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The Growth of Information Workers in the U.S. Economy, 1950-2000: the Role of Technological Change, Computerization, and Structural Change

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ABSTRACT. *Using data from the decennial U.S. Censuses of 1950, 1960, 1970, 1980, 1990, and 2000, I construct matrices of employment by 267 occupations and 64 industries and then aggregate the occupations into four categories: (i) knowledge producers; (ii) data processors; (iii) service workers; and (iv) goods-processing workers. I find that information workers (the sum of the first two categories) increased from 37 percent of the workforce in 1950 to 59 percent in 2000. Then, using an input-output decomposition analysis, I find that the growth in information workers was driven not by a shift in tastes toward information-intensive goods and services (as measured by the composition of final demand) but rather by a roughly equal combination of the substitution of information workers for goods and service workers within the structure of production of industries and the unbalanced growth effect (from differential rates of industry productivity growth). Finally, on the basis of regression analysis, I find that R&D expenditures and computer investment are positively associated with the growth in knowledge workers but negatively associated with the growth of data workers.*

KEY WORDS: Information workers, input-output, R&D, computerization, productivity

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1. Introduction

Fritz Machlup's classic 1962 book, *The Production and Distribution of Knowledge in the United States*, found that with the growth of clerical occupations at the turn of the century, "the ascendancy of knowledge-producing occupations has been an uninterrupted process... a movement from manual to mental, and from less to more highly trained labor" (Machlup, 1962, p. 396-7). Since the book's appearance, several studies, including Porat (1977), Beniger (1986), Rubin and Huber (1986), Baumol *et al.* (1989), and Reich (1991) have documented the growth in the relative size of the information economy. Baumol *et al.* (1989, Chapter 7), in particular, found that information workers increased from about 42 percent of the workforce in 1960 to 53 percent in 1980.

In this paper, I document the growth of information workers in the U.S. economy over the postwar period and analyze the sources of their growth. The paper is divided into five parts. In Section 2, I review the pertinent literature on skill-biased technological change and the effects of international trade on skill composition. Particular attention is paid to the role of Information Technology (IT) on skill change. I also include a model derived from Autor *et al.* (2003) on the effects of IT on occupational composition.

Section 3 updates the statistics on the composition of the workforce between information and non-information jobs to 2000. Particular interest in focused on the post-1980 period, which has seen a tremendous growth in the use of computers in production and which Freeman (1987) and others have termed a new "techno-economic paradigm," based on computer-driven information technology. For this analysis, I rely on matrices of employment by occupation and industry derived from the decennial U.S. Censuses of 1950, 1960, 1970, 1980, 1990, and 2000. The occupations are aggregated into four categories: (i) knowledge producers; (ii) data processors; (iii) service workers; and (iv) goods-processing workers.

I find that information workers (the sum of the first two categories) increased from 37 percent of the workforce in 1950 to 59 percent in 2000, with the rate of increase for knowledge-producing workers peaking in the 1960s and 1970s and then slowing down somewhat, while that of data workers peaked in the 1960s and then tapered off after that. Yet, all in all, most of the growth in information employment did not take place among high-skilled, high-payed professionals and managers but rather among moderate-skilled, relatively low-payed clerical and sales workers. Another interesting finding is that while in 1950, over half of total employment was found in blue-collar jobs, this proportion slipped to under a quarter by 2000. As Machlup predicted, we have moved from society in which we work with our hands to one in which we work with our mind.

Section 4 uses an input-output decomposition analysis to break down the changes in the information workers' share of the labor force into three parts: (i) the substitution of information labor for labor of other types within the production process -- that is, the change in the proportion of information workers in each industry's labor force; (ii) the change in each industry's share of the economy's total output; and (iii) the change associated with relative variations in labor productivity of the different industries.

The first of these three components indicates the extent to which the composition of the labor force in a typical industry has become more information-intensive (assuming all other things remain the same). The second element relates to different industries' shares of the economy's final output and is pertinent in determining the extent to which the expansion in information-related employment is attributable to an increase in the economy's demand for products with a high information content. The third component plays the part in testing the role of unbalanced growth in the information explosion -- that is, the extent to which growth of information workers can be attributed to relatively lower productivity growth in industries using more information.

I find that the growth in information workers was driven not by a shift in tastes toward information-intensive goods and services (as measured by the composition of final demand) but rather by a roughly equal combination of the substitution of information workers for goods and service workers within the structure of production of industries and the unbalanced growth effect.

Section 5 relies on econometric analysis to analyze the sources of growth of information workers on the industry level. The dependent variables are the changes in knowledge and data workers as a percent of total employment in the industry over the period. Independent variables include (1) total factor productivity (TFP) growth, (2) expenditures on research and development, (3) investment in new equipment, (4) investment in office, computer and accounting machinery (OCA), and (5) the degree of international competitiveness of an industry.

R&D expenditures is the most significant factor that contributes to the growth in knowledge workers and it is negatively associated with the growth of data workers. Investment in OCA also exerts a positive effect on the knowledge worker employment and a strong negative effect on the employment of data workers. Concluding remarks are made in the final section of the paper.

2. Review of Related Literature

A considerable literature has now accumulated on factors that might have caused changes in the occupational distribution, particularly since the early 1970s in the U.S. In particular, much of this literature maintains that IT and organizational changes over this period have led to changes in labor demand that favor more skilled workers. Here I review some of the pertinent literature on the role of technological change, information technology, and international trade.

2.1. Skill-biased Technological Change

The most prevalent view on changes in skill composition is biased technological change, due to the introduction of computers and the general diffusion of IT. The argument is that the last thirty years have witnessed a major technological revolution led by widespread computerization and the consequent diffusion of IT. This change has skewed the income distribution by placing a high premium on college-educated and skilled labor while reducing the demand for semi-skilled and unskilled workers. One important piece of evidence is that the rate of return to a college education (the wage premium paid to a college graduate relative to a high school graduate) almost doubled over the decades of the 1980s and 1990s.

This argument has been made by Bound and Johnson (1992) and Berman *et al.* (1994), who identify the declining ratio of production to non-production workers *within* *industry* as the major determinant of changes in relative wages between skilled and unskilled workers. The fact that both the employment share and relative wages shifted in favor of non-production workers is evidence of biased technological change.

Davis and Haltiwanger (1991), using data on production and non-production workers in U.S. manufacturing plants from 1963 to 1986, provided some of the early evidence to support this hypothesis They found that the employment shift toward non-production workers occurred disproportionately in large plants between 1977 and 1986, and this was accompanied by a sharp upgrading of worker education and occupational skill levels. Katz and Murphy (1992) developed a model that accounted for changes in both the demand and supply of unskilled and skilled labor. Using CPS data over the period 1963 to 1987, they concluded that while the supply of college graduates fluctuated over time, there was a steady increase in the demand for skilled labor in the U.S. over the period.

Berman *et al.* (1994), using data from the Annual Survey of Manufactures over the period 1979 to 1987 for 450 manufacturing industries, found that over two-thirds of the increase in the ratio of non-production to production workers within manufacturing was due to the increased use of non-production workers within industry, and less than one third to a reallocation of labor between industries. They inferred from this the existence of skill biased technological change. Berman *et al.* (1998) also provided evidence that the increase in the share of skilled (non-production) workers in total employment occurred across a wide range of OECD countries. Yet, they also found that the trend decelerated in almost all OECD countries during the 1980s (with the notable exception of the United States). Machin and van Reenen (1998), using data for seven OECD countries, found that R&D intensity was positively linked to the relative growth of high skilled workers. Allen (2001) also concluded that technology variables accounted for 30 percent of the increase in the college wage premium over the period from 1979 to 1989.

2.2. The IT "Revolution"

Two relatively early papers have called the rapid introduction and diffusion of computers and associated Information Technology (IT) a “technological revolution.” Christopher Freeman, writing in 1987, termed this transformation as a new "techno-economic paradigm," based on microprocessor driven information technology. According to Freeman (1987, p. 51), information technology has "emerged in the last couple of decades as a result of the convergence of a number of inter-related radical advances in the field of microelectronics, fibre optics, software engineering, communications and computer technology." He defined IT "both as a new range of products and services, and as a technology which is capable of revolutionizing the processes of production and delivery of all other industries and services." David (1991) referred to “the paradigmatic shift” from electromechanical automation to information technologies and argued that the shift to information technologies might entail major changes in the organizational structure of companies.

One result of this technological revolution is a transformation of the skills required in the labor market. According to Freeman (1987, p. 66), the results of extensive research conducted by the Science Policy Research Unit (SPRU) of the University of Sussex showed that information technology “reduces the requirements for inspection and lower management (and clerical) employees, but increases the requirement for skilled systems designers and engineers and the level of responsibility for skills for maintenance..." There is also some suggestion from the case study literature that with the introduction of new information technologies there is a growing demand for various professional, technical and skilled production occupations, while the shares of lower and middle level managers and supervisors, inspectors, semi-skilled operatives and many clerical occupations decline. Strong support for this pattern was found by Milkman and Pullman (1991) in their study on employment restructuring at a GM auto assembly plant. Osterman (1986) found that a ten percent increase in company computing power led to a one percent reduction in managerial employment. Zuboff (1988, pp. 284,358-359) in a study of several manufacturing plants concluded that lower and middle managers were particularly "vulnerable" to deskilling and displacement by the introduction of information technologies.

Leontief and Duchin (1986) used U.S. input-output to analyze the effects of computer-driven automation on employment in four sectors -- manufacturing, office work, education, and health care. Taking account of the increased need for workers in the production of computer-based equipment, the authors concluded that automation will not cause serious displacement of workers if the economy is able to achieve a smooth transition from the old to new technologies.

In my own work, I also presented evidence on the transformative effects of computerization on the labor market and the consequent structural adjustments that have ensued. In Wolff (2002), I used employment data for 267 occupations and 44 industries that were obtained from the decennial Census of Population for years 1960, 1970, 1980, and 1990 (see Section 5 below). I constructed an index of occupational dissimilarity that measures how much occupational composition had shifted within industry over 3 time periods (1960-70, 1970-80, and 1980-90). The econometric results indicated that the coefficient of computerization as measured by the rate of growth of OCA per worker is statistically significant at the one percent level and that computerization is strongly and positively associated with the degree of occupational restructuring within industry over time.

