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INFORMATION TECHNOLOGY AND THE DEMAND FOR EDUCATED WORKERS: DISENTANGLING THE IMPACTS OF ADOPTION VERSUS USE

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Abstract—This paper examines the effect of information technology (IT) on the relative demand for educated workers in U.S. industries from 1960 to 1996. After decomposing this effect into IT use and adoption, I find that the use of IT is complementary with educated workers, and that educated workers have a comparative advantage in the adoption of IT. In total, IT use and adoption effects account for almost 40% of the acceleration in demand for educated workers since 1970. Moreover, the adoption of IT explains about one-third of the total IT effect on the acceleration in skill upgrading in the 1970s.

I. Introduction

THE structure of employment and wages by educational attainment has changed rapidly in the last few decades. Changes in the allocation of workers between and within industries have favored highly educated and skilled workers during this period. Many studies attribute the change in the pattern of employment and wages to skill-biased technological change.[1] The diffusion of information technology (IT) is emphasized as one of the most important factors contributing to skill-biased technological change.

The impact of technology on the demand for educated or skilled workers has been analyzed in two different ways. A technology can be intrinsically complementary, with educated or skilled workers in the production process (Griliches, 1969; Tinbergen, 1975; Berman, Bound, & Griliches, 1994). This technology-skill complementarity predicts that the demand for educated workers rises as long as the use of such technology increases. However, some studies focus on the role of education or skill in the process of adopting new technologies (Nelson & Phelps, 1966; Welch, 1970; Schultz, 1975; Bartel & Lichtenberg, 1987; Greenwood & Yorukoglu, 1997). If a new technology embodied in a new machine requires educated or skilled workers for successful adoption, the increase in newer machine vintages is also skill-demanding. In contrast to technology-skill complementarity, the effect of technology adoption on the demand for educated workers will disappear as the adoption process is completed.

This paper examines both the use and adoption effects of IT on the relative demand for educated workers. Using data from 56 U.S. industries for the period 1960–1996, my empirical findings show that the demand for educated workers interacts with IT use as well as with IT adoption. Educated workers are complementary with the use of IT as measured by the IT capital stock. Using the average age of IT capital as a proxy for IT adoption, the demand for educated workers increases as the age of IT capital declines. In total, the IT use and adoption effects account for almost 40% of the acceleration in the rate of relative demand growth for educated workers since 1970. Furthermore, the IT adoption effect contributed about one-third of the total IT effect on the acceleration in skill upgrading in the 1970s.

The paper is organized as follows. Section II examines the role of education in the implementation of new technologies, and reviews previous studies on the effect of IT on the demand for educated workers. Section III describes the data and empirical framework used. Section IV provides estimation results for IT adoption and use effects on the relative demand for educated workers. Conclusions are contained in section V.

II. The Role of Education in Technology Adoption

As with the case of electrification in the early twentieth century, computerization is often considered a skill-biased technological revolution.[2] There have been many empirical studies on the complementary relationship between the use of IT and the demand for skilled or educated workers. Most studies used the IT capital stock or IT investment per worker as a measure of IT use. Using data on detailed U.S. manufacturing industries, Berman, Bound, and Griliches (1994) show that the increase in skilled labor input is positively correlated with the increase in computer investment.

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[1] See Berman, Bound, and Griliches (1994) and Autor, Katz, and Krueger (1998) for the change in employment structure; Katz and Murphy (1992) and Allen (2001) for the change in wage structure; and Berman, Bound, and Machin (1998) and Machin and Van Reenan (1998) for international evidence about skill-biased technological change. Katz and Autor (1999) provide an excellent survey of the literature.

[2] Goldin and Katz (1998) provide evidence for the complementarity between electrification and skilled labor in the early twentieth century. Caselli (1999) analyzes two different interactions between skilled labor and technology, such as the skill-bias and deskilling technological revolutions. For example, the assembly line is a deskilling technological revolution.

Similarly, the findings of Berndt, Morrison, and Rosenblum (1992) indicate that skill upgrading toward educated workers occurs along with the increase in the ratio of high-tech capital to total capital. Analyzing several data sets for U.S. industries, Autor, Katz, and Krueger (1998) showed that the rate of skill upgrading has been greater in more computer-intensive industries. Moreover, Bresnahan, Brynjolfsson, and Hitt (1999) found that IT use as well as IT-enabled organizational change is an important source of skill-biased technological change.

