Wage Premiums for On-the-Job Computer Use: A Metro and Nonmetro Analysis.
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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, 10 to 11 percent, is associated with using 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. In nonmetro areas, the computer use wage premium is only about 6 percent. This suggests that computer literacy skills may only modestly advance the earnings of low-wage workers within their current occupations in rural areas.

Keywords: wages, skills, computers, rural, nonmetro.

Acknowledgments

The author wishes to thank Elizabeth Greenberg and Timothy Parker of ERS for assistance with data used in the study, as well as Peter Schaeffer of West Virginia University, Robert Gibbs and Fred Gale of ERS, and Jennifer Olmsted, formerly of ERS, for helpful comments.

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December 2002

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Summary

Computer use at work has become widespread. By 1997, almost half of all U.S. workers used computers on the job, and such workers 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. But is computer use instrumental in explaining the metro-nonmetro wage gap?

Recent public policy discussions of the digital divide centered on strategies to improve the economic well-being of certain groups of employees--for instance, nonmetro workers, the less educated, and racial and ethnic minorities--by increasing their access to computer skills and computer technology. This report, by focusing on metro-nonmetro differences in computer use and the returns to computer use, addresses several questions that shed light on the potential effects of efforts to bridge the digital divide.

A simple comparison of wages for on-the-job computer users versus other workers shows a wage difference of 32 percent in 1997. Much of this gap reflects differences between the jobs held by computer users and other workers, or differences in worker characteristics, and not solely the effect of computer use. However, even after taking into account differences in industry and occupation, worker education and skill level, and other worker and job characteristics, there is still a 10-percent to 11-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 associated wage premium, could help to explain the metro-nonmetro wage gap. However, taking into account the magnitudes of both the computer use wage premium and the metro-nonmetro gap in use, the computer effect accounts for only about 5 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 6 percent, about half the computer wage premium found in metro areas in 1997. Little of this difference can be explained by differences in the job and worker characteristics considered in this study. Perhaps rurality itself dampens 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, improving such workers' computer literacy may contribute only slightly to reducing urban-rural wage inequality, although such training may also allow some workers to move into higher paying occupations. Computer literacy programs may improve the earnings of some racial and ethnic minorities, for whom the computer use wage premium appears to be substantially larger. Some of these conclusions may have to be modified with the recent explosive growth in the economic significance of the Internet, which is not reflected in the data used here.

Wage Premiums for On-the-Job Computer Use

A Metro and Nonmetro Analysis

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 percentage of U.S. workers using computers on the job rose from about one-fourth in 1984 to about one-half by 1997.

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.

On-the-job computer use is more common in metro areas than in nonmetro areas (Kusmin, 1996). Metro and nonmetro 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). Given all these caveats, does on-the-job computer use partly explain the current magnitude of the metro-nonmetro wage gap?

Table 1—Real annual earnings in nonfarm jobs, metro and nonmetro areas, 1970-97

Year	Nonmetro	Metro	Ratio
	Dollars		*Percent*
1970	22,147	28,937	76.5
1975	23,543	29,503	79.8
1980	24,025	29,849	80.5
1985	23,798	30,680	77.6
1990	22,737	31,209	72.9
1993	22,925	31,842	72.0
1997	22,986	32,799	70.1

Note: Values are in 1997 dollars.
Source: Calculated by Economic Research Service, USDA, using data from the Bureau of Economic Analysis.

Finally, recent public policy discussions of the digital divide raise the question, “How far can improved access to computer skills and computer technology improve the economic well-being of groups such as rural workers and racial/ethnic minorities?” This report addresses that question by looking at how wage returns to computer use vary across groups.

Computer Use and the Wage Structure

In his 1993 *Quarterly Journal of Economics* article, “How Computers Have Changed the Wage Structure,” Alan Krueger found that workers who used computers on the job received a wage premium of 10 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.

Krueger concluded that this premium represented a return to their use of computer skills, and further argued that such premiums helped drive growth during the 1980s in the apparent wage premium to education. 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.[1]

[1] Baldwin and Cain (2000) report that a general equilibrium analysis suggests "education-biased technical change that is greater in education-intensive sectors" as a major factor in the growth of the wage premium for education in the 1979-87 period, a result which appears consistent with Krueger's argument.

Both conclusions have been challenged. DiNardo and Pische (1997) 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. Goss (2000) also offers some evidence that unobserved differences between computer users and other workers may bias the estimation of the computer use wage premium, although the sources of parameter identification are unclear in his instrumental variables analysis. DiNardo and Pische further note that while the returns to higher skill levels grew most rapidly during the 1980s, there is little evidence of increases in productivity associated with computer use before the 1990s.

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. 1185-86).

In addition, the lack of visible productivity gains from the computer revolution during the 1980s 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 including additional variables 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.[2] 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 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 on the wage distribution.

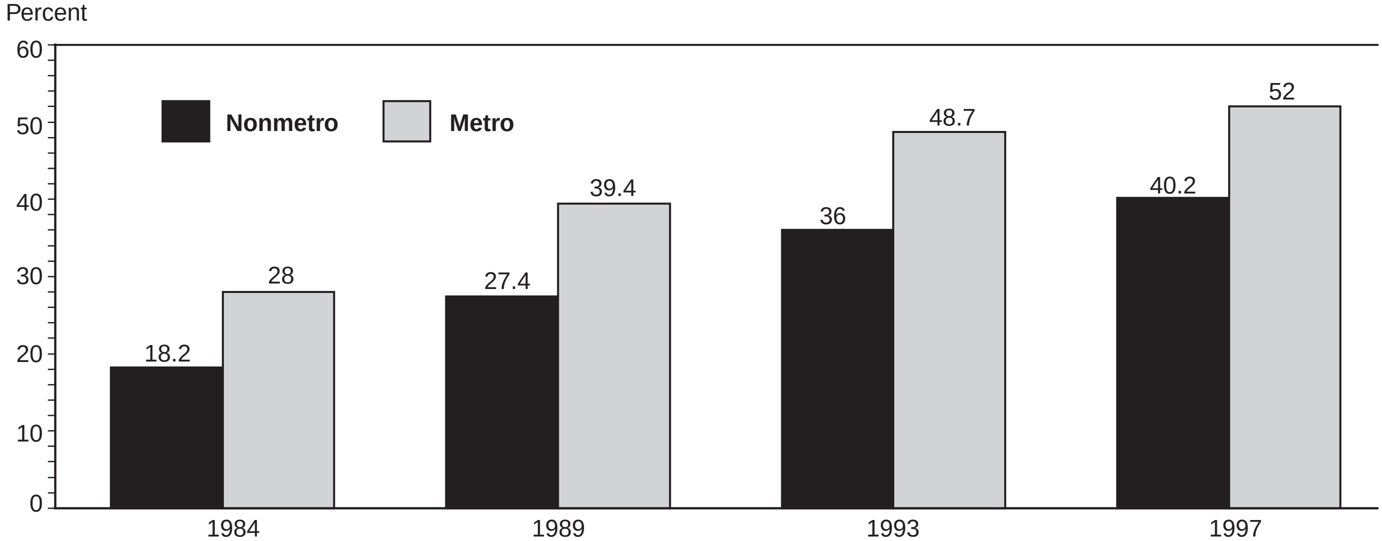
A second objective is to assess the relevance of the computer wage premium for explaining nonmetro wages and the metro/nonmetro wage gap. In this context, the analysis will consider not only metro/nonmetro differences in rates of computer use, but also metro/nonmetro differences in the size of the wage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

It may be interesting 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 returns to education during the 1980s. On the other hand, 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 the metro/nonmetro wage

[2] 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).

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 the Economic Research Service, USDA from Current Population Survey, 1984, 1989, 1993, and 1997.

gap. Would policies to promote computer literacy in more isolated areas contribute to reducing urban-rural inequality?

Computer Use at Work

The share of employed U.S. adults using computers at work more than doubled between 1984 and 1997. By 1997, about 50 percent of all workers used computers on their jobs.

The proportion of jobs involving computer use was higher in metro areas in both 1984 and 1997, 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. By 1997, 40 percent of nonmetro and 52 percent of metro workers used computers on the job (fig. 1).

What accounts for the urban-rural difference in computer use? Predictors of on-the-job computer use in 1997 have been identified using a linear probability regression that relates the probability of on-the-job computer use to various job and personal characteristics (appendix table 1).[3] An analysis using the parameters of that regression, together with urban-rural differences in the percentage of workers with each of the relevant characteristics, indicates that differences in job characteristics such as occupation and industry account for more than half of the urban-rural computer use difference (table 2).

In particular, the concentration of managerial, professional, technical and clerical workers in urban areas explains much of the urban-rural computer use gap. Rural workers, in contrast, are more likely than urban workers to be in those service, blue-collar, or agricultural occupations that are less likely to involve on-the-job computer use.

[3] A linear probability model was used in order to allow comparability with a similar analysis of 1993 data presented in an earlier piece (Kusmin, 1996) where linear probability was used to make the analysis more accessible to nontechnical readers. A logit or probit model would likely be more accurate in assessing the probability of on-the-job computer use for individuals or populations with extreme characteristics (e.g., non-high school graduates working as laborers in the rural South).

