terms\ in\ numerator\}$$

Rewriting the terms in the numerator gives,

$$n_{22}\left\{\left[n_{11}n_{33}g_4+\underline{n}_{13}g_3n_{41}+g_1n_{43}\underline{n}_{31}\right]-\left[g_1n_{33}n_{41}+g_3n_{43}n_{11}+g_4\underline{n}_{31}\underline{n}_{13}\right]\right\}=n_{22}\left\{n_{11}n_{33}g_4+\underline{n}_{13}\left(g_3n_{41}+g_1n_{43}\right)-g_1n_{33}n_{41}-g_3n_{43}n_{11}-g_4\underline{n}_{31}\underline{n}_{13}\right\}$$

$$=n_{22}\left\{n_{11}n_{33}g_4+\left(wrU_{XX}+f_{t_c\kappa}U_\tau+f_{t_c}f_\kappa U_{\tau\tau}\right)\left(g_3n_{41}+g_1n_{43}\right)-g_1n_{33}n_{41}-g_3n_{43}n_{11}-g_4\underline{n}_{31}\underline{n}_{13}\right\}$$

$$=n_{22}\left[\left(f_{t_c\kappa}U_\tau\right)\left(g_3n_{41}+g_1n_{43}\right)-g_1n_{33}n_{41}-g_3n_{43}n_{11}-g_4\underline{n}_{31}\underline{n}_{13}\right]+n_{22}\left[n_{11}n_{33}g_4+\left(wrU_{XX}+f_{t_c}f_\kappa U_{\tau\tau}\right)\left(g_3n_{41}+g_1n_{43}\right)\right]$$

Signing the terms,

$$\frac{\partial L}{\partial\theta}=\frac{\underbrace{\overbrace{n_{22}}^{-}\left[\left(\overbrace{f_{t_c\kappa}U_\tau}^{+}\right)\left(\overbrace{g_3n_{41}+g_1n_{43}}^{-}\right)\overbrace{-g_1n_{33}n_{41}-g_3n_{43}n_{11}-g_4\underline{n}_{31}\underline{n}_{13}}^{-}\right]}_{+}}{\underbrace{H}_{+}}+\frac{\underbrace{\overbrace{n_{22}}^{-}\left[\overbrace{n_{11}n_{33}g_4}^{+}+\left(\overbrace{wrU_{XX}+f_{t_c}f_\kappa U_{\tau\tau}}^{-}\right)\left(\overbrace{g_3n_{41}+g_1n_{43}}^{-}\right)\right]}_{-}}{\underbrace{H}_{+}}\ \substack{\geq\\<}\ 0$$

$$\frac{\partial L}{\partial\theta}=\frac{[Positive]}{H}+\frac{[\text{Negative}]}{\text{H}}\ \substack{\geq\\<}\ 0\quad\begin{cases}\dfrac{\partial L}{\partial r}\ \substack{\geq\\<}\ 0\\[2ex]\dfrac{\partial L}{\partial\kappa_0}\ \substack{\geq\\<}\ 0\end{cases}\qquad\text{(A2-9)}$$

Appendix A3: Signing the Impacts of the Change in Non-Labor Income

(3a) Effects of non-labor income on computer/Internet time

From (24b),

$$\frac{\partial t_c}{\partial Y}=\frac{\begin{vmatrix} s_1 & 0 & \underline{n}_{13} & n_{14} \\ 0 & n_{22} & 0 & 0 \\ s_3 & 0 & n_{33} & n_{34} \\ s_4 & 0 & n_{43} & n_{44} \end{vmatrix}}{H}=\frac{n_{22}\begin{vmatrix} s_1 & \underline{n}_{13} & n_{14} \\ s_3 & n_{33} & n_{34} \\ s_4 & n_{43} & n_{44} \end{vmatrix}}{H}=\frac{n_{22}\left\{\left[s_1 n_{33} n_{44}+\underline{n}_{13} n_{34} s_4+n_{14} n_{43} s_3\right]-\left[n_{14} n_{33} s_4+n_{34} n_{43} s_1+n_{44} s_3 \underline{n}_{13}\right]\right\}}{H}$$

$$sign\left\{\frac{\partial t_c}{\partial Y}\right\}=sign\left\{terms\ in\ numerator\right\}$$

Rewriting the terms in the numerator,

$$n_{22}\left\{\left[s_1 n_{33} n_{44}+\underline{n}_{13} n_{34} s_4+n_{14} n_{43} s_3\right]-\left[n_{14} n_{33} s_4+n_{34} n_{43} s_1+n_{44} s_3 \underline{n}_{13}\right]\right\}$$

$$\begin{aligned}
n_{22}\left\{\left[s_1 n_{33} n_{44}+\underline{n}_{13} n_{34} s_4+n_{14} n_{43} s_3\right]-\left[n_{14} n_{33} s_4+n_{34} n_{43} s_1+n_{44} s_3 \underline{n}_{13}\right]\right\} &= n_{22}\left\{s_1 n_{33} n_{44}+n_{14} n_{43} s_3+\underline{n}_{13}(n_{34} s_4-n_{44} s_3)-n_{14} n_{33} s_4-n_{34} n_{43} s_1\right\} \\
&= n_{22}\left\{s_1 n_{33} n_{44}+n_{14} n_{43} s_3+\left(wrU_{XX}+f_{\iota_c\kappa}U_\tau+f_{\iota_c}f_\kappa U_{\tau\tau}\right)\left(n_{34} s_4-n_{44} s_3\right)-n_{14} n_{33} s_4-n_{34} n_{43} s_1\right\} \\
&= n_{22}\left[s_1 n_{33} n_{44}+n_{14} n_{43} s_3+\left(wrU_{XX}+f_{\iota_c}f_\kappa U_{\tau\tau}\right)\left(n_{34} s_4\right)+f_{\iota_c\kappa}U_\tau(-n_{44} s_3)\right] \\
&\quad +n_{22}\left[\left(wrU_{XX}+f_{\iota_c}f_\kappa U_{\tau\tau}\right)\left(-n_{44} g_3\right)+f_{\iota_c\kappa}U_\tau(n_{34} s_4)-n_{14} n_{33} s_4-n_{34} n_{43} s_1\right]
\end{aligned}$$

Signing the terms,

$$\frac{\partial t_c}{\partial Y} = \frac{\underbrace{\overbrace{n_{22}}^{-}\left[\overbrace{s_1 n_{33} n_{44} + n_{14} n_{43} s_3}^{-} + \left(\overbrace{wrU_{XX} + f_{t_c} f_\kappa U_{\tau\tau}}^{-}\right)\left(\overbrace{n_{34} s_4}^{+}\right) + \overbrace{f_{t_c\kappa} U_\tau (-n_{44} s_3)}^{-}\right]}_{+}}{\underbrace{H}_{+}}$$

$$+ \frac{\underbrace{\overbrace{n_{22}}^{-}\left[\left(\overbrace{wrU_{XX} + f_{t_c} f_\kappa U_{\tau\tau}}^{-}\right)\overbrace{(-n_{44} s_3)}^{-} + \overbrace{f_{t_c\kappa} U_\tau (n_{34} s_4)}^{+} \overbrace{- n_{14} n_{33} s_4 - n_{34} n_{43} s_1}^{+}\right]}_{-}}{\underbrace{H}_{+}} \gtrless 0$$

$$\frac{\partial t_c}{\partial Y} \gtrless 0 \qquad \text{(A3-1)}$$

(3b) Effects of non-labor income on home production time

From (24b),

$$\frac{\partial t_h}{\partial Y} = \frac{\begin{vmatrix} n_{11} & s_1 & \underline{n}_{13} & n_{14} \\ 0 & 0 & 0 & 0 \\ \underline{n}_{31} & s_3 & n_{33} & n_{34} \\ n_{41} & s_4 & n_{43} & n_{44} \end{vmatrix}}{H} = 0 \qquad \text{(A3-2)}$$

(3c) Effects of Non-labor Income on the Choice of Computer/Internet Technology

From (24b),

$$\frac{\partial \kappa}{\partial Y} = \frac{\begin{vmatrix} n_{11} & 0 & s_1 & n_{14} \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & s_3 & n_{34} \\ n_{41} & 0 & s_4 & n_{44} \end{vmatrix}}{H} = \frac{n_{22}\begin{vmatrix} n_{11} & s_1 & n_{14} \\ \underline{n}_{31} & s_3 & n_{34} \\ n_{41} & s_4 & n_{44} \end{vmatrix}}{H} = \frac{n_{22}\left\{ \left[n_{11}s_3n_{44} + s_1n_{34}n_{41} + n_{14}s_4\underline{n}_{31} \right] - \left[n_{14}s_3n_{41} + n_{34}s_4n_{11} + n_{44}\underline{n}_{31}s_1 \right] \right\}}{H}$$

$$sign\left\{\frac{\partial \kappa}{\partial Y}\right\} = sign\left\{terms\ in\ numerator\right\}$$

Rewriting the terms in the numerator yields,

$$\begin{aligned} n_{22}\left\{ \left[n_{11}s_3n_{44} + s_1n_{34}n_{41} + n_{14}s_4\underline{n}_{31} \right] - \left[n_{14}s_3n_{41} + n_{34}s_4n_{11} + n_{44}\underline{n}_{31}s_1 \right] \right\} &= n_{22}\left\{ n_{11}s_3n_{44} + s_1n_{34}n_{41} + \underline{n}_{31}\left(n_{14}s_4 - n_{44}s_1\right) - n_{14}s_3n_{41} - n_{34}s_4n_{11} \right\} \\ &= n_{22}\left\{ n_{11}s_3n_{44} + s_1n_{34}n_{41} + \left(rwU_{XX} + f_{\kappa l_c}U_\tau + f_\kappa f_{l_c}U_{\tau\tau}\right)\left(n_{14}s_4 - n_{44}s_1\right) - n_{14}s_3n_{41} - n_{34}s_4n_{11} \right\} \\ &= n_{22}\left[n_{11}s_3n_{44} + s_1n_{34}n_{41} + \left(rwU_{XX} + f_\kappa f_{l_c}U_{\tau\tau}\right)\left(n_{14}s_4\right) + f_{\kappa l_c}U_\tau\left(-n_{44}s_1\right) \right] \\ &\quad + n_{22}\left[\left(rwU_{XX} + f_\kappa f_{l_c}U_{\tau\tau}\right)\left(-n_{44}s_1\right) + f_{\kappa l_c}U_\tau\left(n_{14}s_4\right) - n_{14}s_3n_{41} - n_{34}s_4n_{11} \right] \end{aligned}$$

$$\frac{\partial \kappa}{\partial Y} = \frac{\underbrace{\overbrace{n_{22}}^{-}\left[\overbrace{n_{11}s_3n_{44} + s_1n_{34}n_{41}}^{-} + \left(\overbrace{rwU_{XX} + f_\kappa f_{t_c}U_{\tau\tau}}^{-}\right)\left(\overbrace{n_{14}s_4}^{+}\right) + \overbrace{f_{\kappa t_c}U_\tau\left(-n_{44}s_1\right)}^{-}\right]}_{-}}{\underbrace{H}_{+}}$$

$$+ \frac{\underbrace{\overbrace{n_{22}}^{-}\left[\left(\overbrace{rwU_{XX} + f_\kappa f_{t_c}U_{\tau\tau}}^{-}\right)\left(\overbrace{-n_{44}s_1}^{-}\right) + \overbrace{f_{\kappa t_c}U_\tau\left(n_{14}s_4\right)}^{+} \overbrace{-n_{14}s_3n_{41} - n_{34}s_4n_{11}}^{+}\right]}_{+}}{\underbrace{H}_{+}} \gtrless 0$$

$$\frac{\partial \kappa}{\partial Y} \gtrless 0 \tag{A3-3}$$

(3d) Effects of non-labor income on leisure

From (24b),

$$\frac{\partial L}{\partial Y} = \frac{\begin{vmatrix} n_{11} & 0 & \underline{n}_{13} & s_1 \\ 0 & n_{22} & 0 & 0 \\ \underline{n}_{31} & 0 & n_{33} & s_3 \\ n_{41} & 0 & n_{43} & s_4 \end{vmatrix}}{H} = \frac{n_{22}\begin{vmatrix} n_{11} & \underline{n}_{13} & s_1 \\ \underline{n}_{31} & n_{33} & s_3 \\ n_{41} & n_{43} & s_4 \end{vmatrix}}{H} = \frac{n_{22}\left\{\left[n_{11}n_{33}s_4 + \underline{n}_{13}s_3n_{41} + s_1n_{43}\underline{n}_{31}\right] - \left[s_1n_{33}n_{41} + s_3n_{43}n_{11} + s_4\underline{n}_{31}\underline{n}_{13}\right]\right\}}{H}$$

$$sign\left\{\frac{\partial L}{\partial Y}\right\} = sign\left\{terms\ in\ numerator\right\}$$

The terms in the numerator can be rewritten as,

$$n_{22}\left\{\left[n_{11}n_{33}s_4+\underline{n}_{13}s_3n_{41}+s_1n_{43}\underline{n}_{31}\right]-\left[s_1n_{33}n_{41}+s_3n_{43}n_{11}+s_4\underline{n}_{31}\underline{n}_{13}\right]\right\}=n_{22}\left\{n_{11}n_{33}s_4+\underline{n}_{13}\left(s_3n_{41}+s_1n_{43}\right)-s_1n_{33}n_{41}-s_3n_{43}n_{11}-s_4\underline{n}_{31}\underline{n}_{13}\right\}$$

$$=n_{22}\left\{n_{11}n_{33}s_4+\left(wrU_{XX}+f_{\iota_c\kappa}U_\tau+f_{\iota_c}f_\kappa U_{\tau\tau}\right)\left(s_3n_{41}+s_1n_{43}\right)-s_1n_{33}n_{41}-s_3n_{43}n_{11}-s_4\underline{n}_{31}\underline{n}_{13}\right\}$$

$$=n_{22}\left[n_{11}n_{33}s_4+\left(wrU_{XX}+f_{\iota_c}f_\kappa U_{\tau\tau}\right)\left(s_3n_{41}+s_1n_{43}\right)\right]+n_{22}\left[\left(f_{\iota_c\kappa}U_\tau\right)\left(s_3n_{41}+s_1n_{43}\right)-s_1n_{33}n_{41}-s_3n_{43}n_{11}-s_4\underline{n}_{31}\underline{n}_{13}\right]$$

Signing the terms,

$$\frac{\partial L}{\partial Y}=\frac{\underbrace{\overbrace{n_{22}}^{-}\left[\overbrace{n_{11}n_{33}s_4}^{-}+\left(\overbrace{wrU_{XX}+f_{\iota_c}f_\kappa U_{\tau\tau}}^{-}\right)\left(\overbrace{s_3n_{41}+s_1n_{43}}^{+}\right)\right]}_{-}}{\underbrace{H}_{+}}+\frac{\underbrace{\overbrace{n_{22}}^{-}\left[\left(\overbrace{f_{\iota_c\kappa}U_\tau}^{+}\right)\left(\overbrace{s_3n_{41}+s_1n_{43}}^{+}\right)\overbrace{-s_1n_{33}n_{41}-s_3n_{43}n_{11}-s_4\underline{n}_{31}\underline{n}_{13}}^{+}\right]}_{+}}{\underbrace{H}_{+}}\gtrless 0$$

$$\frac{\partial L}{\partial Y}\gtrless 0 \qquad \text{(A3-4)}$$

Appendix A4: Measurement of Time (Dependent Variables, from ATUS 2003 Data)

ATUS code	**Minutes spent on:**	**Description**
	Computer/Internet uses	
020904	CI use for household activities	Checking, sending, reading, or writing e-mail
120308	CI use for Leisure activities	Playing computer games (excluding other games)
150101	CI use for volunteer activities	Volunteer activities
	CI use (total): t_c	All computer/Internet uses at home (total time)
	Market work	
0501xx+(1705xx)	Main and other jobs	Hours spent doing specific tasks at one's main or other jobs (+ travel time)
0502xx, 0599xx	Work-related activities	Socializing, eating & drinking, sports and exercises, as part of job
0503xx	Other activities	Other income generating activities (hobbies, crafts, performances, services)
0504xx	Job search	Job search and interviewing
060101, 060301, 060401+(170601)	Education for degree	If for degree, education is classified as market work (+travel time).
	Market work (total): t_m	All market work (total time)
	Home production	
02xxxx+(1702xx)	Household activities	Housework & household management, food prep & clean-up, maintenance and repair, lawn & gardening, care for pets, vehicles, etc.(+travel time)
03xxx, 04xxxx + (1703xx, 1704xx)	Care giving	Caring for & helping household & non-household members (+ travel time)
07xxx+(1707xx)	Shopping	Grocery & non-grocery shopping, researching purchases (+travel time)
08xxxx, 09xxxx, 10xxxx+(1708xx, 1709xx, 1710xx)	Services	Professional & personal care services, household services, government services & civic obligations (+ travel time) (+ telephone calls from service providers: 160803 to 160198, 169999)
	Housework (total): t_h	All household activities (total time)
	Leisure activities	
0101xx	Sleeping	Sleeping (personal care)
0102xx – 0199xx, 0805xx+(1701xx)	Personal care	Other personal care (grooming, health care, personal activities) (+travel related to personal care)
11xxxx+(1711xx)	Eating and drinking	Eating and drinking alone or with others (+travel time)
12xxxx+(1712xx)	Socializing	Socializing, relaxing and leisure (+travel time) (+mail & messages, telephone calls: 020903, 160101, 160102)
1301xx, 130301+ (171301, 171399)	Sport and exercising	Participating in sports, exercises & recreation, & waiting time (+travel time)
1302xx, 130302, 130399+(171302)	Attending sport	Attending sporting/recreational events, & waiting time (+travel time)
14xxxx+(1714xx)	Religious activities	Religious and spiritual activities (+travel time)
15xxxx+(1715xx)	Volunteering	Volunteer activities (+travel time)
06xxxx+(170602, 170699)	Education (personal)	Education for personal interest (+travel time) (except 060101, 060301, 060401)
	Leisure activities (total): t_l	All leisure activities (total time)

Appendix A5: Marginal Effects of Determinants of Minutes Spent in CI Use, Leisure, Market Work and Housework, and Choice of CI Technology

	Computer or Internet time	Total leisure	Market work time	Housework time	Choice of CI technology
Log of predicted wage	82.25*** (18.81)	-152.5*** (14.01)	316.6*** (36.15)	96.79*** (13.47)	0.231*** (0.0886)
Family income ('000)	0.0237 (0.159)	-0.510*** (0.134)	0.960*** (0.295)	0.186 (0.128)	0.00744*** (0.000886)
Unit price of Internet use	179.9 (142.4)	56.99 (63.27)	178.8 (144.6)	-160.0** (60.03)	-0.387 (0.470)
Age/10	-17.08*** (2.963)	15.57*** (2.586)	-74.07*** (5.812)	6.741*** (2.287)	-0.0367** (0.0153)
Some college or associate degree	31.27*** (10.16)	7.045 (8.897)	-30.91* (18.71)	-7.916 (7.847)	0.0521 (0.0520)
Bachelor's degree or above	23.76* (13.58)	39.53*** (11.87)	-98.96*** (25.63)	-27.96*** (10.54)	0.227*** (0.0714)
Female	4.765 (8.673)	-59.46*** (7.593)	-76.98*** (19.03)	133.9*** (6.767)	-0.00836 (0.0454)
Nonwhite	-35.13*** (11.51)	54.28*** (9.479)	-12.29 (19.92)	-48.58*** (8.449)	-0.212*** (0.0548)
Noncitizen	-8.331 (18.39)	-54.81*** (15.11)	69.04** (30.62)	18.95 (13.44)	-0.255*** (0.0867)
Government job	-38.51*** (12.32)	-96.82*** (11.32)	335.9*** (22.73)	-38.04*** (10.02)	-0.110 (0.0692)
Private job	-38.39*** (8.427)	-109.5*** (7.681)	375.5*** (16.34)	-50.61*** (6.810)	-0.0514 (0.0465)
Live with spouse or partner	-7.911 (8.890)	-2.197 (7.977)	-51.72*** (19.50)	24.95*** (7.082)	0.204*** (0.0469)
Number of children ages 0 to 2	-27.00** (10.87)	-50.24*** (9.398)	-77.39*** (22.29)	88.12*** (8.301)	-0.107* (0.0567)
Number of children ages 3 to 5	-20.22** (9.757)	-42.84*** (8.622)	-18.69 (16.96)	48.83*** (7.611)	-0.00962 (0.0533)
Number of children ages 6 to 9	-27.93*** (8.172)	-25.83*** (6.900)	-26.56* (16.04)	40.19*** (6.097)	-0.00401 (0.0430)
Number of children ages 10 to 12	-15.39* (9.287)	-10.48 (8.138)	-41.35** (18.91)	35.03*** (7.198)	-0.0221 (0.0494)
Number of children ages 13 to 17	1.209 (7.107)	-17.62*** (6.538)	15.62 (14.94)	15.92*** (5.816)	0.0507 (0.0405)

Appendix A5 – Continued

	Computer or Internet time	Total leisure	Market work time	Housework time	Choice of CI technology
Metropolitan area	-16.61 (10.73)	57.30*** (9.259)	-131.6*** (19.63)	-22.19*** (8.178)	0.0569 (0.0541)
Northeast	11.54 (10.21)	9.681 (9.218)	-26.99 (22.45)	2.847 (8.137)	0.0774 (0.0553)
Midwest	4.624 (9.433)	-3.212 (8.409)	-17.86 (20.31)	11.55 (7.145)	0.0181 (0.0499)
West	5.787 (10.07)	-0.205 (9.041)	-11.03 (21.90)	5.014 (8.020)	0.254*** (0.0557)
Weekdays	14.65** (7.139)	-178.2*** (5.894)	473.6*** (14.03)	-42.79*** (5.638)	-
Constant	-471.2*** (144.4)	1299*** (76.67)	-720.8*** (194.7)	1.633 (67.70)	-0.0712 (0.507)
Observations	5188	5188	5188	5188	5188
R-squared		0.197			

Standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
Note: Total leisure and choice of CI technology are estimated by OLS and *Probit*, respectively, while censored regression (T*obit*) is used for the rest of the estimations since all involve significant number of zero observations.

