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HUMAN CAPITAL RESPONSES TO TECHNOLOGICAL CHANGE IN THE LABOR MARKET

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ABSTRACT

In a broad sense, the relation of human capital to economic growth is reciprocal. This study focuses more narrowly on labor market consequences of human capital adjustments to the pace of technological change. Using Jorgenson's multifactor productivity growth indexes for industrial sectors in the 1960's and 1970's the study explores effects of differential pace of technological changes on industry demands for educated and trained workers as reflected in PSID data covering the 1968 to 1983 period. The findings show relative increases both in quantity demanded (utilization) and in price (wages) of skilled workers in the more progressive sectors. Steeper wage profiles, lesser turnover, and lesser unemployment characterize labor in sectors whose productivity grew faster in preceding years. The growth of sectoral capital intensity produces similar effects. But, as newer vintages of capital contain new technology, the skill bias of capital intensity partly reflects the skill bias of technology.

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1. Introduction

In my view, human capital plays a dual role in the process of economic growth: (1) As a stock of skills -- produced by education and training -- it is factor of production, coordinate with physical capital and with "raw" (unimproved, unskilled) labor, in producing total output. (2) As a stock of knowledge it is a source of innovation, a basic cause of economic growth.[1]

A particular elaboration of the view of human capital as a factor of production implies that the marginal contribution of human capital to output is greater the larger the volume of physical capital. This is so, if physical capital is more complementary with human capital than with unskilled labor.[2] In the older analyses, physical capital accumulation was the mainspring of economic growth. In it, the complementarity hypothesis implies a differential growth of demand for skilled and unskilled labor, as capital accumulates. The resulting increase in skill wage differentials induces increased acquisition of human capital. In turn, the increased supply of human capital limits the wage differentials to an equilibrium level, at which this investment is as profitable at the margin as other kinds of investment.

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1 An exposition of this view is contained in Mincer (1984).

2 Griliches (1969).

In the above analysis, the growth of human capital is a consequence of exogenous accumulation of physical capital. If so, the growth of human capital contributes to economic growth, but is not the prime cause of it. But by the same complementarity hypothesis, the growth of physical capital could analogously be a response to exogenous increases in human capital. However, theoretical and empirical economic analysis rejects the notion of exogenous investments. Instead, emerging opportunities for profit must be looked to for the source of growth creating investments: Cost reducing and product innovating changes in technology are the engines of growth which propel all factors of production by increasing their productivity. According to this theory (Solow, 1957), growth in output results from growth of physical capital, growth of labor, and improvements in technology.

Whether or not technological improvements are exogenous, as scientific and practical knowledge grows, or endogenous to, for example, R&D investments, the complementarity hypothesis may be extended to include technological change. That is to say that technological change is more complementary with human capital than with raw (unskilled) labor. The implications of growth of technology for human capital remain the same as before, mutatis mutandis. Also, to the extent that technical change is "embodied" in physical capital, human capital is complementary with new vintages of physical capital, a hypothesis tested by Bartel and Lichtenberg (1987) for the school education component of human capital. Indeed, the "embodiment" of technical change in both physical and human capital, that is the improvement in their "quality" is another way of perceiving complementarity of both capital factors with technological change.

We should note, that although we focus here on human capital as a factor of production which responds to technical change rather than as a source of the latter, this does not mean that the growth of such human capital is merely an effect rather than a cause of economic growth: Even in the narrow sense of imporvement in labor "quality," the growth of human capital contributes to economic growth by raising productivity.[3]

Several implications of the complementarity or skill-bias hypothesis are explored empirically in this initial study:

1. A more rapid pace of technological progress should induce increased inputs of human capital, formed at school and on the job, by making their acquisition more profitable. Both utilization and wage effects ought to be observable.

2. To the extent that technical innovations are firm specific, needed on the job investments in worker training or retraining lead to more durable attachments of workers to firms, that is to lesser job mobility. Regardless of the degree of firm specificity, increased worker investment in job training should steepen their wage profiles.

3. The time sequence in these human capital adjustments may differ as between the hiring of workers with needed education and the training and retraining of others. Skill adjustments may first be obtained by hiring policies, and later by training as the processes become more routinized. If so, effects on labor mobility are also different in their time sequence.

4. The job mobility phenomena have implications for the incidence of unemployment in the relevant sectors. The much debated and little or partially explored question of technological unemployment can be more thoroughly and comprehensively explored in our empirical analysis.