Table 2—Urban-rural gap in computer use at work, 1997

Gap accounted for by	Percentage points	As share of total gap
		Percent
Job characteristics	**7.9**	**63**
Occupational mix	6.3	51
Industrial mix	1.0	8
Other job characteristics	0.5	4
Personal characteristics	**1.6**	**13**
Education level	2.9	23
Racial/ethnic background	-0.8	-6
Origin/citizenship status	-0.8	-7
Other personal	0.3	2
Effect of urban residence (residual)	**3.0**	**24**
Total	**12.4**	**100**

The concentration in urban areas of some industries with high computer use-such as professional services and communications-plays a significant but much smaller role than do occupational differences in explaining the utilization gap. The higher frequency of self-employment in rural areas also explains a small portion of the gap. Since the incidence of part-time work varies little between urban and rural workers, lower computer use rates by part-time workers explains little of the gap.

Among personal characteristics, education plays a substantial role in the urban-rural gap. Even after controlling for occupation, age, and other characteristics, college graduates were 17 to 21 percentage points more likely to use computers on the job in 1997 than were high school graduates with no college. Further, urban residents are more likely than rural residents to hold college or advanced degrees. In tandem, these differences account for nearly one-fourth of the difference in the rate of computer use between urban and rural areas (table 2).

On the other hand, the higher rate of on-the-job computer use in urban areas occurs despite the lower rates associated with several population groups that are concentrated in urban areas. Regression analysis shows that Black, Hispanic, and Asian workers were 4 to 8 percentage points less likely to use computers on the job than were comparable White workers. In addition, foreign-born citizens and aliens were 7 to 9 percentage points less likely to use computers than were otherwise comparable U.S.-born citizens. All of these groups are more highly represented in urban than rural populations. However, the concentration of these groups in urban areas is not sufficient to offset the other factors that lead to higher computer use rates in urban areas. Other personal characteristics such as age and gender appear to have little or no influence on differences in computer use between urban and rural areas.

After accounting for job and personal characteristics, a difference of 3.0 percentage points between urban and rural rates of on-the-job computer use remains. This modest difference may reflect slower diffusion of computer skills or computer-based ways of working into rural areas. Firms in urban areas may have more opportunities to observe and imitate the adoption of computer technology by suppliers, customers, or competing firms. The gap may also reflect differences between urban and rural areas in the detailed mix of jobs and/or in personal characteristics not taken into account.

Estimating Returns to Computer Use at Work

Is a wage premium associated with using computer skills on the job, and if so, how large? A simple comparison of average wages indicates that computer users earn far more than other workers—32 percent more in nonmetro areas and 49 percent more in metro areas (table 3). At the same time, earnings are higher in metro areas for computer users and nonusers alike, suggesting that computer use differences are not driving the metro-nonmetro wage gap.

However, this comparison ignores many other characteristics of workers and jobs that influence wages. A better assessment of the effect of computer use on wages should control for such characteristics as education level and labor force experience.

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

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

Table 3—Average hourly earnings by metro status and on-the-job computer use, 1997

Item	Nonmetro	Metro	Metro-nonmetro difference
	Dollars		*Percent*
Don't use computer	9.83	11.17	13.6
Use computer	12.98	16.62	28.1
		Percent	
User-nonuser difference	32.0	48.8	

Source: Current Population Survey, Oct. 1997.

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.[4] 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. Data are taken from the October 1997 CPS subsample (see appendix), and the hourly wage is defined as reported weekly earnings divided by usual hours worked.[5] 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, national origin and citizenship, 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.[6]

This analysis suggests that use of a computer on the job raises hourly earnings by about 21 percent (see table 4, model 2) when worker characteristics are held constant.[7] This wage effect is considerable, but much smaller than the raw difference (32-49 percent) shown in table 3. It is similar to the corresponding estimates (19-21 percent) found by Krueger for 1984 and 1989.[8]

Given this, to what extent do differences in computer use account for metro-nonmetro wage differences? The otherwise unexplained metro-nonmetro difference in wages is about 18 percent when OTJ computer use is left out of the model, and about 16 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.[9,10]

[4] For another recent example, see Barron et al. (1999).

[5] This may lead to some upward bias in the hourly wage values for managerial employees who are exempt from overtime laws, since they are probably more likely to often work longer hours than what they report to CPS as their "usual" hours. This may lead to some overstatement of the wage premium for managerial employees, and to some overstatement of the wage premium for computer use in those wage regressions where there is no control for occupation.

[6] There are minor differences between Krueger's specification and the one presented here. Krueger omits controls for Asian race, for Hispanic origin, for national origin and citizenship status, 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.

[7] 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 .192 in the logarithm of the wage corresponds to a difference of 21.2 percent in the wage itself.

[8] 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.

[9] 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 1980s that had been reported by other studies. However, the education effects are qualitatively similar in both models.

[10] 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—Wage model with and without computer use

Variable	Model 1 Wage model without computer use		Model 2 Basic model with computer use variable	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Uses computer	NA	NA	0.192	18.69***
Metro area	0.162	14.22***	0.145	12.91***
Labor force experience	0.030	22.40***	0.029	21.87***
Labor force experience (squared)	-0.052	-18.04***	-0.050	-17.42***
Non-HS graduate	-0.208	-11.50***	-0.168	-9.36***
Some college	0.140	11.94***	0.103	8.80***
Bachelor's degree	0.426	32.71***	0.360	27.06***
Advanced degree	0.588	33.62***	0.512	28.96***
Black	-0.144	-8.94***	-0.118	-7.44***
Asian	0.004	0.15	0.015	0.57
Native American	0.004	0.09	0.021	0.46
Hispanic	-0.154	-8.05***	-0.135	-7.17***
Foreign-born citizen	-0.136	-4.13***	-0.111	-3.43***
Noncitizen	-0.173	-7.04***	-0.141	-5.82***
Years in U.S.	0.003	3.09**	0.003	3.06**
Union	0.119	9.63***	0.140	11.44***
Veteran	-0.021	-1.34	-0.013	-0.84
Adj. R-squared	0.3574		0.3795	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Note: Intercept and coefficients for sex, marital status, region, part-time status, and self-reporting status have been omitted, but are reported in appendix table 2.

Industry, Occupation, and Skill Effects Versus Computer Use Effects

Is the apparently large premium to OTJ computer use (21 percent) actually a return to computer-specific skills, or is it due to other factors? It 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 and new technologies. In this case, the premium should disappear from a model with appropriate industry and occupational controls.

Or, as noted earlier, computer use may 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. Including a set of 21 categorical industry variables in the model causes the computer use premium to fall only slightly, from 21 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

Table 5—Wage models with controls for industry and occupation

Variable	Model 3 Wage model with controls for industrial sector		Model 4 Wage model with controls for industry and occupation	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Uses computer	0.169	16.19***	0.125	11.22***
Metro area	0.144	12.92***	0.133	12.19***
Labor force experience	0.026	20.36***	0.025	19.87***
Labor force experience (squared)	-0.045	-16.03***	-0.043	-15.66***
Non-HS graduate	-0.167	-9.50***	-0.151	-8.75***
Some college	0.107	9.33***	0.079	6.92***
Bachelor's degree	0.373	27.74***	0.283	20.04***
Advanced degree	0.549	29.47***	0.434	22.27***
Managers	NA	NA	0.064	4.30***
Professionals	NA	NA	0.091	2.83**
Technical	NA	NA	-0.044	-1.84+
Clerical	NA	NA	-0.176	-11.15***
Service	NA	NA	-0.231	-12.79***
Craft occupations	NA	NA	-0.034	-1.74+
Operators	NA	NA	-0.175	-8.87***
Laborers	NA	NA	-0.275	-11.14***
Farmers, fishers, and foresters	NA	NA	-0.199	-1.72+
Black	-0.119	-7.59***	-0.097	-6.31***
Asian	0.009	0.35	0.016	0.60
Native American	0.009	0.19	0.017	0.39
Hispanic	-0.127	-6.85***	-0.106	-5.82***
Foreign-born citizen	-0.102	-3.21**	-0.078	-2.50*
Noncitizen	-0.130	-5.45***	-0.113	-4.84***
Years in U.S.	0.003	2.98**	0.002	2.19*
Union	0.135	10.46***	0.156	12.23***
Veteran	-0.021	-1.41	-0.018	-1.23
Adj. R-squared	0.4056		0.4324	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Note: Intercept and coefficients for sex, marital status, region, part-time status, self-reporting status, and industry effects have been omitted, but are reported in appendix table 3.

skills may permit individuals to find employment in higher paying industries.[11]

The rate computer use varies widely across occupational categories. Occupations that tend to use computers more 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 further—from 18 percent

[11] 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 through 11 have been omitted for reasons of space. When retail trade is treated as the base (omitted) category, the estimated industry wage differentials range from -21 percent for private household services to +43 percent for mining.