CHAPTER III

EXPLAINING CHANGES IN THE DIGITAL DIVIDE IN THE UNITED STATES FROM 1997 – 2003: THE ROLE OF RACE AND GENDER

3.1 Introduction

The number of households that report the adoption and use of computer or the Internet (CI) has been growing rapidly in the United States since the mid-1980s. Nevertheless, examining the prevalence of home CI by various social groups reveals that there are differences in access to these technologies among different social groups. Such inequalities among different groups in accessing CI technologies are termed as the digital divide (DeMaggio and Hargittai, 2001). Certain groups of society have higher than average levels of CI ownerships. Those with high levels of CI ownership are whites, males, residents of metropolitan areas, and those with higher income, education and other resources. In contrast, the social groups that exhibit lower levels of CI ownership are blacks, Hispanics, and those with lower income and education levels (NTIA, 2000).

Home CI has become an increasingly important tool in our day-to-day activities. Some of the uses or advantages of home CI include (1) enhancing the capacity to search, achieve and retrieve large quantities of information on various issues, (2) expanding access to education, job search, business transactions, (3) enhancing individuals' participation in political discussions, decision-making at all level, and access to government services, (4) creating better job opportunities, and (5) uses for personal correspondence, entertainment, household financial management and record keeping. (Hoffman et al, 1998; NTIA, 2000; DiMaggio and Hargittai, 2001).

This wide range of uses indicate that CI is an important resource. Consequently, lack of access to home CI (i.e., inequality in CI) has a potential to exacerbate the inequalities existing in society. The implication of this is that the social groups listed above with lower access to CI are at a greater disadvantage compared to those with greater access. Consequently, investigating the factors that contribute to the observed digital gaps becomes an important undertaking.

This chapter analyzes the differences observed in home CI ownerships across racial, ethnic and gender groups in the United States. The data for this study are drawn from the 1997 – 2003 Current Population Survey (CPS) Computer and Internet Use Supplements. The issues involved are addressed in three steps. First, the study shows the discrepancies observed among various social groups in access to CI at home. The inequalities among different groups in accessing CI technologies are termed as the digital divide (DeMaggio and Hargittai, 2001). Second, the study investigates in detail whether the digital gaps observed between the identified groups have narrowed, remained constant, or widened over the period of analysis (1997 – 2003). Finally, a variant of the Blinder-Oaxaca decomposition technique is employed to identify the factors that contribute to the observed digital gaps.

Decompositions of the digital gaps are carried out in two different time frameworks: within a given year and across time. The first is a cross-sectional study and is useful for investigating the extent to which differences in characteristics between any two categories (say, whites and blacks) explain the observed digital gaps between them in a given year. The second approach incorporates a time series aspect to the decomposition technique. This type of decomposition is used to identify the factors that explain the observed increase in CI ownership across time in each category (say, among whites or blacks).

The rest of the chapter is organized as follows. Section 3.2 provides a brief description about the source of data employed in the study and presents a detailed description on the distributions of home CI in the United States. Section 3.3 focuses on the econometric methodology and equation specification issues. Section 3.4 presents the estimation results, and the last section provides a summary and conclusions.

3.2 Data and Descriptive Analyses

3.2.1 Data Sources

The data used in this study are drawn from 1997, 1998, 2000, 2001 and 2003 Current Population Survey (CPS) Computer and Internet Use Supplements.[1] The CPS is representative of the entire U.S. population and conducted by the U.S. Bureau of the Census for the Bureau of Labor Statistics. In addition to the basic monthly labor force data, these Supplements provide detailed information on CI usage both at the household and individual levels (the latter for persons 3 years old and over). The information provided by the CPS Computer and Internet Use Supplements includes whether there is a

[1] While the 1997 and 2003 Supplements were conducted in October, the 1998, 2000 and 2001 surveys, respectively, were carried out in September, August and December. Since the surveys are conducted in different months, these could partly contribute to the variations in year-to-year comparisons of the statistics drawn from the various surveys. For instance, the total number of computers in the household reported in the December survey is likely to be higher and more reflective of the actual number in a particular year than those reported in earlier month surveys, such as August, September and October.

computer in a household, if anyone in the household uses the Internet at home or away from home, and where and how the Internet is used.

The above five years of surveys are selected for this study because 1997 is the first year the Bureau of the Census started collecting the information on Internet use at home, although information on computer use has been gathered in selected years starting from 1984. In addition, 2003 is the most recent survey in the series.[2] The main reasons for incorporating all the five surveys are to make year-to-year comparisons on the dissemination of CI and to study the trend of the distribution of the two technologies among different socioeconomic groups of the society in the seven years period covered by the surveys. However, the bulk of time comparisons focus on the years 1997 and 2003.

Based on the statistics resulting from the supplementary data, it is possible to calculate estimates on the distribution of computers and Internet in United States' households and make inferences on their uses by the population as a whole. The sample statistics are adjusted using the relevant weights provided by the CPS, so that they reflect the estimates for the entire U.S. households and population.[3] The CPS final weights consist of the base weight adjusted for non-interview and variations in the distribution of the selected sample *vis-a-vis* the population as a whole in such characteristics as age, sex and state of residence.[4] The sample groups used in this study vary depending upon the issue under investigation. For instance, a sample of individuals ages 15 and over is used

[2] The data for the Computer and Internet Use Supplement scheduled for the year 2007 has not been released at this time.
[3] The two relevant weights used to adjust the estimates for the households and individuals are *pwhhwgt* and *pwsswgt*, respectively.
[4] The base weight is the inverse of the probability of a person being in the sample and is a rough measure of the number of actual persons that the sample person represents. [See various years CPS technical documentations for the details.]

to examine the extent of CI dissemination among the youth. However, the sample used for the regression analyses incorporates adults of 25 years and older.

3.2.2 Distributions of Home Computer and Internet Access in the United States

The primary aim of this study is to examine how evenly home computer and access to the Internet at home are distributed over the country's varied demographic groups and whether these groups exhibit similar trends of access to these technologies. The racial/ethnic digital divide is well documented (e.g., Hoffman et al, 1998; Bikson and Panis, 1999; Chaudhuri et al, 2005; Fairlie 2004, 2006, 2007). However, this study investigates whether there are other underrepresented social groups (stratified by age, education, income and gender). Before trying to find the causes for the digital divide, it is necessary to look at the dissemination and trends of home computers and home Internet access among different social groups. This can be done in two ways: first, by examining the distributions of home computers and the Internet among various social groups (Tables 3.1 and 3.2), and second, by studying how the digital divide is changing over time (Tables 3.3 and 3.4). In the subsections to follow, the two technologies are described separately in order to provide a broader picture about the patterns of their dissemination across time. However, the two are treated jointly in the regression analyses.[5]

[5] Computer and Internet is abbreviated as CI in later section and denotes individuals who both own home computers or have access to the Internet at home.

3.2.2.1 Trends of the Distributions of Home Computer and Home Internet Access

Tables 3.1 and 3.2 show the general patterns of home computer ownership and access to the Internet at home by household and individual characteristics. The proportions of households owning home computers and with home Internet access have been on the rise throughout the survey years. While households' home computer ownership rate increased from nearly 37 percent in 1997 to 62 percent in 2003, access to the Internet from home rose from about 14 percent to 55 percent in the same period. On average, each household has at least one computer and this has remained the same throughout the survey years. However, the addition of newly purchased computers on the available number of home computers seems to show a slight decreasing trend over time. On the other hand, the proportion of households that use their home computers to connect to the Internet has been steadily increasing over time. In 1997, about 39 percent of households use their home computers to connect to the Internet. This figure rose to 88 percent in 2003.

Ownership of home computers and home Internet access appears to rise steadily with the level of a household's income as well as across time. In both cases, the ownership rates are large for higher income families and small for those with annual income of less than $25,000. The maximum proportion of households in the latter income group with either home computers or Internet access is about 36 percent in the period under consideration. In particular, less than 30 percent of the low-income households have access to the Internet from home in 2003. In contrast, home computer ownership rates for the high-income groups have been well above 75 percent since 1997. This group's home Internet access rates are also relatively higher. The rates have increased by about 50 percentage points in 7 years time since 1997. Generally, the distributions of home computers and home Internet access show a wide discrepancy among different income groups. The pattern of inequality among the various income groups might reflect differences in purchasing power and tastes (Fairlie, 2007). Finally, Tables 3.1 and 3.2 also show that computer ownership rates and home Internet access vary with the location of the households. More households in metropolitan areas own home computers and access the Internet from home than those located in non-metropolitan areas.

The previous statistics describe the patterns of the distribution of home computer and home Internet access at the household level. Turning to the examination of the distribution patterns at the individuals' level, the proportions of individuals in the United States who own home computers and access the Internet from home have been consistently rising during the period under consideration. While home computer ownership rates have risen from about 41 to 67 percent, the rise in home Internet access is from nearly 15 percent to 60 percent.

The gender disaggregation shows that, on average, more males than females have access to home computers and the Internet throughout the survey years. However, the difference in the distributions between the two groups is only about 3 percentage points at any point in time. Interestingly, variations are also observed in the distributions of computer ownerships and access to home Internet among married and unmarried individuals. In both aspects, married couples have more access to home computers and the Internet. For instance, in 1997, forty-seven percent of married couples own home computers, and the rate rose to 73 percent in 2003. The figures for unmarried individuals are lower by about 13 percentage points for the same period. In the case of home Internet access, the differences in terms of marital status seem to increase with time (from 4 percentage points in 1997 to about 14 percentage points in 2003).

As expected, computer ownerships and Internet access at home are observed to vary by the level of education. Home computer ownership among university graduates is about 66 percent in 1997 and 86 percent in 2003. Those with only high school education lag behind the university graduates by more than 30 percentage points at each time period. The ownership rates for individuals with some college education have increased from about 49 to 76 percent during the survey years. The distributions of home Internet access show the same patterns in terms of level of education. However, compared to computer ownership rates, the proportion of individuals in each group that have access to the Internet at home is smaller. Less than 50 percent of individuals with high school or lower education have access to home Internet in 2003, while the corresponding figures for those with some college education and university graduates are about 68 and 81 percent, respectively.

Very wide variations are also observed in home computers and Internet access rates among different age groups. Home computer ownership seems to be concentrated among individuals in the age groups of 35 to 54 years. Home computer ownership rates for these groups range on average from 50 percent in 1997 to 75 percent in 2003. The second and third highest ownership rates are for individuals in age groups 15 to 24 and 25 to 34, respectively. The former has about 3 percentage points lead over the latter. Those in the age group of 55 to 64 follow closer, trailing behind the 25 to 34 age group with only 4 to 8 percentage points. It is the elderly (65 years old and above) who lag behind the rest of the age groups by the largest margin. The home computer ownership rate for this group is only 40 percent in 2003. Home Internet access also shows similar patterns of distributions as home computer ownerships when viewed in terms of age groups. The only difference is in the sizes of the distributions. As before, the leading groups are those in age groups of 35 to 44 and 45 to 54. The individuals in these two age groups have almost identical Internet access rates. Those in age groups of 15 to 24 and 25 to 34 are the second, having again almost identical Internet access rates. Those in age group of 55 to 64 rank third in access rates, lagging behind the second by 4 to 9 percentage points. As was the case for computer ownership, individuals 65 years of age and above have a very low home Internet access rates. These have implications on the provision of social services such as unemployment income claims.

The distributions of home computers and home Internet access show variations when viewed in terms of the racial composition of the population of the United States. However, both home computer ownership and Internet access rates have increased over time among all racial categories. Asians and Pacific Islanders have the highest proportions of home computer ownership and home Internet access compared to the other races. Whites take second place, followed by American Indians (including Aleuts and Eskimos). The shares of home computer ownership and home Internet access are the lowest for the black population. Nearly 55 percent of Asians own home computers in 1997, and the ownership rate has risen to about 77 percent in 2003. For the same period, the home computer ownership rates of the whites are in the range of 44 to 69 percent. In all the survey years, the whites lag behind the Asians by an average of 10 percentage points. The ownership rates of American Indian, Aleuts and Eskimos are 8 to 18 percentage points lower than that of the whites. The blacks' home computer ownership rates are the lowest in the group. The average ownership rate in 2003 is only 50 percent, rising from approximately 22 percent in 1997.

Home Internet access rates follow the same patterns of distributions among the four racial categories, with the exception that the proportion of individuals in each group with home Internet access are less than home computer owners throughout the survey years. Moreover, a wide difference is observed when the distributions of the two technologies are examined in terms of ethnicity; i.e., Hispanic and non-Hispanic origin. On average, the proportions of the Hispanic population who own home computers and access the Internet from home are lower by more than 20 percentage points compared to the non-Hispanic population.

Finally, a rising trend is observed, in both home computer ownership and home Internet access rates, among the employed and not employed, and among those working in government or private institutions, or self-employed individuals. In all instances and along each year, currently employed individuals have more access to both technologies at home. The difference in the home computer ownerships between the employed and the not employed individuals is between 11 and 18 percentage points. In the case of home Internet access, the gap is 7 to 13 percentage points. Variations are also detected by place of work. Home computer ownerships and home Internet access are higher among individuals working in government institutions, followed by self-employed individuals and those working in private organizations. In all cases, the distributions among these last three groups are so close that the gaps between them at each level are within the range of 6 percentage points.

Based on the above descriptions of the distributions of home computers and home Internet access, the following observations can be made. (1) There is a rising trend in home computer ownership and home Internet access rates over time in each of the social groups considered. (2) The proportion of households and individuals with home computers are higher than those with home Internet access. (3) Disparities are observed in the distributions of home computer ownership and home Internet access among different social groups. Particularly, wide and noticeable variations in the distribution patterns of the two technologies are observed with respect to income, education, age and race. Hence, those with the lowest access to home computers and Internet are (a) household with annual income of $25,000 or less, (b) individuals who are high school graduates or lower, (c) the elderly, (d) individuals in the race categories of American Indians, Aleuts and Eskimos and blacks, and (e) those with Hispanic ethnic origin.

In conclusion, although ownerships of home computers and access to the Internet at home are consistently rising over time (Figure 3.1), the rates at which the two technologies are expanding are slowing over time. That is, home computer ownerships and home Internet access are increasing at decreasing rates in the United States. Figure 3.2 indicates these decreasing growth rates. The figure is plotted by calculating the growth rates from the data given in Tables 3.1 and 3.2. For instance, home computer ownership has been growing annually at the rates of approximately 15, 21, 11 and 9 percent starting from 1997, while the corresponding rates for home Internet access are 79, 59, 24 and 8 percent. The same trend of expansion also holds when the distributions of the two technologies are examined in terms of various social groups.

3.2.2.2 How is the Digital Divide Changing over Time?

The preceding section shows the ownership patterns of home computers and the Internet as well as the disproportionate distributions or disparities among different social groups. Such disparities manifest the digital divide or gaps existing among the groups. The question, then, is whether the digital gaps are increasing or decreasing over time. This question can be answered by examining how the gaps are changing over time. The digital gaps are computed using Tables 3.1 and 3.2 and taking the category with the highest proportions of computer ownership and home Internet access in each socioeconomic group as a reference. In all the comparisons in this study, such categories are termed as the majority categories. In contrast, the categories with the lowest ownership and access rates are termed as the minority categories.

Tables 3.3 and 3.4 present the gaps for home computer ownership and home Internet access, respectively. While the size of the gaps represent the extent of the digital divide between the majority and minority categories, the change in the gaps over time (or the trend of the gaps) shows whether the digital gaps are narrowing, widening or remaining the same over time. Figures 3.3 to 3.8 plot the computer ownership and Internet access gaps for selected socioeconomic groups.[6] Those exhibiting a sizable digital gap and relatively noticeable time trend are selected for detailed analyses.

Digital divide with respect to household income: Relative to households with higher income (the majority category), the difference in home computer ownership and Internet access increases as the level of income decreases. In other words, the size of the digital gap gets larger as the level of household income becomes smaller. This indicates

[6] For ease of presentation, the figures use the absolute values of the gaps. The "bold" portion of the time axis denotes the trend line of the reference category.

that the proportion of households that own home computers and access the Internet at home gets smaller as one moves from high to low income households (Figures 3.3a and 3.3b). However, the trend of the change in these gaps is different for home computer ownership and Internet access. While the home computer ownership gap between high-income households and those earning less than $25,000 shows a slight declining trend (only 4 percentage points decrease in 7 years time), the decline of the gaps for the other income categories is relatively larger. For instance, the gap between the high-income households and those in the income category of $25,000 – 49,999 has narrowed by about 9 percentage points during the survey period.

On the other hand, except for the middle-income households ($50,000 – $74,999), the gaps in home Internet access are widening over time for all the income categories. The difference between this latter category and the majority category in the proportion of households that have access to home Internet has declined only by 1 percentage point from 1997 to 2003. For the households in the income categories of under $25,000 and between $25,000 - $49,999, the gaps in home Internet access show an increasing trend. In other words, compared to the high-income households, the proportions of low- and middle-income households that do not have home Internet access have increased by about 28 and 9 percentage points, respectively, during the survey years.

Digital divide with respect to gender: As shown in Tables 3.3 and 3.4, the gender digital gap is relatively small, but highly statistically significant, throughout the survey years. However, this gap has been narrowing over time (Figures 3.4a and 3.4b). While the gap in home computer ownership declined only slightly (by about one-half percentage point), that of home Internet access dropped by nearly 46 percent (by about 2 percentage points) from 1997 to 2003. Generally, the digital gap between females and males in home computer and Internet access are declining over time and the gender digital gap is only about 2 percentage points in 2003.

