WORKERS, WAGES, AND TECHNOLOGY*

MARK DOMS
TIMOTHY DUNNE
KENNETH R. TROSKE

This paper documents how plant-level wages, occupational mix, workforce education, and productivity vary with the adoption and use of new factory automation technologies such as programmable controllers, computer-automated design, and numerically controlled machines. Our cross-sectional results show that plants that use a large number of new technologies employ more educated workers, employ relatively more managers, professionals, and precision-craft workers, and pay higher wages. However, our longitudinal analysis shows little correlation between skill upgrading and the adoption of new technologies. It appears that plants that adopt new factory automation technologies have more skilled workforces both pre- and postadoption.

I. INTRODUCTION

Over the past several decades there have been dramatic changes in the types of technologies available to businesses. The rapid development and diffusion of new information technologies such as computers and networks has altered the production process in many workplaces. Along with these fundamental changes in the physical capital of firms, it is also widely believed that the introduction of these new technologies has altered the structure of employment. Specifically, it is argued that many of these new technologies increase the demand for skilled workers. This skill-biased technical change hypothesis is offered as the primary explanation for the increased returns to education and the increased wage differential between skilled and unskilled workers recently seen in the United States [Welch 1970; Bound and Johnson 1992; Davis and Haltiwanger 1991; Katz and Murphy 1992; Sachs and Shatz 1994].

The possibility that skill-biased technical change is the cause of increased wage dispersion has led to a number of recent stud-

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ies using industry, worker, and employer data, which examine whether technological change in the United States is in fact skill-biased.[1] Berndt, Morrison, and Rosenblum [1992], Berman, Bound, and Griliches [1994], and Autor, Katz, and Krueger [1996] all model changes in workforce skill as a function of changes in industry capital intensity and industry-level investment in computer equipment. All of these studies find evidence of capital skill complementarity and a strong positive correlation between the level of computer investment in an industry and changes in the skill of workers in the industry. Krueger [1993] and Autor, Katz, and Krueger [1996] use worker data to look at the correlation between wages and computer use by workers, and both studies find a strong positive correlation. Finally, Dunne and Schmitz [1995] and Siegel [1995] use plant-level data to show that plants that use more factory automation technologies employ more highly paid workers.

While the evidence to date certainly suggests that technical change in the last several decades in the United States has been skill biased, there are still very few microeconomic studies that directly examine how the adoption and use of new technologies affect the structure of the workforce at the plant- or firm-level.[2] This paper aims to extend this literature by using a number of new data sources that contain information on both technology use and adoption, and the characteristics of workers in plants. Our analysis is twofold. First, using a cross-sectional data set that contains detailed information on both worker characteristics and plant-level technology use, we address three questions. (1) Do technologically advanced plants employ more educated workers? (2) Do technologically advanced plants employ more skilled occupations such as managers, scientists, engineers, and skilled blue-

1. There are also a large number of studies of skill-biased technical change that rely on even more aggregate data. For example, Mincer [1991] reports that the returns to education are positively correlated with aggregate R&D expenditures (his proxy for technical change). In addition, there are a few case studies that examine the effects of technical change on worker skill. For select industries the Bureau of Labor Statistics conducted a series of case studies that investigate the effects of technology adoption on the labor force. For example, in a study of the apparel and textile industries, Bailey [1990] finds skill upgrading within occupational classes when there is increased automation.

2. Two studies that have data from other countries on both workers and employer technology are Entorf and Kramarz [1995] and Reilly [1995]. Entorf and Kramarz use data on French firms, and a sample of employees who work in those firms, to show that technology use by workers is associated with higher wages even after controlling for firm and worker characteristics. Reilly, using a small set of Canadian firms and workers, finds that firms which have access to computers pay higher wages.

collar workers? (3) Do technologically advanced plants employ more high wage workers? Second, using a plant-level panel data set, we examine whether the adoption of new technologies by plants is associated with corresponding within-plant changes in the occupational mix of the workforce, wages, and labor productivity. The objective of both of these exercises is to provide a more comprehensive picture of the relationship between workforce characteristics and technology adoption at the plant-level.

The data we utilize come from three main sources. The information on technology use and adoption comes from the 1988 and 1993 Survey of Manufacturing Technology (SMT). These surveys asked a sample of manufacturing plants about their use and adoption of new factory automation equipment such as computer-automated design, numerically controlled machines, local area networks, and programmable controllers. The information on worker characteristics comes from a matched employer-employee data set. Finally, the plant-level longitudinal data come from the Census Bureau's Longitudinal Research Database—a panel data set of manufacturing plants.

Our cross-sectional results are consistent with the view that "high tech" plants employ more skilled workers. In particular, we find a high proportion of college-educated workers employed in technologically advanced plants. This positive correlation between the education of workers and technology use is found for both production and nonproduction workers. Likewise, we find that the fraction of workers employed in scientific, engineering, managerial, and precision-craft occupations increases with the use of new technology. In addition, we find that technologically advanced plants employ more high wage production and technical/clerical/sales workers.

In contrast, our time-series results show little correlation between changes in workforce characteristics and our measures of technology adoption. Plants that adopt a large number of new technologies do not appear to increase their relative share of nonproduction labor or high wage workers compared with plants that adopt a small number of new technologies. However, we do find that plants that adopt a large (small) number of new technologies employ high (low) wage workers both prior to and postadoption. Our findings suggest that, at the plant level, the correlation between technology use and worker wages is primarily due to the fact that plants with high wage workforces are more likely to adopt new technologies.

Our finding that the adoption of new factory automation technologies is uncorrelated with plant-level changes in workforce skill stands in sharp contrast to the strong positive correlation between changes in workforce skill and computer investment found in industry-level studies (e.g., Berndt, Morrison, and Rosenblum [1992], Berman, Bound, and Griliches [1994], Autor, Katz, and Krueger [1996]). It is important to emphasize that the types of technologies we study here are quite distinct from computing equipment. The technologies we examine are directly used in the production of manufactured goods, whereas computing equipment is often a main tool of managerial and clerical labor. When we include a plant-level measure of computer investment into our analysis, we find results similar to the industry-level studies—plants that invest relatively more in computing equipment have larger increases in the share of nonproduction labor. Our conclusion is that the effect of new technologies on workforce structure depends critically on the type of technology being adopted. For the sample of plants we study, it appears that the adoption of factory automation technologies is less correlated with skill upgrading than investment in new computing equipment.

The rest of the paper proceeds as follows. The next section describes the cross-sectional analysis of technology use and worker skills and wages. Section III reports on the longitudinal analysis of technology adoption and changes in the skill mix of workers. The fourth section provides closing remarks.

II. Cross-Sectional Analysis of Worker Skills and Wages

In this section of the paper we report the results from our cross-sectional analysis of technology, worker skills, and wages. We start with a description of our data sets and technology measures and then we examine how the education, occupation, and wages of workers vary with the use of advanced technology equipment.

A. Data and Measurement Issues

The data used in this analysis come from the 1988 Survey of Manufacturing Technology (SMT) and the Worker-Establishment Characteristic Database (WECD).[3] The 1988 SMT contains plant-

3. For a more complete description of the 1988 SMT, see Dunne [1994]. For a more complete description of the WECD, see Troske [1995b].

level responses to a U. S. Census Bureau survey on the use of advanced technology at U. S. manufacturing plants. The survey was sent to over 10,000 plants with twenty or more employees in the fabricated metal products, nonelectrical machinery, electrical and electronic equipment, transportation equipment, and instruments and related products industries (SICs 34–38). The WECD is an employer-employee matched database containing approximately 199,000 manufacturing workers matched to approximately 16,000 establishments. The data on workers come from individual responses to the 1990 Decennial Census long form, while the data on plants come from the Census Bureau's Longitudinal Research Database (LRD). The data set used in this study is formed by matching the worker-level data in the WECD with the plant-level data on technology use in the 1988 SMT. To minimize the effects of outliers, we only keep workers who report working more than 30 weeks in the previous year, who report working between 30 and 65 hours a week, and who report an hourly wage between \$2.50 and \$100. To ensure that we have a representative sample of workers in a plant, we only keep matched worker-plant records where at least ten workers and over 3 percent of the plant's workforce are matched to the plant. The final data set contains 34,034 worker records matched to 358 plant records.[4]

A description of the data set's representativeness can be found in the Data Appendix. Briefly, the plants in our sample are much larger than average (averaging 961 employees) and are more technologically advanced than plants in the population (Appendix 1). The characteristics of the workers in our sample are fairly similar to the population characteristics with one important exception—workers in our sample typically earn higher wages than workers in the population (Appendix 2). This is most likely due to the fact that workers in our sample are predominantly employed in large plants, and it is well-known that workers in large plants receive higher wages [Brown and Medoff 1989; Troske 1995a]. Finally, comparing worker-reported earnings with plant-reported earnings shows that the average earnings constructed from the sample of workers in the plant is quite similar to the average earnings reported by the plant (available from the authors).