In contrast to the use of technologies, some studies emphasize the role of education or skill in the adoption of new technologies. In an earlier work, Welch (1970) distinguishes a worker effect and an allocative effect as two different effects on the value of education.[3] The worker effect is defined as the increased output per unit change in education, holding other inputs constant. However, the allocative effect results in a change in other inputs, including new technologies. A recent study by Greenwood and Yorukoglu (1997) argues that educated or skilled workers can facilitate the adoption of new technologies; that is, skilled workers convey a skill advantage in technology adoption. Bartel and Lichtenberg (1987) distinguish technology implementation from technology adoption. For example, a more highly educated workforce may lead to earlier adoption of a new technology, while also facilitating the implementation process for realization of the benefits. Although the implementation of a new technology is conditional on adoption, my paper does not distinguish between implementation and adoption. In fact, given the adoption of new information technology, my study analyzes how education facilitates the implementation of new IT.

In a similar vein, Helpman and Rangel (1999) and Caselli (1999) attempted to explain the interaction between technological change and labor markets. If educated workers face smaller costs in the use of new machines than less-educated workers, new machines will more likely be assigned to educated workers, who in turn will increase their productivity and hence the demand for educated workers. Focusing on the cost of new-technology adoption, Hornstein and Krusell (1996) and Helpman and Trajtenberg (1998) analyze the impact of new-technology adoption on productivity as well as employment structure, and provide a theoretical possibility of negative growth in productivity during the initial stage of new-technology adoption if the cost of adopting the new technology is large.[4]

Evidence of this technology adoption effect on the demand for educated workers is also found in other empirical studies. Nelson and Phelps (1966) show that farmers with high levels of education tend to adopt productive innovations earlier than farmers with less education. Based on evidence that the rate of flow of new inputs enhances the productivity of a college graduate, Welch (1970) stresses the importance of the allocative effect of educated workers on U.S. agriculture. Using the average age of capital as a proxy for the implementation of technologies, Bartel and Lichtenberg (1987) show that the relative demand for educated workers increases as the age of capital falls in U.S. manufacturing industries.

The use and adoption effects have different implications for the future behavior of the employment structure by educational attainment. If educated workers are complementary with IT capital, then as long as the stock of IT capital rises, so will the demand for educated workers. This implies that there can be a long-run increase in the demand for educated or skilled workers. However, the increase in the demand for educated workers during the adoption process will disappear as technology implementation is completed. For example, if a number of educated workers are required to implement new IT successfully, the IT adoption effect can cause a short-run burst in the demand for educated workers.

III. Data and Empirical Framework

A. Data

The data sets used in this study were obtained from several sources. To construct employment and wages by educational attainment, I use the 1% Census Public-Use Micro-Samples (PUMS) from 1960, 1970, 1980, and 1990.[5] The Census data are combined with the Current Population Survey (CPS) Merged Outgoing Rotation Group (MORG) from 1990 and 1996 to extend the sample period to 1996. Labor input is divided into two groups by educational attainment: educated workers (college graduates) and less-educated workers (all other workers).

In most studies, the definition of skill is based on either occupational mix (nonproduction versus production workers, or white versus blue collar workers) or educational attainment (high school versus college workers). The occupational mix is more sector-specific than educational attainment. Therefore, a definition of skill based on educational level is preferable in a study using industries with different production processes, such as the manufacturing and service sectors.

The IT capital stock and the average age of IT capital were obtained from the Bureau of Economic Analysis (BEA). Three different capital stocks are constructed from 57 detailed assets. IT capital is defined as office, computing,

[3] Schultz (1975) and Greenwood and Jovanovic (1998) also find this distinction.

[4] This IT adoption cost is also closely related to the IT productivity paradox. See Allen (1997), Brynjolfsson and Hitt (1998), and Haimowitz (1998) for several possible explanations of the IT paradox, including the diffusion lag in technology impact, adoption cost, learning by doing, and measurement errors.

