Computers and the Wage Structure

by

Michael J. Handel

Resident Scholar

The Jerome Levy Economics Institute

Working Paper No. 285

INTRODUCTION

It is no secret that wage inequality in the United States has grown dramatically since the late 1970s (e.g., Katz and Murphy 1992; Levy and Murnane 1992; Danziger and Gottschalk 1994). Considerable debate persists, however, over the reasons for this growth.

The rise in the returns to education directed attention to the possibility that skill requirements were rising as a result of the spread of new technology, such as computers. According to this view, consistent with human capital and neoclassical economic theory, technology has reduced demand for less educated labor by both reducing the number of production and other low-skill jobs, a between-job compositional shift, while increasing the skill requirements of remaining positions, a within-job skill shift (c.f. Spenner 1979, p.969). Lower demand for less skilled workers, in turn, implies lower wages relative to the more skilled.

Within sociology, post-industrial theory predicted a similar evolution of work and the occupational structure, except that post-industrial theory argued that rising skill requirements would increase the size of the middle class and reduce class divisions, rather than raise earnings inequality (Bell 1976; Zuboff 1988). The high technology explanation for the growth of earnings inequality rests on the assumption that the relative supplies of less and more skilled labor are not changing as rapidly as the relative demand for them, a skills mismatch idea that post-industrial theory did not anticipate.

Not all are convinced that the growth of wage inequality is a question of shifting human capital requirements and simple supply and demand adjustments. Harrison and Bluestone (1988; Harrison 1994) take a more institutional view and argue that growing inequality reflects "low road" labor policies adopted by business and the state in response to the competitiveness crises of the late 1970s-early1980s. This strategy favored wage cuts and a strong line against labor as a way to lower costs and boost profits, rather than a positive-sum strategy to promote higher productivity through more cooperative industrial relations. Indeed, econometric studies confirm that deunionization and the declining real value of the minimum wage had large effects on the growth of wage inequality in the 1980s (DiNardo, Fortin, and Lemieux 1996).

The present paper examines the technology explanation for inequality growth by investigating the relationship between computers and wages to see whether claims for the importance of increased skill demands from this source are warranted.

II. CURRENT RESEARCH

What is most notable about the technology-based account of the growth of earnings inequality is the paucity of direct evidence that supports it. The returns to education rose to historic heights in the 1980s, recovering from their historic low in the 1970s, but it is not clear that technology was the cause. Similarly, inequality within education-experience-gender groups (residual inequality) grew dramatically during the 1980s, but it is not clear that this was due to greater returns to unmeasured within-group skill differences of any kind, as some suggest, much less to diffusion of computers in the workplace (Katz and Murphy 1992). Occupational shifts in the predicted direction have been documented within industries, as well as resulting from industry composition shifts, but it is hard to know how much of the change is due to automation as opposed to increasing use of offshore production and outsourcing.

Virtually the only direct evidence that computers have altered the wage structure is a much-cited study by Krueger (1993), which examines within-job skill shifts using Current Population Survey (CPS) questions on computer use at work in 1984 and 1989.[1] Krueger found positive rates of return to using computers at work, net of standard human capital variables, on the order of 17-19%, depending on the year. Krueger also found that the returns increased over time despite the increased supply of workers using computers, which he argues might be expected to dampen the growth in returns to that skill. After considering different specifications, Krueger concluded that actual returns to computer use ranged from 10%-15%, depending on the kind of worker, year, and control variables included. These findings are notable and received a great deal of attention, though sometimes those citing Krueger's findings mention only the upper bound figure he suggests for the effects of computer use (i.e., 15%).

[1] A subsequent study replicates and extends results using the October 1993 CPS (Autor Katz, and Krueger 1997).

Krueger also reported that computer use explained about 40% of the .01 increase in the return to years of education observed during 1984-1989. This is the closest anyone has come to explaining the increased returns to schooling on the basis of the spread of high technology (Krueger 1993, p.51ff.; Autor, Katz, and Krueger 1997, p.17).

Though settling on a coefficient range somewhat below the .17-.19 estimates from the basic human capital equation represented an implicit acknowledgment of coefficient bias, Krueger tried to rule out the possibility that the .10-.15 estimates were biased by the omission of unmeasured employee characteristics or firm attributes (e.g., firms more able to afford computers may be more able to pay higher wages). He found that the returns to computer use remained in the 10-15% range even after controlling for home computer use and two-digit occupation and industry. Non-union workers earn a substantially higher premium for using computers than unionized workers, which Krueger took as casting doubt on the possibility that the computer use coefficients were simply picking up rent-sharing by unusually prosperous firms, since organized workers are presumably better able to capture such rents. Finally, Krueger controlled for school grades, achievement test scores, home computer use, and other variables using the High School and Beyond Survey (1984 wave). Again, the coefficients for computer use at work remained in the .10-.15 range, though most of these workers had been in the labor force only two to four years. Krueger concluded that the observed premium for computer use reflected actual returns and not returns to other, unmeasured variables. He suggested government-sponsored computer training programs as an effective way to moderate wage inequality in the short-term, until such time as computer knowledge becomes so widespread it commands small earnings advantage or contributes little to overall inequality.

But there are reasons to doubt that Krueger has settled the question of coefficient bias or has shown that computer use accounts for a large part of the growth of inequality during the 1980s.

First, Krueger's estimates of the return to computer use are more than twice the estimated return to a full year of education. This relationship is stable over time and not restricted to a small group of early computer users. It persists through the nearly ten-year period for which data are available (1984-1993), during which time the proportion of all workers using computers nearly doubled from 25% to 47% (Krueger 1993, p.52; Author Katz, and Krueger 1997, Tables 4,5). Following human capital theory, this implies that the average computer user needs training equivalent to two years of schooling to use a computer at work. This seems unlikely. The relative size of the computer and education coefficients, which seems to have passed unnoticed in Krueger's work and subsequent discussion, suggests that the estimated returns to computer use remain upwardly biased by the omission of relevant regressors.

Approaching the issue of coefficient bias from another angle, DiNardo and Pischke (1996, 1997) analyze three German surveys from the late 1970s-early 1990s. They show that using calculators, telephones, and pens/pencils at work or even sitting down while working are associated with premia comparable in size to those for computer use when entered individually in a standard wage equation. They argue that it is unlikely that the actual productivity differential associated with each characteristic could produce such similar results. Likewise, the large coefficients for working with pens and pencils and sitting at work suggests that these variables do not primarily measure scarce, productivity-enhancing skills, such as the ability to use pencils, sit down, or even use a computer, but mostly some unobserved aspect of either human capital or occupational position, for which the different measured variables served as proxies. The effects associated with computer use remained among the largest when all job characteristics were entered together into a wage equation, but DiNardo and Pischke argue that each variable is an imperfect proxy for worker ability or type of job, with some picking up this variation better than others. They suggest that unobserved heterogeneity in either human capital or occupational position may yet explain the measured effects of computer use and that technology per se may explain little of the growth in earnings inequality over the 1980s.

Second, even taking Krueger's coefficient estimates at face value, his regression analysis does not directly address whether computers account for a large part of the growth of inequality during the 1980s. There are two issues left unaddressed: 1) whether the timing of the trend in earnings inequality matches the trend in computer use and 2) the limits of regression coefficients in accounting for changes in the overall variance of wages.

Howell (1995, 1997) speaks to the first issue, noting that most of the between-occupation employment shift against the less skilled occurred prior to 1983, during the deepest recession since the Depression, while the sharpest increases in business computer investment came afterward. In addition, using Dictionary of Occupational Titles data, Howell finds that rates of skill upgrading overall seem to have fallen in the 1980s relative to the 1960s and 1970s (Howell and Wolff 1991). Thus, the timing of any demand shift against the less-skilled does not seem consistent with the trends in computer diffusion and suggests a rise in wage inequality that is disproportionate to any change in the distribution of job skill requirements. Howell concludes that Harrison and Bluestone's "low road" thesis is a more convincing explanation of the forces responsible for the growth of wage inequality.