Several other papers have looked at the effects of computer usage or IT on earnings. Reich (1991) argued that American workers are divided into two distinct groups -- "symbolic analysts" who produce knowledge and new Information Technology and ordinary clerical and production workers, who are outside the IT revolution. Globalization has rewarded the first group of workers with increased earnings but depressed the earnings of the second group.

Krueger (1993) argued that pronounced declines in the cost of personal computers caused their widespread adoption in the workplace and shifted the production function in ways that favored more skilled workers. He also estimated the rate of return to computer usage at 15 to 20 percent. This finding was later challenged by DiNardo and Pischke (1997), who estimated, using German household data, a similar return to the use of pencils. They argued that computer use *per se* was not causing workers to earn a premium but, rather, was associated with unmeasured skills that were being rewarded in the workplace. However, in later work, Autor *et al.* (1998) supplied new evidence that there was a substantial and increasing wage premium associated with computer use, despite a large growth in the number of workers with computer skills.

Dunne *et al.* (2004), using manufacturing establishment data for the U.S., concluded that a substantial portion of the rising dispersion in wages is due to increases in wage differentials between establishments. The latter, in turn, are attributable to plant-level productivity differences and are correlated with both computer intensity and overall capital intensity. In similar fashion, Bartel *et al.* (2003) used plant level data for the valve manufacturing industry in the U.S. and found evidence of a strong correlation between IT use and skill demand on the plant level. In particular, more IT-intensive plants demanded more computer programming and math skills, as well as a broader range of problem-solving skills.

Some recent theoretical literature has also laid the ground work toward understanding the relation between skill demand and IT. Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1998) introduced the notion of a "General Purpose Technology" (GPT). They argued that at any given time, there are typically a few technologies that play a far-reaching role in generating technical change in a wide range of user sectors. One example is the steam engine during the first industrial revolution. A second is the role of electrification in the early twentieth century, as well as automotive technology. A third is the diffusion of computers, micro-electronics, and information technology in the last two or three decades of the twentieth century. Such GPTs may be responsible for causing sustained and pervasive productivity gains throughout a wide number of industries in the economy.

A GPT has the following three characteristics: (1) It is used as inputs by a wide range of industries in the economy. This results from the fact that the GPT performs some general function, such as continuous rotary motion in the case of the steam engine or binary logic in the case of micro-electronics. (2) A GPT has the potential for continuous technical advances, which manifests itself *ex post* in the form of continuous advances in productivity. (3) A GPT has complementarities with the user sectors, especially in manufacturing.

In this regard, a GPT plays an important role as an "engine of growth." As an improved GPT becomes available, it is adopted by an increasing number of user industries and it fosters complementary advances that make it more attractive to adopt in the future. These two effects lead to an increase in the demand for the GPT, which in turn induces further technological advances in the GPT, and additional advances in the using sector (through its complementarity with the technologies of the using sector). This "virtuous circle" leads to further technological advances, and as the use of the GPT spreads throughout the economy its effects show up as increased productivity growth at the aggregate level of the economy.

Helpman and Trajtenberg (1998) developed a GPT-based growth model to analyze the long-run dynamics that result from the introduction of new GPTs within fixed time intervals. Their theoretical analysis predicts a two-phase effect from the introduction and diffusion of a GPT. During the first phase, output and productivity decline in absolute terms. However, during the second phase, the benefits of a more advanced GPT come into play, after a sufficient number of complementary inputs are developed. During the latter phase, there is a spell of growth, with both output and productivity rising. The implication of this model is that it may explain the behavior of productivity arising from the introduction of Information Technology, with very slow productivity growth during the 1970s and 1980s, followed by a burst of productivity growth in the latter half of the 1990s. They argue that the first phase can be quite long – 25 or 30 years in the case of electrification or IT.

Helpman and Trajtenberg (1998) also extended their model to consider the case of two types of workers – skilled and unskilled. In their model, skilled labor is considered complementary to GPT (in our case, Information Technology) and R&D, while unskilled labor is assumed to be a substitute. Over time, their model predicts that the relative demand for unskilled labor will fall and that for skilled labor will rise during phase one. However, during the second phase, relative demand shifts toward unskilled workers. It is probably safe to assume that the period from 1970-2000, covered in this paper, is still part of the first of the two technological phases in the Helpman-Trajtenberg model.

Bresnahan *et al.* (2002) provide evidence of a positive relation between IT and the demand for skilled level. Analyzing data for about 400 large U.S. firms over the period 1987-1994, they found evidence that IT is complementary to a new workplace organization which includes broader responsibilities for line workers, greater decentralized decision-making, and more self-managing teams. In turn, both IT and the new organizational structures are complements with worker skills measured in a variety of dimensions, including cognitive skill requirements.

Autor *et al.* (2002, 2003) provided empirical evidence of complementarity between computerization and skilled labor. Autor *et al.* (2002) investigated the effects of computerization in the form of the introduction of image processing of checks on the demand for two types of labor in a large bank. In the deposit processing department, image processing led to the substitution of computers for relatively low skilled (high school educated) workers. In the exceptions processing department, which requires conceptual and problem-solving skills and employs primarily college-trained workers, the introduction of image processing led to an increase in the demand for workers with these particular skills.

Autor *et al.* (2003) provided a more general analysis of the effects of computerization on skill demand. They considered different skill types in their exploration. They found that computers substitute for a limited set of skills – in particular, those involving routine or repetitive cognitive and manual tasks. Conversely, computerization is complementary with tasks involving non-routine problem solving and interactive tasks. Using data on job skill requirements from the Department of Labor Dictionary of Occupational Titles over the period from 1960 to 1998, they found evidence of a positive correlation between the degree of computerization and the relative shift in skill demand within industries, occupations, and educational groups toward more skilled (that is, more non-routine) jobs and away from less skilled (that is, less routine jobs).

They also developed a pertinent model whose main elements I summarize here (more details can be found in their paper). Their assumptions are as follows: (i) There are two types of tasks or skills – "routine" R and "non-routine" N. (ii) Computer technology is more substitutable for routine than non-routine skills. (iii) Routine and non-routine tasks are themselves imperfect substitutes. (iv) Greater intensity of routine inputs increases the marginal productivity of non-routine inputs. (v) The aggregate production function is a constant returns to scale Cobb-Douglas production function of the form:

$$q = R^{1-\beta}N^{\beta} \tag{1}$$

where $0 < \beta < 1$ and where q is output, which sells at price one. Further assumptions are: (vi) Computer capital, C, and workers are perfect substitutes in carrying out routine tasks, R; (vii) Computer capital is supplied elastically at market price P per efficiency unit; (vii) P is falling exogenously over time due to technical advances; (viii) On the labor supply side, the authors assume that each worker i can be characterized according to his (her) relative efficiency in routine and non-routine tasks by $\alpha_i = N_i / R_i$, where $\alpha_i > 0$. It then follows from the perfect substitutability of computers and routine skills that the wage per efficiency unit W_R is given by:

$$W_R = P \tag{2}$$

Workers choose their occupation to maximize their earnings. As a result, the marginal worker with relative efficiency units α^* is indifferent between working in an R or an N occupation when

$$\alpha^* = W_R / W_N \tag{3}$$

Workers with $\alpha_i < \alpha^*$ supply routine labor and those with $\alpha_i \geq \alpha^*$ supply non-routine labor. Let $g_1(\alpha)$ and $g_2(\alpha)$ denote the functions that give the population endowment in efficiency units of routine and non-routine tasks, respectively, as a function of α. Then

$$R^* = \int_0^{\alpha^*} g_1(x)\,\mathrm{d}\,x \quad \text{and} \quad N^* = \int_{\alpha^*}^{\infty} g_2(x)\,\mathrm{d}\,x$$

where R^* is the supply of routine labor and N^* is the supply of non-routine labor.

Define $\theta = (C^* + R^*) / N^*$, the ratio of routine (including computer) tasks to non-routine tasks inputs in production. It follows that if factors are paid their marginal product, then

$$W_R = \partial q/\partial R = (1 - \beta)\theta^{-\beta} \text{ and } W_N = \partial q/\partial N = \beta\theta^{1-\beta} \quad (4)$$

Thus, factors that raise the relative intensity of routine task input (that is, increase θ) lower the wage per efficiency unit of routine task input and raise the wage paid to non-routine task input. From (2) and the first order condition for W_R it follows that:

$$\partial(\ln W_R)/\partial(\ln P) = 1 = -\beta\, \partial(\ln \theta)/\partial(\ln P) \quad (5)$$

so that $\partial(\ln \theta)/\partial(\ln P) = -1/\beta$. As a result, a decline in computer prices will reduce the wage per efficiency unit of routine tasks and increase the relative intensity of routine tasks in production. Since, by assumption, routine and non-routine tasks are complementary inputs,

$$\partial(\ln W_N)/\partial(\ln P) = (\beta - 1) / \beta. \quad (6)$$

In other words, a decline in computer prices will increase the wages of non-routine tasks. From (3), (5), and (6), it follows that:

$$\partial(\ln \alpha^*)/\partial(\ln P) = 1 / \beta. \quad (7)$$

A decrease in computer prices and a rise in IT investment will therefore decrease the *relative labor supply* to routine tasks and increase the *relative labor supply* to non-routine ones. These categories line up fairly well with two occupational groupings that I develop below. The first is knowledge workers, which corresponds to non-routine labor, and the second is data workers, which corresponds to routine labor. As will be seen in Section 5, the predictions of this model are borne out very well.

2.3. International Trade and Skill Composition

A large literature has also accumulated on the effects of international trade on wage differentials. The main approach derives from the factor content of trade model, which puts primary emphasis on the effective supplies of less skilled and more skilled labor (see, for example, Berman *et al.*, 1994). Imports embody both unskilled and skilled labor, which when added to the domestic supply of these two factors, determines their effective supply. Because imports to the U.S. are generally less skill intensive than domestic production, the opening of the domestic economy to imports augments the relative effective supply of low skilled workers and lowers that of high skilled workers and thereby puts downward pressure on the wages of the former relative to the latter.

