COMPUTERIZATION AND RISING UNEMPLOYMENT DURATION

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INTRODUCTION

It is widely recognized that in the industrialized economies there has been a dramatic rise in the average duration of unemployment during recent decades. Though it has been most severe during periods of high unemployment rates, even at other times the length of time between jobs of an average unemployed worker has increased substantially. Here I offer one such hypothesis, ascribing at least part of the phenomenon to the information technology "revolution," and provide empirical evidence for this proposed explanation. I will argue here that when the rate of technical transformation is high, the average duration of unemployment is likely to rise. Moreover, the duration of unemployment is likely to increase *relatively* more for older workers than younger ones and for the poorly educated than those with more schooling.

While there is a voluminous literature on causes of unemployment and the unemployment *rate,* there is a much smaller literature on technological factors that influence unemployment *duration*. For example, Richard Layard and Stephen Nickell, who have worked extensively on unemployment issues, argued in a 1991 paper that the persistence of unemployment depends on the benefit and wage determination systems, and also on the degree of employment flexibility.

However, there are a couple of papers related to this subject. Aaronson and Housinger [1999] looked at the effects of new technology on the reemployment of displaced workers. They found that increases in new technology, as measured by R&D intensity and computer usage, decreased the likelihood of displaced workers finding new employment after being laid off. Their results also indicated that both older and less skilled workers had greater difficulty finding a new job after displacement. Friedberg [2001], using data on individual workers from the Current Population Survey, concluded that impending retirement reduces the incentive of older workers to acquire new skills, particularly with regard to computer usage. Then using data from the Health and Retirement Survey, Friedberg [2001] found that computer users retire later than nonusers. On the basis of Instrumental Variables regression analysis, Friedberg [2001] estimated that computer use directly lowered the probability of retiring.

Section 1 will review the basic data on unemployment duration for the United States. In Section 2, I will provide a rather elementary discussion, arguing that the introduction of a new technological "regime" might increase search time for displaced workers. Section 3 shows time trends and provides descriptive statistics on the key

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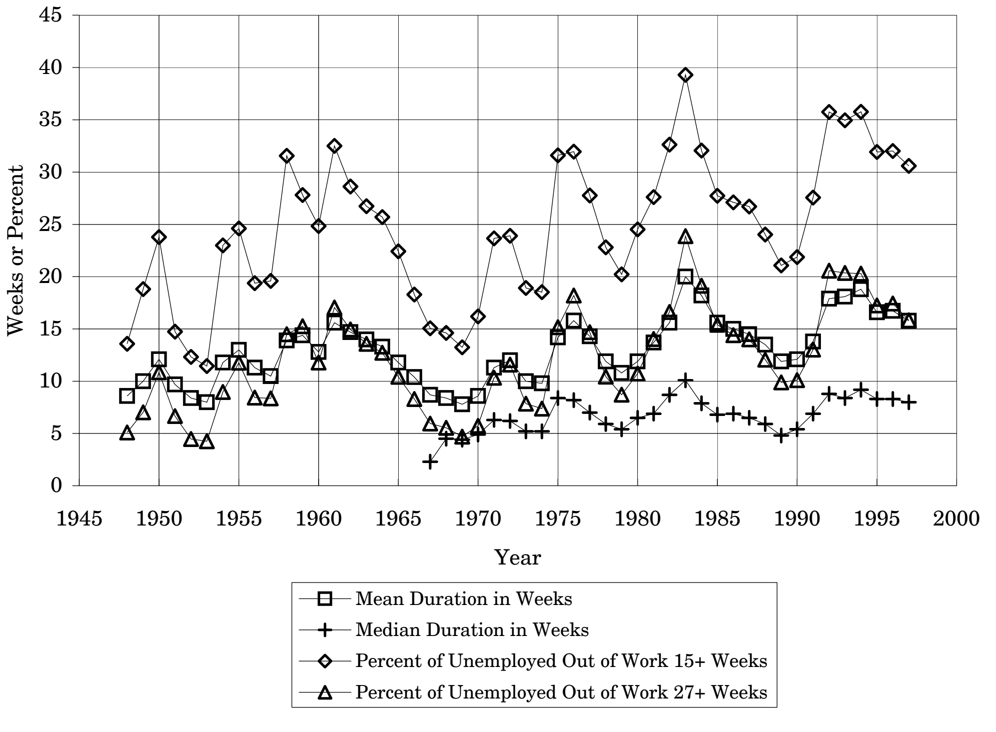
variables of interest in the analysis. The fourth section provides an econometric investigation of the relation between computerization and the duration of unemployment. Concluding remarks are provided in the fifth and final section.

It should be stressed at the outset that in saying that duration of unemployment can be increased by a technology revolution as occasioned by the diffusion of information technology, I am not asserting that this is the *only* source of that development. Clearly, duration is affected by many other influences—the structure of the unemployment insurance system, other elements of public policy, union power and behavior, international trade developments, and a profusion of others. The econometric study seeks to take account of such variables, as well as measures of the speed of technical change. Its results shed light on the role of these other variables and provide support for my hypothesis.

TRENDS IN THE DURATION OF UNEMPLOYMENT

With a given unemployment rate, duration of joblessness can vary substantially. The unemployment rate will be the same if four million workers are unemployed for three months on average, as when one million workers loose their jobs for a full year. Yet the consequences for the mental state of the people without jobs, for their behavior, and for the functioning of society are probably far more severe when the average period between jobs is much longer.[1]

FIGURE 1
Trends in the Duration of Unemployment, 1948-1997



Before turning to the theory and empirical evidence on our hypothesis, it is appropriate to review the evidence on trends in the length of joblessness, though the information is well known to specialists. In the U.S., the length of time a typical jobless person spends "between jobs" has increased substantially and fairly steadily since World War II.[2] Figure 1 summarizes data provided by the Bureau of Labor Statistics for the U.S. (see Table 1 for data sources and methods). It indicates that over the 49-year period from 1948 through 1997 the average duration of the period of unemployment has almost doubled. The share of the unemployed composed of persons jobless over 15 weeks more than doubled and the share unemployed half a year or more (the longest period covered in the BLS data) has almost exactly tripled. There were substantial fluctuations in this trend. A regression of the natural logs of the data yields a growth rate of nearly 1 percent compounded for average duration of unemployment, and an annual growth rate of 1.2 percent in the proportion of the unemployed who were jobless 15 weeks or more (see Figure 2). By 1997, the share of the unemployed who were jobless for more than 15 weeks reached over 30 percent of the total and those unemployed six months or more 16 percent of the total.

FIGURE 2
Duration of Unemployment,1948-97
Regression Line Estimates

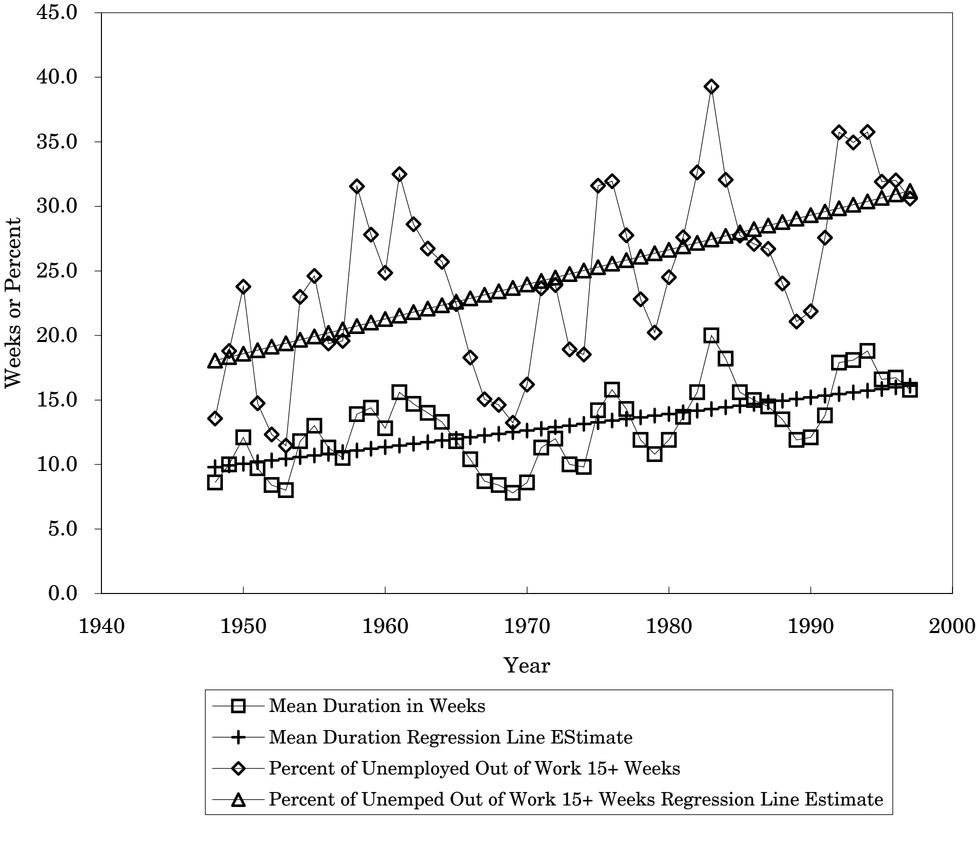


TABLE 1
Correlation Coefficients between the Duration of Unemployment and Technological, Institutional, and Demographic Variables, 1948-1997

