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ABSTRACT

We explore the response of employment (unemployment) skill differentials to skill-biased shifts in demand touched off by the new and spreading technologies. We find that skill differentials in unemployment follow at least in part the same pattern as skill differentials in wages: They widen initially but decline after a roughly 5-year lag, allowing time for training and learning to handle the new technologies.

In the micro (PSID) cross-section the differentials show up as sectoral differences defined by technology. In the aggregate time series relative unemployment is defined by educational unemployment differentials. We find that the pace and turnaround in the "unemployment gap" is twice as fast as in the "wage gap". Apparently, the hiring and training response is quicker than the wage response.

We also observe in time series that the pace of technology has unclear effects on aggregate unemployment in the short run, but appears to reduce it in the longer run. In addition to technology, maturing of the workforce, and growth of international trade reduce unemployment in the longer run. The same variables also significantly reduce inflation in both the short and long run.

Given the actual changes in these factors in the early 90's we are able to predict a little over a half of the decline in unemployment and about 70% of the reduction in inflation in the latter half of the last decade.

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Introduction: Recent Research

Recent research attributes much of the changing skill structure of wages to the development and increasing pace of new information and related technologies (NIT). There is evidence that "high tech" sectors of the economy utilize human capital (educated and trained workers) to a greater extent than other sectors and that relative wages are higher for more educated workers in such sectors (Bartel and Sicherman, 1998). Other findings show workers wage profiles to be steeper in these sectors as a result of greater profitability of training and learning in them (Bartel and Sicherman 1999, Mincer, 1998). Taken together the findings of larger relative numbers and increased relative wages of skilled workers in "high tech" sectors indicate greater demands for skills that are complementary with the new technology, much of which is embodied in new capital goods. The widely accepted hypothesis of skill biased increases in labor demand in recent decades rests on this complementarity. Its importance is growing as the NIT component of total capital equipment has grown from single digits in the 70's to close to a third in the late 90's (Economic Report of the President (ERP), 2000).

The growth of workers skills defined as the proportion of total annual hours contributed by workers with post secondary education, almost doubled – from 28% in 1970 to 53% in 1995 - among male workers. Among women the increase was even greater (from 20% in 1970 to 54% in 1995), while the proportion of females in total employment grew from 37% in 1970 to 47% in 1995.[1] Also, according to the BLS (1985,

[1] Source Table 16 and 17, Report on the American Work Force, U.S. Department of Labor, 1997.

1992) the incidence of job training for skill improvement increased[2] from 29% of workers in 1983 to 38% in 1991.

The growth of new technologies and of skills is linked causally: The new technology generates skill-biased increases in demand which increase the (relative) skill wage differential. The (percentage) wage differential for a one year increment of schooling which declined to around 5% in the late 70s, rose to close to 15% in the late 80's. This rising "wage premium" – an approximate measure of the rate of return to schooling, provided a growing incentive for increases in school enrollments. After a lag due to time in school and early experience in the labor force, growth of enrollments resulted in substantially higher levels of human capital in the 90's.

The linkage of the wage premia to school enrollment and to investment in training is documented in a recent study (Mincer, 1998). The increased supply of skills which follows increases in demand for skills with an 8-10 year lag, eventually tends to reduce the skill wage differential. A turnaround appears to have started in mid or late 90's, following the peaking of wage premia in the late 80's and early 90's. Whether the implicit decline of the "wage gap" will continue depends on the speed of human capital accumulation relative to the speed of technological diffusion.

The growth of skill wage differentials, or "wage gap" between more and less skilled workers is viewed by many with alarm as a dangerously widening social divide. This view misses the above described instrumental nature of this "gap" as an incentive factor for building up the social stock of human capital in the economy. Thus, nearly

[2] U.S. Department of Labor, BLS Bulletin, How Workers get their Training, 1985; Updated in BLS Bulletin 2407, 1992.

tripling the wage premium over two decades prior to the 90's led to doubling of the proportion of workers with post-secondary education whose earnings prospects are correspondingly higher, and to a reduction of low wage high school drop outs from one third of the work force in 1975 to nearly 10% in 1997 (Report on the American Work Force, 1997). The wage premium which widens with surges of technology is expected to return to long-run competitive levels once the supply of human capital catches up with increased demand. In effect, human capital grows continuously propelled by successive waves of technology. This implication shows why economic growth generates growth of human capital apart from income effects on education as consumption (Mincer 1996). The increased supply of human capital in turn advances economic growth through its complementarity with new technologies which create increasing labor and capital productivities.