[5] David Autor and Alan Krueger generously provided the Census and CPS data files and the industry classification concordance tables between the Census data and other data sets. See the Data Appendix of Autor, Katz, and Krueger (1998) for a complete description of the Census and CPS data.

and accounting machinery (OCAM) aggregated from the following eight assets: mainframe computers, personal computers, direct-access storage devices, computer printers, computer terminals, computer tape drives, computer storage devices, and other office equipment. The Törnqvist index method is used to aggregate these assets.

The definition of IT capital in the literature varies. OCAM is usually used as IT capital in industry-level studies, such as those of Autor, Katz, and Krueger (1998) and Wolff (1999). Since OCAM consists mainly of computers and peripheral equipment, this definition of IT capital emphasizes the role of computers. However, Berndt, Morrison, and Rosenblum (1992) use a broader measure of IT capital (so-called high-tech capital) that includes other information-related equipment such as communications equipment, instruments, and photocopy and related equipment in addition to OCAM.

Following the study by Bartel and Lichtenberg (1987), the average age of (net) capital is used as a proxy for the adoption of new technologies.[6] The average age of capital can be used as a measure of technology adoption, because it decreases as the proportion of newly implemented capital increases. Changes in the age of capital depend on the size of the preexisting capital stock, as well as on the growth rate of investment.[7] Some firm- or plant-level studies, such as those of Doms, Dunne, and Troske (1997) and Siegel (1998), use direct measures of technology adoption, such as the number of newly adopted technologies. In contrast to firm- or plant-level studies, it is difficult to find a proxy for technology adoption at a more aggregated level, such as with industry-level data. Since the adoption of a new technology usually incurs the purchase of new capital specific to the technology, the proportion of new capital can represent the adoption of this new technology, and can therefore be related to the adoption process.

I use the nominal output series of the National Income and Product Accounts (NIPA), which is converted to real output using output deflators from the Bureau of Labor Statistics (BLS). Research and Development (R&D) data were obtained from the National Science Foundation. Industry classifications of all data are converted into 56 industries, which represent all private sectors in the U.S. economy. The sample includes 21 manufacturing and 35 nonmanufacturing industries.

Table 1 presents the average annual growth rate of each variable for four subperiods. I use two different measures of educated workers: college graduates and college equivalents. College equivalents are defined as the sum of those with a college degree and half of those with some college education. Compared to the 1960s, the labor cost share of educated workers increased rapidly from 1970 to 1990. In particular, the rise in the labor cost share of educated workers in the 1970s was caused mainly by an increase in the supply of educated workers, rather than an increase in the wage premium of educated workers. Educational wage differentials narrowed in the 1970s, with the rise in the supply of educated workers. After correcting for the change in relative wage, the increase in the employment share of educated workers in the 1970s was much higher than in the 1980s.

For example, Autor, Katz, and Krueger (1998) found that the relative demand for college graduates grew faster between 1970 and 1996 than between 1940 and 1970. In spite of the increase in the demand for educated workers since the 1970s, educational wage differentials between college and high school graduates only increased after the 1980s, because of the growth in the supply of college graduates in the 1970s (Bound & Johnson, 1992; Katz & Murphy, 1992). However, we observe a decrease in the labor cost share of educated workers in the first half of the 1990s relative to the 1970–1990 period, which is partly due to a decline in educational wage differentials in this period.

The stock of IT capital has increased at a very high rate since the 1970s. Although the annual growth rate of the IT capital stock (per output) was higher in the 1980s than in the 1970s, the different sizes of preexisting IT capital stock induced different changes in the average age of IT capital. Since the existing IT capital stock was relatively small in the 1970s, the average age of IT capital decreased at a much faster rate as new IT investment increased. In contrast to the 1970s, the age of IT capital increased slightly in the 1980s, due to the sizable preexisting capital. This shows that the average age of IT capital depends on the preexisting capital stock, as well as on the investment growth rate.