All these implications are relevant to economies differing in rates of technological progress, or to the same economy in different periods, or to different sectors of the same economy in a particular time period. This study uses industry sectors for an initial analysis. Changes over time and

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3 According to Jorgenson (1989), the contribution of labor quality over the period 1947-1985 to annual growth of output per hour worked in the US was about two-thirds of the contribution of the (physical) capital stock per hour worked.

differences among countries will be considered at a later stage, although data for such analyses are much-less adequate.

2. 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 in the statistical applications. Among the other factors, 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, as inputs grow.

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 are the only ones that contain the more detailed adjustments of labor inputs for their "quality" components, such as education, age, and sex composition. The productivity growth residuals are thus largely purged of human capital components. For our purposes this insures that shifts of the production function are not attributable to human capital, that is 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 and by use of unemployment rates as "standardizing" variables.. Our results are attenuated (understated) if sizable random errors, or extraneous factors remain in the averages.

We proceed to the empirical analysis which explores the effects of productivity growth 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). A summary and concluding remarks follow (section 7).

Although the focus of this paper is on the relation between technological change and human capital, a preliminary attempt is also made to explore the effects of capital-skill complementarity, given technological change. This is done by including growth of capital-labor ratios (GR) alongside the sectoral productivity growth (PG) variables in the equations.[4]

3. 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

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4 In the version presented at the Conference, the capital intensity variable (GR) was not included. In addition, the PSID data set was augmented by the 1984 and 1985 surveys.

whole economy have been studied by Bartel and Lichtenberg (1987) and by Gill (1988), 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 more educated workers are utilized the younger the age of equipment, and that this effect is magnified in R&D intensive industries.[5] 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 levels of education in annual pooled CPS data to Jorgenson's measures of multifactor productivity growth (PG) 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.

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 1960's and early 1980's. 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 1983-4 jobs, and a negative effect on outside (classroom) training. In the shorter run (1973-79) productivity growth had the

5 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.

opposite effect: classroom training increased, while on-the-job training was either unaffected or declined. It is not clear whether the (73-79) 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 used here is restricted to males, non-students, age 18-60. The usable sample covers about 1,100 persons each year from 1968 to 1985. The Conrad-Jorgenson indexes for 28 industries have been allocated (averaged) to the more aggregated, hence smaller number of industries (18) in the PSID. The are shown in Table 1 together with two other industry variables: Growth of capital-labor ratios (GR) and growth of employment (EG) over the 1960-1979 period.

The distribution of education and of training across the PSID industries is reported in Table 2, as affected by productivity growth (PG) and capital-intensity (GR) variables. Other independent variables included in the equations, but not shown in the Tables are listed in the summary statistics of Table 7. They are: Years of education, years of work experience, marital status, race, union membership, unemployment rates, region (the latter not listed). All Tables also distinguish young workers (defined as having 12 or fewer years of work experience) from older workers.

The upper panel (A) of Table 2 shows the proportion of workers with more than high school education[6] as a function of productivity and capital-intensity growth, standardizing for the rate of employment growth in the industry. Employment growth is likely to involve more frequent new hires, and these are progressively more educated, given overall trends in education. The estimates shown in this panel confirm findings of Bartel and Lichtenberg and of Gill to the effect that concurrently and over the longer run more technologically progressive industries tend to utilize more educated workers -- as shown by the positive and significant coefficient on PG (70-79) and on PG (60-79). As was suggested, this is also true of industries with growing employment, given productivity growth -- as shown by the coefficient on employment growth (EG) over the 1960-79 period. Net of the other

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

factors, growth of capital intensity (GR) also appears to call for greater utilization of educated workers, as implied by the capital-skill complementarity hypothesis.

Although concurrent productivtiy growth (PG 70-79) has the predicted positive effect on utilization of educated workers, the effect of past or lagged productivity growth (PG 60-70) in a sector is to reduce the share of educated workers in it. The finding implies that as technology ages (making PG (70-79) small or zero), fewer educated workers are needed to handle it. Apparently, worker training substitutes for the use of more educated workers in handling technologies that were new a decade ago, as is suggested by findins in the two lower panels.

The dependent variables in lower panel (B) of Table 2 is the incidence of training reported in 1976 when a question was asked on the presence of a learning content in the job.[7] The variable is 1 if the answer was positive, zero otherwise. The estimated coefficients show no significant effects of current productivity growth on learning on the job (panel B) but positive effects of lagged productivity growth. No significant effects apply to older workers. Apparently, training processes follow technological change with a lag, while increased utilization of educated workers is the first response. With technology a decade old training is common practice and the need for more educated workers subsides.

