Technological Change and the Skill Acquisition of Young Workers

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Since technological change influences the rate at which human capital obsolesces and also increases the uncertainty associated with human capital investments, training may increase or decrease at higher rates of technological change. Using the National Longitudinal Survey of Youth, we find that production workers in manufacturing industries with higher rates of technological change are more likely to receive formal company training. At higher rates of technological change, the training gap between the more and less educated narrows, low-skilled nonproduction workers receive significantly more training than higher-skilled nonproduction workers, and the proportion of individuals receiving training increases.

I. Introduction

Economists have been long interested in the effect of technological change on the labor market. In the 1950s, the Bureau of Labor Statistics

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began its case studies of the effect of "automation" on employment. More recently, researchers' attention has focused on the effect of technological change on the wage structure (Lillard and Tan 1986; Mincer 1989; Allen 1992; Krueger 1993; Berman, Bound, and Griliches 1994; Bartel and Sicherman 1997), the demand for educated workers (Bartel and Lichtenberg 1987, 1991), intercountry differences in wage structures (Mincer and Higuchi 1988), and retirement decisions of older workers (Bartel and Sicherman 1993). The observed increase in wage inequality between college and high school graduates in the 1980s might be interpreted to imply that the status of less educated workers will deteriorate with the pace of technological change. But this prediction ignores other adjustments that may occur in the marketplace, one of which is a change in the postschooling investment of different education groups. In this article, we utilize a cross-sectional framework to investigate the effect of industry rates of technological change on young workers' investments in on-the-job training. While two earlier studies, Lillard and Tan (1986) and Mincer (1989), did consider the effect of technological change on the training of young workers, both of these papers have limitations which our article overcomes.[1]

Economic theory does not provide a clear prediction on the sign of the relationship between technological change and investments in training. Observed investments in training are the outcome of a supply and demand interaction of employers and workers, and technological change will influence the incentives of both parties. One argument is that technological change makes formal education and previously acquired skills obsolete. As a result, both workers and firms will find it optimal to invest in on-the-job training in order to match the specific requirements of each wave of innovation.[2] In accordance with this view, technological change should spread investment in human capital, thus increasing investment in training and reducing investment in formal education. The alternative view is that general education enables workers to adjust to and benefit from technological change (Welch 1970). Workers who expect to experience higher rates of technological change on the job should, therefore, invest more in schooling and rely less on acquiring specific training on the job. This prediction is based on the assumption that differences in expected rates of technological change do affect educational choices. For the young workers whom we study, differences in the rates of technological change

[1] Lillard and Tan (1986) used the Current Population Survey and the National Longitudinal Survey Samples of Young Men and Young Women, while Mincer (1989) analyzed the young workers in the Panel Study of Income Dynamics. Unlike this study, they use limited information on training and rely on only one measure of technological change.

[2] This is the argument underlying the model developed by Tan (1989).

across industries are likely to reflect differences in expectations faced by young workers that chose different careers.[3]

Higher rates of technological change are also likely to increase the uncertainty associated with investments in human capital in the sense that the output from a given level and type of human capital is more uncertain. Levhari and Weiss (1974) have shown, however, that uncertainty has an ambiguous effect on human capital investments. If increased uncertainty implies an increase in the variance of the returns to human capital, investments will decrease (under standard assumptions such as risk aversion of workers.) But some types of human capital (e.g., general education) may facilitate adjustment to future shocks, which would lead to a decrease in the variance of returns. Investments in this type of human capital would increase, while investments in more specific types of human capital would decrease.

We can also derive implications for the way in which technological change is likely to affect the relationship between education and training. In general, more educated workers train more, either because human capital is an input in the production of new human capital (Mincer 1962; Rosen 1976) or because individuals who are better "learners" will invest more in both schooling and training. They will train less, however, the greater the substitutability is between schooling and training in performing job tasks. As we later show, in general, the complementarity between training and schooling dominates the substitutability.[4] However, if the general skills of the more educated enable them to adapt faster to new technologies, the substitutability between schooling and training will be greater at higher rates of technological change. If this is true, then, at higher rates of technological change, we will observe a narrowing of the postschool-training gap between the less and more educated workers.

In sum, there are a number of avenues by which technological change influences training decisions, and as we have shown, unambiguous predictions do not exist. We conduct a detailed empirical analysis that can assess the relative importance of the competing effects. Our work improves on previous research in this area in a number of ways.

One problem with earlier work on training and technological change was the limited available information on training. We use the National Longitudinal Survey of Youth (NLSY), which is unique in terms of the comprehensiveness of the training information that is reported. Unlike

[3] For older workers, these same differences may reflect unexpected changes that cannot affect schooling decisions and will, therefore, be more likely to increase training as part of the existing human capital is destroyed. In Bartel and Sicherman (1993), we also studied the effects of expected and unexpected technological change on the retirement decisions of older workers.

[4] Sicherman (1991) provides evidence of the substitutability between schooling and training.

other data sets, it includes detailed information on all formal training spells experienced by the individual, including the duration of the training.[5] With this data set, we conduct a more comprehensive and reliable study of the training effects of technological change. The NLSY has the added advantage of providing data through 1992, enabling us to conduct a more current analysis than previous studies.

The second way in which we improve on previous research is by utilizing a variety of measures of technological change. Estimating the rate of technological change faced by the worker in his job is very difficult. Since the measurement of technological change outside the manufacturing sector is very problematic (Griliches 1994), our analysis is restricted to workers in manufacturing. Even within this sector, however, no single proxy is likely to be perfect. We, therefore, link the NLSY with several alternative data sets that contain proxies for industries' rates of technological change. Specifically, our analysis uses the Jorgenson productivity growth series, the National Bureau of Economic Research (NBER) productivity data, the Census of Manufactures series on investment in computers, the R&D-to-sales ratio in the industry, and the industry's use of patents. Previous studies on training and technological change relied primarily on the Jorgenson productivity growth series. Our analysis enables us to examine the robustness of alternative measures of technological change, thereby increasing confidence in the results.

Third, unlike the earlier research, we carefully dissect the relationship between technological change and training in order to answer the following questions: (1) How does technological change affect training investments for workers with different levels of education? (2) Does technological change increase both entry-level training and training of more experienced workers? (3) Does the pool of trainees increase in response to technological change, or is it mainly the previously trained workers who train more intensively? To our knowledge, this is the first article to address these important questions.

In Section II, we discuss the data sources for our study, explain the various measures of training and technological change, and present the basic equations that we estimate. Regression results are discussed in Section III, and a summary is given in Section IV.

II. Empirical Framework

A. Microdata

We use the main file and the work-history file of the 1987–92 National Longitudinal Survey of Youth ages 14–21 in 1979 and restrict our analysis

[5] Although Lynch (1991, 1992*a*) used the National Longitudinal Survey of Youth (NLSY) data to study the determinants of private-sector training, her

to males in manufacturing (see app. A). The main file is the source of information on personal characteristics such as main activity during the survey week, education, age, race, marital status, health status, and so forth. An individual enters our sample when he first reports that his 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 separations, constructed from the main NLSY file. For each respondent, employment information is reported for a maximum of five jobs in each survey year. The work-history file enables us to distinguish information for each job, especially the reasons for and timing of job transitions. One of these jobs is designated as a "CPS job," and it is the most recent or current job at the time of the interview. Typically it is also the main job. There are a host of important questions that are asked for the CPS job only, such as industry, occupation, and firm size. Hence, our analysis is restricted to CPS jobs.

The NLSY is particularly well suited for a study of employee training because of the vast amount of information on the subject that is recorded.[6] Data on a maximum of seven different training programs taken at any time since the last interview are included. Beginning with the 1988 survey, data on the following items are available for each of the seven training programs, excluding government programs: starting and ending dates of the training program, the number of weeks that the individual attended the program, what type of program it was,[7] and how many hours he usually devoted per week to this program. In the NLSY, company training encompasses three types of training: (1) training run by the employer; (2) training run at work, not by employer; and (3) company training outside of work.

Prior to 1988, detailed information on type of private-sector training, as well as the weeks and hours per week spent in training, were only recorded if the training spell lasted at least 4 weeks. In other words, for the 1979–86 time period, the researcher can measure incidence of private-sector and government training, but it is impossible to determine if the private-sector training was company-provided training, an apprenticeship program, or obtained in other ways, such as a vocational or technical institute, business college, or correspondence course. In addition, even if the training spell lasted at least 4 weeks, the measure of training duration

work did not analyze the role played by technological change. In addition, as we discuss in Section IIA, we use a more accurate estimate of training duration.

[6] Like most other data sets, the NLSY provides information only on formal training. Ignoring informal training, a major portion of on-the-job training, is a drawback (see Sicherman 1990).

[7] Types of training programs are apprenticeships, company training, technical or vocational training off the job (such as business college, vocational and technical institutes, and correspondence courses), and government training.

provided in the pre-1988 surveys is extremely unreliable because it is based on the starting and ending dates of the training program.[8] In 1987, no training questions were asked. However, training information for 1987 can be imputed from the 1988 data, thereby enabling us to add 1 more year of data to our analysis; the regressions we report cover the time period 1987–92.

