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Wage Premiums for On-the-Job Computer Use in Metro and Nonmetro Areas

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Wage Premiums for On-the-Job Computer Use in Metro and Nonmetro Areas. By Lorin D. Kusmin. Food and Rural Economics Division, Economic Research Service, U.S. Department of Agriculture. Staff Paper No. AGES 00-02.

Abstract

An analysis of on-the-job computer use shows that such use is more common in metro areas than in nonmetro areas. A substantial wage premium, on the order of 10 percent to 12 percent, is associated with use of a computer on the job, even after other job and worker characteristics are taken into account. However, this wage premium accounts for only a small proportion of the wage differences between metro and nonmetro areas. Further analysis shows that the computer use wage premium is about 5 percent in nonmetro areas, and is also lower among workers with less education and/or in lower-status occupations. This finding suggests only a small role for computer literacy skills in enhancing the earnings of low-wage workers in rural areas.

Keywords: Nonmetropolitan, rural, metropolitan, urban, computers, wages, jobs, skills.

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Summary

Computer use at work has become widespread in American society, and the proportion of U.S. workers using computers on the job nearly doubled over the past two decades. By 1997, almost half of all U.S. workers used computers on the job. Further, workers who use computers on the job generally receive higher wages. However, on-the-job use is less common in nonmetro areas than in metro areas, and wages for nonmetro workers are generally lower. These findings raise questions about the role of computer usage in explaining the metro-nonmetro wage gap. Recent public policy discussions of the digital divide between computer "haves" and "have-nots" have focused attention on the efficacy of employment strategies to improve the economic position of many employees in groups of particular concern, including nonmetro workers, the less-educated, and racial and ethnic minorities, by increasing their access to computer skills and computer technology. Focusing on metro-nonmetro differences in computer use and the returns to computer use, this report addresses several questions that shed light on potential effects of efforts to bridge the digital divide.

A simple comparison of wages for on-the-job computer users and other workers shows a wage difference of 35 percent or more between the two groups. Much of this gap reflects differences between the jobs held by computer users and other workers, or differences in worker characteristics, and not the effect of computer use itself. However, a wage regression analysis suggests that even after taking into account differences in industry and occupation of employment, worker education and skill level, and other worker and job characteristics, there is still a 10-percent to 12-percent wage premium associated with on-the-job use of computers.

On-the-job computer use is significantly more common in metro areas than in nonmetro areas (52 percent versus 40 percent in 1997). This higher incidence, together with the wage premium found for use of computers on the job, could help to explain the metro-nonmetro wage gap. However, a computation taking into account the magnitudes of both the computer use wage premium and the metro-nonmetro computer use gap shows that this effect can account for only a small proportion (about 4 percent) of the overall metro-nonmetro wage gap. About 30 percent is accounted for by other differences between jobs and workers in metro and nonmetro areas, particularly worker education and the distribution of jobs across occupations. The majority of the gap is explained by factors not included in the analysis.

The wage premium associated with computer use in rural areas is only about 5 percent, less than half the computer wage premium found in metro areas. Some of this difference is explained by differences in job and worker characteristics, as the characteristics of an average computer user in nonmetro areas include less education and lower occupational status associated with lower returns to computer use. Perhaps an independent effect of rurality produces lower returns to worker skills in nonmetro areas, as suggested in other research.

As returns to computer use on the job are smaller for rural workers, less-educated workers, and workers in low-status occupations, improving such workers' computer literacy may contribute only slightly to reducing wage inequalities. Computer literacy programs may improve the earnings of racial and ethnic minorities, for whom the computer use wage premium is somewhat larger.

Wage Premiums for On-the-Job Computer Use in Metro and Nonmetro Areas

Lorin D. Kusmin

Introduction

Computer use has become widespread in American society over the past two decades. One aspect of this change has been the increasing use of computers at work. The fraction of Americans workers using computers on the job rose from about one-fourth in 1984 to nearly one-half by 1993.

Previous research has indicated that workers who use computers on the job receive higher wages, and that this may help to explain changes in the wage distribution (Krueger, 1993). This study reassesses those findings by taking into account metro/nonmetro location, industry wage effects, and the skill content of occupations.

Also, on-the-job computer use is more common in metro areas than in nonmetro areas (Kusmin, 1996). Metro- and nonmetro-area workers differ in another important respect: average wages in nonmetro areas are substantially lower than in metro areas. In 1997, average weekly earnings for nonmetro wage and salary workers were 79 percent of the metro average (Gibbs and Parker, 1999). This difference is longstanding (table 1) and is not fully explained by metro/nonmetro differences in education level; indeed, the metro-nonmetro wage gap is greater for workers with higher levels of education (McGranahan and Ghelfi, 1991). Is there a link between these two findings, that is, do differences in on-the-job computer use play a role in explaining the current magnitude of the metro-nonmetro wage gap? Exploring this link is a second objective of this paper.

Finally, recent public policy discussions of the digital divide between computer "haves" and "have-nots" raise the question, "How far can improvements in access to computer skills and computer technology go to improve the economic position of groups of particular concern, including rural workers, less educated workers, and members of racial and ethnic minorities?" By looking at how the wage returns to computer use vary across groups, we can begin to address this question.

Computer Use and the Wage Structure

In his 1993 *Quarterly Journal of Economics* article, "How Computers Have Changed the Wage Structure," Alan Krueger assessed how on-the-job use of computers influenced wages. Krueger found that workers who used computers on the job received a wage premium of 10 percent to 15 percent. This estimate reflected the wage differential between computer users and others after taking a variety of other personal and job characteristics into account.

Table 1--Real annual earnings in nonfarm jobs, metro and nonmetro areas, 1970-1996

	Nonmetro	Metro	Ratio
	Dollars		*Percent*
1970	21886	28592	76.5
1975	23263	29152	79.8
1980	23742	29493	80.5
1985	23515	30315	77.6
1990	22464	30838	72.8
1993	22651	31465	72.0
1996	22493	31697	71.0

Note: Values are in 1996 dollars.

Source: Calculated by Economic Research Service, USDA, ERS using data from the Bureau of Economic Analysis. Reported in "Rural Conditions and Trends", Volume 9, No. 3 (Rural Industry Issue), Economic Research Service, USDA, 1999, page 67.

Krueger concluded that this differential represented a return to their use of computer skills. Krueger further argued that the existence of this wage premium explains a substantial proportion of the growth during the 1980's in the apparent wage premium to education, as more highly educated workers are much more likely to use computers on the job, and their rates of computer use have risen much further over time.

Both conclusions have been challenged. DiNardo and Pische find that a wage premium similar to that for computer use can be estimated for "using pencils on the job," and argue that both are serving primarily as proxies for unobserved differences in jobs and workers (DiNardo and Pische, 1997). They also note that while the returns to higher skill levels grew most rapidly during the 1980's, there is little evidence for increases in productivity associated with the use of computers in the workplace before the 1990's.

Both of these positions suggest that a productivity increase associated with the adoption of computers in the workplace should be reflected in a return to computer-specific skills that will be captured only by those actually using computers on the job. However, this interpretation is open to question. To the extent that computer skills either include or are correlated with a broader set of capabilities that are in demand in the labor market, an increasing demand for computer skills would bid up the market wages for workers who possess those capabilities whether or not their jobs involve direct computer use. (This point is acknowledged in Autor, Katz, and Krueger (1997, p.18*fn.*)) Further, as suggested by Autor, Katz, and Krueger (1998), the increasing use of computers in the workplace may also increase the relative wages of more-skilled workers generally because computers have been able to substitute for humans in performing many simple, repetitive tasks that previously contributed to the demand for less-skilled labor (pp.1, 185-86).

In addition, the lack of visible productivity gains from the computer revolution during the 1980's is not inconsistent with a wage premium to workers with computer-related skills. Helpman and Trajtenberg (1995) show that under some reasonable assumptions, the diffusion of what they term a "general purpose technology" may engender a two-phase cycle of economic change, with the first phase marked by both stagnating productivity and an increasing relative wage for skilled workers, while the productivity benefits of the new technology emerge only in the second phase.

Objectives

This analysis builds on Krueger's 1993 wage model to look further at the wage premium associated with the use of a computer on the job, and at how that premium varies with location, job, and personal characteristics. The study follows Krueger in using data from one of the periodic supplements to the Current Population Survey (CPS) that has included questions about subjects' use of computers at work (see appendix).

One objective of this study is to reassess Krueger's findings by taking additional variables into account in the wage model. The study assesses the extent to which taking account of metro-nonmetro differences affects estimates of the apparent wage premium for on-the-job (OTJ) computer use.[1] Further, some additional data are brought to bear on the question of the extent to which omitted occupational or personal characteristics can "explain" the computer wage premium. However, as already noted, the returns to such characteristics may themselves have increased over time in

[1] A more detailed discussion of the difference between on-the-job computer use rates in metro and nonmetro areas and the factors accounting for those differences appears in Kusmin (1996).

response to the increasing demand for workers with capabilities that are associated with computer use. Hence, including some of these characteristics in the wage model may yield a smaller and more accurate estimate of the "direct" effect of computer use on wages, but may also lead to an understatement of the overall effect of computers in the workplace on the wage distribution.