	Variable	Period	Correlation Coefficient with *MEANDUR*	*UNEMPL15*	*UNEMPL27*
A.	Unemployment Variables[a]				
1.	*MEANDUR*: Mean duration of unemployment	1948-97	1.00	0.97	0.99
2.	*UNEMPL15*: Percent of unemployed workers who are unemployed for 15 weeks or more	1948-97	0.97	1.00	0.98
3.	*UNEMPL27*: Percent of unemployed workers who are unemployed for 27 weeks or more	1948-97	0.99	0.98	1.00
4.	*UNEMPRATE*: Civilian unemployment rate	1948-97	0.74	0.81	0.77
B.	Technology Variables				
5.	TFP Growth[b]	1948-97			
	a. *TFPGRT1*: One-year rate		0.13	0.07	0.14
	b. *TFPGRT3*: Three-year running average		–0.20	–0.29	–0.23
	c. *TFPGRT5*: Five-year running average		–0.35	–0.41	–0.37
6.	*RDGDP*: Industry R&D expenditures/GDP[c]	1953-97	0.30	0.26	0.30
7.	*SCIENG*: Scientists and engineers/FTEE[d]	1957-97	0.51	0.38	0.42
C.	Net Investment Variables[e]				
8.	*EQUIPPEP*: Private non-residential equipment/PEP	1948-97	0.00	–0.05	–0.02
9.	*OCAPEP*: Office, computing, and accounting machinery (OCA)/PEP	1948-97	0.46	0.40	0.41
D.	Institutional Variables				
10.	*UICOVER*: UI insured coverage rate[f]	1950-97	0.53	0.50	0.52
11.	*UIREPLA*: UI replacement rate[f]	1950-97	0.62	0.61	0.61
12.	*UIREPLB*: ratio of UI average benefit	1950-97	0.36	0.45	0.40
13.	to average wage[f]				
14.	*UIINSCOV*: percent of unemployed workers receiving UI benefits[f]	1950-97	–0.41	–0.27	–0.36
15.	*UIWEEKS*: maximum weeks of UI coverage[f]	1950-97	0.42	0.50	0.49
16.	*MINWAG87*: Minimum wage (1987$)[g]	1950-97	–0.39	–0.27	–0.30
17.	*UNIONRATE*: Union members as a percent of the total labor force[h]	1948-97	–0.62	–0.58	–0.58
E.	Share of Total Employment[i]	1950-97			
18.	*MAL1619*: Males, 16-19		–0.59	–0.49	–0.51
19.	*MAL2024*: Males, 20-24		–0.10	–0.03	–0.03
20.	*MAL2554*: Males, 25-54		–0.33	–0.34	–0.35
21.	*MAL55*: Males, 55 and over		–0.59	–0.53	–0.56
22.	*FEM1619*: Females, 16-19		–0.34	–0.25	–0.27
23.	*FEM2024*: Females, 20-24		0.10	0.12	0.14
24.	*FEM2554*: Females, 25-54		0.64	0.56	0.59
25.	*FEM55*: Females, 55 and over		–0.02	0.07	0.05

a. The source for the aggregate unemployment data is: Jacobs [1998]. The data were originally tabulated by the Bureau of Labor Statistics. Mean duration of unemployment by demographic group is computed from Bureau of Labor Statistics, *Employment and Earnings,* Washington, D.C.: U. S. Government Printing Office, various years.

TABLE 1—*Continued*
Correlation Coefficients between the Duration of Unemployment and Technological, Institutional, and Demographic Variables, 1948-1997

b. The total factor productivity (TFP) calculations are based on Gross Domestic Product (1992 dollars), Persons Engaged in Production (PEP), and fixed non-residential net capital stock (1992 dollars). The source for the data is the Bureau of Economic Analysis, National Income and product Accounts and Net Stock of Fixed Reproducible Tangible Capital accounts, provided on the Internet. See Katz and Herman [1997] for a description of the methodology used to construct the net capital stock data.
c. R&D expenditures include company, federal, and other sources. Source: National Science Foundation, *Research and Development in Industry,* Arlington, Virginia: National Science Foundation, various years.
d. Full-time equivalent scientists and engineers engaged in R&D per 1,000 full-time equivalent employees (FTEE). Source: National Science Foundation, R*esearch and Development in Industry*, Arlington, Virginia: National Science Foundation, various years.
e. Net investment in 1992 dollars is measured as the change in the net capital stock in 1992 dollars. The source is the Bureau of Economic Analysis, Net Stock of Fixed Reproducible Tangible Capital accounts, provided on the Internet.
f. *UIREPLB* is computed as the ratio of UI average weekly benefits to the average weekly earnings for total private nonagricultural employees. *UIWEEKS* is based on the maximum number of weeks for which extended benefits, Federal Supplemental Benefits, Supplemental Compensation or Emergency Unemployment Compensation is allowed. Sources: Committee on Ways and Means, U. S. House of Representatives, *1997 Green Book*, and Council of Economic Advisers, *Economic Report of the President, 1998*.
g. Source: U. S. Bureau of the Census, *Statistical Abstract of the United States: 1997* (117th edition), Washington, D.C., 1997.
h. Sources: Bureau of Labor Statistics worksheets. Estimates for 1983-1995 are annual averages from the Current Population Survey. Estimates for 1950-83 are the annual average number of dues paying members reported by labor unions. Data exclude numbers of professional and public employee associations.
i. Employment by gender and age. Sources: 1950-1974. U. S. Bureau of Labor Statistics, *Handbook of Labor Statistics*, Washington, D. C.: U. S. Government Printing Office, 1985, Bulletin 2217. 1975-1997. U. S. Bureau of Labor Statistics, *Employment and Earnings*, Washington, D. C.: U. S. Government Printing Office, January issues, various years. Figures are based on annual averages for household data.

THE COMPUTER "REVOLUTION" AND THE DURATION OF JOBLESSNESS

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 IT. According to Freeman [1987, 51], IT 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." Paul David, writing in 1991, refereed to "the paradigmatic shift" from electromechanical automation to information technologies.

One result of this technological revolution is a transformation of the skills required in the labor market. According to Freeman [1987, 66], the results of extensive research conducted by the Science Policy Research Unit (SPRU) of the University of Sussex showed that IT "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...."

Doeringer [1991, 166] wrote that "New information technologies may be particularly important for facilitating organizational adjustment" and referred to Osterman's [1986, 164] finding that "a 10% increase in company computing power led to a 1% reduction in managerial employment." And in the plants that she observed, Zuboff [1988, 284, 358-59] noted that lower and middle managers were particularly "vulnerable" to deskilling and displacement by information technologies. David [1991] argued that the shift to information technologies might entail major changes in the organizational structure of companies.

In my own work, I also presented evidence on the "disruptive" effects of computerization on the labor market and the consequent structural adjustments that have ensued. In my 1996 paper I constructed a measure of "cognitive skills" on the basis of skills measures provided in the Fourth (1997) Edition of the Department of Labor's Dictionary of Occupational Titles. Average industry skill scores are computed as a weighted average of the skill scores of each occupation, with the occupational employment mix of the industry as weights. Computations are performed for 1960, 1970, 1980, and 1990 on the basis of occupation by industry employment matrices for each of these years constructed from decennial Census data. There are 267 occupations and 44 industries. Using a sample consisting of 44 industries and 3 time periods (1960-70, 1970-80, and 1980-90), I found that computerization as measured by investment in Office, Computing, and Accounting (OCA) equipment per worker is positively and significantly associated with the growth in cognitive skills.

In Wolff [2002], I used the same employment data for 267 occupations and 44 industries that were obtained from the decennial Census of Population for years 1950, 1960, 1970, 1980, and 1990. First define:

> **M** = occupation-by-industry employment coefficient matrix, where m_{ij} shows the employment of occupation i in industry j as a share of total employment in industry j.

The similarity index for industry j between two time periods 1 and 2 is given by:

$$SI^{12} = \left(\Sigma_i m_{ij}^1 m_{ij}^2\right) \Big/ \left[\Sigma_i \left(m_{ij}^1\right)^2 \Sigma_i \left(m_{ij}^2\right)^2\right]^{1/2}$$

The index SI is the cosine between the two vectors $\mathbf{s}^{t1}$ and $\mathbf{s}^{t2}$ and varies from 0—the two vectors are orthogonal—to 1—the two vectors are identical. The index of occupational dissimilarity, DI, is defined as:

$$DIOCCUP^{12} = 1 - SI^{12}$$

The sample consists of 44 industries and 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 1 percent level and that computerization is strongly and positively associated with the degree of occupational restructuring within an industry over time. Interestingly, the effects of IT on structural change in the labor market appear to date from the 1970s. In contrast, positive effects of IT on productivity growth do not seem to occur until the 1990s (see Wolff [2002] for a review of the relevant literature).

Some recent literature has laid the groundwork toward understanding the relation between skill demand and IT. On the theoretical side, 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, microelectronics, and IT 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 microelectronics. (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 IT, 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, IT) 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. As a consequence, the relative wage of skilled workers also rises during the first phase. During the second phase, however, relative demand shifts toward unskilled workers and their relative wage starts to rise. The empirical work presented in the next section covers the period from 1947 to 1997. It is probably safe to assume that the period from 1970 to 1997 represents the first of the two technological phases in the Helpman-Trajtenberg model (the second phase may still be a long way off).

An alternative model was developed by Autor, Levy, and Murnane [2001]. I summarize the main elements of the model here (more details can be found in their paper). They first assume that there are two types of tasks or skills—routine (R) and nonroutine (N). Second, they add the crucial assumption that computer technology is more substitutable for routine skills than for nonroutine skills. Third, they assume that routine and nonroutine tasks are themselves imperfect substitutes. Fourth, they assume that greater intensity of routine inputs increases the marginal productivity of nonroutine inputs. Fifth, they assume 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.