Table 1 reports the incidence and duration of private-sector training, by education and size of firm, for the manufacturing sector for the 1988–92 time period. In panel I, the production and nonproduction workers are combined, while panels II and III show the separate results for each of the occupation groups. Incidence and duration are calculated on an annual basis. On average, 17% of the individuals reported receiving private-sector training during the "12"-month period between consecutive surveys.[9] For production workers, the incidence is 13%, while it is 25% for nonproduction workers. Median duration of training (for workers with positive hours) was 40 hours, that is, approximately 1 week, and the mean duration was 137 hours, or approximately 3 ½ weeks. The results in panels II and III show that, while the incidence of training is lower for production workers, duration of training is higher. Production workers have a median duration of 48 hours and a mean duration of 180 hours, while nonproduction workers have a median of 40 hours and a mean of only 101 hours. The probability of receiving private-sector training increases monotonically with education, with the exception of nonproduction workers with 13–15 years of education. The relationship between training duration and education is not monotonic; as we show below, this occurs because of the association between type of private-sector training and education level.

The detailed data from the 1988–92 surveys can be used to calculate the distribution of private-sector training across three categories: (1) company, or in-house, training; (2) apprenticeships; and (3) other training, such as training received in a business college, a vocational or technical institute, or a correspondence course. For the entire sample, approximately 76% of private-sector training is provided by the company. This percentage ranges from a low of 55% for the lowest education group to a high of 95% for the highest education group. For production workers, 64% of private-sector training is provided by the company, while nonproduction workers receive 88% of their private training through the company. In panel I, we see that company training has a median duration of

[8] For example, if an individual reported starting a training program in January of the survey year and finishing it in December of that year, training duration would be recorded as 52 weeks, even if the individual had only received 1 day of training per month.

[9] Fifty-six weeks is the average length of time between survey dates.

Table 1
Annual Incidence and Duration of Private-Sector Training, by Type of Training and Schooling Level, for Males in Manufacturing Industries, 1988–92

	All Workers			Schooling < 12			Schooling = 12			Schooling 13–15			Schooling 16+		
		Hours Trained			Hours Trained			Hours Trained			Hours Trained			Hours Trained	
	% Trained	*M*	Median	% Trained	*M*	Median	% Trained	*M*	Median	% Trained	*M*	Median	% Trained	*M*	Median
I. Production and nonproduction workers:															
All firms:															
All training	17.4	137	40	10.1	122	48	15.7	194	40	17.6	111	40	30.6	93	40
	[4,045]	(319)		[929]	(176)		[1,722]	(424)		[607]	(230)		[723]	(240)	
Company	13.2	102	40	5.6	77	40	10.5	130	40	14.2	95	40	28.9	87	36
		(260)			(104)			(322)			(219)			(240)	
Apprenticeship	1.1	482	290	1.1	500	400	1.5	552	174	1.0	52†	52	.1	560*	N.A.
		(686)			(316)			(893)							
Other	3.6	215	80	3.8	100	48	4.2	286	80	3.4	168	55	1.9	140	98
		(377)			(116)			(476)			(260)			(133)	
Large firms:															
All training	23.2	129	40	10.2	126	48	18.7	176	40	22.8	102	40	39.2	106	40
	[1,842]	(311)		[284]	(205)		[796]	(408)		[302]	(225)		[460]	(265)	
Company	19.8	99	40	7.4	73	40	14.7	111	32	18.9	88	32	36.7	98	40
		(247)			(94)			(257)			(208)			(266)	
Apprenticeship	1.1	758	525	.7	600†	600	1.6	1,012	525	1.6	3.2*	3.2	.2	560*	N.A.
		(886)						(1,115)							
Other	3.1	181	54	2.8	103	48	3.0	253	70	4.0	142	40	3.0	140	98
		(322)			(104)			(441)			(282)			(133)	
Small firms:															
All training	12.5	152	40	10.1	120	52	13.2	219	50	12.4	131	52	15.2	44	24
	[2,198]	(333)		[641]	(155)		[975]	(448)		[305]	(241)		[263]	(80)	
Company	7.7	107	36	4.8	82	44	7.0	164	40	9.5	109	40	15.2	44	24
		(289)			(116)			(416)			(244)			(80)	
Apprenticeship	1.0	206	100	1.2	433‡	400	1.3	91‖	40	.3	100*	N.A.	0	0	
		(211)													
Other	4.0	243	80	4.2	99	68	5.2	304	80	2.9	240§	192	0	0	
		(419)			(125)			(498)							

II. Production workers:															
All firms:															
All training	13.3	180	48	9.8	122	44	13.8	210	40	16.6	194	84	.248	75	50
	[2,635]	(357)		[802]	(182)		[1,417]	(424)		[325]	(323)		[77]	(94)	
Company	8.5	133	40	5.5	70	40	8.6	151	39	12.0	174	50	.234	53	50
		(317)			(82)			(376)			(326)			(38)	
Apprenticeship	1.4	386	290	1.2	500	400	1.5	333	167	1.5	100*	N.A.	0	0	
		(403)			(316)			(470)							
Other	3.8	239	80	3.5	90	36	4.0	313	80	4.3	204	84	.013	400*	N.A.
		(399)			(120)			(484)			(311)				
Large firms:															
All training	16.8	160	42	9.9	135	44	16.2	169	40	23.8	181	72	.428	91	65
	[1,052]	(305)		[232]	(225)		[634]	(338)		[151]	(319)		[35]	(104)	
Company	13.3	123	40	7.3	83	40	12.8	131	31	18.5	159	40	.410	63	50
		(267)			(101)			(298)			(305)			(38)	
Apprenticeship	1.5	681	525	.9	600*	600	1.6	735‡	525	2.6	...		0	0*	N.A.
		(509)													
Other	2.9	179	48	2.6	68	32	2.5	209	80	5.3	172	44	.028	400*	N.A.
		(279)			(98)			(304)			(329)				
Small firms:															
All training	10.9	208	50	9.9	113	44	11.8	268	52	10.3	222	109	.095	26	26
	[1,578]	(417)		[566]	(150)		[782]	(519)		[174]	(345)		[42]	(22)	
Company	5.3	153	40	4.8	58	40	5.1	202	40	6.3	211	60	.095	26	26
		(402)			(60)			(518)			(387)			(22)	
Apprenticeship	1.3	206	100	1.4	433‡	400	1.5	91	40	.6	100*	N.A.	0	0	
		(211)						(138)							
Other	4.4	279	96	3.9	99	40	5.2	365	88	3.4	332†	332	0	0	
		(460)			(130)			(550)							
III. Nonproduction workers:															
All firms:															
All training	25.1	101	40	12.0	127	80	23.4	158	45	18.9	46	28	.313	94	36
	[1,407]	(278)		[126]	(151)		[355]	(426)		[281]	(56)		[645]	(249)	
Company	22.0	82	36	6.3	111	43	18.0	87	40	16.7	40	32	.296	90	32
		(214)			(183)			(169)			(39)			(250)	
Apprenticeship	.4	855	314	0	0		1.1	1,429*	N.A.	.3	32*		.001	560*	
		(1,313)													
Other	3.2	155	72	5.5	159‡	140	5.1	205	36	2.5	96	55	.020	103	96
		(316)						(459)			(95)			(89)	

Table 1 (*Continued*)

	All Workers			Schooling < 12			Schooling = 12			Schooling 13–15			Schooling 16+		
	% Trained	Hours Trained *M*	Hours Trained Median	% Trained	Hours Trained *M*	Hours Trained Median	% Trained	Hours Trained *M*	Hours Trained Median	% Trained	Hours Trained *M*	Hours Trained Median	% Trained	Hours Trained *M*	Hours Trained Median
Large firms:															
All training	31.8	109	40	11.5	91	56	28.4	191	40	21.8	37	15	.390	107	40
	[190]	(314)		[52]	(99)		[162]	(547)		[151]	(43)		[425]	(275)	
Company	28.3	85	36	7.7	25‡	10	22.2	62	36	19.2	35	14	.365	101	39
		(234)						(67)			(40)			(276)	
Apprenticeship	.6	855	314	0	0		1.8	1,429*	N.A.	.7	3.2*		.002	560*	
		(1,313)													
Other	3.4	184	96	3.8	190†	N.A.	4.9	367	36	2.6	61‡	25	.030	103	96
		(399)						(726)						(89)	
Small firms:															
All training	16.5	81	33	12.2	171	88	19.2	120	50	15.4	63	40	.164	46	24
	[617]	(330)		[74]	(208)		[193]	(224)		[130]	(74)		[220]	(85)	
Company	13.9	73	31	5.4	197‡	80	14.5	115	40	13.8	48	40	.164	46	24
		(152)						(236)			(38)			(86)	
Apprenticeship	.2	0		0	0		.5	0		0	0		0	0	
Other	2.9	111	64	6.7	96*	N.A.	5.2	104	49	2.3	147†		0	0	
		(150)						(171)							

NOTE.—N.A. = not applicable. Numbers in square brackets are *N*. Numbers in parentheses are SDs for hours trained. *M* and median hours are calculated for positive hours only.
* 1 observation.
† 2 observations.
‡ 3 observations.
§ 4 observations.
‖ 5 observations.