Table 6—Wage models with control for skill level

Variable	Model 5 Wage model with controls for industry and for occupational skill level		Model 6 Wage model with controls for industry, occupation, and occupational skill level	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Uses computer	0.100	9.20***	0.106	9.45***
Metro area	0.127	11.69***	0.129	11.90***
Labor force experience	0.025	19.66***	0.025	19.57***
Labor force experience (squared)	-0.042	-15.37***	-0.042	-15.31***
Non-HS graduate	-0.142	-8.25***	-0.145	-8.43***
Some college	0.073	6.47***	0.072	6.36***
Bachelor’s degree	0.278	19.88***	0.265	18.73***
Advanced degree	0.412	20.99***	0.397	19.95***
Managers	NA	NA	0.020	1.23
Professionals	NA	NA	0.034	0.98
Technical	NA	NA	-0.047	-1.94+
Clerical	NA	NA	-0.088	-4.86***
Service	NA	NA	-0.119	-5.00***
Craft occupations	NA	NA	-0.023	-0.90
Operators	NA	NA	-0.029	-1.08
Laborers	NA	NA	-0.079	-2.41*
Farmers, fishers, and foresters	NA	NA	-0.117	-1.00
GED-Language	0.025	2.29*	0.020	1.36
GED-Math	0.012	1.13	-0.001	-0.12
SVP	0.050	8.95***	0.043	5.93***
Black	-0.092	-6.00***	-0.089	-5.85***
Asian	0.009	0.35	0.013	0.52
Native American	0.022	0.51	0.022	0.51
Hispanic	-0.105	-5.82***	-0.102	-5.67***
Foreign-born citizen	-0.076	-2.44*	-0.071	-2.30*
Noncitizen	-0.108	-4.65***	-0.109	-4.68***
Years in U.S.	0.002	2.22*	0.002	2.08*
Union	0.162	12.79***	0.161	12.68***
Veteran	-0.016	-1.06	-0.016	-1.08
Adj. R-squared	0.4362		0.4391	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Note: Intercept and coefficients for sex, marital status, region, part-time status, self-reporting status, and industry effects have been omitted, but are reported in appendix table 4.

to 13 percent (model 4). This result is also similar to Krueger's 1993 findings.

But using such broad occupational groups is a crude proxy for actual skill levels. To better control for 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 three DOT occupational characteristics that have been considered include the "general educational development" (GED) levels of the job with respect to math and language skills, and the extent of "specific vocational preparation" (SVP) required for a job. The SVP 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).[12]

These measures of the skill levels required for detailed Census occupations turn out to be fairly powerful as factors accounting for wage variation. When these three variables are substituted for the eight occupational categories/variables used in the previous model (table 6, model 5), the extent of wage variation explained actually increases slightly. All three variables are positively related to wages, as might be expected.[13] The effect of specific vocational preparation is significant at the 0.1-percent level, while the effect of language skills is significant at the 5-percent level. The effect of math skills is not statistically significant.

Model 5's results are consistent with the suggestion that a 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 substantially, to slightly over 10 percent. However, the computer use effect remains 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 demanding higher general skills if those workers also possess 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, 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 aptitude. Thus, the return to general skills may itself be influenced by the increasing role of computers in the workplace. Both this and the preced-

Table 7—Wage model with controls for industry, occupation, and specific vocational preparation

Variable	Model 7 Parameter estimate	Model 7 T-statistic
Uses computer	0.107	9.58***
Metro area	0.130	11.95***
Labor force experience	0.025	19.53***
Labor force experience (squared)	-0.042	-15.27***
Non-HS graduate	-0.146	-8.48***
Some college	0.073	6.42***
Bachelor's degree	0.267	18.95***
Advanced degree	0.401	20.46***
Managers	0.013	0.87
Professionals	0.033	1.03
Technical	-0.052	-2.21*
Clerical	-0.095	-5.48***
Service	-0.137	-6.86***
Craft occupations	-0.049	-2.51*
Operators	-0.051	-2.23*
Laborers	-0.099	-3.37***
Farmers, fishers, and foresters	-0.139	-1.21
SVP	0.051	10.85***
Black	-0.090	-5.89***
Asian	0.013	0.50
Native American	0.023	0.51
Hispanic	-0.103	-5.71***
Foreign-born citizen	-0.072	-2.33*
Noncitizen	-0.109	-4.70***
Years in U.S.	0.002	2.10*
Union	0.161	12.67***
Veteran	-0.016	-1.07
Adj. R-squared	0.4391	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Note: Intercept and coefficients for sex, marital status, region, part-time status, self-reporting status, and industry effects have been omitted, but are reported in appendix table 5.

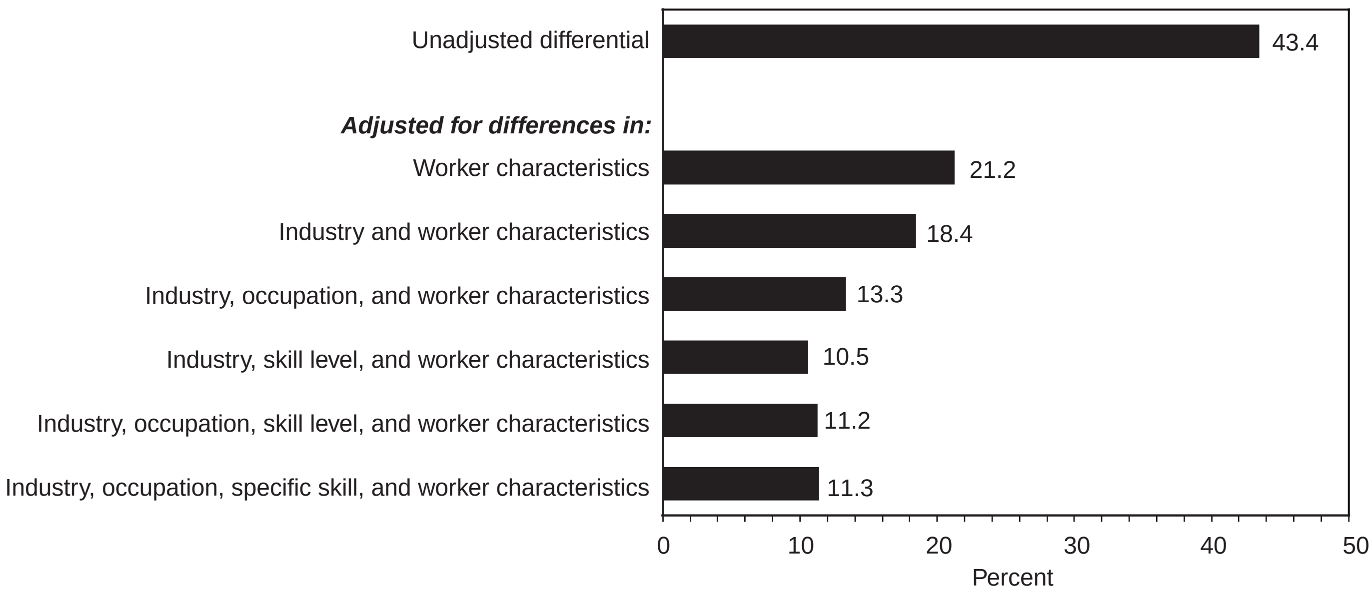
[12] In an earlier paper, the effects on wages of variation in the general reasoning GED level (in 1993) were also estimated, but this variable was not significant in the analysis of 1997 data and has been dropped to simplify the analysis.

[13] 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 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.

Figure 2

Wage premium for computer use, 1997

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



Source: Calculated by the Economic Research Service, USDA from Current Population Survey, 1997.

ing 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 increase in the adjusted R-squared of the model. The estimated direct computer use premium for this specification is about 11 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 (fig. 2).

When occupational categories and skill measures are both included in the model, as in model 6, neither the language skill nor the math skill variable is significant, but the specific vocational preparation (SVP) variable remains highly significant. This suggests that only the SVP variable among these three is capturing an aspect of occupational skill that is not already captured by occupational category or educational attainment. Accordingly, model 7 drops the language and math skill variables to yield a more parsimonious model as the basis for further analysis. This change has almost no effect on the estimated size of the return to on-the-job computer use.

Computer Use Wage Premium and the Metro-Nonmetro Wage Gap

OTJ computer use rates are substantially higher in metro areas, and the analyses above indicate a wage premium of 10 to 11 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/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 7, it appears that differences in computer use rates explain only 5 percent of the overall wage gap (table 8).[14] About 29 percent of the gap can be explained by differences in education level and/or specific vocational preparation, 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.[15] Part of the unexplained wage gap probably reflects cost-of-living differences between metro and nonmetro areas.[16] However, comprehensive area-specific cost-of-living indices that would allow us to fully quantify this factor are not available.

Table 8—Factors accounting for the metro-nonmetro wage gap, 1997

Variable	Wage difference explained	Wage gap explained
	Percentage points	*Percent*
Education	3.7	18.6
Occupational skill level	2.1	10.4
Race and ethnicity	-0.9	-4.8
Industry	-0.03	-0.1
Occupation	0.8	4.0
Computer use	1.1	5.5
Other[1]	0.2	1.0
Total explained	6.8	34.5
Unexplained	13.0	65.5
Total metro-nonmetro gap	19.8	100.0

[1] "Other" includes gender, marital status, union membership, veteran status, citizenship and origin, part-time status, labor force experience, and region.