Sixth, they assume that computer capital, C, and workers are perfect substitutes in carrying out routine tasks, R. Seventh, computer capital is supplied elastically at market price P per efficiency unit. Eighth, they assume that P is falling exogenously over time due to technical advances. Ninth, on the labor supply side, the authors assume that each worker i can be characterized according to his or her relative efficiency in routine and nonroutine 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 nonroutine labor. Let $g(\alpha)$ and $h(\alpha)$ denote the functions that give the population endowment in efficiency units of routine and nonroutine tasks, respectively, as a function of α. Then

$$R^* = \int_0^{\alpha^*} g(x)\mathrm{d}x \text{ and } N^* = \int_{\alpha^*}^{\infty} h(x)dx,$$

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

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

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

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 nonroutine task input. From Equation (2) and the first order condition for W_R it follows that:

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

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 nonroutine tasks are complementary inputs,

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

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

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

A decrease in computer prices will decrease the *relative labor supply* to routine tasks. This result has pertinent implications for the duration of unemployment. In particular, as IT investment rises, the demand for unemployed low-skill workers will fall and, consequently, the duration of their unemployment spell should rise. If we add the assumption that new entrants into the labor market are more skilled (in this model, have higher values of α_i) than displaced workers, then it will follow that the overall average duration of unemployment will rise in step with the level of IT investment.

Two recent papers by Autor, Levy, and Murnane provide empirical evidence of complementarity between computerization and skilled labor. Autor, Levy, and Murnane [2000] 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, Levy, and Murnane [2001] provide a more general analysis of the effects of computerization on skill demand. They considered different skill types in their exploration. They find 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 nonroutine 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 detailed industries, within detailed occupations, and within educational groups within industry toward more skilled (that is, more nonroutine) jobs and away from less skilled (that is, less non-routine jobs).

Bresnahan, Brynjolfsson, and Hitt [1999] provide further evidence of a positive relation between IT and the demand for skilled labor. 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 that 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.

One paper has looked at the relation between IT investment and unemployment. Mincer and Danninger [2000] investigated the effects of computerization on differences in unemployment rates between skilled and unskilled workers. Using annual time-series data for the U.S., they reported a very strong and highly significant relation between both real computer expenditure per worker and real computer expenditure as a fraction of total real equipment expenditure and the *ratio* of unemployment rates between high school graduates and college graduates.

There are several other elements that may provide a link between a "technological revolution" as occasioned by IT and the length of time an average jobless person is unemployed. The first is that the greater the degree of structural adjustment in the labor market that ensues from technological change, the greater the rate of *obsolescence* of existing skills. This is self-evident, since as occupations are no longer required in the labor market, the associated skills become useless.

Second, because older workers are closer to retirement age, they will offer the employer a briefer stream of incremental revenues with which to recoup the sunk costs of their retraining (cf. Becker [1975]). As a result, the prospects for recouping those training costs will be dimmer for older employees, leading to their replacement by younger workers when technical progress accelerates.

Third, older workers may be harder to retrain than younger workers because the elderly may have become set in their ways and because their education from far in the past may be less helpful in adaptating to the latest technical developments. The old adage that "you can't teach an old dog new tricks" may have a germ of truth to it. Moreover, casual observation also suggests that children may be much more adept at picking up new technology (like computer or video games) than adults. This argument implies that it is more expensive to retrain older workers than younger ones. A similar argument may also apply to unskilled or uneducated workers relative to better educated ones.

There are three implications. First, an acceleration in the pace of technological change—particularly one occasioned by a technological "revolution"—will increase search time for the average unemployed worker and thus the mean duration of unemployment among all unemployed workers. The rationale is that if existing skills become obsolete, then experienced unemployed workers may enjoy no particular advantage over new entrants in terms of being hired. As a result, the former's search time will increase.

Second, search time and the duration of unemployment will increase *relatively* more for older unemployed workers than for younger unemployed ones. This is due to the fact that older workers have a shorter recoupment period and may be harder to train (or retrain) for jobs requiring new sets of skills. Third, search time and the duration of unemployment will increase *relatively* more for less educated unemployed workers than for more educated unemployed workers. This is due to the fact that less educated workers may be harder to train (or retrain) for jobs requiring new sets of skills. The first two implications are testable with existing data on unemployment spells. The third, unfortunately, is not testable since data on unemployment spells by educational group are not available.

In the econometric analysis, we should thus expect a positive association between indices of the pace of technological change and the mean duration of unemployment. Moreover, we should expect that the association should be stronger for older workers than younger ones. With regard to indicators of technological transformation, the primary focus is on computerization and other indices of the diffusion of IT, since by my argument IT has caused a major upheaval in the economy and, in particular, in the labor market. I shall also investigate other indicators of technological change, including (1) the rate of total factor productivity growth; (2) investment in R&D; and (3) investment in noncomputer equipment, since new equipment may also embody new technology.

A couple of qualifications are in order. First, it is *not* necessary that training (or retraining) costs increase in general with the advent of new technology for this argument to hold. Indeed, computerization may lead to a reduction of training costs for many jobs. It is only necessary that the rate of obsolescence of existing skills increase with the introduction of new technology.

Second, it may be the case that among older workers and less educated ones, the unemployed in these two groups may contain a substantial number of persons who may never be employed again. In fact, dismissed older workers whose skills are obsolete may constitute a substantial share of so-called "discouraged workers" who drop out of the labor force entirely. If this is the case, then the reported duration of unemployment among older workers may be biased downward from this "drop-out" effect. If anything, the truncation effect should *bias downward* the estimated effect of technological transformation on the duration of unemployment for all workers in general and for older workers in particular.

EMPIRICAL INVESTIGATION: DATA AND SIMPLE CORRELATIONS

We next explore what the data show about the hypotheses. I will use regression analysis to seek to explain duration of unemployment using the explanatory variables that will be described next. In this section I will also provide simple correlations between the dependent variable and the various independent variables to suggest the pattern of their relative behavior.

Technology and Investment Variables

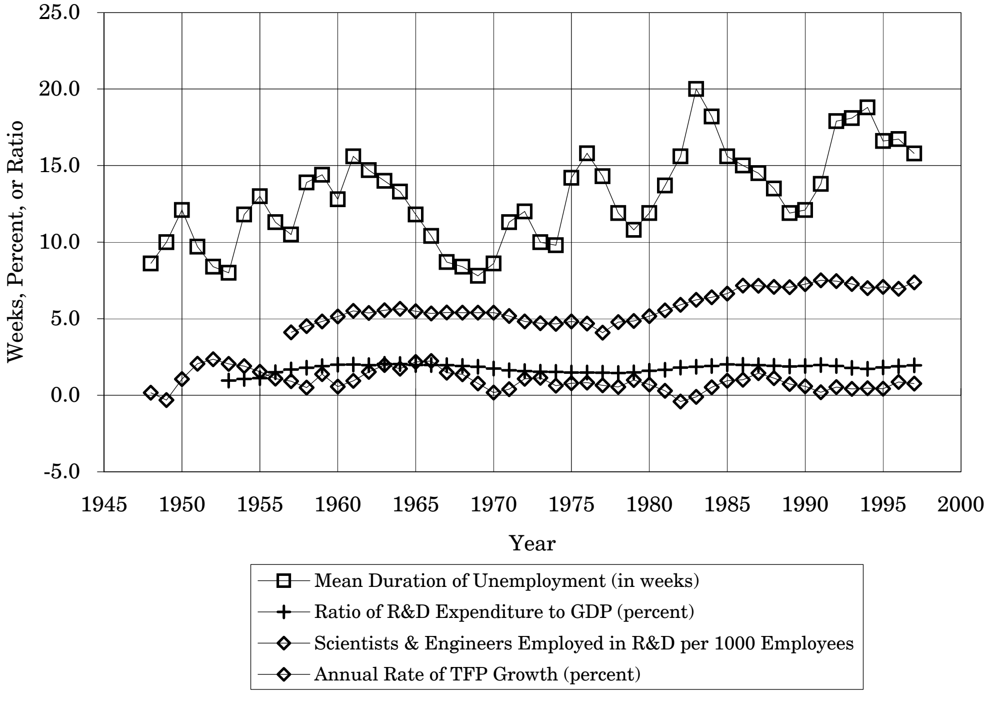
Since the pace of technical change is itself almost impossible to observe directly, we use three alternative indices to measure technological activity. The first is the standard rate of total factor productivity (TFP) growth, *TFPGRTH*, defined as:

$$TFPGRTH = Y^* - \alpha L^* - (1 - \alpha)K^*, \tag{8}$$

where Y^* is the annual rate of output growth, L^* is the annual growth in labor input, K^* is the annual growth in capital input, and α is the average wage share over the period. We measure the labor input using Persons Engaged in Production (PEP) and the capital input by the fixed nonresidential net capital stock (1992 dollars).[3] The second and third are indices of R&D activity—the ratio of R&D expenditures to GDP and the number of full-time equivalent scientists and engineers engaged in R&D per 1,000 full-time equivalent employees (FTEE).

Figure 3 shows time trends in these technology variables and Table 1 provides correlation coefficients between these variables and average unemployment duration. These variables are all based on economy-wide data unless otherwise indicated. Annual rates of TFP growth have virtually no correlation with unemployment duration, whereas three-year and five-year running averages have a negative correlation. The explanation is that while unemployment duration has trended upward over the post-war period, TFP growth, as discussed above, has trended downward. TFP growth was at its highest point in the 1950s and 1960s, at 1.3 and 1.4 percent per year, respectively, when unemployment duration was low. Annual TFP growth then fell to 0.7 percent during the 1970s, 0.8 percent during the 1980s, and 0.7 percent during the 1990s.

