Can Technological Change Explain Inequality Within Age, Schooling, and Gender Groups?

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I. Introduction

Despite a substantial and ongoing research effort, the increasing earnings inequality that has characterized the U.S. economy over the past two decades is not well understood.[1] The ongoing shift to service sector employment, once thought to be the proximate cause, explains less than a fifth of the increase. Changes in the age, education, and gender composition of the work force also leave the bulk of the increase unexplained; Katz and Murphy (1992) estimate that inequality *within* age, education, and gender groupings increased 30 percent between 1970 and 1987. In their recent survey of the earnings inequality literature, Levy and Murnane (1992:1372) conclude that this within-group trend is the "most important unresolved puzzle" in current inequality research.[2]

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[1]For men, earnings inequality began to increase in the 1970's; the rate of increase accelerated in the 1980's. For women and all earners, the increase did not begin until the 1980's (Henle, 1972; Henle and Ryscavage, 1980; Blackburn, 1990; Burtless; 1990, Karoly, 1992; Juhn, Murphy and Pierce, 1993).

[2]The within-group trend began to increase almost a decade before the overall trend. In the 1970's, the declining wage differential between college- and high-school-educated workers overwhelmed the within-group trend. When the college premium began to increase again in the 1980's, the overall trend began to show an increase. (See Levy and Murnane, 1992).

Several authors have suggested that skill-biased technological change may explain this within-group trend (Juhn, Murphy, and Pierce, 1993; Levy and Murnane, 1992).[3] According to this hypothesis, technological change has altered the demand for "unobservable" job skills, and hence earnings, within groups defined by age, education, and gender. Of course, in order to explain trends within educational groupings, these job skills would have to be uncorrelated (or at least imperfectly correlated) with education. While Howell and Wolff (1991) have shown that the educational attainment of job incumbents is not a perfect proxy for all dimensions of skill required in a given occupation, educational attainment remains the only measure of skill available in the Census and Current Population Survey (CPS) data used to analyze earnings trends. Due to this lack of readily available data, there is no evidence to date indicating exactly what these within-group skills might be or how they may have affected within-group inequality.

[3]Skill-biased technological change is also a popular explanation of the increase in the return to education that occurred in the 1980s. The simultaneous rise in the price and quantity of college-educated workers, it is argued, implies a shift in production methods that favor the more educated.

In this paper, I address this gap in the existing research. I assess the effects of changes in the demand for skills on within-group inequality by linking direct measures of job skill derived from the Dictionary of Occupational Titles (U.S. Department of Labor, 1977) with earnings and demographic data from the CPS.[4] This analysis tests whether the increase in within-group inequality is a function of changes in the demand for skills that are not captured by changes in the distributions of age, education, race, or gender.[5] CPS data

[4]The cognitive skill measures reflect analytical and synthetic reasoning skills; the interactive skill measure reflects the relative authority, autonomy, and degree of responsibility (for people and things); and the motor skill measure reflects various physical and manipulative requirements.

[5]It is possible that some or all of these skill changes are due to outsourcing abroad rather than technological change. If firms outsource those parts of their production process that use low-skill labor, as seems likely, then outsourcing may well have an effect on the distribution of skills within industries. While it is difficult to get at this question with existing data, Berman, Bound and Grilliches (1994) use Census of Manufacturing data on the purchase of foreign materials by establishments to estimate that 16 percent of the decline in the production worker share of employment may be due to

for individuals and direct measures of cognitive, motor, and interactive skill from the Dictionary of Occupational Titles (DOT) for over 500 occupations are used to investigate the relationship between the distributions of skills and earnings in 15 goods industries and 18 service industries over the 1972-90 period.[6]

A variant of the human capital model of earnings distribution is estimated to assess the effects of changes in the skill mix on the level of earnings inequality within industries and within groups. While the standard human capital model examines the effects of changes in the distributions of *worker characteristics* (usually education and experience) on wage inequality, the model developed in this paper incorporates job-based skill measures into this framework to assess the effects of changes in the distributions of *job characteristics* (cognitive, interactive, and motor skill requirements) on the level of inequality *within* groups defined by these worker characteristics. If skill-biased technological change is

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outsourcing. Nevertheless, the use of DOT data to investigate the role of skills that may be uncorrelated with those proxied by educational attainment will provide important information on changes in the demand for skills within education, experience, and gender groups.

[6]Note that this analysis will account only for the effects of skill changes resulting from changes in the mix of occupations within industries; changes in the skill requirements of particular occupations are not reflected in the DOT data.

responsible for increasing within-group inequality, changes in these job skill measures should be associated with changes in the distribution of earnings within these groups.

The results presented here indicate that skill changes explain very little of the within-group trend for the 1970's; they explain none of the trend for the 1980's, when the largest increases occurred. While further research is necessary, these results are consistent with recent studies by Howell (1994) and Mishel and Bernstein (1994) that also suggest technological change may not be the driving force behind the increased earnings inequality of the past two decades.

Section II provides a brief review of the literature on earnings inequality, focusing on the evolution of proposed explanations. Section III presents the model to be estimated, section IV discusses the regression results, and section V provides a conclusion.

II. Recent Literature

In the early 1980's, it was often argued that increased inequality was the result of the labor market entrance of the baby-boom generation (Lawrence, 1984). While the glut of young workers in the 1970's did lead to depressed wages for workers with little work experience (Freeman, 1979; Welch, 1979), human capital models of earnings distribution that incorporated the effects of changing distributions of education and experience left the bulk of the variation unexplained (Dooley and Gottschalk, 1984; Plotnick, 1982). The baby-boom explanation cannot account for the increased inequality *within* age, education, and gender cohorts that has characterized this trend. Further, it cannot explain the continued and accelerated growth in earnings inequality in the 1980's, when large cohorts of young workers were no longer entering the labor market.

By the mid-1980's, researchers began to abandon supply-side explanations. The "shift to services" hypothesis, which held that the ongoing shift to low-wage, high-inequality service sector employment was responsible for increased inequality, gained popularity. However, studies by Harrison and Bluestone (1988), Karoly (1992) and Juhn, Murphy and Pierce (1993) indicate that inter-industry shifts account for only 15-20 percent of the overall increase.[7] Similarly, Blackburn (1990) finds that these shifts explain only 15 percent of the within-group trend. Most of the increase, therefore, reflects intra-industry rather than inter-industry trends.