1. Technology and Unemployment

An issue which used to dominate discussions of the impacts of technology on the labor market was the question of "technological unemployment". This issue provokes little interest when unemployment is low, as it has been over a decade (with the exception of the short recession in 1989-91). A summary on this matter (Cyert and Mowery, 1987) concluded that technologically based unemployment is more likely to appear in the short run than to persist in the longer run. Most recently, however some research is again devoted to unemployment[3] in connection with the search for the elusive “natural rate of unemployment (NAIRU)”. The research is prompted by the persistence of very low unemployment rates without touching off inflation while the “high tech” economy is booming. It appears that technology is not a “specter” but a boon, as low unemployment coexists with low inflation and a more widely shared income growth due to revived productivity growth. Another look at the relation between technology and employment (unemployment) is warranted, regardless of the “natural rate” puzzle. We seek empirical evidence in both cross-section and time series data.

The usual analysis of changes in the demand for labor due to cost reducing and product enhancing innovations relies on low income and price elasticities of product demand in the short run resulting in short-run declines in derived labor demand and a revival of demand in the long-run, based on higher price and income elasticities in the longer run. This approach, though useful, ignores the heterogeneity of labor which is central in the skill bias hypothesis. In this context, employment dynamics is expected to parallel the previously described wage dynamics. Relative demand and supply adjustment effects on employment differentials by skill should move as wage differentials do though timing may differ. Induced growth in supplies of human capital carry with them implications of changes (reduction) in turnover and unemployment. We would expect that as the wage structure widens with increased demand for skills, so would employment (unemployment) differentials by skill. The supply adjustments in skill training would subsequently reduce the employment (unemployment) differentials.

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[3] See Symposium in the Journal of Economic Perspectives, Winter 1997. Also Katz and Krueger in the Brooking Papers on Economic Activity, 1999.

The training responses, documented by Bartel and Sicherman (1988) carry implications for unemployment. As the theory of human capital suggests turnover is likely to decline as training intensifies after the initial technological stimulus. The decline in turnover is, in principle, tied to firm or industry specificities in skill training. By adding to the supply of skills and by reducing turnover, training reduces unemployment as well as the unemployment skill differentials.

To some degree the rapid pace of technology may discourage training. Skills acquired in training may become rapidly obsolete so incentives of workers to invest in training are impaired. However, firms must persist in technological adaptation to remain competitive. If that adaptation is to some extent firm specific the firm is likely to bear much of the cost of worker training after initially hiring more technically competent and educated workers. These processes imply a reduction in layoffs of trainees at the same time or following increased "downsizing" (increased layoffs or decreased hiring) of unskilled non-trainees. In the long run the spread and simplification of technologies should reduce the specificities in training and return turnover to its "normal" level, as training becomes largely "general", that is easily transferable.

We explore the empirical implications for the unemployment that emerge from this analysis.

1. In the cross section we should observe a lesser incidence of unemployment in the technologically progressive sectors of the economy, where training processes reduce turnover, and possibly also the incidence of unemployment. Note that the incidence or probability of unemployment within a period is:

$$P(u) = P(s)\, P(u|s)$$

Where $P(s)$ is the turnover rate or the probability of separating from a job, and $P(u|s)$ is the conditional probability of encountering unemployment when separating. The latter is likely to be reduced if training affects layoffs more than quits, as would happen in firms which bear most of the training costs.

2. While the relative unemployment effects of technology are visible in the cross-section in terms of sectoral differences, the picture in aggregate time series is likely to be less clear: A small or static new technology (NIT) sector would exert little if any effects in the aggregates. In fact marked growth to substantial size from initially low-levels of NIT became prominent only in the last decade.