40 hours for all education groups. This is considerably shorter than the median duration of apprenticeships and somewhat shorter than the duration of other private-sector training. Thus, although more educated individuals are more likely to receive private-sector training, their training duration is shorter because their skills are acquired in company training programs rather than apprenticeships or other outside programs.[10]

We distinguished large from small firms on the basis of whether the number of employees in the individual's firm was at least 1,000. Panel I shows that the incidence of company-provided training in large firms is 20% compared with only 7.7% in small firms, confirming the earlier findings of Barron, Black, and Loewenstein (1987). The positive effect of firm size on the incidence of training holds for all education groups.

B. Measures of Technological Change

In the absence of a direct measure of the rate of technological change faced by the individual in his place of work, we link the NLSY with several alternative data sets that contain proxies for the industry's rate of technological change.[11] Below we describe each of these measures and analyze their strengths and weaknesses. Since no single proxy is a perfect measure, we feel it is important to use several alternative measures in our analysis. If similar results are obtained with different measures, we can have more confidence in the reliability of the findings.[12]

The five measures of technological change that we use are (1) the total factor productivity growth series calculated by Jorgenson, Gollop, and Fraumeni (1987) and updated through 1989; (2) the NBER total factor productivity growth series; (3) 1987 Census of Manufactures' data on investment in computers; (4) the R&D-to-sales ratio in the industry as reported by the National Science Foundation, and (5) the number of patents used in the industry. Each of these measures has advantages and disadvantages as we describe below.

The Jorgenson total factor productivity series has been used extensively in previous research (e.g., Lillard and Tan 1986; Mincer and Higuchi

[10] This also explains why training duration is longer for production workers than nonproduction workers. Production workers receive a greater share of their training outside the firm where average durations are longer.

[11] An alternative approach would be to collect data from a small sample of firms that are undergoing technological change and analyze the effect on their employees. The disadvantage of this approach 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.

[12] Another approach is to create a composite index of technological change similar to the one used by Lichtenberg and Griliches (1989). Because of the different levels of aggregation in our measures of technological change, we do not employ this method here.

1988; Tan 1989; Gill 1990; and Bartel and Sicherman 1993). 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.[13] One problem with this approach is that, in addition to technological change, other factors, such as fluctuations in capacity utilization and nonconstant returns to scale, are also likely to affect productivity growth. In order to account for such effects, the empirical analysis will include controls for the industry unemployment rate, the rates of entry and exit of firms in the industry, and the capacity utilization rate. The Jorgenson series is currently available for the time period 1947–89. The main advantage of the Jorgenson series is that changes in the quality of labor input are carefully used to correctly measure net productivity growth. Also, the new Jorgenson series utilizes the Bureau of Economic Analysis constant-quality price deflator; 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 change. In addition, the data are reported for only 22 broad industry categories in the manufacturing sector, equivalent to 2-digit standard industrial classifications.

The NBER manufacturing-productivity database, described in Bartelsman and Gray (1996), contains annual information on total factor productivity growth for 450 (4-digit) 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 83 3-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 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 (see Bound and Johnson 1992) that the most concrete example of technological change in the 1980s was the "computer revolution."[14] Hence the extent to which

[13] There is some evidence that total factor productivity growth is a good indicator of innovative activity in an industry. For example, using data on 28 sectors from the Census-Penn-Stanford Research Institute data set, Griliches and Lichtenberg (1984) found that, for the time period 1959–76, there was a significant relationship between an industry's intensity of private R&D expenditures and subsequent growth in productivity. Lichtenberg and Siegel (1991) also found that this relationship existed at the company level in the 1970s and 1980s.

[14] Krueger (1993) used data from the October 1984 and 1989 Current Population Surveys to show that workers who use computers on their job earn 10%–15% higher wages.

firms invest in information technology can serve as a good proxy for the rate of technological change at the workplace. Using data from the 1987 Census of Manufacturers, we calculate the ratio of investment in computers to total investments. The advantages of this 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 4-digit industries in the manufacturing sector, which reduces to approximately 100 3-digit industries for the NLSY sample. A disadvantage of this measure is that it may not capture other types of innovations.

A 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 where 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 2-digit manufacturing industries.[15] 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 2-digit manufacturing industries analyzed by Lach (1995). For the 1957–83 period, Lach (1995) found that this measure is highly correlated with total factor productivity (TFP) growth. Because the likelihood of an innovation being patented has differed historically across technology fields, and, hence, across industries, we control for these systematic differences by constructing the following variable for each 2-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. Another concern is that the patent data are only reported for 20 manufacturing industries.

We have examined the rankings of the various industries on the basis of

[15] See Griliches (1990) for evidence of the link between patent statistics and technological change.

Table 2
Correlations between the Different Measures of Technological Change

	Jorgenson TFP	NBER TFP	R&D-to-Sales Ratio	Patents
NBER TFP	.31			
R&D-to-sales ratio	.47	.65		
Use of patents	.35	.65	.71	
Investment in computers	.40	.52	.65	.65

NOTE.—NBER = National Bureau of Economic Research. TFP = total factor productivity. These correlations are calculated by using the individual-level data that contain the five technological change proxies for each individual's industry.

the five different measures of technological change in order to determine whether the five proxies produce similar patterns regarding high and low technological change industries in the manufacturing sector. The listings, not reported here to conserve space,[16] showed that some industries consistently appear at or near the top of each measure's list. When 2-digit industry classifications were used, nonelectrical and electrical machinery ranked at the top. When a more detailed classification was used, the top-ranking industries were electronic computing equipment; radio, television, and communication equipment; and office and accounting machines—all subcategories of the broader nonelectrical machinery and electrical machinery categories.

A closer look at the five measures indicated, however, that they are different enough so that they each capture a facet of the industry rate of technological change. For example, according to the computer-investment measure, the leather-product industry has a relatively high rate of technological change, but this is not captured by the other proxies. By comparison, petroleum refining ranks high for the Jorgenson and NBER productivity measures and the patent variable but not for the other three proxies. Additional comparisons of the five listings also demonstrated that, in many cases, the rankings are dissimilar.

The correlations among the five measures, given in table 2, show that no two measures are perfectly correlated, and, therefore, there is no redundancy in using all of them in our analysis. The correlations between the different measures range from .3 to .7, which is consistent with our argument that each proxy is likely to capture a different aspect of technological change.[17] If all proxies produce similar results about the effect of

[16] See Bartel and Sicherman (1995) for the complete listings.

[17] One factor that affects the correlations is the different levels of aggregation used to construct the different measures. We calculated the correlations by using the individual-level data that contains the five technological change proxies for each individual's industry.

technological change on training, confidence in our conclusions will be significantly enhanced.

C. Matching the Microdata and Industry Measures of Technological Change

Since there is a high degree of randomness in annual changes in the measures that are available on an annual basis and the true variation is likely to be greater across industries than within industries, our analysis relies on cross-sectional variations in technological change, where the effects of measurement errors will be less severe.[18] All of 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 effect for all of the occupations in that industry. For example, an innovation in the industry's production processes may have little or no effect on clerical employees. Since, in most cases, production workers are more likely to be affected by technological change in the manufacturing sector, we conduct 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 most recent 10-year time period, that is, 1977–87. In the case of investment in computers, we use data from 1987 as described earlier. The R&D-to-sales ratio for each industry is calculated as a 3-year moving average for the 3-year period prior to the year of analysis, for example, averaging data for 1984–86 for the 1987 NLSY, and so forth. 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. Hence, with the exception of the R&D variable, we use a fixed time-period measure of technological change that 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 training and our measures of technological change. They are the annual industry unemployment rate obtained from Employment and Earnings, annual measures of percent unionized in the industry compiled from the CPS by Hirsch and MacPherson (1993), and the annual rates of job creation and job

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

destruction for both start-up and continuing establishments in the industry constructed by Davis and Haltiwanger (1992).[19]

Another 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. In order to deal with this issue, we reestimated all the models reported in this article, using linear-probability random-effect models. None of the findings reported here were changed in a significant way. We chose to present the logit estimates because a linear model is an inappropriate specification in the case of a discrete-choice model, even though the estimation results are often similar to those obtained by maximum-likelihood estimation (see Dhrymes 1978, pp. 331–34).

D. Econometric Model

Our econometric analysis is restricted to company training because, as was shown in table 1, three-quarters of private-sector training is provided by the firm. We do provide some evidence of the effect of technological change on other forms of private-sector training and contrast these effects with those for company training.

In order to estimate the effect of technological change on the likelihood of company training, we adopt a simple logit framework.[20] In each period, between two surveys, an individual will face one of the following two alternatives described by m: engage in company training ($m = 1$), or not ($m = 0$).

The choice m occurs when the latent variable $Y^*_{it} > 0$, where

$$Y^*_{it} = X_{it}\alpha + \delta T_{it} + \varepsilon_{it}, \tag{1}$$

where i is the individual index, t is time, m is the alternative, and X_{it} is a vector of individual, job, and industry characteristics that may vary over time. The vector X includes the following variables: marital status, race, years of education, residence in a standard metropolitan statistical area,

[19] We also added annual measures of capacity utilization by 2-digit industry, constructed by the Federal Reserve Board. Adding this variable serves two purposes. First, it makes the Jorgenson and NBER productivity growth variables cleaner proxies for technological change. Second, it enables us to test whether firms provide more training during recessionary periods. We found that the capacity utilization variable was insignificant and its inclusion did not affect any of our results.