Digital divide with respect to level of education: Individuals with a university education are the majority category for the analysis with respect to education. Tables 3.3 and 3.4 (and Figures 3.5a and 3.5b) show the wide digital gaps observed among individuals with different levels of education. The digital gaps are also observed to increase as the level of education decreases. In other words, compared to university graduates, the digital gap for individuals with high school education or below is larger than those with some college education. The way the gaps change over time is different for computer ownership and home Internet access. Relative to the majority category, the gap in computer ownership tends to narrow over time, more so for college graduates than high school graduates. On the other hand, the gap in home Internet access shows mixed trends over time. While the gap between individuals with some college education and the majority category seems to narrow, though only slightly, the gap for those with high school education is widening over time. For the latter category, the gap in home Internet access has risen by about 12 percentage points (or 51 percent) during the survey period. This indicates that, instead of improving over time, the digital divide in home Internet access between individuals with low and high level of education is increasing over time.

Digital divide with respect to age: Among the various age groups, individuals in the age groups of 35 – 44 and 45 – 54 show the highest share in home computer ownership and Internet access. Although the distributions in these two age groups are approximately the same, the former is selected to serve as a majority group.[7] Hence, compared to the majority group, the digital gap is observed to increase with age for the majority of the cases under consideration. However, the trend of the change in the gaps over time is different for computer ownership and Internet access as well as for the different age groups.

First considering the case for computer ownership, those in the age group of 55 – 64 and above 65 years of age lag behind the majority group by 16 and 35 percentage points in home computer ownership, respectively (Tables 3.3 and 3.4). The computer ownership gap for the former age group has declined over time while that of the older individuals tends to rise over time. For those in the age range of 15 – 34 years, the computer ownership gap has been narrowing over time (Figure 3.6a).

The trend of the gap in Internet access is slightly different from that of computer ownership (Figure 3.6b). Here also the gap in Internet access for older individuals is relatively large compared to the reference category and it is increasing over time (almost doubled from 1997 to 2003). The Internet access gap for age group 55 – 64 shows a small declining trend (just a 1-percentage point drop in the period of analysis). Unlike the case for computer ownership, the gap in home Internet access between individuals of ages 15 – 34 and the majority group is widening over time. This indicates that the group that constitutes the bulk of the young population (15 – 34) is not having as much access to home Internet as does the majority group. More specifically, the home Internet access gap between those in the age groups of 15 – 24 and 35 – 44 more than doubled (has risen by about 2 percentage points) from 1997 to 2003. Likewise, the gap for age group 25 –

[7] In terms of home computer ownership, the 35 – 44 age group exceeds those in age group 45 – 54. This is the only criterion used to select the former as a majority group.

34 has widened by about 5 percentage points (or more than quadrupled) in the same period.

Digital divide with respect to race/ethnicity: Compared to whites (the majority category), the digital gaps are found to be relatively wider for both blacks and American Indians. At each year of the survey, the digital gap is larger for the blacks than for the American Indians. The trend of the gaps for both races is found to be different for home computer ownership and Internet access. The gaps in home computer ownership for blacks and American Indians show a small declining trend over time (a drop in 3 to 4 percentage points from 1997 to 2003) (Figure 3.7a). Such declining trends in the gaps shows that the home computer ownership rates of both races is increasing over time, though not rising at a rate big enough to catch up with the majority category. In contrast, the gap in Internet access tends to rise over time for both races (Figure 3.7b). While the home Internet access gap for the black population has almost doubled during the survey period, that of the American Indians has increased by about 39 percent during the same period (i.e., an increase in 3 percentage points). This means, the disparities in Internet access at home between the minority categories (blacks and American Indians) and the majority category are increasing over time.

Finally, classification of respondents in terms of ethnicity reveals the presence of a big digital gap between individuals of Hispanic origin and non-Hispanics (the majority category). In 2003, the digital gap between Hispanics and non-Hispanics is more than 20 percentage points. For both home computer ownership and Internet access, the gaps show a rising trend (Figures 3.8a and 3.8b). There seems to be no or little improvement in home computer ownership rates among individuals of Hispanic origin since the home computer ownership gap shows only a slight rising trend (only a 1-percentage point increase) during the survey period. In contrast, the gap in home Internet access rates between Hispanics and non-Hispanics shows a strong rising trend. More specifically, the gap in home internet access between Hispanics and non-Hispanics more than doubled during the survey years.

In conclusion, the above detailed descriptions provide a broad portrait of the dissemination of home computers and access to the Internet at home among the various social groups in the United States, the digital gaps observed within each group, and the trends the groups exhibit in the acquisition of these technologies over time. The descriptions also show how the distributions of these technologies vary with such characteristics as age, education and income. Among the disparities observed in ownership of home computers and Internet access, this study focuses on the digital gaps observed among three demographic categories (race, ethnicity and gender) which exhibit either sizable digital gaps or relatively noticeable time trends.[8] As discussed above, the gender digital gap is relatively small, but highly significant and shows a slight declining trend. The digital gaps for blacks and Hispanics are found to be relatively big and exhibit a rising trend over time.

3.3 Econometric Methodology and Equation Specification

3.3.1 Identification of Estimation Equations and Variables

The adoption of home computer and Internet access (CI) depends on the perceived usefulness of these technologies (Venkatesh et al, 1985; Fairlie, 2004). The

[8] Gender, race and ethnicity are exogenous characteristics compared to education, income and geographic location, which are endogenous.

perceived usefulness of CI, in turn, is influenced by such factors as income (Y), individual characteristics (I), household structure (H), geographic location (L), employment status and occupation (E), and access to CI technology (A) (Fairlie 2004; Kuku et al, 2007). Stated in terms of the traditional theory of consumer choices, individual i decides to own CI at home if the expected utility from using CI at home (V_{1i}) exceeds the expected utility from not using it (V_{0i}).[9] That is, if individual i's expected utilities from using and not using a home CI are given by,

$$V_{1i}(CI_i = 1,\ \ Y_i,\ I_i,\ \ H_i,\ L_i,\ E_i,\ A_i) \tag{1}$$

$$V_{0i}(CI_i = 0,\ \ Y_i,\ I_i,\ \ H_i,\ L_i,\ E_i,\ A_i) \tag{2}$$

then, the probability of deciding to acquire CI is (Kuku et al, 2007):

$$Prob(CI_i = 1) = Prob\{V_{1i}(CI_i = 1, Y_i,\ I_i,\ H_i,\ L_i,\ E_i, A_i) \text{-}\ V_{0i}(CI_i = 0, Y_i,\ I_i, H_i, L_i, E_i, A_i) > 0\}.$$

Using a logit model to express this probability, the impacts of the factors that are expected to influence the decision to acquire CI for home use can be estimated by:[10]

$$Prob(CI_i = 1) = \frac{e^{X'\beta}}{1 + e^{X'\beta}} = F(X'\beta) \tag{3}$$

where $F(X'\beta)$ is the logistic cumulative distribution function, and all the factors included in the above preference functions are summarized by vector $X = Y_i, I_i,\ H_i,\ L_i,\ E_i,\ A_i$. The

[9] Becker (1976) states that an individual maximizes utility obtained directly from the services of goods x_j purchased in the market at price p_j subject to an income constraint: $U = u(x_1, x_2, \ldots\ldots, x_n)$ s.t. $M = \sum_{j=1}^{n} p_j x_j$, where M is money income. Optimization yields the demand for the goods in terms of income, prices, and tastes (T); i.e., $x_j = f(M,\ p_j, T)$. Then, the indirect utility becomes $V = V(M, p_j, T)$. Tastes capture the variations not attributed to changes in income and prices, and are proxied commonly by such variables as individual and household characteristics, occupation, and socio-economic status.

[10] Both probit and logit are the most commonly used models in econometric applications. As they are similar in distribution (i.e., both have bell-shape (symmetric) distributions) and tend to provide similar predictions, it is "difficult to justify the choice of one distribution or another on theoretical grounds" (Greene, 2000). However, some may choose to use either of them for practical convenience. I am marginally inclined to use the logit model just because the diffusion of CI in the United States households follows a logistic distribution. This can be shown by plotting the distributions of home computers against time. In all cases, the distributions exhibit *the standard "S-shaped" curve.*

model parameter vector β denotes the set of coefficients that capture the effects of each of these attributes on the probability of home CI ownership.

The latent dependent variable in equation (3) is a dummy variable representing the probability of owning a home CI. The model is estimated separately for the three demographic groups identified as the focus of this study, namely, race (whites and blacks), ethnicity (Hispanic and non-Hispanic) and gender. Based on their home CI ownership rates, whites, non-Hispanics and males are identified as the majority categories in their respective groups, while blacks, Hispanics and females are minorities.

As shown above, vector X contains sets of variables that are assumed to influence the probability of home CI ownership. These variables are drawn from previous literature and the descriptive statistics provided in the preceding section. Individual characteristics include such variables as age, education, gender, race and citizenship. The variables contained in the household characteristics are family income, marital status, number of children, family size, and type of housing units. In most cases, determining a priori their impacts on CI ownership is difficult. Geographic location is used to capture the variations that might exist in the availability of computer hardware, software and accessories, and in the Internet infrastructure in metropolitan and non-metropolitan areas and in different regions of the country. Employment status and occupation describe whether an individual is employed or not, and the type of jobs and occupations held. Finally, individuals' access to CI at school and at work places are used to measure to what extent access to CI outside the home influences the probability of owning CI at home.

3.3.2 The Blinder-Oaxaca Decomposition and its Applications

Blinder (1973) and Oaxaca (1973) introduce similar decomposition techniques which are used primarily to examine wage differentials between males and females. The central idea of both decompositions is that gender differences in wages can be explained by the differences in the average characteristics of the two groups (e.g., individual differences in age, education, experience, marital status, occupation, industry, and region) and by the differences in the coefficient estimates, i.e., market wage returns to these measurable characteristics. Assume the wage equation to be estimated for each gender category is given in log-linear form as,

$$Y^m = X'\beta + \varepsilon \qquad \text{and} \qquad Y^f = X'\beta + \varepsilon \tag{4}$$

where Y^m and Y^f denote the natural logarithm of male and female wage rates, respectively, X' is a vector of individual characteristics, β is a vector of coefficients, and ε is a disturbance term. Then, the gender wage differential can be decomposed as,

$$\bar{Y}^m - \bar{Y}^f = (\bar{X}^m - \bar{X}^f)\hat{\beta}^m + \bar{X}^f(\hat{\beta}^m - \hat{\beta}^f) \tag{5}$$

The term on the left-hand-side (LHS) indicates the average wage differential between males and females. While the first term on the right-hand-side (RHS) captures the contribution of the differences in average characteristics to the wage differential, the second term denotes the estimated effects of differences in coefficients.[11] More

[11]An alternative and equally valid way of decomposing the wage differential is $\bar{Y}^m - \bar{Y}^f = (\bar{X}^m -$ $Xf\beta f+Xm\beta m-\beta f$. Both decompositions give potentially different results. Blinder (1973) and Oaxaca (1973) refer to this as the *index-number* problem. Since there is no rule to select one from the other, ranges of values from both decompositions are reported in many studies. Note that the difference between the two decompositions is in the weights used. The weights used in the first and second terms of the RHS expression of equation (5) are the males' coefficient estimates ($\hat{\beta}^m$) and the mean characteristics of the females ($\bar{X}^f$), respectively. On the other hand, in the alternative specification, the differences in the characteristics are weighted by females' coefficients ($\hat{\beta}^f$) and the differences in coefficients are weighted by males' mean characteristics ($\bar{X}^m$).

specifically, the differences in the characteristics weighted by the males' coefficient estimates $\left[\text{i. e.}, (\bar{X}^m - \bar{X}^f)\hat{\beta}^m\right]$ measure the part of the wage differential that can be explained by the differences in individual characteristics under the assumption that both males and females are rewarded in their market wages according to their respective marginal productivity (i.e., no labor market discrimination) so that the "current male wage structure would apply to both males and females" (Oaxaca, 1973).[12]

The differences in the coefficient estimates, weighted by females' average characteristics $\left[\text{i. e.}, \bar{X}^f(\hat{\beta}^m - \hat{\beta}^f)\right]$, capture to what extent differences in the estimated coefficients (i.e., the labor market rewards to otherwise identical characteristics) explain the wage gap. Blinder (1973) and Oaxaca (1973) designate the differences in the coefficient estimates as measures of discrimination. Makepeace et al (1999) calls them differences in estimated rewards. In other non-wage studies, the first term on the RHS is termed as the "explained" component while the second is called the "unexplained" component.

The Blinder-Oaxaca decomposition has been applied widely in various studies which focus on explaining the origin of differences in outcomes between any two comparison groups. Some of the studies directly employ the simple basic concepts of the decomposition method while others use different variants of the decomposition by modifying the main framework to fit the issues under investigation. For example, Gomulka and Stern (1989) analyze the factors that contribute to the growth of employment of married women in the U.K. from 1970 – 1983. Wagstaff et al (2003) investigate, among other things, the causes of health sector inequalities in Vietnam. Krieg

[12] Note that $\hat{\beta}^f$ and $\hat{\beta}^m$ are obtained by estimating the log-linear wage equation in (4) via Ordinary Least Squares (OLS) method.

and Storer (2006) measure to what extent individual students' performances are explained by the characteristics of the students themselves rather than by the attributes of the schools they are attending. Schnabel and Wagner (2006) examine the contributions of the differences between the characteristics of Eastern and Western Germany workers to the decline in union density before and after unification. Aguiar and Hurst (2008) investigate the factors explaining leisure inequality between men and women and to what extent the observed gap is attributable to differences in employment status in the United States in the period between 1965 and 2005.

Studies that rely on modifications to the Blinder-Oaxaca type decomposition relevant to this research include Makepeace et al, 1999; Fairlie, 1999, 2006; and Yun, 2003. Since these studies introduce a time series concept and non-linear equation models, they are used as a basis to develop a variant of the Blinder-Oaxaca type decomposition for the current study. This study examines the dispersion in home CI ownership across race, ethnicity and gender using a time series of cross section data.[13]

To address these issues properly, the Blinder-Oaxaca decomposition technique is modified in two ways. First, since the dependent variable, ownership of home CI, is a binary variable which take a value of 1 for individuals owning a home CI and 0 otherwise, the linear model Blinder-Oaxaca decomposition has to be modified to fit this non-linear functional form. Second, the modified version is adjusted easily to analyze the digital gaps across the racial, ethnic and gender groups within a given year, or to investigate the sources of observed changes in these outcomes over time. That is, the modified decomposition method can be transformed further to accommodate both the

[13] The primary contribution of this study lies on its focus on the time series analysis using 1997 – 2003 CPS cross section data in order to explain the changes in the digital gaps over time.

cross section and time series aspects of the analyses. The details of all the modifications are presented below.

3.3.3 The Blinder-Oaxaca Decomposition in the Case of a Binary Dependent Variable

Given the non-linear distributions of home CI ownership in equation (3), the disparity in CI ownership between any two groups (say, whites and blacks) can be decomposed using the Blinder-Oaxaca technique and following the modifications proposed by Fairlie (1999, 2006) and Yun (2003). Using the logit function in (3), the probability of CI ownership for whites (w) and blacks (b) are given by:

$$Prob\ (CI = 1)^w = CI^w = F(X^w \beta^w)$$

$$Prob\ (CI = 1)^b = CI^b = F(X^b \beta^b) \tag{6}$$

The difference in the probability of CI ownership (or the digital gap) between these two racial categories can be decomposed as:

$$\overline{CI}^w - \overline{CI}^b = \left[\frac{1}{N^w}\sum_{i=1}^{N^w} F(X_i^w \hat{\beta}^b) - \frac{1}{N^b}\sum_{i=1}^{N^b} F(X_i^b \hat{\beta}^b)\right]$$

$$+ \left[\frac{1}{N^w}\sum_{i=1}^{N^w} F(X_i^w \hat{\beta}^w) - \frac{1}{N^w}\sum_{i=1}^{N^w} F(X_i^w \hat{\beta}^b)\right]$$

$$\overline{CI}^w - \overline{CI}^b = \left[\bar{\bar{F}}(X_i^w \hat{\beta}^b) - \bar{\bar{F}}(X_i^b \hat{\beta}^b)\right] + \left[\bar{\bar{F}}(X_i^w \hat{\beta}^w) - \bar{\bar{F}}(X_i^w \hat{\beta}^b)\right] \tag{7}$$

where N^w and N^b denote the number of observations in the white and black samples, respectively, and the average value of the logistic function for either of the categories is given by,

$$\bar{\bar{F}}(X_i^k \hat{\beta}^k) = \frac{1}{N^k} \sum_{i=1}^{N^k} \bar{\bar{F}}(X_i^k \hat{\beta}^k), \quad \text{for } k = w, b.$$

Compared to the Blinder-Oaxaca framework, the term on the LHS of (7) indicates the difference in the average probability of CI ownership between whites and blacks.[14] The first term on the RHS denotes differences in the average predicted probabilities of whites and blacks' CI ownerships arising from differences in their respective characteristics. The average predicted probabilities for each racial category are computed at all values of their characteristics and the differences are weighted by blacks' estimated coefficients ($\hat{\beta}^b$). This term measures the part of the digital gap arising from differences in the observed characteristics of whites and blacks (for instance, differences in age, education, marital status and income). The second term on the RHS represents differences between the estimated coefficients of the two categories weighted by the characteristics of whites (X^w). This term captures the proportion of the digital gap due to factors that determine CI ownership but which cannot be directly measured or observed. As a result, it is termed as the "unexplained" component of the decomposition. Due to the difficulty in interpreting this unexplained portion, many studies report the explained part only (e.g., Fairlie, 2004)

[14] Note that the decomposition in (7) is comparable to the Blinder-Oaxaca decomposition in (5). The two differ in the functional forms employed in their respective underlying equations, non-linear vs. linear (i.e., (6) vs. (4)). For the log-linear wage equation, the first term on the RHS of (5) gives the differences in the average characteristics. The corresponding term for the non-linear model is expressed as differences in the average values of the logit functions. Note also that $\overline{CI}^w$ is not necessarily equal to $F(\bar{X}^w \hat{\beta}^w)$ (see Fairlie, 2006). For example, the average probability of CI ownership for whites ($\overline{CI}^w$) is likely to be different from the predicted probability computed using the average values of the independent variables $[F(\bar{X}^w \hat{\beta}^w)]$. In (7) the average value of the predicted probabilities evaluated at all values of X_i^w is taken, $\left[\text{e.g., } \bar{\bar{F}}\left(X_i^w \hat{\beta}^b\right) = \frac{1}{N^w} \sum_{i=1}^{N^w} F\left(X_i^w \hat{\beta}^b\right)\right]$. The same also holds for the black sample.

3.3.4 Decomposition Within a Given Year and Across Time

As mentioned before, this study focuses on the digital divide across racial, ethnic and gender groups in two different time frameworks: within a given year and over a period of time (1997 to 2003). The first type of study is useful for investigating the extent to which the differences between any two groups explain the digital gap between them in a given year. For instance, the digital gap in 1997 between whites and blacks can be decomposed using this approach. In fact, the Blinder-Oaxaca decomposition has been widely applied in studies that investigate group inequalities in a given year.[15] To deal with group differences within a given year (t), equation (7) is adjusted by just adding a time subscript as:

$$\overline{CI}_t^w - \overline{CI}_t^b = \left[\bar{\bar{F}}\left(X_{ti}^w \hat{\beta}_t^b\right) - \bar{\bar{F}}\left(X_{ti}^b \hat{\beta}_t^b\right)\right] + \left[\bar{\bar{F}}\left(X_{ti}^w \hat{\beta}_t^w\right) - \bar{\bar{F}}\left(X_{ti}^w \hat{\beta}_t^b\right)\right] \tag{8}$$

On the other hand, transforming the Blinder-Oaxaca type decomposition to study the changes in the digital inequality over time is not as straightforward as it is in the above case. Equation (8) denotes the digital gap between whites and blacks in terms of two weighted differences. This digital gap changes over time if the values of either the differences in characteristics or the differences in coefficients, or both change (Makepeace et al, 1999). Hence, this information can be used to examine how the digital gap changes when a given category's measured characteristics improve or its coefficients change over time. To develop a decomposition technique that captures both of these changes, assume the characteristics and coefficient estimates of the white sample change

[15] See, for example, Krieg and Storer (2006), Fairlie (1999, 2004, 2006), and Chinn and Fairlie (2006).

over time (i.e., from year t to $t+1$) relative to that of the blacks. Based on this assumption, (8) is modified as:[16]

$$\overline{CI}^w_{t+1} - \overline{CI}^w_t = \left[\bar{\bar{F}}\left(X^w_{t+1,i}\hat{\beta}^w_t\right) - \bar{\bar{F}}\left(X^w_{ti}\hat{\beta}^w_t\right)\right] + \left[\bar{\bar{F}}\left(X^w_{t+1,i}\hat{\beta}^w_{t+1}\right) - \bar{\bar{F}}\left(X^w_{t+1,i}\hat{\beta}^w_t\right)\right] \quad (9)$$

Note that the first term on the RHS denotes the changes in the measured characteristics of whites from X^w_{ti} to $X^w_{t+1,i}$ weighted by $\hat{\beta}^w_t$, and the second term represents the changes in coefficient estimates from $\hat{\beta}^w_t$ to $\hat{\beta}^w_{t+1}$ weighted by $X^w_{t+1,i}$. Equation (9) is formulated based on the assumption that neither the characteristics nor the coefficient estimates of the black sample is changing. As a result, (9) measures the digital gap among whites (i.e., within the same category) arising from changes in the composition of the white sample over time. Similarly, assuming changes in the composition of the black sample over time, the digital gap among blacks can also be measured.