3. We try to explore two questions in aggregate time series. If relative unemployment (or employment) responds to the pace of technology, is this also true of the aggregate level of unemployment? Do the factors affecting unemployment also affect inflation? The answer to the latter is of interest for movements in the "natural rate of unemployment", if such exists.

Two problems create ambiguities in interpreting the empirical findings which we report. First, the measurement of the pace of new technologies is to some extent arbitrary. Plausible indicators can be measures of effects on total factor productivity (TFP), of contributing investment in research and development (R&D), or of new capital deepening such as computers per worker (C/W) or computers as a fraction of total capital equipment (C/E). We utilize each of these as alternatives in the time series, but only two, (TFP and

C/W) in the cross sector analysis. We do not have information on R&D at the level of disaggregation of sectors (2-digit), nor is it appropriate to use the ratio of computers per equipment across sectors as large fractions (C/E) may include small denominators and so produce misleading effects.

The other problem is multicollinearity inherent in time-series of trending variables. Though the common trends may be implicit in the causal hypothesis we use, interpretation of results is insecure. Nevertheless, the report should be of interest, at least as a basis on which improvements can be made as new data accumulate.

2. Cross section Analysis: Micro Data

We turn to the PSID (Panel Study of Income Dynamics) for micro data in which we can distinguish (38) 2-digit sectors. We utilize two technology indexes which are taken from outside sources[4]. Total Factor Productivity (TFP) and Computer per Worker (C/W) in the 38 sectors of the workers employment. The empirical model is augmented by other variables which affect the components of unemployment in order to estimate the net effects of the pace of technology. The dependent variables (components of unemployment) and most of the independent variables are constructed from the PSID micro- data annually from 1980-1993. The full equation for *P(u)*, the incidence of unemployment, is:

[4] Source for TFP is Jorgenson (1987) updated, and computers per worker data are derived from data by Bureau of Economic Analysis BEA and the CPS (see appendix).

$$P(u) = f\,(Tech, X, X^2, Ed, NW \mid Mar, NU, EG, Union) \qquad (1)$$

Other components of unemployment are *P(s)*, the probability of separation during the year, *P(u|s)* the conditional probability of unemployment given separation, and *D* the fraction of weeks during the year spent in unemployment. The same equations are used for each component, a shorter equation (core) which includes the first five independent variables and the fuller (extended) equation which includes all in equation (1). The core variables are the technology measures, TECH, experience X, level of schooling, Ed, and a dummy for being nonwhite, NW. Additional variables are: a marriage dummy, MAR, the national unemployment rate, NU, annual employment growth of the sector, EG, and a dummy for union membership.

The product of the components of unemployment is equal to the unemployment rate (*u*).[5] We focus on *P(u)* as the major component of u in the cross-section, as *u* cannot be calculated for an individual.

The technology variable TFP (total factor productivity) is the 5-year moving average of the Jorgenson series. The lags of the TECH variables run from 0 to 9 years as indicated in the tables.

We restrict the cross section analysis to males in the labor force. Women's components of unemployment are affected by high levels of turnover between the labor market and non-participation. This requires a detailed augmented analysis using data which are not quite adequate.[6] The aggregate unemployment rate of women is quite

[5] See Mincer (1993a) for derivation and qualifications. We use the macro unemployment rate in the time series data. There the components of unemployment are not, or not readily available.
[6] For an attempt to decompose the female unemployment rate in NLS data see Mincer (1993b).

close to that of men[7] and moves in tandem in time. Consequently the cross section analysis for men's unemployment ought to suffice for our purposes. The estimation results are based on linear probability models in order to give a rough estimate of the magnitude of the effects. We also performed Logit estimation with individual random effects and obtained the same qualitative results.

The upper panel of table 1 contains the effects (parameters) of the technology variables in the core equation. Annual data (1980-1993) of the components of unemployment are regressed on the pace of technology, using lags of technology up to 9 years.

