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Home Computers and Married Women's Labor Supply

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Abstract
I consider how the availability of a personal computer at home changed employment for married women. I develop a theoretical model that motivates the empirical specifications. Using data from the US CPS from 1984 to 2003, I find that employment is 1.5 to 7 percentage points higher for women in households with a computer. The model predicts that the increase in employment is driven by higher wages. I find having a computer at home is associated with higher wages, and employment in more computer intensive occupations, which is consistent with the model. Decomposing the changes by educational attainment shows that both women with low levels of education (high school diploma or less) and women with the highest levels of education (Master's degree or more) have high returns from home computers.

Key words: Married women's labour supply, computer skills and labour supply, US CPS
JEL: J24, J22

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1 Introduction

Personal computers have dramatically altered the workplace. Tasks in existing occupations changed and new occupations emerged. Computers also entered our homes. The OECD (2010) stresses that access to digital infrastructure and computer literacy, along with the ability to use a computer productively, are crucial for the development of future generations. Basic computer skills are an integral part of skill training provided by temporary help agencies (Autor 2001), in some countries they are a major part of active labor market policies (e.g. for Germany, Fitzenberger and Speckesser 2007).

The impact of computerization of the workplace has been of interest in numerous studies. Krueger (1993) finds large wage premia for computer use at work, but DiNardo and Pischke (1997) raise concerns that the premia are driven by unobserved skill differences. They show wage premia for the use of pencils and other office material used by white collar workers similar to the wage premia for computer use. In a more recent study Spitz-Oener (2008) shows that, while computer use has similar wage effects as other office materials, only computer use is associated with shifts in the tasks employees perform and therefore likely to drive productivity increases. Autor, Katz, and Krueger (1998) find that skill upgrading (i.e. increased demand for highly educated workers) in industries increases (strongly) with computer utilization. Using decomposition methods on industry and occupation aggregated data, Weinberg (2000) finds that more than half of the growth in female employment from the mid-70s to the mid-90s can be attributed to increases in computer use. Several authors point out that computers by themselves do not have an impact but rather that it is the interaction of computers with skilled users (Black and Spitz-Oener 2010) and organizational procedures (Bresnahan 1999, Garicano and Heaton 2010) that result in productivity increases. Instead of focussing on workers, Malamud and Pop-Eleches (2011) consider the impact of home computer use on children's development. They use school grades and test scores from cognitive tests as measures of human capital and find that cognitive skills improve with computer use, while school grades suffer.

Having access to a computer at home opens up the opportunity to acquire and improve computer skills at low additional cost. This can be a great advantage, especially if a person is not in employment and does not receive on-the-job training. Those skills can range from the basic, e.g. touch typing and word processing, to more advanced uses, like spreadsheets, databases and programming.

In this paper I contribute to the literature by shifting the focus to adult computer skills and the impact of having the ability to acquire job relevant skills at home. In particular, I am investigating whether the availability and the use of a computer at home changes married women's labor supply. Women, especially married women, have lower participation rates and higher labor supply elasticities than men (Killingsworth and Heckman 1987). Married women have been the major force behind women's labor supply changes (Blau and Kahn 2007) and reentry into the market after a period of caring for children might be facilitated by the ability to acquire new skills at home. Women also have a comparative advantage in non-physically intensive skills, skills for which computerization of the workplace increased demand (Weinberg 2000). The focus on married women limits the external validity as labor market behavior of men and single women differs, but married women's importance in the changes in women's labor supply (Blau and Kahn 2007) justifies a separate analysis.

The paper proceeds as follows, first I present a static model of labor supply to motivate the empirical specifications and evaluate the potential sources and directions of omitted variable bias. The model shows that it is crucial to control for offer wages and non-labor income when estimating the impact of home computers on employment. The model predicts that without wage (income) controls the impact of home computers is overestimated (underestimated).

For the estimation I use data from the U.S. Current Population Survey, which includes questions on home and work computer use in several supplements starting from 1984. The data is discussed in section 3 followed by descriptive evidence for the change in computer use and employment over time. The descriptive results show both an increase in computer availability and employment over time.

Section 5 discusses the empirical strategy followed by the estimation results in the next section. Employment probabilities are higher for women who have access to a computer at home. Employment shares are about 3 percentage points higher in the late 80s and 90s, and 6 percentage points in the early 2000s. To establish that the employment effect is indeed driven by computer skills, the following two sections establish that having a computer at home is associated with higher wages, and employment in more computer intensive occupations. The final section concludes.

2 Theory

I consider a static labor supply model[1] to guide the empirical implementation and help to determine the source and direction of bias in the estimates. I simplify the household labor supply decision by assuming a sequential structure. The wife decides on her labor supply only after the husband's choice. In the model the wife chooses consumption C and leisure L to maximize her utility $U(.)$, subject to the budget constraint. I augment the standard model by introducing a third choice variable PC, the demand for computers.[2] I treat the demand for computers as continuous and solely as the woman's choice.[3] The computer has two functions in the model. First, it is a consumption good and owning a computer provides utility. Second, it is an investment good that increases the wage rate.

Having a computer at home offers women the opportunity to (cheaply) acquire computer skills. These skills can range from simple (touch) typing skills to complex programming or network administration skills. If these skills are valued in the market, they raise wages directly. Indirectly the wage is affected by lowering search costs. For example, writing and changing cover letters and resumes is simplified by being able to store digital copies. With the advent of internet based employment websites in the mid- to late 90s job search effort is reduced, which would increase on- and off-the-job search. While neither of those aspects of computer use has a direct impact on the wage, it increases wages indirectly via an improved job offer distribution.

I use a Cobb-Douglas specification for the women's utility function.

$$U\left(C, L, PC\right) = C^{\alpha} L^{\beta} PC^{\gamma} \tag{1}$$

Where, for the time being, I assume that there is no heterogeneity across women, i.e. α, β and γ are the same for everyone. The optimization problem is given by

$$\max_{C,L,PC} \quad U\left(C, L, PC\right) = \alpha \ln\left(C\right) + \beta \ln\left(L\right) + \gamma \ln\left(PC\right) \tag{2}$$

[1]See e.g. Blundell and MaCurdy (1999)

[2]This is similar in spirit to demand models that account for labor supply, see Browning and Meghir (1991).

[3]While discrete demand might be more realistic it makes the model more unwieldy and the predictions of a discrete model do not differ.

$$\text{s.t.} \qquad C + w\,(PC, X)\,L + pPC \leq w\,(PC, X)\,T + I$$

The price of the composite consumption good C is normalized to 1, the price for a computer is p, T is the total time available, $w(PC, X)$ the wage as a function of characteristics (X) and computer availability, and I is the non-labor income (in this case mainly the husband's earnings). To show the dependence of labor supply on computers I first solve the maximization problem for consumption and leisure. The resulting demand for the two goods are functions of demand for computers. I then derive demand for computers in a second step.

For an interior solution, i.e. not all time is spent on leisure, the optimal allocation of time and consumption (denoted by asterisks) equates the marginal rate of substitution $MRS(PC, X)$ between the two goods with their price ratio.

$$\frac{U_L(C^*(PC, X), L^*(PC, X), PC)}{U_C(C^*(PC, X), L^*(PC, X), PC)} = MRS(PC, X) = \frac{\beta}{\alpha}\frac{C}{L} = w(PC, X) \tag{3}$$

A woman chooses to work in the market, if her wage rate exceeds her reservation wage. The reservation wage is defined as the marginal rate of substitution at the corner solution where all time is spend on leisure and only non-labor income is used for consumption.

$$\begin{aligned} T - L > 0 \quad &\Leftrightarrow \quad w\,(PC, X) \geq w^r\,(PC, X) \\ &\Leftrightarrow \quad w\,(PC, X) - \frac{\beta}{\alpha}\frac{I - pPC}{T} \geq 0 \end{aligned}$$

This can be rewritten in terms of conditional expectations using an indicator function E for employment, which equals one if a woman works in the market, i.e. $T - L > 0$ and zero otherwise. I also assume that the wage can be decomposed into three factors. A base component that only depends on characteristics $w(X)$, a second factor that picks up the impact of having a computer at home, and an error term that collects random variation. The wage needs to be concave to ensure concavity of the objective function and to avoid the corner solution of infinite computer consumption. A simple specification is

$$w(PC, X) = w(X) + \delta_1 PC - \frac{1}{2}\delta_2 PC^2 + \epsilon \tag{4}$$

The parameters of the wage function δ_1 and δ_2 are again homogenous, i.e. the returns for computer use are equivalent for all women. Combining and rearranging the terms yields

$$E\left(E \mid PC, I, X\right) = w(X) + (\delta_1 - \delta_2 \frac{PC}{2} + \frac{\beta}{\alpha}\frac{p}{T})PC - \frac{\beta}{\alpha}\frac{I}{T} \tag{5}$$

Without a computer in the household, the labor supply decision is governed by the base wage $w(X)$, the utility parameters for leisure and consumption and the non-labor income I. With a computer, employment becomes more likely for two reasons. First, the return to for computer skills (captured by δ_1 and δ_2) increases the price of leisure (at least initially) and work becomes more attractive. Second buying a computer reduces the endowment in non-labor income by pPC, this increases the likelihood of working in the market to compensate for the loss in consumption. The combination of both effects is depicted in figure 1 for the case where owning a computer changes the supply decision from non-employment to providing market work (solid lines depict the decision without, dashed lines the decision with a computer). As in the basic model without demand for computers, a woman's labor supply choice is positively related to her market wage and negatively to her non-labor income. In the following, I show that wages and income are also correlated with the demand for computers. In a regression of employment on computer availability this leads to inconsistent estimates unless wage and income are included in the set of controls.