Although the growth rate of IT capital has been high since the 1970s, the ratio of total capital to output has

TABLE 1.—DESCRIPTIVE STATISTICS (100 × ANNUAL LOG CHANGE)

Variable	1960–1970	1970–1980	1980–1990	1990–1996
College graduates				
Labor cost share	1.92	3.00	2.16	1.48
Relative wage	0.40	−0.98	0.63	0.23
Employment share	1.78	4.10	1.92	1.68
College equivalents				
Labor cost share	1.70	2.84	2.14	0.77
Relative wage	0.08	−0.74	0.59	0.38
Employment share	1.85	3.67	2.11	0.79
Age of capital stock				
Total capital	−1.14	0.45	1.26	1.22
IT capital	−0.59	−2.24	1.25	−1.74
Equipment	−0.32	1.00	1.14	0.64
Plant	−1.63	−0.42	1.14	1.66
Capital stock per output				
Total capital	1.45	1.66	0.59	0.55
IT capital	4.30	13.35	20.89	12.30
Equipment	1.65	1.12	−0.53	−0.56
Plant	1.45	2.10	0.70	−0.41

NOTES. The Census PUMS are used for constructing the change in labor cost shares for 1960–1970, 1970–1980, and 1980–1990, and the CPS MORG for 1990–1996. College equivalents are defined as the sum of those with a college degree and half of those with some college. The labor cost share of college graduates (college equivalents) is defined as the ratio of wage bills for college graduates (college equivalents) to total labor cost. The employment share is similarly defined for college graduates and college equivalents.

[6] Since the BEA no longer reports the gross stock of capital, the average age of net capital is used in this study.

[7] Flug and Hercowitz (2000) use the ratio of new-equipment investment to output as a measure of technology adoption.

TABLE 2.—ADOPTION EFFECT OF INFORMATION TECHNOLOGY ON THE DEMAND FOR COLLEGE GRADUATES: 56 PRIVATE INDUSTRIES, 1960–1996

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ(Age of IT capital)		−0.0079[a]		−0.0074[b]	−0.0079[a]	−0.0091[a]	
		(0.0030)		(0.0029)	(0.0029)	(0.0028)	
Δ(Age of total capital)			−0.0033[b]	−0.0031[b]			
			(0.0016)	(0.0015)			
Δ(Age of non-IT capital)					−0.0027[b]		
					(0.0014)		
R&D intensity						2.8179[b]	
						(1.4047)	
Δ(Age of IT capital) × (service dummy)							−0.0094[b]
							(0.0042)
Δ(Age of IT capital) × (nonservice dummy)							−0.0068[b]
							(0.0033)
1970–1980 dummy	0.2323[a]	0.2010[a]	0.2861[a]	0.2527[a]	0.2389[a]	0.1726[a]	0.1836[a]
	(0.0632)	(0.0582)	(0.0620)	(0.0580)	(0.0567)	(0.0844)	(0.0526)
1980–1990 dummy	0.2909[a]	0.3133[a]	0.3672[a]	0.3828[a]	0.3822[a]	0.3028[a]	0.3341[a]
	(0.0718)	(0.0694)	(0.0717)	(0.0707)	(0.0705)	(0.0596)	(0.0568)
1990–1996 dummy	0.1486[b]	0.1280[c]	0.2329[a]	0.2075[a]	0.2003[a]	0.0993	0.1393[b]
	(0.0746)	(0.0689)	(0.0790)	(0.0732)	(0.0718)	(0.0648)	(0.0613)
R^2	0.5070	0.5236	0.5205	0.5352	0.5350	0.5574	0.5506

NOTES. For each column, the dependent variable is the change in the labor cost share of college graduates for 1960–1970, 1970–1980, 1980–1990, and 1990–1996. The Census PUMS are used for constructing the change in labor cost shares for 1960–1970, 1970–1980, and 1980–1990, and the CPS MORG for 1990–1996. All regressions are weighted by the industry share of labor cost between two periods. All equations include industry and time dummies. The sample size is 220. Numbers in parentheses are heteroskedastic-consistent standard errors of variables. Δ indicates 100 times the annual change in the variable. R&D intensity is defined as R&D expenditures as a percentage of output.

[a] Significant at 1% level.
[b] Significant at 5% level.
[c] Significant at 10% level.

changed little since the 1980s, because of the slowdown in (non-IT) equipment and plant (structures) investments. For example, equipment per unit output has decreased since the 1980s. This implies that there has been substitution toward IT capital and away from non-IT capital. The slowdown in non-IT investment also increased the average ages of equipment and plant after the 1970s and 1980s, respectively, whereas Boddy and Gort (1971) observed the substitution of equipment for plant from 1945 to 1965. Table 1 shows evidence of the substitution of IT for non-IT capital, at least after the 1980s. This substitution implies a shift toward shorter-lived assets, as well as toward assets with more embodied technical change.