Finally, note that all the decompositions reported in the next section are carried out using equations (8) and (9). These equations are estimated by using a package recently incorporated in Stata by Jann (2008) for decomposing such non-linear binary outcome models. This estimation method reports only the explained component of the decomposition results while the Oaxaca-Blinder decomposition reports both the explained and the unexplained components.

3.4 Estimation Results and Discussion

This section presents the estimation results of the logit model and the non-linear Blinder-Oaxaca decomposition. While the logit regressions identify the factors that

[16] See, for example, Makepeace et al (1999), Schnabel and Wagner (2006), and Aguiar and Hurst (2008).

influence the probability of owning CI for home use, the decomposition estimates quantify the contributions of these factors to the observed digital gaps across racial, ethnic and gender groups. Both estimations employ sets of variables identified in subsection 3.1 as determinants of home CI ownership. For ease of presentation, these variables are summarized under the following broad groups: individual characteristics, household characteristics, employment status and occupation, location variables, and access to CI outside home. Although the period of analysis is from 1997 to 2003, the estimation results of only two selected years (1997 and 2003) are reported for the detailed discussions.[17]

3.4.1 Logit Estimations

The probability of owning a home CI is estimated using the logistic model given in equation (3). Tables 3.5a to 3.5c report the marginal probability estimates for each racial, ethnic and gender groups. The following summarizes the estimation results.

Individual characteristics: Being female has no statistically significant impact on the probability of ownership of home CI for both majority and minority categories of the racial and ethnic groups. Age and being non-citizen of the United States significantly reduce the likelihood of having CI at home for whites and non-Hispanics (the majority categories). These variables do not produce a statistically significant impact on blacks' probability of CI ownership at all times. Only being a non-citizen has a strong and significant negative effect on Hispanics' probability of owning CI. That is, compared to

[17] Using employment status or occupation as a RHS variable creates an endogeneity problem. To avoid the simultaneous equation estimation, Blinder (1973) estimated the reduced form wage equation. However, the following studies use employment status or occupation as a RHS variable: Fairlie (2007), Aguiar and Hurst (2008) and Chaudhuri et al (2005).

non-Hispanics, Hispanics are about 67 percent less likely to own CI at home if they are non-citizens of the United States (Table 3.5b). In contrast, age, being black or Hispanic or non-citizen substantially reduce males and females' likelihood of home CI ownership. For instance, black females are 85 to 90 percent less likely to own CI at home compared to their white female counterparts (Table 3.5c).

On the other hand, the probabilities of CI ownership for home use considerably increase with each level of education across all racial, ethnic and gender groups. Such invariably similar and strong impacts of education on the acquisition of home CI may imply that education is one of the factors that raise the perceived usefulness of home CI.

Household characteristics: Taking the family income of \$50,000 – 75,000 as the base category, individuals in all racial, ethnic and gender groups are observed to be more less likely to own CI at home as family income decreases. Conversely, this means that the probability of CI ownership increases with each level of income for all individuals. One exception is for Hispanics. The marginal effect of the decrease in income from \$50,000 – 75,000 to \$25,000 – 50,000 on the probability of owning CI at home is not statistically significant for Hispanics in 1997 and 2003 samples. This may imply that there is no statistically significant difference in the distributions of home CI among Hispanics in the income groups of \$25,000 to 75,000.

The presence of children ages 0 to 14 in the household decreases whites, non-Hispanics and females' probability of CI ownership by 5 – 12 percent. This variable has mixed effects on males and blacks and a positive but not significant effect on Hispanics' likelihood of owning CI at home. Being married and family size significantly increase the probability of owning CI for all groups. This may arise due to the possibility of having additional income earning household member. Compared to temporary places of residence (such as hotel, rooming house or student quarter), residing in a house, apartment or flat significantly increases the likelihood of CI ownership for whites, non-Hispanics, males and females. The availability of infrastructural facilities (such as cable wiring) in permanent places of residence may facilitate the ownership of the CI. However, this variable does not affect the CI ownership decisions of blacks and Hispanics, implying that there are other factors, rather than places of residence, that influence these groups' CI ownership decisions.

Employment status and occupation: Except for Hispanics, employed individuals (compared to non-employed ones) in all groups are more likely to own CI at home in the 1997 sample. However, the impact of this variable is reversed in the 2003 sample. These results imply that in 1997 when CI were newly emerging technologies, one's employment status may have been a motivating factor (probably through its impact as a source of income) for owning them at home. This is no longer the case in 2003 since employed individuals have become less likely, *ceteris paribus*, to own CI at home. On the contrary, as opposed to non-Hispanics, employed Hispanics are unlikely to own the technologies at home in both years, although the impact is statistically insignificant.

In the majority of the cases, no differences are observed in the impacts of job types on CI ownership rates across race, ethnicity and gender. Hence, compared to self-employed individuals, those working in government and private institutions have lower probability of owning CI at home, probably due the access they have to the CI technologies at their work places. On the other hand, for all individuals in each racial, ethnic and gender groups, working in managerial and professional or in construction and maintenance occupations (as opposed to being engaged in forestry, fishing and agricultural activities) significantly raise the probability of owning CI at home. One important point worth noting is that the types of occupation have strong impacts on the minority categories' probabilities of CI ownership than on the majority categories. For instance, in 2003, blacks, Hispanics and females working in managerial and professional occupations are 65, 71 and 61 percent more likely to own CI at home, respectively, compared to their white, non-Hispanic and male counterparts, whose probabilities of owning CI at home are 57, 50 and 53 percent, respectively.

Location variables: Except for Hispanics, individuals in the other racial and gender categories are more likely to own CI at home if they are residing in metropolitan areas, in the West or Northeast part of the country (as opposed to those living in non-metropolitan areas or in the South). Particularly, the impact of residing in metropolitan areas is stronger for blacks and females than for their white and male counterparts. Location variables have distinctly different impacts on Hispanics' probability of home CI ownership. While living in the metropolitan areas, or in the South or Northeast has no statistically significant influence on CI ownership, residing in the Midwest (compared to living in the South) significantly reduces Hispanics' probability of owning CI at home. The reason why only a single location variable produces a significant impact is hard to explain. However, from the sample mean characteristics reported in Table 3.14 it is can be seen that the proportion of Hispanic population in the Midwest is very small (about 8 percent) compared to other regions of the country.

Access to CI outside home: Having access to CI outside home seems to be a motivating factor for home ownership of these technologies. Over all, those who use CI at work, school and other locations (such as public libraries, Internet cafés, airports and hotels) are more likely to acquire CI for home use. Observe that individuals' access to CI at their work places seems to have a dominant impact in enhancing the ownership of CI at home than accessing CI at school or other locations.

In summary, the majority of the variables contained in the broad categories listed above are found to be significant determinants of the probability of owning CI at home for the racial, ethnic and gender groups. Particularly, education, family income, being married, family size and access to CI outside home significantly increase the likelihood of owning CI at home. On the contrary, age, being non-citizen and presence of young children in the household reduce home CI ownership substantially. However, to what extent these and other variables included in the logistic regression explain the observed racial, ethnic and gender digital gaps remains to be investigated in the subsequent section.

3.4.2 The Non-Linear Blinder-Oaxaca Decomposition Results

This section presents the decomposition results obtained by estimating equations (8) and (9) using the package incorporated in Stata by Jann (2008) for decomposing such non-linear binary outcome models. As discussed before, the aim of this study is identifying the factors that contribute to the gap in home CI ownership between racial, ethnicity and gender groups. The non-liner Blinder-Oaxaca type decomposition breaks the digital gap into two major components: the explained and the unexplained parts. The former quantifies the contributions of each of the variables included in the model to the digital gap. The latter reports the proportion that cannot be explained since it reflects the changes arising from differences in coefficient estimates (as we do not for sure know what causes these coefficients to change). The non-linear model decomposition technique reports only the explained component of the decomposition.

The explained part states that the digital gap is due to differences in individuals' characteristics between the majority and minority categories. Each of the race, ethnic and gender groups consists of two categories: whites and blacks, non-Hispanics and Hispanics, and males and females, respectively. In all the decompositions, while the first category in each group is a majority category (the one with the highest CI ownership rate), the second is a minority category (the one with the lowest CI ownership rate).

The estimation results are presented in two parts. First, the cross-sectional estimation results of equation (8) are reported. This captures the within group differences (i.e., majority vs. minority) in a given year. The second part presents the time series aspects of the decomposition using equation (9). This helps identify the attributes for across time (1997 and 2003) variations of the digital gap among a given category (say, among males or blacks). In all cases, to avoid confusion the decompositions are carried out using only the majority categories as the reference group.

As discussed before, switching the majority and minority categories leads to potentially different results. In addition, only the explained part of the decompositions is reported. Furthermore, the contribution of each variable to the digital gap is computed as a percentage proportion of the overall CI ownership gap. For ease of reporting the decomposition results, variables with some similarities are collected in the following major groups: education, household structure, type of housing unit, employment status, location, and access to CI outside home.[18] In the discussions that follow more emphasis

[18] The variables contained in each group are given below. Education (high school graduate or below; bachelor's degree or above), income (under $25,000; $25,000 – 49,000; $50,000 – 74,000), household

is given to the variables that have relatively large contributions to the observed digital gap.

Finally, note that if a variable has a negative decomposition estimate, it means that the variable does not contribute at all to the observed digital gap between the majority and minority categories. Instead, the variable actually contributes in reducing the existing gap (Blinder, 1973; Oaxaca, 1973; Fairlie, 2006). Unless otherwise stated, the decomposition estimates are found to be significant at 10 percent or better significance levels. The following are the summary listings of the tables that report the decomposition results and the sample mean characteristics. Table 3.6 reports the decomposition of the racial digital gap; Table 3.7 presents the decomposition of the ethnic digital gap; Table 3.8 shows the decomposition of the gender digital gap. Note that these tables report only the explained components of the decompositions.[19] In addition, Tables 3.12, 3.13 and 3.14 present the sample mean characteristics of the racial, ethnic and gender groups, respectively. Often reference is also made to the marginal coefficient estimates of the logit regressions reported in Tables 3.5a, 3.5b and 3.5c.

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structure (being married; number of children ages 0 to 14; family size), type of housing unit (living in a house, apartment or flat; living in a mobile home or trailer), employment status (being employed; working in private institutions; self-employed; being engaged in management, professional, service, sales and office occupations; being engaged in construction, maintenance, production, transportation and material moving occupations), location (metropolitan area; Northeast; Midwest; West), and access to CI outside home (having access to a computer at work; having access to a computer at school; having access to the Internet at work; having access to the Internet at school; and accessing the Internet at other locations). Notice that the variables missing from each group are the dummies omitted from the estimation.

[19] The difference between the total digital gap and the explained portion gives the remaining total unexplained part of the gap.

3.4.2.1 Decomposition of the Racial, Ethnic and Gender Digital Gaps in a Given Year

A. Decomposition of the White/Black Digital Gaps over Time (1997 and 2003)

The decompositions in Table 3.6 report to what extent white/black differences in individual characteristics explain the observed differences in CI ownership at home. The decompositions are estimated using blacks' coefficients presented in Table 3.12 as weights $\left[i.e., \bar{\bar{F}}(X_{ti}^{w}\hat{\beta}_t^{b}) - \bar{\bar{F}}(X_{ti}^{b}\hat{\beta}_t^{b})\right]$. This amounts to giving blacks the same characteristics as whites. By doing so, the decompositions answer the question, "How high would blacks' CI ownership be if the blacks had the same characteristics as the whites?"[20] In other words, the decompositions link the whites' characteristics to the blacks' probability of CI ownership using the coefficient estimates of blacks.

The decompositions indicate that the white/black digital gap is relatively wide at nearly 20 percentage points in 1997 and 2003. The overall contributions of the variables included in the decomposition explain only a small fraction of the observed digital gaps. In 1997, the differences in the control variables contribute to nearly 33 percent (i.e., 0.066089/0.202951 in Table 3.6) of the digital gap observed in that year. However, the contributions of these variables declined over time and in 2003 only about 24 percent of the differences in CI ownerships between whites and blacks are due to differences in individual characteristics. That is, differences in individual characteristics of whites and blacks account for only a quarter to one-third of the digital gap between them. The remaining two-thirds to three-fourths of the disparities in CI ownership are due to differences in the coefficient estimates of the two racial categories. Such differences

[20] Giving blacks the characteristics of whites amounts to advancing the counterfactual assumption that 'what if the blacks were whites?'

cannot be easily explained since the causes for the changes in the coefficients are unknown. The unexplained part could also be due to factors that cannot be directly observable. For example, differences in culture, tastes for the two technologies, type of uses, and amount of time allocated for CI use could be some possible reasons for the variations in CI ownership between whites and blacks.

Among the specific characteristics that explain the disparities in CI ownership, differences in the levels of education, income and household structure between whites and blacks take the largest fraction of the observed digital gap. The part of the digital gap emanating from differences in the levels of education between whites and blacks is about 11 percent in 1997 and 10 percent in 2003.[21] As shown in Table 3.12, whites and blacks have different distributions in education. The percentages of blacks with only high school education are higher and those with university education are lower. Since whites and blacks have the same distribution in college education, the difference in CI ownership could come only from differences in high school and university level education. That is, as the probability of home CI ownership increases with the level of education (see Table 3.5a), the high and low distributions of blacks in the bottom and top education levels, respectively, could be the cause for white/black gap in CI ownership at home.

Differences in income also account for 8 – 11 percent of the variation in CI ownership between whites and blacks. This could also arise from differences in the distributions of these racial categories with respect to family income (see Table 3.12). The percentage of blacks in the bottom income group is larger than whites by more than

[21] In Table 3.6, the percentage contributions of education to the digital gap are computed as $0.02236/0.202951 = 0.1102$ and $0.01968/0.202951 = 0.0987$, respectively)

10 percentage points, and the fraction of the black population earning above $50,000 per year is lower than whites. Particularly, the fractions of whites in the top income group are twice as much as the blacks. As the probability of home CI ownership increase more with higher income than it does with lower income (see Tables 3.5a), the white/black differences in the distribution of income explains a significant fraction of the observed digital gap.[22]

Differences in the household structure between whites and blacks contribute to nearly 8 – 14 percent of the digital gaps observed. Differences in household structure come from differences in marital status, number of young children in the household and family size (see Table 3.12). The percentages of unmarried blacks and those who have young children in their households are higher than the corresponding percentages for whites by 11 – 24 percentage points. As the marginal effect of being married outweighs the marginal effect having young children in the household (see Table 3.5a), the differences between whites and blacks in the distributions of these variables are likely to make the whites' rates of CI ownership higher than the blacks' rates. However, as there seems to be no variations in the distributions of family size between the two racial categories, family size is unlikely to cause any racial discrepancy in CI ownership rates.

Access to computers and the Internet outside home and geographic location are the other two variables that contribute to the racial digital gap. Differences in access to computers and the Internet outside home explain about 6 and 3 percent of the white/black digital gaps in 1997 and 2003, respectively. As shown in Table 3.12, both whites and blacks have approximately the same distributions in access to computers and the Internet

[22] Since the marginal probabilities in Table 3.5a are computed using the income level $50,000 – 74,999 as a reference, they should be interpreted accordingly.

at school and other locations. Nevertheless, the two categories show differences in distributions in the access they have to computers and the Internet at their work places. Hence, these differences in having access to the two technologies at work places seem to contribute to the CI ownership gap observed between whites and blacks.

The contribution to the racial digital gap arising from differences in locations of residence is relatively very small (in the range of 1 – 3 percent). Compared to whites, large percentages of blacks live in the metropolitan areas and in the southern part of the country (see Table 3.12). In contrast, the distributions of whites are larger in the Northeast, Midwest and West. As shown in Table 3.5a, the probabilities of home CI ownership vary with changes in location. Such variations in CI ownership probabilities emanating from variations in locations are therefore responsible for the small part of the digital disparity between whites and blacks.

Finally, differences in the distributions of employment related variables are found to explain only a very small portion of the white/black digital gap in 1997, and no part of the gap in 2003. This shows that the variations observed between whites and blacks in terms of employment status and type of jobs (see Table 3.12) do not lead to noticeable differences in CI ownership at home. Furthermore, Table 3.6 shows that being Hispanic, female and non-citizen of the United do not contribute at all to the gender digital disparity. The age of an individual and the type of housing units do not also explain any part of the digital gap between whites and blacks. Instead, all these variables have negative contributions and tend to widen the racial digital gap.

B. Decomposition of the Hispanic/non-Hispanic Digital Gaps over Time (1997 and 2003)

Table 3.7 reports the decompositions of the digital gaps between individuals with Hispanic origin and non-Hispanics.[23] In this decompositions, the coefficient estimates of Hispanics, reported in Table 3.5b, are used to weight the differences in the characteristics of Hispanics (h) and non-Hispanics (nh) $\left[i.e., \; \bar{\bar{F}}\left(X_{ti}^{nh}\hat{\beta}_t^h\right) - \bar{\bar{F}}\left(X_{ti}^{h}\hat{\beta}_t^h\right)\right]$. This is the same as giving the characteristics of non-Hispanics to the Hispanics. Accordingly, for 1997 and 2003, the observed differences in CI ownerships between Hispanics and non-Hispanics are about 19 and 21 percent, respectively. These gaps indicate that individuals with Hispanic origin lag behind their non-Hispanic counterparts in home CI ownership by an average of 20 percentage points. Differences in the characteristics of Hispanics and non-Hispanics contribute to only 5 to 8 percent of these gaps. This means that a huge proportion of the digital gaps remain unexplained by the individual characteristics included in the estimations. The implication is that there are other factors, which are not directly observable, responsible for the disparities in home CI ownership between these two ethnic categories.

Unlike the racial digital gaps discussed before, education is the single factor that accounts for a relatively large fraction of the ethnic digital divide. Differences in the level of education between Hispanics and non-Hispanics contribute to about 25 and 16 percent of the digital gaps in 1997 and 2003, respectively. Table 3.13 exhibits the differences in the distributions of education. The percentages of Hispanics with only high school education are higher and those with college and university education are lower

[23] In all the Current Population Surveys (CPS), Hispanics are defined as individuals with Mexican, Puerto Rican, Cuban, Central American/South American and other Spanish origins.

than their counterparts' corresponding rates. Particularly, compared to non-Hispanics, the fraction of Hispanics that have university education is less by more than 50 percent. As the probabilities of home CI ownership increases with each level of education for both categories (see Table 3.5b), the non-Hispanics rates of home CI ownership are likely to be higher than the rates for the Hispanics.