These studies generally conclude that increased trade had a minimal effect on skill composition. The reason is that U.S. international trade is just too small to have much impact on wages or employment. Almost all of these studies estimated that the rising volume of imports in the United States accounted for no more than 20 percent of the shift in demand between low skilled and high skilled workers. Borjas *et al.* (1992) estimated that rising trade flows explained at most 15 percent of the increase in the earnings differential between college graduates and high school graduates between 1980 and 1988. Bound and Johnson (1992), Krugman and Lawrence (1994), Berman *et al.* (1994), and Richardson (1995) also found very little effect of international trade on the divergence in compensation between more skilled and less skilled workers. However, Krugman and Lawrence (1994) did find that imports from developing countries significantly reduced employment of unskilled production workers in developed countries. Moreover, Wood (1994, 1998) found large effects, with international trade accounting for as much as half of the decreased demand for low skilled workers (see Freeman, 1995, for a review of these studies).

3. Growth of Information Employment

The basic data are from the U.S. Decennial Censuses of 1950, 1960, 1970 1980, 1990 and 2000. In the calculations, the figures in the Census tables of employment by occupation and industry are first aggregated, in conformity with an internally consistent classification scheme, into 267 occupations and 64 industries (see the Data Appendix for details). The occupations are aggregated once more into six categories: (i) knowledge production; (ii) data processing; (iii) supply of services; (iv) goods production; (v) a hybrid class including both knowledge and data activities; and (vi) a second hybrid class including both data and service activities.

In the classification schema, professional and technical workers are generally classified as knowledge or data workers, depending on whether they are producers or users of knowledge (see Appendix Table 1 for details). The line is somewhat arbitrary at points, and judgment calls have been made. Moreover, in some cases, professional workers are classified as data-service workers. For example, doctors and nurses are treated in this way, since they use information and also perform a personal service. Management personnel are taken to perform both data and knowledge tasks, since they produce new information for administrative decisions and also use and transmit this information. Clerical workers are classed as data workers for obvious reasons. I classify as goods-processing workers all labor that transforms or operates on materials or physical objects. These include craft workers, operatives (including transportation workers who move physical goods), and unskilled labor. The remaining group is made up of the service workers, who, primarily, perform personal services.

I then (somewhat arbitrarily) classify half of those that fall into the hybrid knowledge/data category as knowledge workers and the other half as data workers. In similar fashion, I split the hybrid data/service category half into data and half into service workers. The resulting groups are referred to as the "total knowledge", "total data", and "total service" categories. Information workers are then defined as the sum of (total) knowledge and (total) data workers. The non-information category is composed of the residual -- including (total) service and goods-processing workers.[1]

[1] Other ratios were used to split the hybrid groups (such as one-third and two-thirds), with little effect on the results of the data analysis. I also modified the original classification schema by "upgrading" several occupations, with little difference in results. In particular, medical doctors (occupations 27-29, 31-33), therapists (36), and clergymen (38) were upgraded from "Data/Service" workers to "Knowledge/Service" workers; and insurance agents, brokers, and underwriters (84), real estate agents and brokers (86), and stock and bond salesmen were upgraded from "Data" workers to "Knowledge/Data" workers. By the original classification scheme, the share of total knowledge workers in total employment rose from 7.5 to 15.2 percent from 1950 to 2000 or by 7.7 percentage points. By the new classification scheme, the share increased from 8.3 to 16.4 percent or by 8.1 percentage points.

Table 1 gives a breakdown of total employment by type of worker from 1950 to 2000, the corresponding growth rates in each category, and the percentage composition.[2] Over the five decades, knowledge workers were the fastest growing group, increasing 3.1 percent per year. They were followed by data workers and service workers, at 2.5 percent per year and 2.4 percent per year, respectively. In contrast, goods producers increased their number by only 0.2 percent per year. Altogether, employment of information workers grew 2.6 percent per year (one percentage point above average), while non-information workers increased 0.8 percent per year (about one point below average).

INSERT TABLE 1

The developments differ by decade. Between 1950 and 1960, the fastest growing group was service workers, followed by data workers, and knowledge workers. Goods producers declined in absolute number. In the next decade, knowledge workers led the way, followed by data workers, and service workers. The number of goods producers again fell in absolute terms.

The decade of the 1970s again saw knowledge workers with the highest growth rate, in this case followed by data and service workers, and goods-processing workers, whose employment increased in absolute terms. During the decade of the 1980s knowledge workers again led all groups, followed by data and service workers, and goods-processing workers. The 1990s again saw knowledge workers in the lead, followed by data and service workers, and goods-producing workers again declined in absolute terms.

The last panel of Table 1 provides another way of viewing the growth of the information sector. In 1950, 8 percent of total employment consisted of knowledge workers and 29 percent of data workers. Altogether, 37 percent of the employed labor force was made up of information workers. Goods workers formed a majority of total employment, at 52 percent, while service workers constituted only 10 percent of total

[2] I have made some minor changes in the classification scheme used in earlier work so that the results reported here differ slightly from those reported in Baumol *et al.* (1989, Chapter 7).

employment. By 2000, the proportion of information workers in total employment had increased to 59 percent of the total. The number of knowledge workers had risen to 15 percent and that of data workers to 44 percent of total employment. Service workers were up to 14 percent and goods producers dramatically down to 24 percent.

In sum, knowledge workers grew as a share of total employment in each of the five decades and was the fastest growing group in all but the 1950s. However, its biggest increase in relative terms occurred during the 1980s and 1990s, when its share of total employment increased by about two percentage points in each decade. Data workers enjoyed their largest growth in relative terms during the 1950s and 1960s. There was a marked slowdown in the increase of their share of total employment in the 1970s, and during the 1980s there was virtually no change in their share. The share of service workers in total employment rose quite rapidly in the 1950s and much slower thereafter. The share of goods producers in total employment fell in every decade, and in the 1950s, 1960s, and 1990s its number declined in absolute terms as well.

4. Industry Changes in Information Employment

Since our subsequent analysis depends substantially on comparative shifts in the share of information workers among industries, we first examine the relative information-intensity of the major sectors of the economy. As shown in Table 2, in 2000 the finance, insurance, and real estate sector had the highest percentage of knowledge workers in their employment, about 22 percent, followed by business and other services and the government sector in a virtual tie, at about 19 percent. Mining (largely geologists and engineers), manufacturing, and transportation, communications, and utilities followed in a second group. At the bottom were agriculture, construction, and trade. All told, service industries had a slightly higher share of knowledge workers than goods-producing sectors – 15.6 versus 14.4 percent.

INSERT TABLE 2

There is more variation in the share of data workers among sectors. In 2000, the finance, insurance, and real estate sector led the way at 66 percent, and it was also the most information-intensive: about 87 percent of its employees were knowledge or data workers. The trade sector was next in line, at 61 percent, followed by business and other services, at 45 percent, and transportation, communications, and utilities, at 39 percent, and the government sector, at 38 percent. In agriculture, mining, construction, and manufacturing, data workers comprised between 14 and 28 percent of total employment. The share of data workers in total employment was almost twice as high in services as in goods industries.

There are also marked differences in time trends between goods-producing sectors and services. In the former, there was an almost steady rise in both knowledge workers and data workers as a share of total industry employment between 1950 and 2000. In manufacturing, in particular, information workers constituted 46 percent of total employment by 2000, up from 28 percent in 1950, and blue-collar production workers made up 52 percent, down from 70 percent in 1950 (service workers constituting the remainder). This result confirms the growing "white-collarization" of manufacturing in the U.S., often alluded to in the press.

Among service industries, there was generally a fall-off in the percentage of knowledge workers in employment between 1950 and 1960 (1970 in one case), followed generally by a steady rise through 2000 (with the trade sector an exception). In contrast, data workers increased relative to total employment in all four service sectors between 1950 and 1960. In the trade sector, the share of data workers held steady from 1960 to 1990 and then climbed in 2000; in finance, insurance, and real estate, the share remained relatively constant between 1960 and 1980 and then declined from 1980 to 2000; in business and other services, the share increased from 1960 to 1980 and then remained constant from 1980 to 2000; and in the government sector, there was a gradual decline in the share of data workers in total employment from 1960 to 2000. All told, between 1950 and 2000, information workers increased in number relative to non-information workers in all major sectors except the government.

The growth in the overall share of information workers in total employment is due to two proximate causes. The first is technological change on the industry level which may favor information workers relative to non-information workers. This may be attributable to the increasing sophistication and complexity of productive techniques, which requires more producers, manipulators, and transmitters of knowledge. The second is shifts in the industrial composition of employment. In particular, industries more intensive in their use of information workers may have grown in terms of employment relative to industries which rely more heavily on service and goods-processing workers.

The second, in turn, can be further decomposed into two additional effects. The first of these is from changes in the composition of final output. In particular, an increasingly educated population may be demanding products with an ever increasing information content over time. The second of these may arise from differential movements in industry labor productivity. In particular, from the unbalanced growth hypothesis, employment in activities with relatively slower rates of productivity growth must increase relative to employment in high productivity growth activities, even with constant output proportions (see, for example, Baumol, 1967, or Baumol *et al.*, 1989, Chapter 7). There may be some presumption that information-intensive industries, such as business services and the government, may suffer form relatively stagnant productivity growth.

We can address this issue formally through the use of an input-output model. First, define the following matrix and vector components, where all variables are in constant (2000) dollars, unless otherwise indicated. $\mathbf{x}$ is the 64×1 column vector showing the total output (gross domestic output) by sector, $\mathbf{y}$ the 64×1 column vector showing the final output by sector, $\mathbf{E}$ the 267×64 employment matrix, where e_{ij} shows the total employment of occupation i in industry j, $\mathbf{h}$ the 1×64 row vector showing total employment by industry, where $h_j = \Sigma_i e_{ij}$, and $\mathbf{b}$ the 267×1 column vector of total employment by occupation, where $b_i = \Sigma_j e_{ij}$.