B. Empirical Framework

To explore the relationship between IT and the demand for educated workers, a restricted variable cost function with capital as a quasi-fixed factor is used. The average age of capital also enters the cost function as an index of technology adoption. Assuming that firms minimize their labor costs given output, the stock of capital, and the age of capital, the restricted variable cost function is defined as

$$LC = f(W_C, W_H, Age_K, K, Y), \tag{1}$$

where LC is labor cost, W_C (W_H) is the wage rate of educated (less-educated) workers, Age_K is the average age of capital, K is the stock of quasi-fixed capital, and Y is real output. Assuming a translog cost function with constant returns to scale, and applying Shephard's lemma, I derive the labor cost share equations of both educated and less-educated workers. The relative wage can be inferred from the homogeneity of degree one in input prices. Since the sum of two labor cost shares is equal to one, only one share equation can be estimated independently.

The labor cost share equation of educated workers in first differences is defined as

$$\Delta SLC_{it} = \beta_0 + \beta_W \, \Delta \ln\left(\frac{W_C}{W_H}\right)_{it} + \beta_{AK} \, \Delta Age_{K,it} + \beta_K \, \Delta \ln\left(\frac{K}{Y}\right)_{it} + \varepsilon_{it}, \tag{2}$$

where SLC_{it} is the labor cost share for educated workers in industry i at time t, and W_C/W_H is the wage of educated workers relative to less-educated workers. Capital is decomposed into IT capital and non-IT capital, and, moreover, non-IT capital is also decomposed into (non-IT) equipment and plant. The age of each capital stock is defined similarly.

We can expect a negative sign for β_{AK} if the relative demand for educated workers is positively associated with the increase in the proportion of newly implemented capital. A positive sign for β_K can be interpreted as capital-skill complementarity. The positive sign of the relative wage coefficient (β_W) implies that the elasticity of substitution between two labor inputs is less than one.[8]

[8] To correct for the endogeneity of wages, the relative wage is dropped from the regressions. This problem of wage endogeneity also arises in several previous studies (Bartel & Lichtenberg, 1987; Berman, Bound, & Griliches, 1994; Siegel, 1998). Bartel and Lichtenberg (1991) show that both the age of capital and the stock of capital affect wages, grouped by educational attainment. Furthermore, some recent studies found that computerization affects the wage structure (Krueger, 1993; Entorf & Kramarz, 1998; Dunne et al. 2000). In particular, if the computerization effect on the wage rates of educated and less-educated workers is unequal, the coefficient estimate of IT use or adoption can be biased.

IV. Empirical Evidence

A. *IT Adoption Effect*

Table 2 reports a set of pooled regressions from 56 private industries for four time periods (1960–1970, 1970–1980, 1980–1990, and 1990–1996).[9] Column (1) includes only three time dummies for the 1970–1980, 1980–1990, and 1990–1996 periods.[10] The positive signs of these time dummies imply that there has been an increase in the within-industry growth of the labor cost share of educated workers in the period 1970–1996, relative to the 1960s.

Column (2) presents estimation results for the IT adoption effect on the change in the labor cost share of educated workers (college graduates). The coefficient estimate of the average age of IT capital is -0.0079, and is highly significant. The negative sign of the coefficient implies that a decline in the average age of IT capital by one year will increase the labor cost share of educated workers by about 0.8%. This finding is consistent with the hypothesis that IT adoption increases the demand for educated workers. Moreover, the inclusion of the age of IT capital reduces the coefficients for the time dummies for the 1970–1980 and 1990–1996 periods. These decreases in the coefficients for the time dummies suggest that IT adoption accounts for about 14 percent of the acceleration in relative demand shifts for educated workers in the 1970s and the first half of the 1990s.[11]

The coefficient estimate of the age of total capital in column (3) is -0.0033, which is smaller than the finding of Bartel and Lichtenberg (1987), who used data on three-digit manufacturing industries from 1960 to 1980. The service sector has a lower capital-labor ratio in the production process than the manufacturing sector, and therefore the technology adoption effect associated with new-capital investment in the service sector is likely smaller than that in the manufacturing sector. Consequently, the adoption effect of total capital is smaller in the whole economy than that in the manufacturing sector.

