Scottish Journal of Political Economy, Vol. 52, No. 3, July 2005

TECHNOLOGY ADOPTION AND THE SKILL MIX OF US MANUFACTURING PLANTS

Timothy Dunne and Kenneth Troske***

Abstract

This paper examines the relationship between technology adoption and the skill mix of the workforce in US manufacturing plants. Using information on the use and adoption of seven different information technologies, we find that the relationship between technology adoption and workforce skill varies across the technologies. The use and adoption of engineering and design tasks are associated with workplaces that have a relatively large share of nonproduction labor. When we examine the relationship between technology adoption and skill upgrading of workforces, we find little correlation between the use and/or adoption of technologies and changes in workforce skill at the plant level. However, we do find that plants adopting technologies related to engineering and design tasks grow faster over the period 1987–1997.

I Introduction

It is commonly argued that the diffusion of new information technologies has restructured workplaces and led to changes in the relative demand for skilled workers. Most economic studies of the impact of technical change on workers have looked at the effect of computerization of the workplace. Acemoglu (2002), Katz and Autor (1999), and Link and Siegel (2003) review the economic literature on skill-biased technical change and the general conclusion is that computerization had led to increases in the wages of skilled workers and has increased overall wage inequality.[1] However, what is often overlooked is the fact that information technology is quite heterogeneous and that the relationship

*University of Oklahoma
**University of Missouri
IZA
The views expressed are the opinions of the authors and do not necessarily reflect the views of the US Census Bureau.

[1] Card and Dinardo (2002) offer an opposing view of the impact of technical change on wage inequality. They argue that the skill-biased technical change hypothesis cannot explain important changes in wage structure in the US including the changes in the wage gap associated with gender and race. Dinardo and Pischke (1997) argue that observed computer-wage premium reflects unobserved worker skill as opposed to a technology induced wage premium.

between worker skill and technology may differ by the type of information technology employed.

Consider the possible relationship between computing networks and workforce skill at a manufacturing plant. Since computing networks are complementary with other types of information technology, we might expect that networks are also complementary with skilled labor. Networks link together computer workstations and such networked computers are typically utilized by more skilled workers. Alternatively, computer networks may foster the deskilling of a particular plant by allowing computer-aided design (CAD) information to be transferred from engineering locations to production locations at low cost and by allowing off-site engineers and managers to monitor the production activity at a plant. In fact, our results show that the use of *intercompany* networks (i.e., wide-area networks) is actually negatively correlated with the skill mix of the workforce at the manufacturing plant level. In this way, networks may enable a manufacturing plant to outsource skilled tasks to either other locations within the firm or to other firms.[2]

In this paper, we examine how the technology–skill relationship differs across a variety of new information-based manufacturing technologies. We have data on the adoption and use of seven different information technologies at the plant level. In the first part of the analysis, we use these data to directly investigate whether the relationship between technology and the skill mix of the workforce varies by the type of technology.[3] In the second part of the analysis, we investigate whether the relationship between changes in the skill mix of the workforce and technology adoption varies by the type of technology being adopted. This latter analysis is important because it directly examines the relationship between technology adoption and changes in the skill mix of the workforce.

Our results in the first half of the paper show that the correlation between the use and adoption of technologies and workforce skill differs systematically by the task the technology performs. We find that the likelihood of adopting a computer-aided design (CAD) machine used for design and engineering tasks is highly correlated with the proportion of skilled labor in the manufacturing facility. In contrast, we find that the use of CAD output to control manufacturing machines is relatively uncorrelated with the proportion of skilled labor in the plant. We find similar results for networks. Networks used to transmit design and engineering data are associated with a greater share of skilled labor while networks used for the transmission of data between companies are not.

When we turn to examining the relationship between technology adoption and changes in the skill mix of the workforce, we find that the adoption of new technologies, regardless of the task they perform, is uncorrelated with changes in the skill mix of the workers in the plant. We do find, however, that plants that

[2] Bresnahan (1999) and Bresnahan *et al.* (2002) discuss the impact of technological change on organizational structure. Bresnahan (1999), in particular, focuses on the importance of new information technologies in reshaping the organizational structure of firms.

[3] The measure of the skill of the workforce, or skill mix, is defined as the share of payroll paid to nonproduction labor in the plant. In section III, we discuss the use of this measure as a proxy for workforce skill.

adopt technologies, both CAD and networking, used in design and engineering tasks experience faster employment growth than similar, nonadopting plants. Thus, while changes in the skill mix of plants are relatively uncorrelated with the adoption of these new information technologies, plants adopting design and engineering technologies do gain employment share.

The rest of the paper is organized as follows. The second section provides an overview of the literature on technology adoption and workforce skills. The third section describes the data and examines the relationship between technological adoption and workforce skill focusing on how the relationship varies by the type of technology. The fourth section investigates the correlation between changes in the skill mix of the workforce and the adoption of information technologies. The last section concludes the paper.

II Literature Review

The widespread introduction of information technology into the workplace has been well documented by a number of authors. Data on individual workers in the US show that computer use in the workplace rose from 27% in 1984 to 60% in 2001.[4] This widespread diffusion of new information technology raises the question of what impact have these new technologies had on labor markets? The most common theory in this regard is the skill–bias technical change hypothesis (SBTC), which states that the invention and diffusion of new information technologies has increased the relative demand for skilled workers and this has resulted in an increase in the relative wages of skilled workers as compared with unskilled workers. Acemoglu (2002), Katz and Autor (1999), and Link and Siegel (2003) provide overviews of the SBTC literature. In the remainder of this section, we review the empirical literature that specifically links changes in workforce skills to the introduction of new computing technologies.[5] While we provide brief overviews of the industry- and worker-level studies, our focus is primarily on studies that employ establishment and firm-level data.