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[7] Karoly (1992) finds that 19 percent of the change in the log variance of earnings for full-time year wage and salary earners for the 1975-86 period can be attributed to changing employment shares among 69 industries. However, the proportion of the total increase in inequality attributable to a changing industrial mix declines as the level of industry aggregation increases. When the sample is divided simply into goods and service sectors, fixing the sectoral composition at the 1975 level results in the same level of inequality that actually occurred in 1986. While this finding is in one sense a statistical artifact resulting from the loss of variation that occurs as the level of aggregation increases, it does indicate that the simple "shift-to-services" story may have no explanatory power at all. For instance, public administration and the Transportation, Communications and Public Utilities (TCPU) sector are characterized by high mean wages and a low level of inequality (Henle and Ryscavage, 1980); an increase in relative employment in these service industries might result in a decline in the overall level of inequality.

Increased international trade has also been suggested as the culprit. Proponents argue that wages in blue-collar manufacturing jobs have declined as a result of low-wage competition from abroad while educated workers have benefitted from the globalization of the market for skilled labor (Bluestone and Harrison, 1982). This is not the whole story either, for inequality has increased in virtually every industry, including those that face little or no competition from abroad.[8]

[8] According to my analysis of CPS data, inequality among full-time year-round workers increased in 25 of 33 industries over the 1972-90 period. Inequality among all earners increased in 32 of the 33. (See Appendix A for industry definitions and Appendix E for trend coefficients.)

Most recently, it has been suggested that skill-biased technological change is the driving force behind the growth of inequality (Bound and Johnson, 1992; Acs and Danziger, 1993; Juhn, Murphy and Pierce, 1993; Berman, Bound and Grilliches, 1994). Juhn, Murphy and Pierce find that only a third of the total increase in wage inequality for males over the 1963-89 period can be explained by changes in either the prices (returns to) or quantities of age and education.[9] They suggest that this within-group increase may be the result of technology-induced changes in unobservable dimensions of skill. What evidence is there to support this claim?

Numerous case studies have examined the relationship between technology and the demand for skills. Spenner's 1988 survey indicates that recent innovations have led to deskilling in many jobs as well as a greater demand for highly skilled workers, but he cautions against easy generalizations about the effects of technology on skills. This same technology can be used in a myriad of ways, each of which has different implications for skills. Zuboff (1988) provides extensive case studies in the insurance, paper, banking, and brokerage industries that support this conclusion. She also reviews management surveys that reveal a strong preference to use technology to increase centralized control and deskill the production work force. However, other case studies reveal firms that find it necessary or desirable to upgrade the skills of production workers in conjunction with the

[9] Even for the 1979-88 period, when the return to education increased dramatically, they find that changes in the returns to or quantities of education and experience left 53 percent of the increase in inequality below the median unexplained.

introduction of new technologies (Brown, Reich, and Stern, 1990; Wiggenhorn, 1990; Bailey, 1989; Krafcik, 1986).

While the case study evidence does suggest that recent technological innovations have led to changes in the mix of skills within industries, it is not clear what the aggregate effect is, nor is it obvious what effects these changes may have had on inequality within age, sex, and gender groups. In the absence of direct evidence, the technological change hypothesis has been described as the "most plausible explanation" by some (Bound and Johnson, 1992; Acs and Danziger, 1993; Juhn, Murphy and Pierce, 1993; Berman, Bound and Grilliches, 1994) and "a label for our ignorance" by others (Davis and Topel, 1993; Mishel and Bernstein, 1994).[10]

One recent study does bring some data to bear on the relationship between technological change and within-group inequality. Using measures of equipment accumulation per worker, computerization, and employment of scientists and engineers as proxies for technological change, Mishel and Bernstein (1994) conclude that technological change is not the driving force behind the within-group trend. They find that these technology-related variables explain none of the acceleration in within-group inequality over the 1973-1989 period.[11] The results reported below support their conclusion.

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[10]Other possible explanations for this residual increase include the effects of changes in the regulatory environment, increased use of subcontracting and contingent workers, the weakening of unions, and the declining value of the minimum wage.

[11]In a related line of research, Allen (1993) finds that changes in technology (as proxied by changes

in the share of scientists and engineers, age of capital stock, capital intensity and total factor productivity growth) are strongly correlated with changes in the returns to education and increasing employment for college graduates within industries. Krueger (1991) finds that a wage premium associated with working with computers explains between one-third and one-half of the increase in the rate of return to education between 1984 and 1989. Berman, Bound and Grilliches (1994) hypothesize that if capital and skilled labor are complementary factors of production, then capital accumulation may explain skill upgrading in manufacturing (as measured by the relative share of non-production workers), but find that capital accumulation can explain only a fraction of the increased share of non-production workers in manufacturing industries over the 1979-88 period. Berman, Bound and Grilliches attribute the residual in their wage equations to "production-labor-saving" technological change, but acknowledge that other interpretations are possible and more direct evidence is needed to support this interpretation. However, these studies do not address within-group inequality.

III. The Model

As Figure 1 indicates, the log variance of annual earnings for full-time year-round earners (hereafter VLE) and the log variance of hourly earnings for all earners (hereafter VLE-H) increased substantially in the 1980's.[12] The within-group increase began a decade earlier, but does not show up in the overall trend in the 1970's because it was overwhelmed by the declining wage differential between college and high school graduates. See Levy and Murnane (1992) for a review of the evidence documenting the overall, between-group, and within-group trends.

