Technological Change and Wages: An Interindustry Analysis

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Previous research has shown that wages in industries characterized by higher rates of technological change are higher. In addition, there is evidence that skill-biased technological change is responsible for the dramatic increase in the earnings of more educated workers relative to less educated workers that took place during the 1980s. In this paper, we match a variety of industry-level measures of technological change to a panel of young workers, observed between 1979 and 1993 (NLSY), and examine the role played by observed and unobserved heterogeneity in explaining the positive relationships between technological change and wages and between technological change and the education premium. We find that the wage premium associated with technological change is primarily due to the sorting of more able workers into those industries, and this premium is unrelated to any sorting based on gender or race. In addition, the education premium associated with technological change is the result of a greater demand for the innate ability or other unobserved characteristics of more educated workers.

I. Introduction

During the past decade there has been a considerable amount of research on the impact of technological change on the wage struc-

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ture. One line of research has focused on explaining interindustry wage differentials. These studies found a positive correlation between industry wages and technological change, using the capital to labor ratio or the research and development to sales ratio as proxies for technological change (Haworth and Rasmussen 1971; Lawrence and Lawrence 1985; Hodson and England 1986; Dickens and Katz 1987; Loh 1992). A second line of research attempted to explain the dramatic increase in the earnings of more educated workers relative to less educated workers that took place during the 1980s.[1] These studies, based largely on aggregate data, showed that skill-biased technological change was a major cause of the increase in the education premium (Bartel and Lichtenberg 1987, 1991; Mincer 1991; Berndt, Morrison, and Rosenblum 1992; Bound and Johnson 1992; Berman, Bound, and Griliches 1994; Topel 1994; Allen 1996). A third line of research utilized individual or plant-level data to study the wage impacts of technological change and found a positive relationship between workers' wages and their use of various new technologies (Krueger 1993; Dunne and Schmitz 1995; Doms, Dunne, and Troske 1997).[2]

In this paper, we build on the first two lines of research. Utilizing micro-level data from the National Longitudinal Survey of Youth (NLSY), a sample of 12,686 individuals who were 14–21 years old in 1979 and were interviewed annually through 1993, we study how technological change affected the 1979–93 interindustry wage structure.[3] Currently, data on the rate of technological change faced by workers in their jobs are unavailable in any non-firm-level data set. We therefore utilize industry-level measures of technological change instead.[4] Since the measurement of technological change outside the manufacturing sector is very problematic (Griliches 1994), our

[1] This observation was first made by Murphy and Welch (1989). The college to noncollege wage ratio continued to rise during the early 1990s, but at a slower rate than in the 1980s (see Bound and Johnson 1995).

[2] The results from this line of research may reflect unobserved heterogeneity. Dunne and Schmitz (1995) were unable to control for worker quality. Doms et al. (1997) showed that, although wages are higher in plants that use more new technologies, these plants had higher-paid workers even before the technologies were introduced. DiNardo and Pischke (1996) present evidence suggesting that Krueger's finding that workers who use computers on their jobs earn higher wages may be the result of unobserved heterogeneity.

[3] Our results may not generalize to other time periods: as Goldin and Katz (1996) demonstrate, the relationship between technological change and the demand for skills changed during the twentieth century. The direction of the bias in skill-biased technological change depends on the nature of the technological change.

[4] The disadvantage of using a small sample of firms that are undergoing technological change and analyzing the impact on their employees is that the findings may not hold for individuals who work in other firms. See Siegel (1994) for a study restricted to high-tech firms on Long Island.

analysis is restricted to workers in manufacturing. Even within this sector, however, no single proxy is likely to be perfect. In contrast to previous studies that have relied on one or two proxies for technological change, we link the NLSY with several alternative measures of technological change.[5] Specifically, our analysis uses the Jorgenson productivity growth series, the National Bureau of Economic Research productivity data, the *Census of Manufactures* series on investment in computers, the R & D to sales ratio in the industry, the industry's use of patents, and the share of scientists and engineers in industry employment. This approach enables us to examine the robustness of alternative measures of technological change, thereby increasing our confidence in the results.

An alternative approach to studying the effects of technological change on wages would be to conduct a within-industry time-series analysis using changes over time in industry rates of technological change. Although the NLSY spans 15 years, such an analysis would be problematic for two reasons. First, as Cawley et al. (1997) show, since individuals age over time, it is difficult, with the NLSY data, to separate effects of changes in market conditions over time from the effect of the increased labor market experience of the sample. Blackburn and Neumark (1993) and Farber and Gibbons (1996), for example, have shown that, according to learning models, as workers accumulate experience, schooling may become less important and ability more important for wage determination. Second, a time-series approach would have to utilize *changes* in the measures of industries' rate of technological change. Year-to-year variations in these measures are likely to have significant measurement errors and would not capture variations across industries in the true changes in rates of technological change.[6] Allen (1996) used this approach and concluded that some of his results were unreasonable, likely because of measurement error. The cross-sectional approach that we utilize here has the advantage of relying on interindustry variations in technological change. In doing this we are implicitly assuming that the cross-sectional variations in mean rates of technological change dominate the year-to-year variations within an industry.

Our objective in using different industry-level indicators is to capture variations in the *rate* of technological *change* across industries. From one perspective, we can think of an industry that has a higher

[5] Our approach of matching individual-level data with industry measures (previously used in Bartel and Sicherman [1998]) is similar to that of Mincer (1991) and Allen (1996), who both used Current Population Survey (CPS) data to study time-series changes in the wage distribution.

[6] Griliches and Hausman (1986) show that, when first differences or deviations from means are used, measurement errors are magnified.

rate of technological change as one in which workers are required to make more frequent changes in job tasks and operating procedures (Jovanovic and Nyarko 1995). Economists have suggested that in this environment, firms will increase their demand for workers who can more easily learn the new technology and adapt to change; these are more likely to be the more educated and more able individuals (see, e.g., Nelson and Phelps 1966; Griliches 1969). From another perspective, however, our proxies for the industry rate of technological change may also capture variations in the *nature* of the industry's technology; that is, some industries are ''high-tech'' and others are ''low-tech.'' If physical and human capital are gross complements, then industries that use more sophisticated capital (high-tech) will also employ more skilled workers. In fact, the term ''skill-biased technological change'' refers to the shift from such low-tech to high-tech environments. The data that we use here, like those used by most researchers, do not allow us to differentiate between the two perspectives.[7] We therefore use the terms ''high-tech'' and ''higher rates of technological change'' interchangeably throughout the paper.

The second way in which we build on previous research is to exploit the panel nature of our data in order to study the role of unobserved heterogeneity in explaining both the interindustry wage differences and the variations in returns to schooling that are associated with technological change. We show that wages in industries with higher rates of technological change are higher even after we control for a variety of individual characteristics, including scores on the Armed Forces Qualifications Test (AFQT).[8] This result could reflect wage premia that are due to (1) industry effects such as compensating wage differentials or efficiency wages, (2) labor mobility constraints that cause the effects of demand shocks to persist,[9] or (3) continuous shocks in the industry. Alternatively, it could reflect the sorting of more skilled workers into industries with higher rates

[7] While some of our measures may be more likely to reflect changes than others (e.g., R & D), the high correlation between the different measures makes it difficult to differentiate between the effects of changes in technology and those due to the nature of the technology. In another study (Bartel and Sicherman 1998), we show that a substantial part of the variation in the incidence of job training across industries is the result of both differences in the *rates of change* in technologies and the *nature* of the technology itself.

[8] Ninety-four percent of the 1979 NLSY respondents completed the AFQT. While some have used the AFQT scores as proxies for innate ability, others have argued that these scores also capture skills obtained at home and in school (Neal and Johnson 1996). See App. A for more information on the AFQT.

[9] Neal (1995) has shown that there is substantial industry-specific human capital that is likely to lengthen the effect of differential demand shocks.

of technological change.[10] We use a number of econometric procedures, based on fixed-effects models, to conclude that sorting is the dominant explanation for higher wages in industries with higher rates of technological change. Although, like Gibbons and Katz (1992), we find evidence of an industry wage premium after controlling for individual fixed effects, we show that this premium is not correlated with the industry rate of technological change. In addition, we also document higher returns to education in high-tech industries and show that this education premium is also due to greater selectivity on individual unobserved characteristics. In other words, at higher rates of technological change, there is an increase in demand for the ''ability'' of the more educated workers.[11]

Our findings also address some recent issues that have surfaced in the theoretical and empirical literature on economic growth, where the interrelationships among education, ability, and technological progress have been shown to play a key role in explaining the growth process. Specifically, our findings suggest an explanation for the observed weak link between education and economic growth.

In Section II of the paper we describe the data and the econometric framework for our analysis. Sections III and IV present our findings. Section V discusses the relevance of our findings to the recent economic growth literature. Conclusions and policy implications are discussed in Section VI.

II. Empirical Framework

A. Microdata

We use the main file and the work history file of the 1979–93 National Longitudinal Surveys of Youth aged 14–21 in 1979. The main file is the source of information on personal characteristics such as main activity during the survey week, education, ability scores, age, race, marital status, health status, and so forth. An individual enters our sample when he or she first reports that the main activity during the survey week was ''in the labor force.'' The work history file contains employment-related spell data, such as wages, tenure, and sepa-

[10] Although research on the interindustry wage literature has concluded that unobserved individual components play a role, the magnitude of that role is subject to debate. For example, Murphy and Topel (1987) found that nearly two-thirds of the observed industry wage differences were caused by unobserved individual characteristics. Gibbons and Katz (1992) found that displaced workers maintain 45 percent of their predisplacement industry wage premium when they are reemployed.

[11] We use the term ''ability'' to refer to unobserved characteristics. These characteristics could be innate or they could have been learned in school or in the family.

rations. Our analysis is restricted to the job designated as the individual's "CPS job," which is the most recent or current job at the time of the interview. We exclude individuals who work outside of manufacturing because good measures of technological change are not available for the nonmanufacturing sector. Details on the construction of variables and additional sample restrictions are discussed in Appendix A.