In panel (C) the dependent variable is whether prior training was required for the job held in 1976 and again in 1985, when this question was asked. The results are similar to those in panel (B). The negative sign of the coefficient on concurrent productivity growth may mean that training on the old job is less or not relevant to current technology in the new job.

Shares of educated workers increase in industries where employment is expanding. As shown by the positive coefficients on EG, in such industries training expands also, mainly for younger workers. These positive effects of sectoral employment expansion on human capital may represent

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7 The question was: "Are you learning on the job, so that you could be promoted, or get a better job?"

labor demand induced effects of persistent long-run productivity growth trends. They may also, independently of productivity growth, reflect greater scope for more durable employee attachment to firms in such sectors. Stable or growing industries provide a more secure environment for job training -- to which education appears to be complementary.[8]

In sum, sectoral utilization of educated workers is increased by concurrent productivity growth, especially if it accelerates, by the growth of capital intensity, and by the growth of employment. Training activities lag behind educational utilization when productivity growth accelerates; they are more common in faster growing industries, but somewhat surprisingly, do not appear to be affected by the long-run growth of capital intensity.

The claim that more rapidly growing technology increases demand for education and training is generally consistent with findings on their utilization in Table 2 and in other studies. If so, wages or pay-offs to human capital should be higher, at least for some time, in progressive sectors. We look at such wage effects in the next section.

4. Effects of Productivity Growth on Wage Structures

In studying the effects of sectoral productivity growth on the wage structure, it is important to distinguish its effects 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 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 the product. If the increase in (marginal) productivity is neutral with respect to labor and capital, demand for labor increases if the product price elasticity is greater than unity, and falls otherwise. If productivity growth is labor saving, demand for labor is reduced even with a more

8 For evidence see Mincer (1988b).

elastic product demand function. In the long-run, the adverse employment effect is reduced or reversed because demand elasticities increase. If productivity growth is widespread, income growth also increases the overall derived demand for labor. Thus, in the short run, relative wages may rise or fall in sectors with more rapid productivity growth. In the longer run, income growth and labor mobility spread the real wage gains to all sectors.

The effects on the demand for human capital are more predictable 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 encouraging training in the newer technologies. The bias of technological change toward human capital, therefore, means that in the short run wages of more educated workers increase more, or are reduced less in sectors with more rapid productivity growth. Empirically, 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.

To the extent that trained workers bear some of the costs of investment in training, their wages grow during training as their productivity is raised. Steeper wage profiles in the firm should be observable when productivity growth persists over longer periods-recall that training follows (PG) with some lag in our data.

We may summarize the empirical implications of this analysis:

1. In the short run, relative sectoral 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 should increase relative to demand for less educated workers in these sectors, resulting in a higher rate of return to education in these sectors.

3. In the longer run, this sectoral advantage should erode as educated workers migrate to "progressive" sectors and firms within sectors and as young labor force entrants are hired in these sectors.

4. The profitability of training should increase following the initially increased demand for educated workers. As training spreads, wage profiles in progressive sectors should steepen.

Table 3 shows estimates of pooled wage functions over the years 1976 to 1985 in the PSID.[9] 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.

Table 3 indicates that:

1. In the short run, higher productivity growth reduces wages in the sector relative to wages in other sectors. But in the longer run, this effect reverses: The coefficient on PG (70-79) is negative, but positive and larger on PG (60-70). Long-run effects of employment growth were also positive. Growth of capital intensity showed no effects, given the other variables.

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 concurrent growth (70-79) and in the longer run (60-79). They are significant both for younger and older workers. Somewhat unexpectedly, the coefficients do not decline in the longer period.

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

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9 Prior to 1976 wage rates at the point of the survey are not available. An inferior proxy, average hourly earnings in the preceding year, could be used.

(70-79), as training processes follow the initial 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) is observed net of experience prior to entering the current firm. Wage growth in the firm so measured is ascribable to training whether or not the latter is firm specific.

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.

A test applied to job changers yielded no results: When the difference between destination and origin PG's was regressed on education of inter-industry job movers, no significant results appeared. However, the appropriate direction of mobility is observable among labor force entrants in Table 2, panel A. There PG was interacted with a dummy Dx denoting recent labor market entrance ($D = 1$, when $x < 4$). This variable was positive and significant even among young workers. New entrants who find jobs in more progressive industries are likely to be better educated than those who enter other industries.