A key issue in this study concerns how we measure technol-

4. These plants contain over 500,000 employees which represents 6.5 percent of total employment in these industries in 1988.

ogy. The measure of technology we employ is similar to that used in Dunne and Schmitz [1995] and Doms, Dunne, and Roberts [1995] and is based on the type of production machinery utilized at the factory. The 1988 SMT asks plant managers to indicate whether they used any of seventeen different technologies in the plant in the previous year.[5] These technologies include such innovations as CAD/CAM, computer numerically controlled machines, networks, and robots. For the most part the technologies are general purpose in nature, can be used in a range of industries, and represent machinery and equipment that increase the level of automation in a factory. It is important to note that our measures of technology are distinct from other commonly used measures of technical change based on investment in computers and computer peripherals (e.g., Berndt, Morrison, and Rosenblum [1992]; Berman, Bound, and Griliches [1994]; Autor, Katz, and Krueger [1996]). As opposed to being primarily information-processing technologies, the technologies we study here primarily process materials and control machinery.

Throughout this study we assume that plants using a larger number of technologies are more technologically advanced. For example, if plant A uses twelve technologies while plant B uses eight, then our hypothesis is that plant A is more technologically advanced than plant B. Clearly, this is a crude measure of technology use because no information on the intensity of use is available. The Data Appendix describes several exercises we performed to check whether the number of technologies used is related to the intensity of use. In general, we find that the counts act as a reasonable proxy for technological intensity. Additionally, we have tried a variety of other technology measures, and the results we present are representative of our findings using these alternative measures.[6] Therefore, we present the results for the simplest measure.

One potential problem with our measure of technology use is that it may be capturing differences in both the amount and complexity of capital within a plant. If capital and worker skill are complementary, we may find a positive relationship between technology use and worker skill simply because more technology-

5. Appendix 3 provides a list and description of the seventeen technologies.

6. We grouped the seventeen technologies into both five and eight broad technology groups and constructed a series of dummy variables indicating whether the plant employed any technologies in the group. We also divided technologies into those primarily used by production workers and those primarily used by non-production workers and constructed counts based on this distinction.

intensive plants are also more capital intensive. To control for this possibility, all of the regressions in our analysis include the log of the capital-output ratio in the plant. This ratio is measured as the book value of the capital stock in the plant in 1987 divided by the total value of shipments from the plant in 1987.[7]

Our data set is unique in that it contains plant-level information on both worker skills and technology. However, it is important to point out several limitations of the data before proceeding. First, the data represent only a small number of large plants. Thus, the reported patterns reflect an important, but limited, part of the population. Second, the data are made up entirely of plants in a few manufacturing industries, and skill-biased technical change is argued to be affecting a wide array of industries.[8] Finally, while we know the technology used in the plant and the workers who work in the plant, we do not know whether the workers in our sample actually use the technology. Ideally, we would like to know the technology used by each worker.

B. Advanced Manufacturing Technologies and Workforce Skills

The technologies we examine are primarily used in the design and fabrication of products and the control of machinery and information on the factory floor. According to respondents to the 1993 SMT (which we discuss in detail below), the main reasons for adopting these technologies relate directly to plant production issues. Respondents to the 1993 SMT indicate that the two main reasons for using these technologies are to "improve quality" or "increase output" [U. S. Bureau of the Census 1994, Table 4B]. "Lower labor cost" as a reason for technology adoption comes in a distant third. However, we do expect that the use of these technologies will be correlated with workforce attributes in a number of ways.

First, at a general level the technologies we study are clearly

7. In addition, we have examined the correlation between our measure of technology use and the investment activity in plants. We constructed the percent of the capital stock that was due to investment in the last five years for 1909 plants for which we had continuous data from 1972 to 1988. The correlation between our technology counts and the percent of new capital is 0.22 (p-value = .0001). This suggests that while our measure is positively correlated with recent investment, it is not merely a proxy for recent investment.

8. For example, we miss industries such as software and medical services, where skill-biased technical change may be having the largest impact. However, our data do contain manufacturing plants in industries such as automotives, aircraft, and computers which have experienced large changes in technology.

technologies that increase the level of automation in a factory. The primary way workers control these technologies is through keyboards, pointing devices, and video display terminals. At a minimum, workers using these technologies must be able use such devices and thus have reasonable language skills, reading skills, and, in some cases, basic math skills [Smith 1995, pp. 328–35]. Thus, we expect that plants that are more automated (use more technologies) will employ relatively more educated and skilled workers than plants that rely on more traditional technologies with mechanical interfaces (i.e., levers and switches).

Second, at a more technology-specific level, we think the introduction of these new technologies may directly affect the organization of the workforce. For example, technologies such as computer-automated design workstations are used primarily by scientists and engineers and have altered the design cycle for many products. Previously, teams of engineers, draftsmen, and model builders would spend considerable time drafting plans and building models and prototypes of new products. Physical models were often necessary so that designers could observe their plans in three dimensions. Computer-automated design tools have reduced the need for models in many applications, since CAD workstations can easily render three-dimensional images. In addition, changes to designs can be made relatively quickly without the need to redraft blueprints. Essentially, computer-automated design software and hardware allow engineers to perform many of the tasks that previously required teams of engineers, modelers, and draftsmen. In addition, the data generated in the design stage can be used directly to control production. Robots, computer-numerically controlled machines, and flexible manufacturing cells are regularly configured to take output from CAD systems and process material/products with little human intervention. These manufacturing automation systems require skilled operators/technicians, although they often replace skilled craftspeople such as welders and machinists as well as less skilled workers such as assemblers and operators.

Finally, many of these technologies require significant skilled support staff to install and maintain them. This may impact the type and amount of overhead labor in a plant. Local and wide area networks require telecommunications staff. Computer-automated design systems, computers used on the factory floor, and programmable logic devices require information systems specialists. On the whole, therefore, we think that there are a number of reasons why workforce attributes such as education level and occupation mix may be correlated with the use of these advanced manufacturing technologies.[9]

C. Education, Occupation, and Technology

In this section we examine the correlation between advanced technology use and the education level and occupational mix of workers in the plant. If skilled workers and advanced manufacturing technologies are complements, then we should find that the proportion of workers in skilled occupations and the average education level of a plant's workforce rises as advanced technology use increases.[10]

Table I presents a cross tabulation of the education level and occupation mix of workers broken out by the number of advanced technologies used in plants. The rows of Table I correspond to the number of technologies used in a worker's plant. The first three columns present our measures of worker education: the percent of workers with at least a college degree (column (1)), the percent of nonproduction workers with at least a college degree (column (2)), and the percent of production workers with at least some college education (column (3)). The next three columns present our measures of the occupational mix of workers in the plant: the percent of workers in managerial, scientific, engineering, and precision craft occupations (column (4)), the percent of nonproduction workers (column (5)), and the percent of total wages paid to nonproduction workers (column (6)).

In Table I there is a monotonically increasing relationship between technology use and the education of the workforce. Column (1) indicates that as the number of technologies used in a plant increases, the percent of workers with at least a college degree rises. This increase is quite dramatic. Only 9.4 percent of the workers in plants using less than four technologies have college degrees compared with 33.1 percent of the workers in plants using more than thirteen technologies. Columns (2) and (3) show

9. In addition, changes in workforce structure that arise from changes in scale that accompany technology use may also be important. See Dunne, Haltiwanger, and Troske [1996] for a more complete discussion of this issue.

10. Dunne and Schmitz [1995] find that plants employing more technologies employ a larger fraction of nonproduction workers. The data used in Dunne and Schmitz only distinguish between nonproduction and production workers, and they assume that nonproduction workers represent a more skilled group of workers. By using the matched worker-plant data set, we can examine more detailed occupational categories. Thus, we are able to exclude secretarial and janitor service workers (also nonproduction workers) from our group of skilled workers.