To determine what factors affect the demand for computers, I again consider the interior solution. The demand functions for leisure and consumption, derived from the first order conditions of equation (2), are

$$\begin{aligned} C^*\left(PC\right) &= \frac{\alpha\left(I + w\left(PC, X\right)T - pPC\right)}{\left(\alpha + \beta\right)} \\ L^*\left(PC\right) &= \frac{\beta\left(I + w\left(PC, X\right)T - pPC\right)}{w\left(PC, X\right)\left(\alpha + \beta\right)} \end{aligned}$$

Substituting these back into the woman's utility function defines the indirect utility $V(PC, X) = U\left(C^*(PC, X), L^*(PC, X), PC\right)$, which I then maximize with respect to PC.

$$\begin{aligned}\max_{PC} V(PC, X) &= \alpha \ln\left(\frac{\alpha\left(I + w\left(PC, X\right)T - pPC\right)}{(\alpha+\beta)}\right) \\ &\quad + \beta \ln\left(\frac{\beta\left(I + w\left(PC, X\right)T - pPC\right)}{w\left(PC, X\right)(\alpha+\beta)}\right) \\ &\quad + \gamma \ln(PC)\end{aligned}$$

Let $w'(PC, X)$ be the first derivative of the wage equation with respect to PC. Using this and rearranging the first order condition leads to an implicitly defined demand for computers.

$$PC^* = \frac{\gamma\left(I + w(PC^*, X)T\right)}{(\alpha+\beta+\gamma)\,p + (\alpha+\beta)\left(w'(PC^*, X)\frac{\beta(I+w(PC^*,X)T-pPC^*)}{w(PC^*,X)(\alpha+\beta)} - w'(PC^*, X)T\right)} \quad (6)$$

Consider first the case where computers do not impact earnings, i.e. $w'(PC, X) = 0$. In this case the share of total endowment $I + wT$ spent on computers is determined by the computer's price, p, and the relative taste for computers, $\frac{\gamma}{\alpha+\beta+\gamma}$, which is the standard Cobb-Douglas result. When wages increase with home computer demand, two opposing effects occur. First leisure becomes more expensive. This is captured by the second part of the sum, which is the demand for leisure (net of demand for computers) multiplied by the change in the price of leisure $w'(PC, X)$. The third part of the sum captures the second effect, which is the increase in the value of the time endowment. Clearly both income and wages matter for the demand for computers and are necessary controls for the estimation in section 5 as omitting either will result in biased estimates.

The model can help determine the direction of the bias. An increase in the base wage, $w(X)$, increases the value of the time endowment and the price of leisure, both effects will increase demand for computers. Similarly increasing non-labor income raises consumption of all goods and demand for computers increases. In combination with the correlations in equation 5 this means that, without controlling for income, the impact of computers on employment in a bivariate regression is underestimated and without controlling for wages the estimate is biased upward.

But even with controls for both wages and income, additional sources of bias need to be considered. A plausible concern is reverse causality, i.e. it is employment that drives the demand for computers. Though this link between employment and pc availability at home is conditional on wages and income. That means it will only be a concern if there is an effect of employment net of the increase in wages that might be associated with access to a computer at home. An example would be that employed women might have the option of working from home which would be facilitated by having a laptop or personal computer at home. It might also be the case that using a computer at work raises the utility women derive from a computer at home, i.e. they learn to use a computer at work instead of at home. This channel leads to an upward bias in the regression of employment on pc availability at home.[4]

Another potential source for bias in my estimates arises from introducing heterogeneity in either the utility function or the returns to having a computer at home. To capture heterogeneity I allow the parameters (α, β, γ, δ_1, δ_2) to vary for each woman i. Define $\pi_i = \frac{\beta_i}{\alpha_i}$ and denote mean parameter values by $\bar{\pi}$. Then I can rewrite equation 5 in terms of deviations from the mean.

$$\begin{aligned} E\left(E \mid PC, I, X\right) &= w(X) + (\bar{\delta}_1 - \bar{\delta}_2 \frac{PC}{2} + \bar{\pi}\frac{p}{T})PC - \bar{\pi}\frac{I}{T} \\ &\quad + E\left(\epsilon \mid PC, I, X\right) \\ &\quad + E\left((\delta_{1,i} - \bar{\delta}_1 - (\delta_{2,i} - \bar{\delta}_2)\frac{PC}{2})PC \mid PC, I, X\right) \\ &\quad - E\left((\pi_i - \bar{\pi})\frac{I - pPC}{T} \mid PC, I, X\right) \end{aligned} \tag{7}$$

Bias in this specification arises when deviations from parameter means are correlated with computer demand. If, for example, women with above average wage premium from computer use also enjoy using computers more in their leisure time (γ_i above average), the estimate on PC would be upward biased. On the other hand, if women who have a strong relative taste for leisure (π_i above average) also benefit more from having a computer at home, the estimate would be downward biased. If preferences vary systematically as

[4] The direction of the bias is given by the coefficient of employment in the "reverse" regression, i.e. the regression of computer availability on employment (Stock and Watson 2007, pp. 324–325), and employment in the given examples would increase demand for a computer at home.

a function on observable characteristics, I could control for these characteristics in the regression models and thereby eliminate the bias. But it is unlikely that any data set contains sufficient variables to plausibly capture taste variation.

Since controlling for both reverse causality and taste heterogeniety is not feasible I would have to either find variables that induce exogenous variation in computer demand (i.e. instrumental variables) or randomly assign computers to households to ensure unbiased estimates. Neither is feasible in this study.

3 Data

I use data from the U.S. Current Population Survey (CPS)[5] from 1983–2005 for this study. The CPS is a monthly survey that collects data for all members of approximately 50,000 households. Once a household enters the sample it is surveyed in two waves. In both waves households are interviewed in four consecutive months with a break of eight months in between waves. In each survey the respondents answer the same set of questions on demographics and employment. Occasionally supplemental questionnaires are issued on specific topics. Questions on computer use at home and at the workplace were part of several supplements (October of 1984, 1989, 1993, 1997, December 1998, August 2000, September 2001, and October 2003). In addition to computer availability, the data contain information on number of computers in the household, age of the newest computer, frequency of computer use and what the computer is used for. From 1997 onwards the survey contains additional questions on internet use.

The data are available in ASCII format on the website of the National Bureau of Economic Research (NBER)[6] and code to import the data into Stata is available for all files from 1997 onwards. For the remaining years the data documentation is available and I adapt the available code to import the raw data. Employment information is available in all CPS samples, but information on earnings are only available in the March supplements and in the months that a household leaves the sample[7], i.e. the month of the 4th and the 8th interview. This means that for each of the eight data files, information on earnings[8] is only available for the outgoing rotation group, i.e. a fourth of the sample.

To increase the available information on earnings I add data for all working members of a household from the months that they leave the sample. For this I use the NBER's Merged Monthly Outgoing Rotation Group sample, which is readily available in Stata format. Since the CPS is an address based survey, interviewees are not necessary the same individuals across all interviews. To ensure consistency I only use matches where

[5]See the Census Bureau and Bureau of Labor Statistics' (2002) Technical Paper 63RV for details.

[6]`http://www.nber.org/data/cps_index.html`

[7]The questions were part of the outgoing surveys since 1979, before they were part of the May supplement.

[8]For hourly paid workers earnings are usually hours worked times their hourly wage, for all other workers earnings are usual weekly earnings.

gender and race are the same in both interviews and the age of the person does not change by more than a reasonable margin (1–2 years). Some 5% of the observations fail this test and are discarded. I then use the earnings information that is closest to the computer supplement survey. If available, I use the earnings information of the month itself, otherwise the information from the same wave of interviews and, if those are not available, I add the data from the second wave. This means, the earnings information can come from up to 12 months prior to or after the month of interest.

To facilitate the addition of earnings across survey months the observations need to be uniquely identified. For a few observations the household identifier is not unique, these observations are discarded. For the regression analysis the data is further truncated to include only married women who live with their spouse and who are between 20 and 59 years old. Table 1 reports means, standard deviations and number of observations for each of the eight sample years.

4 Descriptive Results

Personal computers have become an integral part of everyday life, both at home and at work. Figure 2 shows the increase in computer use at the workplace. The solid line depicts the change for all employees, the dashed lines consider only female or male employees. In 1984 24% of all employees were already using a computer at work. The share rose quickly to 45% in the mid-90s and kept rising, albeit at a slower pace, to 55% in 2003. The numbers are very similar to those reported by Spitz-Oener (2006) for West Germany. Although computer use at work is more prevalent among female employees compared to male employees, both groups follow similar trends, with a slightly stronger increase for women. A simple explanation is that men have a comparative advantage in manually intensive tasks[9] and computer are complementary to (non-routine) cognitive task[10].

The reasoning in this paper is, that the availability of a computer at home allows women to acquire valuable skills. Figure 3 shows the change in the share of households with at least one computer (or laptop) at home. Few households had a computer in the

[9] c.f. Rendall (2010)

[10] See e.g. Black and Spitz-Oener (2010)

mid-80s, but the share rose at an increasing rate until 2001. From the mid-90s onwards more people have access to a computer at home than at work. Households with at least one married woman are slightly more likely to own a computer. This is unsurprising as the average married household tends to be older and has higher income than the average unmarried household. There is no direct measure of skill in the data, but using educational attainment as a proxy I find that married women, with better education, are more likely to have access to a computer (figure 4).

How does availability of computers at home relate to employment? Figure 5 depicts employment for all 20–59 year old women (circles) and those 20–59 year old women who are married (diamonds). Female employment is high, peaking at more than 70% in the late 1990s. Employment has been rising for several decades (e.g. Goldin 2006) but stabilizes over the sample period and even seems to drop in the 2000s. Married women have lower levels of employment, which has traditionally been the case (e.g. Killingsworth and Heckman 1987). Crucial for this study, the participation rates are universally higher for women with access to a computer at home. This is in line with the simple model in section 2, where women do not work if their reservation wage exceeds the market wage.[11]

5 Empirical specification I

To estimate the impact of computers on employment I use ordinary least squares regressions on several sets of covariates. With a binary dependent variable the ordinary least squares estimator is usually referred to as "linear probability model" (LPM).[12] The model in section 2 shows that omitting controls for the woman's wage and non-labor income results in biased estimates. By introducing these controls successively I can gauge whether the models predictions are in line with the empirical findings.

A truncation issue arises when controlling for wages, since wages are only observed when a woman is actually working. Therefore, I use a set of covariates to proxy for wages. The set includes age and its square, dummies for education (completed years in

[11]The model does not distinguish between non-participation and unemployment, i.e. all unemployment is voluntary.

[12]I also used a Probit to estimate the equations but qualitatively the results do not differ. I prefer the LPM since the results are easier to interpret and it connects more directly with the theoretical model.

1984 and 1989, degree obtained thereafter), race (three dummies for white, black, any other race), state and MSA dummies.[13] The only direct measure for non-labor income in the CPS is a categorical measure for combined household income from all sources in the last year. This variable has the disadvantage in that it is not possible to separate the woman's contribution from other income. Focussing on married women allows me to treat the husband's earnings as non-labor income.

