Computer Adoption and Diffusion at the Bottom of the U.S. Labor Market: Disentangling the Effects of Skills and Wages on Computer Use*

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12 September 2005

Abstract

This research presents estimates of the determinants of computer technology adoption at the bottom of the skill distribution. Using data from the October Supplements to the Current Population Surveys, we present evidence that computer adoption at the bottom of the labor market is mainly driven by differences in wages and that the role of education in determining computer use is absent. Using instrumental variables for both wages and education we show this effect to be economically important and statistically significant. The implications of this result are important because it suggests no direct relationship between skills and computer technology use at work, an argument often used by policy makers to emphasize the importance of investing in computer literacy and to prepare for working in the "new economy".

* We would like to especially thank Josh Angrist and David Autor for extremely helpful discussions and comments. In addition, we would like to thank David Lee for sharing his data on U.S. state minimum wages. Finally, we both acknowledge financial support from the Netherlands Organization for Scientific Research.

1. Introduction

During the period of rapid diffusion in the 1980s computer technology use at work was mainly concentrated among relatively high-educated workers. This observation has been interpreted as evidence for the importance of computer skills and other skills to use computer technology. Computer technology has been viewed intrinsically complementary with more-skilled labor, so firms with a higher educated and more expensive workforce more heavily adopt computer technology because their workforce adapts more easily to the new technology. However, since the 1990s also a considerably large fraction of the relatively unskilled workforce uses computer technology. For instance, computer use at work for high school graduates increased from 20.3 percent in 1984 to 39.8 percent in 1997. An argument to explain the rise in computer use among relatively unskilled workers is that the costs of using computer technology have fallen considerably over time, which has made computer use also beneficial to less expensive and unskilled workers. In this research we address the questions whether wages are a determinant of computer technology use and to what extent the adoption of computer technology is related to the skill level of the relatively unskilled workers.

To answer these two questions we estimate the determinants of computer technology use in the United States for workers with less than a college degree using the School Enrollment Supplements to the October Current Population Surveys in 1984, 1989, 1993 and 1997. To estimate the determinants of computer technology use we exploit regional differences in federal minimum wages as instruments for individual workers' hourly wages. Since federal minimum wages especially affect relatively low-paid workers, this is an effective instrument for hourly wages of relatively unskilled workers. Instrumenting wages might increase the bias in related variables in case of measurement error. We therefore also instrument a worker's years of education with the years of education of his or her spouse. Besides wages and level of education, the regression analysis also includes the usual worker background controls. Our empirical findings show that wages are the main determinant of computer technology use at work for the relatively unskilled part of the workforce in the United States. Years of education do not significantly contribute to the probability of using computer technology for this group of workers. Exploiting several splits of the sample into different educational categories, computer-intensive industries and splits by gender confirm this pattern. The results imply that the view in which relatively high-wage firms adopt computer technology more intensively seems to apply better to the bottom of the U.S. labor market than the view in which computer skills or other skills are a main determinant of computer use. This finding does not primarily have implications for the literature on skillbiased technological change, since irrespective of the mechanism the adoption patterns shift demand for labor towards more-skilled workers. Our findings are of central relevance to educational policies though, because the estimates suggest that education does not matter for computer use. To promote the use of new technologies the price of the equipment compared to the wages, rather than the skills of the workers, are the key determinant.

We proceed as follows. Section 2 presents the theoretical background and summarizes the main findings of previous studies. We also discuss the empirical strategy of exploiting regional differences in federal minimum wages as instruments for individual workers' hourly wages. In Section 3 we describe the most salient details of the data and present some descriptive statistics. In Section 4 we present the empirical framework and the estimation results of the determinants of computer technology use at the bottom of the labor market in the United States. We end with a conclusion in Section 5.

2. Technology Adoption and Diffusion

2.1. Theoretical Background

Nelson and Phelps' (1966) theory of technology adoption and diffusion provides a simple framework for interpreting the determinants of computer technology adoption and diffusion in the workplace. They focus on the role of education in technology adoption and argue that a higher educated manager will adopt new technology quicker because he is more able to adapt to the changes brought about by technological change. Greenwood and Yorukoglu (1997) and Caselli (1999) also put forward this argument and show that if educated workers face lower adoption costs computer technology will be assigned to educated workers.[1] These models assume technology-skill complementarity to explain the adoption of new technologies and provide some suggestive evidence for the diffusion of innovations among farmers (Nelson and Phelps) and computer adoption in U.S. sectors of industry (Caselli).

Acemoglu (1998) takes a different route to integrate technology adoption into labor-market analysis. He argues that technological change is endogenously directed towards labor inputs that are most widely available, exploiting a demand-pull argument. The increase in college-educated workers since the 1960s in the United States has made the development of technologies complementing this type of workers more profitable. This has increased the demand for college-educated workers and in the end driven up their prices. While this theory

[1] See Acemoglu (2002) and Hornstein, Krusell and Violante (2005) for detailed overviews of these models.

offers a very attractive story of technology development in both the 19th and 20th century, it is unclear how it could be related to computer adoption because relatively low-skilled workers also use computer technology heavily.