Source: ERS from Oct. 1997 Current Population Survey.

Metro Versus Nonmetro Computer Wage Premiums

Do nonmetro workers receive lower returns for computer skills than metro workers do? The above decomposition analysis assumes that the wage premium for OTJ computer use is the same in metro and nonmetro areas. However, the premium is much larger in metro areas. If a variable representing the interaction between metro status and OTJ computer use is added to the wage model, the estimated computer use wage premium is only about 6 percent in nonmetro areas, while it is nearly 13 percent in metro areas; this difference is statistically significant at the 1-percent level (table 9, model 8). This finding implies that the "unexplained" metro-nonmetro wage gap (i.e., the portion of the gap not accounted for by any variables in the model other than metro status per se) for those workers who do not use computers on the job is just over 10 percent, while the corresponding value for OTJ computer users is close to 18 percent.[17]

So while 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 two-fifths of all nonmetro workers who use computers on the job appear to lose out on an additional wage premium of about 7 percent that they would receive if employed in metro areas.[18]

[14] 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.

[15] In particular, while not directly relevant to the topic of this report, differences in industry mix between metro and nonmetro areas account for very little net difference in wage levels.

[16] For example, Gale (1997) finds that a 1-percent difference in the average rent for a two-bedroom housing unit is associated with a 0.13-percent difference in manufacturing wages, and that taking this effect into account reduces the size of the estimated urban-rural wage differential.

[17] The combined logarithmic effect of computer use and the metro-computer use interaction term is .056 + .065 = .121; the percentage equivalent of this combined effect is 12.9 percent. The combined logarithmic effect of metro residence and the metro-computer use interaction term is .097 + .065 = .162; the percentage equivalent of this combined effect is 17.6 percent (see *fn.* 3).

[18] It is also possible that computer-using workers in rural areas are employing particular computer skills that are less well-rewarded than those skills employed by computer-using workers in urban areas. This has not been specifically tested for, in part because preliminary analyses indicated that the estimated returns to particular uses of computers on the job were difficult to interpret as returns to particular skills (e.g., these analyses showed a very high rate of return to using a computer on the job for e-mail).

Table 9—Metro versus nonmetro premiums and estimates with detailed occupation controls

Variable	Model 8 Metro versus nonmetro premium		Model 9 Model with more detailed occupations	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Uses computer	0.056	2.86**	0.061	3.10**
Metro area	0.097	6.39***	0.099	6.56***
Uses computer x metro area	0.065	3.11**	0.060	2.87**
Labor force experience	0.025	19.59***	0.024	19.30***
Labor force experience (squared)	-0.042	-15.34***	-0.041	-15.07***
Non-HS graduate	-0.147	-8.53***	-0.149	-8.69***
Some college	0.073	6.43***	0.067	5.89***
Bachelor's degree	0.267	18.95***	0.260	18.31***
Advanced degree	0.399	20.36***	0.395	19.32***
Managers	0.012	0.80	NA	NA
Professionals	0.032	0.99	NA	NA
Technical	-0.053	-2.24*	NA	NA
Clerical	-0.095	-5.47***	NA	NA
Service	-0.137	-6.88***	NA	NA
Craft occupations	-0.048	-2.50*	NA	NA
Operators	-0.051	-2.24*	NA	NA
Laborers	-0.101	-3.43***	NA	NA
Farmers, fishers, and foresters	-0.150	-1.30	NA	NA
SVP	0.051	10.87***	0.051	7.66***
Black	-0.089	-5.84***	-0.085	-5.59***
Asian	0.013	0.50	0.010	0.39
Native American	0.021	0.47	0.012	0.27
Hispanic	-0.102	-5.64***	-0.098	-5.43***
Foreign-born citizen	-0.070	-2.28*	-0.072	-2.33*
Noncitizen	-0.105	-4.53***	-0.103	-4.46***
Years in U.S.	0.002	2.12*	0.002	2.24*
Union	0.162	12.74***	0.166	12.82***
Veteran	-0.015	-1.04	-0.020	-1.39
Adj. R-squared	0.4396		0.4471	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.Note: Intercept and coefficients for sex, marital status, region, part-time status, self-reporting status, industry effects, and detailed occupation effects have been omitted, but are reported in Appendix table 6.

Supply and Demand for Job Skills in Nonmetro Areas

This last result is broadly consistent with previous work at ERS indicating that returns to education are greater in metro than 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.) The gap in skills (including computer use) and apparently associated wage gap that is seen in rural areas seem to 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 out of rural areas 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. 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.[19] This is consistent with a recent survey of rural manufacturers, which found that lesser use of selected advanced 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).

The sensitivity of our results is further tested by replacing the nine occupational category variables with a more detailed list of occupational categories (model 9). This substitution yields a slightly larger coefficient for the computer wage premium in nonmetro areas (6.3 percent versus 5.8 percent for the previous model in table 9) and small changes in other coefficients, but does not yield substantial changes in any coefficients except for some of the industry effects (not shown). Accordingly, the shorter list of nine occupational category variables is again used in the additional specifications discussed below.

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/personal characteristics in the wage model (table 10, table 11).

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

Union membership. The premium for computer use is reduced by about 11 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.

[19] 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.

Race and ethnicity. The premiums to computer use appear to be greater for some racial and ethnic minorities. The estimated premiums are 10 to 13 percentage points larger for Hispanics and Asians than for non-Hispanic Whites, and nearly 30 percentage points larger for Native Americans (although the number of Native Americans in the sample who use computers on the job is fairly small). However, the coefficient for Blacks is not significantly different from the coefficient for non-Hispanic Whites.

Region. The premium to computer use is significantly greater in the Northeast than in the Midwest; the difference is about 6 percentage points. The estimated premiums for the South and the West are intermediate in magnitude and are not significantly different from the values for other regions.[20]

Labor force experience. The estimated rate of return to labor force experience is about 60 percent greater for those using computers on the job. Thus, the premium for computer use is relatively small for new workers, while it is much larger for those in their peak earning years.[21]

However, further analysis suggests that computer use here is serving in part 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 significant, while the strength of the interaction between computer use and labor force experience is cut in half (tables 10 and 11).

Models 10 and 11 also provide more evidence of an independent effect of metro status on the size of the computer wage premium, as they show that the estimated size of the metro area-computer use interaction effect is more or less unchanged when other interactions are taken into account.

[20] It is likely that other geographic characteristics also influence the size of the computer wage premium, especially in rural labor markets, which are quite heterogeneous. Such influences have not been explored in this paper, and the limited amount of geographic detail available in the CPS would make it difficult to do so.

[21] Labor force experience has been estimated indirectly based on age and years of education; see the appendix. The squared experience term included in the specification is typical for wage regression and captures the normal pattern of wage change over a career, with relatively rapid growth early in a career and little or no growth near the end of a career.

Table 10—Variation in computer wage premium by characteristics

Variable	Model 10 Main effects: Parameter estimate	Model 10 Main effects: T-statistic	Model 10 Interactions with computer use: Parameter estimate	Model 10 Interactions with computer use: T-statistic
Uses computer	-0.117	-1.65+	NA	NA
Metro area	0.094	6.05***	0.068	3.11**
Labor force experience	0.019	10.80***	0.012	4.64***
Labor force experience (squared)	-0.033	-9.10***	-0.020	-3.58***
Non-HS graduate	-0.135	-7.06***	0.021	0.44
Some college	0.080	4.87***	-0.015	-0.67
Bachelor's degree	0.240	9.56***	0.039	1.27
Advanced degree	0.404	9.96***	-0.004	-0.08
Managers	0.028	0.82	-0.032	-0.81
Professionals	0.074	0.62	-0.059	-0.47
Technical	-0.046	-0.87	-0.012	-0.20
Clerical	-0.047	-1.45	-0.063	-1.61
Service	-0.144	-5.41***	0.027	0.61
Craft occupations	-0.043	-1.48	0.011	0.27
Operators	-0.044	-1.45	0.031	0.61
Laborers	-0.108	-2.93**	0.039	0.54
Farmers, fishers, and foresters	-0.180	-1.49	0.549	1.26
SVP	0.050	8.07***	0.004	0.41
Black	-0.095	-4.53***	0.012	0.39
Asian	-0.058	-1.57	0.119	2.31*
Native American	-0.090	-1.57	0.252	2.80**
Hispanic	-0.138	-5.79***	0.091	2.46*
Foreign-born citizen	-0.043	-1.06	-0.045	-0.72
Noncitizen	-0.101	-3.43***	0.028	0.56
Years in U.S.	0.003	2.27*	-0.002	-1.12
Union	0.211	11.83***	-0.105	-4.13***
Veteran	-0.014	-0.67	-0.003	-0.11
Adj. R-squared	0.4444			

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.
Note: Intercept and coefficients for sex, marital status, region, part-time status, self-reporting status, and industry effects, and for interactions involving these variables have been omitted, but are reported in appendix table 7.