The model of earnings distribution used to investigate the effects of changes in the skill mix on within-group earnings inequality is based on the human capital model of

[12]The sample for the log variance of annual earnings includes all full-time year-round workers aged 17 to 65 who are classified as wage and salary workers and have nonzero wage and salary income. (Self-employed workers whose businesses are incorporated are excluded.) Full-time year-round workers are defined as those who worked 35 or more hours per week and 50 or more weeks per year. The sample for the log variance of hourly earnings includes part-time and part-year workers as well. Hourly wages are calculated by dividing annual wages by the product of weeks worked and hours (usually) worked per week. The weeks worked variable is coded in intervals prior to the 1976 CPS, hence the log variance of hourly earnings cannot be calculated for the 1972-74 period.

earnings distribution developed by Chiswick and Mincer (1972), which begins with the

$$\ln(Y)_{ijt} = x + r_i(S)_{ijt} + r_{i'}(E)_{ijt} + \varepsilon_{ijt} \qquad (1)$$

following standard human capital log earnings specification:

$$\begin{aligned} i &= 1,\ldots,N \\ j &= 1,\ldots,M \\ t &= 1,\ldots,T \end{aligned}$$

where $\ln(Y)_{ijt}$ measures the logarithm of earnings of the ith individual in the jth industry at time t, S is years of schooling, E is years of work experience, r is the schooling premium, r' is the experience premium and ε_{ijt} is a normally distributed error term with $E(\varepsilon_{ijt}) = 0$ and $E(\varepsilon^2_{ijt}) = \sigma^2$. (See Appendix A for industry definitions and Appendix B for variable definitions.)[13]

By taking the variance of both sides of equation (1), we can express intra-industry earnings inequality (as measured by the log variance of earnings) as a function of schooling, experience, the schooling premium, and the experience premium:

[13]The measure of work experience is created by subtracting the number of years of schooling attended plus five from each individual's age. The five years are added to adjust for each individual's preschool years, when he or she is neither in school nor in the work force. Note that this is actually a measure of maximum potential work experience, for there is no adjustment made for spells of unemployment or time out of the labor force.

$$\sigma^2(\ln(Y))_{jt} = \beta_1 \sigma^2(S)_{jt} + \beta_2 \sigma^2(E)_{jt} + \beta_3 \sigma(S,E)_{jt} + \beta_4 (\bar{S})^2_{jt} + \beta_5 (\bar{E})^2_{jt} + u_{jt} \qquad (2)$$

$$\beta_1 = (\bar{r} \;\; \bar{r}')^2 + \sigma^2(r) + \sigma^2(r')$$
$$\beta_2 = (\bar{r}')^2 + \sigma^2(r')$$
$$\beta_3 = 2\bar{r}(\bar{r} \;\; \bar{r}') \;\; \sigma^2(r')$$
$$\beta_4 = \sigma^2(r)$$
$$\beta_5 = \sigma^2(r')$$

where

and $\sigma^2(\ln(Y))_{jt}$ is the log variance of earnings in industry j at time t.[14] Thus human capital theory predicts unambiguously that the signs of β_1, β_2, β_4, and β_5 will be positive; increasing the variance of schooling or experience or raising the average level of schooling or experience will increase inequality in an industry. (See Appendix A for industry definitions.) The sign on β_3 is ambiguous. [15]

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[14]Following Chiswick and Mincer, it is assumed that the schooling premium is a random variable independent of the level of schooling; a parallel assumption is made for the experience premium. It is also assumed that the returns to schooling and experience are uncorrelated.

[15]The CPS earnings data were corrected to adjust for the "top-coding" problem first identified by Blackburn and Bloom (1988). See Appendix D for a discussion of this procedure.

Karoly (1989) augments this model to include controls for the variances of sex and race:

$$\sigma^2(\ln(Y))_{jt} = \alpha + \beta_1\sigma^2(S)_{jt} + \beta_2\sigma^2(E)_{jt} + \beta_3\sigma(S,E)_{jt} + \beta_4(\overline{S})^2_{jt} + \beta_5(\overline{E})^2_{jt} + \beta_6\sigma^2(FEM)_{jt} + \beta_7\sigma^2(NW)_{jt} + u_{jt} \tag{3}$$

where FEM = 1 if female, 0 if male, and NW = 1 if nonwhite, 0 if white. The coefficient on the sex and race variables will be positive if an increasingly heterogeneous work force is associated with increased inequality within industries. In other words, if women or nonwhites in a given industry are paid less than other workers in that industry with comparable levels of education and experience, then industries where the work force is balanced with respect to race and gender will be characterized by a greater level of inequality than industries with a more homogeneous work force.[16]

In order to test for the effects of changes in the distribution of skills within age, experience, and gender groups, I further augment the model to include three measures of job skill from the DOT: motor skills (MS), interactive skills (IS), and cognitive skills (CS):

[16] The variance of a (0,1) variable takes on its largest value when the sample is evenly divided between the two values.

$$\sigma^2(\ln(Y))_{jt} = \alpha + \beta_1\sigma^2(S)_{jt} + \beta_2\sigma^2(E)_{jt} + \beta_3\sigma(S,E)_{jt} + \beta_4(\overline{S})^2_{jt} + \beta_5(\overline{E})^2_{jt}$$
$$+ \beta_6\sigma^2(FEM)_{jt} + \beta_7\sigma^2(NW)_{jt} + \beta_8\sigma^2(MS)_{jt} + \beta_9\sigma^2(IS)_{jt}$$
$$+ \beta_{10}\sigma^2(CS)_{jt} + u_{jt} \tag{4}$$

The coefficients of these job skill variables measure the effects of changes in the distribution of skills on the distribution of earnings within industries after controlling for the effects of the worker characteristics education, experience, race, and gender.[17]

According to competitive wage theory, if two equally educated and experienced workers are employed in different occupations, one of which requires a higher level of skill, the worker in the occupation requiring the higher skill level will be paid more. Since the log variance of earnings in an industry will thus increase as the variance of these skill requirements increases, the predicted sign of the coefficients of the job skill variables σ^2(MS), σ^2(IS), and σ^2(CS) is positive. (The correlation between σ^2(ED) and σ^2(MS) is small and negative and the correlations between σ^2(IS) and σ^2(ED) and between σ^2(CS) and σ^2(ED) are small and positive, indicating that the DOT variables do reflect dimensions of

[17]As Karoly (1989) notes, the error term in this model is heteroskedastic. This is corrected by weighting the data by the square root of industry size.

job skill not captured by educational attainment. A complete correlation matrix is contained in Appendix C.)

IV. Results

As described in the preceding section, the model developed to assess the effects of changes in the skill mix on within-group inequality builds on the work of Karoly (1989). In Table 1, Karoly's original OLS and "least squares dummy variable" (LSDV) estimations for the 1967-86 period (models 1 and 2) are presented, along with my estimations for the 1972-90 period (models 3 and 4). The LSDV estimation differs from OLS only in its inclusion of fixed effects (dummy variables) for year and industry, which permits the intercept to vary among time periods and cross-sections (industries). Year fixed effects capture the effects of business cycles and other time-specific factors that affect all industries. The inclusion of time-invarying industry fixed effects is supported by the evidence documenting stable inter-industry wage differentials that are not explained by differences in individual characteristics (Dickens and Katz (1987), Lawrence and Summers (1987, 1988)).

