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ABSTRACT

This document, a review of labor market effects of human capital, focuses on two related topics. Part I describes the following early findings of the research on effects of education and job training on the wage structure, labor turnover, and unemployment: decline of training with experience, positive and significant effects of training on length of completed tenure, less turnover over longer periods for workers who received training, positive effect of training on wage growth, positive effect of training on wage growth in wage trajectories that transcend tenure in one firm, and reduced unemployment for those with job training. This part concludes with an attempt to estimate volumes and profitability rates of job training directly from data on incidence, duration, and wage growth effects of observed training. Part II reports on findings about effects of technological change on the use of human capital and on consequent effects of productivity growth on wages, turnover, and unemployment. Among other things, these findings indicate that: acceleration of technological changes in a sector raises the share of educated workers within it; sectors with more rapid productivity growth show higher rates of return to education; turnover rates decline in sectors with long-run high rates of productivity growth; and technological change tends to reduce unemployment. Contains 33 references and 14 tables for Part I and 21 references and 9 tables for Part II. (YLB)

LABOR MARKET EFFECTS OF HUMAN CAPITAL AND OF ITS ADJUSTMENT TO TECHNOLOGICAL CHANGE

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ABSTRACT

Recently available survey data on the prevalence of on-the-job training and learning have been investigated in several studies to answer questions such as: Who gets training? What are its effects on labor market experience of workers--on wages, wage growth, turnover and employment? What is the magnitude of investments in job training by workers and employers?, and how profitable are such investments? Answers to these questions are described in Part I.

Part II describes studies which utilize recently developed measures of technological change by industry, such as productivity growth indexes or expenditures on R&D (Research and Development). The studies explore effects of technological changes on industry demands for educated and trained workers, and on consequent changes in wage structures, labor turnover, and unemployment.

LABOR MARKET EFFECTS OF HUMAN CAPITAL AND OF ITS ADJUSTMENT TO TECHNOLOGICAL CHANGE

INTRODUCTION

In this review of recent research on labor market effects of human capital, I focus on two related topics: (1) the effects of education and of job training on the wage structure, labor turnover, and unemployment, and (2) the effects of technological change on the utilization of human capital and on consequent effects of productivity growth on wages, turnover, and unemployment.

A huge literature accumulated over the past 30 years contains a wealth of findings on the effects of school education on wage levels and on profitability rates of investments in education at various levels of aggregation. Corresponding estimates of effects of job training were not available until recently. Instead, growth of earnings over the working age, known as the "experience wage profile" was, according to human capital theory, interpreted to reflect worker investments in job training (and in labor mobility). Indeed, a first comprehensive estimate of the volume of on-the-job training costs (Mincer, 1962) was obtained using this interpretation.

The validity of such indirect estimates does, of course, depend on the validity of the theory. Although the theory has proven quite robust in a number of applications, it cannot be claimed as an exclusive factor in any particular application. Not surprisingly, therefore, the absence of direct data on job training spawned a proliferation of alternative theories which attempt to explain upward slopes of wage profiles (though not their deceleration) as devices to economize on costs of supervision (Becker and Stigler, 1974; Lazear, 1979), on costs of turnover (Salop and Salop, 1976), or as consequences of job sorting or "matching" in labor mobility (Jovanovic, 1979). These theories and the human capital job training theory are not mutually exclusive, nor have they been subjected to much, if any, empirical testing. As these theories began to create doubt about the validity or dominance of the human capital interpretation of wage profiles, direct data on job training (still leaving much to be desired) became available from several sources. Clearly, better informed empirical research on the reality and effects of job training was now not only desirable, but also possible. I describe the early findings of this research in Part I. I conclude Part I with a new attempt to estimate volumes and profitability rates of job training directly from data on incidence, duration, and wage growth effects of observed training. A comparison with the indirect estimates of 1962 is both intriguing and illuminating.

A second development in empirical economics is the availability of time-series of recently constructed multifactor productivity growth indexes at industry levels. Human capital as a source and/or complement of technical change is an old theme. Apart from sporadic but limited evidence, empirical verification has been elusive. More systematic attempts are now possible, given the growth of economy-wide industry data. In Part II, I report on findings about effects of productivity growth on labor market behavior, as mediated by human capital responses or adjustments to technological change. Although, broadly construed, human capital is a major source of technical change, the research reported here focuses more narrowly on human capital as a factor of production which responds to it and thereby facilitates technical progress in the labor market.

PART I: DISTRIBUTION AND LABOR MARKET EFFECTS OF JOB TRAINING

Incidence

My own research (Mincer, 1988a) utilizes information on the incidence and timing of training in conjunction with information on wage profiles and mobility behavior of workers in the Panel Study of Income Dynamics (PSID) panel micro-data. Short (within the firms) and longer-run effects of training on mobility and on wages are estimated in PSID panel data which cover intervals as long as 15 years (1968 to 1983).

Aside from PSID data, job training information from households is also available in other data sets, such as the National Longitudinal Panels, and in a recent Current Population Survey (CPS) (1983). Data from firms are available in a two-wave Economic Opportunity Pilot Project (EOPP) Survey (1982). Systematic studies of wage structure in relation to training begin with Duncan and Hoffman (1978) and Brown (1983 and 1988), who used PSID data; Parsons (1986) and Lynch (1988), who used the National Longitudinal Survey (NLS) Young Men's Panels; Barron et. al. (1988), who used the EOPP employer survey; and Lillard and Tan (1986), who analyzed several data sets.

My study extends these efforts in two directions: (1) It analyzes effects of training on mobility, that is, on length of tenure in the firm in which training was received and on the frequency of job change over longer periods of time, and (2) it looks at effects of training on changes in wages over time, distinguishing in-firm and across-firm wage effects. Although the main reliance is on the PSID data, findings in other studies are cited where relevant[1]. The PSID sample is restricted to over 1,200 male heads of households up to age 60, excluding students and self-employed.

Direct information on volumes of job training is provided in the PSID surveys of 1976 and 1978. One of the measures I used is derived from respondents' answers to a question: "On a job like yours, how long would it take the average new person to become fully trained and qualified?" The question followed

[1] Some of the reliability statistics (t-values) in regressions based on the PSID are overstated, when the sample size is measured in person-years. Findings in other studies, therefore, represent an important check as well as corroboration, as they in effect reflect an added sample.

several other questions about training *prior* to the current job, and it "was intended to measure the volume of the training investment attached to the current job."[2]

Table 1 (Column 1) summarizes the distributions of this measure in a regression of the duration of training (RQT) in the 1976 and 1978 jobs on experience, education, marital status, union coverage, and other variables in the 1976 and 1978 pooled cross-sections. It appears that training, as measured, increases with working age (experience) and with education, is lengthier among married than single men, and is longer in nonunion than in union jobs. In Column 1 of Table 2, the coefficients on x and x^2 are positive and negative, respectively. This indicates that training per job increases with experience in a decelerating fashion.

The increase in the length of training (RQT) with experience may seem puzzling: according to human capital theory, investments in human capital, especially if measured in time units, as RQT is, must decline over the life-cycle--for good theoretical reasons, and if such investments are to imply a concave growth of wages over the life-cycle. There is no inconsistency, however, if we realize that RQT is an investment volume per job, not per year. A rough adjustment to convert RQT into a rate per year is to divide it by the length of tenure on the job on which the training was received. When this is done, the regression of RQT/Ten shows a negative coefficient on x and a much smaller positive coefficient on x^2 (Column 2. of Table 1). This means that the rate of training per year declines with experience, at a diminishing rate.[3]

The decline of training with experience is also apparent in Column 3 in which the dependent variable is the incidence or occurrence of training in 1976. Given the length of training (RQT) and the assumption that it started with the start of the current position, we assign a value 1 if the worker received training during the year, 0 if not. The sample for Column 3 is almost twice as large as the of Column 2, as it includes all those in the 1976 job whether or not they left it prior to 1983. The truncated sample of Column 2 contains workers with shorter completed tenure, and significantly, with shorter average training (Mean RQT = 1.8) than the complete sample (Mean RQT = 2.4). It is also worth noting that the respective coefficients on X and X^2 imply that training reaches a minimum at X = 16 in Column 2 and X= 30 in Column 3.

[2] A check on whether the RQT measures in the PSID refer to the length of current training in the firm or to total (cumulated) on-the-job training needed for the particular job was performed by N. Sicherman (1987). A comparison by detailed occupation in PSID responses with DOT (Dictionary of Occupational Titles) estimates supports the assertion that RQT is not a cumulative measure antedating the current firm for most occupations, except for a minority of highly skilled professional occupations where RQT is overstated. When added to probably sizable errors of measurement, this discrepancy creates an additional downward bias on estimates of effects of RQT in statistical regressions.

[3] Both RQT and RQT/Ten level off at about two decades of work experiences. The quadratic smoothing function forces peaks and troughs at about that time. The regression of RQT divided by completed tenure in the 1976 job was restricted to a subsample of workers (about half of the total) who left their 1976 job by 1983.

The net positive coefficients of education in the RQT regression of Table 1 indicates that more educated workers engage in more prolonged job training or learning. The reasons provided by human capital theory (Becker, 1975) are that persons who have greater learning ability and better opportunities to finance the costs of human capital investments do invest more in all forms of human capital, including schooling and job training. Although this answer is sufficient, some analysts claim, in addition, that school education is a complementary factor to job training in producing human capital. In other words, education enhances the productivity of job training at work. It is clear, however, that schooling can also be a substitute for job training: thus, the decline in apprenticeships has been attributed to growth in educational levels over the long run.

There are several shortcomings in the measures of "years of required training on the current job" (RQT) in the PSID: The total period of training, "for the average new workers on this job," is a blunt measure of the individual training periods. Moreover, the intensity of training, that is the actual amount of time devoted to training during the year or week, is not indicated. Supplementary information on intensity is available in a 1980 study of time budgets by Duncan and Stafford. It contains data on the proportion of workers who were engaged in job training during the survey week and the average weekly hours spent in training by those engaged in it. Table 2 provides a check on the decline in training over experience (here age), and the increase in training with education, both of which were indicated in our regression in Table 1. Both percent engaged and their hours declined with age, and increased with education (up to college). Note, however, that the data are not standardized for other characteristics; consequently the gross effects may be exaggerated, as younger people are on average more educated.

