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HUMAN CAPITAL RESPONSES TO TECHNOLOGICAL CHANGE IN THE LABOR MARKET

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Preliminary

Human Capital Responses to Technological Change in the Labor Market

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 a (equilibrium) level, at which this investment is equally 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, its growth 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 applied to or may 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, i.e. 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 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: The efficiency and facility with which human capital responds to technical change is clearly an important factor in the pace of economic growth.

Several implications of the hypothesis formulated on the preceding pages 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 initially 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 but detailed analysis. Changes over time and 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. 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, 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 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.

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).

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 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.[3] The results hold for workers with relatively recent vintages of education; they are not significant for workers above age 45.

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3 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.

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 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 1983. The Conrad-Jorgenson indexes for 28 industries have been allocated (averaged) to the 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[4] as a function of concurrent and lagged productivity growth in the industry, standardizing for the rate of employment growth (over both decades) in the industry.[5] 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 -- theoretically it must be, though either direction and period are possible[6] -- 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 concurrently more technologically progressive industries tend to utilize more educated workers -- as shown by the positive and significant coefficient on PG (70-79). As was suggested, this is also true of growing industries, given productivity growth -- as shown by the coefficient on employment growth (EG) over the 1960-79 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 variables in the lower panel of Table 2 is the incidence of training reported in 1976 when a question on the learning content of the job was asked.[7] The

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

5 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.

6 See section 4, below.

7 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.

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 accelerating technological changes in a sector, i.e. when PG (70-79) exceeds PG (60-70), raise that sector's share of educated workers without increasing training. In the longer run, training increases, both when the technology ages [PG (70-79) < PG (60-70)], and when it grows at a steady rate [when PG (70-79) = PG (60-70)]; the incidence of training is greater the higher the rate. Effects on training are pronounced for younger workers (defined by labor market experience not exceeding 12 years), but not for older workers.

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 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].

The claim that more rapidly growing technology increases demand for education and training is consistent with findings on their utilization in Table 2 and in other studies. But the findings do not prove that these processes are demand generated. If they are, wages or pay-offs to human capital should increase, at least for some time, in such sectors. We look at such wage effects in the next section.

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8 For evidence see Mincer (1988b).

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 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 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 is greater than unity, and falls otherwise. If productivity growth is 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. If productivity growth is widespread, income growth increases the overall 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.

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 1983 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 vanishes: The coefficient on PG (70-79) is negative, but positive and about as large 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

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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.

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 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.

Practically all the findings in Table 3 are consistent with the theoretical implications. A minor puzzle is the estimate of greater profitability of education in the longer (60-79) than in the shorter (70-79) run. With very small average productivity growth in 1970-79, errors in the indexes (which are residuals) may play a bigger role, biasing coefficient estimates downward, or the effects may be non-linear, i.e. only sizable productivity growth makes the effects on wages perceptible.

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 when more educated workers change jobs they tend to move into industries with high level PG: 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 ($x \leq 4$). This variable is positive and significant even among young workers. New entrants who find jobs in "high-tech" 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. But this proposition may be questioned: 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 may 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 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.

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 or 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.

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10 Mincer and Higuchi (1988).

The negligible effect of concurrent productivity growth (70-79) on separation rates conceals details: In the short run, quits actually increase for more educated workers (16+). Quits increase among young workers, whil yoffs 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.

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 came 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 is not observed in effects of training which is not linked to technological change.[11] 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.

6. Effects on Unemployment

The reduction in turnover, and especially in layoffs, implies that the incidence of (permanent) 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 showed that P(s) declines in the longer run, and

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11 Mincer (1988a).

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 predicted by Tables 5 and 6: Unemployment 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. These findings hold also for unemployment which includes temporary layoffs, as shown in Table 6A. For this, even short-run effects are significant, but the long-run reductions in unemployment are twice as large. Consequently, the patterns hold for the incidence (probability) of unemployment whether or not it occurs in separations from a job.

To observe how the effects of technological change (PG) on unemployment differ by education, we used an interaction variable (PG x Ed). This is positive, though small. In other words, the net reduction in unemployment of less educated workers is greater. The already small unemployment of more educated workers is virtually unaffected. The long-term employment attachment of such workers, especially in terms of a negligible risk of layoff, is no more sensitive to general shocks than to more mundane business cycles. In both cases differences in unemployment by education narrow when the shocks are positive.

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 <u>duration</u> 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).[12] 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

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12 Mincer (1988b).

least in the longer run, since layoff unemployment is characterized by longer duration than quit unemployment.[13] Table 7 does, indeed, show reductions in duration of unemployment, small 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.

The finding 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" 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.[14]

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

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13 Mincer (1986).

14 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).

decade) without much of an initial effect on training. In the longer run the use of training increase. (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, 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.

Some additional remarks 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) Growth of the "open" economy, that is of world trade, may place 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 Japan the country that experienced the most rapid productivity growth in recent decades also had the lowest unemployment rates. (3) 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. (4) The statistical analysis is basically cross-sectional. A "fixed-effects" approach may be feasible for some of the tests, and will be attempted.

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 a secular relative stability of rates of return to education[15] 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

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

supplies of educated labor, the profitability of education can be maintained in the long-run at levels roughly comparable to that of other investments.[16]

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16 Stability of rates of return is observed in the U.S. since the Second War. Also, 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.