Finally, with respect to the issue of regression coefficients as inequality measures, it seems to have passed unnoticed that Krueger's analysis does not directly address the main issue of concern, the impact of computers on overall inequality. Even if Krueger's regression coefficient estimates are unbiased, they measure only group differences in mean wages resulting from computer use, not the impact of a computers on the full distribution of wages. A characteristic can have an <u>equalizing</u> effect on the overall wage distribution despite association with a large wage premium if it raises the mean wage of a group of low-paid workers, as many argue is the case for unions, for instance (Freeman 1980; DiNardo, Fortin, and Lemieux 1996).

Although computer use is positively associated with education, which is positively correlated with wages, computers are also associated with being female and a clerical worker, which are negatively correlated with wages. Given this distribution of computer use, it is not obvious that the spread of computers had the large disequalizing impact commonly supposed. Indeed, as will be discussed, Krueger's own results show that computers had an equalizing effect on the gender wage gap, though this seems to have gone unnoticed (Krueger 1993, p.52). Thus, even if Krueger's coefficients are unbiased, any disequalizing effects across education groups may be partly or wholly offset by narrowing pay gaps between genders and between clerical and other occupations.

The following examines both issues of coefficient bias and the contribution of computers to the growth of overall wage inequality. The rest of the paper is organized as follows. Section

III describes the data, principally a previously unexamined supplement to the January 1991 Current Population Survey (CPS), which includes several job content indicators in addition to computer use. Section IV presents a brief descriptive analysis of these measures of job content and Section V uses them to replicate and extend DiNardo and Pischke's investigation of possible omitted variable bias. Section VI considers whether computers can account for a relatively large share of the growth of inequality by examining the timing of the growth in inequality and applying a technique devised by DiNardo, Fortin, and Lemieux (1996) that decomposes changes in the wage distribution into portions attributable to different characteristics, such as rates of computer use. Section VII concludes.

III. DATA

The January 1991 supplement to the Current Population Survey includes eight indicators of the tasks workers perform on the job, including computer use. The survey asked respondents how often they read or used different kinds of materials (e.g., news articles, forms, letters, diagrams, manuals), wrote text to be read by others, used math or arithmetic, and used a computer or terminal (see Table 1). Unlike the October 1984 and 1989 CPS supplements Krueger used, this data includes information on the frequency with which workers perform each job task (1=never, 2=less than once per week, 3=one or more times per week, 4=every day), rather than simply whether or not they performed the tasks.

These reading, writing, math, and computer items can be interpreted within a human capital framework as measuring workers' cognitive skills. Alternatively, these eight variables may be seen as proxies for occupational position, as with DiNardo and Pischke's variables, though none are so plainly lacking in overt skill content as their pencil use or "sit while working" variables as to rule out a human capital interpretation as well.

Following Krueger, I restrict the sample to wage and salary workers, age 18-65, who report earning between $1.50 and $250 per hour in current dollars. Workers paid by the hour are assigned their reported hourly wage. The hourly wage for salaried employees is calculated by dividing reported weekly earnings by reported usual hours worked. Unless otherwise stated, the dependent variable in all regressions is the log hourly wage.

The sample sizes in Table 1 represent all employed workers in the CPS sample for whom data on computer use and other job tasks was available (ca. 45,000). Only one quarter of this group was asked earnings and hours questions, so regression analyses below are restricted to a smaller, though still large, subsample (ca. 11,000).

Unfortunately, there is a high rate of non-response/missing data for the supplement questions, about 20%, compared to usual CPS non-response rates of around 2-4%, perhaps owing to interviewer unfamiliarity with the questionnaire (Greg Weyland, personal communication). The possibility of sample selection bias from this source is discussed where relevant below.

I also use the CPS Outgoing Rotation Group (ORG) annual merge files to estimate a time series for the variance of log wages (1979-1993). The CPS is conducted monthly and collects wage and hour information from one-quarter of each month's sample, known as the outgoing rotation groups. The ORG files merge these monthly quarter-samples into large annual files and are the best available source of hourly wage data, measured in the same manner described above.[2] Current-dollar cutoffs are an inappropriate basis for sample deletions with such a long time series. I restrict the sample in all years to those age 18-65 earning between $1.50 and $250 per hour in constant 1984 dollars to approximate Krueger's sample restrictions. Sample sizes are roughly 150,000-180,000 for each year.

I use the October 1984 and 1989 CPS supplements to decompose changes in wage inequality into portions attributable to changes in computer use and other variables. In these analyses I follow the sample restrictions in Autor, Katz, and Krueger (1997). Sample sizes are about 13,700 for each year.

IV. DESCRIPTIVE ANALYSIS

Table 1 presents means and correlations for the eight job task variables. "Use mathematics or arithmetic," somewhat surprisingly, is the most commonly performed task, though this says

[2] I thank Daniel Feenberg of the National Bureau of Economic Research for making available the CPS ORG files.

little qualitatively about the level of math employed.[3] The variable measuring what one would expect are more specialized tasks, "read or use diagrams, plans, or blueprints," has the lowest mean and the lowest correlations with the other job content variables. The means for most of the other five variables, including computer use, cluster together in the middle.

In addition to these job task questions, workers were asked whether they felt their reading, writing, math, and computer skills were good enough for their current job. Less than 3% of those with data said that their reading, writing or math skills were inadequate. This suggests either that the skills mismatch hypothesis that is the basis of most human capital accounts of the growth of wage inequality is overblown with respect to these skills or that employee self-reports are an unreliable guide to whether employers are satisfied with the skills of their employees. Alternatively, the mismatch story and observed responses may be consistent if those with skill deficiencies are jobless, effectively sorted into low skill jobs, or grow into their jobs over time or if employers simplify jobs, provide compensatory training, or cope with the skills shortage through longer and more costly searches rather than settling for those less than fully qualified.

Complicating the issue is the high rate of non-response and the negative association between non-response and education. Although the rate of non-response/missing data for these questions (22%) is in line with the general pattern in the supplement, if information were available for all individuals it is possible that a greater skills gap would be detected. However, when probabilities of skill inadequacy were imputed to non-respondents using coefficients from various logit models estimated on respondents, there was virtually no change in the percentage with inadequate reading, writing, and math skills; almost all remained under 3% (results not shown).[4] Individuals with missing values on these skill adequacy items would have to be very different from those with non-missing values to alter these results significantly.

---

[3] The skill variables do not distinguish qualitative levels of task complexity with respect to any of the reading, writing, math, or computer tasks.

[4] One group of logit models predicted reading, writing, and math skill deficiencies using all CPS rotation groups and the following predictors: years of education, experience and its square, and dummies for female, black, other non-whites, one-digit occupation, one-digit industry, government worker, part-time status, tenure, married, married*female, veteran, resident of metropolitan area, and region. A second model estimated on the outgoing rotation group quarter-sample added log wages, union status, and hourly worker status as predictors. Since some

By contrast, far more respondents, 21.4% of those with data, acknowledged that their computer skills were not good enough for their current jobs. This suggests the possibility of a skills mismatch even among computer users. If Krueger is correct about the importance of computer skills, one would expect those with inadequate computer skills to earn less than computer users who report adequate skills. Regression analysis below does not confirm this expectation, though the high rate of missing data again complicates the question.[5]

Table 2 presents mean frequency of computer use by different categories of workers. The third column dichotomizes the computer use variable into those who ever and never use a computer or terminal at work to make the figures more comparable to those Krueger reports.[6] The resulting pattern of computer use by worker characteristic similar to that which Krueger reports. Computer use rises monotonically with education. Only about 15% of those without a high school degree use computers, considerably below the sample average of roughly 50%. Among major occupational categories, clerical workers report the highest frequency of computer use (78%), followed closely by managers and professionals (76%). Blue collar and service worker rates are much lower, about 25% and 15% respectively, suggesting the need for caution in making claims that post-industrial technology has greatly shifted cognitive requirements for these lower skill occupations. However, women are 10 percentage points more likely to use computers than men, which, along with the high rate for clerical workers, underscores the heterogeneous distribution of computer use across pay groups and the need to consider how computers may raise wages of traditionally lower paid, as well as higher paid, workers. As in Krueger's samples, frequency of computer use by age shows a curvilinear pattern, with those age 35-44 reporting the highest frequency of use.

The overall rate of computer use for this 1991 sample, 52.6%, is significantly higher than either Krueger's figures for October 1989 or those from a subsequent CPS supplement in

---

cases had missing values for tenure, alternate versions of both models were estimated without this predictor. In only one of the twelve estimates did the percentage with inadequate skills edge over 3%.