B. *Measures of Technological Change*

Since we do not have a direct measure of the rate of technological change faced by the individual in his or her place of work, we link the NLSY with several alternative proxies for the rate of technological change in the industry in which the individual works. As no single proxy is perfect, it is important to use several alternative measures in the analysis; if similar results are obtained with different measures, we can have more confidence in the reliability of the findings.

The six measures of technological change that we use are (1) total factor productivity (TFP) growth calculated by Jorgenson, Gollop, and Fraumeni (1987);[12] (2) the NBER TFP growth series described in Bartelsman and Gray (1996); (3) the ratio of investment in computers to total investments as reported in the 1987 *Census of Manufactures;* (4) the ratio of R & D funds to net sales reported by the National Science Foundation (1993); (5) the number of patents used in the industry, calculated by Kortum and Putnam (1995) and analyzed by Lach (1995); and (6) the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996). Appendix B (table B1) contains the industry means for each of these measures and discusses the advantages and disadvantages of each proxy.

Briefly, our proxies can be divided into two categories: the first two proxies are output-based measures and the next four are input-based measures. The productivity growth variables measure technological change as the rate of change in output that is not accounted for by the growth in the quantity and quality of physical and human capital. The input-based proxies are measured in levels, and all have been shown in previous work to be good proxies for the rate of technological change. For example, in their analysis of the changes in the wage distribution in manufacturing that occurred in the 1980s, Berman et al. (1994) use the computer investment variable as their

[12] This series has been used extensively in previous research (see, e.g., Lillard and Tan 1986; Mincer and Higuchi 1988; Tan 1989; Gill 1990; Bartel and Sicherman 1993, 1998).

proxy for the rate of technological change. Griliches and Lichtenberg (1984) showed that, for the time period 1959–76, there was a significant relationship between an industry's intensity of private R & D expenditures and subsequent productivity growth. Griliches (1990) provided evidence of the link between patent statistics and technological change. And Allen (1996) showed that the scientists and engineers variable is highly correlated with the R & D to sales ratio in the industry.[13]

The correlation matrices included in Appendix B (table B2) show that no two of our proxies for the industry rate of technological change are perfectly correlated, and therefore, there is no redundancy in using all of them in our analysis. This is consistent with our view that each proxy is likely to capture a different aspect of technological change.

C. Matching the Microdata and Industry Measures

Our analysis relies on cross-section variations in technological change. All the measures that we use have a common trait; that is, they are proxies for the *industry* rate of technological change. We recognize that an industry measure of technological change may not have the same impact for all the occupations in that industry. For example, an innovation in the industry's production processes may have little or no impact on clerical employees. We partially deal with this issue by conducting separate analyses for production and nonproduction workers.

In order to match the different measures of technological change to the industrial classification used in the NLSY (the *Census of Population* classification), we use industry employment levels as weights whenever aggregation is required. When we utilize the Jorgenson and NBER productivity growth measures, we characterize industry differences in the rate of technological change by using the mean rate of productivity growth over the 10-year time period from 1977 through 1987.[14] In the case of the share of investment in computers, we use the 1987 level. For the patent data, we calculate the number of patents used during the time period 1980–83 divided by the number used during the 1970s in order to control for systematic differ-

[13] In a study of 22 developed countries, Romer (1989) found that the number of scientists and engineers employed in R & D and the change in the number of scientists and engineers were positively correlated with economic growth.

[14] Although the Jorgenson productivity series is now available through 1991, we have chosen to use the means over the 1977–87 period because this time period captures a complete business cycle.

ences in the likelihood of patenting across industries.[15] In the case of the scientists and engineers variable, we use the 1979 value for the 1979–86 time period and the 1989 value for the 1987–93 time period. We use the annual data on R & D to sales ratios for each industry to calculate a 3-year moving average for the current year plus the preceding two years, for example, averaging data for 1977–79 for the 1979 NLSY and so forth. Hence, with the exception of the R & D and scientists/engineers variables, we use a fixed time period measure of technological change, which may act like a fixed effect for each industry, capturing other fixed attributes of the industry. We deal with this problem by including several industry characteristics in the regressions that may influence the relationship between wages and our measures of technological change. Another estimation issue is that the standard errors of our estimated coefficients may be biased downward because industry-level shocks may be correlated across individuals within a given industry. We deal with this problem by estimating a random-effects model, which is described in the next section.

III. Are Wages Higher in Industries with Higher Rates of Technological Change?

Like previous researchers, we also find a positive correlation between technological change and wages. Figure 1 shows the gross relationships between (real hourly) wages[16] and the various proxies for technological change; each unit of observation is either a two- or three-digit industry, depending on the technological change proxy.[17] The graphs show a positive relationship between wages and technological change. When we distinguish those measures of technological change that are input-based (investment in computers, use of patents, investment in R & D, and scientists/engineers) from those that are output-based (Jorgenson TFP and NBER TFP), we find that the former have a stronger relationship with wages. When input-based technological change measures are used, industries that are one standard deviation above the median have wages that are between 6 and 13 percent higher, whereas the comparable result for the output-based measures is 1.5 percent. Of course, these find-

[15] The latest year for which the patent data are available is 1983. See App. B for details on the construction of the patent variable.

[16] See App. A for more information on the wage data.

[17] Note that each of the graphs in fig. 1 uses the same two-digit industry classification. If data for a particular proxy are available on a three-digit basis (e.g., computer investment), fig. 1 identifies all the three-digit industries by the two-digit industry to which they map.

ings may in part be due to the fact that workers in industries with higher rates of technological change have more human capital, or that the industry rate of technological change is correlated with other industry characteristics that raise wages.

In table 1, we divide our NLSY sample into two groups on the basis of whether an individual is employed in a low-tech industry or a high-tech industry, using the median as the cutoff point. Within each group of industries, we calculated the percentage of employees who are college graduates, for all workers and for production and nonproduction workers separately. For all six measures of technological change, the percentage of college graduates is higher in the high-tech industries. Table 2 reports the AFQT scores for high school graduates and college graduates employed in low- and high-tech industries. For the high school graduates, we observe a dramatic gap in AFQT scores between high-tech and low-tech industries. This gap is not observed for college graduates. In other words, in high-tech industries there is strong selectivity on AFQT scores for high school graduates; workers with relatively low schooling are employed in these industries only if they have relatively high AFQT scores. Perhaps we do not observe this type of selectivity for college graduates because of the nature of the test.[18] Elsewhere (Bartel and Sicherman 1998) we have shown that the incidence of on-the-job training is higher in industries with higher rates of technological change. Hence these findings confirm that workers in industries with higher rates of technological change have more human capital, either by being more educated or more able or by receiving more on-the-job training. In the next subsection, we estimate the correlation between wages and the industry rate of technological change after controlling for a variety of individual and industry characteristics.

A. *Controlling for Commonly Observed Characteristics*

Consider the following linear model:

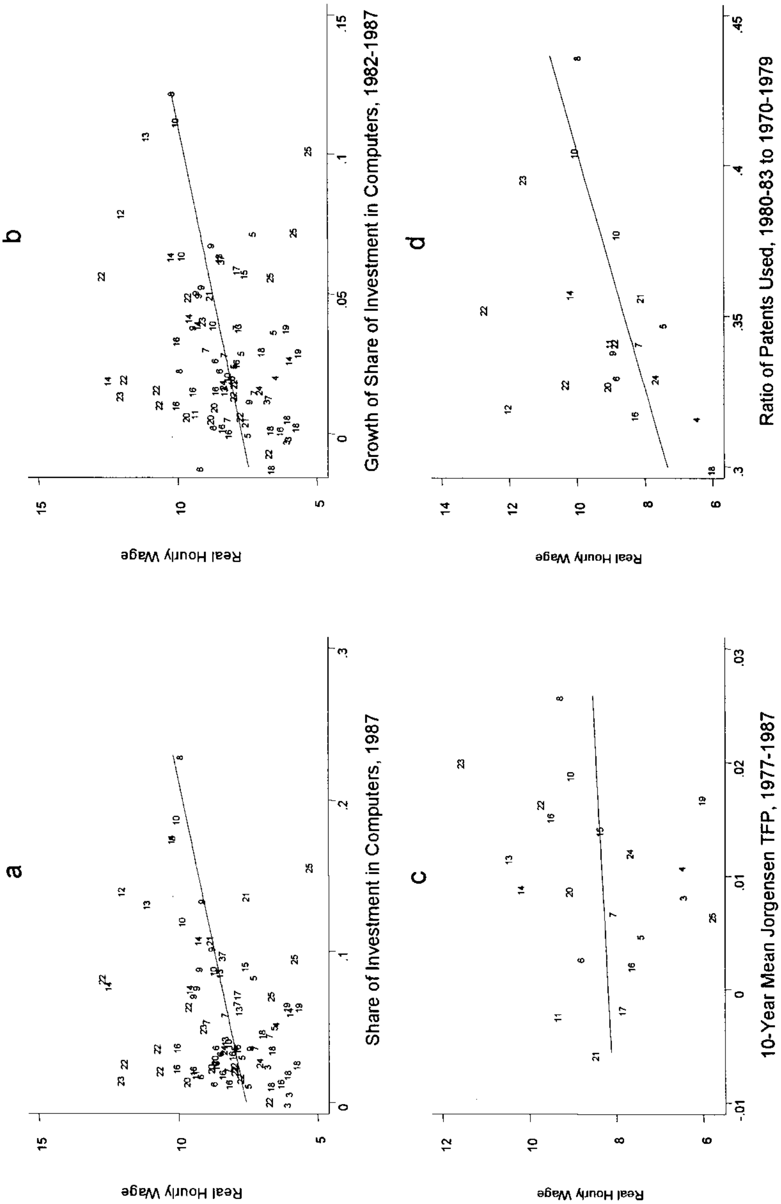
$$\ln W_{ijt} = \mathbf{X}_{it}\beta + \mathbf{Z}_{jt}\boldsymbol{\gamma} + \alpha TC_j + \epsilon_{ijt}, \tag{1}$$

where

$$\epsilon_{ijt} = v_j + e_{ijt}, \tag{2}$$

$\ln W_{ijt}$ denotes the log of the hourly real wage of individual i who works in industry j at time period t, $\mathbf{X}_{it}$ denotes a vector of individual