Conclusion

Some debate has arisen 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 a 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.

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 average national computer wage premium by about half, from 21 percent to 11 percent. However, the latter figure is substantial and statistically significant.

Table 11—Variation in computer wage premium and experience wage premium by characteristics (model 11)

Variable	Main effects		Interactions with computer use	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Uses computer	-0.075	-1.04	NA	NA
Metro area	0.094	6.04***	0.068	3.12**
Labor force experience	0.011	2.57*	0.007	2.30*
Labor force experience (squared)	-0.025	-2.73**	-0.011	-1.66+
Non-HS graduate	-0.034	-0.67	0.017	0.36
Some college	0.092	2.76**	-0.016	-0.70
Bachelor's degree	0.267	6.22***	0.041	1.31
Advanced degree	0.418	6.49***	-0.014	-0.29
Managers	0.024	0.70	-0.031	-0.80
Professionals	0.059	0.50	-0.049	-0.39
Technical	-0.047	-0.89	-0.013	-0.21
Clerical	-0.047	-1.43	-0.065	-1.64
Service	-0.142	-5.34***	0.028	0.64
Craft occupations	-0.044	-1.54	0.012	0.30
Operators	-0.041	-1.35	0.030	0.60
Laborers	-0.114	-3.11**	0.037	0.51
Farmers, fishers, and foresters	-0.186	-1.54	0.573	1.31
SVP	0.018	1.82+	0.005	0.51
Black	-0.095	-4.56***	0.011	0.36
Asian	-0.060	-1.63	0.121	2.36*
Native American	-0.089	-1.56	0.251	2.80**
Hispanic	-0.135	-5.66***	0.090	2.42*
Foreign-born citizen	-0.043	-1.06	-0.046	-0.74
Noncitizen	-0.101	-3.43***	0.029	0.59
Years in U.S .	0.003	2.33*	-0.002	-1.19
Union	0.211	11.84***	-0.103	-4.04***
Veteran	-0.014	-0.66	-0.002	-0.07
	Interactions with LFE		**Interactions with LFE^2**	
Variable	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Non-HS graduate	-0.009	-2.09*	0.015	1.83+
Some college	0.002	0.55	-0.009	-1.19
Bachelor's degree	0.002	0.47	-0.012	-1.27
Advanced degree	0.010	1.71+	-0.042	-2.95**
SVP	0.002	2.57*	-0.002	-1.02
Adj. R-squared	0.4469			

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level; LFE = labor force experience.

Note: Intercept and coefficients for sex, marital status, region, part-time status, self-reporting status, and industry effects, and for interactions involving these variables, have been omitted, but are reported in appendix table 8.

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 primarily 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.

In general, nonmetro workers 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 (McGranahan and Ghelfi, 1991; McGranahan and Kassel, 1995), which has indicated that the demand for worker skills is weaker in nonmetro areas. This difference is likely to be accentuated by trends in industry mix in metro and nonmetro areas, with skill-intensive sectors such as producer services and high-tech manufacturing growing more rapidly in metro areas (Gale and McGranahan, 2001.) 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. These estimates do not take into account the potential for some workers to increase their earnings after computer training by moving into new, higher paying occupations; however, these opportunities also seem likely to be greater in metro areas.

Results also suggest that the returns to computer training may be greater for members of some racial and ethnic minorities than for otherwise comparable nonminorities. While the reasons for this are unclear, this result suggests that computer skills training might be particularly valuable for some disadvantaged minority group members.

However, these conclusions may have to be modified with the recent explosive growth in the 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 lessen the importance of physical proximity to customers, clients, and information resources in some industries, allowing firms in 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.

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Appendix: Data and Methods

Data Sources

Data for this analysis have been taken from responses to the Current Population Survey (CPS). The CPS is conducted monthly by the U.S. Census Bureau to collect data on employment and unemployment. The October 1997 CPS asked a variety of questions about computer use on the job, at home, and at school, and specifically "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.

Data for this survey were collected from a sample of approximately 48,000 households, chosen to represent the civilian noninstitutional population of the United States. 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 10,000 unweighted observations.

Metro and Nonmetro Areas

In this article, "metro" refers to metropolitan areas as designated by the Office of Management and Budget as of 1993, 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 1997, the metro-nonmetro designation of residences in the CPS was based on population and commuting patterns from the 1990 Census of Population. The terms “metro/nonmetro” and “urban/rural” are used interchangeably.

Categorical Variables

Wage regressions 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 one dummy variable (1=union); a categorical variable with n categories (for example, the nine major occupation groups used in this report) 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, p. B-6). The nth category, which is not included in the list of regressors, is referred to as the "omitted" category. Omitted categories for regressions here are: female (sex); not married (marital status); nonveteran; nonunion; non-Hispanic White (race/ethnicity); U.S.-born citizen (citizenship/origin); 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,

$$LFE = \text{Age in Years} - \text{Estimated Years of Education} - 6$$

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 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.[22] To associate skill levels with individuals in the CPS data, these occupations were aggregated to correspond to the level of occupational detail available in the CPS. The DOT data set was originally developed for job placement purposes, and not for statistical purposes; thus 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 computer use differences and wage differences into explained and unexplained components (tables 2 and 8) follows the model of McGranahan and Kassel (1996). To illustrate this method, in the sample studied for the wage analysis, 47.5 percent of nonmetro workers and 57.7 percent of metro workers used computers, a difference of 10.2 percentage points. In the regression model used for this calculation, the estimated effect of computer use on wages is 10.7 percent. Thus, the estimated contribution of differing levels of computer use to metro-nonmetro wage differences is (.107 x .102 = .0109), or 1.09 percent. The overall difference between metro and nonmetro wage levels is 19.8 percent. Thus, differing levels of computer use account for 5.5 percent of the overall wage level difference (.0109/.198 = 5.5 percent). If a similar computation is carried out for each independent variable in the wage equation and the results are summed, 34.5 percent of the overall wage difference can be explained; the remaining 13.0-percent gap is unexplained (20 percent x .655 = 13.0 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.

22 The Department of Labor has replaced the DOT with a system of occupational skill descriptions called O*NET. O*NET is intended to be more useful in the primary function of both DOT and O*NET, which is to assess the match between an individual's skills and potential careers. However, O*NET may not be as well suited as the DOT for assessing "how skilled" a particular occupation is. In particular, while the DOT rates occupational skill demands using multipoint scales on a number of dimensions, the O*NET combines a single scale that rates the amount of education and/or training required for an occupation with several dozen (0,1) variables that rate whether or not a particular skill is required for that occupation.

Appendix: Detailed Regression Tables

Appendix table 1—Predictors of on-the-job computer use

Variable	Parameter estimate	T-statistic
Intercept	0.5292	48.91***
Northeast	-0.0298	-4.77***
South	0.0003	-0.05
West	0.0183	2.97**
Nonmetro Northeast	0.0144	1.06
Nonmetro Midwest	-0.0225	-2.63**
Nonmetro South	-0.0472	-6.32***
Nonmetro West	-0.0276	-2.32*
Age 18-21	-0.0596	-5.13***
Age 25-34	0.0303	3.60***
Age 35-44	0.0316	3.78***
Age 45-54	0.0024	0.28
Age 55-64	-0.0268	-2.74**
Age 65+	-0.1532	-10.00***
Non-HS graduate	-0.0860	-12.45***
Some college	0.1018	21.13***
Bachelor's degree	0.1731	28.97***
Advanced degree	0.2134	26.64***
Managers	0.0995	16.18***
Professionals	0.1743	12.05***
Technical	0.0727	6.69***
Clerical	0.1337	19.41***
Service	-0.3360	-44.17***
Craft occupations	-0.2634	-33.27***
Operators	-0.3626	-44.70***
Laborers	-0.3510	-33.39***
Farmers, fishers, and foresters	-0.2611	-11.15***
Black	-0.0837	-13.51***
Asian	-0.0351	-3.07**
Native American	-0.0314	-1.45
Hispanic	-0.0564	-7.52***
Part-time	-0.1757	-16.89***
Self-employed	-0.1232	-18.79***
Male	-0.0379	-8.70***
Foreign-born citizen	-0.0709	-7.24***
Noncitizen	-0.0879	-9.94***
Self-reporting	0.0399	10.65***

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Appendix table 1—Predictors of on-the-job computer use--continued

Variable	Parameter estimate	T-statistic
Industry effects:		
Agriculture	0.0041	0.24
Mining	0.0828	3.31***
Construction	-0.1039	-10.98***
Durable goods	0.1047	12.80***
Nondurables	0.0907	10.14***
Transportation	0.0157	1.54
Communication	0.2180	14.27***
Utilities & sanitary services	0.1275	7.75***
Wholesale Trade	0.0852	8.34***
Finance, insurance, & real estate	0.1793	19.99***
Private household services	-0.0787	-2.82**
Business services	0.1094	12.37***
Personal services	-0.0100	-0.78
Entertainment services	-0.0370	-2.33*
Hospital services	0.1153	10.76***
Medical services	-0.0238	-2.37*
Educational services	0.0362	4.05***
Social services	-0.0707	-5.28***
Professional services	0.1188	11.69***
Forestry & fishing	0.0766	1.25
Public service	0.2046	20.49***

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level;
*** = significant at 0.1-percent level.