The first set of studies linking changes in workforce skill to technological change focused on industry-level analysis. These studies relate the change in the share of skilled workers in an industry to measures of technology change. The industry-based studies typically use two alternative measures of skill. One measure is constructed from broad occupational categories that are usually available in establishment-level data – nonproduction labor vs. production labor or white- vs. blue-collar workers. The alternative approach aggregates worker-level data by education or occupational grouping to the industry level. The advantage of using establishment-level based measures of skill is that industry data are typically more detailed (four-digit SIC) than the industry cells

[4] Tashiro (2004) examines changes in the use of computers by US workers from 1984 through 2001 using data from the US Current Population Survey.

[5] In addition to the implications for labor markets, the investment in information technologies appears to be positively correlated with increased productivity in the last decade, see Stiroh (2002).

one can form by aggregating individual worker data (two- to three-digit SIC level). The downside of establishment-based studies is that the measures of workforce skill are usually much cruder than the measures constructed from worker data. With respect to technology measures, the industry studies typically use data on R & D expenditures, expenditures on computing equipment, or estimates of the computer capital stock for the industry.[6]

Papers by Autor *et al.* (1998), Berman *et al.* (1994), and Berndt *et al.* (1992) and modeled changes in the share of skilled labor in the United States as a function of computer investment in an industry. These studies find general support for the SBTC hypothesis – increases in computer investment were positively correlated with increases in the share of skilled labor within an industry. Berman *et al.* (1998) confirm these findings in a cross-country analysis. More recent studies that utilize richer measures of technology and/or more advanced econometric methodology (e.g., Haskel and Heden (1999) and Siegel (1997)) also find support for the SBTC hypothesis.

While the industry-level studies point to a relatively consistent relationship between skills and technology, the results using microdata, specifically worker, firm, and establishment data, are considerably more mixed. Krueger (1993) analyzes individual data on US workers and looks at the relationship between computer use and wages. He finds that there is a significant wage premium associated with computer use by workers and interprets the results as consistent with the SBTC hypothesis. This finding is supported by a more comprehensive study by Autor *et al.* (1998) that uses a wider range of both data sets and measures of technological change. However, Dinardo and Pischke (1997) challenge the conclusions from studies that analyze computer use and wages in worker data. They use data on German workers and find that not only is computer use positively correlated with a worker's wages but so is the use of pencils and sitting down on the job, as well. They argue that more productive workers are given tasks that utilize tools like computers and pencils, and that the observed correlations between technology and wages reflect differences in worker ability that are not captured by the standard human capital variables (i.e., education, experience, and other basic controls).[7] Card and Dinardo (2002) also make the point that much of the growth in wage inequality is because of within-group changes in wages and these cannot be readily explained by shifts in technology.

[6] The results from studies that utilize the stock of computer capital based on the US National Wealth Accounts are difficult to interpret because the allocation of computer capital across industries by the BEA is based, in part, on the occupational distribution of workers. Hence, industries with a high proportion of skilled, computer-oriented occupations will be allocated a higher proportion of computer investment.

[7] More recently, Dolton and Makepeace (2004) examine the earnings premium associated with computer use in a panel of British workers. Using a number of different econometric methods, they conclude that the observed computer premium in their data cannot be explained by unobserved worker ability. This finding stands in contrast to Entorf and Kramarz (1997) who report no evidence of a computer premium using a fixed effects panel model on French data.

In addition to research that utilizes individual worker data, a number of studies have examined how the skill distributions of firms and establishments have been affected by changes in technology. These studies are similar in spirit to the industry studies and examine how changes in workforce skill are related to changes in technology used at the workplace. With regard to the measures of skill available in workplace studies, these vary from simple distinctions such as white- vs. blue-collar workers and production vs. nonproduction labor to more detailed disaggregations of the workforce based on occupation or education groupings. The measures of technology change typically utilized include changes in capital intensity, R & D expenditures, indicator variables of the use of specific technologies and expenditures on computer equipment.

Dunne and Schmitz (1995) is one of the first studies to utilize establishment-level data to look at the correlation between the skill composition of the workforce and the use of advanced manufacturing technologies such as CAD, flexible manufacturing cells and networks.[8] Their data come from merging establishment-level production data from the longitudinal research database (LRD) to detailed information on technology use from the Survey of Manufacturing Technology (SMT). Their measure of skill is the share of production workers in the labor force of the plant. Production workers are generally viewed as less skilled, on average, than nonproduction workers. They find that US manufacturing plants that use a greater number of advanced manufacturing technologies employ a lower share of production workers. However, their analysis is entirely cross sectional and thus does not address the issue of skill upgrading and technology change.

Doms *et al.* (1997) address the 'skill upgrading' issue using similar manufacturing plant-level data but also analyze plants across time and link the plant-level data to individual worker data. They find that plants that utilize a greater number of advanced manufacturing technologies employ a more educated workforce, have a greater share of nonproduction labor, and pay higher wages. However, when they examine the relationship between advanced technology adoption and *changes* in the skill of the workforce from 1977 to 1992, the results are quite different. There is little correlation between these advanced manufacturing technologies and the *changes* in workforce skill. Plants that adopted more of these technologies over time did not appear to upgrade the skill of their workforce as compared with nonadopters. A somewhat different analysis in this paper does show that skill upgrading is correlated with investments in computer equipment. Plants with a greater share of investment in computing equipment in 1992 experienced skill upgrading from 1977 to 1992. This study indicates that the relationship between skill upgrading and

[8] Reilly (1995) using Canadian data looks at the impact of computers on the employer-size wage effect. He finds that the inclusion of a computer variable in a regression of wages on employer size diminishes the employer size effect. His conclusion is that differences in wages because of employer size are because of differences in the kinds of workers that large employers hire rather than a premium for size.

technology differs by type of technology and the type of technology measure employed.