5. Effects of Productivity Growth on Labor Turnover

Training received on the job increases productivity and therefore wages. It is likely that such training contains some elements of specificity, that is that the training is somewhat (or much) more valuable in the firm in which it was received than in other firms: 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. If so, workers trained in the firm are less likely to leave the firm than those trained elsewhere or not trained because they risk a loss in wages. Similarly, employers are more reluctant to lay off such workers, since they invested in their training and would therefore suffer a capital loss.

In a recent study based on the PSID (Mincer, 1988a), I confirmed the proposition that workers trained on the job stay longer in the firm than others, and that more educated workers are also likely to be more permanently attached to firms, partly because they are more likely to obtain training.

We found in Section 3 that training is more prevalent where productivity growth is more rapid: the technological changes in production processes that underlies productivity growth require training and retraining of workers. This proposition may be questioned: If skills acquired in training become rapidly obsolete, the incentives of workers to invest in training would be reduced. However, if obsolescence is gradual or partial, successive training or retraining would add to skills, and incentives would not be impaired, especially if employers share the training costs.

Although the threat of even partial obsolescence may deter workers from investing in training, firms must persist in technological adaptation to remain competitive, employing work forces with complementary and changing skills. The latter may be achieved either by training workers for flexibility (by rotation) 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 recent education. However, if technological adaptation or changes are in some degree firm specific, the firm will tend to train its workers after initially hiring more adaptable and educated workers who, in turn, serve as the "teachers." Human capital management in Japanese firms illustrates these responses under conditions of most rapid productivity growth in recent times.[10] 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.

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10 Mincer and Higuchi (1988).

We have seen in Table 2 that the response to faster productivity growth is an increase in the proportion of educated workers, while the longer run response is an increase in training. Table 4 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 negligible effect of concurrent productivity growth (70-79) on separation rates conceals details: In the short run, quits actually increase mainly among young and educated[11] 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 especially for older workers.

The capital intensity variable (GR) appears to compete with productivity growth: When included it shows negative effects on separations, but coefficients of productivity growth become insignificant. Effects of short-run PG (70-79) survive (positive) in quits and (negative) in layoffs, while capital-intensity has a negative effect on both. Effects of employment growth (EG) on separations are not significant. Again this conceals (weak) positive effects on quits and negative effects on layoffs.

An interpretation of these findings is that, in the short run, rapid technological changes increase hiring of young, more educated workers. Some of the new hires may have 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 came from labor force entrants into sectors with higher rates of productivity growth, as was indicated in Table 2. 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 is not observed in effects of training

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11 An interaction of PG (70-79) with Education was positive and significant in quits of Young Workers.

which is not linked to technological change.[12] 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. The larger share of investments by firms deters layoffs more than quits.

6. Effects on Unemployment

The reduction in turnover, and especially in layoffs, implies that the incidence of (permanent) unemployment is also likely to 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 4 showed that P(s) declines in the longer run and only slightly in the short-run among older workers. Thus, unless P(u/s) increases as much as or more than P(s) declines, P(u) must decline. Table 5 shows that conditional unemployment, P(u/s), that is unemployment of movers also declines in both age groups in the short and long run. The short run decline can be attributed to the increased proportion of quits in short-run separations, as found in Table 4.

Table 6 shows the effects predicted by Tables 4 and 5: Unemployment incidence declines in sectors with rapidly growing productivity in the long run among all workers, but less so in the short run. These findings hold also for unemployment which includes temporary layoffs, as shown in panel B. Here, even short-run effects are sizable, and the long-run reductions in unemployment are larger. Consequently, the patterns hold for the incidence (probability) of unemployment whether or not it occurs in separations from a job.

Growth of capital intensity (GR) also reduces the incidence of unemployment. It reduced separations (Table 4) and had no effect on conditional unemployment. Following its effects on

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12 Mincer (1988a).

separations, it competes with the lagged PG in the upper panel of Table 6 where recall unemployment is excluded. Otherwise, its effects are additional to those of the other variables.

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).[13] 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.[14] Table 6 does, indeed, show reductions in duration of unemployment, smaller in the short run and larger in the longer run. Effects on educational differentials in duration, which are normally quite small, are not detectable in this sample. Duration is also shorter in industries in which employment is expanding more rapidly.

Summing up the findings on unemployment: All components of unemployment decline in consequence of productivity growth: (a) Incidence P(u) declines because both separations P(s) and unemployment of job movers P(u/s) declines. The latter's decline is due to the asymmetric effect of PG on quits and layoffs. The decline in unemployment incidence is small in the concurrent period, but pronounced in the longer run. It is even more pronounced when recall unemployment is included. (b) Duration of unemployment is also reduced somewhat in consequence of productivity growth, again more so in the long run. The reduction of duration may be attributed, as was the reduction of conditional unemployment, to the asymmetric effects of PG on quits and layoffs.