Appendix table 2—Wage model with and without computer use

Variable	Model 1 Wage model without computer use		Model 2 Basic model with computer use variable	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Intercept	6.349	296.85***	6.280	294.24***
Uses computer	NA	NA	0.192	18.69***
Metro area	0.162	14.22***	0.145	12.91***
Labor force experience	0.030	22.40***	0.029	21.87***
Labor force experience (squared)	-0.052	-18.04***	-0.050	-17.42***
Non-HS graduate	-0.208	-11.50***	-0.168	-9.36***
Some college	0.140	11.94***	0.103	8.80***
Bachelor's degree	0.426	32.71***	0.360	27.06***
Advanced degree	0.588	33.62***	0.512	28.96***
Black	-0.144	-8.94***	-0.118	-7.44***
Asian	0.004	0.15	0.015	0.57
Native American	0.004	0.09	0.021	0.46
Hispanic	-0.154	-8.05***	-0.135	-7.17***
Foreign-born citizen	-0.136	-4.13***	-0.111	-3.43***
Noncitizen	-0.173	-7.04***	-0.141	-5.82***
Years in U.S.	0.003	3.09**	0.003	3.06**
Union	0.119	9.63***	0.140	11.44***
Male	0.142	9.37***	0.170	11.38***
Married	0.032	2.30*	0.022	1.59
Married male	0.122	6.43***	0.116	6.25***
Veteran	-0.021	-1.34	-0.013	-0.84
Northeast	0.060	4.38***	0.061	4.56***
South	-0.027	-2.17*	-0.028	-2.24*
West	0.035	2.67**	0.029	2.24*
Self-reporting	0.043	4.57***	0.032	3.40***
Part-time	-0.234	-7.64***	-0.180	-5.95***
Adj. R-squared	0.3574		0.3795	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Appendix table 3—Wage models with controls for industry and occupation

Variable	**Model 3** Wage model with controls for industrial sector		**Model 4** Wage model with controls for industry and occupation	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Intercept	6.191	269.67***	6.348	259.91***
Uses computer	0.169	16.19***	0.125	11.22***
Metro area	0.144	12.92***	0.133	12.19***
Labor force experience	0.026	20.36***	0.025	19.87***
Labor force experience (squared)	-0.045	-16.03***	-0.043	-15.66***
Non-HS graduate	-0.167	-9.50***	-0.151	-8.75***
Some college	0.107	9.33***	0.079	6.92***
Bachelor’s degree	0.373	27.74***	0.283	20.04***
Advanced degree	0.549	29.47***	0.434	22.27***
Managers	NA	NA	0.064	4.30***
Professionals	NA	NA	0.091	2.83**
Technical	NA	NA	-0.044	-1.84+
Clerical	NA	NA	-0.176	-11.15***
Service	NA	NA	-0.231	-12.79***
Craft occupations	NA	NA	-0.034	-1.74+
Operators	NA	NA	-0.175	-8.87***
Laborers	NA	NA	-0.275	-11.14***
Farmers, fishers, and foresters	NA	NA	-0.199	-1.72+
Black	-0.119	-7.59***	-0.097	-6.31***
Asian	0.009	0.35	0.016	0.60
Native American	0.009	0.19	0.017	0.39
Hispanic	-0.127	-6.85***	-0.106	-5.82***
Foreign-born citizen	-0.102	-3.21**	-0.078	-2.50*
Noncitizen	-0.130	-5.45***	-0.113	-4.84***
Years in U.S .	0.003	2.98**	0.002	2.19*
Union	0.135	10.46***	0.156	12.23***
Male	0.143	9.48***	0.136	9.05***
Married	0.022	1.62	0.010	0.77
Married male	0.105	5.73***	0.095	5.34***
Veteran	-0.021	-1.41	-0.018	-1.23
Northeast	0.063	4.82***	0.059	4.62***
South	-0.027	-2.22*	-0.032	-2.71**
West	0.035	2.76**	0.024	1.93+
Self-reporting	0.032	3.51***	0.029	3.19**
Part-time	-0.136	-4.58***	-0.131	-4.48***

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Appendix table 3—Wage models with controls for industry and occupation, continued

Variable	Model 3 Wage model with controls for industrial sector		Model 4 Wage model with controls for industry and occupation	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Industry effects:				
Agriculture	-0.054	-1.38	0.064	1.54
Mining	0.355	7.17***	0.360	7.33***
Construction	0.253	11.28***	0.243	10.20***
Durable goods	0.209	11.69***	0.221	11.48***
Nondurables	0.193	9.70***	0.214	10.31***
Transportation	0.148	6.04***	0.203	8.09***
Communication	0.226	6.13***	0.230	6.34***
Utilities & sanitary services	0.285	7.34***	0.301	7.82***
Wholesale trade	0.146	5.94***	0.154	6.33***
Finance, insurance, & real estate	0.175	8.51***	0.193	9.36***
Private household services	-0.231	-3.35***	-0.132	-1.95+
Business services	0.123	5.68***	0.135	6.26***
Personal services	-0.009	-0.28	0.037	1.18
Entertainment services	0.044	1.09	0.087	2.21*
Hospital services	0.196	8.16***	0.222	9.37***
Medical services	0.152	6.49***	0.182	7.80***
Educational services	0.010	0.48	0.028	1.35
Social services	-0.005	-0.15	-0.008	-0.23
Professional services	0.174	7.03***	0.180	7.30***
Forestry & fishing	0.208	0.83	0.237	0.97
Public service	0.220	9.87***	0.269	12.02***
Adj. R-squared	0.4056		0.4324	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Appendix table 4—Wage models with control for skill level

Variable	Model 5 Wage model with controls for industry and for occupational skill level		Model 6 Wage model with controls for industry, occupation, and occupational skill level	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Intercept	5.929	235.73**	6.056	156.15***
Uses computer	0.100	9.20***	0.106	9.45***
Metro area	0.127	11.69***	0.129	11.90***
Labor force experience	0.025	19.66***	0.025	19.57***
Labor force experience (squared)	-0.042	-15.37***	-0.042	-15.31***
Non-HS graduate	-0.142	-8.25***	-0.145	-8.43***
Some college	0.073	6.47***	0.072	6.36***
Bachelor's degree	0.278	19.88***	0.265	18.73***
Advanced degree	0.412	20.99***	0.397	19.95***
Managers	NA	NA	0.020	1.23
Professionals	NA	NA	0.034	0.98
Technical	NA	NA	-0.047	-1.94+
Clerical	NA	NA	-0.088	-4.86***
Service	NA	NA	-0.119	-5.00***
Craft occupations	NA	NA	-0.023	-0.90
Operators	NA	NA	-0.029	-1.08
Laborers	NA	NA	-0.079	-2.41*
Farmers, fishers, and foresters	NA	NA	-0.117	-1.00
GED-Language	0.025	2.29*	0.020	1.36
GED-Math	0.012	1.13	-0.001	-0.12
SVP	0.050	8.95***	0.043	5.93***
Black	-0.092	-6.00***	-0.089	-5.85***
Asian	0.009	0.35	0.013	0.52
Native American	0.022	0.51	0.022	0.51
Hispanic	-0.105	-5.82***	-0.102	-5.67***
Foreign-born citizen	-0.076	-2.44*	-0.071	-2.30*
Noncitizen	-0.108	-4.65***	-0.109	-4.68***
Years in U.S.	0.002	2.22*	0.002	2.08*
Union	0.162	12.79***	0.161	12.68***
Male	0.138	9.39***	0.133	8.91***
Married	0.009	0.70	0.007	0.55
Married male	0.093	5.24***	0.094	5.28***
Veteran	-0.016	-1.06	-0.016	-1.08
Northeast	0.061	4.76***	0.061	4.75***
South	-0.032	-2.68**	-0.033	-2.76**
West	0.027	2.20*	0.025	1.98*
Self-reporting	0.026	2.93**	0.027	3.04**
Part-time	-0.114	-3.93***	-0.114	-3.94***

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Appendix table 4—Wage models with control for skill level, continued

Variable	**Model 5** Wage model with controls for industry and for occupational skill level		**Model 6** Wage model with controls for industry, occupation, and occupational skill level	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Industry effects:				
Agriculture	-0.040	-1.05	-0.019	-0.45
Mining	0.347	7.18***	0.342	6.99***
Construction	0.210	9.29***	0.207	8.61***
Durable goods	0.199	11.38***	0.193	9.91***
Nondurables	0.201	10.33***	0.189	9.06***
Transportation	0.175	7.32***	0.180	7.15***
Communication	0.190	5.31***	0.201	5.55***
Utilities & sanitary services	0.270	7.16***	0.280	7.29***
Wholesale trade	0.146	6.08***	0.139	5.73***
Finance, insurance, & real estate	0.146	7.21***	0.160	7.63***
Private household services	-0.165	-2.46*	-0.120	-1.75+
Business services	0.104	4.90***	0.111	5.12***
Personal services	0.001	0.04	0.023	0.75
Entertainment services	0.042	1.07	0.060	1.53
Hospital services	0.155	6.55***	0.179	7.31***
Medical services	0.111	4.78***	0.141	5.82***
Educational services	-0.033	-1.55	-0.017	-0.76
Social services	-0.047	-1.45	-0.041	-1.27
Professional services	0.113	4.61***	0.131	5.15***
Forestry & fishing	0.188	0.77	0.217	0.90
Public service	0.181	8.19***	0.214	9.20***
Adj. R-squared	0.4362		0.4391	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Appendix table 5—Wage model with controls for industry, occupation, and specific vocational preparation