Let us now define the following coefficients: $\mathbf{A}$ is the 64×64 matrix of interindustry input-output coefficients, where a_{ij} indicates the amount of input i (in 2000 dollars) required per unit of output j (in 2000 dollars); $\mathbf{z}$ the 64×1 column vector showing the percentage distribution of total final output by sector, where $z_i = y_i / \Sigma_i y_i$; $\mathbf{F}$ the 267×64 employment coefficient matrix, showing employment by occupation per unit of output, where $f_{ij} = e_{ij} / x_j$; $\mathbf{C}$ the 267×64 employment distribution matrix, showing the percentage distribution of employment by occupation within each sector, where $c_{ij} = e_{ij} / h_j$; and $\boldsymbol{\mu}$ the 64×1 vector of labor coefficients showing total employment per unit of output, where $\mu_j = h_j / x_j$. To derive the basic relationship, I start with the basic Leontief identity

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}. \tag{8}$$

It then follows that

$$\mathbf{b} = \mathbf{Fx} = \mathbf{F}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} = \mathbf{C}\hat{\boldsymbol{\mu}}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} = \mathbf{C\Psi y}$$

where $\boldsymbol{\Psi} = \hat{\boldsymbol{\mu}}(\mathbf{I} - \mathbf{A})^{-1}$, which shows the direct plus indirect labor requirements per unit of final output and a circumflex (or "hat") connotes a diagonal matrix whose elements are those of the associated vector. Then, for a given percentage final output vector **z**,

$$\mathbf{b}_{\mathbf{z}} = \mathbf{C\Psi z} \tag{9}$$

where $\mathbf{b}_{\mathbf{z}}$ shows employment by occupation generated by the final output vector **z.** We then have:

$$\Delta\,\mathbf{b}_{\mathbf{z}} = (\Delta\,\mathbf{C})\mathbf{\Psi z} + \mathbf{C}(\Delta\,\mathbf{\Psi})\mathbf{z} + \mathbf{C\Psi}(\Delta\,\mathbf{z}) \tag{10}$$

where the symbol Δ indicates change over the period. Two decompositions are used. Following the work of Dietzenbacher and Los (1998), I use average period weights in the first to yield an approximate decomposition as follows: **Ψ**

$$\begin{aligned}\Delta b \approx{}& \tfrac{1}{4}(\Delta C)(\Psi_0 + \Psi_1)(z_0 + z_1) + \tfrac{1}{4}(C_0 + C_1)(\Delta\Psi)(z_0 + z_1) \\ &+ \tfrac{1}{4}(C_0 + C_1)(\Psi_0 + \Psi_1)(\Delta z)\end{aligned} \tag{10a}$$

These results are shown in Table 3. The second is based on two exact polar decompositions as follows:

$$\Delta b = (\Delta C)\Psi_1 z_1 + C_0(\Delta\Psi)z_1 + C_0\Psi_0(\Delta z) \qquad (10b)$$

$$\Delta b = (\Delta C)\Psi_0 z_0 + C_1(\Delta\Psi)z_0 + C_1\Psi_1(\Delta z) \qquad (10c)$$

From Dietzenbacher and Los (1998), the average of the last two polar decompositions yields a Fisher-type index and I show these results in Table 4.

Equation (10) decomposes the change in the occupational composition of employment into three parts. The first term corresponds to the change in the employment shares of different occupations within industry. In other words, this term reflects the extent to which production processes within industries have changed their techniques so as to substitute information labor for labor of other types. This term is referred to as the *substitution effect*.

The second term involves the change in the vector of quantities of direct plus indirect labor per unit of output, by industry -- that is, the change in the reciprocal of each industry's "total" labor productivity. This approach derives from the work of Pasinetti (1973), who first introduced the concept of a vertically integrated industry (that is, incorporating direct and indirect coefficients). The total labor productivity approach has also been used by Wolff (1985) and Dietzenbacher, Hoen, and Los (2000). This term also captures the unbalanced growth effect -- that is, the fact that (total) labor productivity grows at different rates in different industries. I call this the *productivity effect*.[3] The final

[3] Like other standard output series and deflators, the standard input-output framework is not well equipped to handle product innovations because of the assumption of homogenous outputs. (They are much better at capturing process innovation). As a result, measures of productivity growth in the input-output framework are likely to be biased downward because of the failure of adequately capturing quality improvements in products.

term reflects changes in the composition of final output among different industries, which I call the (final) *output effect*.[4]

If the last term turns out to be significant and substantial in an empirical calculation, this will imply that the growth in information employment is indeed attributable to an information revolution. For a large third term indicates that buyers are typically turning increasingly to outputs whose production has a large information content. The same may also be true, in part, of a large first term, which may indicate that a typical production process has increased in reliance on information labor. However, if the second term turns out to be substantial and significant it will suggest that a corresponding portion of the increase in share of information labor is attributable not to an upsurge in information use, but rather to unbalanced growth -- the shift of labor out of activities whose productivity growth is atypically large.

The primary data source consists of U.S. standard 87-order (benchmark) Bureau of Economic (BEA) analysis input-output tables for years 1947, 1958, 1963, 1967, 1972, 1977, 1982, 1987, and 1992, and the "annual" BEA input-output table for 2000, which are used to compute the vector of final demand and the vector which shows the direct and indirect labor requirements (see the Data Appendix for details on sources and methods for the input-output data.) These data are aggregated to 64 sectors to align with the occupation by industry matrices already described above.[5]

INSERT TABLE 3

[4] The output effect also captures changes in both the relative share and the composition of investment demand. In principle, this can also be considered a technology-related effect, since investment demand is at least partly determined by technological factors just like the demand for intermediate inputs included in the productivity effect. The incorporation of this added effect would require a full series of U.S. capital stock matrices, which are, unfortunately, not available for the time span covered in this analysis.

[5] Since the occupation-by-industry matrices are for different years than the input-output data, geometric interpolation of industry employment for the input-output data was used to align industry employment in the input-output data with the Census years from 1950 to 2000.

On the basis of average period weights, the substitution effect gained continuing strength over time as a source of growth of employment for knowledge workers (Panel 1 of Table 3). During the 1950s, in fact, the effect was negative, indicating that industries substituted other types of workers for knowledge workers in their industry employment. During the 1960s, this effect contributed 0.8 percentage points to the increase in the share of knowledge workers in total employment; in the 1970s, 1.1 percentage points; and in the 1980s and the 1990s, 1.5 percentage points.

In contrast, the productivity effect was a generally diminishing source of growth for knowledge workers between 1950 and 1980, accounting for 0.9 percentage points in the period 1950-60, 0.6 percentage points in 1960-70, and 0.2 percentage points in 1970-80, and then picking up to 0.3 percentage points in 1980-90 and 0.8 percentage points in the 1990s. Differences in productivity growth between information-intensive industries and other industries fell considerably between the first two decades of the period and the second two, a reflection mainly of the sharp drop in overall labor productivity growth between the two 20-year periods (from 1.8 to 1.0 percent per year on the basis of GDP per fulltime equivalent employee), and then widened in the last decade, as overall productivity growth rebounded (to 1.5 percent per year).

Changes in (final) output composition played virtually no role at all in the growth of the share of knowledge workers in the labor force. All told, about three fifths of the growth in this share over the half century was attributable to the substitution of knowledge workers for other types of workers within industry and the other two fifths or so to the unbalanced growth effect.

Results for data workers differ with those for knowledge workers. The substitution effect was much stronger in the decades of the 1950s and 1960s than the 1970s and 1980s. In fact, the substitution effect fell from 1.6 percentage point in the 1950s to virtually zero in the 1980s. However, as with knowledge workers, the productivity effect shows a diminishing influence over time, falling from 3.4 percentage points in the period 1950-60 to 0.3 percentage points in 1980-90, though it did rebound to 0.8 percentage points in the 1990s. Changes in the composition of final output did play a modest role on changes in the share of data workers in total employment in the 1960s, though the effect was negative (-0.6 percentage points). In the other decades, the effect was very small. Over the entire five decades, output changes had only a very minor bearing on the growth of data workers in total employment. The dominant effect was uneven productivity growth, which accounted for about two-thirds of the increase in its share of total employment, while the substitution effect contributed the other one third or so.

For service worker employment, the substitution effect was positive and relatively strong in the 1950s, contributing 1.1 percentage points to the growth in their share of total employment. However, the effect was very weak thereafter and during the 1960s, 1980s, and 1990s, the effect was actually negative, indicating that information workers were substituted for service employees. The unbalanced growth effect was also strong in the 1950s, 1.2 percentage points, gradually lessened over time, reaching 0.1 percentage points in the 1980s, but then climbing to 0.9 percentage points in the 1990s. Changes in output composition had a positive effect on the employment of service workers. It generally increased over time, from 0.4 percentage points in the 1950s to 0.7 percentage points in the 1980s, reflecting primarily the increased demand for medical, educational, social, and personal services, but then tailing off to virtually zero in the 1990s. Over the entire 1950-2000 period, the principal source of growth in the share of service employment in total employment was the productivity effect, which accounted for about 70 percent of its growth, followed by changes in output composition, which accounted for 34 percent, and, lastly, the substitution effect, which accounted for only about -4 percent.

The story for goods-processing workers is very different than that for the other types of workers. All three effects were strongly negative, and each played a role in the decline in the share of goods-processing workers in total employment. The strongest influence was the differential productivity effect, which accounted for over half its total decrease between 1950 and 2000. The effect was extremely strong in the 1950s and 1960s -- -5.3 and -4.6 percentage points, respectively -- and accounted for over 60 percent of the relative decline of goods workers in those two decades. In the 1970s and 1980s, the effect had fallen to -1.3 percentage points, though, here too, strengthened in the 1990s, to -2.5 percentage points. The substitution effect explained another third of the decrease in the share of goods-processing workers in total employment over the entire half century. The effect gradually diminished over time, from -2.3 percentage points in the 1950s to -0.8 percentage points in the 1980s, though once again picked up to -2.0 percentage points in the 1990s. Changes in output composition also played a role, accounting for 11 percent of its overall decline as a share of total employment over the entire period. The effect was particularly strong in the 1970s, when it contributed -1.4 percentage points or 31 percent of the drop in its share.

INSERT TABLE 4

Results on the basis of the average of the two polar decompositions, shown in Table 4, are very close to those of Table 3. Over the five decades, the substitution effect is slightly weaker and the productivity effect slightly stronger for knowledge workers on the basis of the Fisher-type weights. For service workers, the substitution effect is slightly more negative and the productivity effect slightly stronger on the basis of the Fisher-type weights.

In sum, on the production side of the economy, a large contribution was made by technological change within each industry which substituted information labor for other types of labor. The substitution component explained almost three fifths of the growth in the share of knowledge workers and over a third of the growth in the share of data workers. It also accounted for over a third of the decline in the share of goods-processing workers, though none of the growth in the percentage of service workers in total employment.