An alternative question asked in the 1976 PSID, which does not attempt to measure cumulative or duration of training but measures incidence, can be used to check the results. The question asks: "Are you learning on the job, so that you could be promoted, or get a better job?" The results are reported in Part II (Panel B of Table 2). It shows the same signs and somewhat larger parameter magnitudes as in Table 1 here. The inferences based on rather imperfect measures of training in the PSID can also be checked with results in other studies based on other sources of data. Lillard and Tan (1986) analyzed the distribution of training across workers in larger and in some respects more detailed CPS and NLS samples. The training measure there is its incidence during the year between surveys, and it is distinguishable by its locus, inside or outside the workplace. Despite minor differences in some of the variables, the estimated regression coefficients on education, experience, and marital status for in-house training (Table 3) are similar to those based on PSID data.

Of special interest is the study of Barron, Black, and Loewenstein which analyzed the EOPP survey of employers. Here the variable studied is the number of hours a new employee spends in training during the first 3 months. The regression results shown in Table 4 confirm the positive relation of training with education. It also shows that training declines with years of (relevant) experience, and that there is less training in unionized jobs and among women. Training is more frequent in larger firms and where machinery is more costly.

Effects of Job Training on Turnover

The idea that job investments, such as job training, contain elements of firm-specificity introduced by Becker (1962) and Oi (1962) produces a link between human capital investments and inter-firm labor mobility, or labor turnover. The training data I utilized do not contain information on degrees of firm specificity. A working assumption which obviates this problem is that, at the firm level, training, even if largely transferable to other firms, perforce contains some elements of firm specificity. Since the greatest opportunities for training are likely to exist in firms in which training processes are closely related to and integrated with their production processes, we may infer a positive relation between volumes of general and specific training received in firms. Hence the hypothesis that the larger the volume of training in the firm the stronger the attachment of trained workers to the firm.

Attachment to the 1976 Firm. Effects of training in the 1976 job on the probability of leaving the firm in which training was received are observed in Table 5. In panel A, the dependent variable is the completed length of the 1976 job, which is observable for close to a half of the PSID respondents whose tenure was listed in 1976. A little over a half of the 1976 sample changed jobs by 1983. The effects of RQT reported in 1976 on the length of completed tenure were positive and significant, despite the truncation which selects shorter-tenured workers into the sample.

The same is true of an alternative measure of training shown in the second row. This measure, e_{RQT}, which is the percent growth of wages over the training interval, was constructed in an attempt to combine intensity with length of training. It relies on the observed effect of training on wage growth, shown in section 4: despite severe errors of measurement which beset both measures of training, the effects appear to be significant, even if biased downward.

The information is extended beyond the truncation in panel B. Here the dependent variable is the probability of staying in the 1976 firm beyond 1983. Again, the effect of training (RQT) is positive and significant. In both panels, the sample is also split between younger and older workers. The training effects apparently increase with age. There are no effects for young workers (working age $\leq$ 12 in 1982, in Panel B). In the upper panel, the young workers are 6 years older (working age $\leq$ 12 in 1976) and the effects on truncated completed tenure are positive but smaller than the effect at older ages.

These age differences in effects of training are clearly not due to differential intensity of training. The latter *declines* with age, as was shown in Table 2, and is presumably, though imperfectly, captured in the

e_{RQT} variable. More likely the age differences reflect lesser specificities of training and of work experience among younger workers.

Training and Turnover over the Working Life

While training obtained in one firm reduces the worker probability of leaving there, it should not affect his tendency to stay in or leave from subsequent employers, unless workers who engage in more training in one firm continue to do so in subsequent employment.

It appears, indeed, that workers who received training in the 1976 job had lesser turnover over longer periods. Table 6 shows a negative effect of the 1976 training variables RQT and of e_{RQT} on numbers of moves (N) over the period 1968-1982. Such persistence is predicted by a lifetime optimization hypothesis on human capital investment behavior. Workers with better abilities and opportunities (though both are, in part, stochastic) tend to invest more in their human capital both at school and in a successive series of jobs. The serial correlation of training in successive jobs can be tested directly by: (a) regressing the volume of training attached to 1978 jobs of those who left their 1976 job (about one-third of the workers) between 1976 and 1978 on reported training attached to their prior, 1976 jobs; (b) regressing the volume of training in 1976 on training that was needed prior to entry into the current job (Prior Training); and (c) regressing the presence of a learning content on the 1976 job (Learning Dummy) on prior training. The resulting (partial) correlations are clearly positive, as shown in Table 7.

The persistence of training over time can also be inferred from the NLS data on the incidence of training[4] provided by Lillard and Tan (1986). Although the persistence of mobility behavior is related to the persistence of training, one cannot rule out reverse causality. A possible, and to some extent, plausible alternative interpretation of the same findings (in Table 3) is that workers who do not move much tend to receive more training, rather than conversely. If employers invest in specific capital and if their turnover and hiring costs are large for this or other reasons, they have incentives to select less mobile workers for training. If so, the mobility of workers is not reduced by more training--it was less frequent even before the training took place. To test this proposition, I regress separations between 1976 and 1983 on training, holding prior mobility frequency (between 1958 and 1975) constant. The results in Tables 8 and 8A show that the post-1976 mobility is reduced by training, given prior mobility. At the same time, there is a positive serial correlation in turnover behavior as shown by the coefficient on the prior mobility variable. This may imply some degree of selection in hiring, or effects of persistent earlier training.

[4] As shown in Mincer (1988a).

The negative effects of training on separations are stronger in the older sample. and they appear to be symmetric in quits and in layoffs. These effects as well as the coefficients of other independent variables in Table A regressions are shown in Table 8A.

Job Training and Wage Growth in the Firm

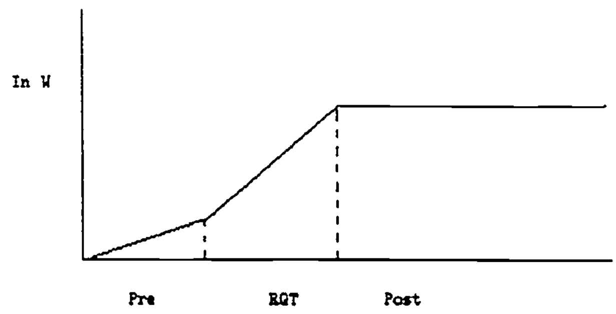
That greater volumes of job training imply steeper wage profiles, on the job, and over longer experience is a theorem in human capital analysis. The availability of the training measures in the PSID makes it possible to observe more directly individual wage differences and growth in relation to the observed volumes of their training.

A positive relation between measured volumes of training and slopes of wage profiles was observed by Duncan and Hoffman (1978), Gronau (1982), Brown in an unpublished paper (1983), Parsons (1986), and most recently Brown (1988), Barron et al. (1989), and Lynch (1988).

A more comprehensive empirical exploration of the relation between training and the wage structure is available in the study by Lillard and Tan (1986). The study utilizes CPS cross-sections and NLS panels. It contains measures both of incidence and of hours of training. The effects of training on wages is strong in cross-section wage functions. In the NLS panel of young men, the effects are strongest for company (in-house) training.

Brown's earlier study had shown that, when the tenure profile of wages is decomposed into three segments (see Figure 1 below), wages grow slowly before the training period (Pre), rapidly during training (RQT), and level off after it (Post). The pre-training period may actually contain some training, but this was not reported in the data. It suggests that the usually observed concavity of the tenure-wage profile is due to the completion of RQT.

Figure 1



I replicated the regressions with tenure decomposed into the three segments in the 1976 and 1978 cross-section. The regression coefficients in Table 9 show that wage growth during the training period is most rapid (4 to 5% per year). Wage growth is only 1 to 2% prior to training and about 1% thereafter.

In order to detect effects of RQT on wage growth rather than on wage differential in the cross-section, I observe changes in wages of the 1976 workers over time in table 10. The dependent variable is the year-to-year growth in (real) wages of workers in the 1976 job whether or not their tenure was completed. RQT and learning are (1,0) dummies. The coefficient in the left-hand column measures the effects of reported training compared to no or unreported training[5] each year between *1968 and 1982*. This RQT coefficient shows that a year of training increased wage growth by 4.4%. When restricted to the 1975-1976 period (Column 2) the effect was 6.7%. The Learning variable (Column 3) showed a similar effect, 6.4%. None of the other independent variables were significant, including a very small negative and decelerating effect of prior experience, measured at the start of tenure in the 1976 job. Perhaps surprisingly, the training coefficients are no smaller than those shown in the cross-section.

The effect of training on wage growth is greater at younger ages (9.5% for $x \leq 12$, 3.6% for $x > 12$), reflecting greater intensity of training among young workers, a fact already shown in Table 2B in terms of age differences in weekly hours of job training. With these findings, Table 5 documents the importance of job training or learning in producing the upward sloping and concave experience-wage profiles.

In a recently completed revision of his earlier study, Brown (1988) finds larger effects of training on contemporaneous wage growth in the PSID data covering the years 1976 to 1984. These effects emerge when the incidence of training (RQT) is interacted with the learning dummy (LD) during the first few years of tenure in the 1976 job. To avoid various possible misclassifications, Brown narrowed the sample to workers who did not require prior training to enter the 1976 firm and who are in their first job position in

[5] Note that training was not reported in jobs preceding the 1976 firm nor in jobs which started after 1978. Consequently the effect of training on wage growth in Column 1 is understated.

that firm. For these workers, training-related wage growth is close to 9% per year. Although the average training period in their sample is a little over one year, the first-year wage growth, which some researchers attributed to considerations other than training, appears to be of large magnitude only if skill acquisition (training or learning) took place. Indeed, early tenure effects appear to be present only for workers who report that they are learning additional skills. Brown's study leads to the strong conclusion that wage growth in the firm is largely and perhaps exclusively related to skill acquisition in the firm.

Training, Turnover, and Wage Growth in the Long Run

We now turn our attention to effects of job training on wage growth in wage trajectories which transcend tenure in one firm. A positive effect is expected on the human capital hypothesis, given largely transferable skills and some persistence in training. Using the longest interval--from 1968 - 1983--in our PSID data, we found a positive effect, even though our training measure (e_{RQT}) is reported only for the 1976 job. The measure we use is the growth of wages over the training period, which reflects both the length and intensity of training. Table 11 (upper row) shows the coefficient of this variable in the regression in which the dependent variable is the average annual rate of growth of wages over the observed interval.