FIGURE 3
Mean Duration of Unemployment and Technology Indicators, 1948-1997

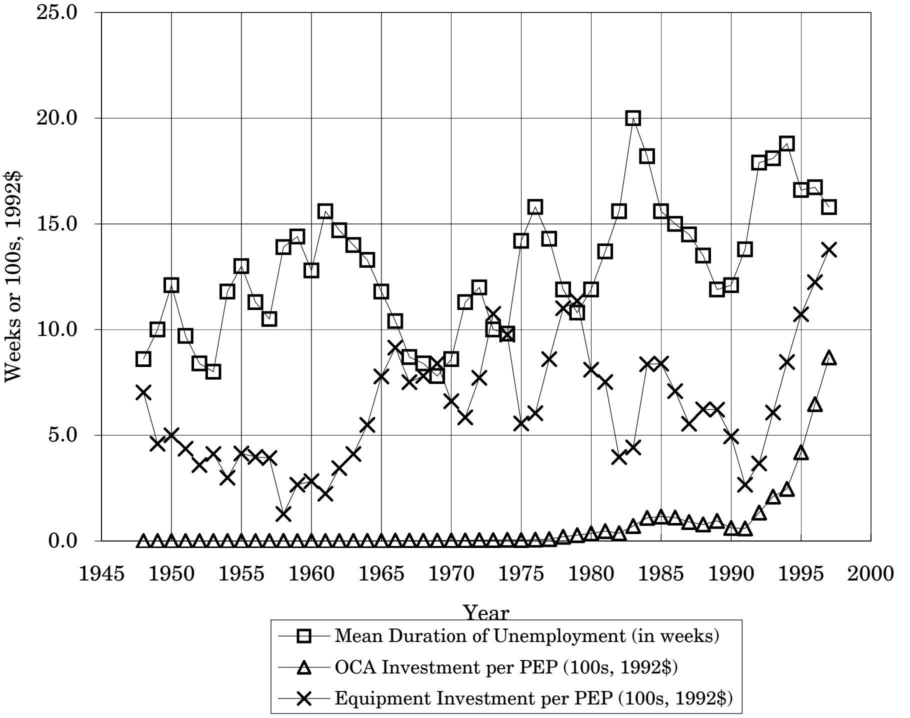


Both scientists and engineers engaged in R&D per 1,000 FTEE and the ratio of R&D expenditures to GDP are positively correlated with unemployment duration. The former rose by almost 80 percent from the late 1950s to the late 1990s, whereas the latter rose sharply between the 1950s and 1960s, fell off in the 1970s, increased in the 1980s, and then stabilized in the 1990s.

Two measures of investment are used. The first is investment in new equipment and machinery as a ratio to PEP. This index is included to allow for the possibility that some portion of new technology may be embodied in capital investment. Standard measures of TFP growth do not adequately capture this effect. Because, as I argued above, computers may play a particularly important role as transmitters of new technology, I use as the second measure investment in computers (or, more specifically, office, computing, and accounting equipment, or OCA) per PEP.

Net OCA investment per PEP has a correlation coefficient of 0.46 with mean unemployment duration. It increased gradually from virtually nothing in the 1950s and 1960s to $9 (in 1992 dollars) per PEP in the 1970s, and then jumped to $73 per PEP in the 1980s and $282 per PEP in the 1990s (see Figure 4). Net equipment investment per PEP more than doubled between the 1950s and 1990s. However, it tended to move counter-cyclically with the duration of unemployment and, on net, is virtually uncorrelated with unemployment duration.[4]

FIGURE 4
Mean Duration of Unemployment and Investment, 1948-1997



Institutional Variables

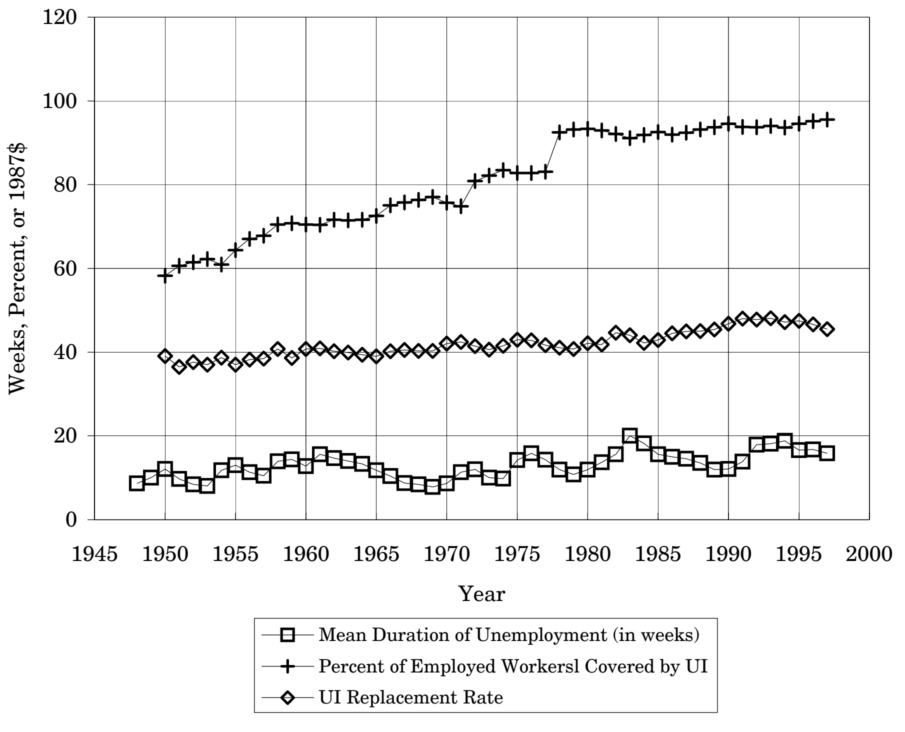
The structure of unemployment insurance (UI) itself may also have an important effect on the duration of unemployment. In particular, by reducing the cost to an individual of being jobless, the UI system will, it may be expected, generally prolong the duration of unemployment for many workers (see, for example, Feldstein [1974]).

The original architects of the UI system explicitly recognized this and argued, in fact, that the added security individuals had while unemployed would enable them to select a job more compatible with their skills and interests.

The UI system reduces the costs of remaining unemployed, so the reservation wage for those searching for a new job will be higher on average than without UI benefits. As a result, we can expect an increase in their average duration of unemployment. The higher the UI benefits, the longer will be the average unemployment spell. Most empirical studies using cross-sectional or panel data on individuals have confirmed a positive relation between the UI replacement rate (the ratio between the UI benefit and the previous wage) and the average duration of unemployment. Typically, an increase in the replacement rate of 0.1 is associated with a half week to a week increase in the average duration of unemployment. All told, the UI system may cause covered workers to remain unemployed 16 to 31 percent longer than those not covered.[5]

In Panel D of Table 1, we have selected four features of UI programs (also see Figure 5). The first is the UI coverage rate, the percent of all employees covered by the UI system, which rose substantially over the postwar period, from 58 to 96 percent of employment. The second is the replacement rate, the ratio between mean UI benefits and the average previous wage, which has shown a slight upward trend over the postwar period. Both variables are positively correlated with unemployment duration.[6]

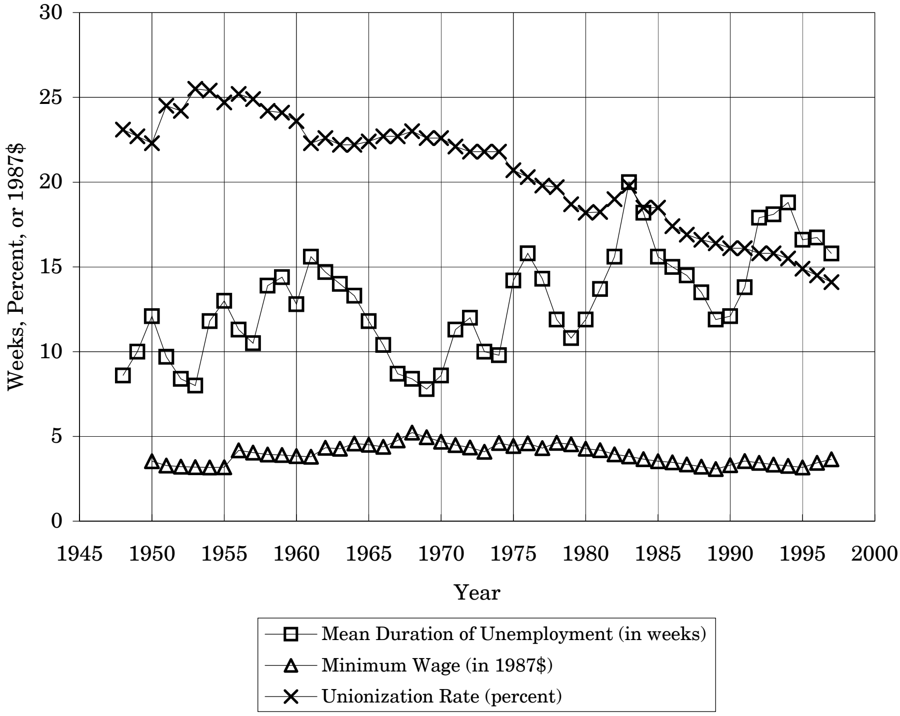
FIGURE 5
Mean Duration of Unemployment and UI Variables, 1948-1997



The third relevant feature of UI programs is the insured coverage rate, the percent of unemployed workers receiving benefits. Changes in this share may stem from any of three sources: (1) changes in the coverage of the UI system; (2) increased or reduced failure to meet the eligibility criteria (either insufficient wages or time worked); or (3) changes in the frequency of exhaustion of benefits (normally after 26 weeks). The insured coverage rate has been dropping over time, from 53 percent in the 1950s to 36 percent in the 1990s, at the same time that unemployment duration has been rising. This is not surprising, since rising unemployment duration will cause more unemployed workers to exhaust their benefits, causing the insured coverage rate to fall. As a result, the two series are negatively correlated.

The fourth parameter of the system is *UIWEEKS*, the maximum number of weeks UI benefits are allowed. This is based on the normal period of time, 26 weeks, plus the time for which extended benefits, Federal Supplemental Benefits, Supplemental Compensation or Emergency Unemployment Compensation are provided. *UIWEEKS* varies from 26 to 65 weeks (in 1975 and 1976). This series is, not surprisingly, positively correlated with mean unemployment duration, since both rise when the overall unemployment rate increases.