A second objective is to assess the relevance of the computer wage premium for explaining nonmetro wages and the metro/nonmetro wage gap. In this context, the analysis will consider not only metro/nonmetro differences in rates of computer use, but also metro/nonmetro differences in the size of the wage premium to those who do use computers.

In addition, it may be useful to note whether the results of this analysis are consistent with Krueger's contention that OTJ computer use can explain much of the apparent growth in the returns to education during the 1980's. While of considerable interest, the relationship of the computer use wage premium to productivity growth is not directly addressed here.

Finally, the results may shed some light on the role of public policy in addressing wage inequality and the metro/nonmetro wage gap. Would policies to promote computer literacy among less-skilled workers and/or in more isolated areas contribute to reducing inequality?

Computer Use at Work

The proportion of employed adults using computers at work nearly doubled between 1984 and 1993. By 1993, more than 45 percent of all workers used computers on their jobs.

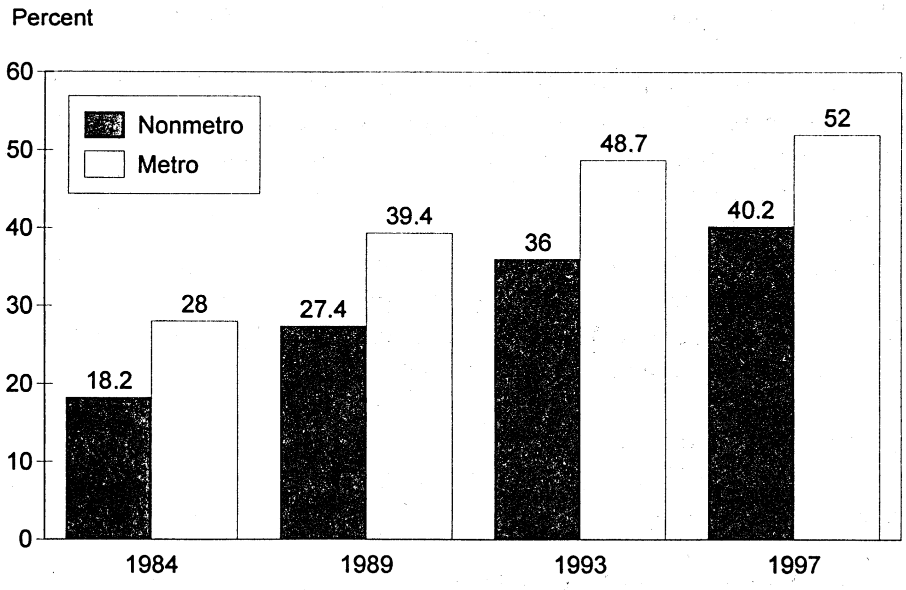
The proportion of jobs involving computer use was higher in metro areas in both years, and the absolute size of the gap has grown slightly over time. In 1984, 18 percent of nonmetro and 28 percent of metro workers used computers on the job, a difference of 10 percentage points. By 1993, 36 percent of nonmetro and 49 percent of metro workers used computers on the job, a difference of 13 percentage points (fig. 1).

Data more recent than 1993 were not available at the time the analysis for this paper was done. A recent report from the Census Bureau on computer use in 1997 (Newburger, 1999) indicates that on-the-job computer use increased only modestly, from 45.8 percent to 49.8 percent, between 1993 and 1997. A preliminary examination of the 1997 data shows that the metro-nonmetro use gap also changed only slightly over the same time, narrowing from 13 percentage points in 1993 to 12 percentage points (52 percent versus 40 percent) in 1997. These results suggest that patterns of on-the-job computer use probably did not change sharply between these two years. An update of the present study reflecting these more recent data is planned for the future.

Figure 1

Workers using computers on the job by residence, 1984-97

The percentage of the workforce using computers on the job has remained higher in metro areas



Source: Calculated by Economic Research Service, USDA, from Current Population Survey, October 1984, October 1989, October 1993, and October 1997.

The analysis presented in Kusmin (1996) indicates that about two-thirds of the difference between metro and nonmetro computer use rates can be accounted for by metro-nonmetro differences in occupational mix and educational level (table 2). In particular, the concentration of managerial, professional, technical, and clerical workers in metro areas, as well as the larger proportion of metro workers who are college graduates, plays a large role in explaining the metro-nonmetro use gap. The growth in this use gap between 1984 and 1993 reflects more rapid increases in use by occupational, industrial, and educational groups that tend to be concentrated in urban areas. It also reflects, to a lesser extent, changes in the occupational composition of the urban and rural workforces.

Estimating Returns to Computer Use at Work

This study addresses three questions:
Is a wage premium associated with using computer skills on the job. If so, how large?
What is the extent that differences in computer use account for metro-nonmetro wage differences?
Do nonmetro workers receive lower returns for computer skills than metro workers?

A simple cross-tabulation indicates that computer users earn far more than other workers in both metro and nonmetro areas; the difference in average wages between the two groups is 35 percent in nonmetro areas and 43 percent in metro areas (table 3). At the same time, these figures show that earnings are higher in metro areas for computer users and non-users alike, suggesting that computer use differences are not the main source of metro-nonmetro wage differences.

This cross-tabulation ignores many other characteristics of workers and jobs that influence wages and that differ between metro and nonmetro workers, and/or between computer users and other workers. To assess the affect of computer use per se on wages, such characteristics as education level and labor force experience must be taken into account.

To do this, we estimate a wage regression model, similar to those presented in Krueger (1993), of the form

$$\ln w = X\beta + \gamma,$$

where w is the wage rate, X is a vector of job and worker characteristics, and γ is an error term assumed to have the standard properties.[2] To assess the effect of computer skills, OTJ computer use is included as one of the X's that are predictors of the log wage. The data are taken from the October 1993 CPS subsample (see appendix), and the hourly wage is defined as reported weekly earnings divided by usual hours worked. The model controls for a number of personal and job characteristics often found to be associated with wage levels. Personal characteristics taken into account include sex, marital status, veteran status, race and ethnicity, region of residence, metro/nonmetro residence, labor force experience, and education level. Job characteristics include whether or not the worker is covered by a union contract, and whether the job is full-time or part-time. The specification parallels that presented by Krueger (1993, p. 38, table II) in his analysis of 1984 and 1989 CPS data.[3]

Insert table 2 here

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[2] For another recent example, see Barron, Berger, and Black (1999).

[3] There are minor differences between Krueger's specification and the one presented here. Krueger omits controls for Asian race, for Hispanic origin, and for whether or not data are for self-reporting respondents. In addition, he models the effect of education as linear in years of schooling, while here it is captured by dummy variables for several distinct levels of education.

Table 2-- Urban-rural gap in computer use at work, 1993

	Percentage points	As percent of overall gap
		Percent
Gap accounted for:		
Job characteristics	7.4	58
Occupational mix	5.8	46
Industrial mix	1.0	8
Other job characteristics	0.6	5
Personal characteristics	1.9	15
Education level	2.6	20
Racial/ethnic background	-0.9	-7
Other personal characteristics	0.2	2
Gap not accounted for:		
Effect of urban residence	3.2	25
Total gap	12.7	100

Figures may not add to total due to rounding.
Source: Estimated by Economic Research Service, USDA using a linear probability regression model and data from the October 1993 Current Population Survey. Reprinted from Kusmin (1996), p. 14.

Table 3--Average hourly earnings by metro status and on-the-job computer use, 1993

	Nonmetro	Metro	Metro-nonmetro difference
	Dollars		*Percent*
Don't use computer	9.0	10.5	16.6
Use computer	12.1	15.1	24.1
	Percent		
User-nonuser difference	34.7	43.4	

Source: Current Population Survey, October 1993.

With respect to the wage premium associated with using computer skills on the job, the results of this analysis suggest that use of a computer on the job raises hourly earnings by about 22 percent (see table 4, model 2).[4] This wage effect is considerable, and is similar to the magnitude of the corresponding estimate found by Krueger in his 1993 study.[5]

With respect to whether differences in computer use account for metro-nonmetro wage differences, the otherwise unexplained metro-nonmetro difference in wages is about 17 percent when OTJ computer use is left out of the model, and about 15 percent when OTJ computer use is taken into account. This finding suggests that computer use on the job explains only a small portion of metro-nonmetro wage differences. Note, however, that the analysis here assumes that the returns to computer use are the same for all workers; this assumption will be relaxed later in this report.

Most of the estimated coefficients on other variables (experience, education, union membership, and others) are consistent with past findings in this area. Thus, labor force experience has a positive but decreasing effect on wages; higher levels of education are associated with higher wages; and unionized workers earn more per hour.[6,7]

Industry, Occupation, and Skill Effects Versus Computer-Use Effects

Is the apparently large premium to OTJ computer use actually a return to computer-specific skills, or is it due to other factors? The apparent premium to computer use might be explained by higher wages in those occupations or industries where computer use is more common, perhaps because these are higher-status jobs, or because some industries are willing to pay more for both desirable workers or new technologies. In this case, the premium should disappear from a model with appropriate industry and occupational controls.

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[4]The dependent variable in these models is the logarithm of the hourly wage. In general, for small values of k, a difference of k in the logarithm of any variable x corresponds approximately to a difference of 100k percent in the level of x. As k grows larger, there is an increasing divergence between differences in the logarithm of x and percentage differences in x. Thus, a difference of .202 in the logarithm of the wage corresponds to a difference of 22.4 percent in the wage itself.