It is unlikely that the impact of computers has been constant over time. I therefore estimate the model for each cross-section separately.[14] The regression specification is given by

$$y_{it} = \beta_t^0 + \gamma_t pc_{it} + \beta_t^w x_{it}^w + \beta_t^n x_{it}^n + \nu_{it} \tag{8}$$

Where i denotes the individual woman, t the different cross-sections and γ, β^0, β^w, β^n the parameters to be estimated. The covariates are split into those that affect the wage rate x^w , and those that account for non-labor income x^n. Finally, ν is the error term. The dependent variable y is employment with non-employment (unemployed or out of the labor force) as base category and pc is a dummy that is equal to one if the household owns at least one computer. I also consider a specification where pc indicates that the household owns a computer and the woman actually uses it. Computer use might be a better indicator for a women having computer skills, but this measure has two main disadvantages. While a woman might not currently use an available computer, she might have used it in the past, thus making computer availability a better indicator for computer use. In addition computer use is not available in two of the eight cross-sections. I therefore focus the discussion on computer availability, reporting results for computer use only for my preferred specification.[15] Finally, I allow for heterogenous effects of home computers by interacting the availability of a computer with the woman's education level. I account for sampling weights in all regressions and I use White (1980) heteroscedasticity

[13]Imputing wages in this manner introduces another possible source of bias. The bias arises if the proxy error, i.e. the deviation of the predicted wage based on the set of proxy variables from the true (potential) wage, is correlated with demand for computers.

[14]An additional advantage of not pooling the cross-sections is that variables with different definitions over time, e.g. education or occupation, do not need to be harmonized.

[15]The differences between computer availability and computer use in this specification are representative for the pattern exhibited by the other specifications.

robust[16] standard errors.

Following the theoretical arguments from section 2, I first consider the unconditional impact before successively introducing additional controls. The first specification (a) does not include any controls, beyond the availability of a computer. The second set (b) adds controls that proxy for the wage rate, these are education (dummy variables[17]), age (and its square), race (two dummies for white and black women), state dummies and a dummy for metropolitan standard area status. For the third set (c) I control for non-labor income. The controls in this specification are a dummy for home ownership, husband's weekly earnings, and its square, as well as an indicator that is equal to one if the husband does not have any earnings (i.e. is unemployed or not in the labor force). Specification (d) then combines both wage and income controls. Specification (e) includes all the controls from specification (d) and, in addition, the husband's education[18], age (and its square), and dummies for the number of 0–5 and 6–15 year old children in the household.

The final specification adds controls that do not affect wages or non-labor income directly, but both are likely to influence labor force participation and might be correlated with the choice to acquire a computer. Child care is one of the main factors that influences labor supply[19] and the household's computer might have been purchased for the child's benefit. Similarly the husband's characteristics might correlate with the demand for computers and the woman's labor supply. For example, employment is less stable for men with lower levels of education and the women's market work acts as an insurance mechanism.[20]

[16]I also ran the regressions using standard errors that are clustered at the state level to account for spatial correlation (Moulton 1986). The results did not differ.

[17]Depending on the survey year, the education dummies are either completed years of education (1984 or 1989) or degree obtained (1993 and thereafter). For years of education I pool all women with 11 or less years of completed education in one category and all women with 16 or more years in another. For degrees I also pool all women without a high school diploma and those with a master's degree or more.

[18]The same changes apply to husband's education that apply to the woman's own education.

[19]See e.g. Hotz and Miller (1988).

[20]See e.g. Lundberg (1985)

6 Empirical results I

Table 3 reports the coefficients for home computer availability in the employment regressions. The unconditional impact of having a computer at home (1a) is positive. On average, women in households with a computer are more likely to be employed. The correlation is increasing over time, starting with a 6.6 percentage points higher employment share in 1984 that increases to 15.3 percentage points in 2003. All coefficients are statistically significant at the 1% level.

The estimates capture the causal impact of home computers, if computers were as good as randomly assigned. As I discuss in section 2, this is not very likely. Specifications (1b) and (1c) confirm this suspicion. Adding controls that capture productivity differences, i.e. controls that proxy for the potential wage, reduces the impact of computer availability dramatically. The coefficients are only statistically significant from 1998 onwards and the largest effect (in 2003) is reduced to an 8.3 percentage points increase in employment; about half of the unconditional mean difference. Controlling for measures of non-labor income results in much smaller changes in the coefficient estimates. Compared to the unconditional specification (1a), the estimates are slightly smaller in all years except 1989, with most differing by less than a percentage point. The direction of the changes is as expected when adding wage controls. For non-labor income the model predicts an increase in the coefficient estimates. Surprisingly the opposite is true.

This might be due to measurement error. With classical measurement error in PC, adding a correlated control reduces omitted variable bias, but at the same time increases attenuation bias due to measurement error. With computer use as explanatory variable, there should be less attenuation bias; assuming computer use is less affected by measurement error than computer availability. This would be the case if, for example, computer skills are more prevalent among the women who not only have access to but also use a computer at home. When I estimate regressions (1a) and (1c), and substitute computer use for computer availability, I find the same pattern as in table 3. Which does not rule out that PC is affected by measurement error, since it might be present in both computer use and availability, but makes this explanation unlikely.

Another possibility is (non-classical) measurement error of non-labor income. Apart from the home ownership dummy, I use only remuneration from the husband's employment. Other sources of income, e.g. earned interest, are not captured. In addition some 15% of the married women live with a spouse who does not have any market earnings (see table 1). However, they might receive benefit payments, scholarships or pensions. This means that the proxy underestimates the true value of non-labor income. With positive correlation between the unobserved component of non-labor income and demand for computers in combination with a negative correlation between the unobserved component and employment, this leads to downward biased estimates of the coefficient on PC. To check the plausibility of this explanation I re-estimate the regressions (1a) and (1c) on a constraint sample, which includes only married women whose husbands report positive market earnings. This excludes the group of women for whom the measurement error is likely to be the most severe. With this constraint I find for all years, except 2003, that coefficient estimates increase compared to the unconditional specification when controlling for non-labor income (upper panel of table 4). The increase is moderate, ranging from 1–2 percentage points in the late 80s and early 90s to less than 1 percentage point in the 90s and early 2000s. Measurement error in non-labor income seems to be present but its impact is limited.

When controlling for both sets of covariates in (1d) and (1e), the direction of the bias is theoretically indeterminate. It turns out that the unconditional effect overestimates the impact compared to a full specification that includes both (potential) wage and non-labor controls. In both specifications, (1d) and (1e), I find a moderate increase of 1.5–3 percentage points in the employment probability in the data from 1984 to 1997. From 1998 onwards the estimates are larger, averaging at about 6 percentage points. The estimates are statistically significant at the 5% level in all years except 1984.

So far I have considered the impact of the availability of a computer. The simple presence of a computer should not increase a woman's market productivity without her actually making use of it. But far from all women use the available computer. Table 2 shows the share of women who use the available computer for three groups, all women, married women and married women with children. For all three groups the user shares are very similar. In 1984 only 42–48% were using the household's computer. The share increased over time with about 86% of women making use of an available computer in 2003. While it might indicate a general disinterest for the available computer, the lack of current use does not rule out that the computer has been used in the past. It still raises the concern, that the estimates suffer from self-selection bias, since women who benefit the most from computer use would choose to use the computer to acquire computer skills.

I therefore consider a specification with computer use, rather than computer availability, as the dependent variable. The middle panel of table 4 shows the results for the most comprehensive set of controls. The CPS supplements in 1998 and 2000 did not include questions on computer use at home, so those two years are omitted.[21] The estimated coefficients are in line with the previous results. They are, with 2.5–4 percentage points, slightly higher from 1984 to 1997, and with 5–5.5 percentage points slightly lower in 2001 and 2003, than the comparable estimates for computer availability (specification (1e) in table 3). Self-selection does not appear to be a major concern.

Blau and Kahn (2007) show that female employment increased strongly in the 1980s with a slow-down in the increase during the 1990s. However my results indicate that for women who had access to a computer, employment kept rising, even after the 1990s. To put the results into perspective I consider the descriptive trends in employment and computer availability in figure 3 and 5 again. Computer availability rose from 13 to 60% from 1984 through 1998. The share of married women in employment increased from 60 to 71% over the same period. The coefficient estimates for computer availability (specification (1e) in table 3) imply that the computer skills acquired using a computer at home account for 3 percentage points of the 11 percentage point increase in employment.[22]

The timing of the increase in the impact of computer availability in table 3 coincides with the rise of the internet and the proliferation of employment websites. While it is tempting to attribute the increase to improved job search options, Kuhn and Skuterud (2004) find, using CPS supplements data, that internet search did not reduce unemployment duration.[23] On the other hand internet related job opportunities and the ability to

[21] The focus in those CPS supplements is on internet use.

[22] $\Delta = 0.056 * 0.6 - 0.014 * 0.13 = 0.032$

[23] There is evidence for positive effects of internet availability, Beard, Ford, Saba, and Seals (2012) using

(partly) work from home might have increased employment.

As discussed in section 2, studies considering the impact of computer use at the workplace find that demand for skilled workers increases. To investigate whether home there is a relationship between home computers and skill I allow for heterogeneity in the impact of home computers on employment. The lower panel of table 4 reports the coefficient estimates of home computer availability interacted with educational attainment.[24]

While most of the coefficients are positive, few remain statistically significant. Standard errors increase markedly, compared to the regressions that focus on the overall average effect. Interestingly it is both at the lower and the upper end of the educational distribution that computer availability matters most. The estimates are positive and most of them statistically significant for women who dropped out of high school. The size of the coefficients varies across years but averages around 9 percentage points. For women who finished high school but did not pursue any further education the estimates vary around an average of 5 percentage points, excluding 1984 where the coefficient is negative and statistically indistinguishable from zero.

The coefficients at the upper end of educational attainment (Master's, Professional or PhD degrees) are of similar size, but the estimates are not precise enough to distinguish the majority of coefficients from zero. For all other education groups the estimates are mostly insignificant. Autor, Levy, and Murnane (2003) find that computer use at work favors non-routine tasks and increased demand for highly educated employees strongly. The results here suggest that having access to a computer at home, and thereby the opportunity to acquire computer skills, increases employment for women with low levels of education.

One possible explanation is that while computers substituted for many skills at the workplace, they also require employees capable of using the technology. Many tasks performed by, for example, bank tellers[25] might be substituted with Automated Teller Machines, but the remaining tasks bank tellers perform rely heavily on the use of com-

CPS data from the 2007 supplement, find positive effects of internet availability on job search efforts.

[24]For 1984 and 1989 educational attainment is measured in completed years of education. I interpret 11 years or less of completed education and 12 years of education where the 12th year was not completed as "High school drop-out" and 12 years of completed education as "High school graduate".