The choice between the OLS or LSDV model is made using an f-test comparing the residual sum of squares associated with the two estimation procedures. Since the OLS model includes more parameter restrictions than the LSDV model (the intercepts are restricted to be equal across time and across industries in the OLS model), one would expect the residual sum of squares to be higher for the OLS model. If the increase in the residual sum of squares is not significant when the restrictions are added, the restrictions are appropriate and the standard OLS model is applied. If the residual sum of squares changes significantly (as determined by the f-test), the LSDV model is used. The

$$F_{N+T2,\, NTK(N+T2)} = \frac{(RSS_1 RSS_2)/(N+T2)}{(RSS_2)/(NTK(N+T2))}$$

appropriate test statistic is:

(5)

where RSS_1 and RSS_2 are the residual sum of squares from the OLS and the LSDV models, respectively, K is the number of parameters in the OLS model, N is the number of industries, and T is the number of time periods. The numerator represents the increase in the residual sum of squares divided by the number of additional parameters in the LSDV model (relative to the OLS model); the denominator represents the residual sum of squares for the LSDV model divided by the number of degrees of freedom in the LSDV model. On the null hypothesis that the equal intercept restrictions are correct, the test statistic above follows the F distribution with N + T - 2 and NT - K - (N + T - 2) degrees of freedom.

F-statistics for industry and time fixed effects are reported for each estimation of the LSDV model in Tables 1 through 6. The addition of these fixed effects greatly increases the adjusted R^2 relative to the OLS estimation in every instance, in some instances doubling the explained variation. Since the f-statistics indicate a rejection of the null hypothesis (the OLS model) in each case, only the LSDV estimates are reported in Tables 2 though 6.[18]

While Karoly's OLS estimates indicate that the human capital and demographic variables are significant and explain 37 percent of the variation in industry VLE over the 1967-86 period (Table 4, model 1), the joint significance of the year and industry fixed effects dictate that this model be rejected in favor of the LSDV model (Table 4, model 2). The LSDV model explains 81 percent of the variance in industry VLE, but the human capital and demographic variables, though of the "correct" sign, are no longer significant. As Table 2 indicates, Karoly obtains similar results for the goods and service sectors (models 5 and 7, respectively). Only the year and industry fixed effects are significant in the estimation for the goods industries, though 89 percent of the variation is explained. When the sample is restricted to the service industries, only one of the human capital

[18]It should be noted, however, that the use of dummy variables is only an attempt to adjust for important missing information in the model. A substantial portion of the variation in the LSDV model is "explained" by the dummy variables, yet they impart little information about the underlying causes of increasing inequality within industries. While the fixed effects capture what Maddala (1977) calls "specific ignorance", in contrast to the "general ignorance" captured by the error term, they are nonetheless necessary to reduce potential bias in the parameter estimates for the other variables in the model.

variables is significant, though 76 percent of the variance is explained. These results lead Karoly to conclude that "With a few exceptions, estimates for the pooled sample as well as for the two subsamples indicate that industry wage dispersion can be explained by industry or time fixed effects with almost no explanatory power associated with the human capital or demographic variables" (1989:19).

When I estimate this LSDV model for the 1972-90 period (Table 1, models 3 and 4; Table 2, models 6 and 8), the human capital variables are more often significant. This result is more consistent with previous studies, which generally find that changes in age and education explain some of the increase.[19] The coefficients for σ^2(FEM) are also significant at the one or five percent level in each of these estimations, indicating that increasing gender diversity within industries is associated with increasing inequality. Overall, however, the results support Karoly's conclusion that the bulk of the variation in industry VLE in each estimation can be explained by industry and time fixed effects. Fixed effects alone explain between 77 and 94 percent of the variation in the VLE in these models, leaving little variation to be explained by worker and job skill characteristics.

[19]This difference may be the result of the difference in the time period examined.

In Tables 3-6, the job skill variables σ^2(MS), σ^2(IS), and σ^2(CS) are included in the model to test for the effects of changes in the skill mix of employment on within-group inequality. Table 3 reports results for all industries for 1972-81 (model 9) and 1982-90 (model 10).[20] The coefficients for σ^2(IS) and σ^2(CS) are positive and significant for the 1972-81 period, but none of three job skill coefficients are significant for the 1982-90 period.

When the model is estimated separately for goods and services (models 11-14), only the coefficient for σ^2(CS) for the service industries in the 1972-81 period is positive and significant; the coefficient for σ^2(IS) is no longer significant. As was the case for the combined sample, none of the job skill coefficients are significant for the 1982-90 period. The results thus provide little support for the hypothesis that changes in the variance of job skill requirements are responsible for the increased within-group inequality of the 1970's and 1980's.

Tables 5 and 6 report LSDV estimates for the log variance of hourly earnings (VLE-H). Unlike the previous estimations for the log variance of annual earnings, which include only FTYR workers (in order to control for differences in hours worked), the use of hourly earnings allows all earners to be included in the analysis, and thus gives a more complete picture of the distribution of skills within industries. However, as Tables 5 and 6

[20]Because the DOT data for these two periods are not comparable, the model must be estimated separately for each time period. See Appendix D for further explanation.

indicate, the job skill variables are not significant predictors of the VLE-H for the complete sample, or for the goods or service subsamples, for either time period.[21] Again, the fixed effects explain most of the variation.

V. Conclusion

Skill-biased technological change is often invoked to explain the within-group increase in earnings inequality that occurred in the 1970's and 1980's. The results detailed in section IV provide very little evidence to support this hypothesis. There is no evidence at all to support the technology explanation for the 1980's, when the overall increase was most dramatic.