TABLE I

TECHNOLOGY, EDUCATION, AND OCCUPATION CROSS TABULATIONS

	Percent of workers with at least a college degree (1)	Percent of nonproduction workers with at least a college degree (2)	Percent of production workers with at least some college (3)	Percent of workers in managerial, scientific, engineering, or precision-craft occupations (4)	Percent of nonproduction workers (5)	Percent of total wages paid to nonproduction workers (6)
Plants using less than 4 technologies	9.4	24.1	21.2	33.7	32.7	41.0
Plants using 4 to 6 technologies	12.2	31.2	24.2	35.6	33.3	42.2
Plants using 7 to 8 technologies	14.0	34.5	27.1	36.6	34.9	39.5
Plants using 9 to 10 technologies	16.2	34.9	27.7	37.4	40.7	46.2
Plants using 11 to 13 technologies	15.2	37.5	29.7	33.1	34.3	37.3
Plants using more than 13 technologies	33.1	53.9	34.9	48.6	56.9	62.4
Full sample	18.3	40.1	27.9	38.5	40.5	47.2

Data source the 1988 SMT-WECD matched sample for SICs 34–38. There are 3251 workers in our sample that work in plants using less than 4 technologies, 4690 work in plants using 4 to 6 technologies, 6403 work in plants using 7 to 8 technologies, 5914 work in plants using 9 to 10 technologies, 5931 work in plants using 11 to 13 technologies, and 7844 work in plants using more than 13 technologies.

that this educational upgrading occurs within broad occupation classes. Column (2) shows that only 24.1 percent of the nonproduction workers in plants using less than four technologies have a college degree compared with 53.9 percent of nonproduction workers in plants using more than thirteen technologies. Column (3) shows that 21.2 percent of production workers in plants using less than four technologies have some college education compared with 34.9 percent of production workers in plants using more than thirteen technologies.

While not monotonic, the numbers in Table I also show that there is a positive relationship between technology use and the occupational mix of workers in the plant. Column (4) indicates that the percent of workers in skilled occupations rises significantly with the number of technologies employed.[11] However, most of this increase is the result of plants utilizing more than thirteen advanced production technologies having a much higher proportion of skilled workers than plants utilizing thirteen or fewer technologies. Columns (5) and (6) show a very similar pattern, both in terms of numbers and wages; plants utilizing more than thirteen technologies employ a much higher percentage of nonproduction labor.

To examine the relationship between technology use, education, and occupational mix more closely, Table II presents basic regressions that show how the educational attainment and occupational mix of workers within plants varies with technology use. The regressions control for other characteristics of the employer, such as industry, size, and plant age, which may influence the patterns seen in Table I. The dependent variables are based on the occupational and educational information from all matched workers in the plant. Technology use is modeled with a group of dummy variables where the dummies reflect the technology quartile the plant falls in based on the number of advanced production technologies used in the plant. The omitted group is plants in the least technology intensive quartile (plants using 0–3 technologies). Besides our measures of technology use we also include controls for the log of the capital-output ratio, the log of plant employment, and the log of plant age. Not shown, but included in the regressions, are controls for two-digit industry, the

11. Analysis of more detailed occupations shows that the positive relationship between technology use and the percent of skilled workers is primarily due to a dramatic increase in the percent of scientists and engineers in the most technologically advanced plants.

TABLE II
REGRESSIONS OF EDUCATIONAL AND OCCUPATIONAL MIX OF WORKERS IN PLANTS

	Percent of workers with at least a college degree (1)	Percent of nonproduction workers with at least a college degree (2)	Percent of production workers with at least some college (3)	Percent of workers in managerial, scientific, engineering, or precision-craft occupations (4)	Percent of nonproduction workers (5)	Percent of total wages paid to nonproduction workers (6)
Intercept	.209(.076)	.243(.123)	.568(.096)	.544(.091)	.577(.117)	.606(.128)
Technology use:						
First quartile (0–3 technologies)	omitted	omitted	omitted	omitted	omitted	omitted
Second quartile (4–6 technologies)	.019(.018)	.076(.029)	.031(.022)	.018(.021)	.018(.027)	.014(.030)
Third quartile (7–9 technologies)	.020(.019)	.069(.031)	.045(.024)	.042(.023)	.014(.029)	−.001(.032)
Fourth quartile (10+ technologies)	.044(.023)	.117(.037)	.099(.029)	.052(.028)	.011(.035)	−.006(.039)
Log (capital-output ratio)	.006(.008)	.007(.013)	.016(.010)	.019(.009)	−.001(.012)	−.004(.013)
Log (plant employment)	.018(.008)	.014(.013)	.009(.010)	−.007(.010)	.016(.012)	.016(.013)
Plant age	−.015(.009)	−.020(.014)	−.007(.011)	−.016(.011)	−.017(.014)	−.020(.015)
n	353	353	353	353	353	353
Mean of Y	.136	.280	.266	.362	.368	.421
R^2	.179	.123	.242	.195	.176	.159

Standard errors are in parentheses. The regressions are based on the 1988 SMT-WECD matched sample of plants in SICs 34–38. All regressions include controls for two-digit industry, region, and whether the plant is located in a metropolitan statistical area (MSA).

nine census regions, and whether the plant is located in an MSA.[12]

The findings in Table II regarding the education of workers in these plants reaffirm the patterns seen in the cross tabulations—plants that use more advanced production technologies employ a more educated workforce. For example, the results in column (1) show that plants in the fourth quartile (10+ technologies) employ 4.4 percent more workers with at least a college degree than plants in the first quartile (0–3 technologies). The results in columns (2) and (3) again show that this educational upgrading of the workforce occurs within broad occupational groups. In column (3) we see that plants in the fourth technology quartile employ 9.9 percent more production workers with some college education than plants in the first technology quartile. These findings are consistent with Berndt, Morrison, and Rosenblum [1992], who show that industry-level investment in "high technology" capital goods, such as computers, is positively correlated with the educational attainment of production and nonproduction workers in the industry.

The results in Table II regarding the occupational mix of workers are somewhat different from the results seen in Table I. The coefficients on the technology dummies indicate that plants using more technologies employ proportionately more skilled workers. However, there now appears to be little difference across the technology groups in either of our measures of the share of nonproduction labor in the plant (columns (5) and (6)).[13] It is important to note that this last finding is partially an artifact of the specialized sample. A regression using a larger sample of 1988 SMT plants (6900+ plants) indicates that the percent of nonproduction workers and the percent of wages paid to nonproduction workers rise as technology intensity increases.[14] However, even in these regressions the size of the technology effect is substantially smaller than those observed in columns (4) and (5) of Table II. We interpret these results as being largely consistent with the conclusions in Berman, Bound, and Griliches [1994] that technologically advanced plants employ more skilled workers.

12. We have repeated the analysis dropping these controls with no substantial change in the technology coefficients.

13. If these technologies are primarily designed to control the quality of the output, then it may be that plants substitute technologies for supervisors. To investigate this hypothesis, we have repeated the analysis in Table II substituting supervisors for precision craft workers. The results are the same.

14. Results are available from the authors upon request.

With respect to the remaining variables in the regression, the capital-output ratio is in general positive, indicating that capital-intensive plants generally employ more educated workers (although the coefficient is only significant in column (4)). The estimated coefficients on plant size and plant age are generally not statistically significant across the four regressions. Thus, it does not appear that, after controlling for technology, larger plants employ more educated workers than smaller plants in our sample. However, note that our sample is composed almost entirely of very large, capital-intensive plants so the size results should be viewed with caution.

C. Wages and Technology

In this section of the paper we examine the relationship between the average wages paid to workers in a plant and the plant's use of advanced production technologies. This analysis is motivated by an increasing body of literature that finds a positive correlation between technology use and worker wages [Krueger 1993; Chennells and Van Reenen 1995; Dunne and Schmitz 1995; Entorf and Kramarz 1995; Reilly 1995; Autor, Katz, and Krueger 1996]. To examine the relationship between wages and technology use, we estimate the following model:

$$\bar{w}_p = \boldsymbol{X}_p'\beta + \boldsymbol{Z}_p'\gamma + \mu_p, \tag{1}$$

where $\bar{w}_p$ is the log of the average hourly wage paid to workers in plant p, $\boldsymbol{X}_p$ is a vector of average characteristics of workers in plant p, $\boldsymbol{Z}_p$ is a vector of plant characteristics (including our technology measures), and μ_p is a random error term.[15] We report the results from estimating equation (1) setting $\beta = 0$ and the results from estimating equation (1) without constraining β. There are two reasons for reporting both sets of results. First, comparing the results from estimating equation (1) setting $\beta = 0$ shows how well these results can replicate previous results concerning the technology-wage relationship (in particular, Dunne and Schmitz). Second, the results from estimating equation (1) setting $\beta = 0$ provide a base with which to compare the relationship between wages and advanced production technologies once we control for cross-plant differences in worker quality.

Table III presents the results from estimating equation (1). To allow for a complete interaction between a worker's major oc-

15. We have also estimated equation (1), where $\bar{w}_p$ is the average of the log of the hourly wages of workers in plant p. The results are identical.