[5] Imputing missing values using the models described in Note 4 increases the percentage of those with inadequate computer skills by only about 2%.

[6] This seemed the best choice for maximizing comparability with the October CPS supplements Krueger used. They asked, "Does _______ directly use a computer at work?"

October 1993 (Autor, Katz, and Krueger 1997, p.16). This may reflect the non-randomness of non-response/missing data suggested above; non-users may be more likely to have missing data, producing an over-representation of computer users among those for whom information is available.

V. ARE THE ESTIMATED RETURNS TO COMPUTER USE TRUSTWORTH?

To estimate the returns to computer use, Krueger estimated the model,

$$\ln W_i = X_i \beta + C_i \alpha + \varepsilon_i ,$$

where W_i = hourly wage for individual *i*

X_i = vector of control variables[7]

C_i = a dummy that equals one if individual *i* uses a computer at work

ε_i = error term

As noted, the estimates for α are large and significant and the addition of *C* to basic wage equations for 1984 and 1989 explains about 40% of the observed growth in the returns to education between those years. Krueger concluded that the diffusion of computers was an important cause of the growth of earning inequality in the 1980s (Krueger 1993).

The validity of Krueger's conclusion depends on whether 1) observed returns to computer use reflect actual returns, rather than coefficient bias, and 2) whether the spread of computers accounts for a relatively large share of the growth of overall inequality.

To answer the first question, consider what happens when each of the eight job task items from the January 1991 CPS is entered individually in a standard wage equation. Table 3 presents results for models with the form

$$\ln W_i = X_i \beta + Z_i \alpha + \varepsilon_i ,$$

where all variables are defined as above with the exception of *Z*, which replaces *C* with dummies indicating the frequency with which an individual performs any one of the eight job task items, depending on the model.

Table 3 shows that when entered individually, each of the eight job tasks is associated with very large wage differentials of roughly similar magnitude. The coefficients for computer use tend to be in the upper end of the range of estimates, but are in no sense exceptional. Nor are the estimates for computer use peculiar to this sample or low relative to Krueger's estimates.[8] The results indicate that those who perform <u>any</u> of the eight tasks every day earn roughly 21% more per hour than those who never perform them, while the corresponding figures for those who perform any of the tasks once or more per week and less than once a week are about 17% and 14%, respectively.

These results are largely consistent with DiNardo and Pischke's findings using German data and raise the same questions regarding the trustworthiness of the estimates. While all of the eight tasks are likely associated with some productivity advantage, it is unlikely that they all have roughly equal effects (DiNardo and Pischke 1996). The similarity of the estimated returns to these eight tasks, as well as some of the specific coefficients, suggests that in addition to any true returns, all eight job task variables may be picking up unmeasured variation in human capital, occupational position, or firm characteristics to varying degrees. For example, the results in Table 3 imply that those reading or using letters every day earn about 30% more than those never doing so, a differential equivalent to more than three years' worth of schooling, as estimated in the baseline model.[9] More than likely this reflects other factors, such as an individuals' occupational status or general abilities, at least as much as any true returns to a

[7] Years of education, experience, experience^2, and dummies for female, black, other non-whites, part-time status, union status, resident of metropolitan area, married, married*female, veteran, and region.
[8] If the computer variable is dichotomized to make it comparable to the CPS supplements Krueger used the coefficient is .215, which is a bit <u>higher</u> than Krueger's estimates for October 1989 (.188) and October 1993 (.203), perhaps reflecting some peculiarity of the January 1991 sample (Krueger 1993; Autor, Katz, and Krueger 1997).

[9] Percentage wage differences associated with a unit difference in years of education and using letters every day are calculated using the formula: $e^b - 1$.

specific ability to read or use letters. This suggests the strong possibility that the large returns to computer use may also reflect the omission of important regressors, in addition to any true returns.

One can partially test for bias in the computer coefficients by including all seven non-computer variables, as well as other controls such as occupation and industry, in a single model with computer use and comparing the results with those in Table 3. Insofar as the seven non-computer variables either directly measure aspects of job complexity not due to computers or proxy for occupational status or general cognitive abilities, they control for usually unmeasured human capital and occupational position. Since the seven non-computer job task variables do not appear in the CPS supplements Krueger used, they are a potentially valuable test of the robustness of the measured returns to computer use.

Model 3 of Table 4 shows that when all eight job task variables are entered together, the coefficients for computer use fall from .234, as reported in Table 2, to .146 for those who use computers at work every day and from roughly .15 to .07 for those who use computers less frequently, declines of about 40-55%. When a dichotomized computer variable similar to Krueger's is used, its coefficient falls from about .215 to .127, a decline of 40% (results not shown).

The latter may still be an overestimate since the baseline coefficient estimate, .215, is about .015-.025 higher than Krueger's estimates using either 1989 or 1993 data (see note 8). This suggests that sample selection in the January 1991 data may be biasing upward all estimates of the computer coefficient reported here, though no strong test is possible in the absence of an exclusion restriction (Winship and Mare 1992, p.341).[10]

In any case, the coefficient estimates in Model 3 are basically consistent with Krueger's suggestion that the actual returns to computer use, measured dichotomously, are in the 10-15% range. The main difference is that infrequent users receive a return below this range which is less than half the upper bound that is often cited as the estimated return to computer use. However, even infrequent computer use is associated with significantly higher wages net of the seven other job content variables and the magnitude of the effects are among the largest. This is also consistent with DiNardo and Pischke (1997), who find that the effects associated with computer use in Germany remained among the largest when all job content variables are included in a single model.

Also consistent with DiNardo and Pischke, most of the coefficients for the seven non-computer job tasks remain significant when entered jointly. One notable exception, in light of the debate over technology's role in increasing the cognitive requirements of work, are the coefficients for using math or arithmetic at work, which are not significant in this model. Even when computer use is omitted only the most infrequent use of math is associated with a significant wage differential (see Model 2, Table 4). This contrasts with Murnane, Willett, and Levy (1995), who find significant and increasing returns to basic math test scores among young people over the period 1978-1986.

These results are not necessarily inconsistent. Murnane et al. used math test scores primarily because they are a more reliable indicator of general cognitive skills than verbal test scores, not because they thought math skills per se were the most important skills used at work or most important for labor market rewards (Richard Murnane, personal communication). The non-math job task indicators in the January 1991 CPS may simply capture the variation in cognitive skill requirements of most jobs better than the CPS math item.

The results in Table 4 also should not be taken as a measure of the return to high level math skills, since the large fraction reporting frequent math use in the CPS suggests most use math for relatively simple tasks. Nevertheless, the results in Table 4 suggest that most math tasks at work are neither very sophisticated nor specifically rewarded, in contrast to expectations of both post-industrialism and the human capital/skills mismatch thesis.

To further test for coefficient bias in the estimates of returns to computer use, Model 4 in Table 4 adds further controls to Model 3 for occupational position and industry. Some of these controls were unavailable to Krueger, others he chose not to include, and others he did use. The additional controls are for whether an individual is an hourly worker, received managerial or

[10] A simple Heckman sample selection model does not detect any bias, though a logit for the probability of missing data on the computer use variable indicates that those with higher wages are more likely to be missing,

supervisory training from his or her employer, works for the government, 47 occupation dummies, 45 industry dummies, employee tenure, and length of time in current occupation. Since returns to computer use may reflect computers' association with firm characteristics that positively affect wages, such as size, profits, or capital intensity, firm-level variables would be desirable. Unfortunately, there are no direct firm-level measures in any of the CPS supplements that measure computer use.

Model 4 shows that the effect of the additional controls is to reduce the size of the computer coefficients by 35-40%, from .146 in Model 3 to .084 for those who use computers at work every day and from roughly .068 to .045 for those who use computers less frequently. When a dichotomized computer variable similar to Krueger's is used, its coefficient falls from about .127 to .073, a decline of 43% (results not shown). Although the computer coefficients remain large compared to most of the other job content variables, this estimate for the dichotomous computer variable is <u>one-half</u> the commonly-cited 15% figure that Krueger estimates and equivalent to less than a year of education. This coefficient may still be upwardly biased, but seems more plausible than the range Krueger suggests.