The effects of training on the long-run wage trajectory accord with expectations, given that most of the training is likely to be transferable across firms. A more interesting question regarding the existence of firm-specificity in training is whether the slope of the wage trajectory is flatter for the more frequent movers: the hypothesis that general and specific training are positively linked in one package has this implication. The second row of Table 11 answers this question. The coefficients of AN are negative and significant for all and especially beyond the first decade of working life. Apparently, for the young workers who are not yet settled into long-term jobs, training is largely general, so wages grow as a result of training, but effects on turnover are weak. Both effects are pronounced for older workers.

We should note that these findings hold also for the slope of the wage trajectory which excludes tenure effects, namely, in which Tenure in 83 is the same as Tenure in the beginning. In other words, slopes of experience-wage profiles which reflect only transferable human capital were also steeper for the less frequent movers. This is consistent with our hypothesis that larger investments in human capital contain larger transferable and firm-specific components.

The findings in the second row of Table 11 imply that per-year growth of wages *within firms* is smaller when tenure in the firm is, on average, shorter. This finding has recently become controversial in the econometric literature.[6] It is not likely to be an artifact in our approach, especially after account is taken of

[6] Altonji and Shakotko (1985), Abraham and Farber (1987), Marshall and Zarkin (1987), and Topel (1987).

an important qualification. A qualification is required because the wage growth analyzed in Table 11 includes gains due to inter-firm moves: total wage change over an interval is the sum of intra-firm growth and of inter-firm (mobility) wage changes (m). A sufficient condition for the conclusion to be correct is that the sum of mobility gains (defined as wage change between starting wage on the new job and last wage on the previous job) should not be greater for the less frequent movers.

A regression of m_i on N_i with the other independent variable as before showed a negative coefficient of less than .1% with t-values close to zero. Thus the wage gain per move was about the same for frequent and infrequent movers, so the differences in intra-firm wage growth between "stayers" and "movers" were actually greater than the differences in total growth shown in the coefficients of AN in Table 11. The conclusion that the more frequent is mobility, the lesser is wage growth within firms is reinforced.

A numerical example illustrates these results. At the observed mean, individual wage growth was 3.1% per year. Wage gain per move (m_i) was 2.2%, and the average number of moves 2.25 (probably an underestimate). Thus wage growth over the 15-year period was 46%, of which 5% were mobility gains. Growth *within* jobs was therefore 41%. According to the coefficient of AN in Table 6, doubling of moves would reduce growth over the 15 years by (2.25 x .028 =) 6.3%, while doubling mobility gains to 10%. Hence wages of workers who move twice as frequently as the average would grow 40% (compared to the 46% average) over the period, while their growth within jobs would be 30% (compared to the 41% average). On average, mobility gains accounted for less than 15% of total growth over the period. The bulk of the rise in the wage trajectory cannot be ascribed to mobility, as is sometimes claimed.

Effects of Skill Training on Unemployment

The unemployment rate of a labor force group in a period of time is affected by the probability of experiencing unemployment, the duration of its spell, and the proportion of time spent in the labor force during the period.[7] In the male experienced labor force, non-participation plays a negligible role, and unemployment differentials among skill groups (by education or occupation) are largely due to differences by incidence of unemployment P(u) rather than by its duration.

In a recent study of PSID data, I found that the incidence of unemployment is 170% greater, while duration of unemployment is at most 30% greater in those with the least education (< 12 years), compared to male workers with the most education (16+ years). In turn, incidence of unemployment P(u) is influenced by

[7] The relation is multiplicative (see Mincer, 1988b):

$$u = P(u) \cdot \frac{du}{1-d(o)}$$

Here d(u) is duration of unemployment, d(o) of non-participation.

turnover, or the probability of separation P(s), as well as the probability of encountering unemployment when separated P(u/s), as P(u) = P(s) P(u/s). Table 12 shows that job training reduced P(u), because it reduced P(s) as we already know, as well as P(u/s). In turn the ubiquitously observed negative relation between education or other measures of skill (including wage rates) and the probability of unemployment is due, in part, to the fact that the more educated and skilled workers are more likely to continue training and learning on their jobs. I found that the reduction in turnover and the lesser exposure to unemployment are about equally important in creating differential unemployment by skill levels.

In explaining the lesser conditional unemployment of educated workers and the somewhat lesser duration of their unemployment, we focus on search behavior. Moving from one firm to another without unemployment implies search on the job. The lesser risk of unemployment in job changing suggests greater efficiency of on-the-job, than off-the-job, search. Largely indirect evidence shows that (1) costs of on-the-job search relative to costs of searching while unemployed are lower for more educated and trained workers, (2) that these workers are also more efficient in acquiring and processing job search information, compared to less educated workers, and (3) that firms and more educated workers search more intensively to fill more skilled vacancies. Factors (2) and (3) underline also the greater efficiency of educated workers conducting off-the-job search, hence the shorter *duration* of unemployment of educated workers.

The interrelation between human capital investment behavior and search behavior can be seen in the following mutual links: since educated workers tend to invest more in training, they expect to continue doing so when they move to the next firm. Consequently they expect to stay there longer than other workers. According to the economic model, they will, therefore, search more thoroughly (though not necessarily longer) and obtain greater wage gains in moving, as we indeed observed (Mincer, 1988b).

Although the analysis referred to unemployment in job changes, the patterns are quite similar for unemployment due to temporary layoffs (job recall to the same employer). This is because trained workers are less likely to be laid off and more likely to be recalled when laid off.

Effects of Job Training on Wage Growth in Other Data Sets and Some Estimates of Profitability and Volumes of Training

In view of the various data errors and misclassifications in the PSID with which Brown deals so valiantly, the findings I reported must be checked with other data sets. Those naturally contain their own errors. Such independent analyses are now available. None of these studies looks closely at the question of portability of training, but all estimate effects of training on wage growth. I now briefly summarize these findings.

Barron, Black, and Loewenstein (1989) use the 1982 EOPP survey of over 2,000 employers located in 31 areas across the country. They measure training in hours spent in training by new hires and by their supervisors and co-workers during the first three months of employment in the firm. The mean training hours were 151 in the three months. In a two year period, they report that training raised wages by 15% or 7.5% per year. It will be recalled that a year of training in the PSID raised wages of young workers, whose average age was about the same as of the new hires in EOPP, by 9.5%, and by 3.6% for workers who, on average, were 15 years older, and who had a correspondingly smaller intensity (hours per week) of training. This is also consistent with the 9% effect per year found by Brown (1988) for new hires, who had no training before.

Lynch (1988) uses the new youth cohort of the NLS. Here information is available on all training spells of recent male entrants into the labor force during the 3-year period 1980 to 1983. She finds that wages of young workers with job training during the year rose by 11%, while an additional year of tenure without training increased wages by 4%.

Lillard and Tan (1986) also find significant effects of training on wages in the CPS and in the 1963-1980 youth cohort of the NLS. In the CPS (their Table 4.1), company training raises wages by 11.8%; in the NLS (their Table 4.5), job training raises wages also by about 12% in the current year.

In sum, estimated effects of an additional year with training appear to range from 7.5% in the EOPP for new hires, to 9% for new hires in the PSID, 9.5% for young workers in the PSID, 7% for the new youth cohort in the NLS, and 12% for the previous youth cohort in the NLS. The 12% effect for CPS men appears to be high, as it covers mature men together with younger men. It is omitted from the profitability analysis.

Prima facie, these estimates of effects of a year with training on wages are comparable to effects of an additional year of schooling at the average level of schooling. Yet, viewed as measures of profitability, or as rates of return on the cost of job training, these numbers appear to be much too large.

The reason is that job training is not a full time (full year) activity. If it takes 25% of work-time during an average week of a year with training, the rates of return on worker opportunity costs are four times higher than the estimated rates of wage growth. Let (k) be the fraction of work time devoted to job training by the worker. Then wage growth over the year $\dot{w} = r.k$, or $r = \dot{w}/k$. Table 13 shows estimated r - the rate of return on worker investment in training for each of the studies.

These rates of return appear to be implausibly high. However, the estimates are overstated mainly because they ignore depreciation of skills acquired in particular episodes of training. The only available estimate, by Lillard and Tan (Table 4.3), suggests that the wage gain due to training depreciates at the rate of about 15-20% per year. If so, the corrected rates of return are shown[8] in Table 13.

It is noteworthy that with depreciation of 15-20% per year, half-life of the investment is no more than 2 years and 75% of its life in less than 4 years. If the profitability rates are not overstated in Table 13, this suggests that risks of capital loss resulting from technological change or from firm separations in the case of specific training do not produce a very strong deterrent to investment by firms nor a long-lasting inhibition of labor mobility.

Interestingly, fragmentary estimates of rates of return on apprenticeships in my 1962 study ranged from 9 to 18% in 1949, a similar range to the one shown in the last two columns of table 13. In that study I also estimated total volumes of investment in job training of men in three Census years (1939, 1949, and 1958--the last based on CPS) using earning growth observed in experience profiles. The procedure is described there (Mincer, 1962). That heroic approach assumed that growth of wages in the profile was due exclusively to worker investments in the labor market, including primarily job training and labor mobility (the latter accounts for less than 15% of total wage growth in my recent study). Although the data currently available still leave much to be desired, it provides more reliable estimates based on direct information on job training.

More directly than in the former study, we can estimate job training investment volumes as opportunity costs (foregone earning) of workers: if a worker who engages in training during the year spends

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[8] The estimate of corrected rates of return (r) is obtained as follows: Given the annual depreciation rates (d), equate costs or foregone earnings while training (kw) to the present value of the stream of gains (Δw) the first year following training,

$\Delta w \frac{1-d}{1+r}$ the next year,

$\Delta w \left(\frac{1-d}{1+r}\right)^2$ the year after, and so on):

$$kw = \Delta w \left[\frac{1-d}{1+r} + \left(\frac{1-d}{1+r}\right)^2 + \ldots \right] = \Delta w \frac{1-d}{r+d}$$

or

$$\frac{kw}{\Delta w} = \frac{k}{\dot{w}} = \frac{1-d}{r+d}$$

It follows that corrected $r = \frac{\dot{w}}{k} \cdot (1-d) - d$

a fraction k of his work time on training, k is the fraction of his annual earnings invested in training. If in a year the proportion of workers engaged in training is p, the fraction of their annual wages and salaries invested in training is k.p. Table 14 column 3 shows estimates of that figure for the groups studied in the PSID, NLS and CPS. These are estimates for all males.