David (1969) advances the idea that agents adopt new technologies to replace older technologies when the costs equal the gains. The costs of adopting new technologies include the replacement of the old technology by the new one, investments in learning, the specific tasks the new technology is used for and so on. Most importantly, they also include the wage costs saved from using the new technology because production becomes more efficient. Borghans and ter Weel (2004) develop this argument further for the adoption of computer technology and their model shows that (i) the importance of the tasks for which computer technology is used (as emphasized by Autor, Levy and Murnane, 2003) and (ii) the wage costs saved because of efficiency gains. Hence, a firm gains more by letting a high-wage worker carry out this task using a computer. This result is consistent with the evidence that computer users earn higher wages both prior to and after adoption.[2] What is most interesting about this theoretical approach is that it reverses the causality between wages and computer use assumed by others because higher wages induce the adoption of efficiency enhancing technologies.

These theoretical approaches can be summarized in one straightforward computer adoption equation. Suppose that there are computer tasks in all jobs and that the annual per worker costs of computer technology use equal V, which is the same for all workers. In addition, assume that computer use reduces the time needed to perform a job by k_i. This efficiency gain could depend on worker i's skills or level of education, $k_i(s_i)$. If worker i earns wages w_i, computer adoption is profitable once $w_i k_i(s_i) > V$. Now, workers earning higher wages adopt computers earlier than workers earning lower wages because V is lower in terms of their individual wages. Autor, Katz and Krueger (1998) report computer investments per full time equivalent worker to be $2,545 in 1990, which is equivalent to approximately $5,000 per full time equivalent computer user.[3] This figure makes up a substantial part of the average U.S. worker's annual wage and might explain why computer use is profitable for higher earning workers and not (yet) for workers with relatively low wages. In addition, workers with more computer skills or workers with higher levels of education might experience a larger efficiency gain k if this gain is increasing in s. The wage and skill mechanism to

[2] In addition, computer adoption induces skill upgrading because of a reemphasis on the non-routine job activities at the expense of routine tasks.
[3] Figures for 1960, 1970 and 1980 yield comparable investments per full-time equivalent computer user.

explain computer adoption and diffusion are very different in nature. The first explains computer adoption as a way to save on wage costs, while the second explains adoption by emphasizing skill differentials between workers. Empirically it is not trivial to disentangle wages and skills, since an increase in skills will typically also increase wages. Particularly when part of the skills remains unobserved in *s*, but is reflected in the wages and wages are measured with measurement error, identification requires an instrumental variables research strategy.

2.2. Previous Research on Computer Technology Adoption and Diffusion

Most empirical research on the labor-market impact of computer technology adoption and diffusion looks at the effects of computer use on wages and labor demand. The body of quantitative evidence on the relationship between wages and computer use indeed suggests a strong link. The most influential study in this respect is Krueger's (1993) study for the United States in the period 1984-1989. He argues that "[a] variety of estimates suggest that employees who directly use a computer at work earn a 10 to 15 percent higher wage rate. Furthermore, because more highly educated workers are more likely to use computers on the job, the estimates imply that the proliferation of computers can account for between one-third and one-half of the increase in the rate of return to education observed between 1984 and 1989" (pp. 54-55). This research has induced many studies revealing similar findings for other countries.

Other studies of computer technology diffusion effects on wages and labor demand include Bartel and Lichtenberg (1987), Doms, Dunne and Troske (1997), Autor, Katz and Krueger (1998) and Chun (2003). These studies use firm-level or industry-level information and present correlations between wages and computer use and between labor demand and computer technology adoption rates. Bartel and Lichtenberg (1987) show a positive correlation between new technology adoption and the relative level of education of an industries' workforce. Doms, Dunne and Troske (1997) present suggestive evidence of a positive link between the level of education of a firm's workforce and computer adoption but do not find evidence that firms adopting new technologies are increasing labor demand towards higher educated workers. Autor, Katz and Krueger (1998) suggest a strong link between computerization and skill upgrading at the industry level over the period 1940-1996 by showing that skill upgrading has been particularly concentrated in computer-intensive industries. Finally, a recent paper by Chun (2003) decomposes the Autor, Katz and Krueger findings into a computer adoption and use effect. He finds that two-thirds of the effect of computerization on skilled labor demand can be attributed to computer use. A study by Autor, Levy and Murnane (2003) also extends the Autor, Katz and Krueger findings by investigating what it is what computers do. They find that computer technology use complements workers in performing non-routine problem solving and complex communications tasks.

A number of empirical papers argue that selection processes are at work determining computer adoption among high-skilled workers first. For example, Entorf and Kramarz (1997) and Entorf, Gollac and Kramarz (1999) find in estimates for a panel of French workers in the 1980s and 1990s that computer-adopting workers do not experience a substantial discontinuity in their wages when they compare wages before and after adoption. Their findings suggest only a modest (1-2 percent) rise in the slope of earnings over time. Chennells and Van Reenen (1997) report similar findings for a panel of U.K. workers in the early 1990s. These results seem to suggest that high-wage workers adopt computers first and that their productivity is rising relatively modestly after adoption, which is reflected in a somewhat steeper wage profile. A study by Lewis (2005) seems to point into this direction as well. Using plant level data from the Surveys of Manufacturing Technology, he shows how exogenous variation in the supply of unskilled labor affects that adoption of computer technologies by firms. His estimates suggest that the supply of labor is likely to determine the diffusion of computer technologies and not the other way around.