[25]Using an example given by Autor, Levy, and Murnane (2003)

puters. In addition, the relative value of basic computer skills, like touch typing or being able to use standard software packages, is higher for low levels of education. Finally, as Weinberg (2000) points out, computerization reduces the relative value of physical skill. This, in turn, reduces the comparative advantage of men in classically "muscle intensive" occupations and leads to increased demand for female workers.

In this section I establish sizable positive correlation between home computer availability and employment. The interpretation that having a computer at home increases labor supply and employment hinges on the assumption that the computer increases productivity and wages. The next section analyzes this link.

7 Empirical specification II

Based on the model in section 2 home computers increase employment, if access to a computer increases productivity and thereby the (potential) market wage. Computer skills should also only be valuable if they can be applied at work. Therefore, I estimate in the following whether women who have access to a computer at home have higher wages and whether they are more likely to work in occupations with a high share of computer users.

Ideally I would like to test whether computer skills increase the productivity of, or the wage earned by, a woman, if she was working. But wages are truncated and only observed if the woman actually works. The unobservable factors that determine a woman's decision to work are likely correlated with the unobservable factors that determine a woman's earnings. This leads to (selection) bias in the simple OLS framework. Heckman (1979) suggests a control function approach to account for this bias. Wages (lhw) are observed only if a person is working ($y = 1$), and they are missing otherwise.

$$lhw_{it} = \begin{cases} lhw^*_{it} & \text{if } y_{it} = 1 \\ \text{missing} & \text{otherwise} \end{cases} \tag{9}$$

Where employment (y) is determined by the same process as in equation 8. The potential market wage lhw^* is given by

$$lhw^*_{it} = \delta_t pc_{it} + \alpha^w_t x^w_{it} + \eta_{it} \tag{10}$$

If the error terms ν in equation (8) and η in equation (10) are correlated, a simple regression of (log) hourly wages on computer availability and covariates x^w will be biased. Heckman (1979) shows that, if both error terms are normally distributed, the selection bias is given by the covariance of the two error terms multiplied with the inverse Mills ratio. To correct for the bias either a two-step procedure, first estimating the inverse Mills ratio using a Probit model, and then controlling for it explicitly in a second stage OLS regression for wages, or a (partial) maximum likelihood (MLE) approach that accounts for the truncation, can be used. The MLE requires stronger distributional assumptions and tends to have problems with convergence (Wooldridge 2002, p. 566), which makes the two-step procedure more robust. However, in Stata the two-step estimator does not allow for sampling weights nor for non-homoscedastic standard errors. Consequently I use the MLE estimator.

Other than the computer indicator, which is used in both the wage and the selection equation, the two models include the same controls x^w as above (education, age, race, state and MSA status) for both the wage and the selection equation. For the selection model (8) I use the full set of exclusion restrictions, given by the earnings and family measures used in the previous section, i.e. a dummy for home ownership, the husband's education, age (and its square), weekly earnings (and its square), a dummy if the husband does not report any earnings, and dummies for the number of 0–5 year old and 6–15 year old children.

8 Empirical results II

The estimated coefficients on PC in the selection corrected wage equation are reported in table 5. Underneath the coefficient and the standard error (in parenthesis) I report the p-value of a test for correlation between the error terms of the wage and selection equation, which are uncorrelated under the H0. In two out of eight years accounting for selection into employment is warranted.[26] Non-correlation can be rejected at least at the 1% level (5% level in 2003). Convergence is achieved in all specifications.

The first panel shows the coefficient for computer availability, the second for computer use. In both cases the computer at home is associated with higher wages. These findings are in line with the increase in demand for women with computer skills (Weinberg 2000). For 1984 the coefficients are small and not statistically significant, however the coefficients increase over the following years and become statistically significant . The estimates from 1989 onwards indicate large returns in the range of 5 to 10% higher wages. The results are smaller than those found by Krueger (1993) for computer use at the workplace and larger than the findings by Zoghi and Pabilonia (2007). Using the 1999–2002 Canadian

[26]While simple OLS for the two other years would be more efficient than the selection correction model, the coefficients are estimated precisely enough to err on the side of caution and stick with the selection model.

Workplace and Employee survey, they estimate a 3.6 percent wage premium for adopting a computer at work, accounting for both employee and establishment fixed effects. Zoghi and Pabilonia (2007) also find that returns increase with education levels. I cannot confirm the same for home computers. As can be seen in the lower panel of table 5. While the estimates in the late 80s show some evidence for returns for highly educated women (16–17 and 18 or more years of education). The stronger effects are at the lower end of the education distribution from the 90s onwards. I do find positive and significant effects for women with low levels of education, high school dropouts, graduates and women with some college. For these women, the returns from 1993 onwards are in the range of 6 to 14%, averaging below 10% across years. While most of the coefficients for women with a Bachelor's degree are significant, the returns are lower, averaging around 8%.

If the computer at home is used to acquire skills and increase productivity at work, I would expect women to choose employment in occupations where they use a computer. To see whether this is the case I estimate the same model as above, but instead of log hourly wages I use the share of computer users in the woman's occupation as dependent variable.[27] The results are reported in table 6. Again, all models converge and selection matters in four of the six available years.[28]

I find that in all years women who have (and use) a computer at home work in occupations that have a higher share of computer users. In 1984, women with a computer at home worked in occupations with, on average, a 1.5 percentage points higher computer user share. The estimates increase throughout the 80s and 90s and fall in the 2000s. The peak is in 1997 where women with a computer at home work in occupations with 7.8 percentage points more computer users than comparable women without a computer at home. Disaggregated by level of education I find mostly positive coefficients and again the strongest effects for both women with little formal education and women with Master's degrees and more.

The results are in line with home computers increasing employment, as having a computer at home is associated with finding employment in more computer intensive

[27]The shares are calculated based on computer use at work for both men and women and leaving out the computer use of the respondent.

[28]See the comments in footnote 26.

occupations and higher wages.

9 Discussion

In this paper I estimate the impact of home computers on married women's employment. Using data from the U.S. CPS supplements between 1984 and 2003, I find that employment increases with the availability of a home computer. The unconditional impact ranges from 6.5 percentage points higher employment shares in 1984 to 15 percentage points in 2003. I present a theoretical model that shows that the unconditional estimates are misleading and several bias inducing factors are identified. Most importantly adding controls that account for (offer) wage differences and non-labor income reduce the impact to a range of 1.5 to 7 percentage points.

Employment in the model rises due to computer skills leading to improved offer wages. Therefore, I estimate whether wages differ for women with a computer at home. Accounting for selection into employment, I find that wages are indeed higher for women with a computer at home. The returns are lower in the 80s, starting from 2–5% and increasing to 8–10% higher wages in the 90s and 2000s.

Decomposing the effect by education level shows that gains, both in employment and wages, are strong for women with little formal education. Married women with a Master's degree or higher also seem to benefit, but estimates are very imprecise and few coefficients are statistically significant.

How can these results be interpreted? Skills acquired using a home computer are most useful if they are general enough to be of use on a computer at work and scarce enough to warrant a wage premium. In 1984 the most prevalent home computer was the Commodore 64 while commercial use relied on IBM and IBM compatible computers. The late 80s and especially early 90s saw IBM compatible computers running MS-DOS and Windows take over the market for both home and commercial users. Standard software packages became available and affordable for home users and, consequently, skills acquired on a home computer became more easily transferable to the workplace. At the same time computer use became more widespread, rising more steeply than in the 2000s. This might have lead to demand for computer skills rising more quickly than supply, which gave rise to the wage premium.

The main caveat of this study is that a causal interpretation of the coefficients hinges on (conditional) random assignment of computer availability (or use). The results show that it is crucial to control for both income and wage measures. Whether the available information in the CPS used in this paper suffices to adequately control for all selection effects is not clear. Ideally I would find an instrument for having a computer at home.[29] A promising alternative would be the use of a regression discontinuity design as used by Malamud and Pop-Eleches (2011). They exploit an allocation rule for home computer vouchers issued by the Romanian government. While the computers were meant to improve the education of children, they should also have an impact on the mothers in the household.

[29]The share of computer users in the husband's occupation yields a strong first stage, but implausible estimates in the second stage.