They are pieced together (averaged) for the younger and older NLS cohorts. For the CPS, p is taken from Lillard and Tan (1986), while k is assumed the same as in the PSID. Column (k.p) represents the fraction of wages and salaries of male workers. These accounted for about $1.4 trillion in 1985. Multiplying k.p by 1.4 trillion yields dollar estimates of men's job training costs. Women's job training costs were estimated to be a half per trainee, hence 25% of the total training costs of users. Added to costs of men, this yields total dollar estimates which range from over 50 to over 100 billion as shown in column 5. Total education costs of men were estimated at $200 billion in 1985, and total education costs of men and women at $375 billion.[9] The ratios of training to education costs are shown in columns 6 and 7.

Worker investments represent a part of total investment on job training. Employer investments are the other part. How large are these? Accounting data from employers usually provide costs of *formal* training programs. That these account for a smaller part of the total is apparent from the findings of a recent survey (*Training Magazine*, 1988) where the average time a recipient spent in such a program per year was 32 hours, much less than the 150 hours in 3 months of EOPP or 11 weeks per year in the NLS. But even if such data were complete and also covered informal training, it is not at all obvious that these are costs borne by firms, that is, that they are not offset by initial reductions in wages of workers. A nearly complete offset would indeed be expected, if skills enhanced by training received in the firm were easily transferable to other firms. Firm specificity in training would, of course, enable and indeed compel firms to bear additional costs to those of workers. In principle, the best way to assess how much firms invest is to compare increases in productivity resulting from training with increases in wages. Assume that firms profit from investments in employees' work skills as much as workers do. If productivity increases more than wages, the excess is the return on costs borne by the firm. Two recent studies using very different data and approaches suggest that the productivity increase is about twice that of the wage increase caused by training. This is found by Barron et al. in the EOPP data, where a productivity scale is used to gauge the increase. Blakemore and Hoffman use aggregate production and turnover data to estimate effects of tenure on wages per hour and compare these with effects of tenure on output per hour. They too find a similar doubling of productivity compared to wages.

If these estimates are correct, total volumes of job training investments shown in Table 14 column 5 should be doubled. As shown in column 8, this would double the ratio of job training investments to

[9] Direct education costs were $250 billion for all. Opportunity costs are assumed to be 50% of direct costs (60% for men, 40% for women).

educational investments shown in column 7 to between 30% and 60% of total educational investments. For men the ratios shown in column 6 would double to between 42% and 84% of educational investments. Ratios to GNP are shown in the last column (9) on the right.

It is of some interest to note that the survey of companies (with 100 or more employees) reported expenditures on formal training programs of about $40 billion in 1987. These do not include opportunity costs of trainees in such programs nor the presumably much larger costs of informal training processes. If this figure is right, it would suggest that our high estimates are more acceptable than the low ones. The estimated hours per trainee in the micro-data we cited exceed the hours in formal programs as much as ten-fold.

The ratios of job training to educational investments of males shown in column 6 are useful for comparative purposes. In the 1962 study, this ratio was .67. If mobility gains are excluded, the ratio was .57. If a ratio calculated the same way as in 1962 has not fallen since 1958, it would mean that between 40% and 75% of observed wage growth (ration of .21 and .42 to .51) of men is attributable to their investment in training rather than 100% as was assumed in the old study. That would still make job training the major factor. However, it is quite likely that this ratio has fallen, because between 1958 and 1985 educational subsidies and educational expenditures rose 12 fold (in current dollars), while wages and salaries grew 8 fold. If training grew at the same rate as wages and salaries, we would conclude that over 60% of on-the-job wage growth is attributable to job training. Judging by my 1962 study, the decline in the ratio of job training investments to schooling investments goes back at least two decades before 1958, so it may indeed by a consequence of relative prices (to trainees) moving in favor of schooling, as already noted. If so, the role of job training in wage growth may well be nearer to our higher estimate.

From a policy perspective, the question of interest is the profitability of job training investments. The range in table 13 is quite wide. While the lower figures (column 4) do not suggest underinvestment, the higher figures do. The safe and not surprising conclusion is that overinvestment appears to be unlikely. The same conclusion, based on much more fragmentary data, was reached in 1962. If the stability is true, a hypothesis of continued long-term underinvestment would represent a challenge to research.

Even if there is no underinvestment in training, *given* the current efficiency in producing human capital, it is likely that more training would be optimal, if the quality of our education (which is widely questioned, especially at the elementary and high school levels) were improved. If training efficiency is enhanced by quality of schooling, an improvement in the latter would raise the profitability of training and the demand for it, by workers and employers. As Part II indicates, increases in demand could also result from a revival of technological progress. But such progress, too, requires a sound base of educational quality.

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TABLE 1

Factors Associated With Job Training

(1976 and 1978 cross-sections, pooled)

	RQT (1)		RQT/Ten* (2)		Incidence of Training in 1976 job (3)	
	b	t	b	t	b	t
Intercept	-1.52	3.4	.49	2.9	.16	7.0
Ed	.24	6.8	.065	2.5	.014	10.1
X	.107	3.6	-.016	6.4	-.012	8.0
X^2	-.0013	1.6	.0005	6.0	.0002	5.4
Mar	.46	1.8	.058	1.5	.011	1.8
Union	-.56	2.9	-.056	1.8	-.023	2.7
R^2	.19		.11		.15	
n	1,216		564		10,916	

TABLE 2

Job Training in Survey Week
(1976 PSID Survey)

Age	% Engaged	Their Hours	Average* Hours	Education	% Engaged	Their Hours	Average* Hours
<25	76	12.7	9.7	0-8	39	3.1	1.2
25-34	72	9.3	6.7	9-11	56	8.2	4.6
35-44	58	8.1	4.7	12	59	9.6	5.6
45-54	48	2.5	1.2	13-15	71	9.7	6.9
55-64	29	3.9	1.1	16+	58	7.2	4.2

* The third column is the product of the first two columns, yielding average hours in training of all workers.

Source: Duncan and Stafford (1980).

TABLE 3

Incidence of Company Training

Variables*	CPS Men	NLS Young Men	NLS Mature Men
Education	(1983)	(1973-1980)	(1967-1971)
<12	-.48	-.44	-.33
	(7.1)	(6.2)	(4.8)
13-15	.23	.30	.19
	(5.9)	(6.8)	(2.4)
16	.48	.45	.11
	(11.0)	(8.8)	(.9)
17+	.31	.26	-.08
	(7.0)	(4.9)	(.7)
Nonwhite	-.25	-.17	-.22
	(4.8)	(3.9)	(3.1)
Union	-.09	-.06	-.59
	(1.8)	(1.2)	(3.4)
X	-.008	+.009	-.016
	(4.0)	(2.2)	(3.2)
Tenure	.034		.004
	(11.2)		(2.0)
Mar	.39		
	(5.2)		
NU		-.02	.014
		(.1)	(2.8)

Source: Lillard and Tan (1986)

TABLE 4

Table 5: Estimates of Linear Training Equation with Machinery Costs*

Independent Variables	Full Sample	Male Only	Female Only
Constant	11.91 (0.32)	29.91 (0.59)	-31.56 (0.58)
Worker's Age	-0.020 (0.03)	0.087 (0.09)	0.055 (0.07)
Worker's Education	11.06 (4.02)	10.04 (2.68)	12.59 (3.13)
Worker's Relevant Experience	-0.258 (2.59)	-0.312 (2.15)	-0.193 (1.41)
Firm Size	0.051 (2.04)	0.046 (1.55)	0.078 (1.51)
Percentage Union	-0.385 (2.18)	-0.457 (1.95)	-0.134 (0.49)
Temporary or Seasonal Worker	-53.31 (4.02)	-73.41 (3.91)	-20.35 (1.11)
Vocational Education	28.92 (2.74)	20.66 (1.32)	41.30 (3.02)
Female Worker	-9.44 (0.95)	----	----
Cost of Machinery/10^3	0.422 (4.81)	0.428 (4.01)	0.402 (2.28)
Number of Observations	1832	1027	805
R^2	0.0472	0.0533	0.0414

* Absolute value of the t-statistics are presented in the parentheses.

Source: D. Black (personal communication), based on EOPP.

TABLE 5

(A) Effects of Training on the Duration of Tenure

Training Variables	All	Younger[a]	Older
$RQT_{>6}$	.63	.48	.86
	(3.9)	(3.0)	(2.5)
e_{RQT}	2.89	1.91	3.06
	(4.0)	(4.4)	(1.6)
n	564	330	234

(B) Effects of Training on the Probability of Staying in the 1976 firm beyond 1983

	All	Younger[b]	Older
$RQT_{>6}$	.018	.001	.019
	(2.9)	(.14)	(2.5)
n	1,437	550	887

(A) Tenure Completed by 1983.

e_{RQT} = Growth of wages over the training period.

[a]Younger, if experience in 76 was ≤ 12.

[b]Younger, if experience in 82 was ≤ 12.

Other RHS (Right Hand Side) variables as in the list in Table 8A, from "c" through "Union," plus the variable "Region."

TABLE 6

Effects of Training Reported in 1976 on Number of Separations[a] (N) in the 1968 - 1982 Period

Training Variables	All	Young[b] ($X \leq 12$)	Older (>12)
RQT	-.072 (2.4)	-.126 (2.4)	-.051 (1.6)
e_{RQT}	-.85 (3.8)	-.78 (1.8)	-.97 (3.8)
n	1471	777	694

Other RHS variables as before

[a] Per year in sample, multiplied by 15.

[b] X (Experience) in 1976.

TABLE 7

Persistence of Training Across Jobs

	RQT_{78}		RQT_{76}		$Learning_{76}$	
Indep. Var.	b	t	b	t	b	t
RQT_{76}	.29	6.4				
Prior Training			.18	1.6	.078	2.2

Other right hand variables as in Table 1.