FIGURE 6
Mean Duration of Unemployment, the Minimum Wage, and the Unionization Rate, 1948-1997



Two other institutional factors that may affect the duration of unemployment are the presence of unions and the minimum wage. These have both supply and demand effects. On the supply side, we would expect that a high rate of unionization will raise entry wages and, therefore, *ceteris paribus*, increase the probability of an unemployed worker finding a wage offer exceeding the reservation wage. On the demand side, however, the higher wages may truncate the wage-offer distribution and reduce the availability of jobs. The net effect may be indeterminate. Likewise, a higher minimum wage (in real terms) may raise entry wages for new jobs. On the supply side, workers with a given reservation wage may thus have more opportunities of finding jobs with wage offers above their reservation wage. On the demand side, the higher minimum will also truncate the wage-offer distribution.

The results in Panel D of Table 1 show negative correlations between mean unemployment duration and both the unionization rate and the minimum wage, suggesting that the supply effects dominate. The unionization rate has been falling rather steadily since the 1950s, from 24 percent to 14 percent in the late 1990s. Likewise, the minimum wage in 1987 dollars, after increasing between the 1950s and 1970s, from $3.60 per hour to $4.52, fell to an average of $3.39 during the 1990s (also see Figure 6). Both trends may be associated with rising unemployment duration.

Demographic Influences

One of the most notable changes in the postwar period has occurred in the demographic composition of the labor force. In the U.S. there has been a rising rate of labor force participation of females and a decline in the labor force participation rate of older men. As a result, the gender composition of the labor force has been shifting over time toward females and away from males, particularly older men. Because the incidence of unemployment and labor force attachment differs among different demographic groups (unemployment rates have historically been higher for women than men, at least until 1980 or so, and for younger workers than older ones), it is likely that these demographic changes may partly account for the rise in unemployment duration.

Figure 7 provides time trends of employment composition for selected gender and age groups between 1950 and 1997. Between 1950 and 1997, females as a percent of employed workers increased from 29 to 46, while men declined as a share from 71 to 54 percent. The changes were not uniform over the various age groups, however. Young men (under age 25) fell from 10.9 percent of total employment in 1950 to 7.3 percent in 1997. The share of men of prime working ages (25 to 54) in total employment declined from 46 to 39 percent. The biggest change was the decline in the share of older men (55 and over) in total employment, from 13.3 to 7.2 percent. Among female workers, the only very substantial change is the share of females of prime working age in total employment, which surged from 19 percent in 1950 to 34 percent in 1997. Moreover, this share shows a very sharp increase between the 1970s and 1980s, coincident with the big increase in mean unemployment duration. The correlation coefficients (Panel E of Table 1) confirm the strong negative relation between average unemployment duration and the share of both teenage men and men 55 or over in total employment and the strong positive relation between unemployment duration and the share of prime working age women in the labor force.

FIGURE 7
Mean Duration of Unemployment and the Demographic Composition of Employment, 1950-1997

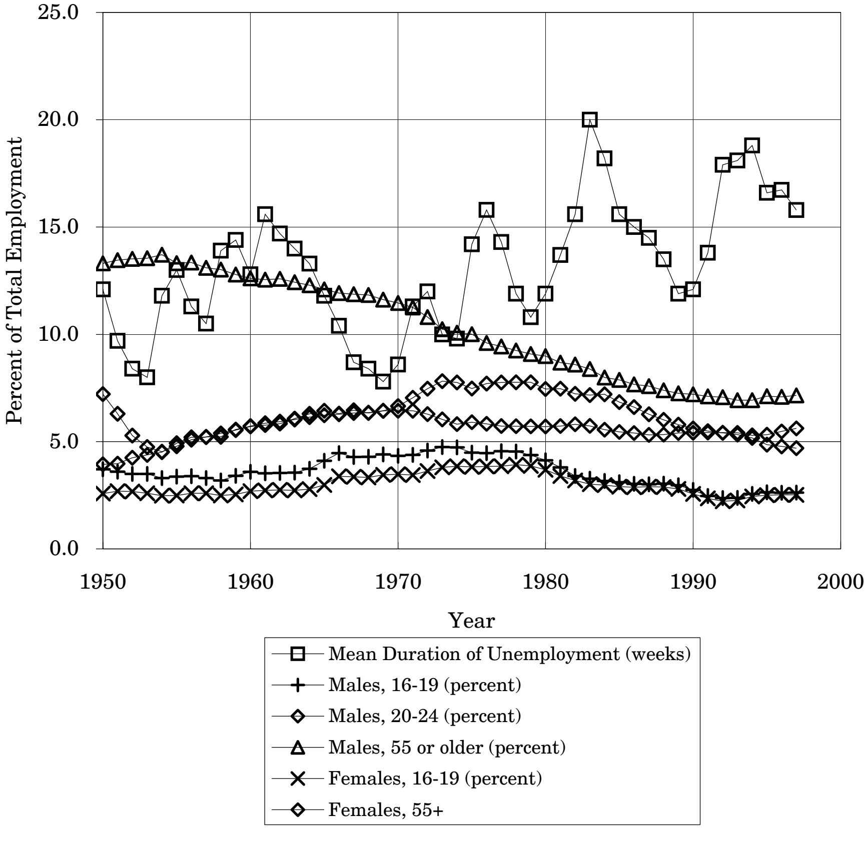


Table 2 highlights another side of the issue by showing the mean duration of unemployment by demographic group. We have used all the demographic details on unemployment duration published by the Bureau of Labor Statistics.[7] The results show that the rise in unemployment duration between the 1970s and 1980s was almost universal among demographic groups, with the average number of weeks of unemployment rising on the order of three to four weeks. Between the periods 1980-89 and 1990-93, however, the picture is much more mixed, with the average duration of unemployment rising for some groups but not for others.

Another striking result is that the average duration of unemployment is considerably greater for older workers than younger ones. Among both men and women, the average weeks of unemployment rose almost monotonically with age. Moreover, between 1980-89 and 1990-93, unemployment duration increased for older workers (45 and over for men and 35 and older for women), whereas it declined for younger age groups. Partly as a result of this, the spread in unemployment duration widened between older and younger workers from the 1970s to the early 1990s. The difference in average time of unemployment between men aged 16 to 19 and men aged 55 to 64 increased from 10.8 to 17.1 weeks; the corresponding change for women was from 9.0 to 12.6 weeks.

TABLE 2
Mean Duration of Unemployment by Demographic Group
(period averages)

Demographic Group	1970-79	1980-89	1990-93
Men			
All Men	13.1	17.1	17.2
16 to 19 years	8.3	9.3	8.5
20 to 24 years	11.6	14.5	12.6
25 to 34 years	14	18.3	17
35 to 44 years	16.8	21.1	20.3
45 to 54 years	18	22.7	24.1
55 to 64 years	19.1	23.8	25.6
65 years and over	21	19.3	24.5
Women			
All Women	10.5	12.4	13.3
16 to 19 years	7.5	7.8	7.5
20 to 24 years	9.5	10.8	9.5
25 to 34 years	10.8	12.9	13.2
35 to 44 years	12.1	14.7	16
45 to 54 years	13.9	16.1	18.1
55 to 64 years	16.5	17.8	20.1
65 years and over	18.2	15.6	19.6
White, 16 years and over	11.7	14.4	15.2
Men	12.8	16.6	16.9
Women	10.2	11.6	12.9
Black, 16 years and over	12.8	17	16.6
Men	14.2	19.3	18.6
Women	11.4	14.6	14.4
Men, 16 years and over			
Married, spouse present	14.8	19.4	19.6
Widowed, divorced, or separated	14.4	20.9	20.3
Single (never married)	11.2	14.3	14.3
Women, 16 years and over			
Married, spouse present	10.6	12.2	14
Widowed, divorced, or separated	10.9	15.4	15.7
Single (never married)	9.4	10.9	11.2

Note: See Table 1 for variable defintions and sources and methods.

There are also differences in unemployment duration among gender and racial groups, though they are not as pronounced as those among age groups. Unemployment duration has been higher for men than for women and this has widened over time, from 2.6 weeks (13.1 less 10.5) in the 1970s to 3.9 weeks in the early 1990s. The mean duration of unemployment has also been somewhat higher for black workers than white ones and has also increased modestly over time. The difference in average duration between black and white men rose from 1.4 weeks in 1970-79 to 1.7 weeks in 1990-93 and from 1.2 to 1.5 weeks between black and white women.

Differences by marital status appear to be less important. Single (never married) persons have experienced lower average unemployment duration than married or previously married (widowed, divorced, or separated) persons, though this may to a large extent reflect the fact that singles are, on average, younger than the latter group. Mean unemployment duration has been very similar for currently married and previously married men, though it has tended to be lower for currently married women than previously married ones. This latter result, however, may simply reflect the greater likelihood that a married woman will drop out of the labor force after an extended period of unemployment than one who is widowed, divorced, or separated.

Summary

Let us sum up the principal observations garnered from the descriptive statistics and from other sources. (1) Unemployment duration has been lengthening secularly since the 1960s into the late 1990s, despite the recent decline in the rate of unemployment. (2) By all measures, computerization has been rising dramatically since the 1960s. (3) Nevertheless, the rate of TFP growth slowed in the 1970s and has not yet recovered. (4) The duration of unemployment has been much greater for older than for younger unemployed workers and this difference has widened over time.

MULTIVARIATE REGRESSION ANALYSIS

We turn next to our main empirical study, the multivariate regression analysis, to sort out the effects of technological, institutional, and demographic variables on changes in unemployment duration. The analysis is based on aggregate time-series data for the U.S., covering the period from 1948 to 1997.