The other variables that have small to moderate contributions to the ethnic digital divide include family income, being non-citizen, employment status and type of jobs, and access to CI outside home. Differences in the distributions of these characteristics account for 1 – 10 percent of the digital gaps observed between Hispanic and non-Hispanic samples. Differences in family income between Hispanics and non-Hispanics explain approximately 8 percent of the digital gap in both years. This indicates that part of the ethnic digital gap is due to Hispanics' lower level of family income compared to non-Hispanics. Particularly, large differences in income are observed in the higher income categories ($50,000 – 75,000 and above $75,000) where the fractions of Hispanics in these income categories are nearly half of their non-Hispanic counterparts (see Table 3.13).

Being a non-citizen of the United States also accounts for about 7 and 4 percent of the digital gaps in 1997 and 2003, respectively. This variable contributes to the digital divide for two reasons. First, the proportion of non-citizen Hispanics is more than 30 percentage points higher than non-Hispanics (see Table 3.13). Second, the marginal impact of being a non-citizen (i.e., in reducing the predicted probability of home CI ownership) is higher for Hispanics than for non-Hispanics (see Table 3.5b). The other variable that contributes to ethnic digital gap is access to CI outside home. It accounts for 8 – 10 percent of the digital gaps observed in 1997 and 2003 between Hispanics and non-Hispanics. The two ethnic categories show large differences particularly in the access they have to computers and the Internet at their work places. Hence, these differences in having access to the two technologies at work places contribute to the observed ethnic digital gaps.

On the other hand, many variables are found to have negative contributions to the ethnic digital gaps compared to cases in the decompositions of the racial digital gaps. Accordingly, being black, being female, age of the individual, household structure, type of housing unit, and geographic locations do not explain any part of the inequalities between Hispanics and non-Hispanics in ownerships of CI at home. All these variables tend to narrow the existing ethnic digital gaps.

C. Decomposition of the Male/Female Digital Gaps over Time (1997 and 2003)

Table 3.8 reports the decomposition of the differences in home CI ownership between males and females in 1997 and 2003. In all cases, the females' coefficients, reported in Table 3.5c, are used to weight the differences in the individual characteristics of the two races $\left[i.e., \bar{\bar{F}}(X_{ti}^{m}\hat{\beta}_t^{f}) - \bar{\bar{F}}(X_{ti}^{f}\hat{\beta}_t^{f})\right]$. By doing so, this decomposition links the males' characteristics to the females' probability of CI ownership using the coefficient estimates of females.

The male/female digital gap is relatively small at 3.7 percent in 1997. The gap narrows with time, reaching 2.6 percent in 2003. Generally, differences in individual characteristics between males and females explain about 81 to 89 percent of the gender gap in CI ownership at home. The remaining unexplained part (11 – 19 percent) could be due to factors that cannot be measured directly or other factors not included in the regressions. Education, income and household structure are the major variables that explain large fraction of the observed digital gap between males and females. Sex differences in the level of education account for about 26 and 25 percent of the gender gap in 1997 and 2003, respectively. Females have 2 – 3 percentage points lead over males in terms of high school and college education. However, the proportion of males with a university education exceeds that of females by 3 – 5 percentage points (see Table 3.14). As the probabilities of home CI ownership increase more with university education than with college education (see Table 3.5c), the gender digital gap attributable to education differential seems to emanate from male/female differences in university level education.[24]

The other variable that contributes highly to the gender digital differential is family income. Variations in family income between males and females explain about 21 to 36 percent of the observed differences in home CI ownership between the periods 1997 to 2003. As shown in Table 3.14, not only that the proportion of females in the lower income category (i.e., under $25,000) is larger than their male counterparts, but also the proportions of females in the rest of the income categories steadily decrease as the level of income rises and are below those of males at all times. The decomposition reveals that such variations in the distributions of family income significantly contribute to the overall differential in home CI ownership between males and females.

Differences in home CI ownership also stem from differences in the type of household structure (whether being married, have children under age 14, or the number

[24]The fact that both the digital gap and the contribution of education are positive attests that males are more probable in having access to home CI and this difference is explained significantly by females' low level of education.

of family members in the household). Table 3.8 shows that gender differences in the structure of a household explain 13 to 23 percent of the CI ownership gap between men and women. Men and women show differences in the distributions of household structure in two cases. Compared to men, the proportions of married women are small, and those living in households where children between the ages of 0 to 14 are present are lower as well. Since being married increases the probability of home CI ownership more than number of children decreases it (see Table 3.5c), men's CI ownership rates are likely to be higher than those of females. As both men and women live in households with an average of three family members, family size is unlikely to cause any gender differential in CI ownership.

The other two variables that contribute to gender digital gap are age and being black. Differences in age between males and females account for about 6 to 19 percent of the variation in home CI ownership. On average, males are one or two years younger than females (Table 3.14) and hence are more likely to own CI at home.[25] Being black was not a factor to cause a big disparity in CI ownership in 1997 since it attributes to only about 2 percent of the gender digital gap. However, its contribution to the digital gap increases in the subsequent years and becomes one of the major factors that contribute to the digital divide between males and females. In 2003, nearly 15 percent of the gender digital gap is due to the low level of black females' home CI ownership rate compared to that of black males.

Finally, observe that being Hispanic and a non-citizen of the United States do not contribute at all to the gender digital disparity. Instead, both variables have negative contributions and tend to narrow the gender digital gap. In addition, employment status

[25] Table 3.5c indicates that the probability of CI ownership at home decreases with age.

and having access to computers and the Internet outside home explain a small part of the gender digital gap (about 8 percent) in 1997. However, in the subsequent years, while the impact of employment status becomes statistically insignificant, access to the CI outside home becomes one of the factors that contribute to the widening of the digital gap. Furthermore, the type of housing units and locations of residence have statistically significant but small contributions to the gender variation in home CI ownership in 1997. In 2003, both have become factors that contribute negatively to the existing gender digital gap.

3.4.2.2 Decomposition of the Racial, Ethnic and Gender Digital Gaps Across Time

Equation (9) is used to decompose differences in home CI ownership across time for each race, ethnic and gender categories separately. Such decompositions capture the contributions of changes in a given category's characteristics over time to home CI ownership differentials. For instance, the decomposition estimates show how changes in the composition of whites' sample affect their predicted probabilities of CI ownership at home. Conversely, based on the decomposition estimates it is also possible to tell whether the characteristics of whites have been improving over time. Since ownership of CI at home is higher in 2003 than in 1997 for whites (and for each category), whites in the 2003 sample are taken as a majority category and those in the 1997 sample as a minority category.

The coefficient estimates of the minority category are used to weight the across time differences in characteristics $\left[\text{i.e.}, \bar{\bar{F}}\left(X^{w}_{2003,i}\hat{\beta}^{w}_{1997}\right) - \bar{\bar{F}}\left(X^{w}_{1997,i}\hat{\beta}^{w}_{1997}\right)\right]$. The decompositions for the other racial, ethnic and gender categories are also done in the same way. The following tables report the decomposition estimates for each category. Table 3.9 presents the across time decompositions for whites and blacks; Table 3.10 depicts the across time decompositions for Hispanics and non-Hispanics; and Table 3.11 shows the across time decompositions for males and females.

As shown by Table 3.9, the difference in CI ownership rates between whites in 1997 and 2003 samples is about 27 percentage points. The decomposition results show that differences in the compositions of the 1997 and 2003 whites' samples explain only the small portion (about 7 percent) of the observed increase in CI ownership rates in these periods. The unexplained 93 percent of the gap implies that the differences in the characteristics of whites (i.e., those included in the decomposition estimation) do not explain why the ownership rates have gone up during the given periods. In other words, this means that there are other variables which cannot be directly measured or not included in the decomposition but which contribute to the observed CI ownership gap. Similarly, the CI ownership gap between blacks in 1997 and 2003 samples is also about 27 percentage points, and the variables included in the estimation account for about 11 percent of this gap. The unexplained portion constitutes 89 percent of the total CI ownership gap.

Turning to the contributions of specific variables, the three major variables that contribute to the differences in CI ownership rates are level of education, family income and access to CI outside home. Education and income each account for nearly 4 and 6 percent of whites and blacks' CI ownership gaps, respectively. The 3 percentage points increase (between 1997 and 2003) in the fraction of whites' with bachelor's degree or above seems to be responsible for the 4 percent contribution of education to the digital gap for the white sample (see Table 3.12). Likewise, the 2-percentage point rise in the proportion of blacks with some college education or university education may be the cause for the 6 percent contribution of education to the observed increase in CI ownership during the two periods. Moreover, access to CI outside home accounts to 2 and 3 percent of the across time differences in whites and blacks' CI ownership rates, respectively. On the contrary, the rest of the variables included in the model have either a small or no contribution at all to the observed differences in CI ownerships among whites and blacks.

Table 3.10 reveals that the across time decomposition results for Hispanics and non-Hispanics are identical to whites and blacks' decompositions discussed above. The differences in CI ownership between 1997 and 2003 for Hispanics and non-Hispanics are 25 and 27 percentage points, respectively. Only 10 and 8 percent of these gaps, respectively, are explained by all variables included in the estimations. As was the case for the racial categories, education, family income and access to CI outside home are the major factors that explain the gaps.

Table 3.11 also depicts the same picture for males and females. The difference in CI ownerships between males in 1997 and 2003 samples is about 26 percentage points. Differences in males' level of education, family income and access to CI outside home contribute to nearly 6 percent of this gap. For females, the CI ownership gap is about 27 percentage points, nearly 9 percent of which is explained by the above same variables.

In sum, the above across time decompositions provide almost identical results for each racial, ethnic and gender category. The results show that each category's home CI ownership rate is higher in 2003 than in 1997. The CI ownership gaps between these two years are in the range of 25 to 27 percentage points. The decompositions of these differences in home CI ownership across time for each race, ethnic and gender categories reveals that only a small portion (6 – 11 percent) of the gaps are explained by the variables included in the estimations. In all cases, the proportions of the gaps explained by the minority groups are higher than the gaps explained by the majority groups. This implies that more differences are observed over time in the characteristics of the minority than the majority groups. In addition, in all decompositions for each racial, ethnic and gender category, across time differences in the level of education, family income and access to CI outside home are found to contribute significantly to the observed increase in CI ownership.

3.5 Summary and Conclusions

Using the data from the 1997 – 2003 CPS Computer and Internet Use Supplements, this paper examines in detail (1) how evenly home computers and access to the Internet at home are distributed over the country's varied demographic groups, and whether these groups exhibit similar trends of access to these technologies, (2) whether the digital gaps observed between the identified groups have narrowed, remained constant, or widened over the period of analysis (1997 – 2003), and (3) what factors contribute to these disparities (or digital gaps).

The descriptive statistics provide the general picture for the dissemination of home computers and access to the Internet at home among the various social groups in the United States, the digital gaps observed within each group, and the trends the groups exhibit in the acquisition of these technologies over time. The descriptions also show how the distributions of these technologies change with such characteristics as age, education and income. Among the disparities observed in ownership of home computers and Internet access, this study focuses on the digital gaps observed among three demographic groups (race, ethnicity and gender) which exhibit either sizable digital gaps or relatively noticeable time trends. The gender digital gap is relatively small, but highly significant and shows a slight declining trend. The digital gaps for blacks and Hispanics (compared to whites and non-Hispanics, respectively) are relatively big and exhibit a rising trend over time.

The paper employs two estimation techniques, the logit model and the non-linear Blinder-Oaxaca decomposition. While the logit regressions are used to identify the factors that explain the adoption of CI for home use, the decomposition estimates are used to quantify the contributions of these factors to the digital gaps observed across racial, ethnic and gender groups. Both estimations use sets of variables identified as determinants of home CI ownership based on the traditional theory of consumer choice as well as the previous literature, and using the intuitions drawn from the descriptive statistics. These variables are summarized under the following broad categories: individual characteristics (age, education, gender, race and citizenship status), household characteristics (family income, marital status, number of children in the household, family size and type of housing unit), employment status and occupation (whether employed or not, job and occupation types), location variables (places of residence in terms of metropolitan/non-metropolitan areas and regions), and access to CI outside home (access at work, school or other locations).

The logit regressions indicate that the majority of the above variables are significant determinants of the probability of owning CI at home for the racial, ethnic and gender groups. Particularly, education, family income, being married, family size and access to CI outside home significantly increase the likelihood of owning CI at home. On the contrary, age, being non-citizen and presence of young children in the household reduce home CI ownership substantially. However, to what extent these and other variables contained in the logistic regression explain the observed racial, ethnic and gender digital gaps is further investigated using the non-linear Blinder-Oaxaca decomposition method.

The decomposition results of the racial, ethnic and gender digital gaps for two given years (1997 and 2003) are summarized as follows. The difference in home CI ownership between whites and black is relatively wide at about 20 percentage points. All the variables included in the decompositions contribute to 24 – 33 percent of the observed racial digital gap. Differences between whites and blacks in the level of education, family income and household structure explain the largest fraction (8 – 14 %) of the digital gap. In contrast, being Hispanic, age and type of housing unit contribute negatively to the observed digital gap. That is, these variables favor the minority category (blacks) and tend to widen the existing digital gap.

Averaging at about 20 percentage points, the ethnic digital gap is also relatively large. Differences in the characteristics of Hispanics and non-Hispanics explain a small fraction (5 – 8 %) of the observed digital gap. This implies that a huge proportion of the gap cannot be explained by the measurable factors included in the decompositions. Hispanics' low level of education is the primary factor that accounts for a relatively large fraction (16 – 25%) of the ethnic digital gap. In addition, differences between the two ethnic categories in family income, in being a non-citizen, employment status and in having access to CI outside home also have small to moderate (1 – 10 %) contributions to the observed digital gap. On the other hand, being black, being female, age and location do not contribute at all to the existing ethnic digital gap.

A very small gap (3 - 4 percentage points) is observed in home CI ownership between males and females. Differences in the characteristics of males and females contribute to 81 – 89 % of the digital gap. The variables that contribute substantially to the observed digital gap include education (26%), family income (21 – 36%), and household structure (13 – 23%). That is, these variables explain the largest fraction of the gender digital gap. Furthermore, differences in age and race between males and females also account for 6 – 9 percent of the variation in home CI ownership. Being non-Hispanic and being a non-citizen negatively contribute to the observed gender digital gap.

Finally, in all decompositions, differences in education, family income, household structure and access to CI outside home are found to be the primary factors that explain the racial, ethnic and gender digital gaps. On the contrary, many of the variables contained in the decompositions have either small or no contributions to the observed digital gaps. For instance, age, type of housing unit and being a non-citizen are some of the factors that contribute negatively to the digital gaps in the majority of the cases.

A decomposition method that incorporates a time series aspect is also employed in order to identify the attributes for across time variations in CI ownership in each racial, ethnic and gender category. More specifically, this type of decomposition is used to identify the factors that explain the observed increase in CI ownership across time in each category. Surprisingly, the decompositions provide almost identical results for each racial, ethnic and gender category. The estimation results show that each category's home CI ownership rate is higher in 2003 than in 1997. The CI ownership gaps between these two years are in the range of 25 to 27 percentage points for all categories. Decomposing these differences in home CI ownership across time for each race, ethnic and gender categories reveals that only a small portion (6 – 11 percent) of the gaps are explained by the variables included in the estimations. In all decompositions for each racial, ethnic and gender category, across time differences in the level of education, family income and having access to CI outside home are found to contribute significantly to the observed increase in CI ownership. In addition, in all cases, the proportions of the gaps explained by the minority groups are higher than the gaps explained by the majority groups. This implies that significant improvements in the characteristics of the minority groups are observed over time. Examples include improvements in the level of education and family income over the period of analyses (1997 to 2003).

Figure 3.1: Trends of Computer Ownership and Internet Access in United States Households (%)

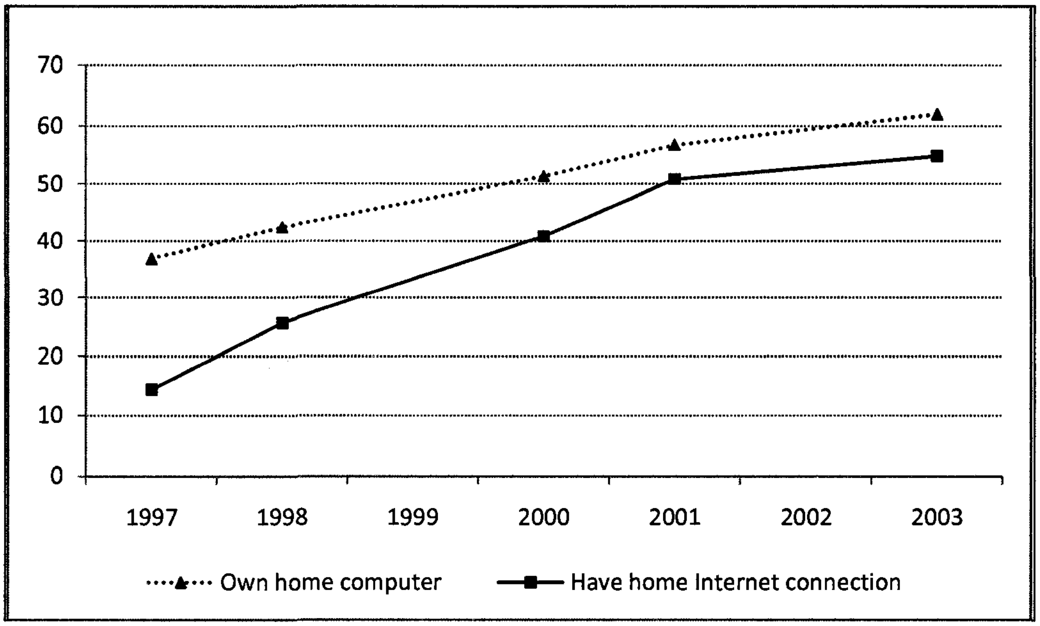

Figure 3.2: Computer Ownership and Internet Access Growth Rates in United States Households (%)

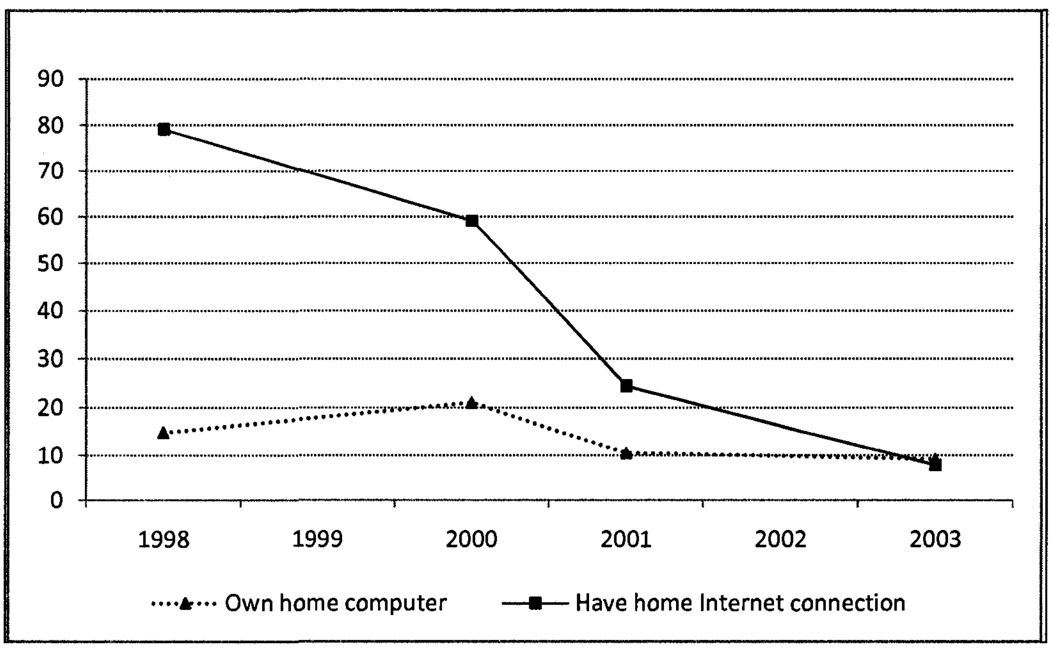

Figure 3.3a: Trends of Home Computer Ownership Gaps by Household Income
(Percentage Point Difference)