[18] It should be noted that the AFQT was normed for high school graduates, not college graduates; i.e., the test is, in effect, too easy for those with more education. As a result, AFQT scores do a better job of measuring ability differences for the former group.


a
Real Hourly Wage
Share of Investment in Computers, 1987
b
Real Hourly Wage
Growth of Share of Investment in Computers, 1982-1987
c
Real Hourly Wage
10-Year Mean Jorgensen TFP, 1977-1987
d
Real Hourly Wage
Ratio of Patents Used, 1980-83 to 1970-1979

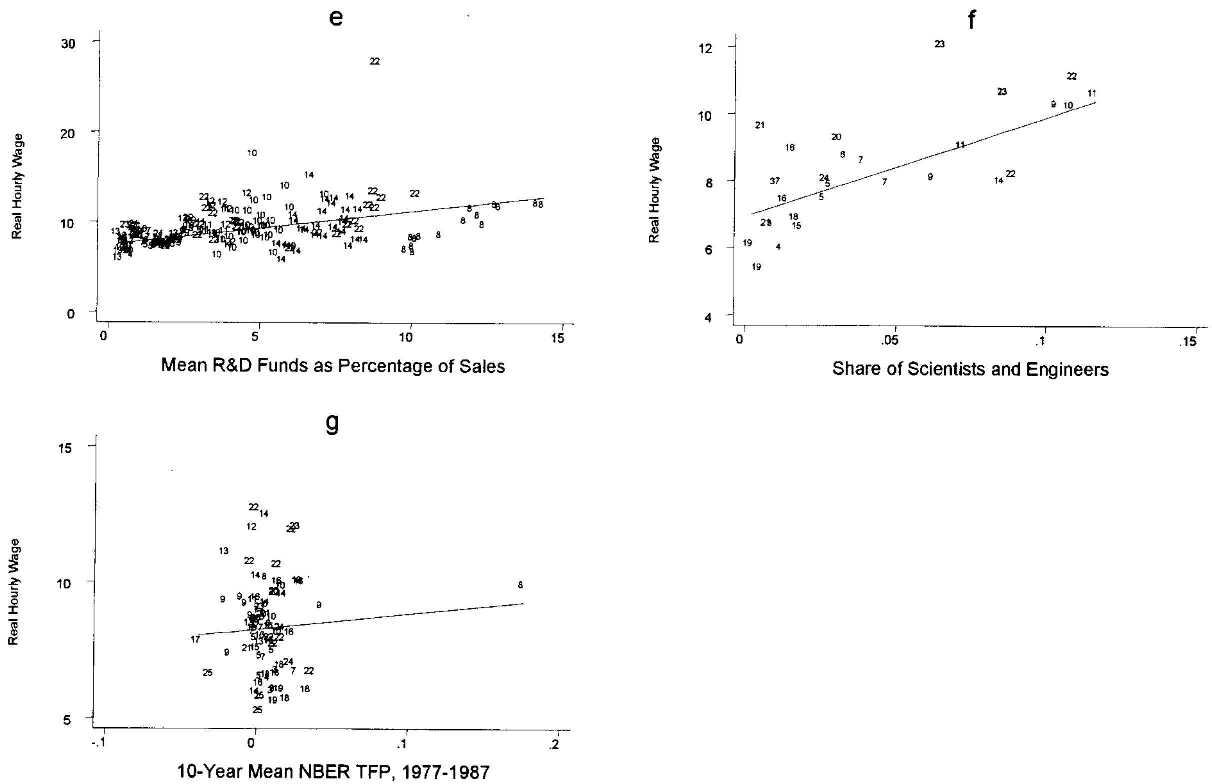


FIG. 1.—Average industry wages vs. industry rates of technological change: 1970 two-digit industry reported. *a*, Wages vs. 1987 computer investment ratio, 1979–93; *b*, wages vs. 1982/87 computer investment ratio, 1979–93; *c*, wages vs. 1977/87 Jorgenson TFP ratio, 1979–93; *d*, wages vs. patents, 1979–93; *e*, wages vs. R & D/sales ratio, 1979–93; *f*, wages vs. percentage of scientists and engineers, 1979–93; *g*, wages vs. NBER TFP growth, 1979–93.

TABLE 1

Percentage of College Graduates and the Rate of Technological Change, Manufacturing Industries, 1979–93

Measure and Rate of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987):			
Low	6.04	1.20	20.29
High	14.30	2.41	29.02
Use of patents:			
Low	6.46	1.11	20.96
High	12.64	2.28	28.10
Investment in R & D:			
Low	7.12	1.32	22.09
High	13.72	2.31	28.71
Percentage of scientists and engineers:			
Low	7.24	1.46	21.86
High	11.85	1.82	27.71
Jorgenson TFP (1977–87):			
Low	8.28	1.52	23.96
High	10.44	1.70	25.92
NBER TFP (1977–87):			
Low	8.97	1.58	24.68
High	10.51	1.69	25.96

* Industries are considered low-tech if their rate of technological change is below the median. They are high-tech if their rate is above the median.

characteristics that may vary over time, $\mathbf{Z}_{jt}$ denotes a vector of industry characteristics that may also vary over time, and TC_j denotes the industry rate of technological change.[19] The variables in vector $\mathbf{Z}_{jt}$ are the annual industry unemployment rate obtained from *Employment and Earnings* (1979–93), annual measures of percentage unionized in the industry compiled from the CPS by Hirsch and MacPherson (1993), and the annual rates of job creation and job destruction for both start-up and continuing establishments in the industry constructed by Davis and Haltiwanger (1992). We use several alternative measures of technological change, which are, with two exceptions (R & D/sales and scientists/engineers), fixed over time. The parameter ϵ_{ijt}, the random error associated with the observation ln W_{ijt}, is assumed to be the sum of the random effect associated with the j industry (v_j) and the t observation of individual i in industry j (ϵ_{ijt}). Notice that we use this specification in order to obtain the correct standard errors for the estimated coefficient of the technological change variable. Later on we use a different specification (fixed effects) that better fits the data.

Table 3 reports the estimated coefficients of the random-effects

[19] Note that TC_j varies within individuals as they change industry affiliation.

TABLE 2

AFQT Scores and the Industry Rate of Technological Change, High School and College Graduates

Measure and Rate of Technological Change*	All Workers		Production Workers		Nonproduction Workers	
	High School	College	High School	College	High School	College
Investment in computers:						
Low	34.8	74.2	32.4	69.0	44.4	75.0
	(24)	(19)	(23)	(20)	(24)	(19)
High	43.8	78.5	41.5	68.9	48.5	79.4
	(25)	(19)	(25)	(22)	(24)	(19)
Jorgenson TFP:						
Low	38.8	77.6	36.2	71.5	47.8	78.5
	(25)	(19)	(24)	(19)	(25)	(18)
High	37.6	76.3	34.7	66.6	45.4	77.3
	(24)	(20)	(24)	(23)	(24)	(19)
Use of patents:						
Low	35.7	75.8	33.3	70.1	45	76.6
	(24)	(19)	(23)	(20)	(25)	(18)
High	41.3	77.4	38.5	68.2	48	78.5
	(25)	(20)	(25)	(22)	(24)	(19)
R & D/sales ratio:						
Low	36	76.5	33.6	71.3	44.6	77.2
	(24)	(18)	(24)	(17)	(25)	(18)
High	42.8	77.2	39.9	66	49	78.4
	(25)	(21)	(25)	(25)	(24)	(20)
Percentage of scientists and engineers, 1979:						
Low	34.4	76.9	32.1	71.8	42.8	77.7
	(24)	(17)	(23)	(16)	(24)	(17)
High	43.0	76.8	40.2	65.9	49.8	77.9
	(25)	(21)	(25)	(25)	(24)	(20)
Percentage of scientists and engineers, 1989:						
Low	35.3	76.5	43.9	77.2	33	71.4
	(24)	(18)	(25)	(18)	(23)	(17)
High	43.0	77.2	49.4	78.3	40.1	66.0
	(25)	(21)	(24)	(20)	(25)	(25)
NBER TFP:						
Low	39.4	76.5	48.1	77.4	36.7	69.3
	(25)	(19)	(24)	(19)	(24)	(20)
High	35.3	77.7	43.1	78.6	32.4	68
	(24)	(20)	(24)	(19)	(24)	(24)

Note.—Standard deviations are in parentheses.

TABLE 3

Effect of the Rate of Technological Change on Wages, Workers in Manufacturing Industries, 1979–93: Industry Random-Effects Regression Results

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	.026	.024	−.008
	(1.86)	(1.25)	(.88)
Use of patents	.023	.013	.027
	(1.92)	(1.43)	(1.53)
Investment in R & D	.012	.015	.029
	(1.31)	(1.78)	(4.48)
Percentage of scientists and engineers	.060	.045	.073
	(4.19)	(2.71)	(4.22)
Jorgenson TFP (1977–87)	.037	.021	.050
	(3.11)	(2.07)	(4.05)
NBER TFP (1977–87)	.012	.012	.007
	(.68)	(.64)	(1.02)

Note.—Log of real hourly wages (see App. A for more details). Absolute *t*-statistics are in parentheses. Details on the derivation of the estimated parameters and standard errors are available on request.