However, further research is necessary before we can conclude that technology is not an important factor underlying the increasing dispersion of wages in the United States. The DOT data used in this study reflect only those skill changes resulting from changes in the mix of occupations within industries; changes in the skill requirements of particular occupations are not reflected in the DOT data. Further, the use of a new occupational

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[21]One difference between the results for annual and hourly earnings is that the human capital variables are less often significant in the LSDV models for VLE-H in the 1970's than in the LSDV models for VLE for the same time period. This may be because many part-time workers are unable to obtain employment that fully utilizes their human capital.

classification by the CPS after 1982 required matching the old and new classifications in order to use DOT data for the 1982-90 period. Since the match is not perfect, the DOT data will not be as accurate for the latter period. This may explain why the DOT variables were not significant for the 1982-90 period. While Mishel and Bernstein (1994) also fail to find a relationship between technological change and within-group inequality, their approach abstracts from differences among firms (within industries) with respect to investment and wage strategy. Davis and Haltiwanger (1991) find that growth in wage differentials among plants accounts for over half of the growth in wage inequality in manufacturing. This suggests, as does the case study evidence on technology and skills, that there is not a simple, one-to-one relationship between investment in new technology and the array of skills required for production. The skills demanded (and wages paid) by a particular firm are determined by management within the confines of an existing workplace culture and local labor market. Further research is needed to understand the process of wage determination within firms.

Table 1

OLS and LSDV Parameter Estimates for the Log Variance of Industry Wages
For All FTYR Wage and Salary Workers - All Industries
Dependent Variable: VLE (Var (Ln (FTYR Annual Earnings)))

	Karoly Sample Years: 1967-86		Wieler Sample Years: 1972-90	
	OLS	LSDV	OLS	LSDV
VARIABLE	1.	2.	3.	4.
$\sigma^2(S)$	.036**	.025	.015*	.011*
$\sigma^2(E)$	.003**	.001	.001*	.001*
$(\bar{S})^2$	-.001**	.0004	-.0002*	.001*
$(\bar{E})^2$	-.0002**	.0001	-.0002*	.0001*
$\sigma(S,E)$	.020**	.006	.008*	.004*
$\sigma^2(FEM)$	.365**	.876**	.272*	.387*
$\sigma^2(NW)$	.088	.234	-.122**	.059
YEAR***		23.10*		22.20*
IND***		24.10*		37.67*
F	57.3*	50.7*	85.7*	98.9*
$\bar{R}^2$	.374	.814	.487	.899

* significant at the 1% level
** significant at the 5% level
*** F-ratios for joint significance of YEAR and IND fixed effects

Sources: Current Population Survey March Annual Demographic Files, 1973-91; Karoly (1989).

Table 2

LSDV Parameter Estimates for the Log Variance of Industry Wages
For All FTYR Wage and Salary Workers -Goods Industries and Service Industries
Dependent Variable: VLE (Var (Ln (FTYR Annual Earnings)))

	Goods		Services	
	Karoly 1967-86	Wieler 1972-90	Karoly 1967-86	Wieler 1972-90
VARIABLE	5.	6.	7.	8.
$\sigma^2(S)$	.058	.010*	.025	.008*
$\sigma^2(E)$	.0004	.0002	.001	.0004*
$(S)^2$	.001	.001**	.001	.0003
$(E)^2$	-.0003	.0001*	.0002**	.00001
$\sigma(S,E)$	.018	.002*	.003	.004*
$\sigma^2(FEM)$	.728	.205**	.957	.372*
$\sigma^2(NW)$	-.392	.111	.415	.046
YEAR***	30.20*	10.73*	10.02*	10.38*
IND***	42.30*	51.00*	10.80*	28.20*
F	8.5*	47.5*	28.1*	83.4*
R^2	.893	.865	.764	.910

* significant at the 1% level
** significant at the 5% level
*** F-ratios for joint significance of YEAR and IND fixed effects

Sources: See Table 1.

Table 3

LSDV Parameter Estimates for the Log Variance of Industry Wages
For All FTYR Wage and Salary Workers - All Industries
Dependent Variable: VLE (Var (Ln (FTYR Annual Earnings)))

	1972-81	1982-90
VARIABLE	9.	10.
σ^2(S)	.002	.007*
σ^2(E)	.001*	.0001
$(S)^2$	.001**	.001
$(E)^2$	.0001*	.0001**
σ(S,E)	.003*	.001
σ^2(MS)	-.003	.001
σ^2(IS)	.015**	-.007
σ^2(CS)	.016*	.001
σ^2(FEM)	.391*	.119
σ^2(NW)	.027	.046
YEAR***	10.00*	6.82*
IND***	18.80*	30.00*
F	54.6*	64.2*
R^2	.892	.914

* significant at the 1% level
** significant at the 5% level
*** F-ratios for joint significance of YEAR and IND fixed effects

Sources: Current Population Survey March Annual Demographic Files, 1973-91; Miller, c

Table 4

LSDV Parameter Estimates for the Log Variance of Industry Wages
For All FTYR Wage and Salary Workers - Goods and Service Industries
Dependent Variable: VLE (Var (Ln (FTYR Annual Earnings)))

	Goods Industries		Service Industries	
	1972-81	1982-90	1972-81	1982-90
VARIABLE	11.	12.	13.	14.
$\sigma^2(S)$	.007**	.008*	-.002	.007*
$\sigma^2(E)$	.001*	-.0001	.0003	.0003
$(S)^2$	.001**	.0004	.001	.001
$(E)^2$	.0001*	.0001	.0001**	.00004
$\sigma(S,E)$	.002**	.001	.002**	.001
$\sigma^2(MS)$	-.016	.001	.007	.001
$\sigma^2(IS)$	.020	.006	.010	-.009
$\sigma^2(CS)$	.003	.002	.018*	-.0001
$\sigma^2(FEM)$	.336*	.217	.414*	.017
$\sigma^2(NW)$	-.077	.091	.094	.031
YEAR***	2.78*	1.35	7.14*	11.00*
IND***	*17.24*	16.39*	14.00*	15.40*
F	20.3*	15.3*	44.7*	76.8*
R^2	.810	.774	.898	.942

* significant at the 1% level
** significant at the 5% level
*** F-ratios for joint significance of YEAR and IND fixed effects

Sources: See Table 3.

Table 5

LSDV Parameter Estimates for the Log Variance of Industry Wages
For All Wage and Salary Workers - All Industries
Dependent Variable: VLE-H (Var (Ln (Hourly Earnings)))

	1975-81	1982-90
VARIABLE	15.	16.
σ^2(S)	.007**	.008*
σ^2(E)	.001*	.0003**
$(\bar{S})^2$	.001	.001
$(\bar{E})^2$	-.0001*	.00004
σ(S,E)	.002**	.002**
σ^2(MS)	.006	.00003
σ^2(IS)	.020	-.019
σ^2(CS)	.005	.0002
σ^2(FEM)	.261	-.224
σ^2(NW)	.036	.008
YEAR***	.74	5.50*
IND***	47.00*	32.00*
F	66.6*	68.4*
$\bar{R}^2$	.932	.919

* significant at the 1% level
** significant at the 5% level
*** F-ratios for joint significance of YEAR and IND fixed effects

Sources: See Table 3.