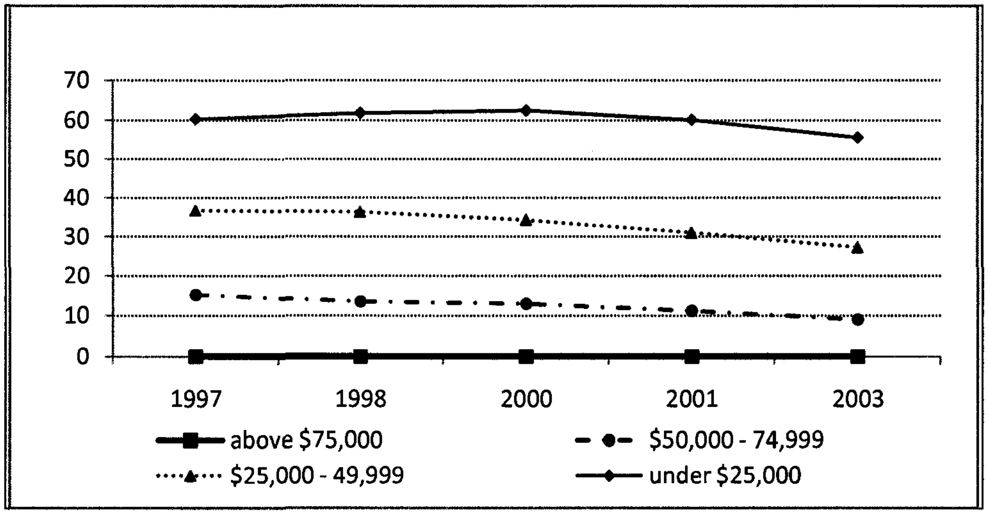

Figure 3.3b: Trends of Home Internet Access Gaps by Household Income
(Percentage Point Difference)

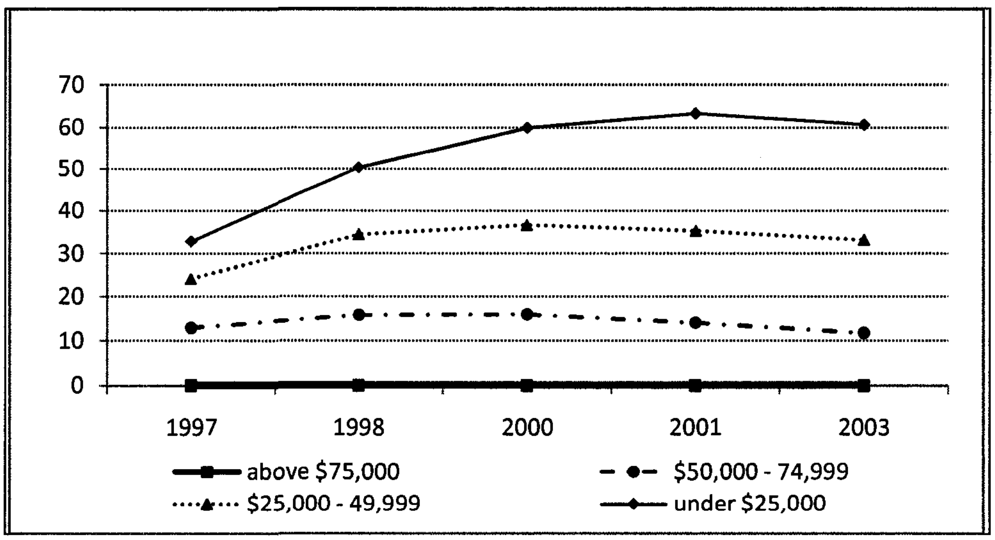

Figure 3.4a: Trends of Home Computer Ownership Gap by Gender (Percentage Point Difference)

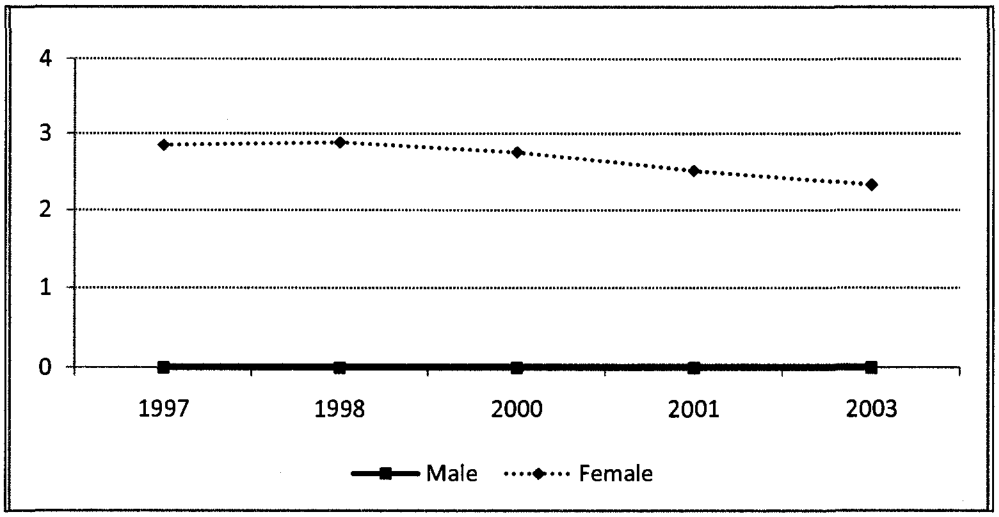

Figure 3.4b: Trends of Home Internet Access Gap by Gender (Percentage Point Difference)

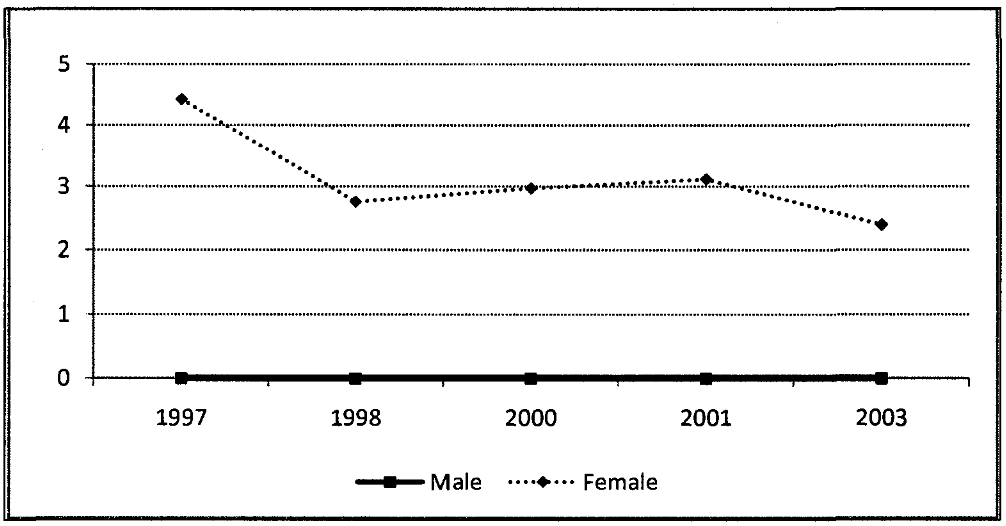

Figure 3.5a: Trends of Home Computer Ownership Gaps by Level of Education
(Percentage Point Difference)

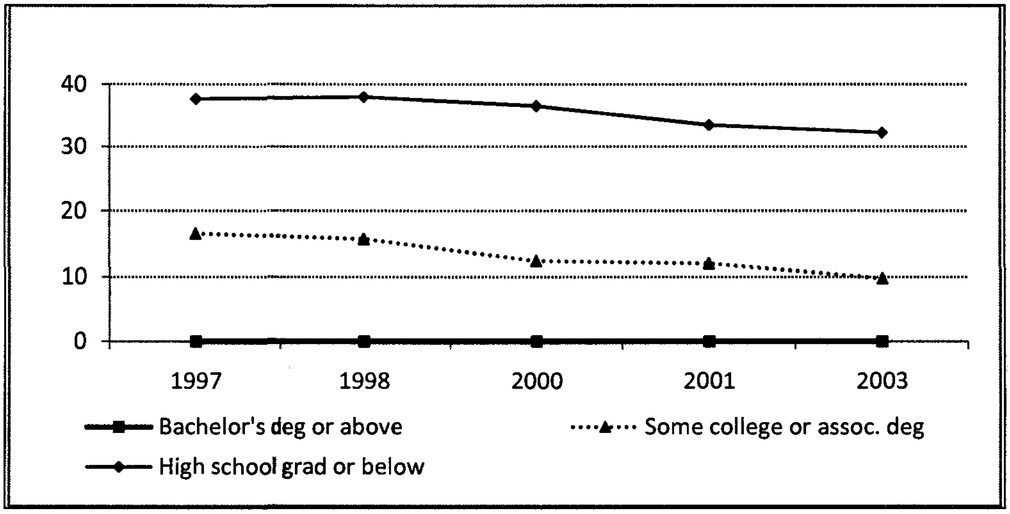

Figure 3.5b: Trends of Home Internet Access Gaps by Level of Education
(Percentage Point Difference)

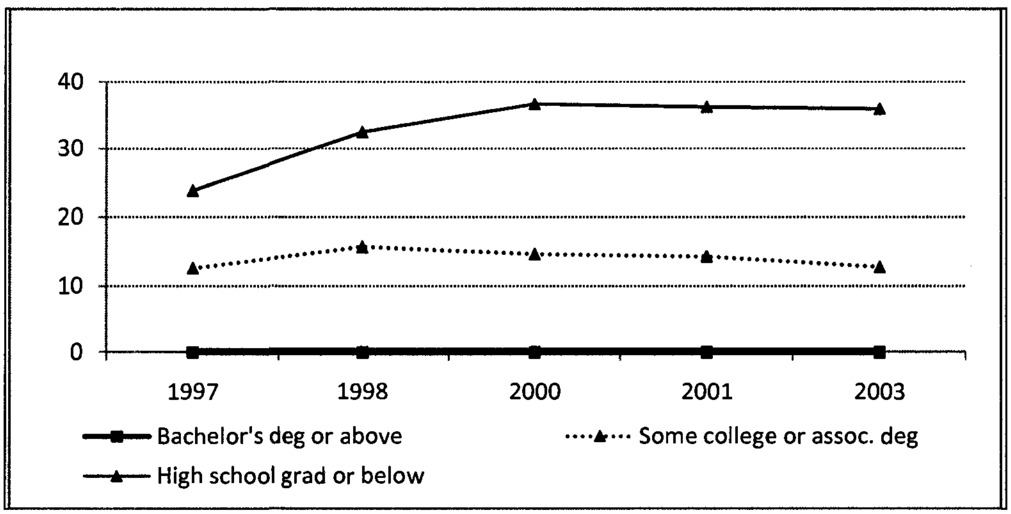

Figure 3.6a: Trends of Home Computer Ownership Gaps by Age (Percentage Point Difference)

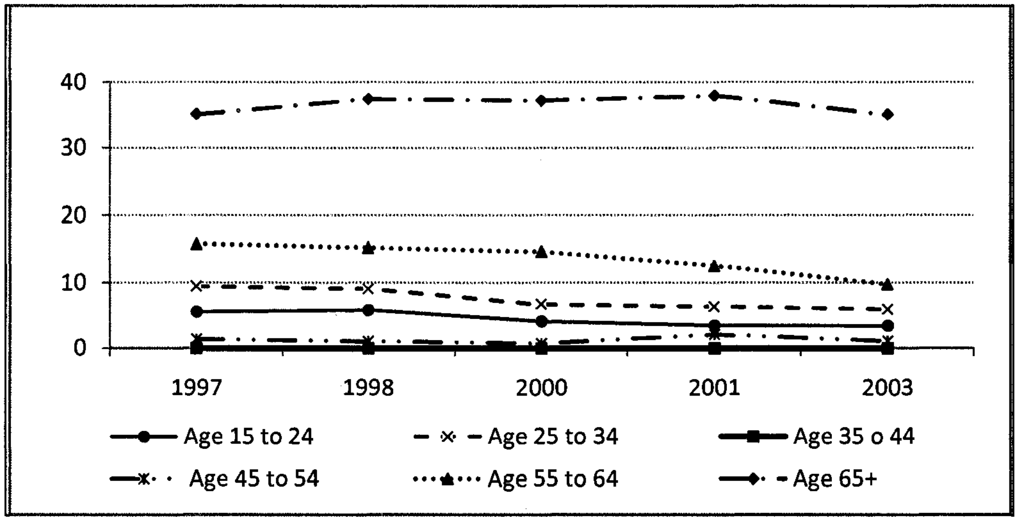

Figure 3.6b: Trends of Home Internet Access Gaps by Age (Percentage Point Difference)

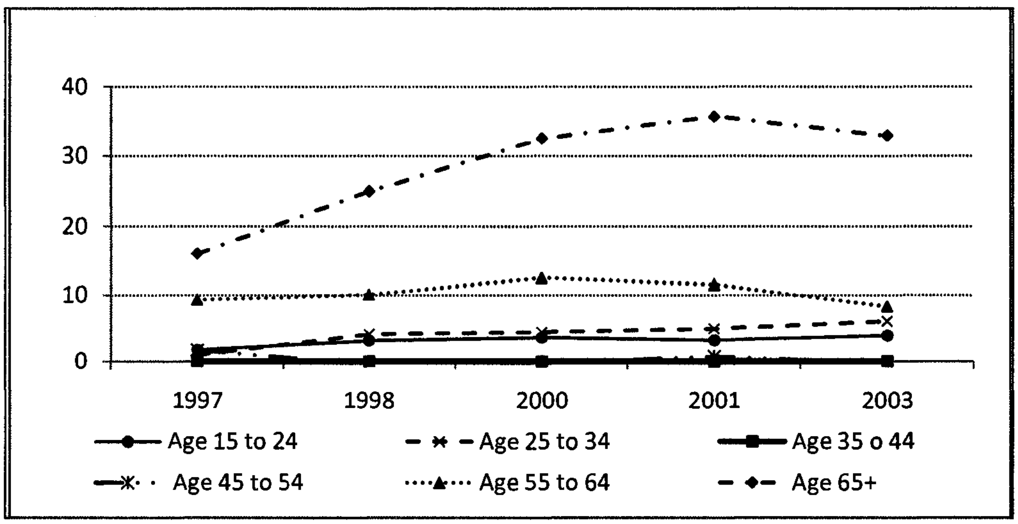

Figure 3.7a: Trends of Home Computer Ownership Gaps by Race (Percentage Point Difference)

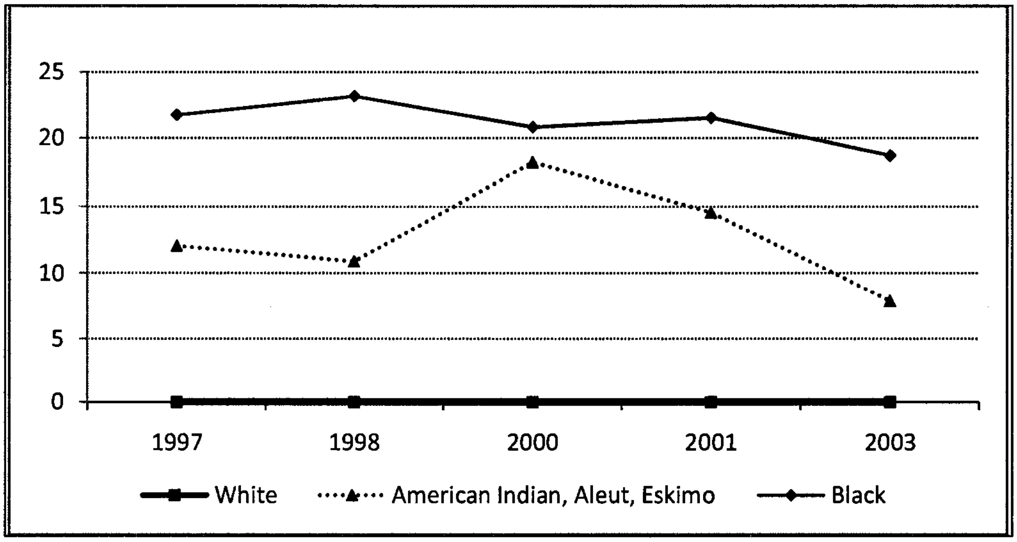

Figure 3.7b: Trends of Home Internet Access Gaps by Race (Percentage Point Difference)

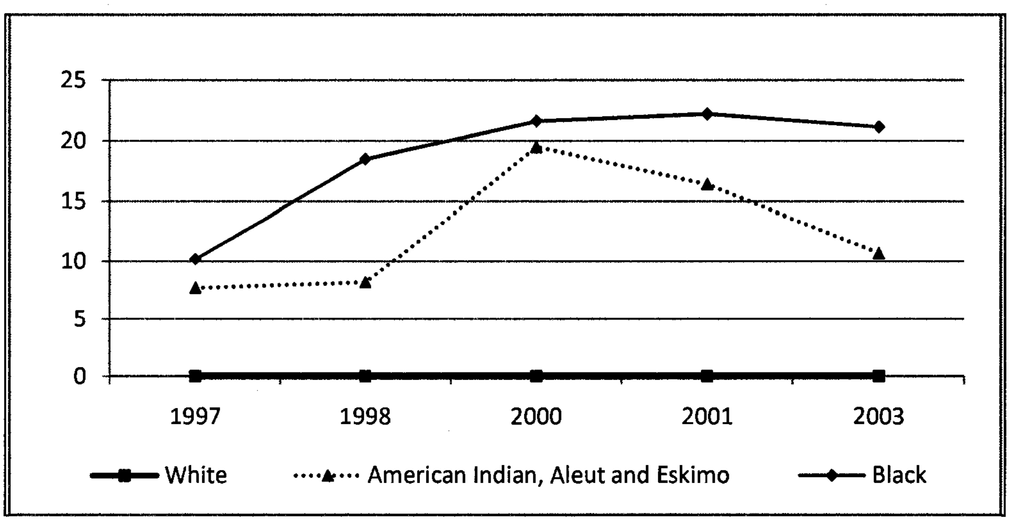

Figure 3.8a: Trends of Home Computer Ownership Gaps by Ethnicity (Percentage Point Difference)

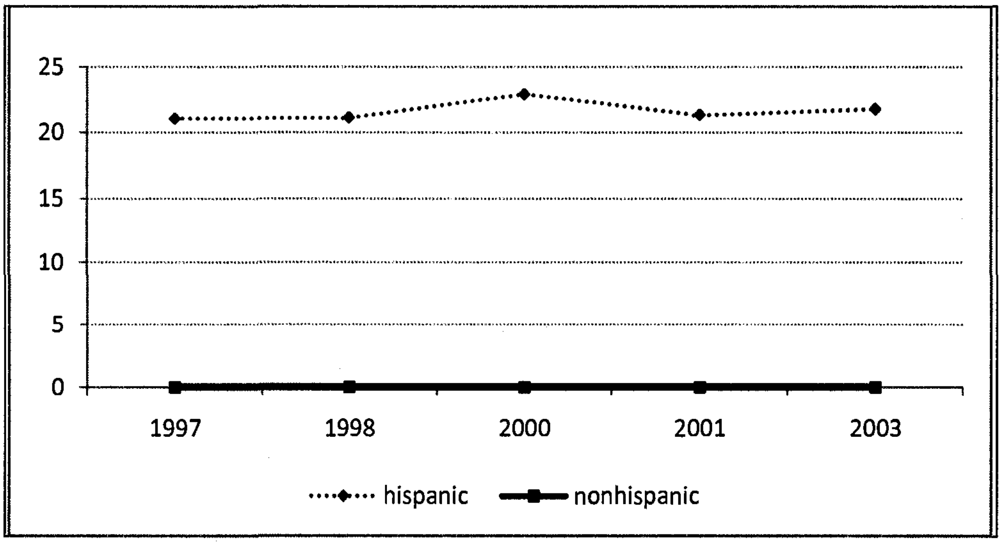

Figure 3.8b: Trends of Home Internet Access Gaps by Ethnicity (Percentage Point Difference)