Unemployment declines also in consequence of growth in capital intensity, but the extent to which the (GR) effect is confounded with (PG) effects is not quite clear.

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[13] Mincer (1988b).

[14] Mincer (1986).

The finding that technological change tends to reduce unemployment in technologically progressive 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 likely in the short-run though less likely in the longer run. Because 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 surprising. Yet what previous analyses overlooked is that two processes are set-off by technological changes: a waning series of job displacements and a waxing process of worker adaptation which makes their 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.[15]

Summary of Findings

The hypothesis that recent technological change is biased toward human capital is tested on 18 US industrial sectors using annual PSID data on the male labor force in 1968-1983 and Jorgenson-Conrad productivity growth indexes for the period 1960-1979.

Consistent with this hypothesis, the PSID data show that more rapidly growing productivity in a sector generates an increased demand for education and training of the sectoral work force: (1) The share of educated workers is raised concurrently (within the same decade) without much of an initial effect on training. In the longer run the use of training increases. (2) Relative wages rise for more educated workers within sectors with rapid productivity growth (RPG) concurrently (3) Mobility of educated, especially young workers into these sectors is observable, but it does not seem to erode much of the educational wage gains even a decade later. (4) Wage-tenure profiles are steeper in RPG sectors after a while - as training incidence increases. (5) Separation rates are not affected on average in the short run, though quits tend to increase. Separations decline in the longer run,

15 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).

presumably because training intensifies. (6) The probability of unemployment and unemployment rates decline slightly in RPG's concurrently and more so in the longer run.

All these findings can be viewed as responses of firms to skill-biased technological change. This is true of the utilization and wage effects, and, with an additional assumption, of the turnover and unemployment effects. The additional assumption is a degree of firm specificity in training investments necessitated by changing technology, or more precisely, significant employer investments in such training.

Our attempts to explore effects of the capital-skill complementarity, given the rate of productivity growth, yielded some positive and some ambiguous results: Capital intensity growth (GR) showed positive effects on utilization of educated labor, but effects on training and on wages were not visible. Effects on turnover and on unemployment were negative, but they may have been confounded to some extent with productivity effects.

We should note that the sectoral unemployment effects are relative to other sectors, and do not imply similar aggregate effects. Thus a decline in unemployment in progressive sectors is equivalent to an increase in the lagging secotrs, and the latter may dominate the aggregate. But this is surely not the sense in which "the specter of technological unemployment" has been perceived or analyzed. Indeed, with the growth of the "open" economy, that is of world trade, these perceptions are changing, and the specter of technological unemployment is now more likely to be seen to threaten technologically lagging rather than leading sectors or countries. This is clearly exemplified by what would be a paradox under the old perception, namely that Japan the country that experienced the most rapid productivity growth in recent decades also had the lowest unemployment rates.

A few qualifications are in order:

(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) We did not distinguish explicitly between technological changes resulting in cost-cutting production of old products and the introduction of new products. The latter are more likely to increase employment even in the short run, and may create new industries at a more detailed level of aggregation. (3) The statistical analysis is basically cross-sectional. A "fixed-effects" approach is needed and may be feasible for some of the tests.

Some applications

1. The remarkably low labor turnover rate (and related unemployment rate) in Japan has attracted a great deal of attention. Often exaggerated as "life-time employment" it is frequently described as a reflection of a culture which puts great emphasis on loyalty. Yet, in the same culture, turnover rates were a great deal higher prior to the Second War. The difference is the remarkably rapid technological progress in Japan since 1950. The technological catch-up required sizable investments in human capital in schools and in enterprises. The phenomenal growth of educational attainment in Japan in the recent decades is well-known. The even more intense effort to adapt, train, and retrain workers for continuous rapid technological changes is not directly visible in available data. However, effects of training on wage growth and turnover are visible in a negative relation between the two within industrial sectors observed in Japan and in the U.S. This was shown in a study by Mincer and Higuchi (1988). The same study showed that industries with more rapid productivity growth had both steeper individual wage profiles and lesser turnover rates. Indeed, using the parameters of those relations, a four-fold rate of productivity growth in Japan compared to the U.S. in the (1960-1980) period, predicted rather well the over three-fold steeper wage profiles and the less than one-third frequency of firm separations in Japan.