TABLE 8

Effects of Training on Separations (1976-1983)
Conditional on Prior Mobility

Indep. Variables	RQT_{76}	Prior Training[a]	Prior Training[b]
b	-.005	-.014	.242
t	(2.6)	(1.6)	(8.8)

[a] Dummy Variable (1,0) whether prior training was required for entry into 1976 job.

[b] Frequency (per year) of interfirm moves prior to 1976.

TABLE 8A

Probability of Separating in 1976-1983
(Effects of Training and of Prior Mobility)

Variables	b	t		
c	.43	13.5		
Ed	-.012	8.1		
X^a	-.006	5.7		
X^2	.0001	2.8	Quits	Layoffs
RQT[b]	-.005	2.6	-.0025 (1.7)	-.0022 (1.9)
Mar	-.064	5.5		
Union	-.092	10.7		
P_2 Training[c]	-.014	1.6		
Sep (1968-76)	.242	8.8	Younger	Older
•RQT[b]	-.044	1.7	n.s.	-.077 (2.1)
n	759			

[a] Experience at start of 1976 job

[b] Alternative variables

[c] Training needed to enter 1976 job

TABLE 9

The Tenure-Wage Profile Components of Wages
(1976 and 1978 Cross-sections)

Sements	1976 b	1976 t	1978 b	1978 t
Pre-pos	.012	7.9	.021	11.5
D(TICP)	.042	5.5	.54	9.1
(1-D)RQT	.054	7.6	.047	8.4
(1-D)Post	.008	1.8	.012	6.8
R^2	.28		.34	

Note: D = 1, when in training; TICP = tenure in current position. Other RHS variables as in the other regressions. Experience was measured at the start of tenure.

TABLE 10

Effects of Training on Year-to-Year Wage Growth

Variable:	RQT_{76} Pooled Sample	RQT In. 'dence in 19'/6	Learning in 1976
b	.044	.067	.064
t	(3.9)	(4.6)	(4.3)

• Dummy = 1, when training or learning during the year.

TABLE 11

Training, Turnover, and Annual Wage Growth, 1968-1983

Variable	All b	All t	Younger b	Younger t	Older b	Older t
e_{RQT}	.028	4.9	.031	3.2	.020	2.7
AN[a]	-.028	2.5	-.025	1.0	-.036	3.4
Prior Trng.[b]	.010	2.5	.015	1.8	.009	2.3

[a] Frequency of separations per year (same as the dependent variable in Table 4). e_{RQT} is an alternative variable in the regression shown in Table A6.

[b] Same variable as in Tables 4A and 4B.

Other RHS variables as before.

TABLE 12

Factors in the Incidence of Unemployment*
(White Men, PSID, 1976-1981)

Variables	P(u)			P(s)		P(u/s)		Means
Intercept (c)	.41 (21.6)	.36 (15.2)	.35 (13.7)	.55 (19.5)	.61 (15.4)	.93 (120)	.81 (6.8)	P(u)=.082 P(s)=.18
Education (Ed)	-.018 (14.6)	-.0132 (11.1)	-.008 (9.8)	-.014 (7.7)	-.008 (7.8)	-.036 (6.4)	-.018 (5.8)	P(u/s)=.47 12.7
Experience (x)	-.012 (10.7)	-.0076 (7.0)	n.s.	-.018 (9.7)	n.s.	n.s.	n.s.	17.2
x^2	.0002 (6.6)	.00012 (4.2)	n.s.	.00026 (5.7)	n.s.	n.s.	n.s.	
Tenure (Ten)			-.021 (15.7)		-.038 (20.2)		-.036 (3.9)	9.1
Ten^2			.00056 (11.8)		.0012 (15.0)		.0011 (2.6)	
Married (mar)			-.038 (4.0)		-.055 (4.0)		-.061 (1.6)	.88
Union Member (Union)			-.024 (3.4)		-.076 (7.3)		.083 (2.2)	.35
Nat'l. Unempl. Rate[a] (NUR)			.007 (1.6)		n.s.		.054 (2.0)	.032
Training (RQT)			-.0026 (1.8)		-.0031 (2.1)		-.010 (2.5)	2.2

* Recall unemployment excluded except for the first left column.

[a] of white men, age 35-44

n.s. = not significant

t = t - ratio

TABLE 13

Rates of Return on Worker Investment in Training

Data Set	Male Labor Force Group	(w)	(k)	(r)%	r corrected[1] for depreciation rate (d) 20%	15%
EOPP[2]	New Hires	7.5	.25	30	4.0	10.5
$PSID_1$[3]	Trainees in 1976	6.7	.20	33	6.4	13.0
$NLSY_1$[4]	New Entrants	7.0	.22	32	5.6	12.2
$NLSY_2$[5]	Youth Cohort	12.0	.25	48	18.4	25.6
CPS[6]	All	12.0	.25	48	18.4	25.6
$PSID_2$[7]	New Hires	9.0	.25	36	6.4	13.0

[1] Corrected for finite payoff period (30 years), and for depreciation.
[2] Based on Barron et al.
[3] Based on Duncan and Hoffman Table 2.
[4] Based on Lynch.
[5] k assumed the same as $PSID_2$.
[6] w from Lillard and Tan. No information on k.
[7] k calculated for workers below age 35, Table 2, due to Duncan and Hoffman.

Note: In col. 3, r=w/k
d=depreciation rate, and corrected r=w/k(1-d)-d, in col. 4 and 5.

TABLE 14

Annual Costs of Workers and of Total Investments in Job Training

				Dollars, 1985[1]		Ratio of Training[2] to Education Costs		Total Training Costs[3]	
Data Base	k	p	(kp)%	Males	All	Males	All	$	Ratio to GNP
PSID	.20	.30	6.0	84.0	105.0	.42	.28	210	5.2%
NLS			3.0	42.0	52.5	.21	.14	105	2.6%
CPS	.20	.25	5.0	70.0	87.5	.35	.23	175	4.4%

[1] Calculated by multiplying (kp) times 1985 Wages and Salaries in billions.
[2] Education costs (in billions) include opportunity cost estimates (60% of direct costs for men, 40% for women.
[3] Doubled by inclusion of employer costs.

Note: k assumed the same in CPS as in PSID, p for CPS and for NLS from Lillard and Tan, kp for NLS is a weighted average of young and old cohort. All estimates pertain to in-house training. Outside courses excluded.

PART II: HUMAN CAPITAL RESPONSES TO TECHNOLOGICAL CHANGE IN THE LABOR MARKET

INTRODUCTION

Education and human capital can be viewed as factors of production coordinate with physical capital and "raw" labor. In this framework, a popular economic hypothesis claims that education is complementary with physical capital and with technology. In other words, the larger the capital accumulation and the greater the technological development, the more productive the trained and educated workers are. In suggesting that technological changes which generate economic growth lead to increased skill formation, the complementarity hypothesis potentially explains both the continuous upward historical trends in education, as well as the apparent puzzle of the long-run relative stability of the rate of return to education. Without growing demands by industry for educated and skilled workers, increasing supplies of such workers would depress wages of more educated relative to less educated workers reducing private and social rates of return to educational investments to zero and below. A suggested conclusion is that, in the long run, growing demands by industry are the major factor in increasing supplies of educated labor, resulting in profitability of education roughly comparable to that of other investments.[1]

The general schema for understanding economic growth is that the growth of knowledge, in which broadly conceived human capital plays a major role, generates technological changes which become embodied in physical capital and in human skills. Productivity grows as a result of the improved quality of machines and of labor. For purposes of this and other recent studies, the complementarity hypothesis provides a way of understanding the processes of improvements in labor quality by means of education and training in response to technological changes which are not (or not yet) embodied in the existing labor force.

Measuring Technical Change

In this study, as in a related previous one (Mincer and Higuchi, 1988), I use multifactor, or total factor productivity growth indices for 28 U.S. industries calculated by Conrad and Jorgenson (1985) for the period 1960-1979 and the two decade subperiods. Productivity growth is, of course, a consequence of technical change, not a measure of it. It may serve as a measure of or proxy for technological change if other factors affecting productivity growth are either unimportant or taken account of (standardized for) in the statistical applications. Thus, business cycles affect productivity growth as hired inputs fluctuate less than output, reducing productivity growth in downswings and increasing it in upswings. Similarly, economies or diseconomies of scale could affect productivity in either direction, without technological change.

[1] Stability of rates of return is observed in the U.S. since the Second World War. Also, based on data for 60 countries, Psacharopoulos (1985) finds that rates of return to education are somewhat higher than rates of return to physical capital in less developed countries and only slightly lower in advanced countries.

Perhaps the major problem arises from the method of calculating productivity growth as the difference between the rate of growth of output and (a weighted measure of) the rates of growth of the capital and labor inputs: different measures are produced depending on the concepts and degree of detail regarding definitions of outputs and inputs, as well as form of the production function connecting the two. Jorgenson's measures used here contain the more detailed adjustments of labor inputs for their education, age, and sex composition. The productivity growth residuals are thus largely purged of human capital components. For our purposes, this insures that there is little, if any, of a spurious correlation in the empirical relations between productivity growth and human capital that we are exploring.

Summarizing, the multifactor productivity growth (PG) indices when used as measures of technological change, contain two kinds of errors: systematic, such as those due to business cycles and economies of scale, and errors of measurement which are absorbed in the statistical residual which is the productivity growth measure. The problem of errors and of business cycles is mitigated by use of averages over longer periods cutting across business cycles. Our results are attenuated (understated) if sizable random errors or extraneous factors remain in the averages.

The empirical analysis reported here explores the effects of productivity growth which is not attributable to "embodied" human capital on the utilization of human capital in the labor market (Section 3), on the wage structure (Section 4), on labor mobility or turnover (Section 5) and on unemployment (Section 6).

Pace of Productivity Growth and the Utilization of Human Capital

Does more rapid technical change resulting in more rapid productivity growth bring about greater utilization of human capital? The proposition that more educated labor can deal more effectively with a rapidly changing environment, or with temporary "disequilibria" resulting from technological change, has been forcefully stated and empirically documented mainly in an agricultural context, by Schultz (1975) and Welch (1970). More recently, the effects of technical change on the educational composition of employment in industrial sectors extending to manufacturing and to the whole economy have been studied by Bartel and Lichtenberg (1987), while the effects on the incidence of job training was explored by Lillard and Tan (1986).