It should be noted that though Krueger also fits models with occupation and industry, he raises some questions about their appropriateness. If knowledge of computers is required to qualify for jobs in higher paying occupations and industries, the inclusion of the latter as controls will cause part of the computer wage effect to be attributed to other variables and bias the computer coefficient downward (Krueger 1993, p.39). The same concern might be raised with respect to other variables in Model 4, including the seven non-computer job task indicators. If, for instance, manuals are used mostly in the context of computer use, then the measured returns to using manuals may reflect mostly returns to computer skills. Likewise, if computers contribute to greater frequencies of all the other reading, writing, and math tasks measured in the January 1991 CPS, then some of the indirect effects of computer use will be attributed to these variables in the models where they are included as regressors and the estimated total returns to computer use will be biased downward. Of course, some job tasks, such as writing text at work, predict frequency of computer use, which suggests that a more appropriate model would involve

---

conditional on the controls in Model 3 (results not shown).

several paths of reciprocal causation among computer and non-computer variables. Unfortunately, there is no obvious way to identify such a model with the data available.

A fixed effects model would provide an alternative method of estimating the true total effect of computers on wages, but there is no panel data available to fit such a model. Consequently, there is not a great deal that can be done to both control for bias in the computer coefficients and measure any indirect effect of computers operating through those controls.

As a final test of whether the measured returns to computer use reflect actual returns to computer skills, two other computer-related variables were added to Models 3 and 4: 1) a dummy for whether an individual reported their computer skills were good enough for their current job and 2) a dummy for whether an individual received computer training after obtaining their current job. If there is a genuine return to using computers, one would expect those who report their computer skills are inadequate would suffer a wage penalty and those who received computer training would reap positive returns.

Table 5 reports results from fitting these models, which also include controls for whether an individual reported their reading, writing, and math skills were good enough for their current job and whether an individual received training in four non-computer areas after obtaining their job: management/supervisory skills, occupation-specific technical skills, reading/writing/math skills, and other skills.

In neither model do those who report their computer skills are inadequate suffer a wage penalty. These results are unchanged when the computer skills variable is interacted with the dummies for frequency of computer use (results not shown). The wages of those who say their reading, writing, or math skills are inadequate also seem unaffected, but this may reflect the lack of variation in these three variables, which is not an issue in the case of the computer skills variable, as noted earlier. If Krueger is correct about the importance of computer skills, one might expect the model to show that those with inadequate computer skills earn less than users who do not report inadequate skills. This does not seem to be the case, though this variable is strongly associated with frequency of computer use and may have an indirect effect on wages. The possibility of significant measurement error in this kind of self-report item and possible selection bias resulting from the high rate of missing data also cloud interpretation.

Nevertheless, it is notable that many at all levels of computer use acknowledge computer skill deficits, yet incur no specific penalty.[11]

Similarly, if computer skills are important one would expect that those who received computer training after being hired would earn more than others, all else held equal. This expectation is also not confirmed. While there are positive returns to other kinds of technical training and managerial/supervisory training, there are no significant returns to computer-related training in either model. This may reflect short training times for the most commonly used computer skills, such as word processing. If this is the case, then computer skills are likely not as scarce and expensive as Krueger suggests.

Clearly there is a potential selection issue here that argues for caution. Those who received post-hire training may have had a computer skill deficit prior to training that is unobserved in the data. If training simply brought them to parity with those already having the necessary skills, then the absence of measured returns in the cross-section may mask a real treatment effect for those receiving training. In the absence of panel data there is no way to test this possibility, but the lack of observed returns to computer training is notable.

In the absence of significant effects for the computer skills adequacy and training variables, it is apparent that the addition of the other training variables in Model 2 of Table 5 also reduces all computer coefficients to levels well below the range Krueger suggested. When dichotomized, the computer use coefficient is now only .066 (results not shown).

Finally, some of Krueger's own results are awkward from a human capital perspective. For 1989, he finds that the returns to computer use varied by the specific job task an individual performed using computers, but the pattern is not easily interpretable within a standard human capital framework. Among computer tasks, e-mail received the highest returns (.149) above the basic return to any computer use, while spreadsheet use was rewarded only half as much (.079), and programming and computer-aided design software use brought no additional returns (Krueger 1993, p.41f.). These relative magnitudes do not reflect likely actual differences in the

[11] After reading this result some suggested that there is no observed wage penalty because it is the highly skilled, who have the most demanding jobs, who are most aware of their computer skill deficits. However, the correlation between education and reporting a computer skill deficit is negative (r=-.16, p<.01), supporting the interpretation above.

costs of acquiring the skills necessary for these four tasks, as human capital theory implies. Krueger acknowledges obliquely that the very large returns to e-mail use likely reflects some form of coefficient bias, but does not otherwise discuss this anomaly.

The preceding suggests that the high measured returns to computer use reported by Krueger overestimate true returns. Any number of other job content indicators are associated with similarly high returns when entered individually into a standard wage equation, suggesting correlation with omitted regressors. When job content variables and other controls for human capital, occupation, and industry are added to the computer wage equation, the coefficient for the dichotomous computer use variable falls to .066, less than one-half Krueger's commonly-cited .15 estimate. Even the size of this coefficient may reflect the computer variable's ability to pick up unmeasured variation in other human capital or structural variables affecting wages (DiNardo and Pischke 1996). The absence of both measured returns to computer training and penalties associated with self-reported computer skill deficits also do not fit simple human capital interpretations of the observed returns to computer use. While possible selection and other issues argue for caution in interpreting these results, they suggest that computer skills per se are not as important in wage determination as Krueger argued.

VI. HOW MUCH OF THE GROWTH IN INEQUALITY DO COMPUTERS EXPLAIN?

Even setting the issue of coefficient bias aside, Krueger's work does not demonstrate the importance of computers for inequality growth because it rests on the large regression coefficient associated with computer use and its ability to explain nearly half the growth in the returns to education. Neither is a sufficient basis for judging the issue even in the absence of coefficient bias, since the timing of the inequality and computer diffusion trends is potentially problematic and regression coefficients do not measure a variable's relative contribution to overall inequality. In addition, the ability of computers to explain the education coefficient is subject to some of the same concerns raised in the preceding section. Consider this last issue briefly.

Results in Table 3 indicates that when each of the eight job content variables is entered individually in a standard wage equation, the computer variable is not distinctive in its ability to explain the education coefficient in the cross-section. In addition, Table 4 indicates that the large effect of computers on the size of the education coefficient declines by two-thirds when the seven non-computer job content variables are controlled.[12] This suggests that the ability of computer use to explain the education premium in the cross-section is significantly overstated when other measures of job content are omitted. This cross-sectional bias need not affect the power of the computer variable to explain the growth in the returns to education over time, but argues for caution in interpreting Krueger's results, especially since the ability to explain the education effect is such an important part of the argument that computers increased the skill content of work.

More critically, Howell's work suggests that the timing of the trend in computer use should be carefully compared to the inequality trend. On the basis of the 1984, 1989, and 1993 October CPS supplements, Krueger and his colleagues suggest that the trend in computer use at work was roughly linear, rising 2.4% per year, from one-quarter (1984) to nearly one-half of the work force (1993) (Autor, Katz, and Krueger 1997, p.16f.).

The growth of wage inequality, however, was distinctly non-linear. The variance of log wages rose from about .20 to over .25 or about 25% over the period 1979-1993, but most of this rapid growth was concentrated in the recession years of the early 1980s, prior to the period covered by Krueger's study. Nearly half the total growth in inequality occurred between 1981-1983, when the jobless rate reached a post-war high of over 9.5%, with successive years accounting for steadily diminishing contributions to total inequality growth (<u>Economic Report of the President: 1994</u>, p.314). Figure 1 plots trends in both the percentage of computer users and the variance of the log of wages.[13] The two figures do not correspond closely to one another.

---

[12] In Table 3, the computer dummies reduce the education coefficient by 13%, consistent with Krueger's estimates (Krueger 1993, p.52; Autor, Katz, and Krueger 1997, Table 5). When added to the model with the seven non-computer variables, however, computer use explains only about 4.7% of the education coefficient (see Table 4, Models 2 and 3). By contrast, the ability of the seven non-computer job content variables to explain the education coefficient is not nearly so sensitive to the inclusion of the computer variable (see Table 4, Models 1-3).