The unbalanced productivity component was the strongest of the three effects. The absorption of workers from industries whose productivity grew relatively slowly explained almost two fifths of the increase in the share of knowledge workers in total employment, two thirds of the increase in the share of data workers, over 70 percent of the rising share of service workers, and over half of the decline in the share of goods-processing workers. The output composition effect contributed almost nothing to the growth of information employment but accounted for almost a third of the growth in the share of service workers in total employment and 10 percent of the decline in the share of goods-processing workers.

These results also imply that the so-called "information explosion" is almost entirely a consequence of unbalanced growth and the substitution of information labor within production. Demand shifts towards heavily information-using products did not play a role in the growth of information workers.

5. Technology and the Growth in Information Employment

Though about half of the growth in information employment has resulted from the less rapid productivity growth of the more information-intensive industries in the economy, the other half has also arisen from changes in employment patterns within industry. This section uses econometric methods to analyze the sources of growth of information workers on the industry level. I use three sets of independent variables: (i) measures of technological activity; (ii) investment, including computerization; and (iii) indices of international competitiveness.

According to the literature reviewed in Section 2, as well as the model developed in this section, we should expect to find a positive relation between the growth of the share of knowledge workers in total employment and the pace of technological change and a corresponding negative relation between the growth of the share of data workers and the pace of technological change. As a result, both TFP growth and R&D intensity, which are indicators of the development of new technology, should be positively correlated with the growth in the share of knowledge workers and negatively correlated with the change in the share of data workers.

Likewise, a positive relation should be expected between the growth of the share of knowledge workers in total employment and the intensity of IT investment and a corresponding negative relation between the growth of the share of data workers and IT investment. Predictions are ambiguous for the shares of service and goods workers in employment since these jobs represent a combination of routine and non-routine tasks.

With regard to non-IT equipment investment, the dominant view is the capital-skills complementarity hypothesis. Greater investment in equipment should be associated with a greater demand for knowledge workers and a reduced demand for the other types of workers. As indicated in Section 1, international competitiveness may also affect the rate of change in the employment of information workers. Greater international trade should be associated with an increased share of knowledge workers and a reduced share of data workers.

The regression analysis uses pooled cross-section time-series data, covering 44 industries in three ten-year time periods, 1960-70, 1970-80, and 1980-90, and 32 industries for the 1990-2000 time period.[6] I use a fixed effect model, with industry dummy variables, as follows:

$$\text{KNOWSHAR}_{jt} = \beta_0 + \beta_1 \,\text{Ln}(\text{TFP}_{jt}) + \beta_2 \,\text{RDKGDP}_{jt} + \beta_3 \,\text{Ln}(\text{EQPKXPEP}_{jt}) + \beta_4 \,\text{Ln}(\text{OCAKPEP}_{jt}) + \beta_5 \,\text{EXPGDP}_{jt} + \beta_6 \,\text{IMPGDP}_{jt} + \Sigma_{43}\, \gamma_{\text{j}} \,\text{INDDUM}_{jt} + u_{jt} \qquad (11)$$

where for industry j at time t, KNOWSHAR_{jt} is the share of knowledge workers, TFP_{jt} is the TFP level, RDKGDP_{jt} is the ratio of R&D capital stock to GDP, EQPKXPEP_{jt} is the total net stock of equipment and machinery less OCA per worker (PEP), OCAKPEP_{jt} is the net stock of OCA per worker, EXPGDP_{jt} is the ratio of exports to GDP, IMPGDP_{jt} is the ratio of imports to GDP, INDDUM_{jt} is a set of 43 industry dummy variables[7] and γ_{j} are the corresponding coefficients, and u_{jt} is a stochastic error term. First-differencing (over time) yields:

$$\Delta\text{KNOWSHAR}_{jT} = \beta_0 + \beta_1 \,\text{TFPGRT}_{jT} + \beta_2 \,\text{RDGDP}_{jT} + \beta_3 \,\text{EQPXPEPGRT}_{jT} + \beta_4 \,\text{OCAPEPGRT}_{jT} + \beta_5 \,\Delta\text{EXPGDP}_{jT} + \beta_6 \,\Delta\text{IMPGDP}_{jT} + v_{jT} \qquad (12)$$

where industry j over the period T (from t-1 to t), $\Delta\text{KNOWSHAR}_{jT}$ is the change in the share of knowledge workers, TFPGRT_{jT} is TFP growth, RDGDP_{jT} is the average ratio of

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[6] See Appendix Table 2 for details on the industry classification. The public administration sector is excluded because of a lack of OCA capital stock data. Also, because of the adoption of the North American Industrial Classification System (NAICS) in 1997, only 33 industries in the 1990-2000 period could be constructed that were compatible with earlier years (the public administration sector is again excluded because of a lack of OCA capital stock data). The 1950-60 period is also excluded because of a lack of industry-level R&D data for this period.

[7] Only 31 industry dummies for 1990-2000.

R&D expenditures to GDP in period T, $\mathrm{EQPXPEPGRT}_{jT}$ is the growth in the total net stock of equipment and machinery less OCA per worker (PEP), $\mathrm{OCAPEPGRT}_{jT}$ is the growth of the net stock of OCA per worker, $\Delta\mathrm{EXPGDP}_{jT}$ is the change in the ratio of exports to GDP, $\Delta\mathrm{IMPGDP}_{jT}$ is the change in the ratio of imports to GDP, and v_{jT} is a stochastic error term. I also include period dummy variables. Moreover, though in principle the industry dummy variables zero out in the first-differencing, I also include a set of these in order to capture any unobserved heterogeneity of industry characteristics on changes over time. In addition, as alternatives to OCAPEPGRT and EQPXPEPGRT, I have also used INVOCAPEP and INVEQPXPEP, investment in OCA and non-OCA equipment per worker. A similar set of specifications is used for $\Delta\mathrm{DATASHAR}_{jT}$, the change in the share of data workers.[8]

Results are reported in Table 5. In the two specifications without industry dummy variables, the strongest effect on the growth of knowledge workers comes from R&D investment (the ratio of R&D expenditures to industry output). Its coefficient is positive and highly significant (at the one percent level.)[9] Its coefficient is negative for the growth in data workers and also significant, though at the five percent level. These results are consistent with the hypothesis that new technology increases the need for highly skilled workers relative to less skilled workers.

INSERT TABLE 5

Computerization has a positive and marginally significant effect on gains in knowledge employment and a highly significant negative effect (at the one percent level) on the growth in data workers.[10] These results are consistent with the hypothesis that

[8] Because of the heterogenous nature of both service and goods-producing workers, no clear predictions are possible regarding the factors that affect the change in their employment shares, so that these equations are not estimated. The White procedure for a heteroschedasticity-consistent covariance matrix is also used in the estimation (see White, 1980).

[9] Part of this result reflects the fact that about half of R&D expenditures are on R&D labor, which almost by definition consists primarily of knowledge workers like scientists and engineers.

[10] Investment of OCA per worker has somewhat stronger effects than the growth of OCA

computerization increases the demand for high-skilled workers relative to lower-skilled ones (skills that are substitutes for IT). Investment in total equipment excluding OCA per worker has a positive but statistically insignificant on the change in the share of knowledge workers. Its effect on the change in the proportion of data workers is also positive but again not significant.

The other variables used in the regression analysis, TFP growth and changes in trade intensity, are not statistically significant except for the change in export intensity in the case of the growth of knowledge workers. Its coefficient is positive and significant at the five percent level. The direction of causation is not clear. On the one hand, these results may suggest that export-oriented industries require knowledge workers for the development of new products, product design and styling, and process innovation (increasing efficiency in the production of existing products). On the other hand, it may be the case that knowledge-intensive industries are better positioned for the export market.

Dummy variables for time periods 1960-70, 1970-80, and 1980-90 are significant for the growth of both knowledge and data workers (results not shown). One other point of interest is that the goodness of fit is much stronger in the case of data workers than knowledge workers. The high R-square for the former is primarily attributable to the extremely significant (and negative) effects of OCA investment on the employment of data workers (a t-ratio of almost 10).

The introduction of the industry dummy variables causes two of the results to change. The coefficient on the change in export intensity in the regression on the change in the share of knowledge workers remains positive but now become statistically insignificant, and the coefficient on R&D intensity in the regression on the change in the share of data workers remains negative but becomes insignificant. These results suggest that these two effects may have resulted from unobserved heterogeneity of industry characteristics. On the other hand, the coefficients on R&D intensity and investment in OCA per worker in the former regression actually become stronger and their t-values rise. The coefficient on OCA investment per worker in the latter equation retains its very significant, negative coefficient.

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per worker.

6. Conclusion

This paper documents the rapid growth of information workers in the U.S. economy. Information workers as a group grew from 37 percent of total employment in 1950 to 59 percent in 2000. However, the time patterns are quite different for knowledge-producing and data workers, with the increase in the share of the former accelerating from 0.5 percentage points during the 1950s to 2.3 percentage points in the 1990s and that of the latter slowing down from 5.0 to 1.7 percentage points.

About two fifths of the growth in the share of knowledge workers in total employment and two thirds of the increase in the share of data workers over the period from 1950 to 2000 is attributable to differential rates of productivity movements among the industries of the economy. However, the unbalanced growth effect diminished over the first four decades, a reflection of the general slowdown in overall productivity growth between the 1950s and 1960s and the ensuing two decades, though it did pick up in the 1990s, as overall productivity growth rebounded.

On the production side of the economy, the substitution component explained almost three fifths of the growth in the share of knowledge workers over the five decades and about a third of the growth in the share of data workers. The substitution effect increased in importance over time in the case of knowledge workers (from -0.4 percentage points in the 1950s to 1.5 percentage points in the 1990s) but generally diminished over time for data workers (from 1.6 to 0.0 percentage points in the 1980s but then up to 0.9 percentage points in the 1990s). It also accounted for a third of the decline in the share of goods-processing workers.

In contrast, demand shifts towards heavily information-using products contributed virtually nothing to the growth of information employment. In other words, the relative growth in information workers has come through changes in production technology, not through the substitution of information-intensive products for others among final consumers.