[5]Some earlier analyses, not presented here, suggest that this result is fairly robust to inclusion of data on home computer use and to some other variations in specification.

[6]Including a control for use of a computer on the job leads to some reduction in the estimated wage effects of education relative to an otherwise equivalent model without this computer use variable (model 1). This is consistent with Krueger's suggestion that returns to OTJ computer use account for some of the apparent increase in returns to education during the 1980's that had been reported by other studies. However, the education effects are qualitatively similar in both models.

[7]Additional details on the regression results, including coefficients for sex, marital status, part-time status, industry effects, and several other variables, are reported in the appendix.

Table 4--Estimated effect of on-the-job computer use on wages, October 1993

Variable	Model 1: Wage model without computer use		Model 2: Basic model with computer use variable	
	Parameter estimate		*Parameter estimate*	
Use computer	NA		0.202	***
Metro area	0.156	***	0.144	***
Labor force experience	0.026	***	0.025	***
Labor force experience**2	-0.044	***	-0.042	***
Non-HS graduate	-0.185	***	-0.145	***
Some college	0.144	***	0.108	***
Bachelors degree	0.424	***	0.358	***
Advanced degree	0.593	***	0.522	***
Black	-0.108	***	-0.091	***
Asian	-0.031		-0.006	
Other race	-0.081	**	-0.072	*
Hispanic	-0.154	***	-0.141	***
Union	0.157	***	0.174	***
Adjusted R-square	0.388		0.412	

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

Note: High school graduate is the basic (omitted) educational group and non-Hispanic white is the basic (omitted) race/ethnicity group.
Note: Labor force experience**2 is the squared value of labor force experience.
Note: Regression intercepts as well as coefficients for effects of sex, marital status, veteran status, region, part-time status, and reporting status are not shown here, but are reported in the appendix tables.
NA=not included in this specification.
Dependent variable=Log (weekly earnings/usual hours).

Source: Computed by Economic Research Service from October 1993 Current Population Survey.

Alternatively, as noted earlier, the use of a computer on the job may instead serve as a proxy for broader capabilities that are rewarded by the labor market--perhaps cognitive skills, detail orientation, or a willingness to learn new methods. In this case, the estimated wage premium may provide some interesting insight into the returns to such capabilities, but may not have any implications for the wage effects of wider computer use.

Some evidence with respect to these issues can be derived by augmenting the wage regression already presented with controls for wage differences across industry, occupation, and skill levels. Looking first at industry effects, including a set of 21 categorical industry variables in the model accounts for only a modest portion of the computer use premium. The estimated premium falls when these industry effects are taken into account, but only from 22 percent to 18 percent (table 5, model 3). This result is similar to Krueger's findings with respect to industry effects (1993, p. 39). Moreover, as Krueger noted, this approach may lead to an underestimate of the return to computer skills, since possession of these skills may permit individuals to find employment in higher-paying industries.[8]

The rate of use of computers on the job varies widely across occupational categories. On the whole, occupations that tend to have higher computer-use rates also tend to pay better, so that some of the estimated premium to OTJ computer use may reflect the higher wages associated with these occupations. When we include controls for eight occupational groups in the wage model in addition to the industry effects already mentioned, the estimated wage premium for computer use falls somewhat further from 18 percent to 14 percent (model 4). This result is also similar to Krueger's 1993 findings.

But use of such broad occupational groups is a relatively crude proxy for controlling for skill levels. For some further insight into whether direct computer use serves as a proxy for other work skills, the Department of Labor's Dictionary of Occupational Titles (DOT) data file has been used to compute approximate skill contents for individual occupations along several dimensions (see "Data and Methods" appendix). The four DOT occupational characteristics that have been considered include the three "general educational development" (GED) levels of the job with respect to math, language skills, and general reasoning, and the extent of "specific vocational preparation" (SVP) required for a job. The specific vocational preparation index ranges from 1 to 9 and represents an estimate of the time necessary to achieve average performance in the job (for example, between 30 days and 3 months are required to achieve average performance in an occupation with an SVP rating of 3).[9]

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[8]The industries for which wage effects were estimated include agriculture; mining; construction; durable goods manufacturing; nondurable goods manufacturing; transportation; communications; utilities and sanitary services; wholesale trade; retail trade; finance, insurance, and real estate; private household services; business services; personal services; entertainment and recreation services; hospitals; medical services (except hospitals); education services; social services; professional services; forestry and fishing; and public administration. Estimated individual industry effects for models 3 through 8 are reported in the appendix tables; industry effects estimated for models 9 and 10 have been omitted for reasons of space. When retail trade is treated as the base (omitted) category, the estimated industry wage differentials range from -13 percent for private household services to +61 percent for mining.

[9]In preliminary analyses, the effects on wages of variation in DOT's "functional level" variables were also taken into account. These variables characterize occupations in terms of the sophistication of the interactions required with people, data, and things. However, the results with respect to these variables were substantially weaker and not particularly consistent with intuitive expectations, and so they have not been presented in this paper.

Table 5--Estimated computer use premium with industry and occupation controls, October 1993

Variable	Model 3: Wage model with controls for industrial sector		Model 4: Wage model with controls for industry and occupation	
	Parameter estimate		*Parameter estimate*	
Use computer	0.169	***	0.130	***
Metro area	0.142	***	0.134	***
Labor force experience	0.023	***	0.021	***
Labor force experience**2	-0.037	***	-0.035	***
Non-HS graduate	-0.132	***	-0.112	***
Some college	0.107	***	0.072	***
Bachelors degree	0.376	***	0.248	***
Advanced degree	0.566	***	0.403	***
Managers	NA		0.163	***
Professionals	NA		0.168	***
Technical	NA		0.087	***
Clerical	NA		-0.113	***
Service	NA		-0.149	***
Craft occupations	NA		0.000	
Operators	NA		-0.143	***
Laborers	NA		-0.200	***
Black	-0.092	***	-0.068	***
Asian	-0.015		-0.005	
Other race	-0.075	*	-0.060	*
Hispanic	-0.118	***	-0.104	***
Union	0.166	***	0.184	***
Adjusted R-square	0.455		0.487	

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

Note: High school graduate is the basic (omitted) educational group, non-Hispanic white is the basic (omitted) race/ethnicity group, and craft occupations are the basic (omitted) occupational group.
Note: Labor force experience**2 is the squared value of labor force experience.
Note: Regression intercepts as well as coefficients for effects of sex, marital status, veteran status, region, part-time status, industry, and reporting status are not shown here, but are reported in the appendix tables.
NA=not included in this specification.
Dependent variable=Log (weekly earnings/usual hours).

Source: Computed by Economic Research Service from October 1993 Current Population Survey.

These four measures of the skill levels required for detailed Census occupations turn out to be fairly powerful as factors accounting for wage variation. When these four variables are substituted for the eight occupational categories variables that were used in the previous model (table 6, model 5), the extent of wage variation explained actually increases slightly. Further, all four variables are statistically significant. The math, language, and specific preparation indices are positively related to wages, as might be expected. Curiously, however, the level of "general reasoning" required for an occupation appears to be negatively associated with its wage level, once all other variables in the model have been taken into account.[10]

The results of estimating this model (model 5) are consistent with the suggestion that some significant share of the previously measured premium to direct computer use is actually a return to broader associated skills. When the wage model is augmented with these four occupational skill level indices, the estimated wage effect of computer use falls considerably, to just over 10 percent. However, the computer use effect does remain statistically significant at the 0.1 percent level.

Moreover, if general skills and computer skills can substitute for each other to some extent as qualification for some skilled occupations, then workers with a given level of individual general skills will more likely qualify for higher-paying jobs in occupations with a higher occupational content of general skills if those workers possess a greater level of specific computer skills. In these cases, a return to the individual's specific computer skills will appear, at least in part, to be a return to general skills.

Further, as noted earlier, the demand for general skills cannot be neatly separated from the demand for computer skills in the labor market as a whole. The increasing demand for people able to operate computers can also be expected to raise the returns to other skills and personal characteristics that are necessary for and/or simply correlated with computer skills, even in those jobs that do not require computer use. Thus, the return to general skills may itself be influenced by the increasing role of computers in the workplace. Both this and the preceding argument suggest that the overall effect of the demand for computer skills on the relative wages of more skilled workers will be understated if we look only at the individual return on computer skills after controlling for occupational skill level.

If both occupational skill levels and broad occupational categories are taken into account, as in model 6, there is a modest but statistically significant further improvement in the model. The estimated direct computer-use premium for this specification is about 12 percent, which is a little higher than in the previous model, indicating that greater detail on occupational characteristics will not necessarily reduce the estimated size of the OTJ computer use premium. A summary of the wage premium for computer use as estimated by each model is shown in figure 2.

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[10]It is important to note that these are measures of occupational characteristics, and not the skill levels of the particular individuals in the CPS sample. It seems reasonable that occupational skill levels may be fairly highly correlated with individual skill levels, or at least with individual skill levels as exercised on the job. However, there is no guarantee that computer users and non-computer users have the same level of general skills, even within the same occupation.