TABLE III
PLANT-LEVEL LOG WAGE REGRESSIONS

	Production worker wages		Technical, clerical, and sales worker wages		Managers and professional worker wages	
Variables	No worker characteristics (1)	With worker characteristics (2)	No worker characteristics (1)	With worker characteristics (2)	No worker characteristics (1)	With worker characteristics (2)
Technology use:						
First quartile (0–3 technologies)	omitted	omitted	omitted	omitted	omitted	omitted
Second quartile (4–6 technologies)	.046(.033)	.002(.023)	.099(.042)	.068(.038)	−.011(.043)	−.036(.035)
Third quartile (7–9 technologies)	.119(.036)	.040(.025)	.136(.045)	.095(.041)	.020(.048)	−.046(.038)
Fourth quartile (10+ technologies)	.203(.043)	.084(.030)	.200(.054)	.127(.050)	.038(.056)	−.029(.044)
Education:						
Percent with						
Less than high school diploma		omitted		omitted		omitted
High school diploma		.259(.077)		.324(.098)		−.113(.237)
Some college		.534(.076)		.339(.096)		.061(.235)
B.S., B.A. or greater		.633(.125)		.745(.119)		.358(.236)
Log (capital-output ratio)	.040(.014)	.021(.010)	.017(.018)	.025(.017)	.040(.019)	.028(.015)
Log (plant employment)	.040(.015)	.036(.010)	.046(.019)	.039(.017)	.041(.019)	.044(.015)
Plant age	.050(.017)	−.014(.012)	.008(.022)	−.002(.020)	.032(.023)	−.019(.018)
n	353	353	348	348	335	335
R^2	.452	.750	.278	.437	.129	.495

Standard errors are in parentheses. The regressions are based on the 1988 SMT-WECD matched sample for SICs 34–38. The dependent variables are the log of the average wages paid to matched workers in the relevant occupations. All regressions include controls for region, MSA, and two-digit industry. The regressions in columns (2) include controls for the percent of workers in the plant between 35 and 54 years old, older than 54, married, male, and white.

cupation and the various controls, we perform a separate analysis for production workers, technical, clerical and sales workers, and managerial and professional workers.[16] This table contains three panels based on the occupational groupings of workers. The first column in each panel presents the results not controlling for worker characteristics (setting $\beta = 0$), while the second column presents the results including these controls.

The production worker results in Table III show that plants that use more advanced production technologies employ production workers who earn higher wages. Dunne and Schmitz [1995] find that production workers in plants with the most technologies receive 14 percent higher wages than production workers in plants with the fewest technologies, while this difference for workers in our data is 20 percent. Comparing the coefficient estimates on the advanced production technology variables in column (1) to regressions where worker controls are included (column (2)), a clear pattern emerges. Including worker quality controls substantially lowers the technology wage premium. For production workers the technology premium falls by about 60 percent from 20 percent in column (1), to 8 percent in column (2). The importance of the average worker characteristics in the plant-level regressions is illustrated by the size and significance of the coefficients on the education variables reported in the second column. These results show that as the proportion of production workers with a college degree rises, average production-worker wages rise markedly as well.

These results are consistent with the results in Krueger [1993], Chennells and Van Reenen [1995], Entorf and Kramarz [1995], and Autor, Katz, and Krueger [1996], all of whom show that technology use is associated with higher worker wages even after controlling for observable worker characteristics. Entorf and Kramarz go on to show that this technology-wage "premium" is primarily the result of workers with higher unobserved abilities being more likely to use advanced technologies. In light of the Entorf and Kramarz results, we interpret the positive correlation between production-worker wages and technology use as further evidence that more technically advanced plants employ more skilled production workers.

The results for technical, clerical, and sales workers are very similar to the results for production workers. Plants using more

16. We require that plants have at least two workers in a given occupation when estimating the model.

advanced production technologies employ technical, clerical, and sales workers who receive higher wages, but once worker controls are added, the technology premium drops significantly. We again interpret this result as showing that technically advanced plants employ more skilled technical, clerical, and sales workers. Finally, the managerial and professional wage results show no relationship between the technology variables and wages rates. These results are consistent with Dunne and Schmitz [1995] who show that the correlation between the technology measures and nonproduction-worker wages is weaker than that observed in the production-worker wage regressions.[17] It appears that, at least for the plants in our sample, there is no correlation between technology use and the skill (as reflected in wages) of managers and professional workers.

The cross-sectional results presented in this section paint a reasonably consistent picture. Plants that use advanced manufacturing technology employ more skilled workers. What our cross-sectional results do not show is how the skill mix of workers in these plants has evolved over time. This is the issue we address next.

III. Analysis of Changes in the Nonproduction Labor Share, Wages, and Labor Productivity

In this section we extend the cross-sectional analysis by examining the relationship between technological adoption and changes in the occupational mix, worker wages, and labor productivity in manufacturing establishments. The focus in the literature has been on relating changes in the workforce skill, usually measured as changes in the nonproduction labor share, to measures of technical change [Berman, Bound, and Griliches 1994; Autor, Katz, and Krueger 1996; Dunne, Haltiwanger, and Troske 1996; Goldin and Katz 1996]. The assumption is that nonproduction workers are on average more skilled than production workers, and a rise in the nonproduction labor share is viewed as evidence of a rise in worker skill in an industry or a plant. We also focus on this variable, but, in addition, we examine changes

17. We have repeated the analysis separately for managers and professionals. Although the samples are small, it appears that plants that employ more advanced technologies also employ more high wage, high skilled professional workers. However, there does not appear to be any relationship between technology use in plants and the skill of managers.

in wages and labor productivity. We do so to capture the possibility of within worker group skill upgrading. If technology adoption increases skill requirements for production workers and nonproduction workers alike, then this should be reflected in both higher wages for these types of workers and higher labor productivity, but may not be reflected in changes in the nonproduction labor share.

A. Model Specification, Data, and Measurement Issues

To examine how changes in technology affect the composition and wages of the workforce, we estimate the following model:

$$\Delta y_p = f\left(TECH_p, \Delta K_p, \boldsymbol{X}_p\right) + \mu_p, \tag{2}$$

where y_p represents the change at plant p between 1977 and 1992 in the nonproduction labor share, average production-worker wages, average nonproduction-worker wages, and labor productivity. $TECH_p$ represents a set of technology adoption variables. When y_p is the change in the nonproduction labor share or the change in worker wages, ΔK_p is the change in the plant's capital-output ratio. When y_p is the change in labor productivity, ΔK_p is the change in the plant's capital-labor ratio. $\boldsymbol{X}_p$ represents a vector of additional plant-level controls, and μ_p is an error term.[18]

The data used in estimating equation (2) come from two main sources. The data for our dependent variables and all plant characteristics except technology adoption come from the 1977 and 1992 Census of Manufactures (CM). The data on technology adoption come from the 1993 SMT.[19] Our sample of 3260 plants used in the analysis consists of all plants that were in the 1977 and 1992 CMs and the 1993 SMT.[20]

18. The variables in $\boldsymbol{X}_p$ include a measure of plant size, the average employment in the plant in 1977 and 1993, controls for nine census regions, whether the plant is located in a high tech MSA, and four-digit industry controls. The high tech areas are the Boston, Houston, Research Triangle, San Francisco, Seattle, and Washington, D.C. MSAs.

19. We match the WECD to the 1988 SMT data for the cross-sectional analysis because the worker earnings information in the WECD is for 1989. However, we use the 1993 SMT data in the time-series analysis so that we can create as long a panel as possible to help ensure that adoption occurs within our time frame.

20. We use observations only from plants that respond to the 1993 SMT and are in both CM's. This restricts our sample to continuing establishments and excludes plants that entered or exited over the period. Thus, our results need to be interpreted with caution because we condition on success but do not adjust for selection bias. In addition, our sample of plants excludes all administrative record cases in 1977 and a number of observations with unreliable data in the capital and labor variables.

The CMs allow us to disaggregate workers into two groups: nonproduction and production workers. The nonproduction labor share for a plant is defined as the ratio of nonproduction-worker wages to total salary and wages.[21] Average wages of nonproduction workers are measured as the total salary and wages paid to nonproduction workers in the year divided by the number of nonproduction workers in the plant. Average wages of production workers are measured in a like fashion. Plant-level labor productivity is measured as the value-added per worker.[22]

The information on technology use and adoption comes from the 1993 SMT. The 1993 SMT contains plant-level responses to a U. S. Census Bureau survey on the use of advanced technology at U. S. manufacturing plants. The 1993 SMT was sent to over 8300 establishments with twenty or more employees in SICs 34–38 and asked about their use of the same seventeen technologies as the 1988 survey. Our measure of technology adoption is again a count-based measure. We count the reported number of technologies used by the plant in 1993 and use this as the measure of technology adoption over the 1977–1992 period. The assumption is that the technologies were adopted after 1977. For most of the technologies, such as LANs, Flexible Manufacturing Cells, Robots, and Automated Material Handling, this is a reasonable assumption given that they are more recent inventions. However, for a few of the technologies, such as numerically controlled machines, we recognize that this assumption may be problematic. Therefore, we explore alternative measures of adoption below.