2. Current research suggests that technological change produces market demands for human capital. The reviewed evidence is stronger on the effects of acceleration of productivity growth than on long-term trends in rates of growth. More research across sectors, periods and countries is needed. Even at this stage, the evidence suggests a resolution of a long-standing puzzle, that of no secular

decline in rates of return to education[16] in the face of continuous upward trends in education: Without growing demands by industry for educated and skilled workers, increasing supplies of such workers would depress educational differentials in wages to the point where rates of return to educational investments would fall to zero or below. But, if growing demands by industry are a major factor in inducing increasing supplies of educated labor, the profitability of education can be maintained in the long-run at levels roughly comparable to that of other investments.[17]

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16 In the short run rates fluctuate a great deal, as swings in the past decade indicate.

17 Based on data for 60 countries, Psacharapoulos (1985) finds that rates of return to education are somewhat higher that rates of return to physical capital in LDC's and only slightly lower in advanced countries.

TABLE 1

Productivity Growth Indexes (Percent per Year)

INDUSTRY	PG6079	PG6070	PG7079	(GR)	(EG)
1. Agriculture	1.18	1.67	0.64	6.24	-2.93
2. Mining	-3.19	0.68	-7.32	1.42	2.50
3. Construction	-0.73	-0.10	-1.43	0.14	2.70
4. Food, etc.	0.00	0.30	-0.33	3.06	-0.003
5. Leather, textile mill, apparel, etc.	1.27	0.99	1.57	2.98	-0.04
6. Stone, clay, glass precision instruments lumber, wood, furniture	0.17	0.45	-0.41	2.29	1.70
7. Printing, etc.	1.01	0.10	2.03	1.17	1.34
8. Chemicals, petroleum, rubber, plastic	0.48	1.51	-0.63	2.13	2.38
9. Metal industries	0.13	0.48	-0.25	1.47	1.37
10. Machinery, including electrical	1.32	0.55	1.31	2.65	2.63
11. Motor vehicles and other transportation equipments	0.63	0.72	0.54	2.62	1.34
12. Misc, manufacturing	-0.05	0.87	-1.06	2.19	0.61
13. Trade	0.92	1.14	0.68	2.48	1.74
14. Finance, insurance	0.41	0.00	0.86	-1.28	3.51
15. Transport and communication	1.01	0.87	1.17	4.31	1.48
16. Utilities	0.00	1.50	-1.64	3.68	1.73
17. Services	-0.27	-0.72	0.24	1.33	3.29
18. Paper, etc	0.45	0.87	0.00	1.53	1.11

Source: Conrad and Jorgenson (1985), Table 1, for PG.
GR calculated from Jorgenson, Kuroda, and Nishimizu, (1986), Table 2
EG calculated from CPS data

TABLE 2

Education Levels and Training in Industry

(PSID Males)

(A) Proportion of Workers with More than 12 Years of Schooling
(1968 to 1985 Pooled)

Variables	All			Younger (x < 12)			Older (x > 12)		
PG(70-79)	.039		.038	.039		.040	.035		.037
	(13.2)		(19.4)	(7.5)		(12.4)	(2.4)		(14.9)
PG(60-70)			-.035			-.034			-.032
			(9.4)			(6.4)			(6.9)
PG(60-79		.027			.034			.021	
		(5.3)			(3.8)			(1.8)	
GR(60-79)			.018			.030			.008
			(7.4)			(8.0)			(2.5)
EG(60-79)	.042	.095	.063	.078	.099	.080			.050
	(4.2)	(30.7)	(24.4)	(20.7)	(20.4)	(19.1)			(15.4)
PG x DX	.071	.101		.038	.065				
	(30.5)	(6.6)		(3.4)	(3.8)				

	(B) Learned on the Job in 1976			(C) Prior Training in 1976 and 1985		
Variables	All	Younger	Older	All	Younger	Older
PG(70-79)	n.s	n.s.	n.s.	-.010	n.s	-.012
				(2.2)		(1.9)
PG(60-70)	.069	.107	n.s.	.045	.044	.037
	(2.6)	(2.6)		(4.2)	(3.0)	(2.4)
EG(60-79)	.031	.049	n.s.	.022	n.s	.025
	(2.1)	(2.3)		(3.1)		(2.6)

<u>Note</u>: t - statistics in parentheses
n.s. - not significant
DX = 1, when x $\leq$ 4
GR was not significant in (B) and (C)
Other independent variables listed in Table 7.