Table 6--Estimated computer use premium with occupational skill controls, October 1993

Variable	Model 5: Wage model with controls for industry and for occupational skill level		Model 6: Wage model with controls for industry, occupational skill level, and occupation	
	Parameter estimate		*Parameter estimate*	
Use computer	0.099	***	0.111	***
Metro area	0.133	***	0.134	***
Labor force experience	0.020	***	0.020	***
Labor force experience**2	-0.034	***	-0.034	***
Non-HS graduate	-0.098	***	-0.104	***
Some college	0.068	***	0.067	***
Bachelors degree	0.255	***	0.237	***
Advanced degree	0.410	***	0.388	***
Managers	NA		0.043	*
Professionals	NA		0.056	**
Technical	NA		0.005	
Clerical	NA		-0.081	***
Service	NA		-0.089	***
Craft occupations	NA		-0.043	
Operators	NA		-0.033	
Laborers	NA		-0.066	*
GED-Reason	-0.042	*	-0.074	***
GED-Language	0.038	**	0.034	*
GED-Math	0.062	***	0.053	***
Specific Vocational Prep	0.045	***	0.049	***
Black	-0.061	***	-0.061	***
Asian	-0.008		-0.007	
Other race	-0.063	*	-0.062	*
Hispanic	-0.101	***	-0.101	***
Union	0.193	***	0.190	***
Adjusted R-square	0.491		0.494	

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

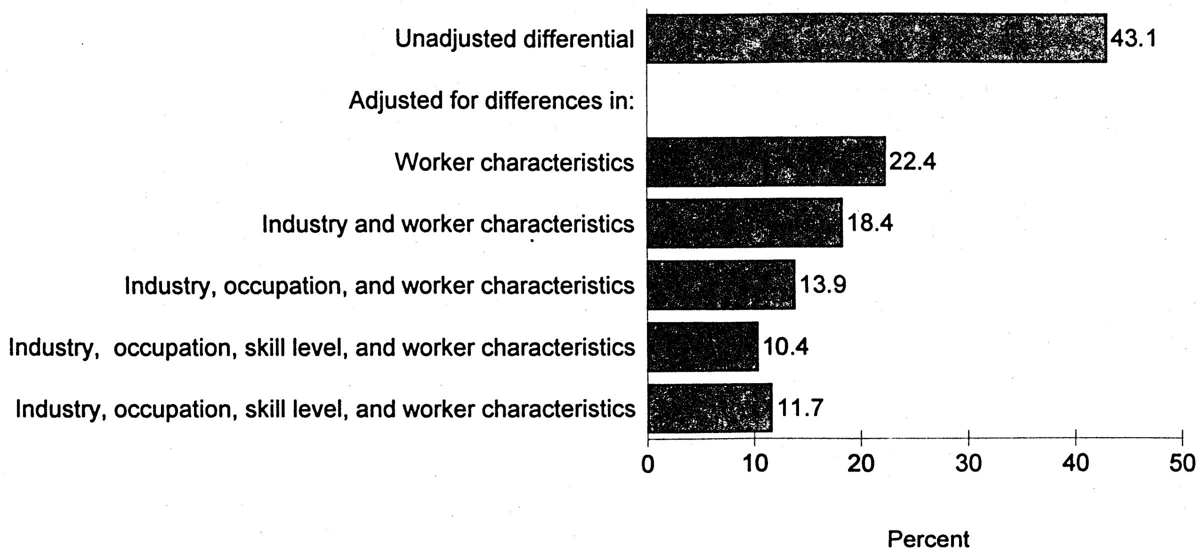
See notes under table 5.

Source: Computed by Economic Research Service from October 1993 Current Population Survey.

Figure 2

Wage premium for computer use, 1993

The wage premium persists when other job and worker differences are considered



Source: Calculated by Economic Research Service, USDA, from Current Population Survey, October 1993.

The Computer Use Wage Premium and the Metro-Nonmetro Wage Gap

As noted above, OTJ computer use rates are substantially higher in metro areas. The results of the analyses described above suggest that there is a wage premium of 10 percent to 12 percent associated with using computer skills on the job, even after differences in industry, occupation and other skills are taken into account. Could this wage premium help account for the persistent wage gap between metro and nonmetro areas?

The importance of a particular worker/job characteristic such as OTJ computer use in explaining the metro-nonmetro wage gap can be assessed using the estimated regression coefficient for that characteristic and data on the metro and nonmetro distribution of that characteristic. If we multiply the estimated effect of OTJ computer use on wages by the difference between metro and nonmetro frequencies of OTJ computer use, we have an estimate of the metro-nonmetro wage difference accounted for by differing rates of OTJ computer use. Comparing this with the overall metro-nonmetro wage difference yields an estimate of the percentage of the wage gap explained. (See appendix, "Data and Methods.")

Applying this technique and using the results of the wage regression in model 5, it appears that differences in computer use rates explain a relatively small part, only about 4 percent, of the overall wage gap (table 7).[11] About 30 percent of the gap can be explained by differences in education level and/or occupational skill level, but about two-thirds of the wage gap is not explained by any variables in the model. The other variables that are included in the model account for relatively little of the metro-nonmetro gap, either because their effects on wages are weak, or because the average metro-nonmetro differences in these variables are not large.[12] Part of the unexplained wage gap may reflect cost-of-living differences between metro and nonmetro areas, but area-specific cost-of-living data that would allow us to quantify this factor are not available.

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[11] The decomposition analysis presented here is directly applicable to the unweighted sample of CPS respondents for whom data on all variables of interest are available. Application of the same analysis to the entire workforce would produce slightly but not substantially different results.

[12] In particular, while it is not directly relevant to the topic of this paper, it may be of some interest to note that differences in industry mix between metro and nonmetro areas account for very little net difference in wage levels.

Table 7--Factors accounting for the metro-nonmetro wage gap

Variable in model	Wage difference explained	Wage gap explained
	Percentage points	*Percent*
Education	3.2	16.2
Occupational skill levels	2.7	13.7
Race and ethnicity	-0.9	-4.4
Industry	-0.05	-0.2
Computer use	0.8	4.2
Other	0.8	4.0
Total explained	6.7	33.5
Unexplained	13.3	66.5
Total metro-nonmetro gap	20.0	100.0

Note: "Other" includes gender, marital status, union membership, veteran status, part-time status, labor force experience, and region.

Source: Computed by Economic Research Service from October 1993 Current Population Survey.

This decomposition analysis assumes that the wage premium for OTJ computer use is the same in metro and nonmetro areas. A test of that assumption, though, indicates that the premium is much larger in metro areas. In particular, if a variable representing the interaction between metro status and OTJ computer use is added to the wage model, we find that the estimated computer use wage premium is only about 5 percent in nonmetro areas, while it is more than 12 percent in metro areas; further, this difference is statistically significant at the 0.1 percent level (table 8, model 7). One implication of this finding is that the "unexplained" metro-nonmetro wage gap[13] for those workers who do not use computers on the job is less than 11 percent, while the corresponding value for OTJ computer users is 19 percent.[14]

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[13]That is, the portion of the gap not accounted for by any variables in the model other than metro status per se.

[14]The combined logarithmic effect of computer use and the metro-computer use interaction term is .047 + .071 = .118; the percentage equivalent of this combined effect is 12.5 percent. The combined logarithmic effect of metro residence and the metro-computer use interaction term is .103 + .071 = .174; the percentage equivalent of this combined effect is 19.0 percent. (See footnote 3.)

Metro Versus Nonmetro Computer Wage Premiums

This decomposition analysis assumes that the wage premium for OTJ computer use is the same in metro and nonmetro areas. A test of that assumption, though, indicates that the premium is much larger in metro areas. In particular, if a variable representing the interaction between metro status and OTJ computer use is added to the wage model, we find that the estimated computer use wage premium is only about 5 percent in nonmetro areas, while it is more than 12 percent in metro areas; further, this difference is statistically significant at the 0.1 percent level (table 8, model 7). One implication of this finding is that the "unexplained" metro-nonmetro wage gap[15] for those workers who do not use computers on the job is less than 11 percent, while the corresponding value for OTJ computer users is 19 percent.[16]

Another implication of these results is that while, as observed above, lower rates of computer use in nonmetro areas account for relatively little of the metro-nonmetro wage gap, lower returns to computer use are a substantial component of that gap. In particular, the more than one-third of all nonmetro workers who use computers on the job appear to lose out on an additional wage premium of about 8 percent that they would receive for their computer skills if they were employed in metro areas.

Supply and Demand for Job Skills in Nonmetro Areas

This last result is broadly consistent with past work at ERS indicating that the returns to higher levels of education are greater in metro as opposed to nonmetro areas, and that, at least until recently, those with higher skill levels have been more likely to migrate to metro areas (McGranahan and Ghelfi, 1991; McGranahan and Kassel, 1995; Swaim, 1995; Gibbs, 1998; Nord and Cromartie, 1998.) Together, these results suggest that the skills gap and apparently associated wage gap that is seen in rural areas reflect weaker demand for such skills in these areas. Stronger demand for skills in urban areas, as expressed by greater wage premiums for those skills, encourages those who possess skills to migrate, leaving lower average skill levels in the remaining rural population. However, perhaps because of imperfect information, and/or because some people with skills prefer to live in rural areas, the migration of skilled workers does not appear to be sufficient to equalize urban and rural wages for these workers. Observed rural wages then appear lower than urban wages in part because the average skill level of rural workers is lower, and in part because the wage premiums paid to those more-skilled workers who remain in rural areas are lower (as well as for other reasons). If the skills gap in rural areas instead reflected a deficit in the ability of rural areas to supply skilled workers to employers, we would expect to see greater skill premiums paid to those skilled workers who are available in rural areas, but in fact we find the reverse.[17] This result is also consistent with the results of a recent survey of rural manufacturers, which found that lower use of selected advanced

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[15]That is, the portion of the gap not accounted for by any variables in the model other than metro status per se.