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Table 1
Productivity Growth Indexes (Percent per Year)

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

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≤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 (60-79) 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		Young	
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 $x \leqslant 4$

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

(B) Quits

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

(C) Layoffs

Variables	All		Younger		Older	
PG (60-79)	-.012	-.050	-.013	-.039 (1.7)	-.011	-.054
	(5.4)	(4.7)	(3.2)		(4.4)	(5.2)
PG x Ed		.003		n.s.		.004
		(3.6)				(4.2)
PG (70-79)	-.006	-.026	-.005	n.s.	-.006	-.029
	(4.3)	(3.7)	(2.2)		(3.9)	(4.3)
PG x Ed		.0016		n.s.		.002
		(3.0)				(3.5)
PG (60-70)		-.009		-.011		-.006
		(3.4)		(2.5)		(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 (3.6)		.029 (3.3)		.027 (2.0)	
PG (60-79)		.029 (2.5)		.039 (2.8)		n.s.
PG (60-70)	n.s.		n.s.		-.043 (1.7)	

(B) Conditional Unemployment

Variable	All		Young		Old	
PG (70-79)	-.014 (1.9)		n.s.		-.032 (2.5)	
PG (60-79)		-.020 (1.7)		n.s.		-.054 (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	7576	0.52	11426	0.35
			(0.49)		(0.49)		(0.47)
LEARN76		1279	0.54	576	0.57	703	0.51
			(0.49)		(0.49)		(0.50)
LOGWAGE	LOG OF SALWAG	12811	1.47	5482	1.39	7329	1.53
			(0.41)		(0.39)		(0.41)
SEPN		19563	0.13	8700	0.20	10863	0.08
			(0.34)		(0.40)		(0.27)
QUIT	1 IF QUIT	19563	0.07	8700	0.11	10863	0.03
			(0.26)		(0.32)		(0.19)
LAYF	1 IF LAID OFF	19563	0.05	8700	0.08	10863	0.03
			(0.23)		(0.27)		(0.18)
QUIT_S	CONDITIONAL QUIT	2714	0.53	1823	0.56	891	0.48
			(0.49)		(0.49)		(0.49)
UNEMP_S	CONDITIONAL UNEMPLYMT	2714	0.48	1823	0.48	891	0.47
			(0.49)		(0.49)		(0.49)
USEPN	INCID. OF UNEMPL. (RECALL EXCL)	19563	0.06	8700	0.10	10863	0.03
			(0.24)		(0.30)		(0.19)
UHRDUM	INCID. OF UNEMPL. (RECALL INCL)	19668	0.15	8747	0.20	10922	0.12
			(0.36)		(0.40)		(0.32)
UNWKS	DUR. OF UNEMPLOYMENT IN WKS	3068	11.26	1754	11.47	1314	10.98
			(11.40)		(11.51)		(11.26)

INDEPENDENT VARIABLES

SAMPLE SIZES, MEANS, AND STANDARD DEVIATIONS

VARIABLES		ALL		YOUNG		OLD	
EDUCI	YRS OF EDUCATION	19002	12.70	7576	13.45	11426	12.29
			(2.86)		(2.35)		(3.06)
PREEXP	EXP - TENH	15117	9.02	5489	3.52	9628	12.17
			(8.46)		(2.97)		(8.96)
EXP	YRS OF EXPERIENCE	18804	17.94	7378	7.02	11426	24.99
			(10.99)		(3.25)		(8.08)
TENH	TENURE	15341	9.63	5713	4.06	9628	12.94
			(8.41)		(3.01)		(8.93)
MRDNOW	MARITAL STATUS	19047	0.89	7621	0.84	11426	0.93
			(0.30)		(0.36)		(0.24)
RACE	1 = BLACK 0 = WHITE	19047	0.06	7621	0.06	11426	0.07
			(0.25)		(0.25)		(0.25)
UNM	UNION MEMBERSHIP	18966	0.31	7567	0.26	11399	0.33
			(0.46)		(0.44)		(0.47)
CUR	NATIONAL UNEMPLYM RATE	19047	6.71	7621	6.87	11426	6.60
			(1.78)		(1.73)		(1.81)
PG6079		17031	0.34	6737	0.30	10294	0.37
			(0.75)		(0.76)		(0.75)
PG6070		17031	0.44	6737	0.41	10294	0.47
			(0.71)		(0.74)		(0.68)
PG7079		17031	0.15	6737	0.13	10294	0.17
			(1.26)		(1.25)		(1.26)
PG6079ED	PG6079 * EDUCI	16986	4.32	6692	3.98	10294	4.54
			(9.76)		(10.29)		(9.39)
PG6079TN	PG6079 * TENH	13706	3.90	5046	1.30	8660	5.25
			(10.39)		(3.75)		(12.53)
PG7079ED	PG7079 * EDUCI	16986	2.34	6692	1.99	10294	2.57
			(16.13)		(16.87)		(15.62)
PG7079TN	PG7079 * TENH	13706	1.87	5046	0.52	8660	2.66
			(17.13)		(6.02)		(21.02)
XD	XD = 1 IF EXP <= 4	18804	0.09	7378	0.24	11426	0.00
			(0.29)		(0.42)		(0.00)