Our primary dependent variable is the (natural) logarithm of the average duration of unemployment. There are statistical problems associated with the use of mean unemployment duration as a dependent variable in a regression. The most serious is that the variable is based on a truncated distribution, since we can observe individuals only while they are in the midst of an unemployment spell. In the Current Population Survey (the source of these data), information on the length of unemployment is collected only from individuals who are unemployed at that time. As a result, these individuals have not completed their unemployment spells, so that the survey essentially interrupts spells that are still in progress (see Kiefer [1988] for an extended discussion of statistical problems associated with unemployment duration data). To avoid some of the pitfalls that beset duration data, most researchers have used the logarithm of duration as the dependent variable (see Devine and Kiefer [1991, Ch. 5]). Alternative dependent variables are the percentage of unemployed workers out of work 15 or more weeks and the percentage out of work 27 or more weeks.

Because the dependent variables trend upward over time, we first use the Augmented Dickey-Fuller Unit Root (ADF) test statistic to test for non-stationarity in the three dependent variables. The results are shown in Table 3. In each case, we can reject the hypothesis of a unit root at the 5 percent level. Moreover, for all three variables, we can reject the stiffer Phillips-Perron Unit Root Test on the hypothesis of a unit root at the 10 percent level.[8] We therefore feel confident in using the level form of each variable in our regression model.

TABLE 3
The Augmented Dickey-Fuller Unit Root Test (ADF) on the Logarithm of the Mean Duration of Unemployment and the Percent of Unemployed Workers Who are Unemployed for 15 or More Weeks or 27 or More Weeks

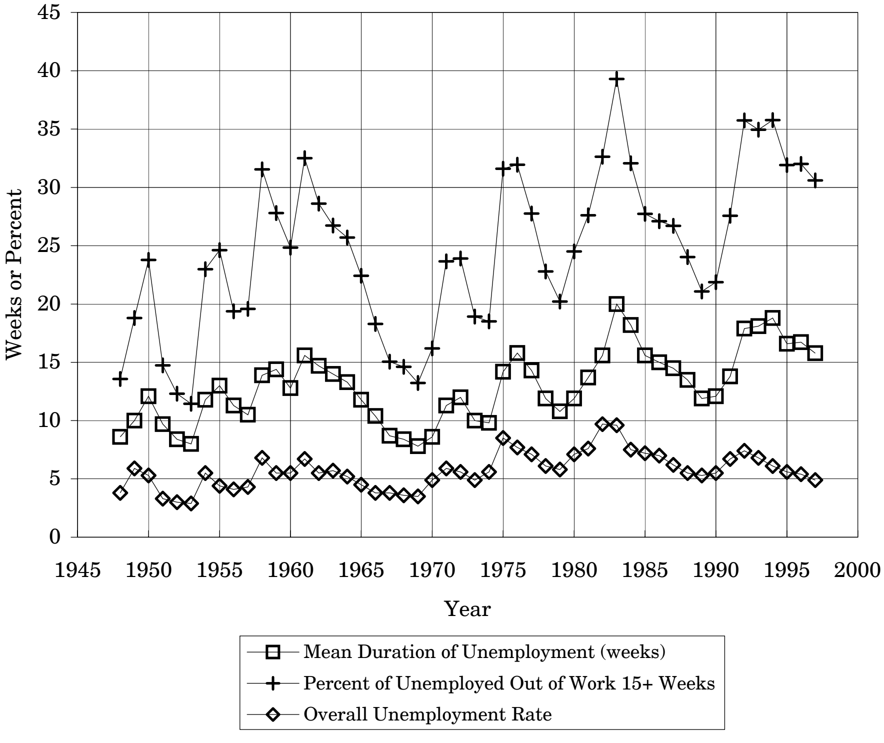
Variable	X Variables Included	ADF Test Statistic	Critical Values		Reject Unit Root?
LNMEANDUR	*LNMEANDUR*(–1)	–2.945	1% Level:	–3.575	No
	Δ[*LNMEANDUR*(–1)]		5% Level:	–2.924	Yes
	Constant		10% Level:	–2.600	Yes
LNMEANDUR	*LNMEANDUR*(–1)	–3.892	1% Level:	–4.163	No
	Δ[*LNMEANDUR*(–1)]		5% Level:	–3.507	Yes
	Constant		10% Level:	–3.183	Yes
	Trend term				
UNEMPL15	*UNEMPL15*(–1)	–3.113	1% Level:	–3.575	No
	Δ[*UNEMPL15*(–1)]		5% Level:	–2.924	Yes
	Constant		10% Level:	–2.600	Yes
UNEMPL15	*UNEMPL15*(–1)	–4.017	1% Level:	–4.163	No
	Δ[*UNEMPL15*(–1)]		5% Level:	–3.507	Yes
	Constant		10% Level:	–3.183	Yes
	Trend term				
UNEMPL27	*UNEMPL27*(–1)	–3.125	1% Level:	–3.575	No
	Δ[*UNEMPL27*(–1)]		5% Level:	–2.924	Yes
	Constant		10% Level:	–2.600	Yes
%UNEMPL27	*%UNEMPL27*(–1)	–4.091	1% Level:	–4.163	No
	Δ[*UNEMPL27*(–1)]		5% Level:	–3.507	Yes
	Constant		10% Level:	–3.183	Yes
	Trend term				

Key: *LNMEANDUR*: the natural logarithm of the mean duration of unemployment.
UNEMPL15: Percent of unemployed workers who are unemployed for 15 or more weeks.
UNEMPL27: Percent of unemployed workers who are unemployed for 27 or more weeks.

We also control for *UNEMPRATE*, the overall unemployment rate, in these regressions. As shown in Figure 8, the duration of unemployment is quite cyclical and is strongly correlated with the overall unemployment rate (the correlation coefficient with mean unemployment duration is 0.74, as reported in Panel A of Table 1), since the higher the unemployment rate, the lower the probability of a jobless worker obtaining a job and, *ceteris paribus*, the longer the spell of unemployment. The coefficient of *UNEMPRATE* is positive and significant at the 1 percent level in all specifications, as shown below.

The first set of results, based on aggregate data, with the logarithm of the mean duration of unemployment as the dependent variable, confirm the basic predictions of our model (see Table 4). The coefficient of *OCAPEP*, investment in office, computing, and accounting equipment in constant dollars per PEP, is positive and statistically significant at the 1 or 5 percent level in all specifications. The effect is quite strong. An increase of $1,000 (in 1987 dollars) of OCA investment per employee is associated with a 40 to 50 percent increase in the mean duration of unemployment.

FIGURE 8
Duration of Unemployment and Civilian Unemployment Rate, 1948-1997



The coefficient of *TFPGRTH5*, a five-year running average of annual TFP growth, is positive and significant at the 1 percent level in all specifications. I use a five-year running average of TFP growth to eliminate most of the cyclical sensitivity of TFP growth. In particular, TFP growth is procyclical, falling during a recession and rising during a recovery. A 1 percentage point increase in annual TFP growth is associated with an 11 percent increase in the mean duration of unemployment. This result is particularly striking since, as we saw, the simple correlation between *TFPGRTH5* and unemployment duration is negative, since the two move in opposite directions over the business cycle. Indeed, a simple bivariate regression of the logarithm of the mean duration of unemployment on *TFPGRTH5* produces a negative (and significant) coefficient. Once the aggregate unemployment rate is added to the regression, however, the coefficient of *TFPGRTH5* turns positive and even in this simple regression becomes significant at the 10 percent level.

It is important to note that the results for *TFPGRTH5* and *OCAPEP* remain remarkably robust across almost all alternative specifications. The coefficient of *TFPGRTH5* remains positive and significant at the 1 percent level in all regressions, while that on *OCAPEP* is positive and significant at the 5 or 1 percent level. The results remain almost unchanged when TFP growth is measured using FTEE instead of PEP, when three-year running averages of and, in most cases, when annual rates of TFP growth are used, and when investment in OCA per employee is measured using FTEE instead of PEP.

TABLE 4
Regressions of the Logarithm of the Mean Duration of Unemployment on Technology and Institutional Variables

Independent Variables	Specifications (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.79**	1.95**	1.74**	3.01**	1.62**	1.82**	2.55**	2.65**
	(13.10)	(17.30)	(14.70)	(6.73)	(6.37)	(9.37)	(7.50)	(9.71)
UNEMPRATE	0.12**	0.10**	0.11**	0.08**	0.08**	0.11**	0.09**	0.08**
	(7.26)	(6.70)	(7.57)	(4.83)	(4.25)	(5.59)	(5.37)	(5.09)
TFPGRTH5	0.10**		0.11**					
	(3.12)		(3.15)					
OCAPEP		0.46*	0.55**					
		(2.65)	(2.76)					
RDGDP				0.49*				
				(2.03)				
SCIENG					0.08			
					(1.95)			
EQUIPPEP						0.15		
						(1.27)		
LNMINWAGE							–0.37	
							(1.67)	
UNIONRATE								–0.03*
								(2.50)
R^2	0.85	0.84	0.87	0.83	0.84	0.82	0.84	0.84
Adj. R^2	0.84	0.83	0.85	0.81	0.82	0.81	0.83	0.83
Std. Err.	0.097	0.100	0.092	0.099	0.101	0.104	0.100	0.100
DW stat.	2.06	1.80	1.91	1.97	2.07	1.76	2.00	1.79
No of Obs	48	48	48	43	39	49	46	48
Est. Tech.	AR(2)	AR(2)	AR(2)	AR(2)	AR(2)	AR(1)	AR(2)	AR(2)

Notes: The dependent variable is *LNMEANDUR*: the natural logarithm of the mean duration of unemployment. t-ratios (absolute values) are shown in parentheses below the coefficient. The sample is based on aggregate data for the U.S. economy over the period 1948 to 1997.