This heterogeneous nature of technology is explored more fully in an extensive study of manufacturing firms on Long Island by Donald Siegel. Siegel (1999) uses data on 79 manufacturing firms and examines the impact of 12 different advanced manufacturing technologies on human resource and management practices. Employing both econometric analysis and case study methodology, he finds that the magnitude of the effect of advanced manufacturing technologies differs by the type of technology adopted. Specifically, he separates technologies into two broad classes – technologies used to streamline production techniques and technologies used in the design or improvement in the quality of a product. Skill upgrading in these firms was most strongly linked to technologies that reduce production inefficiencies. Overall, he interprets his findings as evidence in support of the SBTC hypothesis.

Several studies have used British establishment-level data to examine whether computerization is associated with higher wages and changes in the skill composition of the workforce. Chennells and Van Reenen (1997) show that establishments that *use* new computer technology pay higher wages. However, they also show that the *introduction* of new computer technologies only has a modest effect on wages. Their interpretation is that plants adopting new technologies employ workers with more unobserved abilities. Haskel and Heden (1999) model changes in workforce skill as a function of the share of computer investment in total investment in an establishment using data from the ABI Respondents Database. They find that the share of the wage bill of nonmanual workers increases as the share of computer investment increases. However, their results do vary by econometric specification with the skills–technology effect being significantly muted when panel econometric techniques are employed. This sensitivity of the technology–skills relationship to econometric specification is discussed at length in Chennells and Van Reenen (2002). This point is also illustrated well in a paper by Pavncik (2003) that uses plant-level data from Chile. Once she controls for unobserved plant characteristics, she finds no relationship between skill upgrading and her measures of technology.

Overall, the literature on workforce skill and technology change has resulted in several main findings. First, skills and technology are clearly related at the workplace level. Plants and firms that utilize more advanced technology employ more skilled workers and pay higher wages. Second, the relationship between skill-upgrading and technology adoption is much less clear. The results here depend upon both the econometric methods employed and specific technology measures utilized. An additional issue in this literature is that information on the timing of technology adoption is usually weak. In many cases, while one may observe data on expenditures for computers, the data do not identify when the computing technology was adopted. Link and Siegel (2003) emphasize this point and argue that without such information it is often difficult to assess the relationship between skill upgrading and technology adoption.

III Technological Adoption and Workforce Composition

The first part of this section describes the data sets used to measure technology adoption and the skill mix of the workforce at the establishment level. In the second part, we examine the relationship between technology use and adoption and the skill mix.

Data and measurement issues

This paper utilizes microeconomic data on manufacturing plants to examine the relationship between technology adoption and establishment characteristics. The data come from two main sources. The plant-level data on technology use and adoption come from the 1988 and 1993 SMT. The 1988 SMT was sent to a stratified random sample of 10,590 manufacturing plants with 20 or more employees in the fabricated metal products, nonelectrical machinery, electrical machinery, transportation equipment, and instruments and related products industries (SICs 34–38).[9] This survey asks plant managers about their use of new factory automation equipment such as CAD, numerically controlled machines, local area networks, and programmable controllers. The 1993 SMT was similar in design but surveyed 8336 plants.

We analyze the adoption and use of seven information technologies that include three CAD technologies, three network technologies (NET) and one computing technology (COMP). A description of the seven individual technologies is given in Table 1. The three CAD innovations are CAD used in design and engineering (CAD1), CAD output used to control machines (CAD2), and CAD output used for procurement (CAD3). The three network technologies are networks used to exchange technical data (NET1), networks used for data exchange on the factory floor (NET2), and intercompany computer networks (NET3). The final technology is the use of computers on the factory floor (COMP).

Technology use is measured directly using responses from the 1988 SMT. The variable is coded as a zero for nonusers of the technology and one for users. Our sample includes all respondents to the 1988 SMT that are also found in the 1987 Census of Manufactures (CM). This sample contains 9423 plants.

Technology adoption is measured by comparing a plant's response in the 1993 SMT with the response in the 1988 SMT. This sample includes only plants in both surveys that we can also match to the 1987, 1992, and 1997 CM data. This sample contains 1889 plants. We restrict our sample to these plants for two reasons. First, we will utilize both SMT surveys in order to measure the change in technology use (adoption or de-adoption) over the period. Plants that indicate they did not use a technology in 1988 but indicate they do use a technology in 1993 are called adopters.[10] We should note that this is a much more precise measure of adoption than we have used in earlier papers (e.g., Doms *et al.* 1997).

[9] For a more complete description of the SMT, see Dunne (1994).

[10] Plants indicating they use a technology in 1988 but indicate they do not use the technology in 1993 is called de-adopters. We discuss this phenomenon more completely below.

Table 1
Description of technologies

Technology	Description
Computer-aided design (CAD1)	Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products
CAD controlled machines (CAD2)	Use of CAD output for controlling machines used to manufacture the part or product
Digital CAD (CAD3)	Digital representation of CAD output used in procurement activities
Technical data network (LAN1)	Use of local area network (LAN) technology to exchange technical data within design and engineering departments
Factory network (LAN2)	Use of LAN technology to exchange information between different points on the factory floor
Intercompany computer network (LAN3)	Intercompany computer network linking plant to subcontractors, suppliers, and/or customers
Computers used on factory floor (COMP)	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

Source:
Survey of Manufacturing Technology (1988).