Using census data on the education composition of the labor force in 61 manufacturing industries in each of the years 1960, 1970, and 1980, Bartel and Lichtenberg related the proportion of employees with more than a high school education to the mean age of capital equipment in the industry, as well as to the R&D intensity (ratio of expenditures on R&D to the value of output). The R&D variable was interacted with age of capital on the assumption that new capital is most likely to embody new technology in R&D-intensive industries. They find that the relation is significant. More educated workers are utilized the younger the age of equipment, and this effect of new equipment is magnified in R&D-intensive industries.[2] The results hold for workers with relatively recent vintages of education; they are not significant for workers above age 45.

Gill (1988) relates proportions of full time workers with specified education levels in annual pooled CPS data to Jorgenson measures of multifactor productivity growth in 28 industries covering the whole economy over the periods 1960-1979 and 1970-1979. Positive correlations are observed for workers with more than high school, negative for high school dropouts and zero for high school graduates. Gill also found that the proportion of more educated workers is greater in higher PG industries within each of 8 broad occupation groups.

Lillard and Tan (1986) found a greater prevalence of job training in sectors in which (Jorgenson) measures of productivity growth were higher using CPS, NLS, and EOPP microdata samples between the late 1960s and early 1980s. In an unpublished paper, Tan (1987) focused on the relations between job training and technical change in 1983-84 CPS data, using Jorgenson-Gollop indexes for (1947-1973) and (1973-1979) periods. He found that the lagged, long-term productivity growth (1947-1973) had a positive effect on in-house training, reported in 1980-84 jobs, and a negative effect on outside (classroom) training. In the shorter run (1973-1979) productivity growth had the opposite effect: classroom training increased, while on-the-job training was either unaffected or declined. It is not clear whether the (73-39) effect represents "short-term" as distinguished from "long-run" effects, or whether it is due to the specific historical period in which productivity stagnated.

The PSID data set used in this study was described before. It is restricted to males, non-student, age 18-60. The usable sample covers about 1,200 persons each year from 1968 to 1983. The Conrad-Jorgenson indexes for 28 industries have been allocated (averaged) to the somewhat more aggregated, hence smaller number of industries (18) in the PSID, as shown in Table 1.

The distribution of education and of training across the PSID industries is reported in Table 2.

The upper panel shows the proportion of workers with more than high school education[3] as a function of concurrent and lagged (decade) productivity growth in the industry, standardizing for the rate of

[2] R&D intensity was measured by the ratio of R&D expenditures to industry sales. Griliches and Lichtenberg (1984) found that R&D intensities are positively correlated with productivity growth (PG) across industries. This lends support to the use of PG measures in the present study.

[3] Similar results were found when the proportion of workers with at least college education was used as a dependent variable.

employment growth (over both decades) in the industry.[4] Employment growth is likely to involve more frequent new hires, and these are progressively more educated, given overall trends in education. If employment growth (EG) is correlated with productivity growth, EG must be standardized for, that is, included in, the regression. The estimates shown in this panel confirm findings of Bartel and Lichtenberg and of Gill to the effect that the concurrently more technologically progressive industries tend to utilize more educated workers--as indicated by the positive and significant coefficient on PG (70-79)[5]. As was suggested, this is also true of growing industries, given productivity growth--as shown by the coefficient on employment growth (EG) over the 1960-1979 period. However, past or lagged productivity growth in a sector reduces the share of educated workers in it, as shown by the negative coefficient on PG (60-70). The finding suggests that as technology ages (making PG (70-79) small or zero), fewer educated workers are needed to handle it. This is because worker training substitutes for the use of more educated workers in handling technologies that were new a decade ago.

The dependent variable in the lower panel of Table 2 is the incidence of training reported in the year 1976 when a question on the learning content of the job was asked.[6] The estimated coefficients show no significant effects of current productivity growth on training, but positive effects of lagged productivity growth.

We may summarize the findings in Table 2 as suggesting that acceleration of technological changes in a sector, i.e. when PG (70-79) exceeds PG (60-70) raises the share of educated workers in it without significant initial effects on training. In the longer run, the use of training increases, both when the technology ages and when it grows at a steady rate [PG (70-79) = PG (60-70)]; the incidence of training is greater the higher the rate. Effects on training appear to be pronounced for younger workers (defined by labor market experience not exceeding 12 years); they are not significant for older workers.

The claim that more rapidly growing technology generates an increased demand for education and training of the sectoral work force is consistent with findings on their utilization in Table 2 and in other studies. If these processes are indeed demand-generated, wages or pay-offs to human capital should also increase, at least for some time, in such sectors. We look at such wage effects in the next section.

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[4] Only relevant variables are shown in Tables 2 through 8. A list of all independent variables used throughout is shown in Table 9. Complete regression statistics are available on request.

[5] It is likely that the (positive) coefficient on PG(70-79) is severely underestimated, as the PG measure was especially volatile in the 1970s, probably due to errors.

[6] The question was: "Are you learning on the job, so that you could be promoted, or get a better job?" This question is more suitable for the purpose of this study than alternative questions which dealt with past or cumulative training periods.

Effects of Productivity Growth on Wage Structures

In studying the effects of sectoral productivity growth on the wage structure, it is important to distinguish the effects of productivity growth on wages due to effects on the demand for labor, given its human capital composition, from effects on the demand for human capital. The analysis assumes that relevant supply curves of labor and of human capital are upward sloping, but less steeply in the longer run than in the shorter run.

The short-run effect of a productivity change on the demand for labor depends on the elasticity of demand for labor. If the increase in (marginal) productivity is neutral with respect to labor and capital, demand for labor increases if the product price elasticity of demand is greater than unity, and falls otherwise. If the productivity growth is biased in the direction of labor saving, demand for labor is reduced even with a more elastic product-demand function. In the long-run, the adverse employment effect is reduced or reversed, because demand elasticities increase over time, while consumer incomes rise throughout the economy. If productivity growth is widespread, income growth generates widespread increases in the demand for labor, but relative changes in it are affected by differential income and price elasticities across sectors. Thus, in the short run, relative sectoral wages may rise or fall in sectors with more rapid productivity growth. In the longer run, labor mobility should reduce the relative wage effects, while average wages rise.

The effects on the demand for human capital are less ambiguous, if we assume complementarity between technology and human capital in the production functions. Under this assumption, rapid technical change raises the return on human capital attracting educated workers as well as training in the newer technologies. The bias of technological change toward human capital means therefore that wages of more educated workers increase relative to wages of less educated workers in sectors with more rapid productivity growth. Even if education is held constant in our micro-data, the interaction of education and productivity growth in wage functions ought to be positive, at least in the short run. And, to the extent that workers trained in the new technologies bear some of the costs of investment in training (by accepting initially lower wages), their wages grow over the period of training, as their productivity is raised by training.

We may summarize the implications of this analysis for the purpose of empirical testing as follows:

1. In the short run, relative (to other sectors) wages of labor of given "quality" (human capital composition) may increase or decrease in sectors with more rapid productivity growth.

2. The demand for educated workers would increase relative to demand for less educated workers in such sectors, resulting in a higher rate of return to education in these sectors.

3. In the longer run this sectoral advantage should erode, as a result of greater mobility of educated workers to "progressive" sectors. This mobility may take the form of inter-sectoral flows of experienced workers, or of inflows of young labor force entrants to such sectors.

4. The profitability of training should increase following the initially increased demand for educated workers. Once training spreads and deepens we should observe steeper wage profiles in the wage structure of more progressive sectors.

Table 3 shows estimates of pooled wage functions over the years 1976 to 1983 in the PSID.[7] The dependent variable is the logarithm of wages. A rich set of independent variables (listed in Table 9) is chosen to provide the information to verify or contradict the implications described above.

Findings in Table 3 indicate that:

1. The short run effect of higher productivity growth in a sector is to reduce wages in it relative to wages in other sectors, but in the longer run this effect vanishes. The coefficient on PG (70-79) is negative, but positive though perhaps smaller on PG (60-70).

2. Sectors with more rapid productivity growth show higher rates of return to education -- coefficients on the interaction variable Ed x PG are positive both in the short (70-79) and longer run (60-79). They are significant both for younger and older workers, the latter defined as having more than 12 years of work experience.

3. Since training increases in the longer run in the more progressive sectors we should observe steeper wage growth in industries with higher longer-run productivity growth. This, indeed, is observed in Table 3 in terms of significant positive coefficients of the interaction variable PG (60-79) x Tenure. The interaction coefficient on the long run PG (60-79) is larger than on the short-run PG (70-79), as training processes follow the initial

[7] Prior to 1976, wage rates at the point of the survey are not available. An inferior proxy, average hourly earnings in the preceding year, is usable.

acceleration of more educated hires. The coefficient for younger workers is larger than for older workers, as might be expected.

We should note that wage growth with tenure (measured by the interaction coefficients) are observed net of experience prior to entering the current firm. Wage growth in the firm is ascribable to training whether or not the latter is firm specific, that is whether or not it is usable in other firms. If the training is largely general, wage growth should also be steeper over total work experience in the industry, not only within the current firm. It is unlikely, however that a person observed working in an industry at a particular survey has been employed in it all along, while all of tenure is clearly spent in the indicated industry.

Evidence that rapid productivity growth, ascribable to technical change, generates an increased demand for educated labor and for training appears also in the CPS data (annual, 1963-1984) analyzed by Gill (1988). Using Jorgenson productivity growth indexes in wage regression for full time male workers age 18 to 65, he finds that long-run productivity growth (1960-1973) raises the level and steepens the experience-wage profiles of more educated workers while it lowers and flattens the profiles of less educated workers. No interactions appear as a result of very short-run productivity growth (1974-1979), but wage levels are slightly lowered in all education groups.

A link between findings in Table 3 and those in Table 2 that can be explored is the following: if the increased profitability of education in a sector is the incentive which leads more educated workers into that sector, we should observe a greater probability that more educated labor force entrants and job changers move into the higher productivity growth sector.

The upper panel of Table 4 shows that more educated workers tend to move into industries with high level PG, when they change jobs: holding the level of PG of the past job's industry constant, the higher the level of education the higher the PG in the industry of the new job. The education coefficient is positive, but significant only for the young workers ($X \leq 12$). The moves respond to current (70-79), not to longer run or lagged productivity growth (coefficients are not significant, not shown here).