[13] Because the CPS did not inflation-adjust the top code value for weekly earnings between 1979 and 1988, all variances are calculated on truncated samples to eliminate the progressive negative bias that would result from

As the proportion of computer users rises steadily through the period, inequality growth slows and declines modestly before turning upward.

If the growth of wage inequality were linear over this fifteen year period, like the diffusion of computer use, each year would account for about 7% of the total change. Alternatively, one might expect the increase in wage inequality to be concentrated in the period 1984-1993, as both the relative number of computer users and the observed returns to computer use increased during this period. Clearly, neither expectations of linearity in wage inequality growth nor acceleration after 1984 are confirmed. If anything, the period prior to widespread computer use saw the most rapid growth in inequality and the years of greatest computer usage saw modest declines in inequality. This is not the pattern one would expect if the increased skill requirements of working with computers were driving the growth in inequality.

In short, the timing of the growth in wage inequality is not particularly consistent with Krueger's account. The pattern of inequality growth in Figure 1 is corresponds more to the onset and lingering effects of the Reagan recession, as well as the trade shock of the early 1980s, and is more consistent with Howell (1995).[14]

The timing of inequality growth is not necessarily evidence for Howell's causal explanation that it results from low road employer responses to tighter economic circumstances. Some hypothesize that firms reorganize and retool operations during recessions, when orders are slack, resulting in the kind of nonlinear changes observed here. However, even advocates of this

---

using full samples, where an increasing proportion of high earners is top coded over time. Figure 1 uses estimates of the variance of log wages using the bottom 95% of the weekly earnings distribution, which eliminates all top coded cases in all years. As a check, estimates from samples truncated at the 99th percentile were calculated for years in which this cutpoint eliminates all top coded values (1979-1980, 1989-1993). The patterns for these years across the two sets of estimates are very similar.

Results reported here and below also did not differ substantively when using the full sample and replacing top coded values with calculated values based on formulas for the mean of open-ended income categories derived from Pareto curve estimation (Parker and Fenwick 1983) or imputing a top-code value suggested by Autor, Katz, and Krueger (1997, p.A1).

[14] Note that increased inequality in hourly wages, unlike annual earnings, is not necessarily predicted during recessions since the least paid workers tend to bear the brunt of unemployment and no longer appear in wage data. This will shrink the size of the left tail of the hourly wage distribution. Cyclical real wage declines for those who remain employed, on the other hand, have not generally affected lower paid workers more than others (Solon, Barsky, Parker, 1994, pp.7,14). This suggests that the entire real wage distribution shifts left during a recession, but wage inequality does not increase, all else equal.

view acknowledge that, empirically, investment is procyclic, contrary to the theory's expectation (Dunne, Haltiwanger, and Troske 1996). Still, even Howell acknowledges that there was a permanent shift in the manufacturing occupational distribution toward non-production workers during the recession years, suggesting some kind of a demand shift against the less skilled (Howell 1995, pp.30f.). Whether or not Howell's explanation is correct, the timing and non-linearity of inequality growth do not suggest a primary role for the skill shifts Krueger attributes to increased computer use.

Computer use may still have played a secondary role in the growth of wage inequality in the period 1984-1993. To answer this question one has to consider the impact of computers on all components of the variance. For instance, Krueger's own results show that computer use suppressed growth of inequality between gender groups. In his wage equation omitting computer use, the gender gap grows from .140 (1984) to .142 (1989), but when computer use is controlled, the gap widens from .162 to .172, showing that the changing distribution of and returns to computer use by gender moderated inequality growth across genders even as it contributed to inequality growth across education levels (Krueger 1993, p.52). Reanalysis of the October 1989 data also shows that the residual variance from a standard wage equation is 10% lower for computer users than non-users, implying that a rising share of computer users between 1984 and 1989 also moderated growth of within-group inequality, an important source of inequality growth in the 1980s.[15] In short, the net effect of increased computer use on the

[15] The lower residual inequality among computer users does not seem to reflect selection processes that might lead to greater homogeneity among users on unobservables, since the residual variance among users <u>declined</u> between 1984 and 1989 even as they accounted for a larger share of the work force, while residual variance among non-users increased, as shown in the table below. The top panel uses an imputed value for 1984 top-coded cases suggested by Krueger (1993, p.56) and the lower panel uses truncated samples in both years to eliminate top coded cases. In both panels the residual variance declines for users and increases for non-users.

Residual Variance among Computer Users and Non-users

Variance	All	Users	Non-users
Imputing top code values for 1984			
1984	.1731	.1717	.1673
1989	.1770	.1608	.1779
Deleting top 2.67% of cases in both years			
1984	.1582	.1522	.1548
1989	.1630	.1432	.1663

growth of overall inequality between 1984 and 1989 is indeterminate from the evidence Krueger presents.[16]

One way to evaluate the net effect of increased computer use on overall inequality is to adjust the level of computer use in the 1989 sample to 1984 levels and then compare the wage distributions for the adjusted and unadjusted samples. In a series of papers, DiNardo, Fortin, and Lemieux (DiNardo, Fortin, and Lemieux 1996; DiNardo and Lemieux 1997; Fortin and Lemieux 1997) develop a procedure for making such comparisons and use it to investigate the effects on inequality of declining unionization rates, declining real minimum wage, and industry deregulation.

DiNardo et al. (1996) give a non-parametric illustration of declining unionization's impact on inequality among men with twelve years of education and 10-30 years of experience. The unionization rate for this group declined from 47% (1979) to 35% (1988). In order to adjust the unionization rate of their 1988 sample to the 1979 level they adjust the CPS sample weights. For the 1988 sample, they multiple the weights of union members by .47/.35 and those of non-union workers by .53/.65. This reweighting adjusts the 1988 sample's unionization rate to 1979 levels, while leaving unchanged other differences in variance components, such as within-group variances. The difference in inequality levels between the original and reweighted 1988 samples is a measure of the effect of changing unionization rates on overall inequality for this group.

To apply this method to all workers one can either divide the samples for two years into a large number of cells based on worker characteristic and calculate reweighting factors as described above or one can estimate probabilities for each year parametically and use the results to calculate reweighting factors, the approach taken here. The probability of computer use at work conditional on a vector of non-computer characteristics, $\boldsymbol{X}$, is estimated for the 1984 and

---

[16] In fact, there are even more problems with Krueger's reliance on regression coefficients as measures of contribution to overall inequality. Holding all else equal, if $y= b\,x + c$, where y=log wage, x=use computer (yes/no), and c=other determinants of wage, then $var(y)= b^2 * var(x)$. This quantity is maximized when x=.5. Even assuming no decline in b, the spread of computers will have an equalizing effect on wages once the user group exceeds 50% of the work force, as the group of lesser-paid non-users shrinks to a minority and the wage advantage of computer use is spread more evenly. This tipping point was reached around 1995, assuming continued linear growth of computer use. This implies that recent growth in the use of computers has had an equalizing effect on the wage distribution, assuming no fully offsetting growth in the wage premium, b.

1989 CPS samples using a logit model.[17] The probabilities from the 1989 logit are used to derive the denominator of the reweighting factors, while the 1984 logit coefficients are used to derive the numerator by applying them to the 1989 sample (i.e., $\hat{b}_{84}\ \boldsymbol{X}_{89}$) to obtain predicted probabilities of computer use in 1989 assuming the 1984 relationships remained in effect. Specifically, CPS sample weights are adjusted by multiplying them by factors equal to:

$$\frac{\text{pr(use computers} = 1 | \mathbf{X}_{89},\ t_\beta = 84)}{\text{pr(use computers} = 1 | \mathbf{X}_{89},\ t_\beta = 89)} \quad \text{for computer users and}$$

$$\frac{\text{pr(use computers} = 0 | \mathbf{X}_{89},\ t_\beta = 84)}{\text{pr(use computers} = 0 | \mathbf{X}_{89},\ t_\beta = 89)} \quad \text{for non-computer users,}$$

where $\boldsymbol{X}$ is the vector of control variables whose distributions are to remain fixed at 1989 levels and t_β indexes the year whose coefficients are applied to the 1989 sample. Applying these factors effectively adjusts the 1989 sample's group-specific rates of computer use to 1984 levels, where groups are defined by the variables in $\boldsymbol{X}$, while the distribution of these non-computer characteristics and the structure of wages remain as observed in 1989. Conceptually, this method is analogous to other, more familiar decomposition and standardization techniques (e.g., Kitagawa 1955, Oaxaca 1973, Blinder 1973), but while they typically decompose differences in means or rates into portions attributable to differences in characteristics and the returns to them, this technique decomposes changes in variances or other measures of dispersion.