Table 6

LSDV Parameter Estimates for the Log Variance of Industry Wages
For All Wage and Salary Workers - Goods and Service Industries
Dependent Variable: VLE-H (Var (Ln (Hourly Earnings)))

VARIABLE	Goods Industries 1975-81	Goods Industries 1982-90	Service Industries 1975-81	Service Industries 1982-90
	17.	18.	19.	20.
$\sigma^2(S)$	.001	.010*	.011**	.006
$\sigma^2(E)$	.001*	.0001	.001*	.0003**
$(S)^2$	.001	.001	.001	.001
$(E)^2$	.00002	.00003	-.0001	.000003
$\sigma(S,E)$	-.0003	.002	.002	.002
$\sigma^2(MS)$	-.016	.002	.006	.001
$\sigma^2(IS)$	.036	-.003	.005	-.023
$\sigma^2(CS)$	.002	-.0001	-.002	.002
$\sigma^2(FEM)$	-.131	-.099	.444	-.281
$\sigma^2(NW)$	.190	.129	-.202	-.061
YEAR***	3.77*	1.97	1.86	4.17*
IND***	25.00*	15.39*	36.33*	16.40*
F	46.7*	22.0*	55.8*	78.6*
R^2	.929	.834	.935	.944

* significant at the 1% level
** significant at the 5% level
*** F-ratios for joint significance of YEAR and IND fixed effects

Sources: See Table 3.

Appendix A

Industry Definitions
Standard Industrial Classification (SIC) Codes

		CPS Census Codes	
Industry		1970[1]	1980[2]
Goods-producing			
1.	Mining	47-57	40-50
2.	Construction	67-77	60
3.	Lumber and Furniture	107-118	230-242
4.	Stone/Clay/Glass/Primary Metals	119-149	250-280
5.	Fabricated Metals	157-169,258	281-301
6.	Machinery, exc. electrical	177-198	310-332
7.	Electrical Equipment	199-209	340-350
8.	Automobile	219	351
9.	Other Transportation	227-238	352-370
10	Instruments and Misc.	239-259	371-392
11.	Food and Tobacco	268-299	100-130
12.	Textiles and Apparel	307-327	132-152

[1]Applies for 1973-82 Current Population Surveys, based on 1967 SIC codes.

[2]Applies for 1983-91 Current Population Surveys, based on 1972 SIC codes.

Appendix A, Continued.

13.	Paper and Printing	328-339	160-172
14.	Chemicals and Petroleum	347-378	180-201
15.	Rubber and Leather	379-398	210-222
	<u>Service-Producing</u>		
16.	Railroad	407	400
17.	Other Transportation Services	408-429,907	401-432
18.	Communications	447-449	440-442
19.	Public Utilities	467-479	460-472
20.	Wholesale Trade	507-588	500-571
21.	Eating and Drinking	669	641
22.	Other Retail	607-698	580-640, 642-691
23.	Banking and Finance	707-709	700-710
24.	Insurance and Real Estate	717-718	711-712
25.	Business Services	727-748	721-742
26.	Repair Services	749-759	750-760
27.	Personal Services	777-798	762-791
28.	Entertainment	807-809	800-802
29.	Medical., exc. hospitals	828-837, 839-848	812-830, 832-840
30	Hospitals	838	831

Appendix A, continued.

31.	Welfare and Religious	877-879	861-871
32.	Educational Services	857-868	842-860
33.	Professional Services	849,869, 887-897	841, 872-892

Note: Agriculture, Forestry and Fisheries, private household services, and public administration are excluded from the sample of industries.

Appendix B

Definitions for Variables in the Industry Data Sets

VARIABLE	DEFINITION
VLE	Variance of the natural logarithm of real annual wage and salary income (measured in 1982-84 dollars) for FTYR wage and salary earners
VLE-H	Variance of the natural logarithm of real hourly wage and salary income (measured in 1982-84 dollars) for all wage and salary earners
$\sigma^2(S)$	Variance of years of schooling completed
$\sigma^2(E)$	Variance of years of potential experience (age - years of schooling - 5)
$\sigma(S,E)$	Covariance of years of schooling and years of potential experience
$(\bar{S})^2$	Mean years of schooling squared
$(\bar{E})^2$	Mean years of experience squared
$\sigma^2(FEM)$	Variance of sex, where FEM = 1 if female, 0 if male
$\sigma^2(NW)$	Variance of race, where NW = 1 if nonwhite, 0 if white
$\sigma^2(MS)$	Variance of motor skills required
$\sigma^2(IS)$	Variance of interactive skills required
$\sigma^2(CS)$	Variance of cognitive skills required

Appendix C
Correlation Matrices
FTYR Wage and Salary Workers, 1972-81*

	σ^2(ln(Y)	σ^2(S)	σ^2(E)	σ(S,E)	$(S)^2$	$(E)^2$
σ^2(ln(Y))	1.00					
σ^2(S)	.08	1.00				
σ^2(E)	.33	.48	1.00			
σ(S,E)	.09	-.75	-.70	1.00		
$(S)^2$	.29	-.12	-.34	.45	1.00	
$(E)^2$	-.38	.36	.30	-.50	-.51	1.00
σ^2(MS)	.51	-.19	.05	.31	.59	-.40
σ^2(IS)	.25	.28	.03	.05	.73	-.17
σ^2(CS)	.09	.49	.04	-.11	.34	.07
σ^2(FEM)	.55	.01	.13	.16	.39	-.34
σ^2(NW)	.00	.29	.22	-.34	-.01	.14

	σ^2(MS)	σ^2(IS)	σ^2(CS)	σ^2(FEM)
σ^2(MS)	1.00			
σ^2(IS)	.51	1.00		
σ^2(CS)	.28	.50	1.00	
σ^2(FEM)	.48	.34	.15	1.00
σ^2(NW)	.07	.24	.18	.23

*σ^2(ln(Y)) is calculated for annual earnings of all FTYR wage and salary workers.