In the lower panel, the dependent variable is the education dummy ($Ed > 12 = 1$), and the relevant independent variable (among others) is the interaction of PG with a dummy (d) denoting that the worker is a recent labor force entrant ($x < 4$). We find that this variable is positive and significant even among young workers. New entrants who find jobs in "high-tech" industries are more likely to be better educated than those who enter other industries.

Effects of Productivity Growth on Labor Turnover

We found in Section 3 that more training is likely to be prevalent in sectors where productivity growth is more rapid. The proposed rationale is that technological changes in production processes underlying productivity growth require training and retraining of workers. Theoretically, this rationale may be questioned, for the following reasons: if skills acquired in training become rapidly obsolete, the incentives of workers to invest in training are reduced. However, if obsolescence is only partial, and successive retraining adds to skills, incentives of workers may not be impaired, especially if the employer assumes a major share of the training costs.

Although the threat of even partial obsolescence may be a deterrent to workers' investment in training, the firm must persist in technological adaptation in order to remain competitive. In introducing new technologies it must employ a work force with complementary and changing worker skills. The latter may be achieved by training workers for flexibility and by retraining, or by greater turnover to replace workers without the new skills with workers who are already knowledgeable, perhaps as a result of new vintages of school education. However, if technological adaptation or changes are to some extent firm-specific, the firm will tend to rely on training its workers after initially hiring more adaptable and educated workers who, in turn, will serve as the "teachers." Human capital management in Japanese firms illustrates these responses under conditions of most rapid productivity growth in recent times.[8] Qualitatively similar adjustments characterize high productivity growth sectors in the U.S. To the extent that educational upgrading is the initial response in U.S. firms, turnover may even increase as productivity growth accelerates, but with persistent progress and established training processes, turnover should decline.

We have seen in Table 2 that the response to concurrent productivity growth is an increase in the proportion of educated workers, while the longer-run response is an increase in training. Table 5 shows that turnover (separation) rates behave correspondingly. They decline in the sectors with long-run high rates of productivity growth, and are weakly or not at all affected for younger workers in the sectors with concurrently accelerating productivity growth. The decline in separations is smaller for more educated workers, as the interaction coefficient on (PGxEd) reveals.

The negligible effect of concurrent productivity growth (70-79) on separation rates conceals some interesting findings. In the short run, separations actually increase for the more educated workers (16+). As Table 6 indicates, the increase is due to quits, not to layoffs. Quits increase among young workers, while layoffs decline slightly for all age groups. In the longer run, (60-79) or (60-70 lagged), quits decline and layoffs decline more strongly for older workers.

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[8] Mincer and Higuchi (1988).

An interpretation of these findings is that, in the short run, rapid technological changes increase hiring of more educated workers. Some of the new hires come from other firms within the sector which shows up in increased quits of the more educated, especially younger, workers in the sector. Other new hires of the better educated young workers come from inflows into sectors with higher rates of productivity growth from other sectors, as was documented in Table 4. In the longer run, when training activities increase in high productivity growth sectors (as was shown in Table 2), separation rates in them decrease. Even then, layoffs are reduced more than quits. The asymmetry in effects on quits and layoffs which appears here was not observed in effects of training not linked to technological change.[9] The likely reason, already stated, is that firms adopting technological innovations tend to finance much of the training of workers who may be more reluctant to invest in such training in view of looming obsolescence.

Effects on Unemployment

The reduction in turnover, especially in layoffs, implies that the incidence of unemployment would also decline among experienced workers, at least in the longer run. This is because the probability of encountering unemployment P(u) is a product of the probability of separating from a job P(s) and of the conditional probability of becoming unemployed when separated P(u/s). Table 5 shows that P(s) declines in the longer run, and only slightly in the short-run among older workers. Table 6 shows that conditional unemployment, i.e., unemployment of movers, also declines among older workers while younger movers are not affected.

Table 7 shows the effects made predictable by Tables 5 and 6: unemployment incidence arising during separations declines in sectors with rapidly growing productivity in the long run among all workers, but less so in the short run, especially among young workers.

The probability or incidence of unemployment P(u) is not the same thing as the unemployment rate (u). Does productivity growth reduce the latter as well? To answer this we must observe the effects of PG on the duration d(u) of unemployment, since--ignoring periods of non-participation in the labor force--the unemployment rate is the product of P(u) and d(u).[10] A priori, there is little reason to expect any effects on duration, since, in the short-run at least, PG increases the demand for labor in some sectors and reduces it in others. However, the asymmetric effects on quits and layoffs suggest that duration should decrease, at least in the longer run, since layoff unemployment is characterized by longer duration than quit unemployment.[11]

[9] Mincer (1988a), Part I, Table 8A.

[10] Mincer (1988b).

[11] Mincer (1986).

Table 7 does, indeed, show reductions in duration of unemployment, small in the short run and larger in the longer run.

The findings that technological change tends to reduce unemployment in "high-tech" sectors runs counter to the widely held fear of the "specter of technological unemployment." Economic theorists from Ricardo to Hicks held technological unemployment to be a likely possibility in the short-run but less likely in the longer run. And workers' fear of technological displacement is not uncommon. Our finding that, on average, unemployment is reduced in the longer run and not increased in the short run seems rather surprising. Yet what the old analyses missed is the insight that two processes are set off by technological changes: a waning series of displacements and a waxing process of worker adaptation which makes his attachment to the firm more durable. Our data suggest that the two forces practically cancel in the short run, and that the second--due to human capital responses--dominates in the long run.[12]

Several considerations are worth noting in conclusion: (1) Our "short run" is a decade, which may conceal shorter-run effects. On the other hand, in the very short run, it is difficult to disentangle effects of productivity shocks from effects of business cycle phases. (2) Growth of the "open" economy, that is, of world trade, in recent times may have placed the specter of technological unemployment in productivity-lagging rather than -leading sectors. This is entirely consistent with our findings, and with the apparent paradox that the country (Japan) which experienced the most rapid productivity growth in recent decades had also the lowest unemployment rates. (3) We did not distinguish explicitly between technological changes resulting in cost-cutting in producing old products and the introduction of new products. The latter are more likely to have positive employment effects even in the short run, and may create new industries at a more detailed level of aggregation. (4) Indexes of labor productivity growth (LPG) were also used as alternatives to our total (multifactor) productivity growth (PG) in our equations, but not shown in this report. They were no less significant than the PG indexes, suggesting that human capital complementarity applies both to technical change and to physical capital (see Section 2, above), though vintages of the latter clearly matter. (5) As always, the findings cannot be viewed as definitive until they are replicated on more data sets and longer time periods.

[12] Training and retraining responses appear to be quicker in Japan where productivity growth has been much more rapid than in the U.S. in the recent (post-1950) decades. In Japan all the "longer run" effects show up in the concurrent decade (Mincer and Higuchi, 1988). However, some of the lags in the U.S. data may be an artifact of the more error-prone productivity growth data in the 1970s.

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TABLE 1

Productivity Growth Indexes (Percent per Year)

INDUSTRY	PG6079	PG6070	PG7079	LPG6079
1. Agriculture	1.18	1.67	0.64	5.14
2. Mining	-3.19	0.68	-7.32	-0.39
3. Construction	-0.73	-0.10	-1.43	-1.22
4. Food, etc.	0.00	0.30	-0.33	2.58
5. Leather, textile mill, apparel, etc.	1.27	0.99	1.57	2.61
6. Stone, clay, glass, precision instruments, lumber, wood, furnitures	0.17	0.45	-0.41	2.26
7. Printing, etc.	1.01	0.10	2.03	1.41
8. Chemicals, petroleum, rubber, plastic	0.48	1.51	-0.63	2.26
9. Metal industries	0.13	0.48	-0.25	1.66
10. Machinery, including electrical	1.32	0.55	1.31	2.82
11. Motor vehicles and other transportation equipments	0.63	0.72	0.54	2.27
12. Misc. manufacturing	-0.05	0.87	-1.06	2.02
13. Trade	0.92	1.14	0.68	1.84
14. Finance, insurance	0.41	0.00	0.86	1.16
15. Transport and communication	1.01	0.87	1.17	2.29
16. Utilities	0.00	1.50	-1.64	2.78
17. Services	-0.27	-0.72	0.24	0.94
18. Paper, etc.	0.45	0.87	0.00	2.69

Source: Conrad and Jorgenson (1985)

TABLE 2

Distribution of Education and Training by Industry
(PSID Males)

(A) Dependent Variable: Proportion of Workers with More than 12 Years of Education (1968 to 1983 pooled)

Independent Variables	All		Younger ($X \leq 12$)		Older ($X > 12$)	
PG (70-79)	.032	.043	.031	.045	.035	.044
	(10.8)	(14.8)	(6.5)	(9.5)	(2.4)	(12.1)
PG (60-70)		.040		-.038		-.038
		(6.5)		(3.5)		(4.5)
EG (60-79)		.086		.084		.088
		(21.9)		(13.8)		(17.7)
R^2		.07		.08		.07
n		16,984		6,692		10,294

(B) Dependent Variable: Learning on the Job in 1976

Independent Variables	All	Younger	Older
PG (70-79)	-.012	-.026	-.002
	(1.0)	(1.6)	(.1)
PG (60-70)	.069	.107	.032
	(2.6)	(2.6)	(.9)
EG (60-79)	.031	.049	.006
	(2.1)	(2.3)	(.3)
Educ	.023	.020	.025
	(4.1)	(1.9)	(3.8)
X	-.004	-.011	-.009
	(2.7)	(1.6)	(3.7)
R^2	.04	.03	.05
n	1,121	492	629

Note: t-statistics in parentheses

TABLE 3

Wage Functions
(PSID, 1976-1983, pooled)

Variables[1]	All	Younger	Older
PG (70-79)	-.096	-.074	-.106
	.096	(2.4)	(5.2)
PG (60-70)	.089	.051	.109
	(8.8)	(2.8)	(7.3)
PG (60-79) x Ed	.019	.019	.020
	(9.1)	(5.0)	(7.5)
PG (70-79) x Ed[2]	.005	.004	.006
	(4.1)	(1.6)	(3.5)
PG (70-79) x Ten	.0034	.008	.0025
	(5.1)	(2.4)	(3.2)
PG (70-79) x Ten[2]	.0022	.0036	.0021
	(5.6)	(1.6)	(4.8)
EG (60-79)	.012	.020	n.s.[3]
	(2.8)	(3.2)	
n	6,442	2,573	3,869

[1] Other variables listed in Appendix Table 1.