This restricts us to around 2400 plants. Second, in the next section of the paper, we also examine establishment growth over the periods 1992–1997 and 1987–1997. Ensuring that a plant appears in the 1987, 1992, and 1997 CMs reduces our sample to the 1889 plants that are used in the analysis.[11]

Throughout this analysis, our measure of workforce skill is the share of the establishment's payroll paid to nonproduction workers – what we refer to as the nonproduction labor share or skill mix. Nonproduction labor is composed of highly skilled labor including managers, engineers, and scientists but also contains less skilled clerical and service workers (e.g., secretaries, guards, and janitors). There are extensive discussions in Berman *et al.* (1994), Davis and Haltiwanger (1991), Doms *et al.* (1997), and Dunne *et al.* (1997) on the use of nonproduction labor share as a measure of workforce skill. In the manufacturing sector, nonproduction labor is, on average, more educated than production labor and the recent growth in nonproduction labor share in manufacturing is primarily because of the growth in the engineering and managerial occupations. In addition, evidence presented in Doms *et al.* (1997) shows that plants with a larger nonproduction labor share employ, on average, more educated workers. Thus, while obviously not a perfect measure of workforce skill, there is considerable evidence suggesting that the nonproduction labor share variable is

[11] We have repeated the analysis using the larger set of plants that appear in both the 1992 and 1997 CMs with similar results.

correlated with traditional measures of workforce skill based on occupation and/or education data.

Table 2 presents summary statistics for our plant-level data. The technology use statistics show that CAD technology for design and engineering functions (CAD1) and computers used on the factory floor (COMP) are the most widely used in 1988. CAD1 and networks used to exchange technical data (NET1) are the most widely adopted over the 1988–1993 period. A key difference between our use and adoption samples is plant size. Average plant size, measured by the log of shipments in 1988, is 9.31 in the use sample (9423 plants) but 10.28 in the more limited matched sample (1889 plants). Since adoption is correlated with plant size, the adoption rates in the matched sample are probably higher than the population as a whole. Alternatively, the mean of the skill mix variable is almost identical across the two samples.

Empirical analysis of technology adoption and workforce composition

In this section of the paper, we examine the relationship between the skill mix of the workforce and the adoption of several different, but related, information technologies. The decision that we are examining is the decision of a

Table 2
Summary statistics

Variable	Value
Proportion of plants using CAD1 in 1988	0.515
Proportion of plants using CAD2 in 1988	0.205
Proportion of plants using CAD3 in 1988	0.135
Proportion of plants using NET1 in 1988	0.274
Proportion of plants using NET2 in 1988	0.240
Proportion of plants using NET3 in 1988	0.217
Proportion of plants using COMP in 1988	0.379
Proportion of plants adopting CAD1 in 1988–1993[a]	0.586
Proportion of plants adopting CAD2 in 1988–1993[a]	0.289
Proportion of plants adopting CAD3 in 1988–1993[a]	0.177
Proportion of plants adopting NET1 in 1988–1993[a]	0.419
Proportion of plants adopting NET2 in 1988–1993[a]	0.360
Proportion of plants adopting NET3 in 1988–1993[a]	0.241
Proportion of plants adopting COMP in 1988–1993[a]	0.345
Average plant size in 1988 (log of shipments)	9.31
Average plant size in 1988 (matched sample)	10.28
Average skill mix in 1988 (nonproduction labor share)	0.417
Average skill mix in 1988 (matched sample)	0.415
Proportion of plants owned by multi-units in 1988	0.599
Proportion of plants 0–5 years old in 1988	0.112
Proportion of plants 6–15 years old in 1988	0.314
Proportion of plants 16–30 years old in 1988	0.298
Proportion of plants 30 years and older in 1988	0.276

[a]The proportion of plants not using the technology in 1988 that report using the technology in 1993 based on the matched sample.

manufacturing establishment to adopt a specific technology. Denote the expected profits from adopting a given technology for plant i as Π_i. A plant adopts a specific technology if $\Pi_i > 0$. We model the expected profits as a latent variable by the equation

$$\Pi_i = \beta_0 + \beta_1 \mathrm{SM}_i + \delta X_i + \varepsilon_i, \tag{1}$$

where SM_i represents the skill mix of the workforce in 1988, X_i contains a set of plant characteristics, and ε_i is an error term assumed to be distributed $N(0, 1)$. While the latent variable Π_i is unobservable, we do observe the decision of a plant to adopt a specific technology. Let $Y_i = 1$ if a plant adopts the technology and $Y_i = 0$ if a plant does not adopt the technology. The probability a plant adopts a specific technology is given by

$$\begin{aligned} \text{Prob } (Y_i = 1) = \text{Prob } (\Pi_i > 0) &= \text{Prob } (\beta_0 + \beta_1 \mathrm{SM}_i + \delta X_i + \varepsilon_i > 0) \\ &= \Phi(\beta_0 + \beta_1 \mathrm{SM}_i + \delta X_i), \end{aligned} \tag{2}$$

where Φ denotes the standard normal cumulative distribution function. We estimate the model using standard probit model estimation techniques. For each of the seven technologies, we estimate separate models for the probability of technology use in 1988 and for the probability of technology adoption between 1988 and 1993. All models include a set of three-digit SIC industry dummy variables, a set of nine-census region geography dummies, a variable that indicates whether the plant is owned by a firm operating at more than one location, a measure of plant size (log of plant shipments), a set of dummy variables that indicate the age of the plant, and our measure of the skill mix of the workforce – the nonproduction labor share. All plant characteristics are measured at their 1987 values. The industry, region, size, age, and multi-unit status variables are similar to the variables used in Dunne (1994) and control for basic differences in the characteristics of establishments. This approach of analyzing the use/adoption of technology based on the skill mix of the workforce is similar to that presented in Breshnahan *et al.* (2002).