Hence, computerization has induced skill upgrading, and relatively higher skilled workers have adopted the computer technology in the 1980s. The remaining unanswered question is whether these workers adopted computer technology because of their skill advantages over others or because of their higher wage costs.

2.3. Empirical Strategy

Differences in state minimum wages may provide an experiment for the study of the relationship between computer technology use and wages. Lee (1999) has shown that regional variation in federal minimum wages in the United States can account for a substantial part in explaining wage differences in the lower tail of the wage distribution. We exploit regional differences in the federal minimum wage to address the causality of the relationship between computer use and wages for relatively low-skilled workers, by applying the state's minimum wage as an instrument for an individual worker's hourly wage.

The minimum wages is known to affect the whole bottom part of the wage distribution but its influence diminishes when moving up the wage hierarchy (Lee, 1999). To capture the effect of the minimum wage on hourly wages adequately we include, besides the log of the state's minimum wage itself, the interaction between the worker's level of work experience and experience squared and the state's minimum wage, the interaction between the worker's years of education and the state's minimum wage, and the interaction between education, experience and the state's minimum wage to instrument the worker's log hourly wages.

Besides using instrumental variables for wages, a worker's years of education are also instrumented. The reason for doing so is that the instruments for hourly wages are likely to bias the estimates for years of education. This has been suggested by Griliches (1977) who argues that to tackle this problem education should be instrumented as well. We use a worker's spouse years of education as an instrument for the worker's years of education.

3. Data and Descriptive Statistics

The data we use are taken from the October School Enrollment Supplements to the Current Population Surveys in 1984, 1989, 1993 and 1997. We only use individuals that were employed during the survey aged 18-65. Since we focus on the bottom part of the labor market only workers with less than a college degree are included in our sample for empirical analysis. In the empirical analysis we control for a number of standard worker background characteristics, such as years of education, experience, gender, marital status, race, hours worked, and whether a person is living in a metropolitan area or not. The means and standard deviations of these characteristics by sample year are presented in an Appendix Table A1.

Computer use is defined as answering yes to the question "do you use a computer directly at work?".[4] Table 1 reports computer use by gender and level of education for each of the four years; standard deviations are reported in squared brackets. The first columns report computer use at work for all workers. Computer use is increasing from 26.1 percent in 1984 to 54.8 percent in 1997, with women using computer technology more often than men, which is likely to be the result of women working in occupations more subject to computerization than men (e.g., Weinberg, 2000). Restricting the sample first to workers with less than a college degree and second to workers with a high school degree or less shows that the levels of computer use are lower but still prominently present. For workers with a high school degree or less computer use rises from 16.0 percent to 34.3 percent in the period 1984-1997, which is similar to the rise in computer technology use among the total workforce. For the

[4] Although this question does not necessarily pick up all computer use, it most likely includes the most prominent applications of computer technology at the workplace. See Katz (2000) for a brief discussion of the consequences of defining computer use in this way. In a cross-country and cross-survey comparison of computer technology use at work Borghans and ter Weel (2005) show that the question asked in the CPS does not lead to large differences in computer use compared to other countries and to e.g., the High School and Beyond Survey.

group of workers with less than a college degree the increase in computer technology use is even stronger, from 20.6 percent in 1984 to 45.1 percent in 1997. Again computer technology use at work is higher for women than for men. These numbers suggest that our analysis of explaining the determinants of computer technology adoption is dealing with a substantial group of workers present in a computer-adopting labor market.

The data on federal and state minimum wages is the same as used by Lee (1999). Information on state minimum wages is annually published in the *Monthly Labor Review* in January and we have checked the exact month to exclude changes in minimum wage laws after September. We have excluded Washington DC from our analysis.

4. Empirical Analysis

4.1. Empirical Framework

We estimate the determinants of computer use as a function of wages, skills and other worker background characteristics detailed in Table A1 in the Appendix. Skills are defined as the worker's years of education. The individual worker's probability to use computer technology at work at time t then equals

$$\Pr(C_{i,t}) = f(HW_{i,t}, EDUC_{i,t}, X_{i,t})$$

where $C_{i,t}$ is 1 if individual worker i uses a computer in year t, $HW_{i,t}$ is the worker's wage, $EDUC_{i,t}$ is the workers years of education and $X_{i,t}$ includes a vector of worker background characteristics. Since both wages and education are endogenous and/or subject to measurement error we use a 2SLS approach in which wages are instrumented by a set of variables including the state's minimum wage level and in which education is instrumented by the years of education of the worker's spouse.

We estimate the following equations linearly. The second-stage equation is

$$C_{i,t} = A + b_1 HW_{i,t} + b_2 EDUC_{i,t} + b_3 X_{i,t} + T + S + e_{i,t},$$

in which $X_{i,t}$ also includes an interaction term of education and experience. T includes time dummies for the four years 1984, 1989, 1993 and 1997 and S includes state dummies. Finally, $e_{i,t}$ is the error term with the usual assumptions.