TABLE 3

Wage Functions
(PSID, 1976-1985, pooled)

Variables	All	Younger	Older
PG(70-79)	-.014	-.020	-.008
	(6.8)	(7.1)	(2.7)
PG(60-70)	.089	.051	.109
	(8.8)	(2.8)	(7.3)
EG(60-79)	.012	.020	
	(2.8)	(3.2)	n.s.
PG(70-79).Ed	.005	.004	.005
	(4.1)	(2.7)	(3.5)
PG(60-79).Ed	.004	.005	.004
	(3.9)	(2.4)	(3.3)
PG(70-79).Ten	.002	.004	.002
	(6.9)	(3.4)	(5.0)
PG(60-79).Ten	.007	.021	.002
	(15.3)	(11.6)	(4.9)

Note: – PG(60-79) in interactions is alternative to PG(70-79) in interactions
– GR coefficients were not significant
– Other variables as in Table 2

TABLE 4

Effects of Productivity Growth on Turnover

(Pooled, 1968-1985)

(A) Separations

Variables	All			Younger			Older		
PG(60-79)	-.018 (7.5)			-.020 (4.8)			-.017 (6.1)		
PG(70-79)		-.0046 (3.0)	n.s.		-.0043 (1.6)	n.s.		-.0045 (2.5)	n.s.
PG(60-70)		-.020 (7.5)	n.s.		-.023 (5.2)	n.s.		-.018 (6.1)	n.s.
GR(60-79)			-.014 (8.4)			-.013 (4.4)			-.013 (5.5)
EG(60-79)			n.s.			n.s.			n.s.

(B) Quits

Variables	All			Younger			Older		
PG(60-79)	n.s.			n.s.			-.0047 (2.4)		
PG(70-79)		.0027 (2.3)	.0050 (4.1)		.0054 (2.6)	.0084 (3.9)		n.s.	n.s.
PG(60-70)		-.0094 (4.7)	n.s.		-.0110 (3.0)	n.s.		-.0085 (4.0)	n.s.
GR(60-79)			-.0066 (4.0)			-.0078 (2.6)			-.0045 (2.6)
EG(60-79)			.0036 (2.0)			.0066 (2.0)			n.s.
PG x Ed		.0013 (2.1)							

TABLE 4 (continued)

(C) Layoffs

	All			Younger			Older		
PG(60-79)	-.014			-.016			-.013		
	(8.3)			(5.5)			(6.8)		
PG(70-79)		-.0062	-.0046		-.0073	-.007		-.005	-.003
		(5.8)	(4.2)		(4.0)	(3.4)		(4.4)	(2.5)
PG(60-70)		-.0095	-.0036		-.010	-.010		-.010	n.s.
		(5.2)	(1.6)		(3.3)	(2.2)		(4.9)	
GR(60-79)			-.0065			-.005			-.007
			(4.3)			(1.7)			(4.4)
EG(60-79)			-.0023			-.004			n.s.
			(1.6)			(1.6)			

TABLE 5

Probability of Unemployment of Job Movers

(Pooled, 1968-1985)

Variables	All		Younger		Older	
PG(60-79)	-.032 (4.2)		-.027 (2.9)		-.046 (3.4)	
PG(70-79)		-.021 (4.0)		-.017 (2.8)		-.032 (3.2)
PG(60-70)		n.s.		n.s.		n.s.
EG(60-79)		-.015 (1.9)		n.s.		-.028 (1.9)

TABLE 6

Unemployment Incidence and Duration

(Pooled, 1968-1985)

(A) P(u s) - No recall

	All			Younger			Older		
PG(60-79)	-.016 (9.0)			-.020 (6.1)			-.014 (7.4)		
PG(70-79)		-.007 (6.2)	-.005 (4.3)		-.008 (4.0)	-.006 (3.0)		-.006 (4.9)	-.004 (3.2)
PG(60-70)		-.011 (5.5)	n.s.		-.013 (3.9)	n.s.		-.010 (4.8)	n.s.
GR(60-79)			-.008 5.0)			-.006 (2.2)			-.008 (4.5)
EG(60-79)			n.s.			n.s.			n.s.