[20] In Bartel and Sicherman (1995), we also utilized a standard Tobit model to estimate the effects of technological change on the amount of time spent in company training. We found that technological change had no effect on the duration of training.

years of experience and its square, tenure and its square, union membership, whether or not the individual is employed by a large firm, the industry unemployment rate, union coverage in the industry, and job creation and destruction in the industry. The variable T_{it} is the rate of technological change in the industry in which the individual is working at time t. In order to test whether the effect of technological change varies by education or occupation group, in some of our specifications we interact the proxies for technological change with education or occupation group.

This specification treats technological change as an exogenous variable. It is possible that the decision to adopt a technology will depend on the trainability of a firm's workforce, making technological change an endogenous variable. However, since we measure the rate of technological change at the industry level, using multiyear means, it is reasonable to assume that firms and workers treat these measures of technological change as exogenous.[21]

As the discussion in Section I demonstrated, the sign on T_{it} is indeterminate. If high rates of technological change make previously acquired skills obsolete, workers and employers have an incentive to invest in on-the-job training to match the specific requirements of the new technology. Alternatively, investments in general training (education) may be substituted for specific on-the-job training if such investments enable the worker to more easily adapt to change. Similarly, viewing technological change as contributing to increased uncertainty about the payoffs from investments leads to an ambiguous prediction that depends on the way in which such investments enable the worker to adjust to future shocks.

Assuming that ε is logistically distributed gives rise to a logit model in which the underlying probabilities are

$$P_m = \frac{\exp(Z\beta_m)}{\sum_{k=0}^{1} \exp(Z\beta_k)}, \quad m = 0, 1, \tag{2}$$

where $Z = X$ and T, from equation (1).

In order to identify the parameters, the normalization $\beta_0 = 0$ is imposed, and the estimated parameters are obtained by maximum likelihood.

III. Results

A. Incidence of Company Training

Table 3 reports the mean differences in the incidence of company training for workers in industries with high and low rates of technological

[21] In addition, the simultaneity problem is also minimized by the fact that our technological change proxies are dated prior to the training variables.

Table 3
Annual Incidence of Private-Sector Company Training by Schooling Level, for Males in Manufacturing Industries, 1988–92: "High-Tech" and "Low-Tech" Industries

	Years of Schooling				
	All Schooling Groups	<12	12	13–15	16+
I. All workers:					
A. All firms:					
High	.173	.059	.142	.181	.330
	(2,041)	(388)	(850)	(364)	(436)
Low	.090	.054	.070	.082	.226
	(2,004)	(541)	(922)	(243)	(287)
B. Large firms:					
High	.235	.084	.176	.228	.389
	(1,075)	(131)	(426)	(215)	(303)
Low	.145	.065	.113	.092	.325
	(767)	(153)	(370)	(87)	(157)
C. Small firms:					
High	.104	.047	.106	.114	.195
	(963)	(255)	(423)	(149)	(133)
Low	.057	.049	.042	.077	.108
	(1,235)	(386)	(552)	(156)	(130)
II. Production workers:					
A. All firms:					
High	.103	.060	.106	.138	.250
	(1,392)	(381)	(760)	(203)	(44)
Low	.066	.050	.062	.090	.212
	(1,243)	(421)	(657)	(122)	(33)
B. Large firms:					
High	.157	.099	.151	.191	.421
	(597)	(111)	(357)	(110)	(19)
Low	.101	.050	.097	.171	.375
	(455)	(121)	(277)	(41)	(16)
C. Small firms:					
High	.061	.045	.065	.075	.120
	(792)	(268)	(402)	(93)	(25)
Low	.046	.050	.037	.049	.059
	(786)	(298)	(380)	(81)	(17)
III. Nonproduction workers:					
A. All firms:					
High	.303	.064	.292	.248	.352
	(682)	(31)	(137)	(153)	(361)
Low	.142	.063	.110	.070	.225
	(725)	(95)	(218)	(128)	(284)
B. Large firms:					
High	.343	.062	.301	.292	.389
	(460)	(16)	(73)	(96)	(275)
Low	.200	.083	.157	.018	.320
	(330)	(36)	(89)	(55)	(150)
C. Small firms:					
High	.221	.067	.281	.175	.232
	(222)	(15)	(64)	(57)	(86)
Low	.094	.051	.077	.109	.119
	(395)	(59)	(129)	(73)	(134)

NOTE.—We use R&D-to-sales ratio and define "high" and "low" using the median rate of technological change for the sample. We distinguished large from small firms on the basis of whether the number of employees in the individual's firm was at least 1,000. The same table, using other indicators, is available on request from us. *N*s are in parentheses.

Table 4
The Effects of Technological Change on the Likelihood of Company Training in the Manufacturing Sector: Maximum Likelihood Logit Estimation Results

	All		Production		Nonproduction	
	Coefficient (1)	Derivative (2)	Coefficient (3)	Derivative (4)	Coefficient (5)	Derivative (6)
I. Jorgenson TFP	25.26	.021	32.95	.018	9.56	.013
	(8.18)		(11.5)		(12.8)	
II. Share of investment in computers	2.11	.010	3.90	.012	−.02	−.0002
	(1.25)		(2.06)		(1.67)	
III. NBER TFP	2.36	.006	5.99	.01	.002	.00001
	(1.45)		(2.62)		(1.82)	
IV. R&D-to-sales ratio	.0805	.021	.1622	.026	.0289	.012
	(.024)		(.039)		(.033)	
V. Use of patents	6.13	.016	10.85	.018	1.267	.005
	(2.18)		(3.59)		(2.89)	
N	3,856		2,541		1,312	

NOTE.—The sample is limited to males in the manufacturing sectors who work in the private sector and have been working at least half of the weeks since the previous survey. The time period is 1987–92. In parentheses, below the logit coefficients, are SEs. To the right of each estimated coefficient is the derivative (dP/dX) multiplied by the SD of the measure of technological change. The derivative is calculated as $\beta\hat{P}(1 - \hat{P})$, where $\hat{P}$ is the mean incidence of training in the sample. NBER = National Bureau of Economic Research. TFP = total factor productivity. The values for the SDs are .0086 for Jorgenson's TFP, .05 for investment in computers, .027 for the NBER TFP, 2.57 for the R&D-to-sales ratio, and .027 for use of patents. The mean rates of training for the subsamples in the regressions are .111 for all workers in manufacturing, .067 for production workers, and .196 for nonproduction workers. The other variables in the regressions are marital status, race, educational dummies, a dummy for standard metropolitan statistical area, labor-market experience (and its square), tenure with employer (and its square), union membership, a dummy for large firm (more than 1,000 workers), industry unemployment rate, industry level of unionization, industry rate of job creation (*M* over 1980–88), industry rate of job destruction (*M* over 1980–88), and year dummies.

change.[22] In general, the incidence of training is higher at higher rates of technological change. With a few exceptions, this is true for all schooling groups, in small and large firms, and for production and nonproduction workers.

Table 4 reports a summary of the estimates from our logit models on the incidence of company training in the manufacturing sector.[23] Columns 1–2 report the effects of each of the five technological indicators on the incidence of training for all workers in the manufacturing sector, while columns 3–6 show separate results for production and nonproduction workers. We present the logit coefficient and its standard error (shown

[22] See the table for the definition of high and low rates of technological change.

[23] Complete regression results for one model are given in app. B, where we see the typical patterns regarding the effect of education, firm size, and other characteristics on the incidence of training, using the R&D-to-sales ratio. When other proxies for technological change are used, the coefficients on the nontechnological change variables are very similar to those shown in app. B.

in parentheses beneath the coefficient). To the right of each coefficient, we show the derivative (dP/dX) multiplied by the standard deviation of the measure of technological change. This estimate enables us to compare the magnitudes of the effects of the various technological change measures. The results in columns 1–2 show that all five proxies for technological change have a positive and significant effect on the incidence of training in the manufacturing sector. The robustness of these results is an important finding given our earlier discussion about the limitations of the various technological change measures.

The positive and significant effects of technological change on the incidence of training are consistent with the notion that technological change makes previously acquired skills obsolete, thereby inducing workers and firms to invest in training to match the specific requirements of the latest innovation. It is also consistent with Levhari and Weiss's (1974) argument that an increase in uncertainty will lead to an increase in investments in human capital that facilitate adjustments to future shocks. The largest effects are observed for the Jorgenson TFP measure, the R&D-to-sales ratio and use of patents, where a 1 standard deviation increase in the rate of technological change is associated with a 2 percentage point increase in the incidence of training. Comparing the results in column 3–4 with those in column 5–6 shows that the effect of technological change on the incidence of training is larger for production workers than nonproduction workers, as anticipated. In fact, the estimated coefficients for nonproduction workers are not statistically significant.

B. Incidence of Noncompany Training

Although three-quarters of private-sector training is provided by the firm, young workers do receive some training outside the firm. In table 5, we consider whether technological change also has a positive effect on noncompany training. In columns 1–6, the dependent variable is the likelihood of any type of private-sector training (company or noncompany), and in columns 7–12, we show results for the likelihood of noncompany training. Since the vast majority of private-sector training is company provided, the results in columns 1–6 are quite similar to those reported in table 4. The analysis of noncompany training alone shows that, with the exception of the Jorgenson TFP measure, technological change does not have a significant effect. This is consistent with the notion that the type of human capital investments that will increase with technological change are those that are more firm specific. Hence, the remainder of our analysis is confined to company training.