The first-stage equation is

$$\begin{aligned} HW_{i,t} = {} & B + g_1 MW_{j,t} + g_2 MW_{j,t} * EDUC_{i,t} + g_3 MW_{j,t} * EXPER_{i,t} + \\ & g_4 MW_{j,t} * EXPERSQ_{i,t} + g_5 MW_{j,t} * EDUC_{i,t} * EXPER_{i,t} + g_6 EDUC_{i,t} + \\ & g_7 X_{i,t} + T + S + f_{i,t}, \end{aligned}$$

where $MW_{j,t}$ is the log of the minimum wage in state j at time t, and $EXPER_{i,t}$ is the worker's years of working experience and $EXPERSQ_{i,t}$ the squared term divided by 100. Again $X_{i,t}$ also includes an interaction term of education and experience.

A potential concern when estimating the relationship between minimum wages and wages with fixed effects for years and states for the period 1984-1997, as we do, is that during this period the returns to education increased substantially. To cope with this change we include separate educational variables for each year in the specification of the first and second stage of the 2SLS. If we do not include separate educational variables by year the second-stage results do not change but the first-stage results are more plausible when doing so.

4.2. Estimation Results

Table 2 reports the estimates of the determinants of computer technology for workers with less than college education for the pooled sample of all four years for which we have data. We report both the first-stage and second-stage regression results. The first row of the table indicates the selection of the group of workers we use in the estimation, the second row shows whether the estimates are OLS or 2SLS and the third row indicates which variables have been instrumented. The standard errors reported in all tables in the paper have been adjusted for state-year clustering. Standard errors are comparable when using state clustering only. F-tests for the joint significance of the instruments always exceed the critical value of 10, as suggested by Staiger and Stock (1997).

Columns (1a-1c) report OLS estimates of the determinants of computer use. In column (1a) the determinants of computer use have been estimated using the worker's years of education and a set of control variables, such as years of experience (squared/100), gender, marital status (married=1, unmarried=0), number of hours worked per week, race (white=1, black=0), whether a person is living in a metropolitan area or not, and a battery of state, occupation and year dummies. The estimates suggest that an additional year of education increases the probability of computer use by 3.6 percent, and that computer use is decreasing in worker experience. Women are 5.8 percent more likely to use computer technology than men, and computer technology use at work is also increasing in the number of hours worked, being white and living in a large city.[5] The estimates in column (1b) show the effect of adding the log hourly wages to predicting the determinants of computer use. The estimate for log hourly wages suggests that the probability of computer use is increasing with wages. The

[5] We have experimented with including dummies for part-time working status. The results suggest that part-time workers are less likely to use computers than full-time workers, defined as those workers working weekly on average 36 hours or more.

coefficient on years of education drops to 2.6 percent when adding log hourly wages to the equation. Finally, the results reported in column (1c) report results from estimating the determinants of computer use allowing for education to have a different impact on computer use in every year. The estimates are generally comparable to the ones presented in column (1b). The coefficients on years of education suggest a larger impact of years of education on computer adoption the further in time we move.

Columns (2-5b) in Table 2 report 2SLS estimates for various specifications. In column (2) we report first-stage and second-stage results for married workers with using the set of minimum wage variables to instrument log hourly wages. Column (3) reports results of our most preferred specification in which we instrument both log hourly wages and years of education (by the years of education of the worker's spouse). Column (4a) and (4b) report variants of our most preferred specification instrumenting log hourly wages only and estimating the determinants of computer use for all workers not just married ones (4b). Finally, columns (5a) and (5b) display estimates of the determinants of computer use for women and men separately. In general, the first-stage results using log hourly wages as the dependent variable show a positive relationship between measures of minimum wages and log hourly wages. Also more years of education exert a positive impact on log hourly wages and experience is concave in wages. Finally, female workers earn substantially lower wages, while married workers, whites, those working more hours, and those living in metropolitan areas earn higher wages. These estimates from the first-stage wage regression analyses are standard results to the literature.

The second-stage estimates of the determinants of computer use are our core results. The results suggest a strong positive causal relationship between wages and computer use suggesting that higher log hourly wages increase the probability of computer use significantly. When doubling the wages, the probability of computer use increases by between 95.1 and 170.4 percent for the samples of married and all workers. What is interesting to note from the results shown in columns (5a) and (5b) is that the effect is much stronger for women than it is for men. The second important observation from the second-stage results is that skills, measured by a worker's years of education and level of experience, do not contribute to the probability of computer use. If anything, higher levels of skills lower the probability of computer use. Note that instrumenting years of education by the years of education of the spouse increases the negative coefficient obtained for education (compare (3) to (4a) and (4b)). Together the estimates for wages and skills provide evidence in favor of the theory that wage costs are the main determinant for the adoption of computer technology. The hypothesis that skills have a separate impact on computer adoption is rejected by these estimates.