	Model 7	
Variable	Parameter estimate	T-statistic
Intercept	6.079	175.19***
Uses computer	0.107	9.58***
Metro area	0.130	11.95***
Labor force experience	0.025	19.53***
Labor force experience (squared)	-0.042	-15.27***
Non-HS graduate	-0.146	-8.48***
Some college	0.073	6.42***
Bachelor's degree	0.267	18.95***
Advanced degree	0.401	20.46***
Managers	0.013	0.87
Professionals	0.033	1.03
Technical	-0.052	-2.21*
Clerical	-0.095	-5.48***
Service	-0.137	-6.86***
Craft occupations	-0.049	-2.51*
Operators	-0.051	-2.23*
Laborers	-0.099	-3.37***
Farmers, fishers, and foresters	-0.139	-1.21
SVP	0.051	10.85***
Black	-0.090	-5.89***
Asian	0.013	0.50
Native American	0.023	0.51
Hispanic	-0.103	-5.71***
Foreign-born citizen	-0.072	-2.33*
Noncitizen	-0.109	-4.70***
Years in U.S.	0.002	2.10*
Union	0.161	12.67***
Male	0.132	8.89***
Married	0.008	0.58
Married male	0.094	5.27***
Veteran	-0.016	-1.07
Northeast	0.061	4.75***
South	-0.032	-2.75**
West	0.025	1.99*
Self-reporting	0.027	3.05**
Part-time	-0.115	-3.96***

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Appendix table 5—Wage model with controls for industry, occupation, and specific vocational preparation, continued

Variable	Model 7 Parameter estimate	T-statistic
Industry effects:		
Agriculture	-0.012	-0.28
Mining	0.344	7.04***
Construction	0.207	8.66***
Durable goods	0.196	10.18***
Nondurables	0.193	9.29***
Transportation	0.185	7.42***
Communication	0.205	5.67***
Utilities & sanitary services	0.283	7.38***
Wholesale trade	0.143	5.90***
Finance, insurance, & real estate	0.166	8.03***
Private household services	-0.107	-1.59
Business services	0.116	5.37***
Personal services	0.026	0.84
Entertainment services	0.066	1.70+
Hospital services	0.188	7.89***
Medical services	0.150	6.42***
Educational services	-0.009	-0.42
Social services	-0.036	-1.12
Professional services	0.139	5.58***
Forestry & fishing	0.222	0.91
Public service	0.221	9.75***
Adj. R-squared	0.4391	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level;
*** = significant at 0.1-percent level.

Appendix table 6—Metro versus nonmetro premiums and detailed occupations

Variable	Model 8 Metro versus nonmetro premium		Model 9 Model with more detailed occupations	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Intercept	6.104	171.34***	6.054	153.65***
Uses computer	0.056	2.86**	0.061	3.10**
Metro area	0.097	6.39***	0.099	6.56***
Uses computer x metro area	0.065	3.11**	0.060	2.87**
Labor force experience	0.025	19.59***	0.024	19.30***
Labor force experience (squared)	-0.042	-15.34***	-0.041	-15.07***
Non-HS graduate	-0.147	-8.53***	-0.149	-8.69***
Some college	0.073	6.43***	0.067	5.89***
Bachelor's degree	0.267	18.95***	0.260	18.31***
Advanced degree	0.399	20.36***	0.395	19.32***
Managers	0.012	0.80	NA	NA
Professionals	0.032	0.99	NA	NA
Technical	-0.053	-2.24*	NA	NA
Clerical	-0.095	-5.47***	NA	NA
Service	-0.137	-6.88***	NA	NA
Craft occupations	-0.048	-2.50*	NA	NA
Operators	-0.051	-2.24*	NA	NA
Laborers	-0.101	-3.43***	NA	NA
Farmers, fishers, and foresters	-0.150	-1.30	NA	NA
SVP	0.051	10.87***	0.051	7.66***
Black	-0.089	-5.84***	-0.085	-5.59***
Asian	0.013	0.50	0.010	0.39
Native American	0.021	0.47	0.012	0.27
Hispanic	-0.102	-5.64***	-0.098	-5.43***
Foreign-born citizen	-0.070	-2.28*	-0.072	-2.33*
Noncitizen	-0.105	-4.53***	-0.103	-4.46***
Years in U.S.	0.002	2.12*	0.002	2.24*
Union	0.162	12.74***	0.166	12.82***
Male	0.132	8.89***	0.123	8.25***
Married	0.008	0.63	0.010	0.78
Married male	0.093	5.24***	0.090	5.09***
Veteran	-0.015	-1.04	-0.020	-1.39
Northeast	0.061	4.74***	0.060	4.70***
South	-0.034	-2.87**	-0.034	-2.94**
West	0.025	1.98*	0.024	1.92+
Self-reporting	0.027	3.01**	0.027	3.00**
Part-time	-0.116	-4.02***	-0.111	-3.84***
Industry effects:				
Agriculture	-0.017	-0.42	0.024	0.41
Mining	0.342	7.00***	0.305	6.14***
Construction	0.206	8.63***	0.129	4.37***
Durable goods	0.195	10.10***	0.163	7.42***
Nondurables	0.190	9.19***	0.167	7.12***
Transportation	0.183	7.34***	0.109	3.92***
Communication	0.202	5.57***	0.149	3.96***
Utilities & sanitary services	0.283	7.38***	0.244	6.19***
Wholesale trade	0.142	5.85***	0.079	2.95**
Finance, insurance, & real estate	0.164	7.94***	0.114	4.90***
Private household services	-0.108	-1.60	0.143	0.83
Business services	0.113	5.27***	0.064	2.65**
Personal services	0.027	0.85	-0.021	-0.63
Entertainment services	0.067	1.72+	0.038	0.94
Hospital services	0.187	7.85***	0.094	3.22**

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Appendix table 6—Metro versus nonmetro premiums and detailed occupations, continued

Variable	Model 8 Metro versus nonmetro premium		Model 9 Model with more detailed occupations	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Medical services	0.149	6.35***	0.092	3.22**
Educational services	-0.008	-0.38	0.004	0.17
Social services	-0.037	-1.15	-0.059	-1.72+
Professional services	0.137	5.50***	0.102	3.74***
Forestry & fishing	0.233	0.96	0.184	0.76
Public service	0.222	9.78***	0.184	6.74***
Detailed occupations:				
Public administration	NA	NA	0.079	1.27
Other executives and managers	NA	NA	0.122	3.23**
Management-related occupations	NA	NA	0.105	2.67**
Engineers	NA	NA	0.138	2.90**
Mathematical and computer scientists	NA	NA	0.272	5.29***
Natural scientists	NA	NA	0.032	0.48
Health diagnosing occupations	NA	NA	0.076	1.00
Health assessment/treating occupations	NA	NA	0.288	6.15***
College and university teachers	NA	NA	0.054	0.68
Other teachers	NA	NA	0.002	0.05
Lawyers and judges	NA	NA	0.207	3.04**
Other professional specialties	NA	NA	0.021	0.52
Health technologists and technicians	NA	NA	0.065	1.33
Engineering and science technicians	NA	NA	-0.011	-0.23
Other technicians	NA	NA	0.123	2.46*
Sales supervisors and proprietors	NA	NA	0.080	2.24*
Sales repr.: finance and business service	NA	NA	0.139	3.11**
Sales repr.: commod., exc. retail	NA	NA	0.222	4.52***
Sales-related occupations	NA	NA	-0.033	-0.17
Supervisors-administrative support	NA	NA	0.063	1.09
Computer equipment operators	NA	NA	-0.014	-0.19
Secretaries and typists	NA	NA	-0.046	-1.21
Financial records processing occup.	NA	NA	0.001	0.02
Mail and message distributing	NA	NA	0.137	2.54*
Other administrative support	NA	NA	0.003	0.09
Private household services	NA	NA	-0.377	-2.02*
Protective service occupations	NA	NA	-0.029	-0.66
Food service occupations	NA	NA	-0.087	-2.71**
Health service occupations	NA	NA	-0.071	-1.61
Cleaning and building services	NA	NA	-0.008	-0.20
Personal service occupations	NA	NA	0.033	0.63
Mechanics and repairers	NA	NA	0.071	1.91+
Construction trades	NA	NA	0.090	2.18*
Other craft occupations	NA	NA	0.027	0.69
Machine operators and tenders	NA	NA	0.014	0.39
Fabricators, assemblers, etc.	NA	NA	0.025	0.64
Motor vehicle operators	NA	NA	0.100	2.75**
Other transp. & material moving occup.	NA	NA	0.100	1.96+
Construction laborers	NA	NA	0.163	2.65**
Freight, stock, and material handlers	NA	NA	-0.071	-1.52
Other handlers and laborers	NA	NA	0.007	0.16
Farm operators and managers	NA	NA	-0.337	-1.98*
Farm workers and related occupations	NA	NA	-0.094	-1.51
Forestry and fishing occupations	NA	NA	0.160	0.99
Adj. R-squared	0.4396		0.4471	