Appendix C, continued.
FTYR Wage and Salary Workers, 1982-90*

	$\sigma^2(\ln(Y))$	$\sigma^2(S)$	$\sigma^2(E)$	$\sigma(S,E)$	$(\bar{S})^2$	$(\bar{E})^2$
$\sigma^2(\ln(Y))$	1.00					
$\sigma^2(S)$	.13	1.00				
$\sigma^2(E)$	.18	.48	1.00			
$\sigma(S,E)$	.20	-.70	-.60	1.00		
$(\bar{S})^2$	.18	-.19	-.33	.42	1.00	
$(\bar{E})^2$	-.61	.21	.01	-.27	-.25	1.00
$\sigma^2(MS)$	.30	-.22	.00	.27	.60	-.40
$\sigma^2(IS)$	.10	.35	.14	-.06	.62	.00
$\sigma^2(CS)$	-.08	.46	-.05	-.16	.24	.27
$\sigma^2(FEM)$	.58	.14	.21	.08	.35	-.36
$\sigma^2(NW)$	-.05	.20	.31	-.32	.02	.08

	$\sigma^2(MS)$	$\sigma^2(IS)$	$\sigma^2(CS)$	$\sigma^2(FEM)$
$\sigma^2(MS)$	1.00			
$\sigma^2(IS)$	.36	1.00		
$\sigma^2(CS)$	.02	.34	1.00	
$\sigma^2(FEM)$	.36	.21	.01	1.00
$\sigma^2(NW)$	.14	.25	-.07	.26

*$\sigma^2(\ln(Y))$ is calculated for annual earnings of all FTYR wage and salary workers.

Appendix C, continued.
All Wage and Salary Earners, 1975-81

	σ^2(ln(Y))	σ^2(S)	σ^2(E)	σ(S,E)	$(S)^2$	$(E)^2$
σ^2(ln(Y))	1.00					
σ^2(S)	.09	1.00				
σ^2(E)	.38	.46	1.00			
σ(S,E)	.21	-.70	-.49	1.00		
$(S)^2$	.40	-.06	-.21	.53	1.00	
$(E)^2$	-.47	.38	-.01	-.52	-.26	1.00
σ^2(MS)	.42	-.13	.21	.32	.62	-.29
σ^2(IS)	.34	.41	.25	.05	.71	-.04
σ^2(CS)	.25	.43	.13	.02	.55	.08
σ^2(FEM)	.38	-.02	.20	.29	.29	-.31
σ^2(NW)	-.10	.33	.19	-.30	.00	.26

	σ^2(MS)	σ^2(IS)	σ^2(CS)	σ^2(FEM)
σ^2(MS)	1.00			
σ^2(IS)	.53	1.00		
σ^2(CS)	.39	.62	1.00	
σ^2(FEM)	.39	.24	.13	1.00
σ^2(NW)	.05	.26	.20	.11

*$\sigma^2(\ln(Y))$ is calculated for hourly earnings of all wage and salary workers.

Appendix C, continued.
All Wage and Salary Earners, 1982-90

	$\sigma^2(\ln(Y))$	$\sigma^2(S)$	$\sigma^2(E)$	$\sigma(S,E)$	$(\bar{S})^2$	$(\bar{E})^2$
$\sigma^2(\ln(Y))$	1.00					
$\sigma^2(S)$	.08	1.00				
$\sigma^2(E)$	.38	.34	1.00			
$\sigma(S,E)$	.35	-.65	-.22	1.00		
$(\bar{S})^2$	.32	-.13	-.12	.44	1.00	
$(\bar{E})^2$	-.47	.34	-.26	-.45	-.12	1.00
$\sigma^2(MS)$	.26	-.22	.19	.27	.60	-.29
$\sigma^2(IS)$	.24	.44	.37	-.02	.61	.05
$\sigma^2(CS)$	.09	.52	-.09	-.21	.35	.34
$\sigma^2(FEM)$	.46	.05	.29	.23	.22	-.37
$\sigma^2(NW)$	-.14	.21	.22	-.32	-.06	.12

	$\sigma^2(MS)$	$\sigma^2(IS)$	$\sigma^2(CS)$	$\sigma^2(FEM)$
$\sigma^2(MS)$	1.00			
$\sigma^2(IS)$	.34	1.00		
$\sigma^2(CS)$	.05	.39	1.00	
$\sigma^2(FEM)$	.27	.10	.00	1.00
$\sigma^2(NW)$	.05	.19	-.08	.14

*$\sigma^2(\ln(Y))$ is calculated for hourly earnings of all wage and salary workers.

Appendix D

Data Sources and the Construction of the Data Set

The model is estimated using a pooled time series data set that includes measures of inequality levels, worker characteristics, and job skill requirements within industries over the 1972-90 period. The earnings and demographic data required to create the earnings, experience, education, gender, and race variables are derived from the 1973-1991 CPS March Annual Demographic Files. Earnings data have been adjusted for inflation using the CPI-U-X1, the Consumer Price Index for All Urban Consumers that adjusts the standard CPI-U for the inflationary distortion associated with the treatment of housing in the latter series prior to 1983. Earnings are expressed in 1982-84 dollars.

The population of wage and salary workers is restricted to workers aged 17 to 65 who received positive wage and salary income and who were not self-employed. (Earnings of self-employed workers whose businesses are incorporated are classified as wage and salary earners in the CPS.) Full-time year-round (FTYR) earners are defined as those who worked at least 35 hours per week and at least 50 weeks per year. Hourly earnings are calculated by dividing annual wage and salary earnings by the product of weeks worked and hours (usually) worked per week. (Since data on the exact number of weeks worked by an individual earner in the previous year are not available in the CPS until 1976, hourly earnings cannot be calculated for income years prior to 1975.)

Workers who reported hourly earnings less than or equal to one-half of the non-agricultural minimum wage prevailing in any given year are deleted from the data set, as are workers reporting hourly earnings greater than $100.00 per hour.