Since total capital includes IT capital, the coefficient for the age of IT capital in column (4) has a double-counting problem even though the share of IT capital in total capital is small. Instead, column (5) includes the average ages for two mutually exclusive stocks of IT and non-IT capital. The inclusion of the age of non-IT capital does not affect the estimate of the age of IT capital compared to the estimate in column (2). However, its inclusion increases the coefficients of the time dummies for the 1980–1990 and 1990–1996 periods substantially. As shown in Table 1, new non-IT capital investment has slowed since the 1980s, and this slowdown may have subsequently reduced the demand for educated workers associated with the adoption of non-IT technologies.

The coefficient for the age of IT capital is about twice as large as that for the age of non-IT capital. The magnitudes of the two coefficients are not directly comparable, because of differences in the average age of capital stocks and in the size of preexisting capital stocks. The adoption effects of IT and non-IT capital stocks can be compared in terms of new investment, given the average age and preexisting stock of capital. With the same amount of new investment, the adoption effect decreases with increasing size of the preexisting capital stock, but increases with its average age. This relationship can be formulated as $\partial SLC/\partial I = -\beta_{AK} Age_K/K$, where I is IT or non-IT investment. The average age of IT capital (2.5 years) is lower than that of non-IT capital (13 years), due mainly to the high depreciation rate of IT capital.[12] However, the size of the preexisting non-IT capital stock is much larger than that of IT capital. Comparing these two effects, the size factor dominates the age factor. Therefore, the same amount of new IT investment has a greater effect on the labor cost share of educated workers than has non-IT capital.

In column (6) of Table 2, I include R&D intensity (R&D expenditures as a percentage of output) in the labor cost share equation for educated workers. The R&D variable has been widely used as another technology indicator (Berman, Bound, & Griliches, 1994; Autor, Katz, & Krueger, 1998; Machin & Van Reenan, 1998). The positive sign of the coefficient for R&D intensity suggests that R&D intensity is also positively correlated with the relative demand for educated workers. After controlling for this R&D effect, the coefficient for the age of IT capital remains robust.

It is interesting to check whether the IT adoption effect is similar across industries. Column (7) has different coefficients for the IT capital ages for the service and nonservice sectors. The service sector, including the "wholesale and retail trade" and "finance, insurance, and real estate" sectors, uses IT more intensively than does the nonservice sector, including the "agriculture, mining and construction" and "Manufacturing" sectors. Comparing the coefficients for the age of IT capital for the two sectors, I find that the IT-intensive service sector has a larger coefficient for the age of IT capital than the less-IT-intensive nonservice sector.

B. *IT Adoption and Use Effects*

Table 3 presents estimation results for the IT adoption and use effects on the relative demand for educated workers (college graduates). To examine the IT adoption and use effects, I include the age of IT capital as well as the stock of

[9] I exclude the "farms" and "nonmetallic minerals except fuels" industries in the 1960s and 1970s, because of missing information on IT capital.

[10] I thank two anonymous referees for suggesting the inclusion of time dummies in the regressions.

[11] In column (2), the coefficient estimate of the 1980–1990 dummy increases slightly, which implies that as new IT becomes fully implemented, firms can replace high-paid educated workers with low-paid less-educated workers.

[12] The BEA uses about 30% of the geometric depreciation rate for the construction of IT capital.

TABLE 3.—ADOPTION AND USE EFFECTS OF INFORMATION TECHNOLOGY ON THE DEMAND FOR COLLEGE GRADUATES: 56 PRIVATE INDUSTRIES, 1960–1996