Tables 3 and 4 report the results from plant-level analyses of technology use and technology adoption. Rather than report the probit coefficients directly, we report the marginal effects evaluated at the means of all the independent variables. Table 3 presents the results when technology use in 1988 is the dependent variable. Looking across technologies and focusing on the skill mix variable, we find that the probability of use in 1988 is positively correlated with the skill mix for only three out of the seven technologies. The strongest correlations are present in technologies that are most closely aligned to engineering and white-collar tasks (CAD1, CAD3, and NET1). For example, the probability of using CAD and engineering technology increases as the skill mix of the workforce rises. A 0.10 increase in the skill mix is associated with a 0.04 increase in the probability of CAD1 use in 1988. Similarly, a 0.10 increase in the skill mix is associated with an increase in the probability of using a network for technical data exchange by 0.0165. However, for the technology where the output from CAD technologies is used to control machinery (CAD2), there is no

Table 3
Probability of technology use in 1988 using the full 1988 sample

	Computer-automated design (CAD) technologies			Network technologies			
Variable	CAD1	CAD2	CAD3	NET1	NET2	NET3	Computers: COMP
Skill mix (non-production labor share)	0.384* (0.032)	– 0.008 (0.022)	0.074* (0.018)	0.165* (0.026)	0.022 (0.024)	– 0.107* (0.023)	0.003 (0.030)
Establishment size (log shipments)	0.160* (0.005)	0.071* (0.003)	0.046* (0.003)	0.110* (0.004)	0.095* (0.004)	0.066* (0.003)	0.139* (0.005)
MU indicator variable	0.036* (0.014)	– 0.025* (0.107)	– 0.003 (0.009)	0.015 (0.012)	0.006 (0.011)	0.087* (0.010)	0.046* (0.013)
6–15 years old	– 0.034 (0.020)	– 0.001 (0.015)	– 0.001 (0.012)	– 0.016 (0.016)	– 0.022 (0.015)	0.008 (0.016)	– 0.015 (0.019)
15–30 years old	– 0.043* (0.020)	0.017 (0.015)	– 0.014 (0.012)	– 0.046* (0.016)	– 0.035* (0.015)	– 0.007 (0.016)	– 0.045* (0.019)
More than 30 years old	– 0.021 (0.021)	0.017 (0.016)	– 0.007 (0.012)	– 0.051* (0.017)	– 0.032 (0.016)	– 0.017 (0.016)	– 0.038 (0.020)
Mean of dependent variable	0.515	0.205	0.135	0.274	0.240	0.217	0.379
N	9423	9423	9420	9420	9420	9420	9420
Pseudo R^2	0.210	0.115	0.106	0.154	0.131	0.142	0.157

Note:
All probit models include controls for industry (3-digit level) and controls for region (9 census regions).
*Significant at 5% level.

Table 4
Probability of technology adoption between 1988 and 1993 using a matched sample of plants

	Computer-automated design (CAD) technologies			Network technologies			
Variable	CAD1	CAD2	CAD3	NET1	NET2	NET3	Computers: COMP
Skill mix (non-production labor share)	0.608* (0.139)	0.086 (0.072)	0.198* (0.055)	0.428* (0.095)	0.250* (0.084)	– 0.122 (0.067)	0.112 (0.102)
Establishment size (log shipments)	0.135* (0.022)	0.070* (0.011)	0.051* (0.008)	0.147* (0.016)	0.160* (0.014)	0.067* (0.010)	0.129* (0.016)
MU indicator variable	0.109 (0.056)	0.014 (0.036)	– 0.001 (0.029)	0.103* (0.042)	0.040 (0.040)	0.057 (0.032)	0.011 (0.045)
6–15 years old	– 0.098 (0.092)	– 0.044 (0.052)	0.049 (0.047)	– 0.061 (0.065)	– 0.035 (0.061)	– 0.076 (0.046)	– 0.063 (0.066)
15–30 years old	– 0.088 (0.093)	0.009 (0.054)	0.018 (0.044)	– 0.114 (0.064)	– 0.084 (0.060)	– 0.032 (0.048)	– 0.026 (0.068)
More than 30 years old	– 0.139 (0.095)	– 0.015 (0.055)	0.001 (0.044)	– 0.088 (0.066)	– 0.084 (0.062)	– 0.053 (0.049)	– 0.019 (0.072)
Mean of dependent variable	0.586	0.289	0.177	0.419	0.360	0.241	0.345
N	638	1368	1492	1172	1278	1338	909
Pseudo R^2	0.201	0.101	0.111	0.188	0.174	0.121	0.156

Note:
All probit models include controls for industry (3-digit level) and controls for region (9 census regions).
*Significant at 5% level.

correlation between the skill mix of the workforce and the probability of use. There is also no correlation between the skill mix variable and computers used on the factory floor, and there is a negative and statistically significant correlation between the skill mix and the probability of intercompany network use (NET3). In the latter case, this may reflect the fact that skilled tasks are being outsourced to subcontractors or suppliers or to other parts of the company.

With respect to the other variables in the model, the probability of technology use increases with plant size for all seven technologies. The effect of multi-unit status varies across technology with the strongest effect being observed for intercompany networks. In this case, a plant owned by a multi-unit company has a 0.087 higher probability of using an intercompany network than a plant owned by single-unit company. This makes sense especially since the network technology that underlies intercompany communication also supports intra-company communication and multi-unit companies are likely to experience greater benefits from improving intra-company communications. Finally, the age variables generally do not matter and this is consistent with the findings reported in Dunne (1994). It does not appear that old establishments are particularly disadvantaged as compared with young establishments in the use of new technologies.