A consistent real-value top code has been used to address the top-coding problem identified by Blackburn and Bloom (1988). Prior to the 1982 survey, wage and salary income was top-coded at $50,000 in nominal dollars. The top code was raised to $75,000 in 1982 and $99,999 in 1985. When analyzing trends in inequality over time, this creates two potential problems. First, during the periods when the nominal top-code is held constant, the real upper bound is declining, which biases most inequality measures downward. Secondly, the upward adjustment of the nominal top-code may produce spurious increases in inequality. Since the lowest real value for the top-code on earnings occurred in the 1981 CPS (pertaining to earnings in 1980), earnings above $50,000 in 1980 dollars ($60,753 in 1982-84 dollars) are recoded. (Each CPS file contains earnings data for the previous year.) Thus all values greater than $60,753 in 1982-84 dollars are recoded at $60,753. This recoding affects between one and two percent of the data for each of the CPS years from 1972 to 1990, and thus could result in a slight underestimate of the upward trend in inequality because it will mask any increasing dispersion in the extreme upper tail.

The cognitive skill (CS), motor skill (MS), and interactive skill (IS) variables are derived from job skill measures for over 500 occupations from the fourth edition of the

DOT (U.S. Department of Labor, 1977). Note that the skill measures describe characteristics of the job itself, rather than characteristics of the job holder such as education and experience. Interactive skills are measured by the DOT "People" variable, which indicates the extent to which a job requires mentoring, negotiating, instructing, supervising, directing, persuading, speaking-signalling, serving, or taking instructions. For the 1972-81 period, motor and cognitive skills are measured by factor-based scores created by Roos and Treiman (Miller et. al., Appendix F (1980)). The motor skills score is a positive function of the DOT variables motor coordination, finger dexterity, manual dexterity, color discrimination, visual discrimination, and complexity of interaction with machines and materials. The cognitive skills score is a positive function of the DOT variables general educational development, specific vocational preparation (training time requirements), data (synthesizing, coordinating, analyzing), intelligence aptitude, verbal aptitude, and numerical aptitude; it is a negative function of adaptability in performing repetitive work. These job skill variables are easily matched to the demographic and earnings data for individuals for the income years 1972-81 because both the CPS and the DOT code occupation using the 1970 occupational categories during this time period. Beginning in 1983, however, the CPS began to use the 1980 Census categories, which differ substantially from the 1970 categories. England and Kilbourne (1988) have matched the DOT job skill variables to the new categories, and thus the interactive skills variable can be taken directly from this source. To create the factor-based motor skills and cognitive skills variables for the 1982-90 period, however, it was necessary to recreate

Roos and Treiman's factor analysis for the 1980 occupational categories. As the factor loadings were nearly identical to those obtained by Roos and Treiman, the motor and cognitive skills variables created for the 1980 occupational categories are based on the same DOT skill variables included in Roos and Treiman's original measures.

After the job skill data are merged with the CPS earnings and demographic data for individuals by detailed occupational code, the industry variables required to estimate the model (means, variances, and covariances of worker and job skill characteristics within industries in each year) are calculated. Following Karoly (1989), I have aggregated some of the 2-digit Standard Industrial Classification (SIC) Codes in order to reduce measurement error. There are 15 goods industries and 18 service industries in the pooled data set. (See Appendix A for these industries and codes.) The data sets thus created provide observations on the variables required to estimate the model for annual as well as hourly earnings. There are 627 observations (33 industries X 19 years) for annual earnings of FTYR workers and 528 observations (33 industries X 16 years) for hourly earnings of all workers. The data cover 1972-90 for annual earnings and 1975-90 for hourly earnings.

Because of the change in occupational classification, the DOT-based job skill variables are not comparable across the entire 19 year period. The model is therefore estimated separately for the 1982-81 and 1982-90 periods when these variables are included in the regression equation.

Appendix E

Trend Coefficients for Variance of Log Annual Earnings (VLE) by Industry
for all FTYR Wage and Salary Workers: 1972-90

Industry	IND.	GOODS/SERVICES	β
Automobiles	8	G	.007
Machinery, except Electrical	6	G	.006
Electrical Machinery	7	G	.005
Food and Tobacco	11	G	.005
Textiles and Apparel	12	G	.005
Rubber and Leather	15	G	.005
Business Services	25	S	.005
Mining	1	G	.004
Stone/Clay/Glass/Primary Metals	4	G	.004
Other Trans. Manuf.	9	G	.004
Instruments and Misc. Manuf.	10	G	.004
Paper and Printing	13	G	.004
Entertainment	28	S	.004
Welfare and Religious Org.	31	S	.004
Construction	2	G	.003
Fabricated Metals	5	G	.003
Chemicals and Petroleum	14	G	.003
Other Transportation Services	17	S	.003
Wholesale Trade	20	S	.003
Banking and Finance	25	S	.003
Repair Services	26	S	.003
Lumber and Furniture	3	G	.002*
Communications	18	S	.002
Public Utilities	19	S	.002
Other Retail	22	S	.002*

*significant at the 5% level, all others significant at the 1% level

Source: Current Population Survey Annual Demographic Files, 1973-1991.

Appendix E, con't.

Trend Coefficients for Variance of Log Hourly Earnings (VLE-H)
for All Wage and Salary Workers by Industry: 1975-90

Industry	IND.	GOODS/SERVICES	β
Automobiles	8	G	.009
Textiles and Apparel	12	G	.008
Business Services	25	S	.008
Electrical Machinery	7	G	.007
Instruments and Misc. Manuf.	10	G	.007
Mining	1	G	.006
Machinery, except Electrical	6	G	.006
Food and Tobacco	11	G	.006
Rubber and Leather	15	G	.006
Chemicals and Petroleum	14	G	.005
Communications	18	S	.005
Educational Services	32	S	.005
Fabricated Metals	5	G	.004
Paper and Printing	13	G	.004
Wholesale Trade	20	S	.004
Eating and Drinking Est.	21	S	.004
Other Retail	22	S	.004
Banking and Finance	23	S	.004
Insurance and Real Estate	24	S	.004
Repair Services	26	S	.004
Personal Services	27	S	.004
Entertainment	28	S	.004
Welfare and Religious Org.	31	S	.004
Professional Services	33	S	.004
Lumber and Furniture	3	G	.003
Stone/Clay/Glass/Primary Metals	4	G	.003
Other Transportation Manuf.	9	G	.003
Public Utilities	19	S	.003
Hospitals	30	S	.003
Construction	2	G	.002
Other Transportation Services	17	S	.002
Medical, except Hospitals	29	S	.002

Note: All trend coefficients are significant at the 1% level.
Source: Current Population Survey Annual Demographic Files, 1976-1991.

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