Comparing actual wage inequality in 1989 with inequality in the reweighted sample answers the question, *What would be the level of inequality in 1989 if rates of computer use within groups remained at their 1984 level but the other components of the variance remained as observed in 1989 (i.e., the distribution of non-computer characteristics, the returns to those characteristics net of changes in proportions of computer users within groups, the returns to*

[17] The non-computer characteristics used as predictors in the models were years of education, experience, experience^2, and dummies for female, black, other non-whites, part-time status, union status, one-digit occupation, one-digit industry, resident of metropolitan area, married, married*female, veteran, and region.

computer use, and levels of within-group inequality)?[18] After adjusting the rates of computer usage to 1984 levels, the returns to computer use can also be adjusted to 1984 levels by simply subtracting the growth in the computer premium from the wages of users.

The results of this analysis, presented in Table 6, indicate that the spread of computer use at work between 1984 and 1989 had a very slight equalizing impact on the overall wage distribution, as the variance of log wages is about 1% higher when the 1989 sample is reweighted to reflect 1984 rates of computer use (.3254) relative to the original sample (.3222). Since the variance for both men and women is higher in the reweighted sample, the equalizing impact of the spread of computer use probably reflects the lower within-group variance of computer users more than the equalizing effects of computers on the gender wage gap.

This impression is reinforced when the returns to computer use are adjusted down to 1984 levels, which lowers the variance in the reweighted sample (.3236). This indicates that the rise in the computer premium over this period had a net disequalizing impact, which is not what one would expect if the equalizing effect of computers on the gender gap dominated. Nevertheless, even after taking into account the disequalizing rise in the returns to computer use, the net effect of increased computer use between 1984 and 1989 seems to have been to moderate the growth of wage inequality, rather than to contribute to it. Perhaps most striking, however, is the limited impact of any sort which greater computer use had on the variance of log wages compared to the actual 6% growth the variance of log wages between 1984 and 1989.

VII. DISCUSSION AND CONCLUSION

Aage Sørensen has remarked that one of the attractions of human capital theory is that its deductive quality allows one to judge the plausibility of coefficient estimates on the basis of theory, so that Jacob Mincer, for instance, once rejected one of his own models because the

[18] This comparison between actual and counterfactual wage distributions rests on the assumption that changing rates of computer use did not influence the returns to other characteristics except by changing the composition of groups with respect to computer use, which is controlled. Thus, if computers raised the returns to education through automation and displacement of less educated workers, apart from any skill effects from putting computers on some workers' desks, this effect will not be attributed to computers here, nor in Krueger's study. However,

education coefficient was so large that it implied everyone should remain in school for improbably long periods (Sørensen in Swedberg 1990, p.314). It is precisely on these grounds that Krueger's estimates of the returns to computer use can be questioned. They imply that computer training, which for most tasks one suspects can be accomplished in a matter of weeks, has a market value equivalent to more than two years of schooling. This is inherently implausible. Assuming a straightforward human capital interpretation of Krueger's estimates implies that many students would have abandoned higher education during the 1980s in favor of short computer training classes, such as those offered by proprietary schools advertised on television. In the absence of any evidence for such a development, one suspects strongly that Krueger's estimates of the rate of return to computer use are upwardly biased due to correlation with omitted human capital, occupational, and firm characteristics.

Indeed, results presented above indicate that seven measures of non-computer job content are associated with similarly high returns when entered individually into a standard wage equation, suggesting all share such bias, and when all are entered together with computer use and other human capital and structural variables, the returns to computer use measured dichotomously fall to .066, well below Krueger's .10-.15 estimated range. There are also no returns to computer training in the cross-section and no penalty for computer skill deficits, which do not support a simple human capital interpretation of the returns to computer use, though selection and other issues argue for caution in interpreting these results.

Most difficult for the view that rising inequality resulted primarily from increased skill demands associated with computer use is the fact that inequality rose most rapidly within a few short years in the early 1980s, prior to the widespread use of computers in the workplace. The smooth rise in computer use after 1984 also does not track the non-linear trend in inequality growth. Adjusting 1989 rates of computer use to 1984 levels while holding other variables constant suggests that the spread of computers did not even play a secondary role in raising inequality during the 1980s when all components of its contribution to the overall variance are

---

since the measured returns to computer use likely overestimate actual returns, as argued above, there is also a potential offsetting bias in favor of finding a large effect of computers on the growth of inequality.

taken into account, even assuming Krueger's estimates of the returns to computer use are unbiased.

The sharp rise in inequality did coincide with severe recession, unprecedented import competition, corporate restructuring, and an administration more hostile to unions than any since before the New Deal, suggesting structural factors weakening both the formal and informal bargaining power of workers relative to management. The fact that inequality declined modestly between 1989-1992, when the minimum wage increased about 27% for the first time since 1981, further suggests the importance of structural factors. If the computer premium dominated inequality trends, it is not obvious why inequality would have declined during this time. The timing of the growth of inequality suggests that the dismantling of institutional protections and the scrapping of traditional wage norms account for a larger portion of the rise in inequality than any acceleration in the cognitive demands of work owing to the increased use of computers.

This does not rule out other mechanisms by which technology may have altered the skill and wage distributions. If automation eliminated low skill jobs or increased the relative number of high skilled jobs, such as managers of new information systems, this would not be measured directly by the computer use variables used here and in Krueger's study, which measure changes in within-job skill requirements. It is still possible that technology has played an important role in between-job composition shifts. This is a separate question. The preceding indicates that only modest increases in skill requirements are likely due to using computers at work, contrary to Krueger and much casual reasoning about the implications of high technology.

In short, computer skills do not seem to have been as scarce, expensive, and important in the growth of overall wage inequality as Krueger and many others believe. This is not so surprising if one distinguishes the internal complexity of computers as products from the skills needed to use them at work and the skills of high-level users (computer scientists, systems analysts, programmers) from those of most users. I suspect that good typing skills and knowledge of only a limited set of operating system and word processing operations are required of most computer users. Most workers do not do programming or high-level systems troubleshooting at work.

This points to an important insight that seems to be missing from most discussions of the impact of high technology on labor markets. The prevailing assumption seems to be that workers must adjust to technology. While no doubt true, it is only part of the picture. Product markets as well as labor markets are at work here and the dynamics of product markets impel the technology to adjust to users. Technology that is hard to use is at a competitive disadvantage, all else equal. If word processing required the skills to program in FORTRAN or C, there would be far fewer word processors. The field of human factors and the actual history of computer software suggest that ease of use is an important consideration in product development, most notably with development of the graphical user interface, whose icons and pull-down menus replaced command lines with pictures (Carroll 1997, pp.67ff.). There are some complexities to the process, notably the tendency for software to become feature-rich, hence more complex, even as core functions are simplified. Actual data on computer training times would go a long way toward clarifying their impact on the cognitive complexity of work. In the absence of such data, the preceding provides some caution against accepting too quickly the all too easy equation of high technology and high skill requirements.

BIBLIOGRAPHY

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1997. "Computing Inequality: Have Computers Changed the Labor Market?" National Bureau of Economic Research Working Paper 5956, Cambridge, Ma.

Bell, Daniel. 1976. The Coming of Post-Industrial Society: A Venture in Social Forecasting. New York: Basic Books.

Blinder, Alan S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." Journal of Human Resources. 8:436-455.

Carroll, James M. 1997. "Human-Computer Interaction: Psychology as a Science of Design." Annual Review of Psychology. 48:61-43.

Danziger, Sheldon, and Peter Gottschalk, eds. 1994. Uneven Tides: Rising Inequality in America. New York: Russell Sage.

DiNardo, John E. and Jörn-Steffen Pischke. 1996. "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" National Bureau of Economic Research Working Paper no. 5606, Cambridge, Ma.

______________ and ________________. 1997. "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" Quarterly Journal of Economics. 112:290-303.

DiNardo, John E. and Thomas Lemieux. 1997. "Diverging Male Wage Inequality in the United States and Canada, 1981-1988: Do Institutions Explain the Difference?" Industrial and Labor Relations Review 50:629-651.