Given that our matched sample of plants includes only surviving plants in industries 34 through 38, an important issue is whether our sample is representative of the population.[23] To investigate this issue, Figure I presents the nonproduction labor share from 1977 to 1992 for three different samples of plants: all

21. This measure is preferable to the ratio of the number of nonproduction workers to the total employment in the plant because it better captures within occupational group changes in worker skill.

22. Value-added is defined as the total value of shipments from the plant minus, net changes in inventories, minus the cost of material inputs.

23. In related work, Dunne, Haltiwanger, and Troske [1996] analyze the contribution of entry and exit to changes in the nonproduction labor share. Using data for all plants in the 1972 and 1987 CMs, they find that the change in the nonproduction labor share over this period is .0592. Using only data for continuing plants, which account for about 68 percent of employment in both 1972 and 1987, they find the change in the nonproduction labor share is .0588. Thus, the change in the nonproduction labor share for continuing plants looks quite similar to the change in this variable for the entire population of plants.

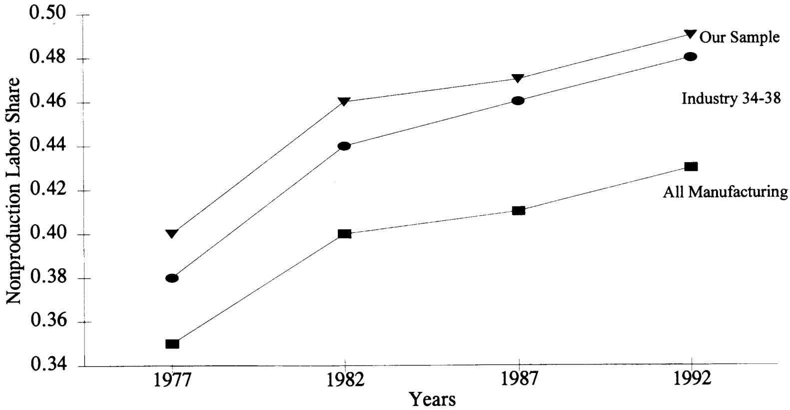

FIGURE I
Nonproduction Labor Share, 1977–1992

manufacturing plants, all plants in industries 34 through 38, and the 3260 plants in our matched sample. Figure I shows that there is a rise in this ratio over the period with most of the increase occurring between 1977 and 1982. While the time-series patterns are quite similar for the three groups, there are obvious differences in the levels of the nonproduction labor share across the three samples. On average the proportion of total wages going to nonproduction workers in our sample is 15 percent higher than that in the manufacturing sector as a whole, and 4 percent higher than that in all plants in industries 34 through 38. This is due to the fact that our sample of plants is skewed toward larger plants and larger plants have a higher nonproduction labor share than smaller plants. A similar pattern holds for the wage variables.

B. Changes in Occupational Mix and Wages: 1977 to 1992

To begin our analysis, Table IV presents the results from estimating equation (2) on the plants in our sample. Technology adoption is modeled with a group of dummy variables where the dummies reflect the technology adoption quintile the plant falls into: 0–1 technologies, 2–3 technologies, 4–5 technologies, 6–8 technologies, and 9+ technologies.[24] The coefficients on the tech-

24. We have also run these regressions dropping the industry, region, and MSA controls with no substantial change in the results. In addition, dropping the capital-intensity variables does not significantly affect the technology coefficients in any of these regressions.

TABLE IV

REGRESSIONS OF CHANGES IN NONPRODUCTION LABOR SHARE, PRODUCTION WORKER EARNINGS, NONPRODUCTION WORKER EARNINGS, AND LABOR PRODUCTIVITY OVER THE PERIOD 1977 TO 1992.

	Change in nonproduction labor share (1)	Change in log production worker earnings (2)	Change in log nonproduction worker earnings (3)	Change in labor productivity (4)
Industry dummies	Yes	Yes	Yes	Yes
Technology adoption:				
First quintile	omitted	omitted	omitted	omitted
Second quintile	−.014(.010)	−.011(.018)	.018(.025)	.012(.034)
Third quintile	−.010(.011)	.026(.020)	.015(.026)	.018(.036)
Fourth quintile	−.017(.011)	.025(.020)	.051(.027)	.021(.037)
Fifth quintile	−.018(.013)	.029(.023)	.003(.031)	.006(.043)
Plant size:				
First quintile	.000(.012)	−.008(.023)	−.107(.030)	−.007(.042)
Second quintile	.004(.011)	−.017(.021)	−.107(.028)	−.040(.038)
Third quintile	−.005(.011)	−.019(.020)	−.089(.026)	−.055(.036)
Fourth quintile	−.007(.010)	.004(.019)	−.016(.025)	.002(.034)
Fifth quintile	omitted	omitted	omitted	omitted
Change in capital-output ratio	.008(.003)	.015(.006)	−.001(.008)	—
Change in capital-labor ratio	—	—	—	.071(.011)
n	3260	3260	3260	3260
Mean of Y	.054	.772	.833	.784
R^2	.075	.068	.089	.092

Standard errors are in parentheses. The data include plants in SICs 34–38 appearing in the 1993 SMT and the 1977 and 1992 CM's. All regressions also include controls for the region, MSA, and four-digit industry. The technology adoptions quintiles represent the number of technologies that plant adopts between 1977 and 1992: 0–1 technologies, 2–3 technologies, 4–5 technologies, 6–8 technologies, and 9+ technologies.

nology adoption variables in Table IV show little correlation between adoption and plant-level changes in the nonproduction labor share, production- and nonproduction-worker wages, or labor productivity. Under a joint hypothesis test, we cannot reject the null hypothesis of no technology effect in any of these four regressions.

With respect to the capital-intensity variables, we find that changes in the nonproduction labor share, production-worker wages, and labor productivity are positively correlated with changes in capital intensity. While the magnitude of the coefficient on the capital-output variable in the nonproduction labor share regression is somewhat lower than that usually found in industry studies [Berman, Bound, and Griliches 1994; Goldin and Katz 1996], it is quite similar to the findings reported in Dunne, Haltiwanger, and Troske [1996], which also uses plant-level data. However, note that while the capital-output ratio is positively correlated with changes in the nonproduction labor share, it should be emphasized that in both industry and micro data the capital-output ratio explains little of the cross-industry or cross-plant variation in the nonproduction labor share.

Returning to the discussion of the technology variables, one obvious question is—why do we find little correlation between the changes in the nonproduction labor share, wages, labor productivity, and technology adoption when we found a positive relationship between the levels of these variables and technology use (except for the nonproduction labor share) in the previous section? One possibility is that our method for measuring technology adoption is inadequate because we do not know the date of adoption. To explore this possibility, we consider two alternative measures of technology adoption. First, the 1993 SMT contains some additional information on the timing of adoption. The survey asks respondents: when did this plant first begin using this technology—within the last two years, two to five years ago, or more than five years ago [U. S. Bureau of the Census 1994, p. B-2]. Using this information, we measure adoption as the number of technologies the plant indicates it adopted over the past five years. Second, for plants that are in both the 1988 and 1993 SMTs, we use the difference in the number of technologies used in 1993 and 1988 as a measure of the number of technologies adopted in the past five years. For this analysis the data for our dependent variables and plant-level characteristics come from the 1987 and 1992 CMs.

It is important to note that there appear to be some problems associated with these indicators of technology adoption. Analysis in Dunne and Troske [1995] suggests that these measures suffer from problems due to recall bias and measurement error.[25] This is why we do not use either of these measures as our primary measure of technology adoption.