[2] Used as alternative to variable above it.

[3] n.s. -- not significant.

TABLE 4

Inter-industry Mobility
of Educated Workers
PSID (68-83)

(1) Dependent Variable: PG (70-79) of Movers' Destination Industry

Variables	All	Younger	Older
PG at Origin	.56	.54	.59
	(28.4)	(21.9)	(18.0)
Educ	.026	.016	.033
	(2.7)	(1.6)	(2.4)
n	2,299	1,463	836

(2) Dependent Variable: Ed>12 (Dummy=1)

Variables	All		Younger	
PG (60-79)	.027		.034	
	(5.3)		(3.8)	
PG (70-79)		.039		.039
		(13.2)		(7.5)
PG x DX[1]	.101	.042	.065	.038
	(6.6)	(4.2)	(3.8)	(3.4)
EG (60-79)	.095	.071	.099	.078
	(30.7)	(30.5)	(20.4)	(20.7)

[1] DX = 1, if $x \leq 4$

Note: Standardized for experience (X) and Year Dummies among all other variables.

TABLE 5

Effects of Productivity Growth on Turnover
(Pooled, 1968-1983)

(A) Separations

Variables	All		Younger		Older	
PG (60-79)	-.016 (4.7)	-.078 (5.1)	-.013 (2.2)	-.094 (2.7)	-.017 (4.5)	-.068 (4.6)
PG x Ed		.005 (4.2)		.006 (2.4)		.004 (3.6)
PG (70-79)	-.004 (2.2)	-.040 (4.1)	n.s.	-.045 (2.0)	-.006 (2.7)	-.026 (3.7)
PG x Ed		.003 (3.8)		.003 (2.0)		.0026 (3.3)
PG (60-70)		-.018 (4.9)		-.018 (2.9)		-.017 (4.0)

(B) Quits

Variables	All		Younger		Older	
PG (60-79)	n.s.	-.019 (1.6)	n.s.	n.s.	-.005 (1.9)	n.s.
PG x Ed		.0015 (1.6)		n.s.		n.s.
PG (70-79)	.003 (2.0)	-.012 (1.6)	.007 (2.4)	n.s.	n.s.	n.s.
PG x Ed		.0013 (2.1)		n.s.		n.s.
PG (60-70)		-.009 (3.1)		-.007 (1.4)		-.010 (3.4)

(C) Layoffs

Variables	All		Younger		Older	
PG (60-79)	-.012 (5.4)	-.050 (4.7)	-.013 (3.2)	-.039 (1.7)	-.011 (4.4)	-.054 (5.2)
PG x Ed		.003 (3.6)		n.s.		.004 (4.2)
PG (70-79)	-.006 (4.3)	-.026 (3.7)	-.005 (2.2)	n.s.	-.006 (3.9)	-.029 (4.3)
PG x Ed		.0016 (3.0)		n.s.		.002 (3.5)
PG (60-70)		-.009 (3.4)		-.011 (2.5)		-.006 (2.1)

TABLE 6

Effects of Productivity Growth on Quits
and on Unemployment of Job Movers
(Pooled, 1968-1983)

(A) Conditional Quits

Variable	All		Young		Old	
PG (70-79)	.026		.029		.027	
	(3.6)		(3.3)		(2.0)	
PG (60-79)		.029		.039		n.s.
		(2.5)		(2.8)		
PG (60-70)	n.s.		n.s.		-.043	
					(1.7)	

(B) Conditional Unemployment

Variable	All		Young		Old	
PG (70-79)	-.014		n.s.		-.032	
	(1.9)				(2.5)	
PG (60-79)		-.020		n.s.		-.054
		(1.7)				(2.7)
PG (60-70)	n.s.		n.s.		n.s.	

TABLE 7

Effects of Productivity Growth on Unemployment Incidence
(1968-1983, pooled)

(A) Recall Unemployment Excluded

Variables	All		Younger		Older	
PG (60-79)	-.013	-.056	-.010	-.061	-.016	-.052
	(5.5)	(5.0)	(2.2)	(2.4)	(5.9)	(4.8)
PG x Ed		.0035		.004		.003
		(3.9)		(2.0)		(3.4)
PG (70-79)	-.006	-.028	-.004	-.029	-.007	-.026
	(3.8)	(3.8)	(1.5)	(1.7)	(4.3)	(3.7)
PG x Ed		.002		.002		.0017
		(3.2)		(1.5)		(2.9)
PG (60-70)		-.010		-.007		-.013
		(3.7)		(1.4)		(4.2)

(B) Recall Unemployment Included

Variables	All		Younger		Older	
PG (60-79)	-.024	-.068	-.023	-.130	-.023	-.038
	(6.8)	(4.2)	(4.2)	(3.9)	(5.3)	(2.1)
PG x Ed		.0035		.008		n.s.
		(2.8)		(3.2)		
PG (70-79)	-.012	-.040	-.013	-.082	-.011	-.022
	(5.7)	(3.8)	(3.7)	(3.8)	(4.3)	(1.9)
PG x Ed		.002		.0054		n.s.
		(2.8)		(3.2)		
PG (60-70)		-.014		-.012		-.016
		(3.7)		(1.9)		(3.2)

Note: Interaction variables pertain to period in the PG variable above it.

TABLE 8

Effects of Productivity Growth on Weeks Spent in Unemployment in the Past Year (1968-1983, pooled)

Variable	All		Younger		Older	
PG (60-79)	-1.01	-1.27	-.65	-.79	-1.39	-1.77
	(4.0)	(4.4)	(1.9)	(2.0)	(3.8)	(4.2)
EG		-.34		n.s.		-.58
		(1.8)				(1.9)
PG (70-79)	-.57	-.56	-.40	-.38	-.75	-.70
	(3.6)	(3.4)	(1.8)	(1.7)	(3.4)	(3.0)
PG (60-70)		-.94		n.s.		-1.23
		(2.1)				(1.7)
EG		-.44		n.s.		-.69
		(1.9)				(1.8)

TABLE 9

Dependent Variables
Sample Sizes, Means, and Standard Deviations

VARIABLES		ALL		YOUNG		OLD	
ED_DUM	1 IF EDUCI > 12	19002	0.42 (0.49)	7576	0.52 (0.49)	11426	0.35 (0.47)
LEARN76		1279	0.54 (0.49)	576	0.57 (0.49)	703	0.51 (0.50)
LOGWAGE	LOG OF SALWAG	12811	1.47 (0.41)	5482	1.39 (0.39)	7329	1.53 (0.41)
SEPN		19563	0.13 (0.34)	8700	0.20 (0.40)	10863	0.08 (0.27)
QUIT	1 IF Q'	19563	0.07 (0.26)	8700	0.11 (0.32)	10863	0.03 (0.19)
LAYF	1 IF LAID OFF	19563	0.05 (0.23)	8700	0.08 (0.27)	10863	0.03 (0.18)
QUIT_S	CONDITIONAL QUIT	2714	0.53 (0.49)	1823	0.56 (0.49)	891	0.48 (0.49)
UNEMP_S	CONDITIONAL UNEMPLYMT	2714	0.48 (0.49)	1823	0.48 (0.49)	891	0.47 (0.49)
USEPN	INCID. OF UNEMPL. (RECALL EXCL)	19563	0.06 (0.24)	8700	0.10 (0.30)	10863	0.03 (0.19)
UHRDUM	INCID. OF UNEMPL. (RECALL INCL)	19668	0.15 (0.36)	8747	0.20 (0.40)	10921	0.12 (0.32)
UNWKS	DUR. OF UNEMPLOYMENT IN WKS	3068	11.26 (11.40)	1754	11.47 (11.51)	1314	10.98 (11.26)

Independent Variables
Sample Sizes, Means, and Standard Deviations

VARIABLES		ALL		YOUNG		OLD	
EDUCI	YRS OF EDUCATION	19002	12.70 (2.86)	7576	13.45 (2.35)	11426	12.20 (3.06)
PREEXP	EXP - TENH	15117	9.02 (8.46)	5489	3.52 (2.97)	96281	12.17 (8.96)
EXP	YRS OF EXPERIENCE	18804	17.94 (10.99)	7378	7.02 (3.25)	11426	24.99 (8.08)
TENH	TENURE	15341	9.63 (8.41)	5713	4.06 (3.01)	9628	12.94 (8.83)
MRDNOW	MARITAL STATUS	19047	0.89 (0.30)	7621	0.84 (0.36)	11426	0.93 (0.24)
RACE	1 = BLACK 0 = WHITE	19047	0.06 (0.25)	7621	0.06 (0.25)	11426	0.07 (0.25)
UNM	UNION MEMBERSHIP	18966	0.31 (0.46)	7567	0.26 (0.44)	11399	0.33 (0.47)
CUR	NATIONAL UNEMPLYM RATE	19047	6.71 (1.78)	7621	6.87 (1.73)	11426	6.60 (1.81)
PG6079		17031	0.34 (0.75)	6737	0.30 (0.76)	10294	0.37 (0.75)
PG6070		17031	0.44 (0.71)	6737	0.41 (0.74)	10294	0.47 (0.68)
PG7079		17031	0.15 (1.26)	6737	0.13 (1.25)	10294	0.17 (1.26)
PG6079ED	PG6079 * EDUCI	16986	4.32 (9.76)	6692	3.98 (10.29)	10294	4.54 (9.39)
PG6079TN	PG6079 * TENH	13706	3.80 (10.39)	5046	1.30 (3.75)	8660	5.25 (12.53)
PG7079ED	PG7079 * EDUCI	16986	2.34 (16.13)	6692	1.99 (16.87)	10294	2.57 (15.62)
PG7079TN	PG7079 * TENH	13706	1.87 (17.13)	5046	0.52 (6.02)	8660	2.66 (21.02)
XD	XD = 1 IF EXP < = 4	18804	0.09 (0.29)	7378	0.24 (0.42)	11426	0.00 (0.00)

col (1), sample size
col (2), mean
standard deviation (in parenthesis)