Table 4 presents the results from the technology adoption analysis. Recall, this analysis uses a matched sample of plants from the 1988 and 1993 SMT. To examine adoption over the period, we only use those plants that are not users of the technology in 1988. Thus, our sample sizes will vary depending upon the number of users in 1988.[12] Table 4 presents the marginal effects of the independent variables on the probability of adoption. With regard to the skill mix variable, the key differences between the use and adoption results are that plants with a higher share of nonproduction labor in 1988 are more likely to adopt networks used on the factory floor (NET2) and the relationship between intercompany networks (NET3) and the skill mix is somewhat weaker.

Our conclusion from this analysis of technology use and adoption and the skill mix of the workforce is that the association between the tasks the technology is performing and the types of workers that perform that task drives the correlation between technology and skill mix of the workforce. When the tasks are clearly related to design and engineering functions (CAD1, CAD3, and NET1), there is a strong positive correlation between nonproduction labor share (skill mix) and technology use/adoption. Alternatively, when the technology tasks are related to production activities (CAD2, NET2, and COMP), the correlations are much weaker between technology use and nonproduction labor share.

[12] We also estimated the technology use probits on the sample of 1889 plants in 1988. The results are quite similar across both samples of plants. For the sample that contains 1889 plants, the coefficient and standard errors for the workforce skill measures by technology are – CAD1: 0.492(0.071); CAD2: 0.086(0.072); CAD3: 0.198(0.045); NET1: 0.179(0.069); NET2: 0.023 (0.065); NET3: -0.103(0.061); and COMP: 0.085(0.072).

IV Technology Adoption and Changes in the Skill Mix of the Workforce and Employment

While the above analysis describes the cross-sectional correlations between use and adoption and workforce skill, it does not relate *changes* in the skill mix of the workforce to technology adoption. In this section of the paper, we examine changes in workforce skill and changes in establishment size as a function of the adoption of information technologies. We estimate the following regression:

$$\Delta L_i = \alpha_0 + \alpha T_i + \gamma Z_i + \mu_i, \tag{3}$$

where ΔL_i is either the change in the skill mix (ΔSM_i), measured as the change in nonproduction labor share, or the change in log total employment in the plant, T_i represents a set of technology variables, Z_i includes a set of control variables, and μ_{i} is the error term of the regression. We examine the change in the two dependent variables over two time periods: 1992–1997 and 1987–1997. The control variables include industry, region, size, age, and multi-unit status and are measured in the initial period.

Our technology variables (T_i) in equation (3) will capture both the initial use of technology in the base period and the change in technology use between 1988 and 1993. The technology variables can take on one of four values describing technology adoption over the interval – (1) establishments using the technology in both 1988 and 1993; (2) establishments adopting the technology in the period 1988–1993; (3) establishments de-adopting the technology in the period 1988–1993; and (4) establishments neither using the technology in 1988 nor adopting by 1993. Surprisingly, there are a number of establishments that report implied de-adoption over the interval. This is especially true in the case of computers used on the factory floor. The 1993 SMT reports that the use of computers declines by 1.1% between 1988 and 1993 while about 17% of the establishments report that they adopt this technology over the same interval (U.S. Department of Commerce, 1993 Table 2a). This implies that roughly 18% of establishments are de-adopting computers used on the factory floor over the period. This pattern of de-adoption may reflect the growing use of imbedded programmable controllers and imbedded computers within machinery that replace stand-alone computer systems used to control machinery and monitor processes. Such imbedded controllers would not be counted as computers used on the floor in the SMT surveys. Alternatively, only 3% of plants report the de-adoption of CAD1.

We focus our attention on a subset of the three technologies analyzed above – CAD1, NET1, and COMP. We include CAD1 and NET1 adoption variables because they had the strongest correlations between the skill mix of the workforce and technology adoption in the previous section.[13] We include

[13] We estimated all models including all seven technologies. The results for the nonproduction labor share regressions are identical. None of the technologies matter in the nonproduction labor share. With regard to the employment growth equations, in the model that examines employment growth from 1987 to 1997, plants adopting or using intercompany networks also experienced higher employment growth.

computer adoption (COMP), as well, since the adoption of computer-related technologies has been the main focus of a great deal of the existing literature. Though to be clear, our measure of computers is very different than that which appears in the literature. Our measure of computers reflects use on the factory floor and such computers may be used to directly control machinery.

Table 5 reports the results of the change in the skill mix and growth in total employment regressions separately for the 1992–1997 and 1987–1997 periods. The first two columns present the results for the change in the skill mix equations. The pattern is easy to explain; none of the technology variables matter. It appears that the use, adoption, or even de-adoption of CAD1, NET1, and COMP technologies is uncorrelated with changes in nonproduction labor share in either the 1992–1997 or the 1987–1997 periods.[14] This is consistent with results reported in Doms *et al.* (1997).

Looking at the employment growth results in columns 3 and 4 of Table 5, the findings are more interesting. First, the age and size results are in agreement with the previous literature that studies the growth of establishment employment. Conditioning on success, younger and smaller establishments grow faster than older and larger establishments. In the case of the technology variables, establishments adopting CAD1 during the period 1987–1993 grew faster over the 1992–1997 period. The strongest results occur when we examine long-term growth. Establishments either adopting or using CAD1 or NET1 during the period 1988–1993 grew considerably faster over the 1987–1997 period. One should be cautious in interpreting the long-term change results. It may be that better managed plants both adopt new technologies and grow faster over the period, as opposed to technology leading to increased growth.