Key: *TFPGRTH5*: Five-year running average of the annual percentage rate of total factor productivity growth (see equation 9).
OCAPEP: Investment in office, computing, and accounting equipment (in 1987 dollars) per PEP.
UNEMPRATE: Annual overall civilian unemployment rate.
LNMINWAGE: The natural logarithm of the minimum wage in 1987 dollars.
UNIONRATE: Percentage of labor force covered by unions.
RDGDP: Total industry R&D expenditures/GDP (current $).
SCIENG: Full-time equivalent scientists and engineers engaged in R&D per FTEE.
EQUIPPEP: Net Investment in private nonresidential equipment (in 1987 dollars) per PEP.
AR: Autoregressive process:
(1) First-order: $u_t = \varepsilon_t + \rho_1 u_{t-1}$
(2) Second-order: $u_t = \varepsilon_t + \rho_1 u_{t-1} + \rho_2 u_{t-2}$, where u_t is the error term of the original equation and ε_t is a stochastic term assumed to be identically and independently distributed.

* Significant at the 5 percent level. ** Significant at the 1 percent level.

The two other technology variables—R&D intensity, scientists and engineers engaged in R&D per FTEE—as well as investment in equipment and machinery per employee, all have positive coefficients but are generally not statistically significant (see Table 4). The only exception is R&D intensity, which is significant at the 5 percent level when included with a constant term and *UNEMPRATE*, but is not significant when *TFPGRTH5*, *OCAPEP*, and the demographic variables are added to the specification (see Table 5). Experiments with other combinations of variables also, with one or two exceptions, yield insignificant coefficients for these technology variables.

TABLE 5
Regressions of the Logarithm of the Mean Duration of Unemployment on Technology, Institutional and Demographic Variables and UI Parameters

Independent Variables	Specifications (1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.62**	6.14	2.10**	2.07**	2.24**	2.63**	2.96**
	(13.60)	(1.84)	(9.71)	(10.30)	(7.48)	(5.35)	(6.43)
UNEMPRATE	0.08**	0.13**	0.10**	0.10**	0.10**	0.10**	0.11**
	(4.74)	(5.79)	(5.09)	(6.75)	(6.58)	(6.34)	(7.13)
TFPGRTH5			0.11**	0.11**	0.11**	0.09**	0.13**
			(3.50)	(3.41)	(3.53)	(2.73)	(4.39)
OCAPEP			0.45**	0.45**	0.38*	0.34*	0.35*
			(2.80)	(2.81)	(2.21)	(2.11)	(2.47)
EMP1619	-0.14**		-0.13**	-0.13**	-0.12*	-0.09*	-0.15**
	(3.03)		(3.47)	(3.24)	(2.52)	(2.22)	(4.07)
MAL2024	0.06		0.10*	0.09*	0.08	0.01	0.06
	(1.10)		(2.12)	(2.08)	(1.38)	(0.51)	(1.30)
UICOVER		-0.77				0.77	
		(0.95)				(1.83)	
UIREPLA		-6.09**				-2.17	
		(3.61)				(1.63)	
UIWEEKS		0.003				0.18	
		(1.43)				(1.08)	
LNMINWAGE				0.04			
				(0.22)			
UNIONRATE					-0.01		
					(0.46)		
RDGDP							0.32
							(1.36)
R^2	0.87	0.87	0.91	0.91	0.91	0.92	0.92
Adj. R^2	0.85	0.86	0.89	0.89	0.89	0.89	0.9
Std. Err.	0.094	0.092	0.08	0.081	0.081	0.078	0.071
DW stat.	1.92	2.01	2.08	2.08	2.09	2.17	1.96
No of Obs	46	46	46	46	46	46	46
Est. Tech.	AR(2)	AR(2)	AR(2)	AR(2)	AR(2)	AR(2)	AR(2)

Notes: The dependent variable is *LNMEANDUR*: the natural logarithm of the mean duration of unemployment. t-ratios (absolute values) are shown in parentheses below the coefficient. The sample is based on aggregate data for the U.S. economy over the period 1948 to 1997.
Key (also see footnote to Table 4):
EMP1619: Percentage of total employees in age group 16-19.
MAL2024: Percentage of total employees who are men in age group 20-24.
UICOVER: the percent of workers covered by the UI system.
UIREPLA: the UI replacement rate.
UIWEEKS: the maximum number of weeks of UI benefits.
* Significant at the 5 percent level. ** Significant at the 1 percent level.

The natural logarithm of the minimum wage in constant dollars, *LNMINWAGE*, has the predicted negative coefficient but the coefficient is not significant. The unionization rate, *UNIONRATE*, has a negative coefficient, which is significant at the 5 percent level when only a constant term and *UNEMPRATE* are included (see Table 4). When *TFPGRTH5*, *OCAPEP*, and the demographic variables are added to the specification, however, the coefficient of *UNIONRATE* becomes insignificant (see Table 5). Likewise, when other combinations of variables are used, the coefficients of both *UNIONRATE* and *LNMINWAGE* are generally insignificant.

After some experimentation, only two of the demographic variables are found to have a significant effect on unemployment duration. The first is *EMP1619*, the percent of total employees in age group 16-19 (see Table 5). This variable is almost always significant at the 1 or 5 percent level, primarily the 1 percent level. The percentage of teenagers in total employment has a negative coefficient, reflecting the transitory nature of teenage employment. If they become unemployed, they are very likely to drop out of the labor force. The second is *MAL2024*, men in age group 20-24 as a percentage of total employment. This variable is usually significant, though only at the 5 percent level. Its coefficient is positive, because male workers in that age group will tend to remain in the labor force when they become unemployed and continue to search for a new job.[9]

Three parameters of the UI system were also included in the regression analysis: (1) *UIREPLA*, the UI replacement rate; (2) *UICOVER*, the percent of workers covered by the UI system; and (3) *UIWEEKS*, the maximum number of weeks of UI benefits.[10] *UIREPLA* is the only one of the three variables that is statistically significant, but its coefficient is (perversely) negative (see Table 5). *UICOVER* also has a negative sign but is not significant, while *UIWEEKS* has the predicted positive sign but is also insignificant. Moreover, when *OCAPEP* and *TFPGRTH5* are added to the regression specification, all three variables become statistically insignificant (see Table 5). In addition, these results remain robust when the UI parameters are included individually in regressions and in various combinations with each other. The same set of results also holds when *UIREPLB* or the logarithm of *UIREPLA* or *UIREPLB* is used in place of *UIREPLA*. These findings, including those for the UI replacement rate, are not surprising for time-series analysis. In fact, the studies that find significant effects of UI parameters are all based on cross-sectional or panel data, where the variation of the UI replacement rate is among individuals, not over time. Moreover, the change in the UI replacement rate between 1950 and 1997 has been quite small (from 33.9 to 35.0 percent).

The same regressions were repeated with two other dependent variables: (1) the percent of unemployed workers who are unemployed for 15 or more weeks; and (2) the percent of unemployed workers who are unemployed for 27 or more weeks. The results, shown in Table 6, are very similar to those reported in Table 5 (specification 3). The main difference is that the coefficient on male workers aged 20 to 24 as a percent of total employment is no longer statistically significant.

Table 7 shows the results of the last set of regressions, in which the dependent variable is the mean duration of unemployment for individual age groups. The results support one of my major hypotheses, that older age groups are more adversely affected by technological change than younger ones in terms of length of unemployment spells. Among men, the coefficient of TFP growth (*TFPGRTH5*) rises almost monotonically with age group, from zero for the youngest to 0.22 for the oldest, though it is only marginally significant in two cases. The coefficient on *OCAPEP* does rise monotonically with age group, from -0.06 for the youngest to 0.76 for the oldest, and it is significant at the 1 or 5 percent level for the four oldest groups.

TABLE 6
Regressions of the Percent of Unemployed Workers Who are Unemployed for 15 or More Weeks or 27 or More Weeks on Institutional, Technological, and Demographic Variables

Independent Variables	Dependent Variables UNEMPL15	UNEMPL27	UNEMPL15	UNEMPL27
Constant	(3.39)	-5.99*	10.02	2.77
	(1.04)	(2.16)	(1.67)	(0.66)
TFPGRTH5	2.27**	1.91**	2.16*	1.36*
	(2.76)	(2.64)	(2.44)	(2.01)
OCAPEP	11.97**	9.64**	9.92*	7.18*
	(2.73)	(2.93)	(2.25)	(2.48)
UNEMPRATE	4.33**	2.69**	3.87**	2.63**
	(10.40)	(7.41)	(9.86)	(7.81)
EMP1619			-1.56*	-1.16*
			(2.30)	(2.62)
R^2	0.88	0.82	0.9	0.84
Adj. R^2	0.87	0.8	0.89	0.82
Std. Err.	2.39	2.11	2.23	2.01
DW stat.	1.94	1.88	2.06	1.92
No of Obs	49	49	46	47
Est. Tech.	AR(1)	AR(1)	AR(2)	AR(1)

Note: t-ratios (absolute values) are shown in parentheses below the coefficient. The sample is based on aggregate data for the U.S. economy over the period 1948 to 1997.
Key (also see footnote to Tables 4 and 5):
UNEMPL15: Percent of unemployed workers who are unemployed for 15 or more weeks.
UNEMPL27: Percent of unemployed workers who are unemployed for 27 or more weeks.
* Significant at the 5 percent level. ** Significant at the 1 percent level.