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Δ(Age of IT capital)	−0.0060[b]	−0.0059[b]	−0.0069[b]	−0.0082[a]	−0.0065[b]	−0.0062[b]
	(0.0028)	(0.0029)	(0.0030)	(0.0028)	(0.0028)	(0.0028)
Δ(Log of IT capital)	0.0715[b]		0.0659[c]		0.0695[c]	0.0655[c]
	(0.0350)		(0.0352)		(0.0370)	(0.0360)
Δ(Log of IT capital per FTEE)		0.0753[b]				
		(0.0353)				
R&D intensity			2.4330[c]			
			(1.3334)			
Δ(Log of total capital per unit output)				0.2369[a]		
				(0.0863)		
Δ(Log of non-IT capital per unit output)					0.0190[c]	
					(0.0102)	
Δ(Log of equipment per unit output)						0.1489[c]
						(0.0812)
Δ(Log of plant per unit output)						0.0013
						(0.0582)
1970–1980 dummy	0.1409[b]	0.1346[b]	0.1355[b]	0.1842[a]	0.1378[b]	0.1445[b]
	(0.0642)	(0.0663)	(0.0630)	(0.0534)	(0.0651)	(0.0604)
1980–1990 dummy	0.1871[b]	0.1739[c]	0.1719[b]	0.3319[a]	0.2201[b]	0.2259[a]
	(0.0848)	(0.0898)	(0.0844)	(0.0569)	(0.0883)	(0.0833)
1990–1996 dummy	0.0436	0.0261	0.0143	0.1409[b]	0.0676	0.0862
	(0.0700)	(0.0740)	(0.0730)	(0.0616)	(0.0732)	(0.0696)
R^2	0.5364	0.5375	0.5418	0.5501	0.5534	0.5527

NOTES. The dependent variable is the change in the labor cost share of college graduates for 1960–1970, 1970–1980, 1980–1990, and 1990–1996. The Census PUMS are used for constructing the change in labor cost shares for 1960–1970, 1970–1980, and 1980–1990, and the CPS MORG for 1990–1996. All regressions are weighted by the industry share of labor cost between two periods. All equations include industry and time dummies. The sample size is 220. Numbers in parentheses are heteroskedastic-consistent standard errors of variables. Δ indicates 100 times the annual change in the variable. Number of full-time equivalent employees (FTEEs) is obtained from the NIPA. R&D intensity is defined as R&D expenditures as a percentage of output.

[a] Significant at 1% level.
[b] Significant at 5% level.
[c] Significant at 10% level.

IT capital in column (1). The coefficient estimate for IT capital is 0.0715. The finding supports the hypothesis of complementarity between IT use and educated workers, which is also consistent with the findings of Berman, Bound, and Griliches (1994) and Autor, Katz, and Krueger (1998). However, the coefficient for the age of IT capital changes little compared to the coefficient in column (2) of Table 2. The coefficient estimate of IT capital per full-time equivalent employee in column (2) is similar to that in column (1).

The inclusion of both the age and stock of IT capital causes all three time dummies to decrease. Declines in the time dummies suggest that the total IT effect (the sum of the IT adoption and use effects) can account for almost 40% of the acceleration in the demand for educated workers in the 1970s and 1980s, relative to the 1960s. The total IT effect on the acceleration in skill upgrading in my study is close to the finding of Autor, Katz, and Krueger (1998), namely, computers contributed about 30%–40% of the increase in the rate of skill upgrading from the 1960s to the 1970s. Compared to the IT adoption effect in column (2) of Table 2, the IT adoption effect explains approximately one-third of the acceleration in skill upgrading associated with IT in the 1970s, while the remaining two-thirds of the total IT effect are attributable to IT use in this period. In addition, the IT use effect on skill upgrading increased in the period 1970–1996. The trend for the IT use effect to increase is also consistent with IT-skill complementarity, predicting that the demand for educated workers increases as long as IT capital grows.

Table A1 in the Appendix uses a broader measure of educated workers, using college equivalents instead of college graduates. Changes in the coefficients for the time dummies in column (2) suggest that IT adoption explains about 9% of the acceleration in skill upgrading using college equivalents. In column (1) of Table 3, the inclusion of the stock of IT capital with the age of IT capital results in a large decline in the coefficient for the 1990–1996 dummy, and makes the coefficient insignificant. However, this overprediction disappears in column (3) of Table A1 when I use college equivalents instead of college graduates. In column (3) of Table A1, the coefficient for the 1990–1996 dummy is significant and decreases by about 40% which is more than the declines in the coefficients for the 1970–1980 and 1980–1990 dummies. In total, the IT effect explains about 30% of the acceleration in the demand for college equivalents since the 1970s. The total IT effect on the acceleration in the demand for college equivalents is smaller than the total IT effect for college graduates. The results suggest that IT is a more important contributor to the increase in the demand for more highly educated workers.