Table V presents our analysis of the changes in the nonproduction labor share, wages, and labor productivity for the period 1987 to 1992 using these two alternative measures of technology adoption. The first four columns in the table report the results based on the timing of adoption question from the 1993 SMT, while the second four columns report the results based on the sample of plants that are in both the 1988 and 1993 SMTs. The results in Table V are quite similar to the results in Table IV. The coefficients on the technology adoption variables show very little relationship between technology adoption and plant-level changes in the nonproduction labor share, production and nonproduction worker wages, or labor productivity. Again, it is the case that under a joint hypothesis test, we fail to reject the hypothesis of no technology effect in any of these regressions.[26]

We have also performed a number of other exercises to check the sensitivity of our results to the assumptions that all of these technologies are adopted after 1977 and that a count is a reasonable measure of the intensity of technology adoption. First, based on the timing of adoption question in the 1993 SMT, we repeat the analysis in Table IV only using technologies for which at least 65 percent of current users report adopting the technology within the last five years. These are the three CAD technologies, the three LAN technologies, and the flexible manufacturing cell technology. Second, we omit numerically controlled machines from our measure of technology adoption. Clearly, numerically controlled machinery is a mature technology that had been widely available well before 1977 and is the most likely technology to

25. Using data on the 2329 plants in both the 1988 and 1993 SMT surveys, Dunne and Troske [1995] show that of the 1469 plants that report using CAD in both the 1988 and 1993 surveys, only 59.6 percent indicate in 1993 that they were using CAD in 1988. This number should be 100 percent. In addition, 37.6 percent of plants that indicate they were using computers on the factory floor in 1988 indicate they were not using computers in 1993. Given the large increase in computer use over this period, this high level of de-adoption suggests that this adoption measure has a large amount of error.

26. Using data for plants in both the 1988 and 1993 SMTs, and that appear in both the 1977 and 1992 CM's, we examined how changes in our four dependent variables between 1977 and 1992 are related to both technology use in 1988 (early adoption) and technology adoption between 1988 and 1993 (late adoption). Again, we find no relationship between either early or late adoption and changes in these variables.

TABLE V

REGRESSIONS OF CHANGES IN NONPRODUCTION LABOR SHARE, PRODUCTION WORKER EARNINGS, NONPRODUCTION WORKER EARNINGS, AND LABOR PRODUCTIVITY OVER THE PERIOD 1987 TO 1992 USING TIMING OF ADOPTION INFORMATION AND MATCHED SAMPLE

	Using timing of adoption information				Using plants in both the 1988 and 1993 SMT			
	Change in non-production labor share (1)	Change in log production worker earnings (2)	Change in log non-production worker earnings (3)	Change in labor productivity (4)	Change in non-production labor share (1)	Change in log production worker earnings (2)	Change in log non-production worker earnings (3)	Change in labor productivity (4)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology adoption:								
First quintile	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Second quintile	.009(.007)	.011(.014)	.016(.018)	.002(.028)	−.001(.010)	−.021(.020)	.012(.026)	−.008(.042)
Third quintile	.005(.007)	.005(.015)	.015(.019)	.002(.030)	−.003(.011)	−.035(.023)	.008(.030)	−.082(.048)
Fourth quintile	.007(.006)	.020(.013)	.009(.017)	.015(.027)	.001(.010)	.004(.020)	.007(.027)	.036(.042)
Fifth quintile	.000(.007)	.026(.014)	.029(.018)	.016(.030)	.011(.010)	−.036(.021)	.040(.028)	−.008(.045)
Change in capital-output ratio	.001(.002)	.003(.005)	−.010(.006)	—	.002(.004)	−.002(.008)	−.007(.010)	—
Change in capital-labor ratio	—	—	—	.105(.010)	—	—	—	.073(.017)
n	5596	5596	5596	5596	2146	2146	2146	2146
Mean of Y	.027	.014	.022	.165	.018	.147	.217	.193
R^2	.043	.044	.033	.061	.092	.090	.072	.112

Standard errors are in parentheses. The regressions in the first four columns are based on plants that are in the 1993 SMT and the 1987 and 1992 CM's. The regressions in the last four columns are based on plants that are in the 1988 and 1993 SMTs and in the 1987 and 1992 CM's. All regressions include controls for plant size (five dummies), region, MSA, and four-digit industry. The technology adoptions quintiles represent the number of technologies that plant adopts between 1987 and 1992: 0–1 technologies, 2–3 technologies, 4–5 technologies, 6–8 technologies, and 9+ technologies. In the first four columns the technology adoption variable is measured as the number of technologies a plant reported it adopted in the past five years in the 1993 SMT. In the last four columns the technology adoption variable is measured as the change in the number of technologies a plant reported using in the 1988 and 1993 SMTs.

violate our assumption concerning post-1977 adoption. Third, we replace the count variables with a set of dummy variables that allow for the technology effects to vary by the type of technology used. Finally, we divide up the technologies into technologies primarily used to process and disseminate information (e.g., LANs, CADs, computers used on the factory floor), and technologies used directly in the production of output (e.g., robots, sensors, guided vehicle systems) and construct a set of dummy variables based on this distinction. In every case the results are similar to those found in Table IV.[27] Technology adoption is relatively uncorrelated with the changes in the nonproduction labor share, worker wages, or labor productivity, over this period.[28]

Our conclusion, therefore, is that for these measures of technology adoption, there appears to be very little relationship between plant-level adoption and plant-level changes in the nonproduction labor share, worker wages, or labor productivity. However, we are still left with the question of how do these results relate to the cross-sectional results reported in the previous section? One possible explanation for these findings is that the plants that adopt new technologies over this period had skilled workforces prior to adoption. We examine this possibility by regressing the technology variables on the nonproduction labor share, production-worker and nonproduction-worker wages, and labor productivity, in plants in both 1977 and 1992. If plants that adopt technologies have more skilled workforces prior to adoption, then we expect that the pre-adoption wages and labor productivity should be correlated with future technology use. The results are given in Table VI.[29]

27. We have also entered the technologies into the regressions as separate dummy variables and included dummy variables for groups of related technologies (e.g., fabrication and machining technologies). Again, the results are quite similar to the count-based results. In particular, it is the case that none of these measures of technology adoption are significantly correlated with changes in the nonproduction labor share.

28. We have also reestimated all the models in Table IV using changes from 1967 to 1992. This matched sample contains 790 plants. The technology results are largely consistent with the findings in Table IV with one exception. The change in production-worker wages over the 1967 to 1992 period is positively correlated with technology use in 1993. However, changes in the nonproduction labor share, labor productivity, and nonproduction-worker wages are uncorrelated with technology adoption. We also performed the analysis in Table IV separately for each two-digit SIC industry. The within-industry results are similar to those reported in Table IV. The results from all of these exercises are available from the authors upon request.

29. In these regressions we measure plant size using total employment in the plant in the given year. In addition, we control for the log of the *level* of the capital-output or capital-labor ratio in the given year.

TABLE VI
CROSS-SECTIONAL REGRESSIONS OF NONPRODUCTION LABOR SHARE, PRODUCTION WORKER EARNINGS, NONPRODUCTION WORKER EARNINGS, AND LABOR PRODUCTIVITY FOR 1977 AND 1992

	1977				1992			
	Non-production labor share (1)	Log production worker earnings (2)	Log non-production worker earnings (3)	Labor productivity (4)	Non-production labor share (5)	Log production worker earnings (6)	Log non-production worker earnings (7)	Labor productivity (8)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology adoption:								
First quintile	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
Second quintile	.023(.009)	.067(.017)	.018(.020)	.071(.027)	.008(.010)	.063(.019)	.034(.021)	.072(.031)
Third quintile	.003(.009)	.056(.017)	.004(.021)	.112(.027)	−.008(.011)	.092(.020)	.014(.022)	.107(.033)
Fourth quintile	.015(.009)	.083(.018)	−.013(.021)	.110(.028)	−.002(.011)	.122(.020)	.034(.022)	.105(.034)
Fifth quintile	.018(.011)	.146(.020)	.060(.024)	.207(.032)	−.002(.013)	.194(.023)	.060(.026)	.176(.040)
Capital-output ratio	.000(.004)	.037(.008)	.011(.010)	—	.008(.004)	.007(.006)	.010(.007)	—
Capital-labor ratio	—	—	—	.234(.012)	—	—	—	.122(.011)
n	3260	3260	3260	3260	3260	3260	3260	3260
Mean of Y	.373	2.41	2.86	3.32	.427	3.18	3.70	4.10
R^2	.283	.327	.122	.278	.346	.308	.127	.227

Standard errors are in parentheses. The data include plants in the 1993 SMT and in the 1977 and 1992 CMs. All regressions include controls for plant size (five dummies), region, MSA, and four-digit industry. The technology adoptions quintiles represent the number of technologies that plant adopts between 1977 and 1992: 0–1 technologies, 2–3 technologies, 4–5 technologies, 6–8 technologies, and 9+ technologies.

The results in Table VI show that there is very little relationship between the nonproduction labor share and technology use both prior to and postadoption (columns (1) and (5)). This is consistent with the results presented in Table II where we found little correlation between the nonproduction labor share and technology use. However, the results in Table VI do show that plants that use the most technologies in 1993 paid the highest wages to their workers and were the most productive in 1977. For example, compared with plants that adopt the fewest technologies (first quintile), plants that adopt the most technologies (fifth quintile) paid production workers 14.6 percent higher wages in 1977 and 19.4 percent higher wages in 1992, and were 20.7 percent and 17.6 percent more productive, respectively. While weaker, the results for nonproduction workers also show that plants using the most technologies (fifth quintile) paid nonproduction workers higher wages in both 1977 and 1992. These findings suggest that plants that adopt a large number of new technologies have more skilled workers both pre- and postadoption.