The results for females are very similar. The coefficient of *TFPGRTH5* rises monotonically with age group, from –0.02 for the youngest to 0.13 for the oldest, and it is significant at the 5 or 10 percent level for the oldest four groups. The coefficient on *OCAPEP* increases almost monotonically by age group, from –0.15 to 0.59, and is statistically significant at the 1 percent level for the oldest four groups and at the 10 percent level for the youngest. It is also striking that the coefficients on *TFPGRTH5* and *OCAPEP* are negative for the youngest age group.[11]

A straightforward decomposition, shown in Table 8, can allow us to understand the sources of the sharp increase in unemployment duration observed over the last 25 years or so. We have selected two years, 1970 and 1997, at about the same stage of the business cycle (the unemployment rate in both years was 4.9 percent). Over this period, mean unemployment duration increased by 84 percent (from 8.6 to 15.8 weeks). The greatest effect is contributed by the increase in investment in OCA per employee over this period, from virtually zero to $870 (in 1987 dollars). It accounted for about 60 percent of the increase in the log mean duration of unemployment (*LNMEANDUR*). An increase in TFP growth of about 0.6 percentage points contributed about another 10 percent. Changes in the demographic make-up of employment (declines in the share of both teenagers and male workers aged 20 to 24 in total employment) added another 30 percent or so.[12]

TABLE 7
Regressions of the Mean Duration of Unemployment by Gender and Age Group on Technological Variables

Demographic Group	Constant	Independent Variables *TFPGRTH5*	*OCAPEP*	*UNEMPRATE*	R^2	Adj. R^2	Std. Error	DW Stat.	# of Obs.
Men by age group									
16-19 years	1.44**	–0.001	–0.059	0.108**	0.89	0.86	0.057	2.15	22
	(14.70)	(0.02)	(1.07)	(8.80)					
20-24 years	1.34**	0.092	0.163	0.168**	0.85	0.8	0.092	2.00	22
	(7.69)	(1.61)	(1.67)	(7.70)					
25-34 years	1.69**	0.096	0.409**	0.143**	0.82	0.76	0.098	2.01	22
	(8.24)	(1.41)	(3.12)	(5.54)					
35-44 years	2.09**	0.125#	0.542*	0.101**	0.72	0.65	0.115	1.72	22
	(8.67)	(1.79)	(2.47)	(3.38)					
45-54 years	2.33**	0.089	0.653**	0.081**	0.79	0.72	0.099	2.12	22
	(11.10)	(1.33)	(4.26)	(3.15)					
55-64 years	1.85**	0.216#	0.763*	0.144*	0.58	0.48	0.187	1.81	22
	(4.27)	(1.79)	(2.65)	(2.61)					
Women by age group									
16-19 years	1.57**	–0.024	–0.145#	0.073*	0.82	0.76	0.063	2.07	22
	(13.10)	(0.60)	(2.00)	(4.80)					
20-24 years	1.54**	0.044	0.018	0.109**	0.82	0.76	0.082	2.01	22
	(9.06)	(0.81)	(0.14)	(5.05)					
25-34 years	1.37**	0.116*	0.422**	0.144**	0.84	0.81	0.083	1.71	22
	(7.77)	(2.26)	(3.38)	(6.45)					
35-44 years	1.35**	0.109*	0.697**	0.156**	0.89	0.86	0.079	1.82	22
	(8.11)	(4.81)	(6.87)	(7.55)					
45-54 years	1.77**	0.116#	0.504**	0.119**	0.84	0.79	0.093	2.21	22
	(9.49)	(1.84)	(3.75)	(5.04)					
55-64 years	1.78**	0.131#	0.586**	0.130**	0.70	0.63	0.120	1.94	22
	(7.42)	(1.74)	(3.42)	(4.34)					

Note: The dependent variable is the natural logarithm of the mean duration of unemployment by demographic group. t-ratios (absolute values) are shown in parentheses below the coefficient. The sample is based aggregate data for the U.S. economy covering years 1972 to 1995. Equations are estimated using second-order autoregressive process. See footnotes to Table 5 for the key.
Significant at the 10 percent level * Significant at the 5 percent level. ** Significant at the 1 percent level.

CONCLUDING REMARKS

The duration of unemployment has risen rather dramatically over the last half century. The mean duration of unemployment has approximately doubled in the U.S. between the late 1940s and the late 1990s, with most of the increase occurring since the early 1970s. The percentage of unemployed workers out of work 15 or more weeks more than doubled over the same period, while the percentage of the unemployed out of work 27 or more weeks tripled. I also found that the rise in unemployment duration between the 1970s and the early 1990s was almost universal among demographic groups, with the average duration of unemployment generally rising about 3 to 4 weeks.

Another striking finding is that average weeks of unemployment rise almost monotonically with age. Moreover, between the 1970s and early 1990s, the spread in unemployment duration widened sharply between older and younger male workers—from 10.8 to 17.1 weeks between teenagers and ages 55-64.

The econometric results provide strong support for the central thesis of the paper, that the duration of unemployment increases when the pace of technological change rises. This result is confirmed mainly by the positive and significant coefficient of OCA per employee on the duration of unemployment and the large contribution of this variable to the increase in the mean duration of unemployment between 1970 and 1997. This result is also in accord with recent theoretical and empirical literature on GPT as an engine of growth and as a factor in increasing the demand for skilled labor relative to unskilled labor. TFP growth is also found to have a positive and significant effect on unemployment duration but its measured contribution to the rise of unemployment duration over the 1970-97 period is relatively minor.

TABLE 8
Decomposition of Change in the Mean Duration of Unemployment between 1970 and 1997 into Technological and Demographic Effects

Year	Value of Each Variable 1970	Value of Each Variable 1997	Contribution of Each Variable[b] 1970	Contribution of Each Variable[b] 1997	Change in Contribution 1970–1997	Percent of Change in *NMEANDUR* Explained
LNMEANDUR	2.15	2.76	2.15	2.76	0.61	
Constant	1.00	1.00	2.10	2.10	0.00	0.0
TFPGRTH5[a]	0.17	0.76	0.02	0.08	0.06	10.7
OCAPEP	0.00	0.87	0.00	0.39	0.39	63.4
UNEMPRATE	4.90	4.90	0.48	0.48	0.00	0.0
EMP1619	7.81	5.14	–1.02	–0.67	0.35	57.5
MAL2024	6.66	4.70	0.64	0.45	–0.19	–30.8
Residual			–0.06	–0.06	–0.01	–0.9
Sum			2.15	2.76		100.0

Note: Dependent variable is *LNMEANDUR*: the natural logarithm of the mean duration of unemployment. The decomposition is based on the coefficients from specification 3 of Table 5. See footnotes to Tables 4 and 5 for variable definitions.
a. Percentage points.
b. Defined as the coefficient value multiplied by the value of the variable in each year

The results support my other hypothesis that technological change affects older workers more adversely than it does younger workers in terms of duration of unemployment. Both investment in OCA per worker and TFP growth bore a much stronger positive relation to length of unemployment among older men than younger and among older than younger women. As noted in Section 2, the coefficient estimates of TFP growth and investment in OCA per worker are, if anything, biased downward for older workers because of the likely "drop-out" effect among unemployed older workers. These results are also consistent with the argument that firms are reluctant to invest in the additional training associated with new technology for older workers because of the shorter pay-off period or, perhaps, because of the greater difficulty of retraining older workers ("you can't teach an old dog new tricks"). Moreover, these results are in accord with the findings of Aaronson and Housinger [1999] and Friedberg [2001].

Demographic variables also have an influence on the duration of unemployment. In particular, the proportion of total employment in age group 16-19 is negatively related to unemployment duration, while the proportion of men in age group 20-24 has a positive bearing.

NOTES

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1. There is a rich and well-documented body of materials in the literature of sociology and social psychology that studies effects of unemployment not widely mentioned in economic discussions. This literature indicates that joblessness has consequences, such as increased suicide, divorce, psychosomatic illness, and, perhaps, increased criminal activity, among other effects whose social cost must surely be added to the foregone output that results from unemployment. Though much of this literature does not distinguish clearly between lengthy and brief unemployment, a short spell of unemployment surely causes little lasting psychic or social damage. References as well as a summary of the evidence are provided in Mallinckrodt and Fretz [1988] (see especially p. 281). More ambiguous evidence on the relationship between unemployment and crime is discussed in Britt [1994].
2. Similar time trends exist for most other industrialized countries as well.
3. It would be preferable to use the gross capital stock to measure TFP but this series was discontinued by the Bureau of Economic Analysis in 1994. TFP growth shows a smaller decline between the period before and after 1970 with the use of net stock than of gross stock.
4. Calculations of TFP and both equipment and OCA investment per worker using FTEE instead of PEP yield very similar time trends and correlation coefficients with unemployment duration.
5. See Marston [1975], Ehrenberg and Oaxaca [1976], Hamermesh [1977], Welch [1977], Classen [1979], Solon [1979], Barron and Mellow [1981], Moffitt and Nicholson [1982], Feldstein and Poterba [1984], Meyer [1990], Katz and Meyer [1990a; b], and Devine and Kiefer [1991, Ch. 5] for a fairly complete review of the literature.
6. An alternative formulation of the replacement rate is the ratio of UI average weekly benefits to the average weekly earnings for total private nonagricultural employees. It has a lower correlation with the mean duration of unemployment, 0.36.
7. Unfortunately, for the purposes of this analysis, unemployment duration by educational group is not available. Moreover, these series were discontinued in 1993.
8. The Phillips-Perron Unit Root Test Statistic is –3.213 for *LNMEANDUR*, –3.361 for *UNEMPL15*, and –3.206 for *UNEMPL27*, compared to a 10 percent critical value of –3.1816. The X variables are the dependent variable lagged one period, a constant term, and a trend term.
9. The coefficient of the percentage of workers aged 55 and over is negative but not statistically significant. The result does suggest that members of this age group may tend to drop out of the labor force when they lose their job.
10. The fourth parameter, *UIINSCOV*, the percent of unemployed workers receiving benefits, is excluded from the regression, since, as noted above, it is endogenous—a rise in unemployment duration will cause more unemployed workers to exhaust their UI benefits.
11. Regressions run by gender and race group do not show very sizable differences in results. The coefficient of TFP growth, for example, varies from 3.7 for black females to 3.9 for black males, 4.0 for white females, and 4.3 for white males. Differences in results among marital groups are also not very substantial.
12. Of course, in a period when the unemployment rate is rising, the decomposition results look quite different. In the period from 1951 to 1992, when the unemployment rate more than doubled, from 3.3 to 7.4 percent, the increase in the unemployment rate explains two-thirds of the increase in the mean duration of unemployment, while investment in OCA per worker accounts for only 10 percent.

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