The coefficients on gender are consistent with the estimates presented by Weinberg (2000), who also shows that women are more likely to use computers than men. He argues that this is likely an industry or occupation effect because women tend to be employed in jobs deemphasizing physical strength and stamina and in the more service-oriented industries. Finally, the coefficients on marital status, number of weekly hours worked, race and living in a city do generally not significantly contribute to the determinants of computer use.

In Table 3 we repeat the same analysis but now restrict the sample to those workers with a high school education or less. A priori we expect the instruments for log hourly wages to work more effectively the further we move down to the bottom of the wage distribution. Indeed, F-tests of the joint significance of the minimum wage instruments for this sample are higher than for the sample including those workers with some college education. The results reported in Table 3 are generally similar to the coefficients reported in Table 2 with wages being the main determinant of computer use and skills being unimportant. Together the results in Table 2 and 3 are also consistent with the findings of Lewis (2005) for the effects of exogenous increases in low-skilled labor supply on computer adoption. He focuses on quantities, whereas we show there is a price effect as well.

Finally, in Table 4 we report estimates for relatively computer-intensive sectors. The main reason for doing so is that the difference in the coefficients on the log hourly wages for men and women in the 2SLS estimates is relatively large. This might be the result of computer using women and men working in different industries. The industries selected are (i) electrical machinery, equipment and supplies, (ii) retail trade, (iii) finance, insurance and real estate, (iv) business and repair services, and (v) personal services. The results in Table 4 show the OLS estimate (column 1) and the 2SLS estimates equivalent to columns (5a) and (5b) in Table 2 and 3, respectively. The results in columns (2a) and (2b) for workers with less than a college degree show that for the computer-intensive sectors log hourly wages are a similarly important determinants of computer use for men and women. For workers with levels of education of high school and less the difference in the coefficients between males and females is reduced substantially compared to the results reported in Table 3, columns (5a) and (5b).

5. Conclusion

This research has contributed to our understanding of how new technologies diffuse through the labor market by estimating the determinants of computer use for relatively low-skilled workers. The 2SLS estimates suggest that the costs of computer technology relative to the worker's wage are a main determinant of computer use and that skills do not seem to matter for the adoption decision.

These results have two important implications. First, the estimates put previous findings of the impact of computerization on labor-market outcomes into perspective by showing that skills do not contribute to the probability of computer use at work. From an economic point of view these estimates suggest that the diffusion of computer technology is driven by a cost-benefit trade-off in which wage costs are a crucial input. Using our results, the observation that computer users earn higher wages and the fact that higher educated workers were the first to adopt computer technology can be interpreted as these workers have higher wages and adopt computer because the cost-benefit trade-off is relevant early on in the diffusion process.

Second, the estimates question the effectiveness of government programs to increase skills in general and encourage computer literacy in particular. Many policy makers and social scientists have emphasized that computer skills and complementary skills are crucial for labor-market success in this ICT era. Recently a lot of money is spent on "computer literacy programs". Our estimates question the effectiveness of these programs and can be interpreted from a technology diffusion point of view in which workers adopt computer technology when the cost of the technology justify adoption.

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Table 1
Computer Use by Gender and Level of Education in the United States, 1984-1997

	All			Less than college education			High school education or less		
	Total	Females	Males	Total	Females	Males	Total	Females	Males
1984	.261 [.439]	.304 [.460]	.224 [.417]	.206 [.404]	.273 [.446]	.145 [.352]	.160 [.367]	.230 [.421]	.100 [.300]
1989	.397 [.489]	.459 [.498]	.342 [.474]	.322 [.467]	.416 [.493]	.233 [.423]	.241 [.428]	.332 [.471]	.160 [.366]
1993	.463 [.499]	.533 [.499]	.398 [.489]	.380 [.485]	.485 [.500]	.282 [.450]	.288 [.453]	.403 [.491]	.189 [.391]
1997	.548 [.498]	.612 [.487]	.484 [.500]	.451 [.498]	.551 [.497]	.352 [.478]	.343 [.475]	.455 [.498]	.243 [.429]

The data are taken from the October School Enrollment Supplements to the Current Population Surveys in 1984, 1989, 1993, and 1997 and include individuals currently employed aged 18-65. Computer use is defined as answering yes to the question "Do you use a computer directly at work?". The numbers in the table reflect the average computer use by year for the respective groups. Standard deviations are reported brackets.

Table 2
The Determinants of Computer Use at Work for Employees with Less than College Education