* The other variables included in the regressions are marital status, race, sex, schooling dummies, residence in a standard metropolitan statistical area, labor market experience (and its square), tenure with employer (and its square), union membership, employment in durables, industry unemployment rate, industry means of job destruction and construction, and year dummies.

regressions, in which we control for a variety of individual and industry characteristics (listed in the note to the table). The complete regression results, using one technological change measure, are shown in Appendix table C1. In order to make the coefficients comparable across the various technological change measures, all the measures are expressed in standard deviation units. In most cases we find a positive and significant correlation between the rate of technological change and wages. In general, the results are stronger for the nonproduction workers: industries with a rate of technological change that is one standard deviation above the mean have nonproduction worker wages that are between −0.8 and 7.3 percent higher. For production workers, the effect is an increase that ranges from 1.2 to 4.5 percent. We compared these results to the coefficients from an ordinary least squares (OLS) estimation (not shown here) and found that, when positive, the OLS coefficients had higher *t*-values, as expected.[20]

One possible explanation for the positive correlation between wages and the industry rate of technological change is that workers in industries with higher rates of technological change are more

[20] In the case of the two computer investment variables, however, the OLS coefficients were negative or zero.

TABLE 4

Effect of the Rate of Technological Change on Wages, Workers in Manufacturing Industries, 1979–93: Industry Random-Effects Regression Results, Controlling for Standardized AFQT Scores

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	.018	.014	.003
	(1.29)	(.75)	(.23)
Use of patents	.015	.010	.017
	(1.37)	(1.11)	(1.04)
Investment in R & D	−.011	.011	.026
	(1.04)	(1.53)	(3.69)
Percentage of scientists and engineers	.053	.041	.071
	(3.72)	(2.42)	(4.35)
Jorgenson TFP (1977–87)	.033	.020	.044
	(2.70)	(1.84)	(4.27)
NBER TFP (1977–87)	.011	.010	.009
	(.60)	(.52)	(.67)

Note.—Log of real hourly wages (see App. A for more details). Absolute *t*-statistics are in parentheses. Details on the derivation of the estimated parameters and standard errors are available on request.

* See table 3 for a list of other variables that are included in the regressions (in addition to the AFQT scores).

able. In other words, the observed premium reflects a selection process based on unobserved characteristics. The availability of ''intelligence'' test scores (AFQT) in the NLSY has been suggested by some researchers as a way to control for ability, an unobserved characteristic in most data sets.[21] While AFQT scores are likely to reflect skills not captured by years of schooling per se, varying from innate ability to home environment and quality of schooling, our working hypothesis is that there is significant unobserved heterogeneity in our data even after we control for AFQT scores.[22] Table 4 reports the estimation results of equation (1) including standardized AFQT scores in the regressions. Comparing tables 3 and 4, we see that the coefficients that were significant in table 3 remain significant in table 4.

B. *Controlling for Individual Fixed Effects*

In order to test the hypothesis that the source of higher wages in industries with higher rates of technological change is worker skills

[21] See, e.g., Blackburn and Neumark (1993), among others. Farber and Gibbons (1996) propose a procedure to separate the component of ability that is also unobserved by the employer initially from that portion that is observed by the employer but not the econometrician.

[22] See Taber (1996) for an analysis using the NLSY that distinguishes between AFQT scores and unobserved heterogeneity.

TABLE 5

Effect of the Rate of Technological Change on Wages, Workers in Manufacturing Industries, 1979–93: Individual Fixed-Effects Regression Results

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	.006	.011	−.019
	(.96)	(1.58)	(1.31)
Use of patents	.003	.001	.002
	(.38)	(.14)	(.18)
Investment in R & D	.003	−.000	−.000
	(.44)	(.03)	(.05)
Percentage of scientists and engineers	.025	.017	.034
	(4.68)	(2.82)	(2.80)
Jorgenson TFP (1977–87)	.009	.017	−.014
	(1.43)	(2.47)	(1.00)
NBER TFP (1977–87)	−.005	−.004	−.018
	(.91)	(.57)	(1.42)

Note.—Log of real hourly wages (see App. A for more details). Absolute *t*-statistics are in parentheses. Details on the derivation of the estimated parameters and standard errors are available on request.
* See table 3 for a list of other variables that are included in the regressions.

not measured in equation (1), we consider the following fixed-effect model:

$$\ln W_{ijt} = \mathbf{X}_{it}\beta + \alpha TC_j + \mu_i + \epsilon_{ijt}, \qquad (3)$$

where μ_i is an individual fixed effect. By construction, this specification assumes that the premium to individual, unobserved skills does not vary across industries or over time.[23]

Table 5 presents the results of estimating this equation. The positive correlation between technological change and wages that was observed in table 3 is significantly weakened in table 5. Any coefficients that remain significant in table 5 are much smaller in magnitude than in table 3. Note that the reduction is much stronger for nonproduction workers since the AFQT score does not adequately control for ''unobserved'' heterogeneity among more educated workers. On the basis of the results in table 5, we can conclude that unmeasured worker characteristics play an important role in accounting for the positive correlation between wages and technological change.[24]

[23] Heckman and Scheinkman's (1987) findings, using the Panel Study of Income Dynamics, reject this commonly used assumption that different skills are uniformly priced across sectors.

[24] If one assumes nonuniform pricing of ''ability,'' it is possible, with the additional assumptions that labor supply is inelastic and ability is priced *higher* in low-tech industries, that our findings could be due to higher demand for *all* workers in industries with higher rates of technological change. It should be noted, however, that we partially control for industry changes in demand by including in all our regressions

C. *Individual and Industry Premia: Two-Stage Double Fixed-Effects Model*

We have shown that, after we control for observed and unobserved heterogeneity among workers, wages are *not higher* in industries characterized by higher rates of technological change, thus providing support for the hypothesis that sorting is the main explanation for the observed higher wages in high-tech industries. In this subsection we provide more direct evidence for the existence and magnitude of sorting that is due to unobserved heterogeneity. In addition, since race and sex are fixed for individuals, it was impossible to identify their impacts using the fixed-effects model of equation (3), and we could not reject the hypothesis that part of the sorting was based on sex or race. The approach we use in this subsection enables us to deal with this issue.

We estimate a ''two-stage double fixed-effects model.'' In the first stage, we estimate a standard fixed-effects model (described below) that also includes industry dummies. This is done in order to obtain two estimated parameters: individual and industry ''premia.'' The individual premium is the fixed component of the wage that is not explained by either observed characteristics or any possible (fixed) premium due to industry affiliation. These characteristics could include those that are observed by the employer but not by the econometrician, as well as characteristics that are unobserved, either by the employer or by the worker initially, but are learned or revealed over time. The industry premium is the component of the wage that is given to individuals while working in the industry, but is not due to any specific individual characteristics, either observed or unobserved. This premium could capture compensating wage differentials, efficiency wages, and demand-induced disequilibria but excludes the effect of the sorting of workers with higher unmeasured ''ability'' into industries with high rates of technological change. In the second stage, we obtain the correlations between the individual premia and the industry rate of technological change.

Three data problems potentially hamper our analysis: (1) ambiguous industry reports resulting in erroneous industry changes,[25] (2) not enough ''true'' industry changes, and (3) nonrandom industry changes. We were able to deal fairly successfully with the first problem for workers who did not change employers. First, we cor-

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annual industry unemployment rates and annual rates of job creation and job destruction. In addition, given the sorting we observe based on schooling and AFQT scores and our findings on returns to schooling (Sec. IV), we prefer our interpretation to this alternative view.

[25] See Murphy and Topel (1987) for a treatment of this problem using a unique data set.

rected for some obvious errors in reported industry.[26] Then, for each worker, we assigned the modal industry for the period in which he or she worked with the same employer. We believe that the second problem listed above is not a significant one, as demonstrated by the data in table 6, where we show the number of corrected industry changes for the individuals in our sample. Table 6 indicates that there is a reasonable amount of industrial mobility; for example, among the 193 individuals who were in the sample for 7 years, 80 percent changed industry at least once.[27] Finally, the third problem is that industry moves are endogenous. While some have tried to deal with this problem using data on displaced workers (e.g., Gibbons and Katz 1992), most studies, including ours, do not attempt to deal with the problem. It is not clear, however, what the sign of the bias is in the NLSY.[28]

Stage I

Consider the following fixed-effect model:

$$\ln W_{it} = \mathbf{X}_{it}\beta + \mu_i + \boldsymbol{\gamma}'\mathbf{d}_{it} + \epsilon_{it}, \tag{4}$$

where $\ln W_{it}$ is the log of the real wage of individual i at time period t, $\mathbf{X}_{it}$ is a vector of individual characteristics, μ_i is the individual "fixed effect," $\mathbf{d}_{it}$ is a vector of dummy variables indicating the industry in which the worker is employed at time period t, and $\boldsymbol{\gamma}'$ is a vector of industry effects. Both the individual and the industry effects are assumed to be constant over time. This specification assumes that all unobserved individual characteristics are valued the same in different industries.[29]

Assuming that ϵ_{it} can be characterized by an independently and identically distributed random variable with mean zero and variance σ^2_ϵ, we estimate equation (4) obtaining two parameters of interest: an estimated individual premium, $\hat{\mu}_i$, and an estimated industry premium, $\hat{\gamma}_j$. The fact that people change industries over the sample period enables us to differentiate the individual premium from the industry premium.[30]

[26] A detailed program of all industry corrections is available on request.

[27] This high number may reflect the young age of our sample.

[28] If, e.g., workers in low-tech industries are more likely to move to a low-tech industry (and the same for workers in high-tech industries), then our estimation procedure will result in an upward bias in the estimated individual premium and a downward bias in the estimated industry premium. An opposite pattern of mobility, however, will cause the opposite bias.

[29] Although industry technologies may be differentially sensitive to ability, ability will be equally rewarded in all industries in equilibrium. See n. 24 for a further discussion of nonuniform pricing.

[30] Details on the derivation of the estimated parameters and standard errors are available on request.