10 Appendix

Figures

Figure 1: Labor supply and computers

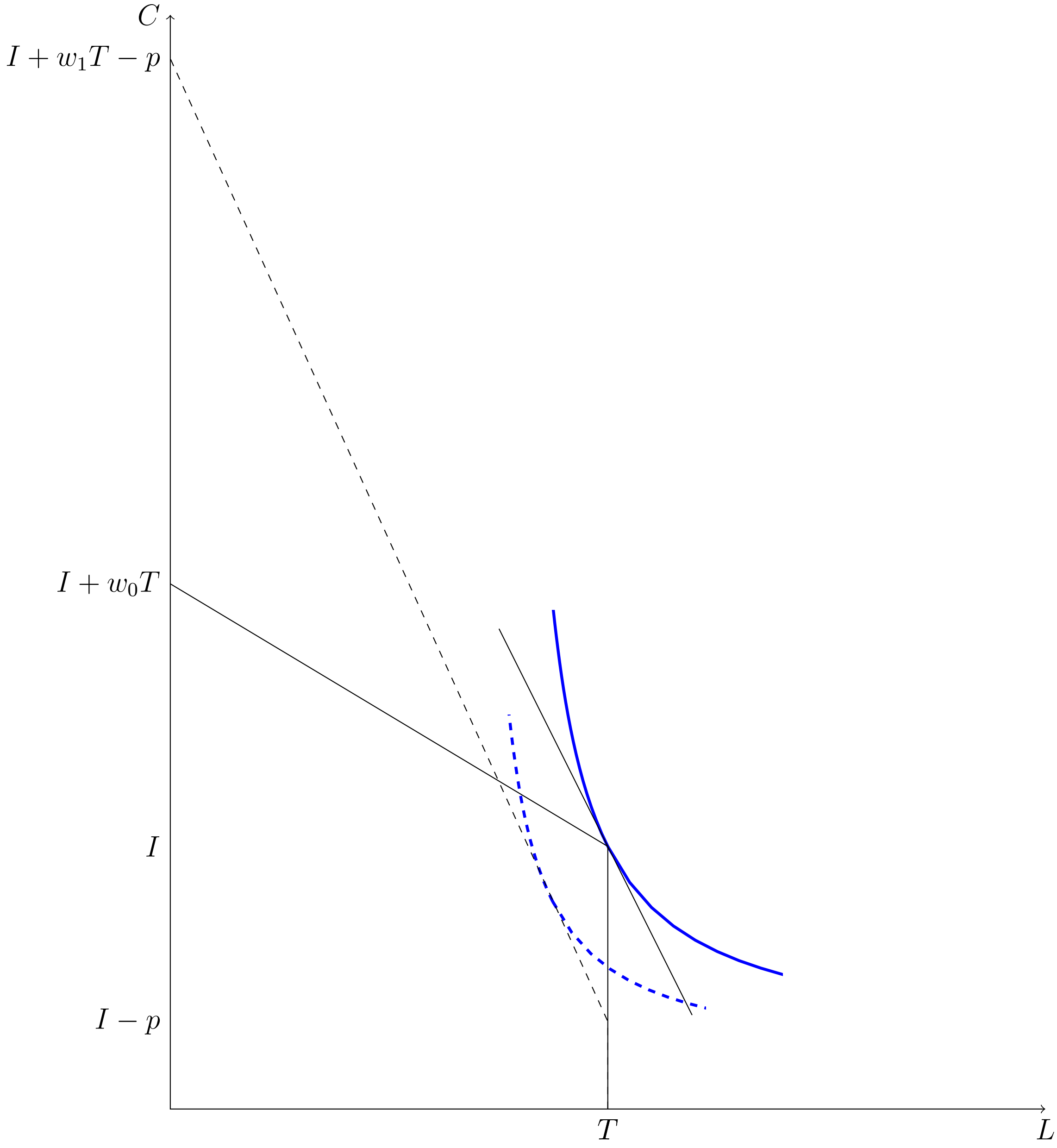
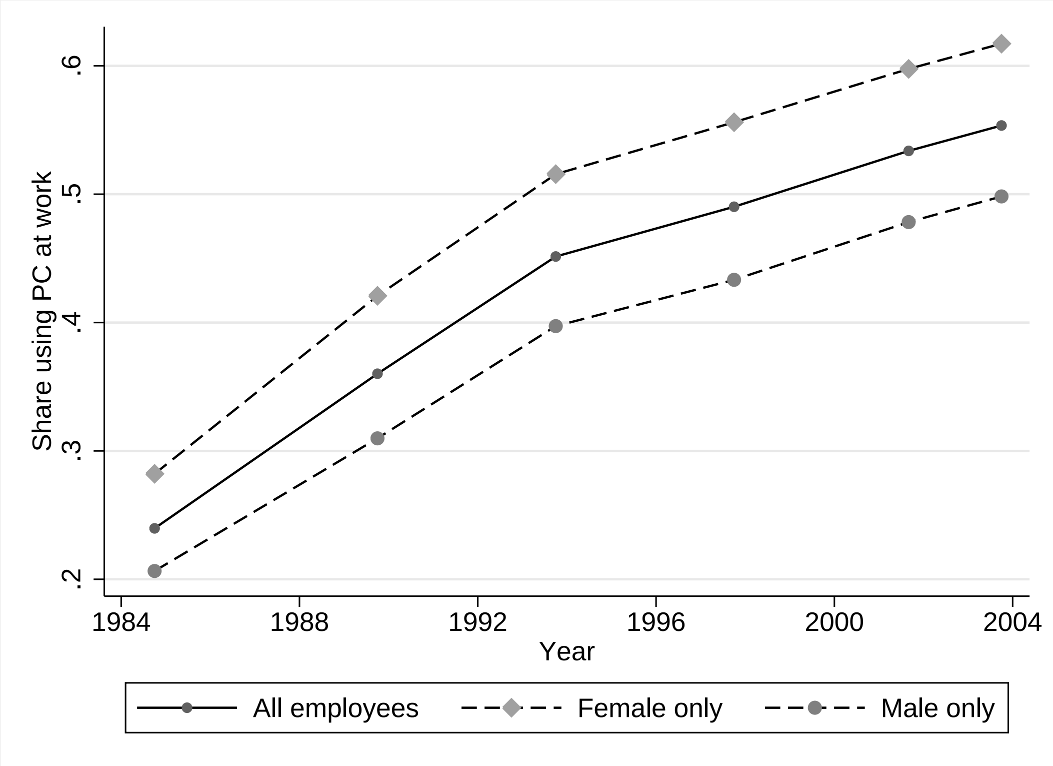


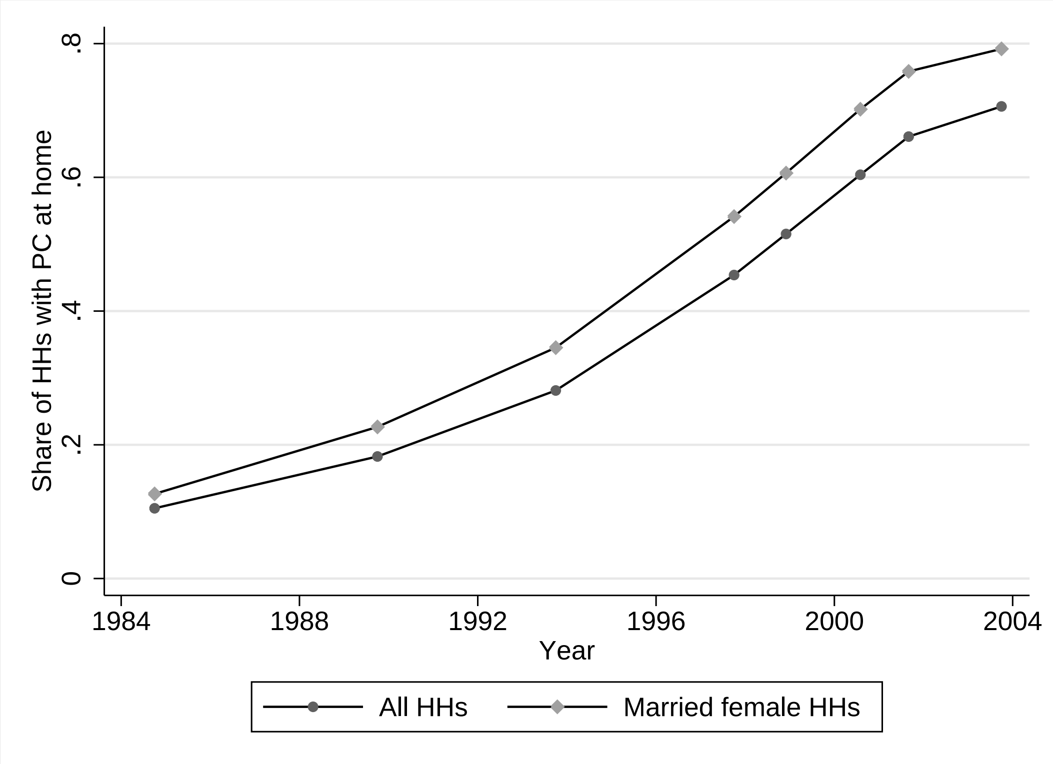
Figure 2: Share of employees using a computer at work



Data source: NBER CPS Supplements Oct. 1984, 1989, 1993, 1997, 2003; Sept. 2001

Solid line depicts share of employees that respond "yes" to the question "Does ... directly use a computer at work?". Dashed lines separate female and male employees. Calculations account for sampling weights.

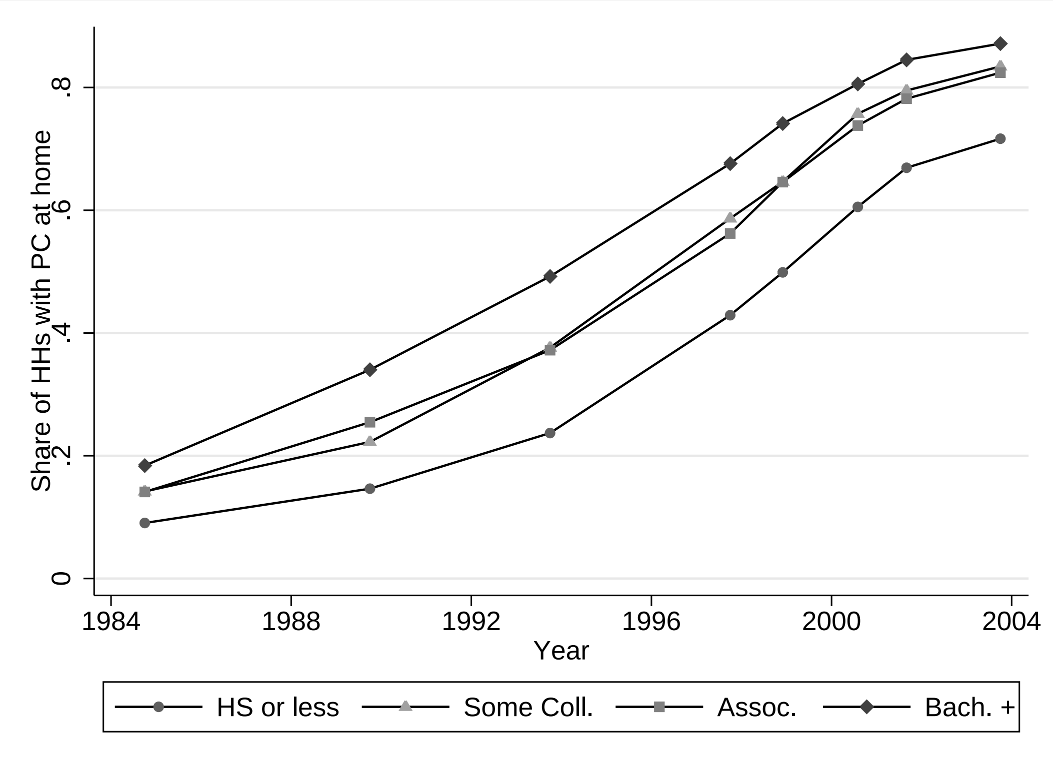
Figure 3: Share of households with access to a computer at home



Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001

Lines depict the share of households that respond “yes” to the question “Is there a computer in this household?” or “Is there a computer or laptop in this household?”. Circles indicate all households, diamonds denote households with at least one married female member. Calculations account for sampling weights.

Figure 4: Share of married women with access to a computer by educational attainment



Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001

Lines depict the share of households with at least one married woman that respond "yes" to the question "Is there a computer in this household?" or "Is there a computer or laptop in this household?". Education levels are aggregated into four categories:

a) High School graduates and High School drop-outs b) Some College c) Associate Degree (both vocational and academic) d) Bachelor's Degree or more (e.g. Master's, Professional Degree, PhD)

Calculations account for sampling weights.

Figure 5: Female employment

Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001

Lines depict the share of 20 to 59 year old women in employment. Circles denote the employment share for all women, diamonds the share of married women. Solid lines are for all households, the dashed line households with a computer. Calculations account for sampling weights.