C. Education and Training

As we discussed in the introduction, the effect of technological change on the incidence of training may vary by education. More

Table 5
The Effects of Technological Change on the Likelihood of All Types of Training and Noncompany Training in the Manufacturing Sector

	Any Training						Noncompany Training					
	All		Production		Nonproduction		All		Production		Nonproduction	
	Coefficient (1)	Derivative (2)	Coefficient (3)	Derivative (4)	Coefficient (5)	Derivative (6)	Coefficient (7)	Derivative (8)	Coefficient (9)	Derivative (10)	Coefficient (11)	Derivative (12)
I. Jorgenson TFP	24.76	.027	36.43	.031	−.93	.001	25.61	.007	41.62	.012	−40.85	.01
	(6.88)		(9.11)		(11.8)		(13.4)		(16.2)		(28.3)	
II. Share of investment in computers	1.88	.012	3.41	.017	.21	.002	−.081	.0001	.444	.001	−.284	.0004
	(1.10)		(1.67)		(1.58)		(2.23)		(2.84)		(4.04)	
III. NBER TFP	1.08	.004	1.89	.005	.64	.003	−3.26	.003	−4.98	.005	.300	.0002
	(1.33)		(2.35)		(1.76)		(3.23)		(5.08)		(4.84)	
IV. R&D-to-sales ratio	.033	.01	.072	.018	.020	.008	−.079	.006	−.069	.006	−.062	.004
	(.02)		(.03)		(.03)		(.05)		(.066)		(.084)	
V. Use of patents	3.13	.011	4.76	.013	.657	.003	−3.51	.003	−5.32	.005	.101	.0001
	(1.94)		(2.99)		(2.74)		(4.07)		(5.16)		(7.06)	
N	3,856		2,541		1,312		3,812		2,524		1,286	

NOTE.—NBER = National Bureau of Economic Research. TFP = total factor productivity. In parentheses, below the logit coefficients, are SEs. To the right of each estimated coefficient is the derivative (dP/dX) multiplied by the SD of the measure of technological change. See table 4 for more details and for a list of variables that are included in the regressions.

Table 6
Interaction Effects of Technological Change and Education on the Likelihood of Company Training in the Manufacturing Sector

	All	Production	Nonproduction
I. Jorgenson TFP:	58.68	−3.92	122.8
	(36.2)	(65.6)	(61.6)
A. Years of education	.26	.09	.31
	(.044)	(.08)	(.07)
B. Jorgenson × Educ	−2.54	3.10	−8.10
	(2.60)	(5.38)	(4.05)
II. Investment in computers:	25.76	49.61	24.76
	(5.86)	(13.1)	(9.22)
A. Years of education	.347	.393	.332
	(.04)	(.09)	(.07)
B. Computers × education	−1.62	−3.74	−1.58
	(.40)	(1.06)	(.59)
III. NBER TFP:	24.45	20.78	28.39
	(8.23)	(18.7)	(12.5)
A. Years of education	.25	.14	.24
	(.03)	(.05)	(.04)
B. NBER × education	−1.52	−1.25	−1.86
	(.56)	(1.51)	(.81)
IV. R&D-to-sales ratio:	.436	.340	.508
	(.10)	(.20)	(.16)
A. Years of education	.291	.147	.303
	(.036)	(.07)	(.06)
B. R&D × education	−.025	−.015	−.031
	(.007)	(.016)	(.01)
V. Use of patents:	37.56	41.68	36.09
	(10.2)	(21.0)	(15.8)
A. Years of education	.987	1.029	1.00
	(.25)	(.60)	(.37)
B. Patents × education	−2.197	−2.59	−2.28
	(.71)	(1.71)	(1.03)
N	3,812	2,524	1,286

NOTE.—NBER = National Bureau of Economic Research. TFP = total factor productivity. Standard errors are in parentheses. See table 4 for a list of variables that are included in the regressions.

educated individuals may require less training in response to technological change if their general skills enable them to learn the new technology and adapt to the changed environment, that is, the substitutability between training and education increases at higher rates of technological change. We test this hypothesis in table 6, where the regressions include an interaction effect between education and the proxy for technological change.

The results in table 6 show that for all workers, production and nonproduction workers alike, the more educated are more likely to receive company training.[24] The interaction effects show, however, that

[24] See app. B for separate coefficients on education groups. The results show a monotonic relationship between years of education and training.

technological change attenuates the effect of education on training. This implies that, at higher rates of technological change, the training gap between the highly educated and the less educated narrows. The separate results for the production and nonproduction workers generally support this conclusion; with the exception of one measure, whenever the technological change indicator has a positive and significant effect on the incidence of training, the education-technological change interaction effect is negative and usually significant. The result is consistent with the model presented in Heckman, Lochner, and Taber (1998), where in a second and longer phase of a technological transition, the narrowing of the training gap acts to widen the wage gap between high- and low-skilled workers.

In order to more fully understand the relationship between technological change and the incidence of training for different education groups, we estimated the regressions in table 6 using a set of dummies for education groups (1–8, 9–11, 12, 13–15, 16, and 17+ years of schooling), in place of the continuous measure, and interacted the dummy variable with the technological change indicator. We used these coefficients to create plots (see figs. 1 and 2) that depict the effect of technological change on the incidence of training for a worker of given characteristics in each education group.[25] Whenever a slope is significantly different from zero, we indicate it with the letter *S*.

Although the education interactions are not monotonic and significant effects are observed for only one or two educational groups, figures 1 and 2 generally support the conclusion that, at higher rates of technological change, the gap between the training incidence of the highly educated and the less educated narrows. In the case of production workers, with the exception of the Jorgenson measure, we find that workers with some high school (9–11) and high school graduates train significantly more at higher rates of technological change, in some cases overtaking the training received by the 13–15 education group. For nonproduction workers, again with the exception of the Jorgenson measure, we find that the 13–15 group trains more at higher rates of technological change, overtaking those with at least 16 years of schooling.

Bartel and Lichtenberg (1987) have argued that highly educated workers have a comparative advantage with respect to learning and implementing new technologies and, hence, that the demand for these workers relative to the demand for less educated workers is a declining function

[25] For these plots, we assumed that the individual had the following characteristics: married, lives in a standard metropolitan statistical area, works in a large firm, has 10 years of market experience, and has 4 years of tenure with his employer. All other variables are the mean values, and the year is 1992.

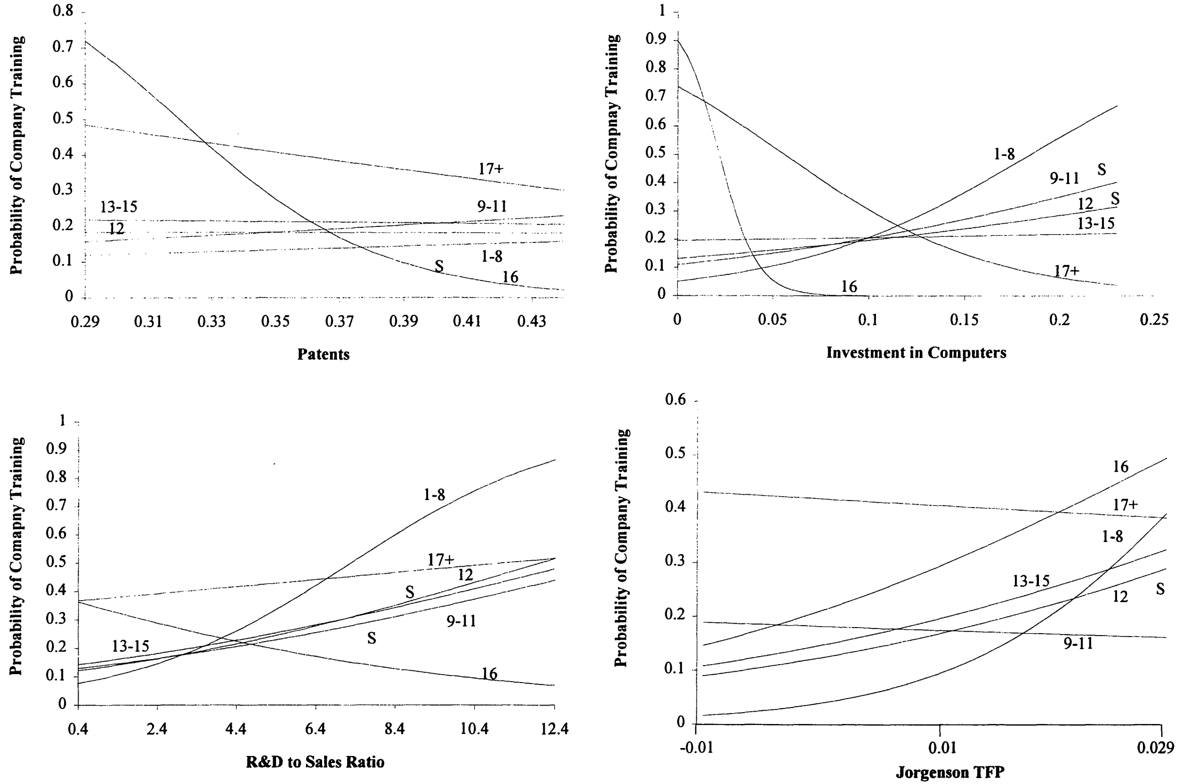

FIG. 1.—Technological change and the incidence of company training, by schooling level, for production workers in manufacturing