[16]The combined logarithmic effect of computer use and the metro-computer use interaction term is .047 + .071 = .118; the percentage equivalent of this combined effect is 12.5 percent. The combined logarithmic effect of metro residence and the metro-computer use interaction term is .103 + .071 = .174; the percentage equivalent of this combined effect is 19.0 percent. (See footnote 3.)

[17]Cost-of-living differences may also help to explain the rural wage gap, but are unlikely to account for the greater rural wage gap faced by more skilled workers.

Table 8--Computer use wage premium: variation by geographic, job, and personal characteristics

Variable	Model 7 (metro versus nonmetro premium)		Model 8 (variation in premium by characteristics)			
	Parameter estimates					
			Direct effects:		Interaction with computer use variable:	
Uses computer	0.047	**	-0.019		NA	
Metro area	0.103	***	0.106	***	0.054	**
Uses computer x metro	0.071	***				
Labor force experience	0.020	***	0.017	***	0.010	***
Labor force experience**2	-0.034	***	-0.028	***	-0.016	***
Non-HS graduate	-0.098	***	-0.096	***	0.034	
Some college	0.069	***	0.061	***	0.019	
Bachelors degree	0.254	***	0.198	***	0.094	***
Advanced degree	0.408	***	0.349	***	0.099	**
GED-Reason	-0.043	*	0.003		-0.103	*
GED-Language	0.040	**	0.041	*	0.009	
GED-Math	0.061	***	0.047	**	0.012	
Specific Vocational Prep	0.045	***	0.024	***	0.052	***
Black	-0.062	***	-0.082	***	0.057	*
Asian	-0.007		-0.035		0.078	
Other race	-0.062	*	-0.019		-0.126	*
Hispanic	-0.099	***	-0.120	***	0.071	*
Union	0.195	***	0.248	***	-0.126	***
Adjusted R-square	0.492		0.497			

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

See notes under table 5.

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

technologies in rural areas was primarily a function of the industry mix in these areas, and thus did not reflect any difficulty specific to rural areas in obtaining labor or other resources needed to use these technologies (Gale, 1997).

Other Factors Associated with the Size of the Computer Use Wage Premium

Other factors are associated with the wage premium, and we look at the interactions between OTJ computer use and other job and personal characteristics in the wage model (table 8, model 8; table 9).

The personal monetary return to computer use seems sensitive to several factors:

Education. College graduates are more likely than high school graduates to have computer skills. If the demand for such skills were similar in the jobs held by high school graduates and college graduates, we would expect the return on those skills to be greater among high school graduates, among whom such skills are scarcer. But we find instead that the return to computer use is about 10 percentage points higher for those with bachelors or advanced degrees than for high school graduates (model 8). This finding suggests that there is a higher demand for computer skills in the kinds of jobs that are filled by college graduates that outweighs any supply effects. Another possibility is that the particular kinds of computer skills that employers seek in many college-educated workers (for example, programming skills or facility with complex accounting programs) are scarcer relative to demand than the skills associated with OTJ computer use in jobs held by high school graduates (for example, data entry or word processing).

Skills. A highly significant interaction exists in the wage model between the use of computers on the job and the degree of specific vocational preparation (SVP) required for the job. In fact, the rather startling results suggest that the returns to SVP are more than 3 times as great when computer skills are used on the job.

Union membership. The premium for computer use is reduced by about 12 percentage points for unionized jobs, which will almost wipe it out for the average worker. This finding is broadly consistent with other studies that have shown that unionization reduces the premium to skill differentials.

Race and ethnicity. The premiums to computer use appear to be greater for racial and ethnic minorities. The estimated premiums are 6 to 8 percentage points larger for blacks, Hispanics, and Asians than for non-Hispanic whites. However, the coefficient for Asians is only significant at the 10 percent level.

Labor force experience. Finally, the estimated rate of return to labor force experience is about 60 percent greater for those using computers on the job. This result also suggests that the premium for computer use is relatively small for new workers, while it is much larger for those in their peak earning years.[18]

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[18]Labor force experience has been estimated indirectly based on age and years of education; see the appendix.

Table 9--Variation in computer use wage premium when experience-education and experience-skill interactions are taken into account

Variable	Model 9			
	Direct effects:		Interaction with computer use variable:	
	Parameter estimates			
Intercept	1.317	***	NA	
Metro area	0.106	***	0.055	**
Uses computer	0.037		NA	
Labor force experience	0.008		0.004	
Labor force experience**2	-0.010		-0.004	
Non-HS graduate	-0.002		0.037	
Some college	0.064	**	0.020	
Bachelors degree	0.193	***	0.089	***
Advanced degree	0.396	***	0.106	**
GED-Reason	0.048		-0.121	**
GED-Language	0.060		0.003	
GED-Math	-0.009		0.032	
Specific Vocational Prep	-0.008		0.055	***
Black	-0.080	***	0.054	*
Asian	-0.032		0.080	
Other race	-0.018		-0.127	*
Hispanic	-0.114	***	0.066	*
Union	0.244	***	-0.122	***
Interaction with experience variable:			Interaction with squared experience variable:	
Non-HS graduate	-0.011	***	0.021	***
Some college	-0.001		0.004	
Bachelors degree	0.003		-0.011	
Advanced degree	-0.006		0.011	
GED-Reason	0.000		-0.006	
GED-Language	0.001		-0.006	
GED-Math	0.000		0.007	
Specific Vocational Prep	0.002		-0.002	
Adjusted R-square	0.500			

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

See notes under table 5.

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

However, further analysis indicates that computer use here is serving as a proxy for employment in more skilled and higher status jobs where the returns to experience are greater. When interactions between skill or education variables and labor force experience are also included in the model, several of the interactions are highly significant, while the interaction between computer use and labor force experience is no longer significant (tables 9 and 10).

Since metro jobs and workers are more likely to have characteristics associated with large computer use wage premiums, these variations in the size of the computer use wage premium across jobs and workers could explain the apparent metro-nonmetro difference in the wage premium described earlier. However, this is not the case. The results of models 8 and 9 show that the estimated size of the metro area-computer use interaction effect is only modestly reduced (from 7 percent to about 5.5 percent of wages) when all other interactions are taken into account.

Table 10--Variation in computer use wage premium when selected experience-education and experience-skill interactions are taken into account

Variable	Model 10			
	Direct effects:		Interaction with computer use variable:	
	Parameter estimates			
Uses computer	0.034		NA	
Metro area	0.106	***	0.054	**
Labor force experience	0.009	**	0.004	
Labor force experience**2	-0.017	**	-0.005	
Non-HS graduate	-0.008		0.034	
Some college	0.059	***	0.017	
Bachelors degree	0.199	***	0.093	***
Advanced degree	0.340	***	0.106	**
GED-Reason	0.007		-0.106	*
GED-Language	0.041	*	0.009	
GED-Math	0.042	**	0.016	
Specific Vocational Prep	-0.001		0.051	***
Black	-0.081	***	0.056	*
Asian	-0.031		0.074	
Other race	-0.020		-0.123	*
Hispanic	-0.115	***	0.065	*
Union	0.246	***	-0.122	***
Interaction with experience variable:			Interaction with squared experience variable:	
Non-HS graduate	-0.011	***	0.022	***
Specific Voc Prep	0.002	***	-0.004	***
Adjusted R-square	0.499			

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

See notes under table 5.

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

Conclusion

An area of some debate centers on whether the apparent return to computer use on the job reflects a return to specific computer skills or whether computer use is serving as proxy for other skills or job characteristics. An answer to this question would help to determine whether public expenditures on the development of computer skills per se are a good investment of education or job training funds.

The results described here suggest that estimated computer wage premiums reflect returns to both computer-specific skills and broader skills. Including controls for other skill measures in the wage model, as well as occupational and industry category variables, reduces the estimated magnitude of the computer wage premium by more than half, from 22 percent to 10 percent. However, the latter figure is substantial and statistically significant.

Is this a factor in explaining the metro-nonmetro wage gap? Rates of computer use on the job are higher in metro areas, a finding explained in part by differences in occupational mix and educational attainment between metro and nonmetro areas. This study finds that this gap, combined with the computer wage premium, explains only a small percentage of the metro-nonmetro wage gap.

Further results suggest that, in general, workers in nonmetro areas may benefit less than metro workers from computer training, as the premium paid for working with a computer appears to be substantially less outside metro areas, a result which persists even after other differences between metro and nonmetro workers are taken into account. This finding is consistent with past work (e.g. McGranahan and Ghelfi, 1991; McGranahan and Kassel, 1995) which has indicated that the demand for worker skills is weaker in nonmetro areas. Such results suggest that, while training in computer skills may benefit workers who now live in nonmetro areas, those workers may have to relocate to obtain the most benefit from such training.