______________, Nicole M. Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." Econometrica 64:1001-1044.

Dunne, Timothy, John Haltiwanger, and Kenneth R. Troske. 1996. "Technology and Jobs: Secular Changes and Cyclical Dynamics." Manuscript.

Fortin, Nicole M. and Thomas Lemieux. 1997. "Institutional Change and Rising Wage Inequality: Is there a Linkage?" Journal of Economic Perspectives 11:75-96.

Freeman, Richard B. 1980. "Unionism and the Dispersion of Wages." Industrial and Labor Relations Review

Harrison, Bennnett. 1994. Lean and Mean: The Changing Landscape of Corporate Power in the Age of Flexibility. New York: Basic Books.

______________ and Barry Bluestone. 1988. The Great U-Turn: Corporate Restructuring and the Polarizing of America. New York: Basic Books.

Howell, David R. 1995. "Collapsing Wages and Rising Inequality: Has Computerization Shifted the Demand for Skills?" Challenge. January-February:27-35.

______________ . 1997. "Institutional Failure and the American Worker: The Collapse of Low-Skill Wages." Paper, Jerome Levy Economics Institute.

______________ and Edward N. Wolff. 1991. "Trends in the Growth and Distribution of Skills in the U.S. Workplace, 1960-1985." Industrial and Labor Relations Review. 44:486-502.

Katz, Lawrence F. and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." Quarterly Journal of Economics. 107:35-79.

Kitagawa, Evelyn M. 1955. "Components of a Difference Between Two Rates." Journal of the American Statistical Association. 50:1168-1194.

Krueger, Alan B. 1993. "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989." Quarterly Journal of Economics. 108:33-61.

Levy, Frank and Richard J. Murnane. 1992. "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations." Journal of Economic Literature. 30:1333-1381.

Murnane, Richard J., John B. Willett, and Frank Levy. 1995. "The Growing Importance of Cognitive Skills in Wage Determination." The Review of Economics and Statistics. 77:251-266.

Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets." International Economic Review. 14:693-709.

Parker, Robert Nash and Rudy Fenwick. 1983. "The Pareto Curve and its Utility for Open-Ended Income Distributions in Survey Research." Social Forces. 61:872-885.

Solon, Gary, Robert Barsky, and Jonathan A. Parker. 1994. "Measuring the Cyclicality of Real Wages: How Important Is Composition Bias?" Quarterly Journal of Economics. 109:1-25.

Spenner, Kenneth I. 1979. "Temporal Changes in Work Content." American Sociological Review. 44:968-975.

Swedberg, Richard. 1990. Economics and Sociology. Princeton, N.J.: Princeton University Press.

Winship, Christopher and Robert D. Mare. 1992. "Models for Sample Selection Bias." Annual Review of Sociology. 18:327-350.

Zuboff, Shoshana. 1988. In the Age of the Smart Machine: The Future of Work and Power. New York: Basic Books.

Table 1. Means and Correlations among Job Task Variables

Variable	Mean[a] (s.d.)	N	Correlations[b] 1. Reports	2. Forms	3. Letters	4. Diagrams	5. Manuals	6. Write	7. Math
At work, how often do you:									
1. Read or use news or magazine articles or reports	2.10 (1.27)	45086	1.0						
2. Read or use forms	2.99 (1.28)	45052	.4168	1.0					
3. Read or use letters	2.39 (1.31)	44784	.5158	.5676	1.0				
4. Read or use diagrams, plans, or blueprints	1.94 (1.24)	44687	.2455	.2338	.2402	1.0			
5. Read or use instruction manuals or rules	2.49 (1.23)	44812	.3560	.4281	.3976	.4230	1.0		
6. Write memos, reports, or other text to be read by others	2.61 (1.31)	45017	.4477	.5120	.5432	.2562	.4067	1.0	
7. Use mathematics or arithmetic	3.13 (1.23)	45070	.2829	.4363	.3494	.2850	.3489	.3711	1.0
8. Use a PC or terminal	2.41 (1.42)	45086	.3401	.4023	.4893	.1512	.3070	.3958	.3387

a. 1=never, 2=less than once per week, 3=one or more times per week, 4=every day. Means were calculated using CPS sample weights.
b. All correlations are significant at the .01 level.

Table 2. Mean Computer Use by Worker Characteristic (1991)

Group	Mean[a]	Standard Deviation	Ever Use Computer[b] (percent)
All Workers	2.41	1.42	52.6
Gender			
Men	2.24	1.39	47.1
Women	2.59	1.42	58.0
Education			
< High School	1.38	0.96	14.5
High School	2.16	1.40	42.6
Some College	2.69	1.41	61.9
College	3.02	1.27	75.7
Postcollege	3.10	1.19	80.9
Race			
White	2.45	1.42	53.9
Black	2.11	1.38	41.7
Age			
18-24	2.15	1.40	42.7
25-34	2.47	1.42	54.5
35-44	2.57	1.41	58.3
45-54	2.44	1.42	53.5
55-64	2.13	1.38	42.4
Occupation			
Manager, Professional, Technical	3.03	1.26	76.2
Sales	2.53	1.42	56.6
Clerical	3.22	1.24	78.2
Service	1.41	0.97	16.7
Blue Collar	1.61	1.14	24.0
Union Status			
Union Member	2.24	1.36	49.3
Nonmember	2.47	1.43	53.9
Part-time Status			
Part-time	1.86	1.28	33.1
Full-time	2.52	1.42	56.4

a. 1=never, 2=less than once per week, 3=one or more times per week, 4=every day

b. Includes those with codes 2,3,4 for computer use variable (see note a.).

Table 3: OLS Regression Estimates of the Effects of Eight Job Tasks on Ln (Hourly Wage) (standard errors in parentheses)

Model	Job Task Frequency[a]			Education	R^2	N
	< once per week	once or more per week	every day			
Baseline[b]				0.0886 (0.0015)	.417	14438
Baseline plus:						
Use a PC or terminal	0.1528 (0.0194)	0.1467 (0.0160)	0.2343 (0.0090)	0.0770 (0.0017)	.454	11465
Read or use new or magazine articles or reports	0.1283 (0.0135)	0.1641 (0.0125)	0.1826 (0.0103)	0.0784 (0.0017)	.439	11466
Read or use forms	0.1176 (0.0170)	0.1445 (0.0141)	0.1945 (0.0102)	0.0814 (0.0017)	.439	11460
Read or use letters	0.1375 (0.0135)	0.1886 (0.0122)	0.2624 (0.0101)	0.0735 (0.0017)	.454	11404
Read or use diagrams, plans, or blueprints	0.1598 (0.0132)	0.1982 (0.0141)	0.1877 (0.0107)	0.0845 (0.0016)	.443	11368
Read or use instruction manuals or rules	0.1377 (0.0116)	0.1825 (0.0117)	0.2007 (0.0105)	0.0821 (0.0017)	.441	11403
Write memos, reports, or other text to be read by others	0.1698 (0.0139)	0.1972 (0.0123)	0.2420 (0.0099)	0.0760 (0.0017)	.450	11456
Use mathematics or arithmetic	0.1647 (0.0180)	0.1389 (0.0152)	0.1487 (0.0106)	0.0848 (0.0017)	.431	11466

a. The omitted category is "never use."
b. Includes variables for experience, experience^2, part-time status, union status, female, black, other non-whites, resident of metropolitan area, married, married*female, veteran, and three region dummies, following Krueger (1993).