TABLE 6

Frequency of Industry Changes

Years Observed in the Sample	Observations	Number of Industry Changes: 0	1	2	3	4	5	6	7	8	9	10
		A. Using 83 Industrial Categories										
1	1,487	1										
2	694	.48	.52									
3	493	.34	.37	.28								
4	366	.33	.28	.28	.11							
5	273	.30	.22	.24	.17	.06						
6	234	.29	.2	.21	.15	.11	.05					
7	193	.20	.19	.20	.24	.13	.04	.01				
8	151	.22	.17	.19	.21	.10	.07	.05	.01			
9	93	.25	.11	.25	.10	.14	.10	.04	.02	. . .		
10	99	.24	.11	.20	.14	.14	.07	.06	.03	. . .	. . .	
11	101	.25	.11	.16	.12	.13	.16	.07	.01	. . .	. . .	. . .
12	66	.26	.12	.12	.08	.11	.12	.12	.04	. . .	.02	.02
13	46	.11	.17	.11	.15	.15	.13	.04	.09	.02	.02	. . .
14	35	.20	.17	.14	.09	.06	.11	.17	.03	. . .	. . .	. . .
15	12	.33	.08	. . .	.08	.08	.25	.17	. . .	. . .	. . .	. . .
		B. Using 20 Industrial Categories										
1	1,487	1										
2	694	.55	.45									
3	493	.42	.36	.22								
4	366	.43	.27	.23	.07							
5	273	.39	.22	.23	.12	.04						
6	234	.37	.25	.20	.09	.06	.04					
7	193	.30	.21	.19	.17	.11	.03	.01				
8	151	.33	.19	.17	.15	.08	.05	.03	.01			
9	93	.37	.16	.18	.06	.12	.10	.01	. . .	. . .		
10	99	.35	.08	.20	.15	.11	.05	.04	.01	. . .	. . .	
11	101	.41	.13	.14	.15	.06	.09	.03	. . .	. . .	. . .	. . .
12	66	.36	.12	.09	.11	.15	.03	.09	.02	. . .	.03	. . .
13	46	.28	.15	.15	.04	.13	.11	.02	.11	. . .	. . .	. . .
14	35	.26	.20	.23	.06	.06	.11	.06	. . .	. . .	. . .	.03
15	12	.58	.17	. . .	.08	.08	. . .	.08	. . .	. . .	. . .	. . .

TABLE 7

Individual Premium and Industry Rates of Technological Change: Two-Stage Double Fixed-Effects Regressions (Second-Stage Estimation Results)

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	.021	.007	.049
	(3.50)	(1.04)	(4.71)
Use of patents	.056	.040	.052
	(9.53)	(6.04)	(5.20)
Investment in R & D	.033	.005	.045
	(5.74)	(.77)	(6.78)
Percentage of scientists and engineers	.070	.044	.096
	(11.1)	(6.31)	(9.73)
Jorgenson TFP (1977–87)	.021	.001	.066
	(3.43)	(.16)	(6.70)
NBER TFP (1977–87)	.010	.000	.023
	(1.65)	(.03)	(2.00)

Note.—Reported are coefficients of the partial correlation between the estimated individual premium (after we controlled for individual and industry fixed effects in the first-stage regression) and the technological change variable. Absolute *t*-statistics are in parentheses. Details on the derivation of the estimated parameters and standard errors are available on request.

* The variables included in the first-stage regressions are listed in table 3. In the second-stage regressions, we control for sex and race in the individual-level regressions.

Stage II

Consider the following model:

$$\hat{\mu}_i = \mathbf{G}_i\boldsymbol{\gamma} + \alpha(\overline{TC_i}) + \epsilon_i, \tag{5}$$

where $\overline{TC_i}$ is the (weighted) mean of the rates of technological change in the industries in which the worker was employed during the sample period, and $\mathbf{G}_i$ is a vector of race and gender dummies.[31] Given that the dependent variable in equation (5) is an estimated parameter, we estimate the equation using weighted least squares, where the weights are the inverses of the standard errors of the dependent variable.

The results of estimating the second-stage equation are shown in table 7. The main finding is the existence of a significant correlation between the individual premia and all six indicators of technological change. When the sample is separated into the two occupational groups, the significant results hold for the nonproduction workers, but only the patents and scientists/engineers variables are significant for the production workers. We also find (not shown here)

[31] The weights are the fractions of time worked in the relevant industry. Note that this approach to measuring $\overline{TC}$ does not enable us to distinguish a person who worked in a low-tech industry for half the working period and in a high-tech industry for the other half from a person who has worked in ''medium-tech'' industries the whole time.

strong correlations between the race and sex dummies and the individual premia. In particular, being female and being nonwhite are both negatively correlated with the individual premium, and the correlation is substantially higher for sex. The inclusion of sex and race did not significantly affect the partial correlation between the industry rate of technological change and the individual premium. We can therefore conclude that the higher wages in industries with higher rates of technological change are not due to sorting based solely on sex or race.

In an earlier version of this paper (Bartel and Sicherman 1997), we also estimated the correlation between the industry premia and the industry rate of technological change. These results basically replicate those presented in table 5, namely that there is no correlation between industry premia and the industries' rates of technological change, when all observed and unobserved individual characteristics are held constant. Therefore, although we confirm the existence of industry wage differentials, our results show that they are uncorrelated with the industry rate of technological change. Hence, we conclude that the observed wage premium associated with technological change is primarily due to the sorting of more skilled workers (based on observed and unobserved characteristics) into those industries.

In order to consider whether the sorting of workers with higher premia to industries with higher rates of technological change occurs relatively early in the working life rather than over time, we conducted the following test. We compared the individual premia of workers in industries below the median rate of technological change to those of workers in industries above the median rate of technological change. We first used the industry affiliation in the individual's first full-time job and, second, used the last industry reported by the worker. Although the results supported our earlier finding, namely that the mean individual premium is higher in industries with higher rates of technological change, we found no evidence that the gap increased over time. We conclude, therefore, that the sorting of better workers into industries with higher rates of technological change is done relatively early.[32]

IV. Why Are Returns to Schooling Higher in Industries with Higher Rates of Technological Change?

As noted in the Introduction, many studies argue that one of the most important explanations for the increase in returns to schooling

[32] This does not rule out the possibility that there are important individual characteristics that are revealed over time (see Farber and Gibbons [1996] for evidence of learning). These characteristics do not, however, seem to be important in explaining interindustry wage differences that are due to technological change.

in the 1980s is skill-biased technological change. An important question is whether the increase in demand for educated workers reflects an increase in demand for schooling per se or an increase in demand for other components of human capital such as ability, quality of schooling, or other factors typically not observed in the data. Several recent studies have shown that part of the increased returns to schooling is due to increased returns to ability. The extent to which returns to schooling are explained by returns to ability is debatable. While some studies find a relatively small effect (e.g., Chay and Lee 1996), others argue that much of the increased returns to schooling in the 1980s is due to an increase in the premium for unobserved skills (e.g., Juhn, Murphy, and Pierce 1993; Murnane, Willett, and Levy 1995; Taber 1996).[33] While previous studies have examined changes in returns to schooling and ability over time, our approach here is to compare these returns across industries.

In order to first test the hypothesis that returns to schooling are higher in industries with higher rates of technological change, we estimate the following model:

$$\ln W_{ijt} = \mathbf{X}_{it}\beta + \mathbf{Z}_{jt}\boldsymbol{\gamma} + \delta(S_{it} \cdot TC_j) + \epsilon_{ijt}, \tag{6}$$

where

$$\epsilon_{ijt} = v_j + e_{ijt}. \tag{7}$$

This specification, assuming industry-level random effects, is similar to that used in equation (1). The only modification is that here we interact S, the individual's level of schooling, with the industry rate of technological change, thus allowing the effect of schooling on wages to vary with the industry rate of technological change. Notice that the vector $\mathbf{X}_{it}$ includes the level of schooling as an independent variable. It is important to remember that, unlike many of the studies cited above, our analysis is cross-sectional, and therefore, the returns to schooling that we calculate will also reflect the influence of factors such as the disequilibria discussed earlier.

The results of estimating equation (6) are shown in table 8. We find a positive and significant correlation between technological change and the returns to education for many of the indicators that we use. It is possible that this premium reflects returns to unobserved individual characteristics or unobserved industry characteristics. Indeed, when individual and industry fixed effects are added to the regressions, the coefficients on the technological change/education

[33] For a critical review of this literature, see Cawley et al. (1997), who argue that many of these findings are not robust to specification changes and hold only for certain subgroups of the population.

TABLE 8

Effect of the Rate of Technological Change on Wages Interacted with Years of Schooling, Workers in Manufacturing Industries, 1979–93: Industry Random-Effects Regression Results

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	.006	−.001	.004
	(3.49)	(.64)	(1.28)
Use of patents	.010	.005	.007
	(6.52)	(2.50)	(2.43)
Investment in R & D	.006	.036	−.050
	(1.32)	(.53)	(.92)
Percentage of scientists and engineers	.012	.002	.013
	(7.33)	(.83)	(4.42)
Jorgenson TFP (1977–87)	.001	−.009	.010
	(.68)	(2.03)	(2.52)
NBER TFP (1977–87)	.004	.001	.003
	(2.82)	(.57)	(.87)

Note.—Log of real hourly wages (see App. A for more details). Reported are the coefficients of the interaction between years of schooling and the industry rate of technological change. Absolute *t*-statistics are in parentheses.

* See the notes to table 3.

interaction term (shown in table 9) become negative and, in two cases, are even significant.

To further test this hypothesis, we estimate the two-stage double fixed-effects model described earlier, adding to both stages interaction terms between education and technological change. The results from the second stage are shown in table 10, where we find a significant correlation between the individual premia and five out of six of the technological change measures (interacted with schooling).[34] Our interpretation of these results is that the observed education premium in high-tech industries is due to the sorting of highly educated individuals based on their unobserved characteristics (ability?) into the high-tech industries. At higher rates of technological change, schooling per se becomes less important relative to other characteristics (e.g., ability) that are correlated with schooling. The result reported in table 2, that there is strong selectivity on AFQT scores for high school graduates in high-tech industries, supports this assessment.

V. Implications for Economic Growth

The analysis presented in this paper is relevant to the recent growing literature on new growth theory, where concepts such as knowl-

[34] Some of the significant relationships between the individual premia and the technological change measures do not hold up when the sample is divided into the two occupation groups.