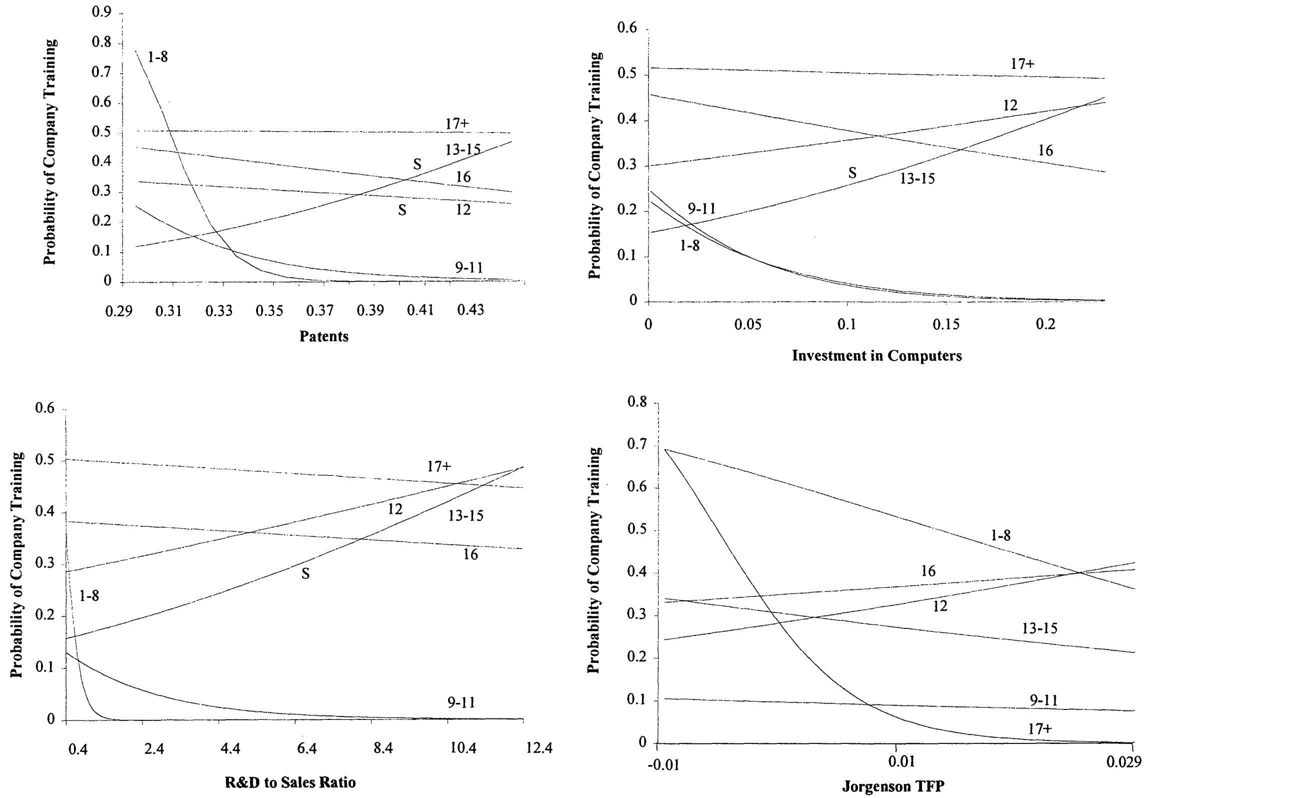

FIG. 2.—Technological change and the incidence of company training, by schooling level, for nonproduction workers in manufacturing

of experience with the technology. When a new technology is first introduced, there is a great deal of uncertainty about job tasks, and highly educated workers are needed to help the firm through this difficult implementation stage. The general skills of the highly educated workforce serve as a substitute for company training. As experience with the new technology is gained, however, it is possible to train the less educated employees to perform the new tasks. In our empirical analysis, we measure "long-term" differences across industries in the rate of technological change, and our finding that the training gap between the more and less educated narrows is consistent with the idea of the firm utilizing training to enable the less educated to work with the new technology.[26] Thus it appears that technological change has acted to reduce the gap in the stocks of human capital accumulated by different education groups through formal company training.

We recognize that one reason for the observed narrowing of the formal training gap between education groups could be selectivity. At higher rates of technological change, firms are less likely to employ or retain the less able employees within each education group. This bias is likely to be more pronounced for the less educated workers, resulting in an overestimate of the effect of technological change on the training of the less educated. We attempted to correct for this bias by including a set of ability test scores (not reported here), and our results on the effect of technological change were virtually unchanged. We did find, however, a positive and significant correlation between ability (holding schooling constant) and the likelihood of training and a smaller coefficient on education.

D. Occupations and Training

It is possible that our findings regarding the effect of technological change on education groups may reflect the fact that, within the categories of production and nonproduction workers, individuals with different amounts of education perform distinct job tasks, some of which are more sensitive to technological change. We, therefore, reestimated the regressions in table 6, adding 1-digit occupation dummies. The estimated coefficients of the interactions between the technological change measures and the education dummies were virtually unchanged.[27]

The question of whether the effect of technological change varies across

[26] If job training is more likely to be informal at higher levels of education, it could bias our results. Notice, however, that we do find a monotonic increase of formal training with the level of schooling. See tables 1, 3, and the complete regression results in app. B.

[27] The occupation dummies were also added to the regressions in table 4, and the coefficients on the technological change variables were unaffected.

occupation groups can be considered directly. We estimated a regression that includes the 1-digit occupation dummies and a set of interactions of these dummies with technological change. The results are shown in table 7. In the case of production workers, we find that, at very low levels of technological change, there are no occupational differences in training incidence. But, at higher rates of technological change, craftsmen receive significantly more training than other production workers.[28] For nonproduction workers, a very different pattern emerges. We find that, at low levels of technological change, clerical and unskilled workers receive the least amount of training among nonproduction workers. However, at high rates of technological change, they receive more training than the other nonproduction workers.[29] It is interesting to note that this group includes occupations such as clerks, computer and peripheral equipment operators, secretaries, and office-machine operators, occupations where the introduction of computers is likely to have had a strong effect on job tasks.[30]

E. Initial Training versus Retraining

We have interpreted our findings as indicating that the observed differences in training are due to higher rates of technological change. Alternatively, one could argue that our results are due to differences in the nature of technology across industries. Perhaps industries that we rank higher using different indicators are simply industries that use more sophisticated technologies. These technologies may require more initial training in order for the worker to learn how to use them. If this hypothesis is correct, we would expect to see more training (especially formal training) when workers join the firm and much less training of more senior workers.

In order to distinguish these two possible effects, we interact the measures of technological change with two dummies, one indicating that the worker has tenure of 1 year or less with the employer and the other indicating tenure of more than 1 year.[31] Our assumption is that the effect of the technological change measure on longer-tenured workers is more likely to reflect the response to technological change.

[28] When the technological change/occupation interaction terms are deleted, we find that craftsmen on average receive more training than other production workers. This result is not reported in the table.

[29] These two findings do not hold for the Jorgenson measure.

[30] A Canadian survey of employers (McMullen 1996) found that the introduction of computer-based technology led to an increase in skill requirements primarily for low-skilled workers. Presumably, these workers would then receive more training.

[31] A more accurate distinction would be based on tenure in job assignment, which we do not observe.

Table 7
The Effects of Technological Change on the Likelihood of Training by Occupational Category

	Jorgenson TFP	Investment in Computers	NBER TFP	Use of Patents	R&D-to-Sales Ratio
I. Production workers (N = 2,541):					
Occupational dummies (omitted: operatives, except transport):					
Craftsmen and kindred workers	−.021	.218	.209	−1.72	−.113
	(.31)	(.30)	(.20)	(2.16)	(.26)
Transport equipment operatives	−.480	.385	−.047	5.40	−.110
	(.66)	(.56)	(.44)	(6.87)	(.44)
Laborers, except farm laborers	−.349	−.324	−.813	−2.13	−.427
	(.60)	(.66)	(.58)	(6.23)	(.62)
Interaction with technological change:					
Craftsmen and kindred workers	44.97	3.86	7.592	12.53	.224
	(14.7)	(2.46)	(3.12)	(4.27)	(.05)
Operatives, except transport	19.21	3.178	2.243	6.82	.073
	(16.0)	(2.94)	(4.65)	(5.49)	(.06)
Transport equipment operatives	44.41	−12.83	−15.05	−10.23	−.017
	(43.7)	(14.3)	(37.4)	(20.9)	(.26)
Laborers, except farm laborers	−32.33	−9.51	.322	10.63	−.250
	(53.2)	(15.0)	(39.7)	(18.0)	(.40)
II. Nonproduction workers (N = 1,312):					
Occupational dummies (omitted: professional, technical and kindred workers):					
Managers and administrators	−.603	−.751	−.430	−2.82	−.600
	(.36)	(.32)	(.22)	(1.87)	(.27)
Sales workers	−.156	.089	−.115	.144	−.320
	(.41)	(.41)	(.28)	(2.22)	(.34)
Clerical and unskilled workers	−.484	−1.65	−.620	−7.89	−1.23
	(.39)	(.47)	(.28)	(2.50)	(.36)
Farm laborers, laborers and foremen, and service workers	−.845	−.680	−.350	−.926	−.744
	(.78)	(.60)	(.61)	(5.13)	(.55)
Interaction with technological change:					
Professional, technical and kindred workers	−2.41	−2.46	−1.761	−2.627	−.015
	(16.7)	(1.94)	(2.21)	(3.51)	(.04)