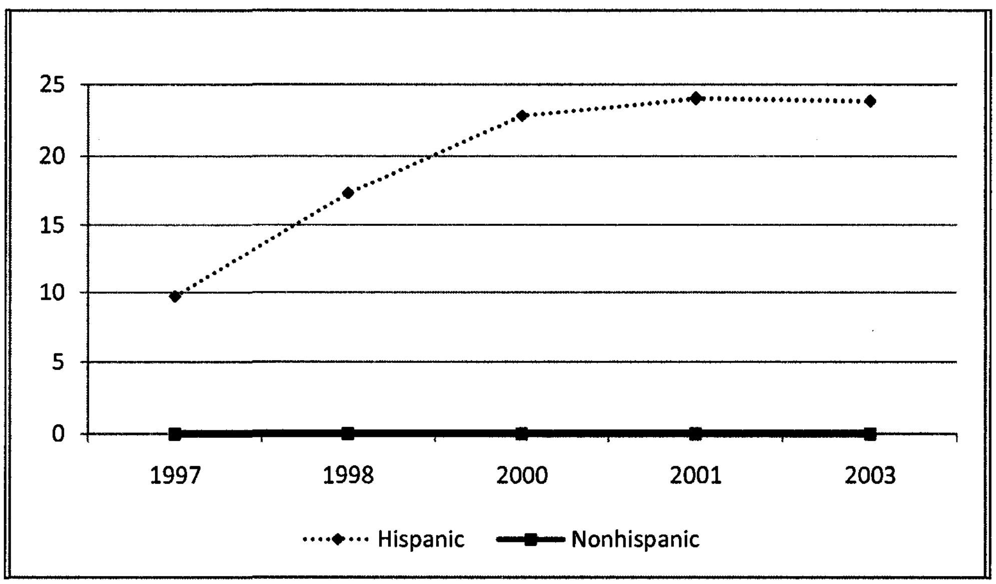

Table 3.1: Home Computer Ownership and Access Rates in the United States by Household and Individual Characteristics, 1997 – 2003

	1997	1998	2000	2001	2003
I. % of all households					
Own home computer	36.9	42.4	51.4	56.8	62.0
Average number of computer	1.3	1.3	1.3	1.3	1.4
Purchased computer in survey year	23.9	30.9	21.8	19.3	19.2
above $75,000	75.9	80.1	86.4	89.1	91.2
$50,000 - 74,999	60.8	66.6	73.5	77.9	82.1
$25,000 - 49,999	39.2	43.7	52.1	58.1	63.8
under $25,000	15.7	18.3	24.0	29.0	35.6
Non-response income	26.8	31.3	40.0	44.9	51.0
Metropolitan area	38.9	44.4	53.6	58.7	63.8
Nonmetropolitan area	29.1	34.3	42.1	48.4	54.2
II. % of all individuals					
Own computer	41.3	47.1	56.2	61.9	66.8
Male	42.7	48.6	57.7	63.2	68.0
Female	39.9	45.7	54.9	60.7	65.7
Bachelor's degree or above	65.7	71.3	78.4	82.3	85.5
Some college or associate degree	49.1	55.5	66.0	70.3	75.8
High school graduate or below	28.0	33.3	41.9	48.8	53.3
Married	47.0	53.3	62.8	68.8	73.0
Not married	34.3	39.6	48.4	53.9	59.4
Age 15 to 24	45.8	51.5	61.4	67.7	71.8
Age 25 to 34	41.9	48.3	58.8	64.8	69.2
Age 35 o 44	51.3	57.4	65.6	71.2	75.2
Age 45 to 54	50.0	56.3	64.9	69.1	74.1
Age 55 to 64	35.5	42.1	50.9	58.6	65.4
Age 65+	16.3	20.0	28.4	33.3	40.1
Asian and Pacific Islander	54.6	60.8	67.0	76.2	77.4
White	43.6	49.6	58.6	64.2	68.8
American Indian, Aleut, Eskimo	31.5	38.7	40.3	49.6	60.9
Black	21.8	26.4	37.7	42.7	50.1
Hispanic	22.3	28.2	35.8	42.9	47.8
Non-Hispanic	43.4	49.3	58.7	64.3	69.6
Employed	48.1	54.5	64.0	69.3	74.0
Not employed	31.4	36.3	50.2	57.5	63.3
Government job	53.9	60.5	70.0	75.2	80.3
Private job	46.0	52.2	62.0	67.5	72.0
Self employed	51.9	58.8	67.5	70.6	75.3
Number of households	47282	47325	46967	55777	55101
Number of individuals	95105	95061	94984	111778	109650

Notes: *The sample consists of individuals ages 15 and older.*
All estimates are weighted means.

Table 3.2: Home Internet Connection in the United States by Household and Individual Characteristics, 1997 – 2003

	1997	1998	2000	2001	2003
I. % of all households					
Have home Internet access	14.3	25.7	40.9	50.8	54.9
Use home computer for connection	38.8	60.0	78.5	88.2	87.7
above $75,000	37.7	58.7	76.1	85.6	88.0
$50,000 - 74,999	24.8	42.9	60.2	71.6	76.3
$25,000 - 49,999	13.6	24.2	39.4	50.3	54.8
under $25,000	4.8	8.4	16.2	22.3	27.3
Non-response income	8.4	16.5	30.9	40.7	43.2
Metropolitan area	15.8	27.8	43.2	53.1	57.0
Nonmetropolitan area	8.4	16.9	31.1	41.2	45.7
II. % of Individuals					
Have home Internet connection	14.7	28.7	44.9	55.7	59.6
Male	16.9	30.1	46.4	57.3	60.8
Female	12.5	27.3	43.4	54.2	58.4
Bachelor's degree or above	30.6	49.9	67.7	78.0	80.9
Some college or associate degree	18.0	34.1	53.0	63.7	68.1
High school graduate or below	6.8	17.4	31.0	41.9	45.0
Married	16.4	32.6	50.7	62.4	66.1
Not married	12.5	23.8	37.9	47.7	51.8
Age 15 to 24	17.1	31.7	49.0	60.7	63.4
Age 25 to 34	17.9	30.7	48.2	59.0	61.3
Age 35 o 44	18.8	34.8	52.6	63.9	67.3
Age 45 to 54	17.2	35.3	52.8	63.2	67.6
Age 55 to 64	9.5	24.7	40.1	52.4	59.0
Age 65+	2.8	9.8	20.1	28.2	34.4
Asian and Pacific Islander	17.8	39.2	57.5	71.3	71.1
White	15.9	30.6	47.2	58.0	61.9
American Indian, Aleut and Eskimo	8.2	22.4	27.7	41.6	51.2
Black	5.7	12.1	25.6	35.8	40.7
Hispanic	5.9	13.1	24.5	34.3	38.7
Non-Hispanic	15.6	30.5	47.3	58.3	62.6
Employed	18.0	33.6	51.7	62.8	66.7
Not employed	11.4	20.6	38.6	50.7	53.8
Government job	20.5	37.4	56.8	68.3	73.2
Private job	17.2	32.2	50.1	61.0	64.6
Self employed	18.3	35.7	53.4	64.0	68.3
Number of households	47282	47325	46967	55777	55101
Number of individuals	95105	95061	94984	111778	109650

Notes: The sample consists of individuals ages 15 and older.
All estimates are weighted means.

Table 3.3: Home Computer Ownership Gaps in the United States (Percentage Point Difference), 1997 – 2003

	1997	1998	2000	2001	2003
(Relative to above $75,000)					
above $75,000	0	0	0	0	0
$50,000 - 74,999	-15.2	-13.5	-12.9	-11.2	-9.1
$25,000 - 49,999	-36.7	-36.4	-34.3	-31.0	-27.3
under $25,000	-60.3	-61.8	-62.4	-60.1	-55.6
(Relative to metropolitan area)					
Metropolitan area	0	0	0	0	0
Nonmetropolitan area	-9.8	-10.2	-11.5	-10.3	-9.6
(Relative to male)					
Male	0	0	0	0	0
Female	-2.8	-2.9	-2.8	-2.5	-2.3
(Relative to Bachelor's degree)					
Bachelor's degree or above	0	0	0	0	0
Some college or associate degree	-16.5	-15.7	-12.4	-12.0	-9.7
High school graduate or below	-37.6	-37.9	-36.5	-33.4	-32.2
(Relative to married)					
Married	0	0	0	0	0
Not married	-12.7	-13.6	-14.3	-14.8	-13.6
(Relative to 35 to 44)					
Age 15 to 24	-5.6	-5.9	-4.1	-3.5	-3.4
Age 25 to 34	-9.5	-9.1	-6.7	-6.4	-6.0
Age 35 o 44	0	0	0	0	0
Age 45 to 54	-1.4	-1.0	-0.7	-2.1	-1.1
Age 55 to 64	-15.9	-15.3	-14.7	-12.6	-9.8
Age 65+	-35.1	-37.4	-37.1	-37.9	-35.1
(Relative to whites)					
Asian and Pacific Islander	11.0	11.3	8.4	12.1	8.7
White	0	0	0	0	0
American Indian, Aleut, Eskimo	-12.1	-10.9	-18.2	-14.6	-7.9
Black	-21.7	-23.1	-20.8	-21.5	-18.7
(Relative to non-Hispanic)					
Hispanic	-21.1	-21.1	-22.9	-21.3	-21.8
Non-Hispanic	0	0	0	0	0
(Relative to employed)					
Employed	0	0	0	0	0
Not employed	-16.7	-18.2	-13.8	-11.8	-10.7
(Relative to government job)					
Government job	0	0	0	0	0
Private job	-7.9	-8.3	-7.9	-7.7	-8.3
Self employed	-2.0	-1.7	-2.5	-4.6	-5.0

Table 3.4: Home Internet Access Gaps in the United States (Percentage Point Difference), 1997 – 2003

	1997	1998	2000	2001	2003
(Relative to above $75,000)					
above $75,000	0	0	0	0	0
$50,000 - 74,999	-12.9	-15.8	-15.9	-14.0	-11.7
$25,000 - 49,999	-24.1	-34.4	-36.7	-35.3	-33.2
under $25,000	-32.9	-50.3	-59.9	-63.3	-60.6
(Relative to metropolitan area)					
Metropolitan area	0	0	0	0	0
Nonmetropolitan area	-7.4	-10.9	-12.1	-11.9	-11.3
(Relative to male)					
Male	0	0	0	0	0
Female	-4.4	-2.8	-3.0	-3.1	-2.4
(Relative to Bachelor's degree)					
Bachelor's degree or above	0	0	0	0	0
Some college or associate degree	-12.7	-15.8	-14.7	-14.3	-12.8
High school graduate or below	-23.8	-32.4	-36.6	-36.2	-35.9
(Relative to married)					
Married	0	0	0	0	0
Not married	-3.8	-8.8	-12.9	-14.7	-14.4
(Relative to 35 to 44)					
Age 15 to 24	-1.7	-3.1	-3.6	-3.2	-3.9
Age 25 to 34	-0.9	-4.1	-4.4	-4.9	-6.0
Age 35 o 44	0	0	0	0	0
Age 45 to 54	-1.7	0.5	0.2	-0.7	0.3
Age 55 to 64	-9.3	-10.1	-12.5	-11.5	-8.3
Age 65+	-16.0	-25.0	-32.5	-35.7	-32.9
(Relative to whites)					
Asian and Pacific Islander	2.0	8.6	10.3	13.3	9.2
White	0	0	0	0	0
American Indian, Aleut, Eskimo	-7.7	-8.2	-19.5	-16.4	-10.7
Black	-10.2	-18.5	-21.6	-22.2	-21.2
(Relative to non-Hispanic)					
Hispanic	-9.7	-17.3	-22.9	-24.1	-23.9
Non-Hispanic	0	0	0	0	0
(Relative to employed)					
Employed	0	0	0	0	0
Not employed	-6.6	-13.1	-13.1	-12.1	-12.9
(Relative to government job)					
Government job	0	0	0	0	0
Private job	-3.3	-5.3	-6.8	-7.3	-8.7
Self employed	-2.2	-1.7	-3.4	-4.4	-4.9

Table 3.5a: Marginal Coefficient Estimates, Whites and Blacks (1997 and 2003)

Variables	Whites 1997	Whites 2003	Blacks 1997	Blacks 2003
Predicted probability of CI ownership	0.397	0.754	0.166	0.495
Age	-0.015*** (0.00075)	-0.020*** (0.00075)	-0.0029 (0.0028)	-0.0085*** (0.0020)
Female	-0.021 (0.020)	0.036* (0.020)	-0.11 (0.070)	0.014 (0.054)
Hispanic	-0.93*** (0.041)	-1.05*** (0.034)	-0.27 (0.22)	-0.40*** (0.15)
Non-citizen	-0.59*** (0.052)	-0.75*** (0.042)	-0.070 (0.15)	0.094 (0.11)
Some college or associate degree	0.68*** (0.022)	0.72*** (0.023)	0.64*** (0.079)	0.85*** (0.059)
Bachelor's degree or above	1.15*** (0.025)	1.11*** (0.027)	1.28*** (0.091)	1.27*** (0.078)
under $25,000	-0.66*** (0.032)	-0.52*** (0.029)	-0.75*** (0.10)	-0.58*** (0.075)
$25,000 - 49,999	-0.074*** (0.026)	0.068** (0.027)	-0.16* (0.095)	0.20*** (0.074)
above $75,000	0.65*** (0.039)	0.89*** (0.045)	0.80*** (0.18)	1.16*** (0.15)
Married	0.52*** (0.022)	0.69*** (0.021)	0.66*** (0.071)	0.56*** (0.055)
Have children aged 0 to 14	-0.048*** (0.015)	-0.074*** (0.017)	0.092** (0.043)	-0.072** (0.035)
Family size	0.27*** (0.0084)	0.30*** (0.0093)	0.076*** (0.024)	0.22*** (0.020)
Live in a house, apartment or flat	0.33* (0.20)	0.65*** (0.20)	1.25 (1.07)	0.32 (0.61)
Live in a mobile home or trailer	-0.12 (0.20)	0.32 (0.20)	1.15 (1.10)	-0.018 (0.63)

Table 3.5a – Continued

Variables	Whites 1997	Whites 2003	Blacks 1997	Blacks 2003
Employed	0.093** (0.045)	-0.19*** (0.048)	0.21 (0.16)	-0.083 (0.11)
Government job	-0.40*** (0.045)	-0.077 (0.050)	-0.33* (0.18)	-0.34** (0.15)
Private job	-0.35*** (0.037)	-0.15*** (0.039)	-0.26 (0.17)	-0.43*** (0.14)
Management, professional, service, sales & office occupation	0.46*** (0.052)	0.57*** (0.056)	0.70*** (0.22)	0.65*** (0.17)
Construction, maintenance, production, transportation & material moving	0.24*** (0.055)	0.45*** (0.059)	0.34 (0.23)	0.73*** (0.18)
Metropolitan area	0.19*** (0.022)	0.19*** (0.021)	0.26** (0.11)	0.054 (0.084)
Northeast	0.0016 (0.026)	0.12*** (0.026)	0.14* (0.087)	0.39*** (0.070)
Midwest	0.00068 (0.025)	-0.020 (0.025)	0.0089 (0.091)	-0.030 (0.067)
West	0.34*** (0.025)	0.29*** (0.026)	0.75*** (0.11)	0.18* (0.091)
Access computer at school	0.73*** (0.10)	0.23* (0.13)	1.06*** (0.24)	0.027 (0.20)
Access computer at work	0.43*** (0.025)	0.42*** (0.037)	0.47*** (0.088)	0.65*** (0.096)
Access Internet at school	0.093 (0.14)	0.98*** (0.16)	0.073 (0.37)	1.06*** (0.27)
Access Internet at work	0.54*** (0.033)	0.36*** (0.039)	0.62*** (0.12)	0.16 (0.10)
Access Internet at other locations	-	0.31*** (0.063)	-	0.47*** (0.14)
Constant	-1.93*** (0.21)	-0.89*** (0.21)	-4.18*** (1.09)	-1.73*** (0.63)
Observations	68395	78045	7333	8602

Table 3.5b: Marginal Coefficient Estimates, Hispanics and Non-Hispanics (1997 and 2003)

Variables	**Hispanics**		**Non-Hispanics**	
	1997	2003	1997	2003
Predicted probability of CI ownership	0.185	0.483	0.389	0.754
Age	0.00017 (0.0030)	-0.0028 (0.0021)	-0.015*** (0.00075)	-0.020*** (0.00075)
Female	0.053 (0.078)	0.086 (0.056)	-0.030 (0.020)	0.032 (0.020)
Black	-0.31 (0.22)	-0.12 (0.15)	-0.87*** (0.035)	-0.87*** (0.029)
Non-citizen	-0.67*** (0.084)	-0.68*** (0.057)	-0.22*** (0.064)	-0.25*** (0.061)
Some college or associate degree	0.82*** (0.088)	0.75*** (0.069)	0.66*** (0.022)	0.73*** (0.022)
Bachelor's degree or above	1.19*** (0.11)	1.19*** (0.093)	1.15*** (0.024)	1.11*** (0.026)
under $25,000	-0.85*** (0.11)	-0.52*** (0.081)	-0.65*** (0.032)	-0.52*** (0.029)
$25,000 - 49,999	-0.16 (0.11)	0.078 (0.079)	-0.068*** (0.026)	0.098*** (0.026)
above $75,000	1.16*** (0.22)	0.97*** (0.17)	0.64*** (0.039)	0.91*** (0.045)
Married	0.52*** (0.082)	0.45*** (0.055)	0.54*** (0.022)	0.69*** (0.021)
Have children aged 0 to 14	0.044 (0.045)	0.020 (0.033)	-0.046*** (0.015)	-0.12*** (0.017)
Family size	0.082*** (0.025)	0.20*** (0.017)	0.27*** (0.0084)	0.32*** (0.0098)
Live in a house, apartment or flat	0.57 (0.78)	1.20 (0.74)	0.39* (0.20)	0.56*** (0.20)
Live in a mobile home or trailer	0.26 (0.80)	0.88 (0.75)	-0.045 (0.20)	0.23 (0.20)

Table 3.5b – Continued

Variables	Hispanics 1997	Hispanics 2003	Non-Hispanics 1997	Non-Hispanics 2003
Employed	-0.054 (0.17)	-0.038 (0.11)	0.14*** (0.045)	-0.17*** (0.048)
Government job	-0.24 (0.18)	-0.38** (0.15)	-0.39*** (0.044)	-0.061 (0.049)
Private job	-0.38** (0.15)	-0.41*** (0.11)	-0.33*** (0.037)	-0.14*** (0.040)
Management, professional, service, sales & office occupation	0.54*** (0.19)	0.71*** (0.13)	0.44*** (0.053)	0.50*** (0.058)
Construction, maintenance, production, transportation & material moving	0.40** (0.19)	0.56*** (0.14)	0.21*** (0.056)	0.44*** (0.061)
Metropolitan area	0.19 (0.12)	0.091 (0.080)	0.20*** (0.022)	0.18*** (0.021)
Northeast	-0.17 (0.11)	0.078 (0.079)	0.026 (0.025)	0.15*** (0.025)
Midwest	-0.26* (0.14)	-0.27*** (0.092)	0.024 (0.024)	0.0086 (0.024)
West	0.025 (0.082)	0.047 (0.060)	0.41*** (0.026)	0.34*** (0.027)
Access computer at school	1.05*** (0.33)	0.38 (0.26)	0.75*** (0.099)	0.12 (0.11)
Access computer at work	0.60*** (0.10)	0.50*** (0.11)	0.42*** (0.025)	0.44*** (0.036)
Access Internet at school	0.37 (0.48)	1.55*** (0.42)	0.061 (0.14)	0.94*** (0.15)
Access Internet at work	0.55*** (0.15)	0.44*** (0.13)	0.54*** (0.033)	0.33*** (0.038)
Access Internet at other locations	-	0.37** (0.18)	-	0.33*** (0.060)
Constant	-2.86*** (0.81)	-2.61*** (0.76)	-2.05*** (0.21)	-0.85*** (0.21)
Observations	5,845	7,929	69,883	78,767