The results of the regression analysis reveal that R&D expenditures had the strongest influence on the growth of knowledge workers. These results are in accord with those of Machin and van Reenen (1998). OCA investment also exerted a positive effect. On the other hand, investment in OCA exerted a strong depressing effect on the growth in data workers. These results are in accord with the Autor *et al.* (2003) model described in Section 2. TFP growth and investment in equipment other than OCA per worker were not significant factors in the growth of either knowledge or data workers. The change in export intensity was found to be significantly related to the growth of knowledge workers but this effect washed out when industry dummy variables were introduced.

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Data Appendix

1. NIPA employment data: Figures are from the National Income and Product Accounts (NIPA), available on the Internet

[http://www.bea.gov/bea/dn2/home/annual_industry.htm]. Persons engaged in production (PEP) equals the number of full-time and part-time employees plus the number of self-employed persons. Unpaid family workers are not included.

2. Capital stock and investment figures are based on chain-type quantity indexes for net stock of fixed capital and investment in 2000$, year-end estimates. Source: U.S. Bureau of Economic Analysis, CD-ROM NCN-0229, "Fixed Reproducible Tangible Wealth of the United States, 1925-97" and the Internet [http://www.bea.gov/bea/dn/home/fixedassets.htm].

3. Research and development expenditures performed by industry include company, federal, and other sources of funds. Company-financed R&D performed outside the company is excluded. Industry series on R&D and full-time equivalent scientists and engineers engaged in R&D per full-time equivalent employee run from 1957 to 2002. Sources: National Science Foundation, Internet. For technical details, see National Science Foundation, *Research and Development in Industry*, (Arlington, VA: National Science Foundation), NSF96-304, 1996; and the Internet [http://www.nsf.gov/sbe/srs/nsf01305/htmstart.htm].

4. The original input-output data are 85-sector U.S. input-output tables for years 1947, 1958, 1963, 1967, 1972, 1977, 1982, 1987, 1992, and 2000 (see, for example, Lawson, 1997, for details on the sectoring). The 1947, 1958, and 1963 tables are available only in single-table format. The 1967, 1972, 1977, 1982, 1987, 1992, and 2000 data are available in separate make and use tables. These tables have been aggregated to 45 sectors for conformity with the other data sources. The 1950, 1960, 1970, 1980, and 1990 input-output tables are interpolated from the benchmark U.S. input-output tables. The 2000 input-output table is provided directly by the BEA as part of their annual input-output series. The source is the Internet [http://www.bea.gov/bea/dn2/i-o_annual.htm]. Import and export data by industry are also derived from the input-output data.

5. The formula for the average annual growth in total factor productivity is: $TFPGRTH_t = (dY_t)/Y_t - \alpha(dL_t)/L_t - (1-\alpha)(dK_t)/K_t$, where Y_t is GDP at time t, L_t is the total labor input, K_t is the capital input, and α is the average wage share in over the period. The labor input is measured by PEP and the capital input by the fixed non-residential net capital stock (in 2000 dollars). The wage share is measured as the ratio of employee compensation to

GDP, both in current dollars, averaged over the relevant time period. Since the data are for discrete time periods, the Tornqvist-Divisia measure, based on average period shares, is used in the actual estimation

Table 1. Employment growth and percentage composition of employment by type of worker, 1950-2000

Type of Worker	Total Employment (in millions)					
	1950	1960	1970	1980	1990	2000
1. Knowledge	2.2	2.8	4.8	6.8	9.4	13.9
2. Data	14.2	19.0	26.9	34.7	41.1	49.1
3. Knowledge/Data	4.5	5.0	5.4	8.2	11.9	14.0
4. Data/Services	1.7	2.0	3.0	4.9	5.4	7.2
5. Services	6.0	8.4	10.2	13.5	16.5	19.5
6. Goods	30.4	28.6	28.3	31.2	34.4	33.2
7. Total Knowledge	4.4	5.3	7.5	10.9	15.3	20.9
8. Total Data	17.2	22.5	31.1	41.2	49.8	59.7
9. Total Information	21.7	27.8	38.6	52.1	65.1	80.6
10. Total Non-Information	37.2	38.0	40.0	47.2	53.6	56.3
11. Total Employment	58.9	65.8	78.7	99.3	118.8	136.9

Type of Worker	Annual Rate of Growth of Employment (in percent)					
	1950-60	1960-70	1970-80	1980-90	1990-2000	1950-2000
Total Knowledge	1.7	3.5	3.7	3.4	3.1	3.1
Total Data	2.7	3.3	2.8	1.9	1.8	2.5
Total Services	3.4	1.9	2.8	2.0	1.7	2.4
Goods	-0.6	-0.1	1.0	1.0	-0.4	0.2
Total Information	2.5	3.3	3.0	2.2	2.1	2.6
Total Non-Information	0.2	0.5	1.6	1.3	0.5	0.8
Total	1.1	1.8	2.3	1.8	1.4	1.7

Type of Worker	Percent Distribution of Employment					
	1950	1960	1970	1980	1990	2000
Total Knowledge	7.5	8.0	9.6	11.0	12.9	15.2
Total Data	29.2	34.2	39.6	41.5	41.9	43.6
Total Services	10.2	12.8	13.0	13.6	13.9	14.2
Goods	51.7	43.5	36.0	31.4	29.0	24.3
Total Information	36.8	42.2	49.1	52.5	54.8	58.9
Total Non-Information	63.2	57.8	50.9	47.5	45.2	41.1
Total	100.0	100.0	100.0	100.0	100.0	100.0

Note: The total for knowledge workers (line 7) is given by the sum of line 1 and half of line 3. The total for data workers (line 8) is given by the sum of line 2, half of line 3, and half of line 4. The total for information workers (line 9) is defined as the sum of line 7 and line 8. The total for non-information workers (line 10) is the residual.

Table 2. Knowledge and data workers as a percent of total employment by major industry, 1950-2000

Sector	1950	1960	1970	1980	1990	2000
A. Knowledge Workers						
Agriculture	0.5	0.9	2.3	3.4	3.6	9.7
Mining	4.5	7.6	10.5	12.6	14.8	13.4
Manufacturing	5.9	7.0	9.3	9.8	11.9	17.8
Construction	4.9	7.2	7.7	7.6	10.1	8.4
Transportation, communications, and utilities	5.8	6.7	7.8	9.5	11.3	14.5
Trade	10.6	7.9	7.0	9.3	10.7	6.0
Finance, insurance, and real estate	9.2	10.6	10.6	12.1	15.4	21.7
Business and other services	12.0	11.1	12.5	13.7	15.6	18.7
Government	12.4	11.8	13.9	15.5	16.1	18.6
Total goods	4.4	6.1	8.3	9.0	10.9	14.4
Total services	11.2	9.9	10.5	12.2	14.0	15.6
Total	7.5	8.0	9.6	11.0	12.9	15.2
B. Data Workers						
Agriculture	0.7	1.4	3.9	6.2	7.2	13.7
Mining	11.2	17.3	23.4	26.3	28.5	24.3
Manufacturing	21.8	22.9	25.9	27.3	27.1	28.3
Construction	7.8	12.2	17.5	19.8	19.2	22.6
Transportation, communications, and utilities	32.4	31.9	35.7	37.1	36.1	39.0
Trade	51.9	54.5	52.9	51.6	53.0	60.8
Finance, insurance, and real estate	69.2	79.1	80.3	79.3	75.8	65.5
Business and other services	31.1	35.1	43.5	45.1	45.0	45.3
Government	53.7	54.2	52.9	51.1	48.2	37.5
Total goods	16.0	19.7	24.4	26.1	25.8	28.3
Total services	45.0	48.2	51.0	51.2	50.9	50.2
Total	29.2	34.2	39.6	41.5	41.9	43.6

Note: Calculations are shown for total knowledge workers and total data workers. The goods sector consists of agriculture, mining, manufacturing, construction, and transportation, communications, and utilities. The service sector includes trade; finance, insurance, and real estate; business and other services; and government.

Table 3. Decomposition of the Change in Employment Composition by Type of Worker into A Substitution, Productivity, and Output Effect Using Average Period Weights, 1950-2000

	Decomposition in percentage points				Percent Decomposition			
Type of Worker	Substitution Effect	Productivity Effect	Output Effect	Total Change	Substitution Effect	Productivity Effect	Output Effect	Total Change
1. Knowledge Workers								
1950-60	-0.32	0.86	-0.03	0.49	-65.8	175.5	-6.1	103.5
1960-70	0.80	0.64	0.02	1.53	52.5	41.8	1.3	95.6
1970-80	1.10	0.21	0.08	1.42	77.7	14.8	5.6	98.1
1980-90	1.50	0.33	0.06	1.94	77.2	17.0	3.1	97.3
1990-00	1.69	0.77	0.03	2.33	72.6	33.0	1.3	107.0
1950-00	4.77	3.01	0.17	7.70	62.0	39.2	2.2	103.4
2. Data Workers								
1950-60	1.59	3.36	0.03	4.91	32.3	68.4	0.6	101.3
1960-70	2.01	4.14	-0.57	5.40	37.2	76.7	-10.6	103.3
1970-80	0.65	1.35	0.02	1.97	32.9	68.6	1.0	102.5
1980-90	0.04	0.34	0.09	0.40	9.3	84.3	22.3	115.9
1990-00	0.78	0.81	0.02	1.69	46.1	47.7	1.3	95.1
1950-00	5.06	9.89	-0.41	14.38	35.2	68.8	-2.9	101.1
3. Service Workers								
1950-60	1.11	1.24	0.38	2.76	40.1	44.9	13.8	98.7
1960-70	-0.61	0.84	0.27	0.57	-105.6	146.3	47.0	87.7
1970-80	0.13	0.58	0.48	1.18	10.9	49.0	40.6	100.5
1980-90	-0.69	0.11	0.69	0.08	---	---	---	---
1990-00	-0.13	0.87	0.10	0.71	-18.0	122.7	14.8	119.5
1950-00	-0.19	3.72	1.82	5.31	-3.6	70.1	34.2	100.7
4. Goods-processing Workers								
1950-60	-2.32	-5.26	-0.59	-8.16	28.4	64.4	7.2	100.1
1960-70	-2.27	-4.61	-0.74	-7.50	30.2	61.5	9.9	101.6
1970-80	-1.87	-1.30	-1.41	-4.57	41.0	28.4	30.8	100.2
1980-90	-0.80	-1.28	-0.37	-2.42	33.1	52.9	15.3	101.2
1990-00	-1.99	-2.49	-0.04	-4.73	42.0	52.7	0.8	95.5
1950-00	-9.25	-15.12	-2.97	-27.38	33.8	55.2	10.8	99.8

Note: Calculations are shown for total knowledge workers, total data workers, total service workers, and goods producers. Average period weights are used in all cases. The substitution, productivity, and output effects refer, respectively, to the three terms of equation (10).