Both the core and the extended equations (lower panel) show negative effects of the pace of TFP (total factor productivity growth) and of C/W (computers per worker) on turnover *P(s)* and on the incidence of unemployment *P(u)*. Peak effects are 3 to 5 years following TFP growth, but with longer lags for the computer (C/W) variable. The conditional unemployment variable *P(u|s)* is not significant for C/W but is negative and significant for the TFP on an (almost) contemporaneous basis. This is consistent with reductions in layoffs by employers who bear much of the cost of training. Duration of unemployment (*D*) is reduced by the pace of TFP only in the core equation, otherwise no significant effects are observed.

The effects of all (8) variables other than technology in the extended equation (1) are shown in appendix table A1. The parameter estimates are very similar without regard to formulations of technology, and in the core equation compared to the extended ones.

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[7] See Economic Report of the President, 2000.

The results shown indicate that work experience and education reduce P(u) and P(s) as does marital status and union membership. Other variables have mixed but plausible effects across components of unemployment.

On the whole the technology effect, the reduction of the incidence of unemployment, is consistent with the reduction in turnover and the reduction or no effect on conditional unemployment in the "high tech" sectors. The maximal effects take 3 to 5 years. The training interpretation fits these findings: training to handle the new technologies, and learning by experience take time.

3. Macroeconomic Effects of New Technologies

The cross-section findings prompt the question whether they can be generalized to the aggregate economy. One implication of changes in relative demand for skills, in addition to changes in relative wages ("wage premia") is parallel change in relative unemployment by skill.

At any given time unemployment rates of skilled workers are lower than those of unskilled workers. For example defining skills by education shows a monotonic decrease in unemployment. The unskilled rates (ed$<$ 12) are four times higher than the skilled ones (ed $\geq$ 16)[8]. Since "wage premia" are defined by education we can test the employment implication of skill biased changes by using education as an index of skill.

[8] See Report on the American Work Force, p.33. 1997. For an analysis of these differentials see Mincer (1993a).

1. The first question is whether the pace of technology affects relative unemployment differences by widening them and whether subsequent supply adjustments eventually reverse the effect.

2. The next question is whether the findings on relative unemployment translate into (absolute) behavior of the aggregate unemployment rate. Note that such generalization need not be expected or clearly visible if the technology sector is small or static. Of course it was not static and grew to a significant size, but mainly in the last decade. Note also, that the widening of the skill unemployment structure (percent differentials) may involve unequal decreases in unemployment by skill or increase for unskilled with decreases for skilled workers. The aggregate effect is therefore not obvious, even if the relative effects are observed.

3. If aggregate unemployment rates are affected by technology it is worth exploring a parallel question on effects of technology on inflation rates. Viewing improvements in technology as a means of increasing the economy's capacity, suggests a force which inhibits inflation even at what otherwise might have been considered "full employment" of resources. If a "natural rate" of unemployment exists, this analysis should contribute to the understanding of its time varying nature.

4.1 Relative unemployment rates

Figures 1 and 2 show time series of relative wages and of relative unemployment. Both define skills by education. Relative Wages show very similar patterns regardless of the choice of higher and lower education levels. Figure 2 is based on the ratio of wages of college graduates to those of high-school graduates. The unemployment ratio is the ratio of unemployment rates of those with ed ≤ 12 to those with post-high school education (ed > 12). A similar effect of technology on both the wage and the unemployment ratio tends to make the series parallel. Higher relative wages are effects of increased demand for skills, and so is higher relative unemployment, as defined. Both decline in the long run following supply adjustments, in schooling and training.

While the supply response of schooling to relative wages takes 8-10 years to reach maximal effect, the training response is quicker. It shows up in the narrowing of unemployment differentials after a 5-year lag. Consequently, the peak of relative unemployment (Fig. 2) is reached several years before the peak of relative wages (Fig. 1).

The unemployment dynamic precedes wage changes as is usually the case when labor markets tighten or loosen.

Table 2 presents a short run (synchronous) analysis of wage premia and of relative unemployment. A comparison of col. 1 with 3 in Table 2 shows that the pace of technology similarly affects the wage differentials and unemployment differentials. Col. 2 and 3 show that replacing technology by its consequence, the wage premium, yields once again similar effects.