Table 7 (*Continued*)

	Jorgenson TFP	Investment in Computers	NBER TFP	Use of Patents	R&D-to-Sales Ratio
Managers and administrators	22.21	3.02	4.715	4.50	.0581
	(20.0)	(2.90)	(3.66)	(4.87)	(.05)
Sales workers	−5.85	−6.16	−4.956	−3.72	.004
	(23.2)	(3.66)	(3.98)	(5.96)	(.06)
Clerical and unskilled workers	7.435	11.86	10.06	18.34	.233
	(21.8)	(3.90)	(4.68)	(6.53)	(.06)
Farm laborers, laborers & foremen, and service workers	57.29	7.45	13.226	−.727	.239
	(49.8)	(8.76)	(39.2)	(15.1)	(.19)

NOTE.—Standard errors are in parentheses. See table 4 for a list of variables that are included in the regressions. NBER = National Bureau of Economic Research. TFP = total factor productivity.

Table 8 reports the estimated coefficients on the technological change variables on the likelihood of training, separated for tenure levels below and above 1 year. If our earlier results were due simply to the cross-sectional differences in the nature of technology, we would not expect to observe significant coefficients for workers beyond their first year of tenure. The results in table 8 show that, although the measured effects of the technological change variables are larger for individuals with less than 1 year of tenure, all of the technological change proxies have positive and significant effects on longer-tenured production workers. Hence these results indicate that what we are indeed measuring is the effect of technological change, not only the nature of technology, and ongoing technological change results in training of workers beyond their first year of tenure.

F. The Effects of Prior Training

The increased likelihood of training at higher rates of technological change could be due to workers training more frequently (intensive margin) or to more workers being trained (extensive margin). In an earlier version of this article (Bartel and Sicherman 1995), we estimated a standard Tobit model, the results of which showed that technological change does not increase the number of hours of training, conditional on participation. In this section, we exploit the panel nature of the NLSY data and examine whether higher rates of technological change induce firms to provide training to individuals who have already received training or to those who did not receive training in the prior period. If the latter is true, then technological change serves an important function; it acts to increase the proportion of workers who

Table 8
First Year and Beyond: Is the Effect of Technological Change Different in the First Year of Tenure?

	Production		Nonproduction	
	Coefficient	Derivative	Coefficient	Derivative
I. Jorgenson TFP:				
Low tenure	39.48	.021	.726	.001
	(17.8)		(17.4)	
High tenure	31.69	.017	11.572	.016
	(11.8)		(13.1)	
II. Investment in computers:				
Low tenure	4.79	.015	−2.38	.019
	(3.12)		(2.44)	
High tenure	3.645	.011	.578	.005
	(2.17)		(1.72)	
III. NBER TFP:				
Low tenure	8.31	.014	−4.74	.02
	(5.00)		(3.81)	
High tenure	5.39	.009	.962	.004
	(2.87)		(1.92)	
IV. R&D-to-sales ratio:				
Low tenure	.165	.027	−.016	.006
	(.06)		(.05)	
High tenure	.162	.026	.038	.015
	(.04)		(.03)	
V. Use of patents:				
Low tenure	10.5	.018	.860	.004
	(3.66)		(2.95)	
High tenure	10.95	.019	1.40	.006
	(3.60)		(2.90)	
N	2,541		1,312	

NOTE.—In parentheses, below the logit coefficients, are SEs. To the right of each estimated coefficient is the derivative (*dP*/*dX*) multiplied by the SD of the measure of technological change. See table 4 for more details and for a list of variables that are included in the regressions. NBER = National Bureau of Economic Research. TFP = total factor productivity.

receive training. We test this hypothesis in table 9 by interacting the various measures of technological change with two dummy variables, one indicating that the individual received training in the prior year (i.e., between t-2 and t-1, since the dependent variable is training between t-1 and t) and the other indicating no training in the prior year. In columns 1 and 2, the sample is restricted to individuals who did not change industries between time periods t-2 and t, and in columns 3 and 4, we restrict the analysis to individuals who did not change employers between the 2 time periods. The results show insignificant effects of technological change for previously trained workers and significant effects for most of the technological change indicators for individuals who did not receive training in the prior year. A test of equality of coefficients for the two groups rejects the hypothesis that they are equal. The higher incidence of training at higher rates of

Table 9
Past Training, Technological Change, and Current Training: Interacting Technological Change with Past-Training Dummies

	Did Not Change Industry (2 Digit)		Did Not Change Employer	
	Production (1)	Nonproduction (2)	Production (3)	Nonproduction (4)
I. Jorgenson TFP:				
Past training	2.42	−6.61	−19.2	−10.6
	(30.3)	(25.23)	(27.9)	(24.6)
No past training	31.55	−.53	26.5	−8.7
	(18.1)	(20.0)	(17.3)	(18.7)
II. Investment in computers:				
Past training	6.12	−3.02	.679	−2.67
	(4.92)	(3.36)	(4.19)	(3.32)
No past training	5.57	.431	4.73	3.61
	(3.28)	(2.79)	(3.19)	(2.54)
IV. NBER TFP:				
Past training	8.38	−.81	−1.72	−1.40
	(7.08)	(3.79)	(5.42)	(3.79)
No past training	9.60	−1.78	6.54	−.58
	(4.23)	(3.15)	(4.20)	(2.82)
V. R&D-to-sales ratio:				
Past training	.151	−.026	.048	−.024
	(.09)	(.06)	(.07)	(.06)
No past training	.206	−.002	.179	.028
	(.06)	(.05)	(.06)	(.05)
IV. Use of patents:				
Past training	11.33	−2.43	2.17	−6.47
	(9.35)	(5.79)	(7.30)	(5.62)
No past training	14.35	4.45	12.26	4.48
	(5.14)	(4.88)	(5.66)	(4.30)
N	1,285	684	1,354	749

NOTE.—NBER = National Bureau of Economic Research. TFP = total factor productivity. The dummies are "past training" = 1 if the person received company training between t-2 and t-1 (the dependent variable is training between t-1 and t); "no past training" = 1 if the person did not train between t-2 and t-1. In the first two columns, the sample is limited to workers who did not change industry since t-2. In the last two columns, the sample is limited to workers who did not change employer since t-2. Standard errors in parentheses. See table 4 for a list of variables that are included in the regressions.

technological change occurs mainly because more individuals are receiving training.[32]

IV. Summary and Implications

The effect of technological change on young workers' investments in on-the-job training is theoretically ambiguous. Technological change

[32] This finding is consistent with the model of Galor and Tsiddon (1997), which postulates that there are two stages of the technological change process: invention and innovation. During the innovation phase, the technology becomes more accessible to a greater number of employees, which would lead to our observation of an increased pool of trainees.

influences the rate at which various types of human capital obsolesce and also increases the uncertainty associated with human capital investments. As we discussed in the introduction, these mechanisms can cause training to increase or decrease at higher rates of technological change. The relationship between education and training will also be affected by technological change. If the general skills of the more educated enable them to more easily adapt to new technologies, we will observe a narrowing of the postschool-training gap between more and less educated workers.

We linked a sample of male workers in manufacturing industries from the 1987–92 waves of the NLSY to five different measures of industry rates of technological change in order to empirically resolve the ambiguous theoretical predictions and found essentially similar results for all five measures. In particular, we found the following. (1) Production workers in industries with higher rates of technological change are more likely to receive formal company training than those working in industries with lower rates of technological change, controlling for a set of worker, job, and industry characteristics. (2) While more educated workers are more likely to receive training, at higher rates of technological change, the training gap between the highly educated and the less educated narrows. (3) The relationship between training and technological change is insignificant for the aggregate group of nonproduction workers (only after controlling for various characteristics). Disaggregating the group, we find that, at higher rates of technological change, the lower-skilled nonproduction workers, that is, clerical and unskilled workers, receive significantly more training compared with the more highly skilled nonproduction workers, such as professionals, technical employees, managers, and sales workers. (4) Technological change acts to increase the extensive margin of training, increasing the pool of trainees. At higher rates of technological change, firms are more likely to train individuals who have not received training in the prior period rather than those who were previously trained.

We remind the reader that these findings pertain to young workers only, do not include informal training, and may not generalize to other time periods. With these limitations in mind, we can conclude from our analysis that, at higher rates of technological change, firms employ more educated workers and provide more formal training to their workforces. At the same time, however, higher rates of technological change induce employers to provide more formal training to their less educated employees; although the more educated still receive more training, technological change shifts the balance in favor of the less educated. This happens because the general skills of the more educated facilitate their adaptation to the new technologies. It is not clear a priori how these effects will impact the wage structure, a topic that we reserve for future research.

Appendix A

Data

I. General

The data are from the 1979–92 NLSY of youth ages 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, are with regard to the time period since January 1, 1978.