Table 4. OLS Regression Estimates of the Effects of Computer Use and Other Job Tasks on Ln (hourly wage) (standard errors in parentheses)

Variable	Model 1	Model 2	Model 3	Model 4[b]
Education (in years)	0.0886 (0.0015)	0.0644 (0.0018)	0.0614 (0.00178)	0.0398 (0.0019)
At work, how often do you:				
Use a PC or terminal:[a]				
< once per week			0.0679 (0.0195)	0.0439 (0.0178)
once or more/week			0.0686 (0.0163)	0.0459 (0.0149)
every day			0.1461 (0.0099)	0.0842 (0.0098)
Read or use news or magazine articles or reports:[a]				
< once per week		0.0448 (0.0139)	0.0433 (0.0138)	0.0175 n.s. (0.0125)
once or more/week		0.0580 (0.0131)	0.0543 (0.0130)	0.0126 n.s. (0.0118)
every day		0.0493 (0.0113)	0.0459 (0.0112)	0.0240 ** (0.0104)
Read or use forms:[a]				
< once per week		0.0155 n.s. (0.0179)	0.0110 n.s. (0.0178)	0.0077 n.s. (0.0161)
once or more/week		0.0110 n.s. (0.0156)	0.0068 n.s. (0.0154)	-0.0010 n.s. (0.0140)
every day		0.0198 n.s. (0.0125)	0.0103 n.s. (0.0124)	0.0068 n.s. (0.0115)
Read or use letters:[a]				
< once per week		0.0470 (0.0148)	0.0310 ** (0.0147)	0.0280 ** (0.0133)
once or more/week		0.0850 (0.0139)	0.0582 (0.0139)	0.0388 (0.0128)
every day		0.1324 (0.0124)	0.0916 (0.0126)	0.0536 (0.0121)

Table 4. (continued)

Variable	Model 1	Model 2	Model 3	Model 4[b]
Read or use diagrams, plans, or blueprints:[a]				
< once per week		0.0904	0.0902	0.0518
		(0.0134)	(0.0133)	(0.0121)
once or more/week		0.1306	0.1328	0.0757
		(0.0144)	(0.0142)	(0.0131)
every day		0.1184	0.1200	0.0599
		(0.0114)	(0.0113)	(0.0110)
Read or use instruction manuals or rules:[a]				
< once per week		0.0450	0.0405	0.0212 *
		(0.0123)	(0.0122)	(0.0110)
once or more/week		0.0517	0.0419	0.0141 n.s.
		(0.0127)	(0.0126)	(0.0115)
every day		0.0462	0.0350	0.0097 n.s.
		(0.0121)	(0.0120)	(0.0111)
Write memos, reports, other text read by others:[a]				
< once per week		0.0838	0.0741	0.0331
		(0.0147)	(0.0146)	(0.0133)
once or more/week		0.0849	0.0744	0.0234 *
		(0.0135)	(0.0134)	(0.0123)
every day		0.1161	0.1034	0.0443
		(0.0118)	(0.0117)	(0.0108)
Use mathematics or arithmetic:[a]				
< once per week		0.0436 **	0.0373 **	0.0177 n.s.
		(0.0184)	(0.0182)	(0.0166)
once or more/week		-0.0016 n.s.	-0.0095 n.s.	-0.0067 n.s.
		(0.0157)	(0.0157)	(0.0143)
every day		0.0019 n.s.	-0.0174 n.s.	-0.0085 n.s.
		(0.0117)	(0.0116)	(0.0111)
R^2	.418	.478	.488	.594
N	14438	11146	11130	10911

a. The omitted category is "never use."
b. Model 4 adds controls for whether an individual received managerial/supervisory training from employer, hourly worker status, tenure, years in current occupation, 47 occupation dummies, and 45 industry dummies.

Note: All models include variables for experience, experience^2, part-time status, union status, female, black, other non-whites, resident of metropolitan area, married, married*female, veteran, and three region dummies (Krueger 1993).

All coefficients significant at the .01 level unless otherwise noted. n.s. p>.10 * p<.10 ** p<.05

Table 5. OLS Regression Estimates of the Effects of Computer Skills, Other Skills, Computer Training, and Other Training on Ln (wage)
(standard errors in parentheses)

Variable	Model 1[a]	Model 2[b]
Use a PC or terminal:[c]		
< once per week	0.0594 **	0.0438 *
	(0.0205)	(0.0186)
once or more/week	0.0540 ***	0.0416 **
	(0.0174)	(0.0160)
every day	0.1305 ***	0.0779 ***
	(0.0121)	(0.0117)
Do you feel your ____ skills are good enough for current job: (1 = no)		
Computer skills	-0.0098	-0.0083
	(0.0112)	(0.0101)
Reading skills	0.0087	-0.0101
	(0.0412)	(0.0375)
Writing skills	0.0239	0.0176
	(0.0294)	(0.0265)
Math skills	0.0236	0.0073
	(0.0306)	(0.0277)
Since obtaining job, any training in: (1 = yes)		
Computer-related skills	0.0029	-0.0029
	(0.0126)	(0.0116)
Other technical skills specific to occupation	0.0569 ***	0.0194 *
	(0.0101)	(0.0093)
Managerial or supervisory skills	0.1167 ***	0.0697 ***
	(0.0138)	(0.0128)
Reading, writing, or math skills	-0.0196	-0.0166
	(0.0180)	(0.0164)
Other skills	0.0324 *	0.0202
	(0.0159)	(0.0144)
R^2	.490	.592
N	9012	8917

a. This model includes the same controls as Model 3 in Table 4.
b. This model includes the same controls as Model 4 in Table 4.
c. Omitted category is "never use"

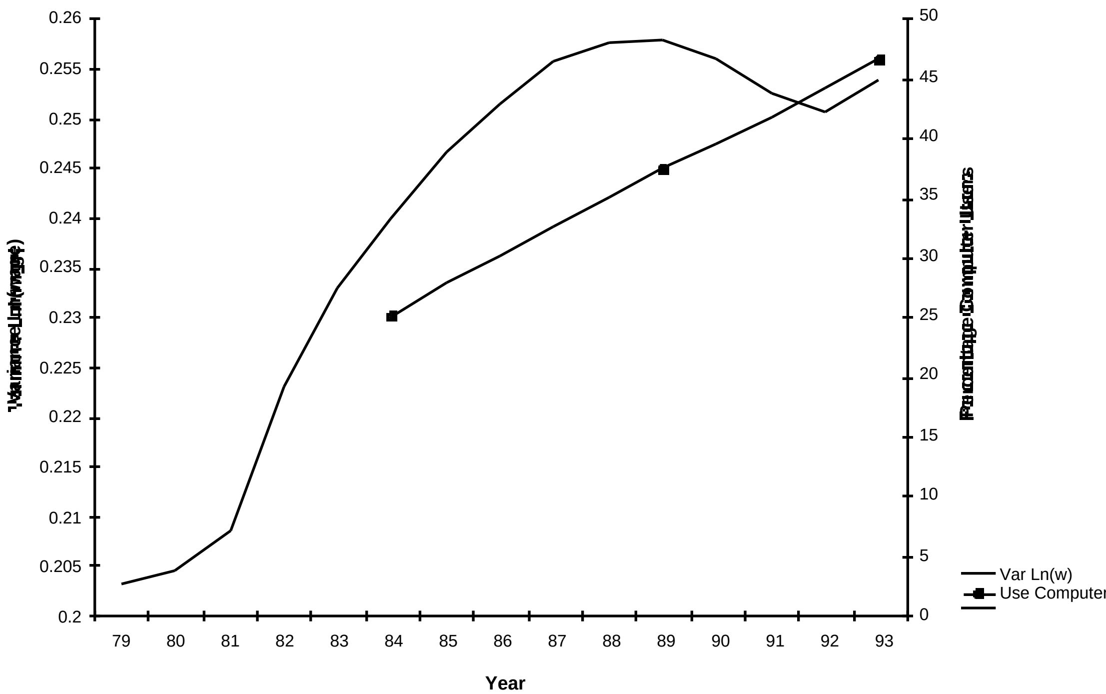
* p<.05   ** p<.01   *** p<.001

Table 6. Estimated Actual and Counterfactual Variance of Log Wages

	Variance[a]	
Reweighting	**1984**	**1989**
Raw values--No reweighting		
All	.3039	.3222
Men	.3057	.3278
Women	.2435	.2735
1984 Rates of Computer Use		
All		.3254
Men		.3296
Women		.2760
1984 Rates of and Returns to Computer Use		
All		.3236
Men		.3277
Women		.2740

a. Figures are calculated from the October Current Population Survey for each year using the sample deletions and wage definition in Krueger (1993). Top coded cases in 1984 are assigned the value estimated by Krueger (1993, p.56).

Figure 1. Trends in the Variance of Ln(wage) and Percentage Computer Users



Sources Variance Ln(wage): author's calculations based on bottom 95% of the weekly earnings distribution to eliminate top coded cases in all years.

Percentage of Computer Users: from Autor, Katz, and Krueger (1997, Table 4). Data available for 1984, 1989, and 1993 only.