(B) P(u) - Recall included

	All			Younger			Older		
PG(60-79)	-.038 (15.2)			-.038 (9.6)			-.039 (12.5)		
PG(70-79)		-.021 (13.3)	-.017 (10.6)		-.020 (8.2)	-.018 (6.9)		-.021 (10.6)	-.017 (8.2)
PG(60-70)		-.017 (6.5)	-.018 (4.9)		-.018 (4.2)	-.024 (4.1)		-.018 (5.4)	-.017 (3.5)
GR(60-79)			-.026 (11.6)			-.023 (6.4)			-.026 (9.6)
EG(60-79)			-.029 (12.0)			-.030 (7.5)			-.028 (9.5)

TABLE 6 (continued)

(C) Weeks of Unemployment During Year

	All			Younger			Older		
PG(60-79)	-.58 (12.9)			-.53 (7.1)			-.64 (12.0)		
PG(70-79)		-.31 (10.8)	-.27 (9.1)		-.28 (6.0)	-.26 (5.4)		-.33 (9.8)	-.28 (8.0)
PG(60-70)		-.26 (5.5)	-.28 (4.2)		-.26 (3.2)	-.34 (3.1)		-.29 (5.2)	-.28 (3.4)
GR(60-79)			-.28 (7.0)			-.19 (2.9)			-.32 (6.9)
EG(60-79)			-.32 (7.5)			-.28 (3.8)			-.34 (6.8)

TABLE 7

Dependent Variables
Sample Sizes, Means, and Standard Deviations
(PSID, 1968-1985, pooled)

Variables		All	Young	Old
ED-DUM	1 if EDUCI > 12	0.43	0.510	0.37
		(0.49)	(0.50)	(0.48)
LEARN76		0.54	0.57	0.51
		(0.49)	(0.49)	(0.50)
Prior Training 76-78-85 combined		10.18	4.29	14.84
		(9.45)	(3.25)	(10.12)
LOGWAGE		1.44	1.34	1.53
		(0.44)	(0.42)	(0.43)
SEPN		0.16	0.25	0.10
		(0.37)	(0.43)	(0.30)
QUIT		0.09	0.14	0.05
		(0.29)	(0.35)	(0.21)
LAYF		0.07	0.09	0.04
		(0.24)	(0.29)	(0.19)
CONDITIONAL QUIT		0.54	0.56	0.49
		(0.50)	(0.50)	(0.50)
CONDITIONAL UNEMPLOYMENT		0.48	0.48	0.46
		(0.50)	(0.50)	(0.50)
INCIDENCE ON UNEMPL. (RECALL EXCL)		0.08	0.12	0.04
		(0.27)	(0.33)	(0.21)
INCIDENCE OF UNEMPL. (RECALL INCL)		0.17	0.22	0.12
		(0.37)	(0.41)	(0.33)
DURATION OF UNEMPL IN WKS		11.86	11.35	11.31
		(11.72)	(10.99)	(11.20)

TABLE 7 (continued)

Independent Variables
Sample Sizes, Means and Standard Deviations

Variables		All	Young	Old
EDUC	YRS OF EDUCATION	12.75	13.33	12.29
		(2.78)	(2.35)	(3.02)
EXP	YRS OF EXPERIENCE	16.80	6.85	24.50
		(10.90)	(3.29)	(8.16)
TEN	TENURE	7.78	2.98	11.48
		(8.36)	(2.91)	(9.23)
PREEXP	EXP-TEN	9.35	4.18	13.11
		(8.64)	(3.17)	(9.38)
MARITAL STATUS		0.87	0.80	0.93
		(0.33)	(0.40)	(0.26)
RACE	1=BLACK 0=WHITE	0.07	0.07	0.07
		(0.25)	(0.25)	(0.25)
UNION MEMBERSHIP		0.28	0.24	0.32
		(0.45)	(0.43)	(0.46)
NATIONAL UNEMP RATE		6.84	6.89	6.73
		(1.68)	(1.61)	(1.72)
PG6079		0.34	0.30	0.37
		(0.77)	(0.79)	(0.76)
PG6070		0.44	0.42	0.46
		(0.71)	(0.74)	(0.69)
PG7079		0.14	0.10	0.16
		(1.28)	(1.30)	(1.28)
PG6079ED		4.19	3.84	4.47
		(9.94)	(10.45)	(9.53)
PG6079TEN		3.04	0.94	4.65
		(9.38)	(3.23)	(11.92)
PG7079ED		2.09	1.66	2.45
		(16.42)	(17.28)	(15.77)
PG7079TEN		1.47	0.36	2.32
		(15.32)	(5.17)	(19.86)
DX	XD = 1 IF EXP $\leq$ 4	0.11	0.26	
		(0.32)	(0.44)	
GR		2.14	2.10	2.17
		(1.42)	(1.48)	(1.37)
EG		2.00	2.01	1.98
		(1.22)	(1.31)	(1.16)

Sample size was 1,279 in 1979, of which 576 had 12 or less years of experience, 703 had more than 12 years. The average number of job changers was 260 per year.

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