TABLE 9

EFFECT OF THE RATE OF TECHNOLOGICAL CHANGE ON WAGES INTERACTED WITH YEARS OF SCHOOLING, WORKERS IN MANUFACTURING INDUSTRIES, 1979–93: INDIVIDUAL AND INDUSTRY FIXED-EFFECTS REGRESSION RESULTS

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	−.005	−.005	−.001
	(1.03)	(.68)	(.11)
Use of patents	−.004	−.003	−.003
	(.90)	(.47)	(.32)
Investment in R & D	−.004	−.002	−.000
	(1.37)	(.66)	(.03)
Percentage of scientists and engineers	−.011	−.012	−.008
	(3.7)	(2.83)	(1.35)
Jorgenson TFP (1977–87)	−.006	−.013	.005
	(1.43)	(2.06)	(.58)
NBER TFP (1977–87)	.003	.002	.006
	(.75)	(.27)	(.73)

NOTE.—Log of real hourly wages (see App. A for more details). Reported are the coefficients of the interaction between years of schooling and the industry rate of technological change. Absolute *t*-statistics are in parentheses.

* See the notes to table 3.

TABLE 10

INDIVIDUAL PREMIUM AND INDUSTRY RATE OF TECHNOLOGICAL CHANGE: INTERACTION OF TECHNOLOGICAL CHANGE AND SCHOOLING (Two-Stage Double Fixed-Effects Regressions and Second-Stage Estimation Results)

Measure of Technological Change*	All Workers	Production Workers	Nonproduction Workers
Investment in computers (1987)	.013	.013	.007
	(4.71)	(3.76)	(1.48)
Use of patents	.010	.006	.006
	(3.96)	(1.91)	(1.41)
Investment in R & D	.010	−.002	.009
	(3.87)	(.60)	(3.13)
Percentage of scientists and engineers	.024	.011	.026
	(8.74)	(3.09)	(6.20)
Jorgenson TFP (1977–87)	.011	.010	.008
	(4.02)	(2.90)	(1.75)
NBER TFP (1977–87)	.001	−.002	.001
	(.31)	(.77)	(.12)

NOTE.—Reported are the coefficients of the partial correlation between the estimated individual premium (after we control for individual and industry fixed effects in the first-stage regression) and the interaction between schooling and the industry rate of technological change. Absolute *t*-statistics are in parentheses.

* See the notes to table 3.

edge capital, human capital, and technological progress, and not the standard tangibles of capital and labor, have become the central engines of growth in most models (Romer 1986; Lucas 1988). Contrary to the predictions of these theories, the empirical literature has not found evidence that the standard human capital variables, such as education and literacy, are a major source of economic growth. For example, the works of Benhabib and Spiegel (1994), Caselli, Esquivel, and Lefort (1996), and Cohen (1996) found that proxies for human capital enter the growth process only indirectly through their effects on technological change, and not as direct inputs.

Our findings, that industries characterized by high rates of technological change have employees who have not only high levels of schooling but also (productive) unobservable skills, offer a possible solution to this tension between theory and empirical findings in the growth literature. Human capital is a composite output of both ability and education. Given the complementarity between ability and education, augmenting one without the other may provide little momentum for growth. Increasing education by itself may not increase economic growth even if knowledge or technological progress is the engine of growth.

Finally, our finding that industries with higher rates of technological change attract more educated and more able workers supports the assumption made by Galor and Tsiddon (1997), who theoretically analyze the relationship between technological change, wage inequality, intergenerational earnings mobility, and economic growth. Their model predicts that sorting by ability will increase wage inequality, increase equality of opportunities, and foster future technological progress.

VI. Conclusions

Previous research has found evidence that wages are higher in industries characterized as high-tech or subject to higher rates of technological change. In addition, there is evidence that skill-biased technological change is responsible for the dramatic increase in the earnings of more educated workers relative to less educated workers that took place during the 1980s. In this paper, we matched a variety of industry-level measures of technological change to a panel of young workers observed between 1979 and 1993 (the NLSY) and examined the role played by unobserved heterogeneity in explaining the positive relationships between technological change and wages and technological change and the education premium.

We found that both the positive correlation between wages and technological change and the positive correlation between the education premium and the rate of technological change are significantly weakened when we control for unobserved heterogeneity among individuals, using fixed-effects estimation. This provides support for the hypothesis that sorting is the main explanation for the observed higher wages and education premium in high-tech industries. Although we confirmed the existence of industry wage differentials, holding all workers' heterogeneity constant, our findings indicate that these differentials are uncorrelated with the industry rate of technological change. Using a fixed-effects model, we estimated the wage premium for each individual that is not due to either observed individual characteristics or industry affiliation. This premium was found to be correlated with the industry rate of technological change, with race and sex held constant. We conclude that the observed effects of technological change on the wage structure are due to the sorting of individuals based on their unobserved characteristics, and not due to sorting based solely on race or sex.

What do these individual unobserved characteristics reflect? There are several possibilities: (1) innate ability, (2) home environment and the skills learned at home, and (3) school curriculum or quality of schooling or both. The implications of our findings for wage inequality and its persistence depend on the relative importance of these factors. For example, if the unobserved characteristics largely reflect individuals' innate abilities, then the wage differentials associated with technological change would be expected to persist over time. Similarly, if these unobserved characteristics capture the home environment, which is also exogenous to the individual, then there will also be a limited role for public policy intervention in influencing the wage differentials induced by technological change. If, however, unobservables largely reflect school curriculum or school quality (which can be viewed as somewhat endogenous), then public policy or individual choice could shape the allocation of these resources and thereby mitigate the effects of higher rates of technological change on wage inequality.

Appendix A

Data

A. General

The data are taken from 1979–93 National Longitudinal Surveys of Labor Market Experience of youth aged 14–21 in 1979. Additional data are obtained from the NLSY work history file. The NLSY work history file contains primarily employment-related spell data constructed from the main NLSY file. Both files are available in CD-ROM format. Many questions are asked with regard to the time since the last survey. For the first survey (1979), the questions, in most cases, refer to the time period since January 1, 1978.

In addition to the NLSY, we use several other data sources that serve as alternative measures of industry rates of technological change. These data are described in Section II.

B. *The Sample*

The NLSY is based on a sample of 12,686 young people aged 14–22 who have been interviewed yearly since 1979. Not all individuals were interviewed each year. The first observation for an individual to be included in our sample is the first survey in which the main activity reported for the week prior to the survey is (1) working, (2) with a job, but not working, or (3) looking for a job. Following that, an individual is included in the sample as long as he or she is interviewed (even if leaving the labor market).

In all the regression analyses the following additional restrictions are imposed: The number of weeks worked since the last survey is at least 15, and the person has worked for at least half of the weeks that elapsed since the previous survey. The panel is unbalanced. The number of observations per individual varies.

C. *Some Details on Specific Variables*

Wages.—We use the log of the hourly rate of pay on the current/most recent job. When individuals did not report their labor income in an hourly rate, the reported income was divided by the time unit in which they were paid. The wage deflator used in the fixed-weighted price index for gross national product, 1987 weights, was personal consumption expenditures (1979 = .658, 1987 = 1, 1993 = 1.281). Hourly wages below $2 and above $200 were set to missing (412 observations).

Weeks between surveys.—The number of weeks between surveys ranges between 26 and 552. The large numbers occur when individuals are not surveyed for several years.

Industry codes.—We use the original reports of three-digit industry codes, using the 1970 census classification. The different measures of technological change that we use are based on different industry classifications (e.g., standard industrial classification [SIC] codes) and different levels of aggregation. We did the maximum matching between those measures and the reported industry in the NLSY. Details on the matching of each of the measures are available from the authors.

Schooling.—This variable is the number of completed years of schooling, truncated at 18. If the variable is missing, we use the previous survey report.

Industry unemployment rate.—This variable is the annual male unemployment rate in the industry, taken from 1966–83 issues of *Employment and Earnings*. There are 31 categories.

Intelligence measures.—During 1980, NLSY respondents were subjects in an effort of the U.S. Department of Defense and Military Services to update the norms of the Armed Services Vocational Aptitude Battery (ASVAB). A total of 11,914 civilian and military NLSY respondents (94 percent of the original 1979 sample) completed this test.

The ASVAB consists of a battery of 10 tests that measure knowledge and skill in the following areas: (1) general science, (2) arithmetic reasoning, (3) word knowledge, (4) paragraph composition, (5) numerical operations, (6) coding speed, (7) auto and shop information, (8) mathematics knowledge, (9) mechanical comprehension, and (10) electronics information. The following information is available for each youth who participated in the profiles testing: individual number correct or raw scores, scale scores, and standard errors for each of the separate sections.

Two approximate and unofficial AFQT test scores are computed from select sections of the ASVAB tests: AFQT81 and AFQT89. The AFQT is supposedly a general measure of trainability and a primary criterion of enlistment eligibility for the Armed Forces.

Appendix B

Indices for Industry Rates of Technological Change

We use six measures of technological change as shown in table B1 (correlations are shown in table B2): (1) the TFP growth series calculated by Jorgenson, (2) the NBER TFP series, (3) *Census of Manufactures* data on investment in computers, (4) the R & D/sales ratio in the industry as reported by the National Science Foundation, (5) the number of patents used in the industry, and (6) the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996).