The estimated interaction effects further suggest that this premium is greatest for workers who also have higher levels of education and/or specific training. Thus, less-skilled workers may need to combine computer training with higher education or other job-specific skills training to obtain a higher wage premium. The results do suggest that the returns on computer training may be greater for members of racial and ethnic minorities than for otherwise comparable nonminorities.

However, these conclusions may have to be modified with the recent explosive growth in economic significance of the Internet, which is not reflected in the data used here. It seems likely that the increasing importance of the Internet has increased the relevance of computer skills in many occupations. Further, the Internet may decrease the importance of physical proximity to customers, clients, and information resources in some industries, allowing firms in relatively isolated areas to participate in the economy in ways that previously required location in metro areas; in turn, this may increase the demand for workers with computer skills and other skills in less densely settled areas.

Appendix: Data and Methods

Data Source

Data for this analysis have been taken from responses to the Current Population Survey (CPS). The CPS is conducted monthly by the Census Bureau to collect data on employment and unemployment. Data are collected from a sample of approximately 57,000 households, chosen to represent the civilian noninstitutional population of the United States.

The data for the analysis come primarily from the October 1993 Current Population Survey, which asked a variety of questions about computer use on the job, at home, and at school. The primary computer use question relevant to this paper was one that asked "Does (person's name) directly use a computer at work?" According to the interviewers' instructions quoted in Krueger (1993), "Using a computer refers only to the respondent's 'DIRECT' or 'HANDS-ON' use of a computer with typewriter-like keyboards" (p. 35). Thus, use of an electronic cash register or hand-held data-entry device with a more limited keypad is excluded.

The sample covered by this analysis includes respondents who were employed, who were asked about weekly earnings in the October survey (a quarter of all respondents are asked about earnings in any single month), and who responded to all of the questions that are used in the analysis, for a total of about 14,000 unweighted observations.

Metro and Nonmetro Areas

In this article, "metro" refers to metropolitan areas as designated by the Office of Management and Budget, while "nonmetro" refers to all other areas. The metro or nonmetro status of respondents is based on their place of residence, and not on their place of work. For 1993, the metro-nonmetro designation of residences in the CPS was based on population and commuting patterns from the 1980 Census of Population. The terms metro/nonmetro and urban/rural are used interchangeably here.

Categorical Variables

The wage regressions reported in this paper have been computed using standard multivariate linear regression. Categorical variables such as region of the country, or whether a worker is covered by a union contract, are normally represented in regression analysis by dichotomous variables, commonly referred to as dummy variables. These are variables that take on only the values 0 or 1, depending on whether an observation satisfies a particular condition. A categorical variable with two categories (for example, union versus nonunion) can be represented with 1 dummy variable (1=union); a categorical variable with n categories (for example, the nine major occupation groups used in this paper can be represented with n-1 independent dummy variables. Inclusion of a dummy variable for the nth category, for example, inclusion of separate 0,1 dummy variables for union and nonunion, would add redundant information to the list of independent variables (Kusmin, Redman, and Sears, 1996, page B-6). The nth category, which is not included in the list of regressors, is referred to as the "omitted" category. Omitted categories for the regressions reported in this paper are: female (sex); not married (marital status); non-veteran; non-union; non-Hispanic white (race/ethnicity); Midwest (region); nonmetro; not self-reporting; full-time; high school graduate (education); does not use computer; and sales occupations.

Labor Force Experience

Labor force experience (LFE) is not directly measured in the Current Population Survey. Thus, LFE (in years) has been estimated from the formula
LFE = Age in Years - Estimated Years of Education – 6
where estimated years of education are derived from the reported highest level of education completed. The term LFE^2 is commonly included in wage regressions to capture the widely observed nonlinear relationship between experience and wages (on average, wages rise rapidly early in working life career and then begin to level off, and may even decline near the end of working life).

'Self-Reporting'

For each household, data are collected on all household members within the sample universe, although not all may be available for interview. Each individual record contains an item indicating whether this individual reported for himself/herself, or whether a parent, spouse, other relative, or nonrelative responded for him/her. Reporting may be less accurate for some variables (such as whether a computer is used on the job) when reported by one household member on behalf of another. Therefore, the analysis reported here includes a variable reflecting whether an individual observation is self-reported or reported on behalf of another individual.

Assignment of Skill Levels to Occupations

The Dictionary of Occupational Titles (DOT) file, which was used to assign skill levels to occupations, contains quantitative assessments of the characteristics of a large number of narrowly defined occupations. To associate skill levels with individuals in the CPS data, these occupations were aggregated to correspond to the level of occupational detail available on the CPS. The DOT data set was originally developed for job placement purposes, and not for statistical purposes; no data on employment totals in DOT occupations are readily available for weighting. Hence equal weights were assigned to each DOT occupation in estimating the average characteristics of individual CPS occupations. This weighting means that the estimated skill content of any CPS occupation will be underestimated (overestimated) to the extent that the DOT component occupations with higher skill levels in reality have more (fewer) workers than are found in those with lower skill levels. However, for the skills considered in this study, the dispersion of skill level values among the various DOT occupations within a single CPS occupation was usually small relative to the dispersion among CPS occupations.

Decomposition of Urban-Rural Differences into Explained and Unexplained Components

The decomposition of urban-rural wage differences into explained and unexplained components used here and reported in table 7 follows the model of McGranahan and Kassel (1996).[19] To illustrate this method, in the sample studied, 40.7 percent of nonmetro workers and 49.2 percent of metro workers used computers, a difference of 8.5 percentage points. In the regression model used for this calculation, the estimated effect of computer use on wages is 9.9 percent. Thus, the estimated contribution of differing levels of computer use to metro-nonmetro wage differences is (.099 x .085 =

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[19]Except that McGranahan and Kassel use dollar earnings as the dependent variable in their wage equation, and this study uses the logarithm of earnings.

.0084), or 0.84 percent. The overall difference between metro and nonmetro wage levels is 20 percent. Thus, differing levels of computer use account for 4.2 percent of the overall wage level difference (.0084/.20 = 4.2 percent). If a similar computation is carried out for each independent variable in the wage equation and the results are summed, 33.5 percent of the overall wage difference can be explained; the remaining 13.3 percent gap is unexplained (20 percent x .665 = 13.3 percent).

This method appears to differ from the traditional Oaxaca decomposition of intergroup wage differences (Oaxaca, 1973). In that approach, group-specific wage equations are estimated separately for each group of interest (in the present study, those groups would be metro and nonmetro residents). Then, the difference between average log wages for the groups is decomposed into two components. One component reflects intergroup differences in the average level of the regression variables, assuming a common set of coefficients--typically the coefficients estimated for one of the two groups. The second component is explained by intergroup differences in estimated regression coefficients, and is often viewed as the "discriminatory" component of the difference.

However, the "explained" and "unexplained" components of the intergroup wage difference derived in the present study are equivalent to the two components of the wage difference that would be derived from a Oaxaca-style decomposition if the common set of coefficients used in that decomposition were derived from running the wage equation on the pooled sample, rather than being chosen from one of the groups.

Appendix: Detailed Regression Tables

Appendix table 1--Basic wage regression models

Variable	Model 1: Wage model without computer use			Model 2: Basic model with computer use variable		
	Parameter estimate	*T for H0: Param=0*		*Parameter estimate*	*T for H0: Param=0*	
Intercept	1.655	95.78	***	1.581	91.71	***
Use computer	NA	NA		0.202	23.38	***
Metro area	0.156	17.17	***	0.144	16.12	***
Labor force experience	0.026	24.00	***	0.025	23.76	***
Labor force experience squared	-0.044	-20.16	***	-0.042	-19.58	***
Non-HS graduate	-0.185	-12.86	***	-0.145	-10.22	***
Some college	0.144	14.54	***	0.108	11.06	***
Bachelors degree	0.424	36.09	***	0.358	30.20	***
Advanced degree	0.593	38.40	***	0.522	33.85	***
Black	-0.108	-8.05	***	-0.091	-6.90	***
Asian	-0.031	-1.31		-0.006	-0.24	
Other race	-0.081	-2.60	**	-0.072	-2.36	*
Hispanic	-0.154	-9.53	***	-0.141	-8.89	***
Union	0.157	14.88	***	0.174	16.83	***
Male	0.098	7.65	***	0.129	10.17	***
Married	0.040	3.37	***	0.028	2.40	*
Married Male	0.149	9.13	***	0.145	9.06	***
Veteran	0.010	0.78		0.016	1.23	
Northeast	0.089	7.88	***	0.093	8.45	***
South	-0.007	-0.64		-0.003	-0.25	
West	0.082	6.93	***	0.080	6.97	***
Self-reporting	0.051	6.16	***	0.034	4.25	***
Part-time	-0.247	-22.46	***	-0.201	-18.37	***
Adjusted R-square		0.388			0.412	

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

NA=not included in this specification

Dependent variable=Log (weekly earnings/usual hours)