Table 3.5c: Marginal Coefficient Estimates, Males and Females (1997 and 2003)

Variables	Males 1997	Males 2003	Females 1997	Females 2003
Predicted probability of CI ownership	0.401	0.749	0.345	0.715
Age	-0.014*** (0.0011)	-0.020*** (0.0011)	-0.014*** (0.00099)	-0.018*** (0.00095)
Black	-0.75*** (0.051)	-0.78*** (0.043)	-0.90*** (0.046)	-0.85*** (0.038)
Hispanic	-0.91*** (0.059)	-1.03*** (0.047)	-0.89*** (0.054)	-1.00*** (0.045)
Non-citizen	-0.57*** (0.073)	-0.70*** (0.057)	-0.50*** (0.067)	-0.58*** (0.055)
Some college or associate degree	0.64*** (0.031)	0.76*** (0.031)	0.71*** (0.029)	0.71*** (0.029)
Bachelor's degree or above	1.06*** (0.035)	1.08*** (0.037)	1.25*** (0.033)	1.15*** (0.034)
under $25,000	-0.63*** (0.042)	-0.57*** (0.040)	-0.70*** (0.046)	-0.52*** (0.037)
$25,000 - 49,999	-0.030 (0.032)	0.051 (0.034)	-0.16*** (0.042)	0.11*** (0.037)
above $75,000	0.65*** (0.046)	0.87*** (0.055)	0.70*** (0.071)	0.97*** (0.072)
Married	0.56*** (0.032)	0.78*** (0.029)	0.51*** (0.030)	0.60*** (0.027)
Have children aged 0 to 14	0.011 (0.019)	-0.054** (0.023)	-0.080*** (0.022)	-0.11*** (0.021)
Family size	0.21*** (0.012)	0.25*** (0.012)	0.27*** (0.010)	0.31*** (0.012)
Live in a house, apartment or flat	0.48* (0.25)	0.49* (0.26)	0.20 (0.30)	0.76*** (0.27)
Live in a mobile home or trailer	0.12 (0.26)	0.17 (0.26)	-0.29 (0.30)	0.43 (0.28)

Table 3.5c - Continued

Variables	Males 1997	Males 2003	Females 1997	Females 2003
Employed	0.20*** (0.058)	-0.20*** (0.059)	0.0046 (0.067)	-0.13* (0.066)
Government job	-0.39*** (0.059)	-0.050 (0.065)	-0.42*** (0.065)	-0.18** (0.073)
Private job	-0.29*** (0.046)	-0.13*** (0.047)	-0.42*** (0.057)	-0.25*** (0.063)
Management, professional, service, sales & office occupation	0.45*** (0.065)	0.53*** (0.069)	0.62*** (0.082)	0.61*** (0.085)
Construction, maintenance, production, transportation & material moving	0.17*** (0.065)	0.46*** (0.069)	0.41*** (0.096)	0.48*** (0.098)
Metropolitan area	0.13*** (0.031)	0.16*** (0.029)	0.26*** (0.029)	0.19*** (0.028)
Northeast	0.019 (0.036)	0.16*** (0.036)	0.028 (0.034)	0.15*** (0.033)
Midwest	0.026 (0.035)	-0.036 (0.034)	-0.0091 (0.033)	0.0018 (0.032)
West	0.36*** (0.035)	0.27*** (0.036)	0.38*** (0.034)	0.30*** (0.034)
Access computer at school	0.83*** (0.16)	0.16 (0.18)	0.75*** (0.12)	0.20 (0.13)
Access computer at work	0.48*** (0.035)	0.52*** (0.051)	0.41*** (0.034)	0.39*** (0.047)
Access Internet at school	0.16 (0.22)	1.12*** (0.24)	0.035 (0.17)	0.91*** (0.17)
Access Internet at work	0.62*** (0.046)	0.36*** (0.057)	0.45*** (0.044)	0.33*** (0.048)
Access Internet at other locations	-	0.32*** (0.090)	-	0.35*** (0.074)
Constant	-2.06*** (0.27)	-0.65** (0.27)	-1.93*** (0.31)	-1.06*** (0.29)
Observations	35,549	41,060	40,179	45,636

Table 3.6: Decomposing Differences in CI Ownership between Whites and Blacks in a Given Year

	Whites vs. Blacks 1997		Whites vs. Blacks 2003	
CI ownership rate: whites	0.423598		0.689896	
CI ownership rate: blacks	0.220646		0.490467	
Total Gap	0.202951		0.199430	
Sample whose coefficients is used to weight differences in characteristics[@]	Black 1997		Black 2003	
Contributions from racial differences in:				
Being Hispanic	-0.0101	-4.98%	-0.0141	-7.07%
Being female	0.0002[†]	0.11%	-0.00034	-0.17%
Age	-0.0061	-3.01%	-0.0052	-2.61%
Education	0.02236	11.02%	0.01968	9.87%
Income	0.02134	10.51%	0.01501	7.53%
Being non-citizen	0.00028	0.14%	-0.00067	-0.34%
Household structure	0.0156	7.69%	0.0272	13.64%
Type of housing unit	-0.0012	-0.57%	-0.00103	-0.52%
Employment status	0.0049	2.41%	-0.00124	-0.62%
Location	0.00599	2.95%	0.00284	1.42%
Access to CI outside home	0.0127	6.26%	0.00557	2.79%
Total contributions by all included variables	**0.066089**	**32.56%**	**0.04794**	**24.04%**
Sample size: Whites	68,395		78,045	
Blacks	7,333		8,602	

[@] Note that this specification treats whites as a majority category.
[†] Shows an estimate not statistically significant.

Table 3.7: Decomposing Differences in CI Ownership between Hispanics and Non-Hispanics in a Given Year

	Hispanic vs. Non-Hispanic 1997		Hispanic vs. Non-Hispanic 2003	
CI ownership rate: Hispanics	0.418585		0.689616	
CI ownership rate: non-Hispanics	0.228914		0.476353	
Total Gap	0.189671		0.213264	
Sample whose coefficients is used to weight differences in characteristics[@]	Hispanic 1997		Hispanic 2003	
Contributions from racial differences in:				
Being black	-0.0112	-5.90%	-0.0128	-6.00%
Being female	-0.00002[†]	-0.01%	-0.00012[†]	-0.05%
Age	-0.0186	-9.81%	-0.0333	-15.61%
Education	0.0466	24.57%	0.0337	15.80%
Income	0.01705	8.99%	0.01731	8.12%
Being non-citizen	0.0141	7.43%	0.00807	3.78%
Household structure	-0.0439	-23.15%	-	-
Type of housing unit	0.00005[†]	0.03%	-0.00023	-0.11%
Employment status	0.00694	3.66%	0.00197	0.92%
Location	-0.0222	-11.70%	-0.014	-6.56%
Access to CI outside home	0.0195	10.28%	0.0166	7.78%
Total contributions by all included variables	**0.008572**	**4.52%**	**0.01718**	**8.06%**
Sample size: Non-Hispanics Hispanics	69,883 5,845		78,767 7,929	

[@] Note that this specification treats non-Hispanics as a majority category.
[†] Shows an estimate not statistically significant.

Table 3.8: Decomposing Differences in CI Ownership between Males and Females in a Given Year

	Males vs. Females 1997		Males vs. Females 2003	
CI ownership rate: males	0.423641		0.683634	
CI ownership rate: females	0.386520		0.657945	
Total Gap	0.037120		0.025688	
Sample whose coefficients is used to weight differences in characteristics[@]	Female 1997		Female 2003	
Contributions from gender differences in:				
Being black	0.00065	1.75%	0.00385	14.99%
Being Hispanic	-0.00176	-4.74%	-0.00045	-1.75%
Age	0.00209	5.63%	0.00477	18.57%
Education	0.00947	25.51%	0.00632	24.60%
Income	0.00788	21.24%	0.00926	36.06%
Being non-citizen	-0.00119	-3.21%	-0.00112	-4.36%
Household structure	0.00837	22.55%	0.00340	13.24%
Type of housing unit	0.00028	0.75%	-0.00006	-0.21%
Employment status	0.00288	7.76%	0.00083[†]	3.24%
Location	0.00131	3.53%	-0.00009[†]	-0.33%
Access to CI outside home	0.00289	7.79%	-0.00587	-22.85%
Total contributions by all included variables	**0.03289**	**88.61%**	**0.02086**	**81.19%**
Sample size: Female	40,179		45,636	
Male	35,549		41,060	

[@] Note that this specification treats males as a majority category.
[†] Shows an estimate not statistically significant.

Table 3.9: Decomposing Differences in CI Ownership among Whites and Blacks Across Time

	Black 1997 vs. Black 2003		White 1997 vs. White 2003	
CI ownership rate in 2003	0.49047		0.68989	
CI ownership rate in 1997	0.22065		0.42360	
Gap	0.26982		0.26630	
Sample whose coefficients is used to weight differences in characteristics@	Black 1997		White 1997	
Contributions from differences in characteristics over time:				
Hispanic	-0.00045	-0.17%	-0.00312	-1.17%
Female	-0.00001†	-0.01%	-0.00005	-0.02%
Age	-0.00218	-0.81%	0.00087	0.33%
Education	0.01353	5.01%	0.01032	3.88%
Income	0.015414	5.71%	0.00882	3.31%
Non-citizen	0.00007†	0.03%	-0.00196	-0.74%
Household structure	-0.00525	-1.95%	-0.00205	-0.77%
Type of housing unit	0.00028	0.10%	0.0008	0.30%
Employment status	0.00071†	0.26%	0.00079	0.30%
Location	-0.00025†	-0.09%	-0.00068	-0.25%
Access to CI outside home	0.0083	3.08%	0.00568	2.13%
Total contribution by all included variables	**0.030087**	**11.15%**	**0.019423**	**7.29%**
Sample size: 1997	7,333		68,395	
2003	8,602		78,045	

@ Note that this specification treats blacks and whites in 2003 samples as majority categories.
† Shows an estimate not statistically significant.

Table 3.10: Decomposing Differences in CI Ownership among Hispanic and Non-Hispanic Across Time

	Hispanic 1997 vs. Hispanic 2003		Non-Hispanic 1997 vs. Non-Hispanic 2003	
CI ownership rate in 2003	0.47635		0.68962	
CI ownership rate in 1997	0.22891		0.41859	
Total Gap	0.24744		0.27103	
Sample whose coefficients is used to weight differences in characteristics[@]	Hispanic 1997		Non-Hispanic 1997	
Contributions from differences in characteristics over time:				
Black	-0.00006[†]	-0.03%	-0.00007[†]	-0.02%
Female	-0.00043[†]	-0.17%	-0.00003	-0.01%
Age	-0.00021[†]	-0.08%	-0.00017	-0.06%
Education	0.00866	3.50%	0.01107	4.08%
Income	0.01217	4.92%	0.009196	3.39%
Non-citizen	-0.00462	-1.87%	-0.00005	-0.02%
Household structure	0.00101	0.41%	-0.00456	-1.68%
Type of housing unit	0.00087	0.35%	0.000694	0.26%
Employment status[†]	0.00248	1.00%	0.00062	0.23%
Location	-0.00127	-0.51%	-0.00068	-0.25%
Access to CI outside home	0.00609	2.46%	0.00603	2.22%
Total contribution by all included variables	**0.024732**	**10.00%**	**0.022083**	**8.15%**
Sample size: 1997	5,845		69,883	
2003	7,929		78,767	

[@] Note that this specification treats Hispanics and non-Hispanics in 2003 samples as majority category.
[†] Shows an estimate not statistically significant.

Table 3.11: Decomposing Differences in CI Ownership among Males and Females Across Time

	Male 1997 vs. Male 2003		Female 1997 vs. Female 2003	
CI ownership rate in 2003	0.68363		0.65795	
CI ownership rate in 1997	0.42364		0.38652	
Total Gap	0.25999		0.27143	
Sample whose coefficients is used to weight differences in characteristics[@]	Male 1997		Female 1997	
Contributions from differences in characteristics over time in:				
Proportions of blacks	-0.00003[†]	-0.01%	-0.00015	-0.06%
Proportions of Hispanics	-0.00321	-1.23%	-0.00166	-0.61%
Age	-0.00062	-0.24%	0.00093	0.34%
Education	0.00741	2.85%	0.01268	4.67%
Income	0.01037	3.99%	0.00903	3.33%
Non-citizen	-0.00193	-0.74%	-0.00105	-0.39%
Household structure	-0.00328	-1.26%	-0.0026	-0.96%
Type of housing unit	0.00085	0.33%	0.00063	0.23%
Employment status	0.00174	0.67%	-0.00004[†]	-0.02%
Location	-0.00037	-0.14%	-0.00044	-0.16%
Access to CI outside home	0.00422	1.62%	0.00728	2.68%
Total contribution by all included variables	**0.01507**	**5.80%**	**0.024554**	**9.05%**
Sample size: 1997	41,060		45,636	
2003	35,540		40,179	

[@] Note that this specification treats males and females in 2003 samples as majority categories.
[†] Shows an estimate not statistically significant.

Table 3.12: Sample Mean Characteristics, Whites and Blacks (1997 – 2003)

Variables	**Whites**		**Blacks**	
	1997	2003	1997	2003
Own home computer	0.42	0.68	0.22	0.49
Have home Internet access	0.15	0.61	0.06	0.40
Access computer at school	0.02	0.02	0.02	0.04
Access computer at work	0.35	0.39	0.26	0.29
Ever connected from home	-	0.04	-	0.05
Access Internet at school	0.01	0.02	0.01	0.02
Access Internet at work	0.12	0.30	0.07	0.20
Access Internet at other locations	-	0.03	-	0.04
Age (years)	49	49	45	46
Female	0.52	0.52	0.56	0.56
Hispanic	0.10	0.13	0.03	0.03
Non-citizen	0.06	0.07	0.05	0.06
High school graduate or below	0.50	0.46	0.59	0.55
Some college or associate degree	0.25	0.25	0.25	0.27
Bachelor's degree or above	0.25	0.28	0.16	0.18
under $25,000	0.17	0.12	0.31	0.21
$25,000 - 49,999	0.16	0.14	0.14	0.14
$50,000 - 74,999	0.09	0.09	0.06	0.06
above $75,000	0.08	0.11	0.03	0.05
Married	0.67	0.67	0.43	0.44
Not married	0.33	0.33	0.57	0.56
Have children aged 0 to 14	0.31	0.29	0.45	0.40
Family size	2.84	2.82	3.03	2.93
Live in a house, apartment or flat	0.94	0.95	0.96	0.96
Live in a mobile home or trailer	0.06	0.05	0.03	0.04
Live in a hotel, rooming house, student quarters or others	0.003	0.002	0.004	0.003
Employed	0.66	0.64	0.64	0.62
Not employed	0.02	0.03	0.05	0.06
Government job	0.10	0.10	0.14	0.14
Private job	0.52	0.52	0.52	0.50
Self employed	0.07	0.06	0.03	0.03
Urban	0.79	0.80	0.86	0.88
Northeast	0.20	0.20	0.19	0.19
Midwest	0.24	0.24	0.17	0.18
West	0.22	0.22	0.08	0.09
South	0.34	0.34	0.55	0.54

Table 3.13: Sample Mean Characteristics, Hispanics and Non-Hispanics (1997 – 2003)

Variables	Hispanics		Non-Hispanics	
	1997	2003	1997	2003
Own home computer	0.23	0.47	0.42	0.68
Have home Internet access	0.06	0.38	0.15	0.62
Access computer at school	0.01	0.02	0.02	0.03
Access computer at work	0.21	0.21	0.35	0.40
Ever connected from home	-	0.04	-	0.04
Access Internet at school	0.01	0.01	0.01	0.02
Access Internet at work	0.05	0.14	0.12	0.31
Access Internet at other locations	-	0.02	-	0.03
Age (years)	43	43	49	50
Female	0.50	0.49	0.53	0.53
White	0.95	0.93	0.83	0.81
Black	0.03	0.03	0.12	0.12
Non-citizen	0.38	0.40	0.04	0.04
High school graduate or below	0.71	0.70	0.49	0.44
Some college or associate degree	0.18	0.18	0.26	0.26
Bachelor's degree or above	0.11	0.12	0.26	0.30
under $25,000	0.28	0.17	0.18	0.12
$25,000 - 49,999	0.13	0.14	0.16	0.13
$50,000 - 74,999	0.04	0.05	0.09	0.09
above $75,000	0.03	0.04	0.07	0.11
Married	0.65	0.63	0.65	0.64
Not married	0.35	0.37	0.35	0.36
Have children aged 0 to 14	0.55	0.49	0.31	0.29
Family size	3.66	3.70	2.82	2.75
Live in a house, apartment or flat	0.95	0.96	0.94	0.95
Live in a mobile home or trailer	0.04	0.04	0.05	0.05
Live in a hotel, rooming house, student quarters or others	0.005	0.003	0.003	0.002
Employed	0.66	0.66	0.66	0.64
Not employed	0.04	0.04	0.02	0.03
Government job	0.08	0.07	0.10	0.11
Private job	0.58	0.59	0.51	0.51
Self employed	0.04	0.05	0.06	0.06
Urban	0.92	0.91	0.79	0.80
Northeast	0.17	0.15	0.20	0.20
Midwest	0.07	0.08	0.25	0.25
West	0.41	0.41	0.20	0.20
South	0.35	0.36	0.35	0.35

Table 3.14: Sample Mean Characteristics, Males and Females (1997 – 2003)

	Males		Females	
Variables	**1997**	**2003**	**1997**	**2003**
Own home computer	0.42	0.67	0.39	0.65
Have home Internet access	0.17	0.60	0.12	0.57
Access computer at school	0.02	0.02	0.02	0.03
Access computer at work	0.34	0.38	0.34	0.37
Ever connected from home	-	0.04	-	0.04
Access Internet at school	0.01	0.02	0.01	0.02
Access Internet at work	0.14	0.30	0.09	0.27
Access Internet at other locations	-	0.03	-	0.03
Age (years)	47	48	49	50
White	0.89	0.89	0.87	0.87
Black	0.11	0.11	0.13	0.13
Hispanic	0.10	0.13	0.09	0.11
Non-citizen	0.06	0.08	0.07	0.07
High school graduate or below	0.49	0.47	0.52	0.48
Some college or associate degree	0.24	0.24	0.26	0.26
Bachelor's degree or above	0.26	0.29	0.21	0.26
under $25,000	0.18	0.11	0.19	0.14
$25,000 - 49,999	0.22	0.15	0.10	0.12
$50,000 - 74,999	0.13	0.11	0.04	0.06
above $75,000	0.11	0.14	0.03	0.07
Married	0.69	0.68	0.60	0.60
Not married	0.31	0.32	0.40	0.40
Have children aged 0 to 14	0.43	0.33	0.23	0.28
Family size	2.91	2.89	2.87	2.80
Live in a house, apartment or flat	0.94	0.95	0.95	0.95
Live in a mobile home or trailer	0.05	0.05	0.05	0.04
Live in a hotel, rooming house, student quarters or others	0.004	0.002	0.002	0.002
Employed	0.74	0.72	0.58	0.57
Not employed	0.02	0.03	0.02	0.03
Government job	0.09	0.09	0.11	0.11
Private job	0.60	0.59	0.45	0.45
Self employed	0.08	0.08	0.04	0.04
Urban	0.81	0.81	0.80	0.81
Northeast	0.20	0.19	0.20	0.20
Midwest	0.23	0.23	0.23	0.23
West	0.22	0.23	0.21	0.22
South	0.35	0.35	0.36	0.36

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