	(1a)	(1b)	(1c)	(2)	(3)	(4a)	(4b)	(5a)	(5b)
Group	All	All	All	Married	Married	Married	All	Married Females	Married Males
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instruments included for				Log wages	Log wages Education	Log wages	Log wages	Log wages Education	Log wages Education
First Stage	*Dependent Variable: Log Hourly Wages*								
Log min. wage (lmw)				.273 (.113)	.226 (.128)	.274 (.109)	.270 (.072)	.333 (.142)	.102 (.141)
lmw*education*experience[1]				.002 (.001)	.002 (.001)	.002 (.001)	.002 (.001)	.002 (.001)	.003 (.001)
lmw*experience				.001 (.008)	.001 (.009)	.001 (.009)	.003 (.005)	.018 (.012)	-.020 (.013)
lmw*education[1]				.041 (.020)	.033 (.041)	.042 (.038)	.029 (.029)	.041 (.041)	.026 (.046)
lmw*experience squared				.015 (.021)	.017 (.021)	.016 (.021)	.002 (.013)	-.028 (.028)	.068 (.032)
Years education [1]				.065 (.003)					
Years education 1984[1]					.032 (.003)	.067 (.007)	.056 (.005)	.025 (.003)	.047 (.004)
Years education 1989[1]					.031 (.003)	.065 (.005)	.060 (.004)	.028 (.003)	.036 (.005)
Years education 1993[1]					.025 (.004)	.059 (.006)	.061 (.006)	.023 (.004)	.030 (.004)
Years education 1997[1]					.029 (.004)	.070 (.011)	.067 (.008)	.023 (.004)	.039 (.004)
Experience				.023 (.001)	.021 (.001)	.023 (.001)	.026 (.001)	.018 (.002)	.031 (.002)
Experience squared/100				-.040 (.003)	-.034 (.003)	-.040 (.003)	-.042 (.002)	-.038 (.004)	-.044 (.004)
Education*experience				-.001 (.000)	.001 (.000)	-.001 (.000)	-.001 (.000)	-.001 (.000)	.001 (.000)
Gender				-.323 (.009)	-.331 (.008)	-.323 (.009)	-.157 (.008)		
Married							.158 (.007)		
Gender*married							-.168 (.008)		
Hours worked				.004 (.000)	.004 (.000)	.004 (.000)	.005 (.000)	.007 (.001)	.000 (.001)
White				.105 (.012)	.101 (.012)	.105 (.012)	.090 (.008)	.041 (.017)	.173 (.016)
Living in metro area				.109 (.010)	.108 (.009)	.109 (.010)	.100 (.007)	.115 (.012)	.100 (.013)
Second Stage	*Dependent Variable: Computer Use at Work*								
Log hourly wages		.158 (.006)	.156 (.006)	1.704 (.586)	1.027 (.397)	1.167 (.464)	.951 (.392)	.881 (.407)	.454 (.253)
Years of education	.036 (.002)	.026 (.002)		-.069 (.037)					
Years of education 1984			.007 (.002)		-.079 (.050)	-.051 (.028)	-.037 (.020)	-.050 (.044)	-.013 (.040)
Years of education 1989			.027 (.003)		-.053 (.047)	-.030 (.029)	-.022 (.021)	-.017 (.046)	-.002 (.034)

Years of education 1993			.037 (.002)		-.045 (.051)	-.024 (.030)	-.016 (.026)	-.033 (.052)	.038 (.038)
Years of education 1997			.046 (.003)		-.060 (.058)	-.030 (.036)	-.015 (.028)	-.023 (.053)	.013 (.047)
Experience	.003 (.001)	-.001 (.001)	-.001 (.001)	-.036 (.013)	-.022 (.009)	-.024 (.011)	-.023 (.010)	-.017 (.008)	-.009 (.007)
Experience squared/100	-.013 (.002)	-.006 (.002)	-.005 (.002)	.055 (.025)	.032 (.018)	.034 (.019)	.032 (.016)	.027 (.018)	.005 (.017)
Education*experience	-.001 (.000)	-.001 (.000)	-.001 (.000)	.001 (.000)	.001 (.001)	.000 (.000)	.001 (.000)	.001 (.001)	-.001 (.001)
Gender	.058 (.006)	.082 (.007)	.081 (.007)	.586 (.191)	.359 (.123)	.412 (.151)	.206 (.061)		
Married	.043 (.006)	.019 (.006)	.018 (.006)				-.105 (.073)		
Gender*married	-.023 (.008)	.003 (.007)	.003 (.007)				.134 (.077)		
Hours worked	.006 (.000)	.005 (.001)	.005 (.001)	-.001 (.002)	.002 (.002)	.001 (.002)	.001 (.002)	.003 (.003)	.003 (.001)
White	.079 (.007)	.064 (.007)	.064 (.007)	-.092 (.068)	-.023 (.045)	-.035 (.050)	-.009 (.036)	.051 (.029)	.007 (.045)
Living in metro area	.042 (.005)	.027 (.005)	.027 (.005)	-.130 (.067)	-.054 (.043)	-.071 (.052)	-.052 (.040)	-.037 (.051)	-.004 (.024)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	36,468	36,468	36,468	16,813	16,813	16,813	36,468	8,860	7,953

[1] In the regression results in columns (3), (5a) and (5b) education is defined as the years of education of the person's partner.

The data are taken from the October School Enrollment Supplements to the Current Population Surveys in 1984, 1989, 1993, and 1997 and include individuals currently employed aged 18-65. The standard errors have been adjusted for state-year clustering.