The results presented here appear somewhat at odds with the findings reported in Berman, Bound, and Griliches [1994] and Autor, Katz, and Krueger [1996].[30] Using published data from the CM's and the Annual Survey of Manufactures (ASM), these studies find that industry-level changes in the nonproduction labor share are positively correlated with computer investment in an industry. We can also examine this issue by linking our plant-level data with the plant-level data on computer investment from the 1992 ASM, which is analogous to the industry-level data used in Berman, Bound, and Griliches and Autor, Katz and Krueger.[31]

30. These results also differ from the results in Siegel [1995]. Siegel, using panel data for a sample of manufacturing plants operating on Long Island, finds that plants that adopt new technologies show an increase in the skill mix of workers in plants after adoption. Again, we do not find this with our data. There are two possible explanations for the different results. First, Siegel's data contain a much finer occupational breakdown for workers in the plant. To the extent that skill upgrading occurs within broad occupational groupings, and is not reflected in changes in the wages of workers in these occupations, then we may be missing this skill upgrading with our, more aggregate, data. Second, Siegel only examines changes in the skill mix of workers after adoption. It may be the case that plants begin adjusting the skill mix of their workforce prior to adopting new technologies and simply continue this adjustment after adoption. This is consistent with both ours and Siegel's results.

31. The resulting matched data set contains 1844 plants. The reduction in plants is due to the fact that the computer investment question is restricted to ASM plants, a subset of the 1992 CM, and the fact that response rate to the computer investment question is lower than the overall survey response rate.

We measure computer investment as the ratio of investment expenditures on new computers and computer peripherals to total investment expenditures in the plant. The mean for our sample is .13.

Table VII presents the results from estimating equation (2) adding the computer investment variable. There are three points to take away from Table VII. First, computer investment is positively correlated with plant-level changes in the nonproduction labor share variable.[32] Evaluated at the mean, the computer investment variable explains about 16 percent of the change in the nonproduction labor share. This is very close in magnitude to the results reported in Autor, Katz, and Krueger [1996]. Second, the addition of the computer investment variable does not greatly increase the overall explanatory power of the model (the R^2 rises from .142 to .146 between columns (1) and (2)). Third, while the computer investment variable is correlated with changes in the nonproduction labor share, it is relatively uncorrelated with changes in average wages paid to either production or nonproduction workers. This implies that the positive relationship between the nonproduction labor share changes and computer investment is due to the fact that the *relative number* of nonproduction workers rises as computer investment increases.

At a minimum, these results suggest that the effect of new technologies on workforce structure varies by the type of technology under study. For our sample of plants it appears that the adoption of factory automation technologies is uncorrelated with changes in the nonproduction labor share, while computer investment is strongly correlated with changes in the share of nonproduction workers in the plant. This should not be too surprising since computers are a primary tool of overhead labor, while many of the factory automation technologies are primarily used by production workers. However, it is important to recall that in the cross-sectional wage regressions in Table III we find a strong positive correlation between the number of new automation technologies used and production worker wages. Thus, while the *change* in the nonproduction labor share is relatively uncorrelated with

32. We also examined how the coefficients on the worker characteristics in Tables II and III change by replacing our technology use measures with the computer investment variable. Using a reduced sample of plants, we found that computer investment is positively related to the percent of workers in a plant with college degrees, the percent of workers in managerial, scientific, engineering, and precision-craft occupations, and the percent of nonproduction workers. However, we also found that computer investment is uncorrelated with the wages paid to any group of workers.

TABLE VII
REGRESSIONS OF CHANGES IN NONPRODUCTION LABOR SHARE, PRODUCTION-WORKER EARNINGS, AND NONPRODUCTION-WORKER EARNINGS OVER THE PERIOD 1977 TO 1992, FOR COMPUTER INVESTMENT IN THE PLANT

	Change in non-production labor share (1)	Change in non-production labor share (2)	Change in log production worker earnings (3)	Change in log non-production worker earnings (4)
Computer investment	—	.056(.022)	−.004(.039)	−.044(.050)
Technology adoption:				
First quintile	omitted	omitted	omitted	omitted
Second quintile	−.016(.012)	−.017(.012)	.017(.022)	−.006(.028)
Third quintile	−.010(.010)	−.010(.010)	−.005(.019)	−.001(.025)
Fourth quintile	−.015(.011)	−.015(.011)	.025(.020)	.020(.024)
Fifth quintile	−.023(.014)	−.022(.013)	.009(.024)	−.028(.031)
n	1844	1844	1844	1844
Mean of Y	.045	.045	.796	.851
R^2	.142	.146	.126	.133

Standard errors are in parentheses. The data include plants appearing in the 1993 SMT, the 1977 and 1992 CM's, and that are respondents to the computer investment question in the 1992 Annual Survey of Manufacturers. All regressions include controls for plant size (five dummies), the change in the capital-output ratio (except in column (4), where we include the change in the capital-labor ratio), region, MSA, and four-digit industry. Computer investment is defined as total computer investment in 1992 divided by total investment. The technology adoption quintiles represent the number of technologies that plant adopts between 1977 and 1992: 0–1 technologies, 2–3 technologies, 4–5 technologies, 6–8 technologies, and 9+ technologies.

the adoption of new factory automation technologies, the average quality of production workers is strongly correlated with the number of technologies used.

IV. CONCLUSION

In summary, our cross-sectional results are consistent with what other researchers have found when examining the cross-sectional relationship between technology use and the skill-mix and wages of workers—plants that use more sophisticated capital equipment employ more skilled workers, and workers who use more sophisticated capital receive higher wages [Berndt, Morrison, and Rosenblum 1992; Krueger 1993; Dunne and Schmitz 1995; Autor, Katz, and Krueger 1996]. At the same time our time-series analysis sounds a note of caution concerning these findings. If we had examined only the cross-sectional data, we would have concluded that the most technologically advanced plants pay their workers 8–20 percent higher wages than the least technologically advanced plants. However, the time-series analysis shows that the most technologically advanced plants paid their workers higher wages *prior* to adopting new technologies. In addition, these technologically advanced plants are high productivity plants both pre- and postadoption. These results suggest that the commonly observed cross-sectional correlation between technology use and worker wages may be due to time-invariant unobserved worker quality differences. The fact that the technology-wage premium drops substantially when worker characteristics are included (Table III) lends support to this interpretation. Alternatively, these results are consistent with worker skill and technology adoption being related to some omitted factor such as managerial ability.

This is not to say that the invention and diffusion of new technologies has not markedly affected employment and wages in manufacturing. Our time-series analysis focuses entirely on within-plant changes in the occupational mix, wages, and labor productivity. Thus, we do not examine changes in the employment shares of producers, nor do we examine the impact that factory automation has on the growth of industries. What our results do show is that the adoption of new technologies is more likely to occur in plants with skilled workforces, but that the act of adoption does not dramatically alter the wages paid or the employment structure of plants. One possible interpretation is that plants at the forefront of manufacturing technology tend to stay at the forefront of manufacturing technology. As managers see new technologies being developed, they adjust their workforces prior to the act of adoption—essentially, setting the stage for adoption. Under this scenario, technology and workforce skill may be tightly linked, though the observed correlation between adoption and upgrading of workforce skills may be low because of timing issues. Given this possibility, a fruitful line of research would be to model, and examine empirically, a firm's initial decision on the type of workers and capital used to produce output, taking into account the impact this investment has on a firm's future ability to adopt new technologies.[33]

33. Chari and Hopenhayn [1991] and Kandel and Pearson [1995] contain models along this line. In the Chari and Hopenhayn model workers undertake investments in using certain types of capital. This investment by workers then impacts the speed by which new technologies diffuse through the economy. Kandel and Pearson model a firm's decision whether to employ more productive permanent workers (who can never be fired) or less productive temporary workers, taking into account the effect this decision has on the future flexibility of the firm.

One should also note that our results do not imply that increases in the rate of technical change do not benefit more skilled workers. Our results show that, holding the level or rate of diffusion of new technologies constant, workers in plants with more advanced manufacturing technologies appear to have higher observed and unobserved abilities. It may be the case that increases in the rate of technical change increase the rate of return to skill. Again, however, because we focus on within-plant changes in technology and wages, we may miss an overall increase in the return to skills that results from a change in the level or diffusion of new technologies.