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

Appendix table 2--Wage regression models with industry and occupation controls

Variable	Model 3: Wage model with controls for industrial sector			Model 4: Wage model with controls for industry and occupation		
	Parameter estimate	*T for H0: Param=0*		*Parameter estimate*	*T for H0: Param=0*	
Intercept	1.475	82.28	***	1.587	80.66	***
Use computer	0.169	19.56	***	0.130	14.20	***
Metro area	0.142	16.28	***	0.134	15.85	***
Labor force experience	0.023	22.26	***	0.021	21.05	***
Labor force experience squared	-0.037	-18.18	***	-0.035	-17.44	***
Non-HS graduate	-0.132	-9.62	***	-0.112	-8.36	***
Some college	0.107	11.28	***	0.072	7.66	***
Bachelors degree	0.376	31.93	***	0.248	19.82	***
Advanced degree	0.566	35.78	***	0.403	23.98	***
Managers	NA	NA		0.163	9.83	***
Professionals	NA	NA		0.168	9.44	***
Technical	NA	NA		0.087	3.70	***
Clerical	NA	NA		-0.113	-7.07	***
Service	NA	NA		-0.149	-9.11	***
Craft occupations	NA	NA		0.000	0.02	
Operators	NA	NA		-0.143	-7.83	***
Laborers	NA	NA		-0.200	-9.58	***
Black	-0.092	-7.22	***	-0.068	-5.43	***
Asian	-0.015	-0.64		-0.005	-0.24	
Other race	-0.075	-2.54	*	-0.060	-2.11	*
Hispanic	-0.118	-7.68	***	-0.104	-7.02	***
Union	0.166	15.63	***	0.184	17.63	***
Male	0.108	8.61	***	0.101	8.15	***
Married	0.018	1.64		0.011	1.00	
Married Male	0.126	8.17	***	0.124	8.23	***
Veteran	-0.002	-0.16		0.002	0.14	
Northeast	0.088	8.27	***	0.083	8.06	***
South	-0.003	-0.26		-0.011	-1.07	
West	0.083	7.42	***	0.080	7.42	***
Self-reporting	0.035	4.46	***	0.036	4.80	***
Part-time	-0.147	-13.71	***	-0.131	-12.49	***

continued

Appendix table 2--Wage regression models with industry and occupation controls (continued)

Variable	Model 3			Model 4		
	Parameter estimate	*T for H0: Param=0*		*Parameter estimate*	*T for H0: Param=0*	
Industry effects:						
Agriculture	-0.106	-3.39	***	-0.007	-0.21	
Mining	0.477	10.89	***	0.479	11.11	***
Construction	0.306	16.25	***	0.289	14.46	***
Durable goods	0.254	16.67	***	0.259	15.80	***
Nondurables	0.207	12.52	***	0.221	12.66	***
Transportation	0.231	11.49	***	0.273	13.18	***
Communication	0.328	10.43	***	0.310	9.99	***
Utilities & sanitary services	0.380	11.71	***	0.379	11.79	***
Wholesale trade	0.172	7.74	***	0.203	9.30	***
Finance, insurance and real estate	0.218	12.35	***	0.225	12.75	***
Private household services	-0.145	-3.68	***	-0.091	-2.34	**
Business services	0.112	5.89	***	0.112	5.86	***
Personal services	-0.021	-0.81		0.005	0.19	
Entertainment	0.032	0.88		0.020	0.58	
Hospital services	0.310	15.85	***	0.268	13.24	***
Medical services	0.221	11.25	***	0.207	10.31	***
Educational services	0.017	1.03		-0.017	-0.96	
Social services	-0.038	-1.32		-0.079	-2.78	**
Professional services	0.152	7.28	***	0.121	5.69	***
Forestry & fishing	0.165	1.85		0.197	2.27	*
Public service	0.246	13.14	***	0.254	13.34	***
Adjusted R-square		0.4549			0.4872	

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

NA=not included in this specification

Dependent variable=Log (weekly earnings/usual hours)

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

Appendix table 3--Wage regression models with occupational skill controls

Variable	Model 5: Wage model with controls for industry and for occupational skill level		Model 6: Wage model with controls for industry, occupational skill level, and occupation	
	Parameter estimate	*T for H0: Param=0*	*Parameter estimate*	*T for H0: Param=0*
Intercept	1.215	46.12 ***	1.377	35.99 ***
Use computer	0.099	11.35 ***	0.111	12.06 ***
Metro area	0.133	15.79 ***	0.134	15.92 ***
Labor force experience	0.020	20.64 ***	0.020	20.43 ***
Labor force experience squared	-0.034	-17.22 ***	-0.034	-16.98 ***
Non-HS graduate	-0.098	-7.36 ***	-0.104	-7.82 ***
Some college	0.068	7.32 ***	0.067	7.23 ***
Bachelors degree	0.255	20.82 ***	0.237	18.95 ***
Advanced degree	0.410	24.90 ***	0.388	23.05 ***
Managers	NA	NA	0.043	2.27 *
Professionals	NA	NA	0.056	2.77 **
Technical	NA	NA	0.005	0.22
Clerical	NA	NA	-0.081	-4.95 ***
Service	NA	NA	-0.089	-4.57 ***
Craft occupations	NA	NA	-0.043	-1.87
Operators	NA	NA	-0.033	-1.46
Laborers	NA	NA	-0.066	-2.51 *
GED-Reason	-0.042	-2.07 *	-0.074	-3.37 ***
GED-Language	0.038	2.82 **	0.034	2.21 *
GED-Math	0.062	6.66 ***	0.053	5.49 ***
Specific Voc Prep	0.045	8.02 ***	0.049	7.03 ***
Black	-0.061	-4.95 ***	-0.061	-4.97 ***
Asian	-0.008	-0.37	-0.007	-0.34
Other race	-0.063	-2.20 *	-0.062	-2.19 *
Hispanic	-0.101	-6.82 ***	-0.101	-6.84 ***
Union	0.193	18.70 ***	0.190	18.34 ***
Male	0.100	8.25 ***	0.091	7.41 ***
Married	0.008	0.70	0.006	0.60
Married Male	0.123	8.26 ***	0.125	8.36 ***
Veteran	0.003	0.23	0.003	0.26
Northeast	0.082	8.01 ***	0.082	8.00 ***
South	-0.009	-0.90	-0.011	-1.08
West	0.085	7.85 ***	0.083	7.76 ***
Self-reporting	0.035	4.63 ***	0.036	4.74 ***
Part-time	-0.119	-11.40 ***	-0.118	-11.27 ***

continued

Appendix table 3--Wage regression models with occupational skill controls (continued)

Variable	Model 5 Parameter estimate	Model 5 T for H0: Param=0		Model 6 Parameter estimate	Model 6 T for H0: Param=0	
Industry effects:						
Agriculture	-0.075	-2.47	*	-0.064	-1.94	
Mining	0.478	11.24	***	0.476	11.12	***
Construction	0.275	14.56	***	0.280	14.03	***
Durable goods	0.244	16.44	***	0.241	14.71	***
Nondurables	0.230	14.32	***	0.220	12.65	***
Transportation	0.266	13.62	***	0.275	13.31	***
Communication	0.290	9.53	***	0.302	9.79	***
Utilities & sanitary services	0.359	11.44	***	0.372	11.63	***
Wholesale trade	0.185	8.57	***	0.189	8.68	***
Finance, insurance and real estate	0.188	10.91	***	0.208	11.63	***
Private household services	-0.088	-2.31	*	-0.062	-1.58	
Business services	0.105	5.68	***	0.112	5.82	***
Personal services	-0.014	-0.55		-0.002	-0.07	
Entertainment	0.027	0.77		0.028	0.80	
Hospital services	0.257	13.44	***	0.264	12.94	***
Medical services	0.185	9.68	***	0.202	9.98	***
Educational services	-0.020	-1.19		-0.013	-0.74	
Social services	-0.061	-2.17	*	-0.064	-2.24	*
Professional services	0.096	4.67	***	0.110	5.09	***
Forestry & fishing	0.112	1.30		0.130	1.51	
Public service	0.218	11.88	***	0.240	12.46	***
Adjusted R-square		0.491			0.494	

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

NA=not included in this specification

Dependent variable=Log (weekly earnings/usual hours)