In addition to the NLSY, we use information from variety of sources. These are industry measures of technological change and other industry-level variables. They are described in the text.

II. The Sample

The number of men interviewed in 1979 is 6,403. Not all individuals are 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 working "1," with a job but not working "2," or looking for a job "3." Following that, an individual is included in the sample as long as he is interviewed (even if leaving the labor market). Other restrictions apply only for specific analyses. The panel is unbalanced, and the number of observations per individual varies.

III. CPS Job

For each respondent, employment information on up to a maximum of five jobs is recorded in each survey year. One of these jobs is designated as a "CPS" job, and it is the most recent or current job at the time of interview. Typically it is also the main job. Each job is identified by a number (1–5), and job 1 in most cases is also the "CPS" job. For only this so-called "CPS" job, there are a host of additional employer/employee related questions that are asked in the NLSY surveys. Our analysis is restricted to CPS jobs.

IV. The Work-History File

We use the work-history file to construct the tenure, separation, and reason for separation variables.

Tracing jobs and tenure with employer.—The tenure variable is already constructed in the work-history file. The major difficulty is tracing CPS jobs over the interview years. A variable called PREV allows matching of employers between consecutive interview years. For each job in a particular survey year, it gives the job number that was assigned to that job in the previous year (assuming of course that the current job existed in the previous year). Our programming strategy was to pick CPS jobs in which the respondents are actually employed at the time of interview and to trace these jobs to the next survey year via the PREV variable in the succeeding survey year. There are, however, a few cases where we cannot trace the current CPS job in the succeeding interview year with PREV. The current tenure value is the total number of weeks worked up to the interview date. A shortcoming of PREV is that it allows for matching employers between consecutive interview years only. If, therefore, a respondent worked for a particular employer say in 1980 but not in 1981 and started working for the same employer in survey year 1982, then there is no way of knowing the total years of tenure with that employer since employer numbers are followed only in contiguous interviews. This may not be a problem for turnover analysis since reemployment with the same employer after an absence of that length (i.e., a period longer than that between 2 successive interview years) may be considered a new job.

V. Weeks between Surveys

The number of weeks between surveys ranges between 26 and 552 weeks. The large numbers are the results of individuals not being surveyed for several years. In all our analyses, we included (when it made sense) the variable WKSSINCE (weeks since last survey). The variable was excluded if it made no difference.

VI. Training

A variety of formal training questions were asked in all survey years, except 1987. Individuals were asked to report on several vocational or technical programs in which they were enrolled since the previous survey. Until 1986, the maximum was two programs, and in 1988 it was increased to four. In addition, individuals were asked to report up to two government programs in which they were enrolled.

Up until 1986, further questions were asked, in particular the type of program and the dates it started and ended, only if the program lasted more than 4 weeks. Starting in 1988, these questions were asked about all programs, regardless of length. The 4 weeks condition up to 1986 is a major shortcoming of the data set. Any analysis that focuses on a specific type of training (e.g., company training) has to be limited to post-1986. The following example illustrates the problem: the percentage of workers in our sample that reported enrollment in company training is 4.7% over the period 1976–90. Limiting the sample to 1988–90, the rate increases to 11%.

In certain years (1980–86, 1989–90), a distinction was made between programs in which the individual was enrolled at the time of the previous interview and programs that started after the previous interview. When such a distinction is made, up to two programs at the time of the last interview can be reported. A person was asked about training that took place at the time of the last interview only if the interviewer had a record indicating so. Therefore, for 1980–86, such a record did not exist if training took less than a month.

For all programs, the starting and ending month and year are reported. Also reported are the average number of hours per week spent in training.

In our programming, we number all programs in the following order: the four vocational or technical programs are numbered 1–4, the two programs at time of last interview are numbered 5–6, and the government programs are numbered 7–8.

Type of training.—Up to 1986, the following categories are reported: 1 = business college, 2 = nurses program, 3 = apprenticeship, 4 = vocational or technical institution, 5 = barber or beauty school, 6 = flight school, 7 = correspondence, 8 = company or military, and 9 = other. We aggregate them into company training (8), apprenticeship (3), and "other" (1, 2, 4, 5, 6, 7, 9). Starting in 1988, the breakdown is more detailed: 1–7 are unchanged; 8 = a formal company training run by employer or military training (excluding basic training); 9 = seminars or training programs at work run by someone other than employer; 10 = seminars or training programs outside of work; 11 = vocational rehabilitation center; and 12 = other. We now aggregate 8–10 as company training and 11–12 as "other."

Below are additional descriptions of some of the variables used.

Any technical or vocational training dummy.—Designates whether the worker received any technical or vocational training since (or at the time of) the last interview.

Any training dummy (TANYD).—Like the above, but TANYD also includes government training.

Company training dummy (TCOMD).—Designates if any of the training programs were 8 up to 1985 or 8, 9, or 10 after 1986. Notice that only after 1986 the type of program was asked of all workers who reported training. Prior to 1988, the program-type question was asked only for those who spent more than 4 weeks on training (see above for more discussion of this problem).

Length of training.—Starting in 1988, in addition to asking when (month and year) different training programs start and end, individuals were also asked, "Altogether, for how many weeks did you attend this training?" The question was not asked of government training. If the answer was zero (less than a week), we recoded it to half a week. For each of the eight programs, individuals were asked for the average hours per week spent training. Multiplying the hours per week in each program with the weeks in each program, we get the total hours in each program.

Imputing training data for 1987.—In 1987, no training questions were asked. We utilize the answers to the 1988 survey to construct training information for the 1987 survey. We do so by using information on the starting and ending dates of training programs. If employees reported in 1988 that they were still in training (end month = 0 and endyr = 0 or 1), we set the end date to the interview date. For some individuals the answer for the beginning date indicates "still in training." This is an error.

Appendix B

Table B1
The Likelihood of Company Training: Estimated Logit Results for Male Workers in Manufacturing

	All Workers		Production Workers		Nonproduction	
Variable	Coefficient	Derivative	Coefficient	Derivative	Coefficient	Derivative
Intercept	−4.889	−.482	−3.649	−.2291	−5.971	−.9406
	(.802)		(1.185)		(1.14)	
If married	.2304	.023	.2986	.0187	.1440	.0227
	(.121)		(.184)		(.165)	
If nonwhite	−.2447	−.024	−.2201	−.0138	−.2487	−.0392
	(.145)		(.196)		(.224)	
1–8 years of schooling	−.6689	−.066	−.2832	−.0178	−1.391	−.2191
	(.429)		(.478)		(1.05)	
9–11 years of schooling	−.4227	−.042	.0103	.0006	−1.677	−.2642
	(.199)		(.225)		(.543)	
13–15 years of schooling	.0807	.008	.1088	.0068	−.3944	−.0621
	(.166)		(.244)		(.241)	
16 years of schooling	.7376	.073	.7315	.0459	.1695	.0267
	(.157)		(.419)		(.207)	
17+ years of schooling	1.212	.120	.8223	.0516	.6579	.1036
	(.209)		(.652)		(.254)	
Lives in SMSA	.0350	.003	−.00371	−.0002	−.1554	−.0245
	(.136)		(.188)		(.209)	
Experience	.1660	.016	.0513	.0032	.3109	.0490
	(.113)		(.160)		(.164)	
Experience^2	−.0076	−.001	−.0040	−.0002	−.0133	−.0021
	(.006)		(.008)		(.008)	
Tenure	.0332	.003	.0671	.0042	.0190	.0030
	(.054)		(.080)		(.078)	
Tenure^2	−.0026	−.000	−.0035	−.0002	−.0043	−.0007
	(.005)		(.006)		(.007)	
Union member	−.1168	−.012	.2006	.0126	−.4278	−.0674
	(.154)		(.189)		(.316)	
Large firm	.8422	.083	.7805	.0490	.8311	.1309
	(.119)		(.176)		(1.66)	
Durables	−.1183	−.012	−.0710	−.0045	−.0331	−.0052
	(.156)		(.240)		(.209)	
Industry unemployment	−.1188	−.012	−.0695	−.0044	−.1696	−.0267
	(.050)		(.073)		(.074)	
Industry union coverage	.0016	.000	.0037	.0002	.0025	.0004
	(.006)		(.008)		(.009)	
Industry jobs creation	−.0751	−.007	−.1598	−.0100	.0143	.0023
	(.084)		(.121)		(.123)	
Industry jobs destruction	.0965	.010	−.0084	−.0005	.1956	.0308
	(.068)		(.097)		(.101)	
Industry R&D/sales	.0805	.008	.1622	.0102	.0289	.0045
	(.024)		(.039)		(.033)	
1988	1.317	.130	1.386	.0870	1.331	.2096
	(.275)		(.443)		(.357)	
1989	1.401	.138	1.479	.0928	1.395	.2198
	(.273)		(.441)		(.352)	
1990	1.630	.161	1.866	.1171	1.548	.2439
	(.272)		(.430)		(.358)	
1991	1.608	.159	1.947	.1222	1.408	.2217
	(.285)		(.447)		(.379)	
1992	1.627	.161	1.954	.1226	1.474	.2321
	(.302)		(.472)		(.403)	
N	3,856		2,541		1,312	

NOTE.—Standard errors are in parentheses. SMSA = standard metropolitan statistical area.

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