Table 3
The Determinants of Computer Use at Work for Employees with High School Education or Less

	(1a)	(1b)	(1c)	(2)	(3)	(4a)	(4b)	(5a)	(5b)
Group	All	All	All	Married	Married	Married	All	Married Females	Married Males
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instruments included for				Log wages	Log wages Education	Log wages	Log wages	Log wages Education	Log wages Education
First Stage	*Dependent Variable: Log Hourly Wages*								
Log min. wage (lmw)				.268 (.181)	.343 (.232)	.149 (.153)	.264 (.103)	.223 (.232)	.189 (.178)
lmw*education*experience[1]				.003 (.002)	.007 (.003)	.003 (.002)	.004 (.001)	.003 (.003)	.011 (.003)
lmw*experience				.017 (.011)	.023 (.012)	.016 (.011)	.009 (.006)	.041 (.016)	.005 (.017)
lmw*education[1]				.041 (.032)	-.021 (.061)	.004 (.034)	.019 (.033)	.010 (.056)	-.059 (.075)
lmw*experience squared				-.005 (.027)	-.005 (.027)	-.005 (.027)	.007 (.016)	-.072 (.033)	.063 (.042)
Years education [1]				.075 (.004)					
Years education 1984[1]					.027 (.004)	.072 (.008)	.058 (.006)	.018 (.004)	.046 (.006)
Years education 1989[1]					.024 (.004)	.068 (.005)	.054 (.004)	.018 (.005)	.033 (.006)
Years education 1993[1]					.026 (.005)	.071 (.008)	.059 (.007)	.022 (.005)	.034 (.006)
Years education 1997[1]					.033 (.004)	.092 (.014)	.071 (.009)	.027 (.005)	.044 (.006)
Experience				.021 (.002)	.024 (.002)	.021 (.002)	.023 (.001)	.021 (.002)	.031 (.002)
Experience squared/100				-.039 (.004)	-.031 (.004)	-.039 (.004)	-.036 (.002)	-.034 (.005)	-.039 (.006)
Education*experience				-.001 (.000)	.002 (.000)	-.001 (.000)	.001 (.000)	.001 (.000)	.002 (.000)
Gender				-.355 (.011)	-.351 (.011)	-.355 (.011)	-.180 (.011)		
Married							.154 (.009)		
Gender*married							-.174 (.012)		
Hours worked				.004 (.001)	.004 (.001)	.004 (.001)	.004 (.000)	.006 (.001)	-.001 (.001)
White				.095 (.013)	.090 (.013)	.095 (.013)	.080 (.009)	.030 (.019)	.153 (.018)
Living in metro area				.109 (.010)	.102 (.010)	.109 (.010)	.096 (.007)	.106 (.013)	.095 (.013)
Second Stage	*Dependent Variable: Computer Use at Work*								
Log hourly wages		.150 (.007)	.148 (.007)	1.358 (.378)	.810 (.289)	.859 (.398)	.864 (.278)	1.077 (.354)	.343 (.162)
Years of education	.027 (.002)	.017 (.002)		-.065 (.029)					
Years of education 1984			.001 (.001)		-.100 (.055)	-.049 (.027)	-.039 (.014)	-.128 (.056)	-.016 (.038)
Years of education 1989			.015 (.002)		-.052 (.047)	-.023 (.025)	-.023 (.014)	-.059 (.055)	-.001 (.033)

Years of education 1993			.032 (.003)		-.035 (.057)	-.014 (.031)	-.015 (.019)	-.074 (.061)	.050 (.042)
Years of education 1997			.039 (.005)		-.086 (.065)	-.016 (.042)	-.022 (.023)	-.110 (.071)	.003 (.045)
Experience	.003 (.001)	-.001 (.001)	-.001 (.001)	-.026 (.008)	-.014 (.005)	-.016 (.008)	-.018 (.007)	-.015 (.005)	-.005 (.004)
Experience squared/100	-.011 (.002)	-.005 (.002)	-.004 (.023)	.041 (.016)	.027 (.015)	.023 (.016)	.023 (.010)	.037 (.018)	.003 (.012)
Education*experience	-.001 (.000)	-.001 (.000)	-.001 (.000)	.001 (.001)	.003 (.002)	.000 (.001)	.000 (.001)	.004 (.002)	-.000 (.001)
Gender	.075 (.009)	.102 (.009)	.101 (.009)	.528 (.137)	.331 (.101)	.351 (.142)	.231 (.051)		
Married	.038 (.008)	.015 (.008)	.015 (.008)				-.095 (.064)		
Gender*married	-.026 (.010)	-.001 (.010)	-.001 (.010)				.123 (.071)		
Hours worked	.005 (.000)	.005 (.000)	.005 (.000)	.001 (.002)	.003 (.001)	.002 (.002)	.002 (.001)	.001 (.002)	.003 (.001)
White	.074 (.007)	.062 (.006)	.062 (.006)	-.044 (.042)	.005 (.031)	.003 (.039)	.005 (.023)	.066 (.028)	.013 (.030)
Living in metro area	.031 (.006)	.017 (.006)	.017 (.006)	-.105 (.044)	-.046 (.033)	-.051 (.045)	-.052 (.028)	-.062 (.054)	-.016 (.022)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	23,488	23,488	23,488	10,643	10,643	10,643	23,488	5,543	5,100

[1] In the regression results in columns (3), (5a) and (5b) education is defined as the years of education of the person's partner.

The data are taken from the October School Enrollment Supplements to the Current Population Surveys in 1984, 1989, 1993, and 1997 and include individuals currently employed aged 18-65. The standard errors have been adjusted for state-year clustering.