Tables

Table 1: Sample means and standard deviations

	1984	1989	1993	1997	1998	2000	2001	2003
Women's variables								
Employed	0.593	0.666	0.681	0.708	0.706	0.678	0.690	0.685
	(0.491)	(0.472)	(0.466)	(0.455)	(0.456)	(0.467)	(0.463)	(0.465)
Log hourly wage (cent)	6.462	6.698	6.879	7.004	7.062	7.133	7.185	7.230
	(0.488)	(0.521)	(0.536)	(0.533)	(0.537)	(0.541)	(0.536)	(0.612)
PC share in occ.	0.276	0.431	0.527	0.578			0.619	0.634
	(0.230)	(0.290)	(0.306)	(0.299)			(0.269)	(0.271)
PC at home	0.126	0.221	0.333	0.528	0.597	0.694	0.752	0.786
	(0.332)	(0.415)	(0.471)	(0.499)	(0.491)	(0.461)	(0.432)	(0.410)
PC use	0.053	0.111	0.205	0.380			0.637	0.677
	(0.224)	(0.314)	(0.404)	(0.485)			(0.481)	(0.468)
Age	38.5	38.8	39.5	40.1	40.4	40.9	41.2	41.6
	(10.7)	(10.1)	(9.8)	(9.7)	(9.7)	(9.8)	(9.8)	(9.9)
≤11/No Degree	0.183	0.140	0.117	0.112	0.110	0.105	0.100	0.100
	(0.386)	(0.346)	(0.322)	(0.316)	(0.312)	(0.306)	(0.300)	(0.300)
12/High School	0.476	0.452	0.387	0.354	0.344	0.328	0.326	0.316
	(0.499)	(0.498)	(0.487)	(0.478)	(0.475)	(0.470)	(0.469)	(0.465)
13/Some College	0.072	0.077	0.186	0.184	0.184	0.187	0.178	0.174
	(0.258)	(0.267)	(0.389)	(0.388)	(0.387)	(0.390)	(0.383)	(0.379)
14/Assoc. Vocational	0.079	0.101	0.048	0.048	0.051	0.050	0.056	0.056
	(0.270)	(0.302)	(0.214)	(0.213)	(0.220)	(0.218)	(0.230)	(0.230)
15/Assoc. Academic	0.030	0.031	0.041	0.050	0.047	0.052	0.053	0.053
	(0.171)	(0.174)	(0.197)	(0.218)	(0.213)	(0.223)	(0.224)	(0.224)
16-17/Bachelor's	0.125	0.149	0.157	0.179	0.187	0.196	0.204	0.206
	(0.331)	(0.356)	(0.364)	(0.383)	(0.390)	(0.397)	(0.403)	(0.404)
18≥/Master's or more	0.035	0.050	0.063	0.072	0.077	0.082	0.083	0.095
	(0.184)	(0.218)	(0.243)	(0.259)	(0.267)	(0.274)	(0.276)	(0.293)
White	0.890	0.900	0.896	0.890	0.891	0.883	0.884	0.871
	(0.313)	(0.300)	(0.305)	(0.313)	(0.312)	(0.322)	(0.321)	(0.335)
Black	0.078	0.078	0.078	0.078	0.079	0.085	0.083	0.082
	(0.268)	(0.269)	(0.268)	(0.269)	(0.269)	(0.279)	(0.276)	(0.275)
Other	0.032	0.021	0.026	0.032	0.031	0.032	0.033	0.047
	(0.177)	(0.144)	(0.158)	(0.177)	(0.173)	(0.177)	(0.179)	(0.211)
Alabama	0.018	0.018	0.018	0.018	0.018	0.018	0.017	0.017
	(0.132)	(0.134)	(0.131)	(0.135)	(0.133)	(0.133)	(0.129)	(0.128)
Alaska	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.046)	(0.045)	(0.045)	(0.049)	(0.049)	(0.046)	(0.048)	(0.046)
Arizona	0.013	0.014	0.014	0.017	0.015	0.017	0.019	0.018
	(0.114)	(0.117)	(0.116)	(0.129)	(0.121)	(0.129)	(0.135)	(0.134)
Arkansas	0.008	0.010	0.011	0.009	0.010	0.010	0.010	0.009
	(0.091)	(0.100)	(0.102)	(0.094)	(0.101)	(0.097)	(0.099)	(0.097)
California	0.103	0.101	0.110	0.105	0.108	0.109	0.113	0.113
	(0.304)	(0.301)	(0.313)	(0.307)	(0.310)	(0.312)	(0.317)	(0.317)
Colorado	0.015	0.014	0.014	0.016	0.016	0.016	0.014	0.016
	(0.121)	(0.118)	(0.116)	(0.125)	(0.124)	(0.127)	(0.119)	(0.126)
Connecticut	0.013	0.015	0.013	0.011	0.013	0.012	0.011	0.012
	(0.115)	(0.120)	(0.115)	(0.104)	(0.112)	(0.109)	(0.104)	(0.111)
Delaware	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.052)	(0.054)	(0.054)	(0.051)	(0.051)	(0.053)	(0.053)	(0.052)
District of Columbia	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.036)	(0.037)	(0.033)	(0.031)	(0.026)	(0.033)	(0.033)	(0.030)
Florida	0.041	0.049	0.048	0.048	0.048	0.050	0.053	0.053
	(0.198)	(0.216)	(0.213)	(0.214)	(0.214)	(0.219)	(0.223)	(0.224)
Georgia	0.026	0.025	0.025	0.029	0.030	0.030	0.030	0.031
	(0.158)	(0.157)	(0.155)	(0.168)	(0.170)	(0.172)	(0.171)	(0.174)
Hawaii	0.004	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.067)	(0.047)	(0.048)	(0.049)	(0.047)	(0.047)	(0.048)	(0.046)
Idaho	0.004	0.004	0.005	0.005	0.005	0.005	0.005	0.005
	(0.063)	(0.062)	(0.069)	(0.069)	(0.070)	(0.070)	(0.070)	(0.070)
Illinois	0.050	0.048	0.047	0.044	0.045	0.046	0.045	0.046
	(0.218)	(0.213)	(0.212)	(0.204)	(0.208)	(0.208)	(0.207)	(0.209)
Indiana	0.026	0.025	0.025	0.027	0.026	0.025	0.025	0.024
	(0.158)	(0.155)	(0.156)	(0.163)	(0.158)	(0.155)	(0.156)	(0.152)
Iowa	0.012	0.012	0.012	0.011	0.011	0.012	0.012	0.010
	(0.108)	(0.111)	(0.108)	(0.105)	(0.103)	(0.111)	(0.107)	(0.100)
Kansas	0.010	0.011	0.011	0.009	0.010	0.010	0.010	0.010
	(0.097)	(0.103)	(0.105)	(0.095)	(0.100)	(0.100)	(0.100)	(0.099)

Continued on next page...

... table 1 continued

	1984	**1989**	**1993**	**1997**	**1998**	**2000**	**2001**	**2003**
Kentucky	0.017	0.016	0.016	0.017	0.018	0.016	0.017	0.015
	(0.131)	(0.125)	(0.124)	(0.129)	(0.134)	(0.127)	(0.128)	(0.120)
Louisiana	0.020	0.017	0.016	0.015	0.015	0.015	0.014	0.016
	(0.139)	(0.130)	(0.125)	(0.123)	(0.120)	(0.123)	(0.118)	(0.125)
Maine	0.005	0.005	0.005	0.005	0.005	0.005	0.006	0.004
	(0.072)	(0.074)	(0.072)	(0.070)	(0.067)	(0.073)	(0.074)	(0.066)
Maryland	0.019	0.019	0.019	0.019	0.019	0.018	0.019	0.018
	(0.138)	(0.136)	(0.136)	(0.137)	(0.136)	(0.134)	(0.136)	(0.133)
Massachusetts	0.023	0.023	0.021	0.023	0.022	0.020	0.022	0.022
	(0.150)	(0.151)	(0.144)	(0.151)	(0.146)	(0.139)	(0.147)	(0.147)
Michigan	0.039	0.040	0.038	0.038	0.041	0.038	0.038	0.035
	(0.194)	(0.196)	(0.191)	(0.192)	(0.198)	(0.190)	(0.191)	(0.184)
Minnesota	0.019	0.018	0.016	0.016	0.018	0.019	0.019	0.018
	(0.136)	(0.134)	(0.127)	(0.127)	(0.134)	(0.136)	(0.135)	(0.135)
Mississippi	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.009
	(0.098)	(0.101)	(0.099)	(0.099)	(0.099)	(0.101)	(0.099)	(0.095)
Missouri	0.021	0.021	0.022	0.022	0.020	0.020	0.019	0.020
	(0.143)	(0.144)	(0.146)	(0.146)	(0.141)	(0.140)	(0.137)	(0.140)
Montana	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.056)	(0.056)	(0.054)	(0.055)	(0.054)	(0.057)	(0.054)	(0.052)
Nebraska	0.006	0.007	0.006	0.006	0.006	0.006	0.006	0.007
	(0.075)	(0.081)	(0.079)	(0.078)	(0.077)	(0.075)	(0.077)	(0.081)
Nevada	0.004	0.005	0.005	0.006	0.007	0.007	0.007	0.007
	(0.066)	(0.068)	(0.073)	(0.080)	(0.082)	(0.086)	(0.083)	(0.086)
New Hampshire	0.004	0.005	0.006	0.005	0.005	0.004	0.005	0.005
	(0.067)	(0.071)	(0.075)	(0.068)	(0.071)	(0.067)	(0.068)	(0.070)
New Jersey	0.032	0.030	0.029	0.032	0.030	0.030	0.031	0.031
	(0.175)	(0.171)	(0.169)	(0.175)	(0.170)	(0.170)	(0.174)	(0.174)
New Mexico	0.006	0.006	0.006	0.006	0.007	0.006	0.006	0.007
	(0.080)	(0.079)	(0.079)	(0.079)	(0.081)	(0.076)	(0.078)	(0.081)
New York	0.071	0.067	0.065	0.062	0.060	0.060	0.059	0.057
	(0.257)	(0.250)	(0.247)	(0.242)	(0.237)	(0.237)	(0.237)	(0.231)
North Carolina	0.026	0.028	0.029	0.028	0.028	0.029	0.029	0.030
	(0.161)	(0.166)	(0.167)	(0.166)	(0.166)	(0.169)	(0.167)	(0.171)
North Dakota	0.003	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.051)	(0.049)	(0.046)	(0.048)	(0.048)	(0.045)	(0.045)	(0.049)
Ohio	0.048	0.048	0.048	0.046	0.044	0.044	0.043	0.042
	(0.214)	(0.215)	(0.213)	(0.209)	(0.205)	(0.204)	(0.203)	(0.200)
Oklahoma	0.013	0.014	0.014	0.012	0.012	0.013	0.013	0.013
	(0.115)	(0.118)	(0.117)	(0.111)	(0.110)	(0.115)	(0.112)	(0.113)
Oregon	0.010	0.012	0.012	0.012	0.014	0.012	0.013	0.013
	(0.101)	(0.107)	(0.108)	(0.110)	(0.118)	(0.109)	(0.112)	(0.114)
Pennsylvania	0.053	0.050	0.050	0.046	0.044	0.044	0.043	0.046
	(0.223)	(0.218)	(0.219)	(0.209)	(0.204)	(0.206)	(0.203)	(0.208)
Rhode Island	0.004	0.004	0.003	0.003	0.004	0.003	0.004	0.004
	(0.064)	(0.062)	(0.059)	(0.058)	(0.061)	(0.054)	(0.060)	(0.060)
South Carolina	0.014	0.015	0.015	0.014	0.014	0.016	0.014	0.013
	(0.116)	(0.121)	(0.123)	(0.119)	(0.118)	(0.126)	(0.118)	(0.111)
South Dakota	0.003	0.002	0.003	0.003	0.002	0.003	0.003	0.003
	(0.051)	(0.050)	(0.051)	(0.051)	(0.049)	(0.052)	(0.051)	(0.051)
Tennessee	0.021	0.021	0.020	0.023	0.023	0.022	0.022	0.021
	(0.144)	(0.142)	(0.139)	(0.149)	(0.150)	(0.146)	(0.147)	(0.143)
Texas	0.066	0.069	0.075	0.077	0.076	0.076	0.074	0.079
	(0.249)	(0.253)	(0.263)	(0.267)	(0.265)	(0.265)	(0.262)	(0.269)
Utah	0.008	0.008	0.007	0.009	0.008	0.009	0.009	0.010
	(0.087)	(0.086)	(0.082)	(0.092)	(0.089)	(0.092)	(0.093)	(0.098)
Vermont	0.002	0.002	0.003	0.002	0.002	0.002	0.002	0.002
	(0.048)	(0.047)	(0.051)	(0.048)	(0.046)	(0.047)	(0.045)	(0.043)
Virginia	0.028	0.026	0.025	0.025	0.026	0.026	0.027	0.026
	(0.166)	(0.158)	(0.156)	(0.156)	(0.160)	(0.158)	(0.162)	(0.159)
Washington	0.019	0.019	0.021	0.021	0.023	0.021	0.022	0.023
	(0.138)	(0.137)	(0.144)	(0.143)	(0.149)	(0.143)	(0.145)	(0.149)
West Virginia	0.010	0.009	0.009	0.008	0.008	0.008	0.008	0.007
	(0.097)	(0.096)	(0.093)	(0.091)	(0.088)	(0.088)	(0.087)	(0.085)
Wisconsin	0.020	0.022	0.021	0.022	0.022	0.021	0.021	0.020
	(0.139)	(0.145)	(0.144)	(0.146)	(0.145)	(0.145)	(0.145)	(0.141)
Wyoming	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.048)	(0.044)	(0.044)	(0.045)	(0.044)	(0.043)	(0.043)	(0.043)