Finally, there are a number of important caveats to consider. First, the sample of plants used in the cross-sectional analysis is relatively small, only 358 plants, and is predominantly composed of large producers. Second, the sample of plants used in the time-series analysis is plants that survive between 1977 and 1992. Both samples are composed of plants exclusively in SIC 34–38. Therefore, the results need to be interpreted as being descriptive of the technology-employment patterns in large, surviving, manufacturing plants in a few select industries. However, we feel these data provide valuable new insights into the plant-level relationship between technology and employment.

DATA APPENDIX

In this appendix we present information on the characteristics of our WECD-1988 SMT matched data set. The first part of the appendix compares the plants and workers in our matched data set with the populations they are drawn from. The second subsection examines whether our measures of technology reflect how intensely the technology is used in the plant.

A.1. WECD-SMT Data Set

Appendix 1 presents summary statistics for all plants in SICs 34–38 in the 1989 ASM (column (1)), all plants in the 1988 SMT (column (2)), and all plants in our WECD-SMT matched sample (column (3)). The first point to note in Appendix 1 is that the plants in our data are much larger, much older, and use more technologies, than plants in either the 1989 ASM or the 1988 SMT. This occurs for two reasons. First, large plants are overrepresented in the WECD [Troske 1995b]. Second, requiring plants in our data to have at least ten workers and 3 percent of the workforce matched eliminates even more small plants from the data.

Appendix 1 also shows that a larger portion of the plants in our data are in the electrical equipment and transportation industries, are part of a multi-establishment firm, and are located in the Northeast and Midwest sections of the country.

Appendix 2 presents summary statistics for all workers in industries 34–38 who responded to the 1990 Decennial Census Long Form (column (1)), and for all workers in the matched WECD-1988 SMT data (column (2)). The numbers in Appendix 2 indicate that workers in the two files are fairly similar in terms of sex, race, and education. However, Appendix 2 does show that workers in the WECD-1988 SMT matched data have higher average annual earnings and higher average hourly wages. Results in Troske [1995a] show that even after controlling for the usual demographic characteristics, workers in large plants earn significantly higher wages. Results in Dunne and Schmitz [1995] show that plants that use the most technologies pay significantly higher wages than plants that use the least technologies. The fact that our data contain larger and more technologically advanced plants implies that our data will also contain higher wage workers.

To examine how representative the matched workers are compared with all workers in a plant, we examined the average worker earnings and wages in a plant based on both the plant and worker data. For both all workers and production workers, we found only a 3 percent difference in the two measures of average earnings. In addition, for production workers we found only a 3 percent difference in the two measures of average hourly wage.[34] Finally, the correlation between either the average earnings measures or the average wage measures is never less than 0.8. Thus, we conclude that our matched workers are representative of all workers in the plant.

A.2. Technology Measures

As discussed in subsection II.A, we use simple counts as our measure of technology use in the plant. The problem with this measure is that it does not capture how intensely a plant uses the technology. To determine whether or not our technology count measure captures how dependent a plant is on advanced production technology, we utilize data from the 1991 SMT which con-

34. The ASM collects data only on the hours worked by and wages paid to production workers. Therefore, we can only construct hourly wage measures from plant data for production workers.

tains information on technology intensity. The 1991 SMT asks, "What percent of your operations depend on a particular technology?" [U. S. Bureau of the Census, 1993, p. A-2] This survey differs from the 1988 SMT in that the seventeen technologies are collapsed into four groups: Design and Engineering—CAD/CAM related technologies; Flexible Machining and Assembly—Robots, Lasers, CNC, FMS technologies; Automated Material Handling; Sensors, Communications and Control—Automated Sensor, Computers, Networks, and Programmable Controllers.

We conduct two exercises to examine whether technology counts and intensity of use are related. First, for all plants in the 1991 SMT, we examine how technology intensity rises with the use of multiple technologies. We found that intensity of use is positively related to the number of technology groups present in the plant. This suggests that plants using a higher number of technologies also use technology more intensively. In addition, for plants that are in both the 1988 and 1991 SMT, we estimate the correlation between the count measure based on the 1988 SMT and the average intensity measure based on the 1991 SMT. The correlation coefficient between the two series was .85. Both of these findings are consistent with our hypothesis that plants that use a larger number of technologies, also use technology more intensively.

APPENDIX 1: SAMPLE STATISTICS FOR PLANTS

	1989 Annual Survey of Manufacturers (1)	1988 SMT (2)	1988 SMT-WECD match (3)
Mean employment	299.8	362.5	961.0
Size class:			
1–99	49.6	45.1	3.6
100–499	38.4	37.7	48.0
500+	12.0	17.2	48.3
Age:			
0–4	8.7	11.4	3.6
5–15	20.3	31.6	18.2
16–30	41.9	29.8	29.6
30+	29.1	27.2	48.6
Mean number of technologies	—	3.8	6.5
Technology classes:			
0–3	—	55.7	24.9
4–6	—	23.5	28.2

APPENDIX 1: CONTINUED

	1989 Annual Survey of Manufacturers (1)	1988 SMT (2)	1988 SMT-WECD match (3)
7–9	—	12.6	25.7
10+	—	8.3	21.2
Industry:			
Fabricated metal	29.4	23.4	24.6
Machinery equipment	31.3	27.3	21.5
Electrical equipment	18.0	22.8	26.5
Transportation equipment	11.6	13.1	23.5
Instruments	9.7	13.4	3.9
Percent in MSA	81.2	80.5	82.1
Region:			
Northeast	21.6	24.9	32.4
Midwest	34.2	34.4	46.9
South	24.9	23.6	17.3
West	19.4	17.2	3.4
Number of establishments	19,005	9,378	358

The numbers in column (1) are based on plants in the 1989 Annual Survey of Manufacturers in SICs 34–38. The numbers in column (2) are based on plants that are in the 1988 SMT and the 1987 CM.

APPENDIX 2: SUMMARY STATISTICS FOR WORKERS

	1990 Decennial census (1)	1988 WECD-SMT match (2)
Mean age	39.2	41.4
Percent male	72.6	75.7
Percent married	69.6	75.1
Percent white	87.6	91.2
Education:		
Less than high school diploma	15.5	15.5
High school diploma	36.9	40.0
Some college—no degree/A.A. degree	29.4	28.2
B.A. or B.S. degree	13.4	13.4
Advanced degree	4.9	5.0
Occupation:		
Managers/managerial related	11.7	9.4
Scientists, engineers, and other professionals	10.2	9.4
Technical and sales and clerical	20.7	18.6
Precision production and repair	25.1	25.5

APPENDIX 2: CONTINUED

	1990 Decennial census (1)	1988 WECD-SMT match (2)
Machine and transportation and laborers	32.3	33.0
Industry:		
Fabricated metal	13.9	14.4
Machinery equipment	28.4	24.0
Electrical equipment	21.8	19.3
Transportation	28.7	40.2
Instruments	7.1	2.0
Region:		
Northeast	20.4	26.2
Midwest	38.4	52.0
South	24.0	12.6
West	17.0	10.1
Mean yearly earnings	29,662	32,980
Mean hourly wage	13.80	15.34
Number of workers	1,176,276	34,034

The numbers in column (1) are based on workers who responded to the long form in the 1990 Decennial census and who work in SICs 34–38.

APPENDIX 3: DESCRIPTION OF TECHNOLOGIES

Technology	Description
Computer-aided design (CAD)	Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products.
CAD-controlled machines	Use of CAD output for controlling machines used to manufacture the part or product.
Digital CAD	Use of digital representation of CAD output for controlling machines used to manufacture the part or product.
Flexible manufacturing systems/cell	Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials and delivery of finished product.
Numerically controlled machines/computer controlled machines	NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC machines are controlled through an internal computer.
Materials working lasers	Laser technology used for welding, cutting, treating, scrubbing, and marking.

APPENDIX 3: CONTINUED

Technology	Description
Pick/place robots	A simple robot with 1–3 degrees of freedom, which transfer items from place to place.
Other robots	A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools, or specialized devices through variable programmed motions.
Automatic storage/ retrieval Systems	Computer-controlled equipment providing for the automatic handling and storage of materials, parts, and finished products.
Automatic guided vehicle systems	Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with workstations for automated or manual loading of materials, parts, tools, or products.
Technical data network	Use of local area network (LAN) technology to exchange technical data within design and engineering departments.
Factory network	Use of LAN technology to exchange information between different points on the factory floor.
Intercompany computer network	Intercompany computer network linking plant to subcontractors, suppliers, or customers.
Programmable controllers	A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system.
Computers used on factory floor	Exclude computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.
Automated sensors used on inputs	Automated equipment used to perform tests and inspections on incoming or in-process materials.
Automated sensors used on final product	Automated equipment used to perform tests and inspections on final products.

Source: U. S. Bureau of the Census [1989].

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