Table 4. Decomposition of the change in employment composition by type of worker into a substitution, productivity, and output effect using Fisher-type weights, 1950-2000

Type of Worker	Decomposition in percentage points: Substitution Effect	Productivity Effect	Output Effect	Total Change	Percent Decomposition: Substitution Effect	Productivity Effect	Output Effect	Total Change
1. Knowledge Workers								
1950-60	-0.40	0.92	-0.03	0.49	-83.1	189.3	-6.2	100.0
1960-70	0.79	0.71	0.03	1.53	51.7	46.6	1.6	100.0
1970-80	1.11	0.24	0.08	1.42	77.8	16.6	5.6	100.0
1980-90	1.49	0.39	0.06	1.94	76.8	20.0	3.3	100.0
1990-00	1.47	0.82	0.03	2.33	63.3	35.3	1.4	100.0
1950-00	4.45	3.08	0.17	7.70	57.8	40.0	2.2	100.0
2. Data Workers								
1950-60	1.57	3.31	0.03	4.91	32.0	67.4	0.6	100.0
1960-70	1.89	4.08	-0.57	5.40	35.0	75.5	-10.5	100.0
1970-80	0.63	1.32	0.02	1.97	31.9	67.0	1.1	100.0
1980-90	-0.03	0.35	0.09	0.40	-8.5	87.0	21.5	100.0
1990-00	0.91	0.76	0.02	1.69	53.8	44.9	1.3	100.0
1950-00	4.97	9.82	-0.41	14.38	34.6	68.3	-2.9	100.0
3. Service Workers								
1950-60	1.14	1.29	0.33	2.76	41.4	46.7	11.9	100.0
1960-70	-0.54	0.92	0.20	0.57	-94.6	159.7	34.9	100.0
1970-80	0.13	0.61	0.45	1.18	10.7	51.6	37.8	100.0
1980-90	-0.69	0.08	0.69	0.08	---	---	---	---
1990-00	-0.29	0.96	0.04	0.71	-41.4	136.3	5.1	100.0
1950-00	-0.26	3.87	1.70	5.31	-4.9	72.8	32.1	100.0
4. Goods-processing Workers								
1950-60	-2.32	-5.31	-0.54	-8.16	28.4	65.0	6.6	100.0
1960-70	-2.14	-4.69	-0.67	-7.50	28.6	62.5	8.9	100.0
1970-80	-1.86	-1.33	-1.38	-4.57	40.7	29.2	30.1	100.0
1980-90	-0.77	-1.34	-0.31	-2.42	31.9	55.5	12.6	100.0
1990-00	-2.18	-2.58	0.03	-4.73	46.1	54.5	-0.6	100.0
1950-00	-9.28	-15.25	-2.86	-27.38	33.9	55.7	10.4	100.0

Note: Calculations are shown for total knowledge workers, total data workers, total service workers, and goods producers. The results are based on the average of two decompositions. The first uses first period weights for the first two terms and second period weights for the third term. In the second decomposition, the weighting is reversed. The substitution, productivity, and output effects refer, respectively, to the three terms of equation (10).

Table 5. Regressions of the share of information workers in total employment on technology and other variables using industry level data, 1960-2000

Independent Variables	Dependent Variable: Change in the Employment Share of Knowledge Workers				Change in the Employment Share of Data Workers			
Constant	0.027	**	0.053	**	0.054	**	0.020	
	(3.59)		(3.06)		(4.85)		(0.81)	
TFP Growth	-0.042		-0.102		-0.093		-0.023	
	(0.47)		(0.92)		(0.71)		(0.15)	
Ratio of R&D Expenditures To Total Output	0.264	**	0.313	**	-0.342	*	-0.316	
	(2.78)		(2.89)		(2.11)		(0.94)	
Investment in Equipment less OCA (in 1000s, 2000$) per Worker	0.062		0.029		0.074		0.199	
	(1.45)		(0.35)		(1.14)		(1.62)	
Investment in OCA (in 1000s, 2000$) per Worker	1.794	#	1.926	*	-13.275	**	-13.537	**
	(1.91)		(2.16)		(9.74)		(8.46)	
Change in the Ratio of Imports to Total Output	0.034		0.027		-0.002		-0.035	
	(1.27)		(0.68)		(0.06)		(0.62)	
Change in the Ratio of Exports to Total Output	0.309	*	0.051		0.329		0.297	
	(2.24)		(1.29)		(1.59)		(1.20)	
Time Dummies	YES		YES		YES		YES	
Industry Dummies	NO		YES		NO		YES	
R^2	0.14		0.37		0.44		0.63	
Adjusted R^2	0.09		0.07		0.41		0.46	
Standard Error	0.0292		0.0296		0.0439		0.0422	
Sample Size	164		164		164		164	

Note: The sample consists of pooled cross-section time-series data, with observations on each of the 44 industries in 1960-70, 1970-80 and 1980-90 (sector 45, public administration, is excluded because of a lack of appropriate capital stock data), and 32 industries in 1990-2000. The coefficients are estimated using use the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient. See the Data Appendix for sources and methods. Significance levels: # - 10%; * - 5% level; ** - 1% level.

Appendix Table 1. Classification of occupations into knowledge, data, service and goods Workers

Occupation Number	Occupation Name	Information Group Category
1	Accountants	Knowledge
2	Architects	Knowledge
3	Computer programmers	Knowledge
4	Computer systems analysts	Knowledge
5	Computer specialists, nec	Knowledge
6	Aero- and aeronautical engineers	Knowledge
7	Chemical engineers	Knowledge
8	Civil engineers	Knowledge
9	Electrical and electronic engineers	Knowledge
10	Industrial engineers	Knowledge
11	Mechanical engineers	Knowledge
12	Metal, material, mining and petro-chemical engineers	Knowledge
13	Sales engineers	Data
14	Engineers, nec	Knowledge
15	Farm management advisers, foresters, conservationists and home mgmt. advisers	Knowledge
16	Judges	Knowledge
17	Lawyers	Knowledge
18	Librarians, archivists, and curators	Knowledge
19	Actuaries, statisticians, and operation research analysts	Knowledge
20	Mathematicians	Knowledge
21	Agricultural scientists	Knowledge
22	Biological scientists	Knowledge
23	Chemists	Knowledge
24	Geologists, physicists, and astronomers	Knowledge
25	Life and physical scientists, nec	Knowledge
26	Personnel and labor relations workers	Data/Services
27	Chiropractors	Data/Services
28	Dentists	Data/Services
29	Optometrists	Data/Services
30	Pharmacists	Data
31	Physicians, medical and osteopathic	Data/Services
32	Veterinarians	Data/Services
33	Podiatrists, and health practitioners, nec	Data/Services
34	Dietitians	Data/Services
35	Registered nurses	Data/Services
36	Therapists	Data/Services
37	Health technologists and technicians	Data
38	Clergymen	Data/Services
39	Religious workers, nec	Data/Services

40	Social scientists	Knowledge
41	Social workers	Data/Services
42	Recreation workers	Data
43	Teachers, college and university	Knowledge
44	Adult education teachers	Data
45	Elementary and secondary teachers	Data
46	Pre- and kindergarten teachers	Data
47	Teachers, except college and university,nec	Data
48	Agricultural, biological, and chemical technicians	Data
49	Draftsmen	Data
50	Electrical engineering technicians	Data
51	Engineering and science technicians, nec	Data
52	Airplane pilots	Data/Services
53	Air traffic controllers	Data
54	Flight Engineers	Data
55	Tool programmers, numerical control	Data
56	Technicians, nec, including radio operators	Data
57	Vocational and educational counselors	Data/Services
58	Designers	Knowledge
59	Editors and reporters	Knowledge
60	Writers, artists,and entertainers, nec	Knowledge
61	Research worker, not specified	Knowledge
62	Bank officers and financial managers	Knowledge/Data
63	Buyers & shippers: farm, wholesale, retail	Data
64	Credit men	Data
65	Funeral directors and embalmers	Data/Services
66	Health administrators	Knowledge/Data
67	Construction inspectors, public admin.	Data
68	Inspectors, except construction, pub. admin	Data
69	Managers and superintendents, buildings	Data/Services
70	Office Managers, nec	Data
71	Ship officers, pilots, and pursers	Knowledge/Data
72	Administrators, public admin., nec	Knowledge/Data
73	Officials of lodges, societies, and unions	Knowledge/Data
74	Postmasters and mail superintendents	Knowledge/Data
75	Purchasing agents and buyers, nec	Data
76	Railroad conductors	Data
77	Restaurant, cafeteria and bar managers	Data/Services
78	Sales managers & department heads, retail	Knowledge/Data
79	Sales managers, except retail trade	Knowledge/Data
80	School admin.,college, elementary,secondary	Knowledge/Data
81	Managers and administrators, nec	Knowledge/Data
82	Advertising agents and salesmen	Data
83	Auctioneers, demonstrators, hucksters,	Data
84	Insurance agents, brokers, & underwriters	Data
85	Newsboys	Data
86	Real estate agents and brokers	Data
87	Stock and bond salesmen	Data
88	Sales representatives, manufacturing and wholesale	Data