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... table 1 continued

	1984	**1989**	**1993**	**1997**	**1998**	**2000**	**2001**	**2003**
MSA	0.624	0.608	0.599	0.657	0.655	0.659	0.661	0.667
	(0.484)	(0.488)	(0.490)	(0.475)	(0.475)	(0.474)	(0.473)	(0.471)
No MSA	0.287	0.220	0.229	0.201	0.204	0.196	0.191	0.188
	(0.452)	(0.414)	(0.420)	(0.401)	(0.403)	(0.397)	(0.393)	(0.391)
MSA not identified	0.089	0.172	0.172	0.142	0.141	0.145	0.148	0.145
	(0.285)	(0.377)	(0.378)	(0.349)	(0.348)	(0.352)	(0.355)	(0.352)
Own home	0.754	0.770	0.778	0.787	0.798	0.811	0.816	0.813
	(0.431)	(0.421)	(0.416)	(0.409)	(0.402)	(0.391)	(0.388)	(0.390)
Home rented	0.229	0.217	0.209	0.201	0.191	0.180	0.174	0.178
	(0.420)	(0.412)	(0.407)	(0.401)	(0.393)	(0.384)	(0.379)	(0.382)
Lives rent free	0.017	0.013	0.013	0.012	0.011	0.009	0.010	0.010
	(0.130)	(0.115)	(0.114)	(0.108)	(0.103)	(0.094)	(0.099)	(0.098)
Spouse's variables								
Weekly earnings (100USD)	3.980	5.241	5.711	6.730	7.106	7.593	7.826	7.955
	(2.685)	(3.788)	(4.309)	(5.032)	(5.561)	(5.940)	(6.221)	(6.532)
No weekly earnings	0.160	0.133	0.155	0.135	0.137	0.138	0.148	0.166
	(0.366)	(0.340)	(0.362)	(0.342)	(0.344)	(0.345)	(0.355)	(0.372)
≤11/No Degree	0.201	0.169	0.134	0.130	0.128	0.123	0.117	0.119
	(0.401)	(0.374)	(0.341)	(0.336)	(0.334)	(0.328)	(0.321)	(0.324)
12/High School	0.380	0.372	0.345	0.319	0.315	0.303	0.308	0.298
	(0.485)	(0.483)	(0.475)	(0.466)	(0.464)	(0.459)	(0.462)	(0.458)
13/Some College	0.062	0.066	0.177	0.179	0.177	0.179	0.172	0.172
	(0.242)	(0.248)	(0.381)	(0.383)	(0.381)	(0.383)	(0.378)	(0.377)
14/Assoc. Vocational	0.088	0.099	0.041	0.046	0.047	0.049	0.051	0.051
	(0.284)	(0.299)	(0.197)	(0.209)	(0.212)	(0.215)	(0.220)	(0.219)
15/Assoc. Academic	0.032	0.033	0.036	0.037	0.039	0.042	0.040	0.041
	(0.175)	(0.180)	(0.186)	(0.189)	(0.194)	(0.201)	(0.197)	(0.198)
16-17/Bachelor's	0.160	0.171	0.173	0.187	0.190	0.193	0.196	0.206
	(0.367)	(0.377)	(0.378)	(0.390)	(0.392)	(0.395)	(0.397)	(0.404)
18≥/Master's or more	0.076	0.090	0.095	0.102	0.105	0.112	0.116	0.113
	(0.265)	(0.286)	(0.293)	(0.303)	(0.307)	(0.315)	(0.320)	(0.317)
Age	41.3	41.6	42.2	42.5	42.9	43.4	43.6	43.9
	(11.8)	(11.2)	(10.9)	(10.7)	(10.6)	(10.7)	(10.6)	(10.8)
Children's variables								
No kids (0–5)	0.701	0.694	0.708	0.714	0.719	0.719	0.732	0.726
	(0.458)	(0.461)	(0.455)	(0.452)	(0.450)	(0.449)	(0.443)	(0.446)
One kid (0–5)	0.199	0.207	0.193	0.198	0.190	0.191	0.180	0.187
	(0.400)	(0.405)	(0.395)	(0.398)	(0.392)	(0.393)	(0.385)	(0.390)
Two kids (0–5)	0.085	0.086	0.085	0.077	0.077	0.077	0.076	0.074
	(0.280)	(0.281)	(0.278)	(0.266)	(0.267)	(0.267)	(0.264)	(0.262)
Three kids (0–5)	0.012	0.012	0.013	0.010	0.012	0.011	0.011	0.011
	(0.109)	(0.107)	(0.114)	(0.100)	(0.108)	(0.103)	(0.104)	(0.106)
Four or more kids (0–5)	0.002	0.001	0.001	0.002	0.002	0.001	0.001	0.002
	(0.048)	(0.038)	(0.039)	(0.041)	(0.044)	(0.037)	(0.037)	(0.043)
No kids (6–15)	0.593	0.606	0.612	0.592	0.595	0.602	0.605	0.602
	(0.491)	(0.489)	(0.487)	(0.491)	(0.491)	(0.490)	(0.489)	(0.490)
One kid (6–15)	0.223	0.213	0.204	0.220	0.216	0.220	0.213	0.214
	(0.416)	(0.409)	(0.403)	(0.414)	(0.411)	(0.414)	(0.409)	(0.410)
Two kids (6–15)	0.138	0.138	0.138	0.140	0.142	0.132	0.135	0.138
	(0.345)	(0.345)	(0.345)	(0.346)	(0.349)	(0.338)	(0.341)	(0.344)
Three kids (6–15)	0.035	0.035	0.035	0.037	0.038	0.037	0.039	0.037
	(0.185)	(0.183)	(0.185)	(0.190)	(0.190)	(0.189)	(0.193)	(0.188)
Four or more kids (6–15)	0.011	0.009	0.010	0.010	0.009	0.009	0.009	0.010
	(0.103)	(0.093)	(0.101)	(0.101)	(0.093)	(0.097)	(0.097)	(0.098)

Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001; MORG 1983–2005

Table 2: Share of women using the available computer

Year	All women	Married women	Married with kids
1984	0.481	.462	.420
1989	0.583	.531	.519
1993	0.663	.632	.625
1997	0.753	.728	.716
2001	0.847	.858	.846
2003	0.864	.876	.858

Share of women that use the available computer for any purpose.
First column shows shares for all 20–59 year old women, second column the share for 20–59 year old women who live with their spouse and the third column refers to 20–59 year old women who live with their spouse and at least one 6–15 year old child.
Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Sept. 2001
Calculation of shares accounts for sampling weights.