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

Appendix table 4--Wage regression models with varying computer use premiums

Variable	Model 7 (metro versus nonmetro premium)			Model 8 (variation in premium by characteristics)				
				Direct effects:			Interaction with computer use variable:	
	Parameter estimate	*T for H0: Param=0*		*Parameter estimate*	*T for H0: Param=0*		*Parameter estimate*	*T for H0: Param=0*	
Intercept	1.236	46.19	***	1.258	36.70	***	NA	NA	
Uses computer	0.047	3.17	**	-0.019	-0.34		NA	NA	
Metro area	0.103	9.34	***	0.106	9.45	***	0.054	3.16	**
Use comp x metro	0.071	4.33	***						
Labor force experience	0.020	20.70	***	0.017	12.83	***	0.010	4.67	***
Labor force experience squared	-0.034	-17.28	***	-0.028	-11.31	***	-0.016	-3.72	***
Non-HS graduate	-0.098	-7.34	***	-0.096	-6.56	***	0.034	0.85	
Some college	0.069	7.36	***	0.061	4.84	***	0.019	1.03	
Bachelors degree	0.254	20.75	***	0.198	10.05	***	0.094	3.67	***
Advanced degree	0.408	24.83	***	0.349	12.12	***	0.099	2.78	**
GED-Reason	-0.043	-2.11	*	0.003	0.10		-0.103	-2.48	*
GED-Language	0.040	2.93	**	0.041	2.18	*	0.009	0.34	
GED-Math	0.061	6.60	***	0.047	2.94	**	0.012	0.60	
Specific Voc Prep	0.045	8.02	***	0.024	3.30	***	0.052	4.50	***
Black	-0.062	-4.98	***	-0.082	-5.17	***	0.057	2.24	*
Asian	-0.007	-0.32		-0.035	-1.23		0.078	1.75	
Other race	-0.062	-2.19	*	-0.019	-0.54		-0.126	-2.13	*
Hispanic	-0.099	-6.66	***	-0.120	-6.58	***	0.071	2.26	*
Union	0.195	18.88	***	0.248	18.28	***	-0.126	-6.03	***
Male	0.102	8.38	***	0.092	5.61	***	0.024	0.96	
Married	0.009	0.83		0.008	0.53		0.005	0.25	
Married Male	0.121	8.14	***	0.134	6.59	***	-0.044	-1.46	
Veteran	0.003	0.24		0.005	0.30		-0.006	-0.25	
Northeast	0.082	7.98	***	0.076	5.32	***	0.008	0.40	
South	-0.010	-1.02		-0.020	-1.52		0.023	1.19	
West	0.085	7.85	***	0.077	5.08	***	0.015	0.70	
Self-reporting	0.035	4.61	***	0.037	3.61	***	-0.004	-0.24	
Part-time	-0.119	-11.39	***	-0.119	-9.29	***	0.002	0.08	

continued

Appendix table 4--Wage regression models with varying computer use premiums (continued)

Variable	Model 7		Model 8			
			Direct effects:		Interaction with computer use variable:	
	Parameter estimate	*T for H0: Param=0*	*Parameter estimate*	*T for H0: Param=0*	*Parameter estimate*	*T for H0: Param=0*
Industry effects:						
Agriculture	-0.080	-2.63 **	-0.072	-2.18 *	0.025	0.28
Mining	0.475	11.18 ***	0.517	9.56 ***	-0.122	-1.40
Construction	0.274	14.50 ***	0.303	13.75 ***	-0.114	-2.41 *
Durable goods	0.241	16.25 ***	0.238	12.12 ***	0.002	0.07
Nondurables	0.229	14.22 ***	0.220	10.64 ***	0.022	0.67
Transportation	0.264	13.55 ***	0.275	10.89 ***	-0.036	-0.89
Communication	0.285	9.37 ***	0.283	4.11 ***	-0.001	-0.01
Utilities & sanitary services	0.361	11.52 ***	0.373	7.96 ***	-0.024	-0.38
Wholesale trade	0.184	8.53 ***	0.202	6.69 ***	-0.036	-0.83
Finance, insurance and real estate	0.186	10.83 ***	0.246	7.22 ***	-0.079	-1.94
Private household services	-0.086	-2.26 *	-0.094	-2.44 *	0.089	0.22
Business services	0.103	5.57 ***	0.083	3.37 ***	0.049	1.30
Personal services	-0.012	-0.49	0.013	0.45	-0.071	-1.29
Entertainment	0.027	0.76	0.013	0.32	0.049	0.64
Hospital services	0.255	13.38 ***	0.282	9.58 ***	-0.040	-1.02
Medical services	0.184	9.62 ***	0.197	8.02 ***	-0.029	-0.75
Educational services	-0.018	-1.12	0.020	0.91	-0.056	-1.66
Social services	-0.060	-2.15 *	-0.098	-2.74 **	0.110	1.91
Professional services	0.093	4.55 ***	-0.012	-0.32 ***	0.136	2.98 **
Forestry & fishing	0.115	1.34	0.199	1.68	-0.152	-0.89
Public service	0.217	11.85 ***	0.238	7.53 ***	-0.037	-0.93
Adjusted R-square		0.492		0.497		

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

Dependent variable=Log (weekly earnings/usual hours)

NA=not included in this specification

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

Appendix table 5--Wage regression model with varying computer use and experience premiums

	Model 9					
	Direct effects:			Interaction with computer use variable:		
	Parameter estimate	*T for H0: Param=0*		*Parameter estimate*	*T for H0: Param=0*	
Intercept	1.317	23.50	***	NA	NA	
Metro area	0.106	9.46	***	0.055	3.24	**
Uses computer	0.037	0.65		NA	NA	
Labor force experience	0.008	1.72		0.004	1.64	
Labor force experience squared	-0.010	-1.04		-0.004	-0.84	
Non-HS graduate	-0.002	-0.05		0.037	0.93	
Some college	0.064	2.66	**	0.020	1.08	
Bachelors degree	0.193	5.73	***	0.089	3.43	***
Advanced degree	0.396	7.35	***	0.106	2.91	**
GED-Reason	0.048	0.92		-0.121	-2.89	**
GED-Language	0.060	1.70		0.003	0.11	
GED-Math	-0.009	-0.33		0.032	1.58	
Specific Voc Prep	-0.008	-0.59		0.055	4.72	***
Black	-0.080	-5.08	***	0.054	2.12	*
Asian	-0.032	-1.12		0.080	1.78	
Other race	-0.018	-0.51		-0.127	-2.15	*
Hispanic	-0.114	-6.27	***	0.066	2.10	*
Union	0.244	18.01	***	-0.122	-5.87	***
Male	0.093	5.70	***	0.023	0.93	
Married	0.007	0.43		0.009	0.43	
Married Male	0.133	6.51	***	-0.045	-1.48	
Veteran	0.002	0.15		-0.009	-0.35	
Northeast	0.076	5.35	***	0.009	0.46	
South	-0.021	-1.59		0.025	1.26	
West	0.076	5.01	***	0.017	0.80	
Self-reporting	0.036	3.55	***	0.000	-0.01	
Part-time	-0.118	-9.21	***	-0.002	-0.08	

continued

Appendix table 5--Wage regression model with varying computer use and experience premiums (continued)

	Interaction with experience variable:			Interaction with squared experience variable:		
Non-HS graduate	-0.011	-3.60	***	0.021	3.75	***
Some college	-0.001	-0.55		0.004	0.75	
Bachelors degree	0.003	1.00		-0.011	-1.57	
Advanced degree	-0.006	-1.23		0.011	1.12	
GED-Reason	0.000	-0.09		-0.006	-0.56	
GED-Language	0.001	0.24		-0.006	-0.86	
GED-Math	0.000	0.13		0.007	1.52	
Specific Voc Prep	0.002	1.60		-0.002	-0.59	
Adjusted R-square		0.500				

Note: Wage effects of individual industry variables are not shown.

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

NA=not included in this specification

Dependent variable=Log (weekly earnings/usual hours)

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

Appendix table 6-- Wage regression model with varying computer use premiums and selected varying experience premiums

Variable	Model 10			
	Direct effects:		Interaction with computer use variable:	
	Parameter estimate	*T for H0: Param=0*	*Parameter estimate*	*T for H0: Param=0*
Intercept	1.345	32.78 ***	NA	NA
Uses computer	0.034	0.61	NA	NA
Metro area	0.106	9.53 ***	0.054	3.17 **
Labor force experience	0.009	3.01 **	0.004	1.70
Labor force experience squared	-0.017	-2.84 **	-0.005	-1.04
Non-HS graduate	-0.008	-0.22	0.034	0.86
Some college	0.059	4.73 ***	0.017	0.93
Bachelors degree	0.199	10.09 ***	0.093	3.61 ***
Advanced degree	0.340	11.79 ***	0.106	2.98 **
GED-Reason	0.007	0.27	-0.106	-2.56 *
GED-Language	0.041	2.15 *	0.009	0.33
GED-Math	0.042	2.64 **	0.016	0.83
Specific Voc Prep	-0.001	-0.06	0.051	4.47 ***
Black	-0.081	-5.10 ***	0.056	2.19 *
Asian	-0.031	-1.07	0.074	1.66
Other race	-0.020	-0.57	-0.123	-2.09 *
Hispanic	-0.115	-6.28 ***	0.065	2.09 *
Union	0.246	18.11 ***	-0.122	-5.85 ***
Male	0.091	5.55 ***	0.025	1.00
Married	0.008	0.50	0.008	0.36
Married Male	0.135	6.62 ***	-0.046	-1.50
Veteran	0.005	0.32	-0.009	-0.37
Northeast	0.077	5.43 ***	0.007	0.34
South	-0.021	-1.53	0.023	1.18
West	0.077	5.09 ***	0.015	0.69
Self-reporting	0.037	3.59 ***	-0.001	-0.09
Part-time	-0.117	-9.13 ***	-0.003	-0.14
Interaction with experience variable:			Interaction with squared experience variable:	
Non-HS graduate	-0.011	-3.83 ***	0.022	4.32 ***
Specific Voc Prep	0.002	4.42 ***	-0.004	-3.55 ***
Adjusted R-square		0.499		

Note: Wage effects of individual industry variables are not shown.

*=significant at 5 percent level
**=significant at 1 percent level
***=significant at 0.1 percent level

NA=not included in this specification

Dependent variable=Log (weekly earnings/usual hours)

Source: Computed by Economic Research Service, USDA from October 1993 Current Population Survey.

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