Controlling for the R&D intensity variable in column (3), the IT adoption and use effects on skill upgrading remain strong. All three decade dummies decrease slightly, which implies that R&D also contributes to the increase in the rate of skill upgrading, but this R&D effect appears to be small compared to the IT effect.

The coefficient for the age of IT capital remains strong after controlling for total capital intensity (the total capital stock per output) in column (4).[13] Columns (5) and (6) add other types of capital to the regressions. The positive coefficient for non-IT capital in column (5) implies that the use of non-IT capital is complementary with educated workers. After decomposing non-IT capital into (non-IT) equipment and plant in column (6), I find complementarity between equipment and educated workers. On the other hand, the statistically insignificant coefficient for plant does not indicate complementarity between plant and educated workers. Therefore, deepening the intensity of IT capital and non-IT equipment causes skill upgrading toward educated workers in all private industries. Similarly, the study by Berman, Bound, and Griliches (1994) showed complementarity between equipment capital and skilled (nonproduction) workers, but substitutability between plant and skilled workers.

V. Conclusions

Using data from 56 U.S. private industries from 1960 to 1996, I found that the relative demand for educated workers is related to both IT adoption and use. My empirical findings show that the use of IT is complementary with educated workers, and that educated workers have a comparative advantage in the adoption of IT.

In total, the diffusion of IT has contributed about 40% of the acceleration in the relative demand for educated workers (college graduates) from 1970 to 1996. The decomposed contributions of IT into the use and adoption effects show that the IT use effect explains a major portion of the IT effect on the acceleration in skill upgrading for the period 1970–1996. However, the IT adoption effect also had a significant impact on the demand for educated workers. In particular, this adoption effect contributed to about one-third of the total IT effect in the 1970s.

Evidence of the technology adoption effect provides a possible explanation for why new technology accelerates the demand for educated workers when it is first adopted. As discussed earlier, a short-run acceleration in the demand for educated workers can occur if a new technology requires many educated or skilled workers for the successful adoption of the new technology. My empirical findings suggest that IT adoption affects skill upgrading in the early period of IT adoption. However, a major portion of the IT effect on skill upgrading during the last three decades can be explained by the IT use effect.

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[13] Compared to the time dummy coefficients in column (2) of Table 2, the coefficient for the 1960–1970 dummy decreases about 10%, but the coefficients for the 1980–1990 and 1990–1996 dummies increase slightly.

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APPENDIX

TABLE A1.—ADOPTION AND USE EFFECTS OF INFORMATION TECHNOLOGY ON THE DEMAND FOR COLLEGE EQUIVALENTS: 56 PRIVATE INDUSTRIES, 1960–1996

Independent Variables	(1)	(2)	(3)
Δ(Age of IT capital)		−0.0093[a]	−0.0076[b]
		(0.0030)	(0.0031)
Δ(Log of IT capital per unit output)			0.0675[b]
			(0.0338)
1970–1980 dummy	0.4152[a]	0.3780[a]	0.3146[a]
	(0.0669)	(0.0602)	(0.0665)
1980–1990 dummy	0.5015[a]	0.5281[a]	0.3998[a]
	(0.0711)	(0.0683)	(0.0916)
1990–1996 dummy	0.2783[a]	0.2539[a]	0.1692[b]
	(0.0745)	(0.0677)	(0.0760)
R^2	0.5960	0.6152	0.6256

NOTES. The dependent variable is the change in the labor cost share of college equivalents for 1960–1970, 1970–1980, 1980–1990, and 1990–1996. College equivalents are defined as the sum of those with a college degree and half of those with some college education. The Census PUMS are used for constructing the change in labor cost shares for 1960–1970, 1970–1980, and 1980–1990, and the CPS MORG for 1990–1996. All regressions are weighted by the industry share of labor cost between two periods. All equations include industry and time dummies. The sample size is 220. Numbers in parentheses are heteroskedastic-consistent standard errors of variables. Δ indicates 100 times the annual change in the variable.

[a] Significant at 1% level.
[b] Significant at 5% level.
[c] Significant at 10% level.