89	Sales clerks, retail; salesmen	Data
90	Bank tellers	Data
91	Bookkeepers	Data
92	Cashiers	Data
93	Collectors, bills and accounts	Data
94	Dispatchers and starters, vehicles	Data
95	File clerks	Data
96	Insurance adjusters and examiners	Data
97	Library attendants and assistants	Data
98	Mail carriers, post office	Data
99	Messengers and office boys	Data
100	Miscellaneous clerical workers	Data
101	Office machine operators	Data
102	Payroll and timekeeping clerks	Data
103	Postal clerks	Data
104	Real estate appraisers	Data
105	Receptionists	Data
106	Secretaries	Data
107	Shipping and receiving clerks	Data
108	Statistical clerks	Data
109	Stenographers	Data
110	Stock clerks and storekeepers	Data
111	Teacher aides, except school monitors	Data
112	Telegraph operators	Data
113	Telephone operators	Data
114	Ticket station and express agents	Data
115	Typists	Data
116	Bakers	Goods
117	Blacksmiths	Goods
118	Boilermakers	Goods
119	Brick, stonemasons, and tile setters	Goods
120	Bulldozer, excavating, grading operators	Goods
121	Cabinetmakers	Goods
122	Carpenters and apprentices	Goods
123	Cement and concrete finishers	Goods
124	Compositors, typesetters & apprentices	Goods
125	Cranemen, derrickmen, hoistmen	Goods
126	Decorators and window dressers	Goods
127	Electricians and apprentices	Goods
128	Electric power linemen and cablemen	Goods
129	Electro- and stereotypers, and engravers	Goods
130	Foremen, nec	Data
131	Forgemen and hammermen	Goods
132	Painters	Goods
133	Glaciers	Goods
134	Heat Treaters, annealers,and temperers	Goods
135	Inspectors nec, scalers, and graders	Goods
136	Jewelers and watchmakers	Goods
137	Job and die setters, metal	Goods
138	Locomotive engineers and firemen	Goods

139	Machinists and apprentices	Goods
140	Air conditioning, heating and refrigeration repairmen	Goods
141	Aircraft mechanics	Goods
142	Machinery mechanics and repairmen, nec	Goods
143	Household appliance mechanics	Goods
144	Loom fixers	Goods
145	Office machine mechanics and repairmen	Goods
146	Radio and television repairmen	Goods
147	Railroad and car shop mechanics	Goods
148	Miscellaneous mechanics and repairmen	Goods
149	Millers of grain, flour, and feed	Goods
150	Millwrights	Goods
151	Metal molders and apprentices	Goods
152	Motion picture projectionists	Goods
153	Opticians, lens grinders and polishers	Goods
154	Pattern and model makers, except paper	Goods
155	Photoengravers and lithographers	Goods
156	Plasterers and apprentices	Goods
157	Plumbers, pipe fitters and apprentices	Goods
158	Power station operators	Goods
159	Pressmen, plate printers, and apprentices	Goods
160	Rollers and finishers, metal	Goods
161	Roofers and slaters	Goods
162	Sheetmetal workers and tinsmiths	Goods
163	Shipfitters	Goods
164	Shoe repairmen	Goods
165	Stationary engineers	Goods
166	Structural metal craftsmen	Goods
167	Tailors	Goods
168	Phone installers, repairmen, and linemen	Goods
169	Tool and die makers and apprentices	Goods
170	Upholsterers	Goods
171	Craftsmen and kindred workers, nec	Goods
172	Asbestos and insulation workers	Goods
173	Assemblers	Goods
174	Blasters and powdermen	Goods
175	Bottling and canning operatives	Goods
176	Chainmen, rodmen, and axmen: surveying	Goods
177	Checkers, examiners and inspectors: manufacturing	Goods
178	Clothing ironers and pressers	Goods
179	Cutting operatives, nec	Goods
180	Dressmakers and seamstresses,except factory	Goods
181	Drillers: earth	Goods
182	Dry wall installers and lathers	Goods
183	Dyers	Goods
184	Filers, polishers, sanders, and buffers	Goods
185	Furnacemen, smeltmen and pourers	Goods
186	Garage workers and gas station attendants	Goods
187	Graders and sorters: manufacturing	Goods
188	Produce graders and packers, nec	Goods

189	Heaters: metal	Goods
190	Laundry and dry cleaning operatives, nec	Goods
191	Meat cutters and butchers	Goods
192	Packers and wrappers, except produce	Goods
193	Metal platers	Goods
194	Mine operatives, nec	Goods
195	Mixing operatives	Goods
196	Oilers and greasers, except automotive	Goods
197	Painters: manufactured articles	Goods
198	Photographic process workers	Goods
199	Drill press operatives	Goods
200	Lathe and milling machine operatives	Goods
201	Precision machine operatives, nec	Goods
202	Punch and stamping press operatives	Goods
203	Riveters and fasteners	Goods
204	Sailors and deckhands	Goods
205	Sawyers	Goods
206	Sewers and stichers	Goods
207	Shoemaking machine operatives	Goods
208	Solderers	Goods
209	Stationary firemen	Goods
210	Carding, lapping, and combing operatives	Goods
211	Knitters, loopers, and toppers	Goods
212	Spinners, twisters, and winders	Goods
213	Weavers	Goods
214	Textile operatives, nec	Goods
215	Welders and flame-cutters	Goods
216	Winding operatives, nec	Goods
217	Machine operatives, misc. specified	Goods
218	Miscellaneous operatives	Goods
219	Transportation operatives	Goods
220	Fork lift and tow motor operatives	Goods
221	Motormen: mine, factory, logging camp, etc.	Goods
222	Parking attendants	Goods
223	Railroad brakemen	Goods
224	Railroad switchmen	Goods
225	Taxicab drivers and chauffeurs	Goods
226	Truck drivers	Goods
227	Animal caretakers, except farm	Goods
228	Construction laborers	Goods
229	Fishermen and oystermen	Goods
230	Freight and materials handlers	Goods
231	Garbage collectors	Service
232	Gardeners and groundskeepers, except farm	Service
233	Longshoremen and stevedores	Goods
234	Lumbermen, raftsmen, and woodchoppers	Goods
235	Stock handlers	Goods
236	Teamsters	Goods
237	Vehicle washers and equipment cleaners	Goods
238	Warehousemen, nec	Goods

239	Miscellaneous laborers	Goods
240	Not specified laborers	Goods
241	Farmers and farm managers	Goods
242	Farm foremen and farm labor	Goods
243	Cleaning service workers	Service
244	Food service workers except private household	Service
245	Cooks except private household	Service
246	Waiters	Service
247	Health aides (including dental assistants and trainees)	Service
248	Nursing aides, Orderlies, and Attendants	Service
249	Practical nurses including lay midwives	Service
250	Airline stewardesses	Service
251	Attendants: recreation and amusement	Service
252	Attendants: personal service, nec	Service
253	Barbers	Service
254	Boarding and lodging house keepers	Service
255	Bootblacks	Service
256	Child care workers except private household	Service
257	Elevator operators	Service
258	Hairdressers and cosmetologists	Service
259	Housekeepers except private household	Service
260	School monitors and ushers (recreation)	Service
261	Welfare service aides	Service
262	Crossing guards and bridge tenders	Service
263	Firemen and fire protection workers	Service
264	Guards, watchmen, marshals, and constables	Service
265	Policemen and detectives	Service
266	Sheriffs and bailiffs	Service
267	Private household workers	Service

Appendix Table 2. Concordance among the various industrial classification schemes used in this paper

45- Sector Classification		1970 Census	BEA 85-Order	1987 SIC	64-Order	10-Order
Number	Name	Codes[a]	Codes[b]	Codes	Scheme	Scheme
1	Agriculture, forestry, and fishing	017-029	1-4	01-09	1	1
2	Metal mining	47	5-6	10	2	2
3	Coal mining	48	7	11,12	3	2
4	Oil and gas extraction	49	8	13	4	2
5	Mining of nonmetallic minerals, except fuels	57,058	9-10	14	5	2
6	Construction	067-078	11,12	15-17	6	3
7	Food and kindred products	268-298	14	20	7-10	4
8	Tobacco products	299	15	21	11	4
9	Textile mill products	307-309,317-318	16-17	22	12	4
10	Apparel and other textile products	329,327	18-19	23	13	4
11	Lumber and wood products	108,109	20-21	24	14-15	4
12	Furniture and fixtures	118	22-23	25	16	4
13	Paper and allied products	328-337	24-25	26	17	4
14	Printing and publishing	338,339	26	27	18	4
15	Chemicals and allied products	347-349,357-359	27-30	28	19-21	4
16	Petroleum and coal products	377,378	31	29	22	4
17	Rubber and miscellaneous plastic products	379,387	32	30	23	4
18	Leather and leather products	388-397	33-34	31	24	4
19	Stone, clay, and glass products	119, 127-128,	35-36	32	25-28	5
20	Primary metal products	139,147-149	37-38	33	29-30	5
21	Fabricated metal products, including ordnance	157-159,167-169 258	13,39-42	34	31-32	5
22	Industrial machinery and equipment, exc. electrical	177-179,187-189 197-198	43-52	35	33-35	5
23	Electric and electronic equipment	199,207-209	53-58	36	36	5
24	Motor vehicles and equipment	219	59	371	37	5
25	Other transportation equipment	227-229,237-238	60-61	37	38-40	5
26	Instruments and related products	239,247-249	62-63	38	41	5
27	Miscellaneous manufactures	259	64	39	42	4
28	Transportation	407-429	65	40-42,44-47	43	6
29	Telephone and telegraph	448-449	66	481,482,489	44	6
30	Radio and TV broadcasting	447	67	483,484	45	6
31	Electric, gas, and sanitary services	467-79	68	49	46	6
32	Wholesale trade	507-599	69A	50-51	47	7
33	Retail trade	600-699	69B,74	52-59	48	7
34	Banking; credit and investment companies	707-709	70A	60-62,67	49	8

35	Insurance	717	70B	63-64	50	8
36	Real estate	718	71B	65-66	51	8
37	Hotels, motels, and lodging places	777,778	72A	70	52	9
38	Personal services	769,779-799	72[part]	72	53,62[c]	9
39	Business and repair services except auto	727-748,758-767	73C, 72[part]	73,76	54,62[c]	9
40	Auto services and repair	749,757	75	75	55	9
41	Amusement and recreation services	807-817	76	78-79	56	9
42	Health services, including hospitals	828-848	77A	80	57-58	9
43	Educational services	857-868	77B[part]	82	59	9
44	Legal and other professional services and non-profit org.	849,869-897	73A,73B, 77B[part]	81,83,84,86 87,89	60-61	9
45	Public Administration	907-947	78,79,84	43[d]	63-64	10

a. 1970 Census of Population industry classification scheme.

b. Bureau of Economic Analysis 85-sector industrial classification system for input-output data (1987 version).

c. Business and Personal Services n.e.c. (Census codes 728-48, 758-67, 779, 789-799 and 64-sector code 62) split proportionately between two sectors.

d. U.S. postal service only.