Table 3: Home PC availability and Employment

	1984	**1989**	**1993**	**1997**	**1998**	**2000**	**2001**	**2003**
(1a) ∅	0.066	0.074	0.078	0.102	0.112	0.123	0.124	0.153
	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
(1b) Wage	0.002	0.014	0.008	0.027	0.050	0.057	0.064	0.080
	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)
(1c) Income	0.059	0.077	0.072	0.089	0.104	0.113	0.110	0.132
	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)
(1d) b) & c)	0.011	0.029	0.018	0.032	0.054	0.059	0.063	0.074
	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)
(1e) d) & Kids)	0.014	0.027	0.016	0.029	0.056	0.060	0.060	0.069
	(0.011)	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)
N	20,885	19,421	18,735	16,287	16,107	16,225	19,249	18,401

OLS regressions (weighted to account for sampling probabilities) with employment (0/1 dummy) as dependent variable. The table shows the coefficient estimate on a dummy that indicates that the household owns a computer (or laptop) with the coefficient's heteroscedasticity robust standard errors below (in parenthesis).
Upper panel reports results for all 20–59 year old women, lower panel reports results for 20–59 year old women who live with their spouse.
Specification a) does not include any controls.
Specification b) includes controls for education (dummies), age, age squared, race (white, black, other dummies) state dummies and msa dummies.
Specification c) includes controls for husband's weekly earnings, weekly earnings squared, a dummy if the husband does not have any earnings and a home ownership dummy.
Specification d) combines b) and c).
Specification e) adds dummies for the number of 0–5 and 6–15 year old children in the household, husband's education (dummies), age, age squared.
Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001; MORG 1983–2005

Table 4: Home PC use and Employment; Heterogenous impact of home PC availability

	1984	**1989**	**1993**	**1997**	**1998**	**2000**	**2001**	**2003**
(1'a) ∅	0.046	0.049	0.053	0.076	0.095	0.096	0.105	0.132
	(0.012)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	(0.010)	(0.012)
(1'c) Income	0.059	0.068	0.062	0.080	0.099	0.103	0.108	0.120
	(0.012)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)
N	17,518	16,821	15,816	14,078	13,897	13,972	16,497	15,414
(2e) PC use & all	0.026	0.041	0.039	0.035			0.051	0.055
	(0.016)	(0.011)	(0.009)	(0.008)			(0.009)	(0.009)
N	20,809	19,305	18,518	16,282			19,235	18,377
(3e) ≤11/No Degree	0.034	0.145	0.040	0.107	0.062	0.094	0.099	0.092
	(0.048)	(0.045)	(0.043)	(0.034)	(0.031)	(0.030)	(0.027)	(0.028)
(3e) 12/High School	-0.004	0.041	0.021	0.040	0.065	0.080	0.051	0.062
	(0.017)	(0.014)	(0.014)	(0.013)	(0.014)	(0.015)	(0.015)	(0.016)
(3e) 13/Some College	0.030	0.041	0.017	-0.010	0.026	0.021	0.060	0.012
	(0.037)	(0.027)	(0.018)	(0.018)	(0.019)	(0.021)	(0.023)	(0.025)
(3e) 14/Assoc. Vocational	0.048	-0.035	0.004	0.043	0.045	0.039	0.063	0.122
	(0.032)	(0.024)	(0.030)	(0.032)	(0.032)	(0.038)	(0.040)	(0.048)
(3e) 15/Assoc. Academic	0.055	-0.013	0.046	0.043	0.039	0.009	0.000	0.106
	(0.055)	(0.042)	(0.035)	(0.033)	(0.034)	(0.040)	(0.043)	(0.051)
(3e) 16-17/Bachelor's	-0.005	0.009	-0.001	-0.000	0.077	0.038	0.042	0.090
	(0.023)	(0.018)	(0.017)	(0.017)	(0.021)	(0.025)	(0.027)	(0.032)
(3e) 18≥/Master's or more	0.074	0.050	0.014	0.062	0.057	0.082	0.154	0.119
	(0.032)	(0.026)	(0.024)	(0.031)	(0.032)	(0.045)	(0.053)	(0.055)
N	20,885	19,421	18,735	16,287	16,107	16,225	19,249	18,401

OLS regressions (weighted to account for sampling probabilities) with employment (0/1 dummy) as dependent variable. Upper panel replicates specifications (1c) and (1e) in table 3 omitting women with husbands that report zero earnings. The middle panel of the table shows the coefficient estimate on a dummy that indicates that the woman uses the available computer (or laptop). The lower panel show the coefficients of the interaction of a set of dummies for educational attainment and a dummy that indicates that the household owns a computer (or laptop). Educational attainment in 1984 and 1989 is measured in (completed) years of education and in terms of highest degree obtained thereafter. Below the coefficients the table reports heteroscedasticity robust standard errors (in parenthesis).
All regressions in both panels include the same covariates as in specification e) in table 3. Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001; MORG 1983–2005

Table 5: Home PC and (log) hourly wage

	1984	1989	1993	1997	1998	2000	2001	2003
(1) PC available	0.018	0.047	0.064	0.100	0.089	0.863	0.086	0.098
	(0.014)	(0.012)	(0.011)	(0.010)	(0.011)	(0.012)	(0.012)	(0.015)
	[0.053]	[0.405]	[0.042]	[0.001]	[0.000]	[0.048]	[0.000]	[0.149]
N	20,885	19,421	18,735	16,287	16,107	16,225	19,249	18,401
(2) PC used	0.041	0.088	0.077	0.117			0.099	0.099
	(0.021)	(0.015)	(0.013)	(0.011)			(0.011)	(0.013)
	[0.050]	[0.400]	[0.010]	[0.000]			[0.000]	[0.160]
N	20,809	19,305	18,518	16,282			19,235	18,377
(3) $\leq$11/No Degree	0.121	0.076	0.063	0.099	0.107	0.114	0.083	0.130
	(0.063)	(0.068)	(0.063)	(0.041)	(0.042)	(0.035)	(0.035)	(0.043)
(3) 12/High School	0.024	0.036	0.099	0.138	0.090	0.099	0.076	0.109
	(0.021)	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.023)
(3) 13/Some College	0.046	0.050	0.076	0.073	0.103	0.054	0.130	0.109
	(0.044)	(0.037)	(0.025)	(0.022)	(0.027)	(0.025)	(0.030)	(0.037)
(3) 14/Assoc. Vocational	0.054	0.016	0.047	0.033	0.077	0.017	0.079	-0.002
	(0.041)	(0.033)	(0.044)	(0.039)	(0.043)	(0.049)	(0.049)	(0.057)
(3) 15/Assoc. Academic	-0.093	-0.079	0.052	0.045	0.105	0.114	0.008	0.172
	(0.076)	(0.067)	(0.046)	(0.051)	(0.047)	(0.058)	(0.050)	(0.072)
(3) 16-17/Bachelor's	-0.048	0.084	0.051	0.086	0.060	0.088	0.079	0.040
	(0.033)	(0.025)	(0.024)	(0.025)	(0.029)	(0.038)	(0.034)	(0.042)
(3) 18$\geq$/Master's or more	0.089	0.091	-0.045	0.129	0.088	0.111	0.102	0.053
	(0.046)	(0.038)	(0.040)	(0.050)	(0.056)	(0.084)	(0.072)	(0.093)
	[0.050]	[0.380]	[0.030]	[0.000]	[0.000]	[0.000]	[0.000]	[0.110]
N	20,885	19,421	18,735	16,287	16,107	16,225	19,249	18,401

Heckman selection model estimations (weighted to account for sampling probabilities) with the log of hourly wages as dependent variable. The table shows the coefficient estimate on a dummy that indicates that the household owns a computer (or laptop) with the coefficient's heteroscedasticity robust standard errors below (in parenthesis). In brackets the table reports the p-value of a test for statistical significance of the selection term.
First panel reports results for pc ownership, second panel for PC use, and the third panel shows the coefficients for pc ownership interacted with education.
The estimates include controls for for education (dummies), age, age squared, race (white, black, other dummies) state dummies and msa dummies in both the selection and the wage equation. Husband's education (dummies), age, age squared, weekly earnings and weekly earnings squared, a dummy if the husband does not have any earnings, a home ownership dummy, and dummies for the number of 0–5 and 6–16 year old children in the household are used in the selection equation only.
Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001; MORG 1983–2005

Table 6: Home PC and PC use in occupation

	1984	1989	1993	1997	1998	2000	2001	2003
(1) PC available	0.015	0.031	0.057	0.076			0.050	0.025
	(0.006)	(0.006)	(0.006)	(0.006)			(0.010)	(0.009)
	[0.000]	[0.000]	[0.030]	[0.190]			[0.000]	[0.000]
N	20,885	19,421	18,735	16,287			19,249	18,401
(2) PC used	0.036	0.069	0.075	0.087			0.092	0.040
	(0.009)	(0.008)	(0.007)	(0.006)			(0.019)	(0.007)
	[0.000]	[0.000]	[0.020]	[0.140]			[0.840]	[0.000]
N	20,809	19,305	18,518	16,282			19,235	18,377
(3) ≤11/No Degree	0.003	0.068	0.098	0.044			0.100	-0.022
	(0.019)	(0.031)	(0.035)	(0.024)			(0.021)	(0.029)
(3) 12/High School	0.024	0.051	0.091	0.115			0.098	0.047
	(0.011)	(0.011)	(0.012)	(0.011)			(0.012)	(0.014)
(3) 13/Some College	0.005	-0.007	0.055	0.087			0.078	0.043
	(0.021)	(0.022)	(0.014)	(0.014)			(0.016)	(0.020)
(3) 14/Assoc. Vocational	0.011	0.005	0.031	0.053			0.072	-0.033
	(0.022)	(0.017)	(0.023)	(0.022)			(0.028)	(0.033)
(3) 15/Assoc. Academic	-0.012	-0.019	0.018	0.091			0.030	0.022
	(0.024)	(0.029)	(0.028)	(0.025)			(0.024)	(0.037)
(3) 16-17/Bachelor's	0.007	0.025	0.023	0.008			0.040	0.029
	(0.011)	(0.011)	(0.011)	(0.011)			(0.014)	(0.023)
(3) 18≥/Master's or more	0.028	0.042	0.037	0.043			0.051	-0.005
	(0.018)	(0.015)	(0.014)	(0.014)			(0.037)	(0.032)
	[0.000]	[0.000]	[0.030]	[0.170]			[0.530]	[0.000]
N	20,885	19,421	18,735	16,287			19,249	18,401

Heckman selection model estimations (weighted to account for sampling probabilities) with the share of computer users in the woman's occupation as dependent variable. The table shows the coefficient estimate on a dummy that indicates that the household owns a computer (or laptop) with the coefficient's heteroscedasticity robust standard errors below (in parenthesis). In brackets the table reports the p-value of a test for statistical significance of the selection term.

First panel reports results for pc ownership, second panel for PC use, and the third panel shows the coefficients for pc ownership interacted with education.

The estimates include controls for for education (dummies), age, age squared, race (white, black, other dummies) state dummies and msa dummies in both the selection and the wage equation. Husband's education (dummies), age, age squared, weekly earnings and weekly earnings squared, a dummy if the husband does not have any earnings, a home ownership dummy, and dummies for the number of 0–5 and 6–16 year old children in the household are used in the selection equation only.

Data source: CPS Oct. 1984, 1989, 1993, 1997, 2003; Dec. 1998; Aug. 2000; Sept. 2001; MORG 1983–2005

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