Finally, Table 6 reports a set of *F*-tests on the technology variables from the regressions in Table 5. This table summarizes hypothesis tests of the technology effects for the three technologies. For the skill mix regressions, we fail to reject the null hypothesis of no technology effect for each of our technology groups. For the employment growth equations, CAD1 has an effect in both regressions while NET1 is significant at the 10% confidence level in the regression on the 1987–1997 data.

Concluding Remarks

This paper examines the patterns of technology use and adoption for a range of information technologies. One main finding is that the relationship between the skill mix of the workforce and technology use and adoption varies by the type of technology under study and by the task the technology is performing. When the technology is associated with design and engineering functions or procurement, there is generally a strong correlation between technology use/adoption and the skill mix of the workforce. However, the use and adoption of technologies more closely associated with production activity show little correlation with our

[14] We also estimated the models for the 1992–1997 period with controls for lagged changes in the dependent variable. The results presented in Table 5 are robust to this change in specification.

Table 5
Analysis of changes in skill mix and total employment from 1992 to 1997

	Change in skill mix (nonproduction labor share)		Growth in total employment: 1992–1997	
Variable	(1), 1992–1997	(2), 1987–1997	(3), 1992–1997	(4), 1987–1997
Log shipments (1988)	– 0.008 (0.003)	– 0.009 (0.004)	– 0.035* (0.010)	– 0.108* (0.015)
MU indicator variable	0.014 (0.010)	0.014 (0.011)	– 0.004 (0.032)	– 0.022 (0.044)
0–5 years old	– 0.048* (0.019)	– 0.010 (0.018)	0.174* (0.060)	0.297* (0.069)
5–15 years old	– 0.010 (0.010)	– 0.011 (0.011)	0.128* (0.031)	0.240* (0.042)
15–30 years old	– 0.025* (0.008)	– 0.015 (0.010)	0.093* (0.026)	0.099* (0.038)
More than 30 years old	Omitted	Omitted	Omitted	Omitted
CAD1 use in 1988 and in 1993	0.019 (0.012)	0.002 (0.014)	0.062 (0.040)	0.160* (0.054)
CAD1 adoption between 1988 and 1993	0.012 (0.013)	0.002 (0.014)	0.108* (0.040)	0.222* (0.055)
CAD1 de-adoption between 1988 and 1993	– 0.003 (0.022)	– 0.028 (0.025)	– 0.053 (0.069)	– 0.057 (0.094)
LAN1 (technical data) use in 1988	– 0.008 (0.011)	– 0.010 (0.013)	– 0.021 (0.034)	0.106* (0.048)
LAN1 (technical data) adoption between 1988 and 1993	– 0.019 (0.010)	– 0.022 (0.011)	0.014 (0.031)	0.105* (0.043)
LAN1 (technical data) de-adoption between 1988 and 1993	– 0.001 (0.013)	– 0.013 (0.015)	0.056 (0.041)	0.085 (0.057)
COMP use in 1988 and in 1993	– 0.003 (0.010)	– 0.013 (0.012)	0.009 (0.033)	– 0.001 (0.045)
COMP adoption between 1988 and 1993	– 0.007 (0.011)	– 0.007 (0.012)	– 0.042 (0.034)	– 0.032 (0.047)
COMP de-adoption between 1988 and 1993	– 0.008 (0.011)	– 0.022 (0.012)	– 0.029 (0.034)	– 0.030 (0.047)
Number of observations	1889	1889	1889	1889
Mean of dependent variable	0.000	0.015	– 0.035	– 0.040
R^2	0.046	0.047	0.099	0.177

Note:
All regressions include controls for industry (3-digit level) and controls for region (9 census regions).
*Significant at 5% level.

Table 6

Hypothesis tests for the effect of technology on the change in skill mix and the change in total employment: 1992–1997 & 1987–1997

	F-statistics for 1992–1997 hypothesis tests	
	Change in skill mix (nonproduction labor share): 1992–1997	Change in total employment: 1992–1997
Joint hypothesis test statistic of no effect of CAD1	0.98	3.60*
Joint hypothesis test statistics of no effect of LAN1	1.34	1.23
Joint hypothesis test statistics of no effect of COMP	0.24	1.05
	F-statistics for 1987–1997 hypothesis tests	
	Change in skill mix (nonproduction labor share): 1987–1997	Change in total employment: 1987–1997
Joint hypothesis test statistic of no effect of CAD1	0.57	7.21*
Joint hypothesis test statistics of no effect of LAN1	1.32	2.45**
Joint hypothesis test statistics of no effect of COMP	1.13	0.31

Note:
*Signifies a rejection of the null hypothesis of no effect at the 5% level.
**Signifies a rejection of the null hypothesis at the 10% level.

measure of workforce skill. The second analysis shows that the observed relationship between changes in the skill mix of the workforce and technology adoption is quite weak. Alternatively, there is some correlation between establishment growth and technology use and adoption. For establishments adopting CAD1 and NET1, the growth in establishment employment is higher. This suggests that technology adoption may be correlated with changes in industry-level skill mix through shifting employment shares between establishments rather than by altering the workforce composition within plants. One piece of conflicting evidence, however, is that most of the upgrading of skill that occurs within manufacturing appears to be a within-plant phenomenon (Dunne *et al.* 1997).

These joint findings of strong cross-sectional correlations between technology adoption and the skill mix of the workforce and relatively weak within-plant correlations between technology adoption and changes in the skill mix of the workforce are consistent with our previous findings (Doms *et al.* 1997). Certainly, most analysts would agree that the diffusion of new computing technology has greatly impacted the organizational structure of firms and has affected labor markets. The question is, can one find these changes using within plant information on technology adoption and workforce skill? The problem as we see it is that the adoption of technology often requires skilled workers to implement. At the workplace level, the adoption of new technology may be preceded by workforce restructurings. Hence, the observed patterns in the micro-data relating technological changes to changes in the workplace may be difficult to identify. Moreover, technological change in the workplace is likely to be incremental in many cases with some firms continually testing out and adopting new technologies and continuously changing the composition of their workforce. In such cases, it will be difficult to find a strong correlation between the adoption of a specific technology and the change in the skill mix of the workforce.