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Appendix table 7—Variation in computer wage premium by characteristics

Variable	Model 10 Main effects: Parameter estimate	Model 10 Main effects: T-statistic	Model 10 Interactions with computer use: Parameter estimate	Model 10 Interactions with computer use: T-statistic
Intercept	6.186	130.04***	NA	NA
Uses computer	-0.117	-1.65+	NA	NA
Metro area	0.094	6.05***	0.068	3.11**
Labor force experience	0.019	10.80***	0.012	4.64***
Labor force experience^2	-0.033	-9.10***	-0.020	-3.58***
Non-HS graduate	-0.135	-7.06***	0.021	0.44
Some college	0.080	4.87***	-0.015	-0.67
Bachelor’s degree	0.240	9.56***	0.039	1.27
Advanced degree	0.404	9.96***	-0.004	-0.08
Managers	0.028	0.82	-0.032	-0.81
Professionals	0.074	0.62	-0.059	-0.47
Technical	-0.046	-0.87	-0.012	-0.20
Clerical	-0.047	-1.45	-0.063	-1.61
Service	-0.144	-5.41***	0.027	0.61
Craft occupations	-0.043	-1.48	0.011	0.27
Operators	-0.044	-1.45	0.031	0.61
Laborers	-0.108	-2.93**	0.039	0.54
Farmers, fishers, and foresters	-0.180	-1.49	0.549	1.26
SVP	0.050	8.07***	0.004	0.41
Black	-0.095	-4.53***	0.012	0.39
Asian	-0.058	-1.57	0.119	2.31*
Native American	-0.090	-1.57	0.252	2.80**
Hispanic	-0.138	-5.79***	0.091	2.46*
Foreign-born citizen	-0.043	-1.06	-0.045	-0.72
Noncitizen	-0.101	-3.43***	0.028	0.56
Years in U.S.	0.003	2.27*	-0.002	-1.12
Union	0.211	11.83***	-0.105	-4.13***
Male	0.154	7.06***	-0.053	-1.75+
Married	0.014	0.62	-0.011	-0.39
Married male	0.081	3.00**	0.029	0.81
Veteran	-0.014	-0.67	-0.003	-0.11
Northeast	0.028	1.48	0.058	2.26*
South	-0.044	-2.47*	0.020	0.86
West	0.015	0.81	0.022	0.89
Self-reporting	0.002	0.18	0.044	2.46*
Part-time	-0.101	-2.90**	-0.073	-1.15

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Appendix table 7—Variation in computer wage premium by characteristics, continued

Variable	Model 10 Main effects Parameter estimate	 T-statistic	Model 10 Interactions with computer use Parameter estimate	 T-statistic
Industry effects:				
Agriculture	-0.018	-0.37	-0.012	-0.13
Mining	0.357	5.31***	-0.065	-0.66
Construction	0.198	6.51***	-0.033	-0.62
Durable goods	0.160	5.68***	0.057	1.45
Nondurables	0.162	5.55***	0.053	1.26
Transportation	0.194	5.53***	-0.045	-0.90
Communication	0.195	2.08*	0.015	0.15
Utilities & sanitary services	0.259	4.17***	0.027	0.34
Wholesale trade	0.134	3.69***	0.006	0.12
Finance, insurance, & real estate	0.140	3.22**	0.030	0.58
Private household services	-0.087	-1.25	-0.178	-0.42
Business services	0.040	1.25	0.130	2.99**
Personal services	0.064	1.62	-0.098	-1.52
Entertainment services	0.085	1.66+	-0.037	-0.47
Hospital services	0.191	4.55***	-0.009	-0.17
Medical services	0.171	5.05***	-0.035	-0.75
Educational services	0.034	1.04	-0.051	-1.16
Social services	-0.049	-1.12	0.036	0.56
Professional services	0.000	0.01	0.166	2.58**
Forestry & fishing	0.288	0.97	-0.271	-0.53
Public service	0.244	5.88***	-0.029	-0.57
Adj. R-squared	0.4444			

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.

Appendix table 8—Variation in computer wage premium and experience wage premium by characteristics

Variable	Model 11 Main effects Parameter estimate	 T-statistic	Model 11 Interactions with computer use Parameter estimate	 T-statistic
Intercept	6.309	108.04***	NA	NA
Uses computer	-0.075	-1.04	NA	NA
Metro area	0.094	6.04***	0.068	3.12**
Labor force experience	0.011	2.57*	0.007	2.30*
Labor force experience^2	-0.025	-2.73**	-0.011	-1.66+
Non-HS graduate	-0.034	-0.67	0.017	0.36
Some college	0.092	2.76**	-0.016	-0.70
Bachelor's degree	0.267	6.22***	0.041	1.31
Advanced degree	0.418	6.49***	-0.014	-0.29
Managers	0.024	0.70	-0.031	-0.80
Professionals	0.059	0.50	-0.049	-0.39
Technical	-0.047	-0.89	-0.013	-0.21
Clerical	-0.047	-1.43	-0.065	-1.64
Service	-0.142	-5.34***	0.028	0.64
Craft occupations	-0.044	-1.54	0.012	0.30
Operators	-0.041	-1.35	0.030	0.60
Laborers	-0.114	-3.11**	0.037	0.51
Farmers, fishers, and foresters	-0.186	-1.54	0.573	1.31
SVP	0.018	1.82+	0.005	0.51
Black	-0.095	-4.56***	0.011	0.36
Asian	-0.060	-1.63	0.121	2.36*
Native American	-0.089	-1.56	0.251	2.80**
Hispanic	-0.135	-5.66***	0.090	2.42*
Foreign-born citizen	-0.043	-1.06	-0.046	-0.74
Noncitizen	-0.101	-3.43***	0.029	0.59
Years in U.S.	0.003	2.33*	-0.002	-1.19
Union	0.211	11.84***	-0.103	-4.04***
Male	0.151	6.91***	-0.048	-1.59
Married	0.009	0.41	-0.005	-0.20
Married male	0.085	3.16**	0.024	0.66
Veteran	-0.014	-0.66	-0.002	-0.07
Northeast	0.028	1.48	0.058	2.25*
South	-0.042	-2.39*	0.021	0.87
West	0.017	0.90	0.021	0.83
Self-reporting	0.002	0.15	0.046	2.56*
Part-time	-0.100	-2.88**	-0.068	-1.08

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Appendix table 8—Variation in computer wage premium and experience wage premium by characteristics, continued

Variable	Model 11 Main effects: Parameter estimate	Model 11 Main effects: T-statistic	Model 11 Interactions with computer use: Parameter estimate	Model 11 Interactions with computer use: T-statistic
Industry effects:				
Agriculture	-0.019	-0.39	-0.007	-0.08
Mining	0.356	5.32***	-0.063	-0.64
Construction	0.206	6.78***	-0.041	-0.76
Durable goods	0.159	5.68***	0.059	1.52
Nondurables	0.162	5.55***	0.053	1.27
Transportation	0.197	5.61***	-0.044	-0.88
Communication	0.190	2.03*	0.016	0.15
Utilities & sanitary services	0.255	4.11***	0.033	0.42
Wholesale trade	0.135	3.71***	0.007	0.14
Finance, insurance, & real estate	0.139	3.20**	0.034	0.67
Private household services	-0.100	-1.44	-0.093	-0.22
Business services	0.039	1.24	0.132	3.03**
Personal services	0.066	1.69+	-0.092	-1.42
Entertainment services	0.094	1.82+	-0.044	-0.56
Hospital services	0.196	4.69***	-0.011	-0.21
Medical services	0.168	4.99***	-0.033	-0.70
Educational services	0.038	1.15	-0.052	-1.19
Social services	-0.045	-1.03	0.034	0.53
Professional services	0.018	0.32	0.151	2.34*
Forestry & fishing	0.272	0.92	-0.264	-0.51
Public service	0.244	5.88***	-0.032	-0.63
	Interactions with labor force experience		**Interactions with labor force experience (squared)**	
	Parameter estimate	T-statistic	Parameter estimate	T-statistic
Non-HS graduate	-0.009	-2.09*	0.015	1.83+
Some college	0.002	0.55	-0.009	-1.19
Bachelor’s degree	0.002	0.47	-0.012	-1.27
Advanced degree	0.010	1.71+	-0.042	-2.95**
SVP	0.002	2.57*	-0.002	-1.02
Adj. R-squared	0.4469			

+ = significant at 10-percent level; * = significant at 5-percent level; ** = significant at 1-percent level; *** = significant at 0.1-percent level.