Table 4
The Determinants of Computer Use at Work for Employees
in Computer-Intensive Sectors

	(1)	(2a)	(2b)	(3a)	(3b)
Group	All	Married Females and less college education	Married Males and less college education	Married Females and high school or less	Married Males and high school or less
Method	OLS	2SLS	2SLS	2SLS	2SLS
Instruments included for		Log wages Education	Log wages Education	Log wages Education	Log wages Education
Second Stage	*Dependent Variable: Computer Use at Work*				
Log hourly wages	.167 (.007)	.896 (.408)	.906 (.442)	1.238 (.444)	.628 (.189)
Years of education 1984	.003 (.002)	-.099 (.071)	-.060 (.140)	-.114 (.152)	-.064 (.074)
Years of education 1989	.017 (.002)	-.021 (.061)	-.072 (.178)	-.073 (.092)	-.058 (.148)
Years of education 1993	.022 (.002)	-.043 (.058)	-.010 (.133)	-.105 (.098)	-.016 (.122)
Years of education 1997	.026 (.002)	-.052 (.069)	-.063 (.181)	-.265 (.168)	-.032 (.102)
Experience	-.003 (.001)	-.018 (.009)	-.034 (.030)	-.014 (.007)	-.016 (.009)
Experience squared/100	-.002 (.003)	.034 (.020)	.050 (.056)	.042 (.025)	.032 (.024)
Education*experience	-.001 (.000)	.002 (.001)	.001 (.004)	.008 (.004)	.002 (.005)
Gender	.023 (.010)				
Married	.018 (.009)				
Gender*married	-.013 (.011)				
Hours worked	.005 (.000)	.004 (.003)	.003 (.001)	.002 (.002)	.005 (.002)
White	.063 (.008)	.046 (.041)	-.062 (.158)	.108 (.035)	-.042 (.054)
Living in metro area	.019 (.008)	-.041 (.063)	-.006 (.054)	-.093 (.063)	-.025 (.045)
State dummies	Yes	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
n	22,838	4,838	1,983	2,680	1,036

Industries selected are Electrical machinery, equipment and supplies, Retail trade, Finance, insurance and real estate, Business and repair services and Personal services.

The data are taken from the October School Enrollment Supplements to the Current Population Surveys in 1984, 1989, 1993, and 1997 and include individuals currently employed aged 18-65. The standard errors have been adjusted for state-year clustering.

Table A1
Descriptive Statistics

	1984	1989	1993	1997
Less than college education				
Log hourly wages	1.920 [.499]	2.129 [.495]	2.222 [.497]	2.335 [.502]
Years of education	11.954 [1.976]	12.166 [1.865]	12.278 [1.604]	12.375 [1.583]
Experience	17.024 [12.021]	19.059 [11.246]	19.077 [10.861]	19.823 [10.882]
Experience squared/100	4.343 [4.957]	4.897 [4.915]	4.819 [4.654]	5.114 [4.638]
Education*experience	194.901 [135.606]	225.912 [132.305]	230.354 [130.359]	241.787 [132.277]
Gender	.47 [.499]	.48 [.500]	.50 [.500]	.50 [.500]
Married	.68 [.468]	.63 [.482]	.62 [.486]	.61 [.488]
Gender*married	.308 [.462]	.291 [.454]	.287 [.453]	.293 [.455]
Hours worked	38.53 [9.678]	39.93 [8.597]	38.88 [9.979]	39.33 [9.537]
White	.867 [.340]	.863 [.343]	.842 [.364]	.849 [.358]
Living in metro area	.58 [.494]	.71 [.454]	.71 [.454]	.77 [.422]
n	9,923	9,058	9,708	7,752
High school education or less				
Log hourly wages	1.889 [.490]	2.068 [.479]	2.164 [.479]	2.266 [.482]
Years of education	11.199 [1.805]	11.301 [1.678]	11.435 [1.361]	11.461 [1.321]
Experience	18.845 [12.138]	20.672 [11.369]	20.593 [10.866]	21.391 [10.891]
Experience squared/100	5.025 [5.260]	5.566 [5.240]	5.421 [4.930]	5.762 [4.920]
Education*experience	203.948 [130.743]	228.913 [126.786]	232.662 [122.913]	242.718 [124.507]
Gender	.47 [.499]	.47 [.499]	.46 [.499]	.47 [.499]
Married	.70 [.458]	.64 [.479]	.63 [.482]	.62 [.486]
Gender*married	.317 [.465]	.289 [.453]	.285 [.451]	.292 [.455]
Hours worked	38.95 [9.070]	39.83 [8.253]	39.33 [9.390]	39.65 [8.854]
White	.867 [.340]	.861 [.346]	.835 [.372]	.850 [.357]
Living in metro area	.56 [.496]	.68 [.465]	.69 [.462]	.75 [.433]
n	7,092	6,000	5,929	4,467

The data are taken from the October School Enrollment Supplements to the Current Population Surveys in 1984, 1989, 1993, and 1997 and include individuals currently employed aged 18-65. The numbers in the table are means. Standard deviations are reported brackets.