References

Acemoglu, D. (2002). Technical change, inequality and the labor market. *Journal of Economic Literature*, **40**, pp. 7–72.

Autor, D., Katz, L. and Krueger, A. (1998). Computing inequality: have computers changed the labor market? *Quarterly Journal of Economics*, **113**, November, pp. 1169–214.

Berman, E., Bound, J. and Griliches, Z. (1994). Changes in the demand for skilled labor within U.S. manufacturing industries: evidence from the annual survey of manufacturing. *Quarterly Journal of Economics*, **109**, May, pp. 367–97.

Berman, E., Bound, J. and Machin, S. (1998). Implications of skill-biased technical change: international evidence. *Quarterly Journal of Economics*, **112**, November, pp. 1245–79.

Berndt, E., Morrsion, C. and Rosenblum, L. (1992). High-tech capital formation and labor composition in U.S. manufacturing industries: an exploratory analysis. NBER Working Paper 4010.

Bresnahan, T. (1999). Computerisation and wage dispersion: an analytical reinterpretation. *Economic Journal*, **109**, June, pp. F390–415.

Bresnahan, T., Brynjolfsson, E. and Hitt, L. (2002). Information technology, workplace organization and the demand for skilled labor: firm-level evidence. *Quarterly Journal of Economics*, **117**, February, pp. 339–76.

CARD, D. and DINARDO, J. (2002). Skill biased technological change and rising wage inequality: some problems and puzzles. *The Journal of Labor Economics*, **20**, October, pp. 733–83.

CHENNELLS, L. and VAN REENEN, J. (1997). Technical change and earnings in British establishments. *Economica*, **64**, November, pp. 587–604.

CHENNELLS, L. and VAN REENEN, J. (2002). The effects of technical change on skills, wages and employment: a survey of micro-econometric evidence. In Y. L'Horty, N. Greenan and J. Mairesse (eds.), *Productivity, Inequality and the Digital Economy*, Chapter 5. Boston, MA: MIT Press, pp. 175–225.

DAVIS, S. and HALTIWANGER, J. (1991). Wage dispersion between and within U.S. manufacturing plants, 1963–1986. Brookings Papers on Economic Activity, Microeconomics, pp. 115–20.

DINARDO, J. and PISCHKE, J.-S. (1997). The returns to computer use revisited: have pencils changed the wage structure too? *Quarterly Journal of Economics*, **112**, February, pp. 291–304.

DOLTON, P. and MAKEPEACE, G. (2004). Computer use and earnings in Britain. *The Economic Journal*, **114**, March, pp. C117–29.

DOMS, M., DUNNE, T. and TROSKE, K. (1997). Workers, wages and technology. *Quarterly Journal of Economics*, **112**, February, pp. 253–90.

DUNNE, T. (1994). Plant age and technology usage in U.S. manufacturing industries. *Rand Journal of Economics*, **25**, Autumn, pp. 488–99.

DUNNE, T. and SCHMITZ, J. (1995). Wages, employment structure and employer size-wage premia: their relationship to advanced-technology usage at US manufacturing establishments. *Economica*, **62**, February, pp. 89–107.

DUNNE, T., HALTIWANGER, J. and TROSKE, K. (1997). Technology and jobs: secular change and cyclical dynamics. *Carnegie-Rochester Public Policy Conference Series*, **46**, June, pp. 107–78.

ENTORF, H. and KRAMARZ, F. (1997). Does unmeasured ability explain higher wages of new technology workers? *European Economic Review*, **41**, 8, pp. 1489–510.

HASKEL, J. and HEDEN, Y. (1999). Computers and the demand for skilled labour: industry and establishment panel evidence for the UK. *Economic Journal*, **109**, March, pp. C68–79.

KATZ, L. and AUTOR, D. (1999). Changes in the wage structure and earnings inequality. In O. C. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, **Vol. 3A**. Amsterdam: Elsevier Science, pp. 1463–558.

KRUEGER, A. (1993). How computers changed the wage structure: evidence from Microdata, 1984–89. *Quarterly Journal of Economics*, **108**, February, pp. 33–60.

LINK, A. and SIEGEL, D. (2003). *Technological Change and Economic Performance*. London: Routledge.

PAVNCIK, N. (2003). What explains skill-upgrading in less developed countries? *Journal of Development Economics*, **71**, August, pp. 311–28.

REILLY, K. (1995). Human capital and information: the employer-size wage effect. *Journal of Human Resources*, **30**, Winter, pp. 1–18.

SIEGEL, D. (1997). The impact of computers on manufacturing productivity growth: a multiple-indicators, multiple-causes approach. *Review of Economic Statistics*, **79**, February, pp. 68–78.

SIEGEL, D. (1999). *Skill Biased Technological Change: Evidence from a Firm-Level Survey*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

STIROH, K. (2002). Information technology and the U.S. productivity revival: what do the industry data say? *American Economic Review*, **92**, December, pp. 1559–76.

TASHIRO, S. (2004). The diffusion of computers and wages in the US: occupation and industry analysis, 1984–2001. Claremont Graduate University Working Paper.

U.S. DEPARTMENT OF COMMERCE (1993). Bureau of the Census, Current Industrial Reports, Manufacturing Technology.

Date of receipt of final manuscript: 28 February 2005.