The Jorgenson TFP series, which is available through 1991, has been used extensively in previous research (e.g., Lillard and Tan 1986; Mincer and Higuchi 1988; Tan 1989; Gill 1990; Bartel and Sicherman 1993, 1998). With the Jorgenson productivity growth series, technological change is measured as the rate of change in output that is not accounted for by the growth in the quantity and quality of physical and human capital. One problem with this approach is that technological change may not be the only cause of productivity growth. Other factors, such as fluctuations in capacity utilization and nonconstant returns to scale, are also likely to affect productivity growth. In order to control for these effects, the empirical analysis includes controls for the industry unemployment rate and the rates of entry and exit of firms in the industry. The main advantage of the Jorgenson series is that changes in the quality of the labor input are carefully used to correctly measure net productivity growth. Also, the new Jorgenson series utilizes the constant-quality price deflator from the Bureau of Economic Analysis; the earlier series underestimated productivity growth in high-tech industries (e.g., the computer industry) since quality improvements were not incorporated into the output price index. The major disadvantage of the Jorgenson series is that it is a residual (rather than a direct) measure of technological

TABLE B1

Indices for Industry Rates of Technological Change

A. Jorgenson's TFP

	Industry	Mean
1	Nonelectrical machinery (22)*	.025861
2	Petroleum refining (16)	.020192
3	Electrical machinery (23)	.019077
4	Apparel and other textiles (10)	.016959
5	Chemicals and allied products (15)	.016570
6	Textile mill products (9)	.015416
7	Miscellaneous manufacturing (27)	.014244
8	Rubber and plastic (17)	.012264
9	Other transportation equipment (25)	.011727
10	Furniture and fixtures (12)	.010903
11	Instruments (26)	.009004
12	Paper and allied products (13)	.008890
13	Lumber and wood products (11)	.008340
14	Fabricated metal (21)	.006900
15	Leather (18)	.006687
16	Stone, clay, and glass (19)	.004865
17	Primary metals (20)	.002812
18	Food and kindred products (7)	.002277
19	Tobacco manufactures (8)	−.001611
20	Motor vehicles (24)	−.002123
21	Printing and publishing (14)	−.005576

B. NBER TFP Data Set: Means over 1977–87

1	Electronic computing equipment	.17557
2	Not specified machinery	.04299
3	Synthetic fibers	.03719
4	Ordnance	.03564
5	Miscellaneous textile mill products	.03456
6	Grain mill products	.02947
7	Radio, TV, and communication equipment	.02815
8	Petroleum refining	.02704
9	Screw machine products	.02677
10	Not specified chemicals and allied products	.02449
11	Confectionery and related products	.02369
12	Miscellaneous plastic products	.02338
13	Knitting mills	.02100
14	Optical and health services supplies	.01840
15	Not specified electrical machinery, equipment, and supplies	.01782
16	Floor coverings, except hard surface	.01733
17	Agricultural chemicals	.01731
18	Rubber products	.01726
19	Miscellaneous fabricated textile products	.01714
20	Household appliances	.01540
21	Beverage industries	.01492
22	Industrial chemicals	.01460
23	Yarn, thread, and fabric mills	.01448
24	Sawmills, planing mills, and mill work	.01423
25	Paints, varnishes, and related products	.01346
26	Pulp, paper, and paperboard mills	.01342
27	Apparel and accessories	.01313
28	Plastics, synthetics, and resins, except fibers	.01288

TABLE B1 (*Continued*)

B. NBER TFP Data Set: Means over 1977–87

29	Structural clay products	.01273
30	Logging	.01255
31	Cement, concrete, gypsum, and plaster products	.01193
32	Electrical machine, equipment, and supplies not elsewhere classified	.01168
33	Miscellaneous wood products	.01124
34	Miscellaneous chemicals	.01021
35	Dairy products	.01015
36	Bakery products	.00957
37	Other primary nonferrous industries	.00953
38	Furniture and fixtures	.00882
39	Fabricated structural metal products	.00835
40	Dyeing and finishing textiles, except wool and knit goods	.00792
41	Printing, publishing, and allied industries, except newspapers	.00780
42	Blast furnaces, steel works, rolling and finishing mills	.00728
43	Not specified professional equipment	.00710
44	Office and accounting machines	.00655
45	Not specified metal industries	.00630
46	Photographic equipment and supplies	.00609
47	Miscellaneous paper and pulp products	.00516
48	Other primary iron and steel industries	.00489
49	Miscellaneous fabricated metal products	.00459
50	Canning and preserving fruits, vegetables, and seafood	.00423
51	Footwear, except rubber	.00415
52	Miscellaneous petroleum and coal products	.003577
53	Mobile dwellings and campers	.003540
54	Meat products	.003251
55	Pottery and related products	.003249
56	Leather products, except footwear	.003090
57	Glass and glass products	.003054
58	Cutlery, hand tools, and other hardware	.001652
59	Paperboard containers and boxes	.001114
60	Not specified food industries	.001097
61	Not specified manufacturing industries	.000785
62	Miscellaneous manufacturing industries	.000784
63	Scientific and controlling instruments	.000705
64	Watches, clocks, and clockwork-operated devices	.000630
65	Miscellaneous food preparation and kindred products	−.000138
66	Miscellaneous nonmetallic mineral and stone	−.000595
67	Drugs and medicines	−.000653
68	Motor vehicles and motor vehicle equipment	−.001119
69	Primary aluminum industries	−.001193
70	Cycles and miscellaneous transportation equipment	−.001255
71	Metal stamping	−.001359
72	Aircraft and parts	−.002037
73	Machinery, except electrical, not elsewhere classified	−.002936
74	Ship and boat building and repairing	−.003132
75	Soaps and cosmetics	−.003367
76	Newspaper publishing and printing	−.004294
77	Metalworking machinery	−.006743
78	Engines and turbines	−.009734
79	Farm machinery and equipment	−.017799
80	Railroad locomotives and equipment	−.020352
81	Construction and material handling machines	−.020607
82	Tanned, curried, and finished leather	−.029667
83	Tobacco manufactures	−.038326

TABLE B1 (*Continued*)

C. Investment in Computers as a Share of Total Investment (1987)

CPS	Industry	Share of Investment
189	Electronic computing equipment	.230
207	Radio, TV, and communication equipment	.189
188	Office and accounting machines	.176
239	Scientific and controlling instruments	.175
397	Leather products, except footwear	.157
227	Aircraft and parts	.141
338	Newspaper publishing and printing	.138
258	Ordnance	.138
198	Not specified machinery	.135
229	Railroad locomotives	.132
209	Not specified electrical machinery, equipment, and supplies	.121
339	Printing, publishing, and allied industries, except newspapers	.109
257	Not specified professional equipment	.109
197	Machinery, except electrical	.103
398	Not specified manufacturing industries	.099
389	Footwear, except rubber	.097
259	Miscellaneous manufacturing industries	.092
187	Metalworking machinery	.090
208	Electrical machinery, equipment, and supplies	.089
228	Ship and boat building and repairing	.087
119	Glass and glass products	.084
357	Drugs and medicines	.083
248	Photographic equipment and supplies	.079
179	Construction and material handling machines	.077
247	Optical and health services supplies	.076
299	Tobacco manufactures	.073
177	Engines and turbines	.072
388	Tanned, curried, and finished leather	.072
158	Fabricated structural metal products	.067
359	Paints, varnishes, and related products	.065
327	Miscellaneous fabricated textile products	.065
319	Apparel and accessories	.065
237	Mobile dwellings and campers	.062
249	Watches, clocks, and clockwork-operated devices	.061
168	Miscellaneous fabricated metal products	.059
157	Cutlery, hand tools, and other hardware	.055
118	Furniture and fixtures	.053
137	Pottery and related products	.051
378	Miscellaneous petroleum and coal products	.050
309	Floor coverings, except hard surface	.047
159	Screw machine products	.046
238	Cycles and miscellaneous transportation equipment	.042
199	Household appliances	.041
138	Miscellaneous nonmetallic mineral and stone products	.038
279	Grain mill products	.038
148	Primary aluminum industries	.038
169	Not specified metal industries	.038
358	Soaps and cosmetics	.037
178	Farm machinery and equipment	.037
379	Rubber products	.037
269	Dairy products	.037
308	Dyeing and finishing textiles, except wool and knit goods	.036
149	Other primary iron and steel industries	.034

TABLE B1 (*Continued*)

C. Investment in Computers as a Share of Total Investment (1987)

CPS	Industry	Share of Investment
278	Canning and preserving fruits, vegetables, and seafood	.033
128	Structural clay products	.031
337	Paperboard containers and boxes	.030
387	Miscellaneous plastic products	.028
369	Not specified chemicals and allied products	.027
307	Knitting mills	.027
297	Miscellaneous food preparation and kindred products	.026
108	Sawmills, planing mills, and mill work	.025
368	Miscellaneous chemicals	.025
329	Miscellaneous paper and pulp products	.024
289	Beverage industries	.024
367	Agricultural chemicals	.023
347	Industrial chemicals	.023
298	Not specified food industries	.023
167	Metal stamping	.023
287	Bakery products	.020
219	Motor vehicles and motor vehicle parts	.020
318	Miscellaneous textile mill products	.020
348	Plastics, synthetics, and resins, except fibers	.018
139	Blast furnaces, steel works, rolling and finishing mills	.018
377	Petroleum refining	.016
328	Pulp, paper, and paperboard mills	.015
147	Other primary iron and steel industries	.014
288	Confectionery and related products	.014
268	Meat products	.014
127	Cement, concrete, gypsum, and plaster products	.012
317	Yarn, thread, and fabric mills	.012
109	Miscellaneous wood products	.007
349	Synthetic fibers	.002
107	Logging	.000

D. Company and Other (except Federal) R & D Funds as a Percentage of Net Sales in R & D–Performing Manufacturing Companies: Means over 1984–90

Industry	Mean R & D
Office, computing, and accounting machines	12.5714
Drugs and medicines	8.7429
Scientific and mechanical measuring instruments	8.5000
Electronic components	8.2143
Instruments	7.3286
Communication equipment	5.2571
Industrial chemicals	4.2714
Motor vehicles and motor vehicle equipment	3.4143
Radio and TV receiving equipment	3.3857
Other chemicals	3.3429
Other machinery, except electrical	2.8714
Other transportation equipment	2.3143
Stone, clay, and glass products	2.2714
Other electrical equipment	2.2286
Rubber products	1.7286

TABLE B1 (*Continued*)

D. Company and Other (except Federal) R & D Funds as a Percentage of Net Sales in R & D–Performing Manufacturing Companies: Means over 1984–90

Industry	Mean R & D
Nonferrous metals and products	1.3143
Fabricated metal products	1.2000
Other manufacturing industries	1.0857
Stone, clay, and glass products	1.0857
Professional and scientific instruments	1.0857
Petroleum refining and extraction	.9286
Paper and allied products	.7286
Lumber, wood products, and furniture	.6857
Ferrous metals and products	.6000
Food, kindred, and tobacco products	.5286
Textiles and apparel	.4429

E. Patents Used by Industry (Total of 1980–83 Divided by 1970–79)

Office and computing machines	.4366
Communication and electronics	.4049
Petroleum refineries and extractions	.3962
Other electrical equipment	.3779
Professional and scientific instruments	.3581
Other manufacturing	.3572
Drugs	.3528
Stone, clay, and glass products	.3478
Transportation equipment	.3418
Industrial chemicals	.3418
Fabricated metals products	.3414
Other nonelectrical machinery	.3386
Primary metals products	.3301
Rubber and plastics products	.3299
Other chemicals	.3280
Paper products	.3275
Aircraft and missiles	.3199
Food and kindred products	.3176
Lumber and furniture	.3166
Textiles and apparel	.2998

F. Share of Scientists and Engineers in Different Industries

Industry	Share in 1989
Transportation equipment	.116
Chemicals	.109
Electrical equipment	.108
Federal public administration	.104
Nonelectrical machinery	.103
Other professional services	.091
Instruments	.085
Utilities	.074
Business services	.070
Mining	.068
Petroleum	.065
Communication	.061

TABLE B1 (*Continued*)

F. Share of Scientists and Engineers in Different Industries

Industry	Share in 1989
State public administration	.044
Fabricated metals	.039
Primary metals	.033
Paper	.031
Stone, clay, and glass	.028
Rubber	.027
Construction	.020
Agriculture	.017
Textiles	.017
Insurance and real estate	.016
Food and tobacco	.0157
Banking and finance	.012
Wholesale	.012
Miscellaneous	.011
Leather	.011
Local public administration	.011
Education	.011
Transportation	.010
Lumber	.009
Hospitals	.008
Furniture	.008
Entertainment	.006
Printing	.006
Postal services	.005
Welfare and religious	.004
Repair services	.004
Medical services	.004
Other retail trade	.0024
Personal services	.002
Apparel	.002
Eating and drinking	.0004
Private household workers	.0

* The codes used by Jorgenson are in parentheses.

change. In addition, the data are reported for only 22 broad industry categories in the manufacturing sector, equivalent to two-digit SIC categories.

The NBER productivity database, described in Bartelsman and Gray (1996), contains annual information on TFP growth for 450 manufacturing industries for the time period 1958–89. The advantage of the NBER database over the Jorgenson database is its narrow industry categories yielding data on approximately 100 three-digit industries in manufacturing. Like the Jorgenson data, the NBER variable also has the disadvantage of being a residual measure of technological change. Another limitation of the NBER data is that the productivity growth measure was not adjusted for changes in labor quality.

The third measure of technological change that we use is investment in computers. During the 1980s, there was an enormous growth in the amount of computer resources used in the workplace. Indeed, it has been argued

TABLE B2

Correlation between the Different Measures of Technological Change

	Jorgenson TFP	NBER TFP	R & D to Sales	Patents	Scientists and Engineers
NBER TFP	.33				
R & D to sales	.38	.61			
Use of patents	.16	.52	.74		
Scientists and engineers	.38	.11	.70	.50	
Investment in computers	.24	.48	.62	.66	.30
	Rank (Spearman) Correlation				
NBER TFP	.32				
R & D to sales	.28	−.06			
Use of patents	.00	−.09	.70		
Scientists and engineers	.31	−.15	.80	.51	
Investment in computers	.24	−.15	.42	.50	.12

Note.—Since each measure is based on a different industrial classification, we use the sample weights for the correlations.

(see Bound and Johnson 1992) that the most concrete example of technological change in the 1980s was the ''computer revolution.'' Hence a more direct measure of technological change in the workplace may be the extent to which firms invest in information technology. Using data from the 1987 *Census of Manufactures*, we calculate the ratio of investment in computers to total investments. Berman et al. (1994) show that this measure is a good proxy for technological change in an industry. The advantages of the computer investment measure are that (1) unlike data on R & D expenditures, it measures *use* (not production) of an innovation and (2) it is available for several hundred four-digit industries in the manufacturing sector, which reduces to approximately 100 three-digit industries for the NLSY sample. A disadvantage of this measure is that it may not capture other types of innovations.

The fourth proxy for technological change is the ratio of company R & D funds to net sales reported by the National Science Foundation (1993) for industries in the manufacturing sector. The advantage of this variable is that it is a direct measure of innovative activity in the industry, but as indicated above, the innovative activity refers only to the industry in which the innovation originates, not the industry in which the innovation is actually used. Another limitation is that some R & D is an input to innovation, not an output.

A fifth indicator of technological change is the number of patents used in two-digit manufacturing industries. Patent data are generally collected by technology field and have not been available at the industry level. Kortum and Putnam (1995) present a method for predicting patents by ''industry of use'' in the United States using the information on the distribution of patents across technological fields and industries of use in the Canadian patent system. The data actually used here are the number of patents used by two-digit manufacturing industries analyzed by Lach (1995). For the 1957–83 period, Lach found that this measure is highly correlated with TFP growth. Because the likelihood that an innovation will be patented has differed historically across technology fields and, hence, across industries, we control for these systematic differences by constructing the following variable for each digit manufacturing industry: the number of patents used during the years 1980–83 (which are closest to our starting year, 1987) divided by the number of patents used during the 1970s. The main advantage of proxying technological change by industry of use is that, like the computer investment variable discussed earlier, it measures the direct use of innovations. However, as usual with patent data, because many innovations are not patented and many patented innovations are not used, patents could still be a noisy proxy for innovations. The disadvantage is that the data are reported for only 20 manufacturing industries.

The sixth measure of technological change is the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996). Allen shows that this measure is highly correlated with the R & D to sales ratio in the industry. Like the computer investment and patent variables, it refers to the industry in which the innovation is used, not produced. But, as Allen points out, since scientists and engineers are more highly paid than other college graduates, the wage impact of the technological change resulting from increased innovative activity may be overstated when this measure is used.

Appendix C

TABLE C1

Industry Random-Effects Regression Results, Workers in Manufacturing Industries, 1979–93 (Sample of All Coefficient Estimates)

Dependent Variable: Log of Real Hourly Wage

Independent Variable	All Workers (N = 13,061)	Production Workers (N = 8,074)	Nonproduction Workers (N = 4,537)
Marital status (married = 1)	.0776	.0879	.0530
	(10.2)	(9.88)	(3.75)
Race (1 = nonwhite)	−.068	−.0600	−.0624
	(8.74)	(6.71)	(4.21)
Sex (1 = female)	−.1729	−.1924	−.1808
	(21.7)	(18.7)	(13.4)
Years of schooling:*			
1–8	−.2241	−.2114	−.2603
	(12.1)	(10.8)	(4.85)
9–11	−.1096	−.0913	−.1478
	(11.1)	(8.56)	(5.95)
13–15	.14316	.07979	.16894
	(12.7)	(5.43)	(9.16)
16	.44408	.24304	.43744
	(29.9)	(7.17)	(20.6)
17+	.62880	.31904	.62661
	(24.9)	(4.70)	(19.4)

TABLE C1 (*Continued*)

Independent Variable	All Workers (N = 13,061)	Production Workers (N = 8,074)	Nonproduction Workers (N = 4,537)
Lives in an SMSA	.12004	.08846	.17904
	(14.2)	(9.32)	(10.3)
Market experience	.03112	.01757	.05219
	(8.05)	(3.83)	(6.93)
Market experience^2	−.0008	−.0001	−.0018
	(4.44)	(.73)	(4.59)
Tenure	.05760	.06167	.04745
	(16.4)	(14.9)	(7.32)
Tenure^2	−.0028	−.0032	−.0020
	(9.51)	(9.27)	(3.73)
Union membership	.11430	.14106	.06483
	(12.8)	(14.7)	(2.97)
Durables	.05038	.07907	.01995
	(2.77)	(3.56)	(1.04)
Industry unemployment	.00246	.00279	.00405
	(.94)	(.51)	(.00)
Industry job creation (1980–88)	−.0264	−.0232	−.0182
	(4.84)	(3.48)	(2.73)
Industry job destruction (1980–88)	.00718	.00538	.0273
	(1.32)	(.859)	(3.97)
Year dummies:†			
1980	−.0639	−.0641	.01356
	(2.52)	(2.37)	(.22)
1981	−.0891	−.0814	−.0174
	(3.58)	(3.03)	(.30)
1982	−.0963	−.0863	.04926
	(3.36)	(2.71)	(.80)
1983	−.1429	−.1285	−.0121
	(5.07)	(4.07)	(.20)
1984	−.1879	−.1632	−.1428
	(7.82)	(6.10)	(2.58)
1985	−.1626	−.1498	−.0780
	(6.55)	(5.50)	(1.35)
1986	−.1761	−.1729	−.0718
	(6.96)	(6.22)	(1.22)
1987	−.1548	−.1671	−.0481
	(6.10)	(5.87)	(.83)
1988	−.1370	−.1440	−.0526
	(5.22)	(4.88)	(.89)
1989	−.1634	−.1868	−.0663
	(6.12)	(6.21)	(1.11)
1990	−.1983	−.2338	−.0625
	(7.21)	(7.55)	(1.02)
1991	−.1986	−.2171	−.0816
	(6.77)	(6.50)	(1.29)
1992	−.2196	−.2337	−.1026
	(7.23)	(6.76)	(1.58)
1993	−.2127	−.2354	−.0795
	(6.86)	(6.67)	(1.20)
Technological change	.02655	.02403	−.0078
	(1.86)	(1.25)	(.88)
Constant	2.0265	2.0806	1.7748
	(29.6)	(25.1)	(19.6)

* 12 years of schooling is excluded.
† The year 1979 is excluded.

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