The analysis of wage premia (Table 2, col. 1) suggests that in addition to technology, trends and cycles which may be independent of technology need to be considered in analyzing relative unemployment: recessions widen the differentials, as shown by the effect of the national u-rate. Both RSG, the ratio of employment in service to goods producing sectors, and Education move upward linearly (Fig. 11 and 12). Their positive effects may be puzzling, or they may simply capture the upward trend in the dependent variables not explained by other variables.

Table 3 presents the effects of technology on the unemployment ratio in the period. We use four alternative measures of technological progress and four additional independent variables that might affect unemployment, and probably the ratio as well. A description of these variables is provided in the data appendix.

The alternate measures of technology are: Total factor productivity growth (TFP), computers per worker (C/W), Research and Development (real) expenditures per worker (RDE). This last variable was not available on a sectoral basis for the cross-section. Finally, computers as a fraction of total capital equipment (C/E) is a variable that was not meaningful in the cross-section (sectoral) basis as indicated before. These measures are shown (in Table 3) synchronously with the dependent variable (the unemployment ratio), as well as with a 5-year lag to infer the results of supply adjustments. This lag was suggested by the findings on timing in the cross-section.

Table 3 shows the effects of the four alternate technology measures on the unemployment ratio in synchronous timing (left hand panel) and with a 5-year lag in technology (right-hand panel). The synchronous widening of differentials is followed by narrowing 5 years later. This is clear in the change of sign – from positive to negative – in the estimated parameter of technology. The other independent variables are included as they might affect unemployment, though perhaps not necessarily the ratios. In reference to Table 2, Table 3 replaces the national unemployment rate by a measure of capacity utilization in manufacturing – a close index of the business cycle. The linear trend may replace or stand for the education variable which trends linearly upward as does the ratio of employment in services to employment in goods (RSG) which also trend linearly upward.

Table 3 which utilizes four alternate measures of technology shows all of them widening the unemployment skill differentials, three of them significantly. But when the technology is observed 5 years before the unemployment ratio, the effect *reverses*: the ratio narrows. This lag may be interpreted as time during which supply adjustments proceed: training activities reduce turnover and unemployment especially of the ed ≤ 12 group. A similar reversal is observable as distinguishing longer from short-run effects of schooling. The relative growth of service employment reduces the ratio in the short run reflecting increased demand for service workers as technology accelerates. The same effect holds for the wage premium (Table 2, col. 1) in the short run with technology (RDE) lagged 3 years. For wage adjustments it takes a longer period to reverse signs. The reduction in the unemployment ratio due to supply effects is observed also when the independent variables added are (linear) trend and cycles (capacity utilization) shown in Table 3a. Here the trend replaces Education and the RSG variable.

4.2 Technology and Unemployment Rates

We now explore the effects of technology on the aggregate unemployment rate as distinguished from the unemployment skill differential. In recessions unskilled unemployment increases more (percentage wise) than skilled unemployment, so the ratio of unskilled to skilled unemployment widens, the opposite happens in upswings. This is why the capacity variable, an inverse index of cyclical unemployment (shown in Table 2), is negative in the ratio equations (Table 3). If in general, increases in unemployment are accompanied by a widening structure and decreases in unemployment by a narrowing structure, we should get similar results for aggregate unemployment as for the ratios in Table 3.

A substantive interpretation makes such a generalization less secure; in the short run increases in the pace of technology increase the demand for skilled labor thereby reducing their low levels of unemployment while unemployment of the unskilled may but need not increase. So the ratio is likely to widen, but aggregate unemployment need not change significantly. In the longer run, when training extends to less skilled groups as well, total unemployment should decrease. In Table 4 we find that the short run effects of technology are negative, but not significant for two out of four technology variables; in the longer run (after 5 years) the negative effects are stronger than in the short run: three out of four estimated parameters are significant.

Other independent variables that affect unemployment are the age distribution, the volume of imports as a ratio to GDP, and a linear trend variable that proxies for a linear schooling trend and the ratio of service to goods producing workers. The trend variable also helps to “detrend” the independent variables which are multicollinear.

The maturing cohorts of “baby boomers” show up in the growing ratio of workers age 25-44 to young ages 16-24. Experienced workers have less unemployment than younger ones because they are less mobile both for reasons of human capital acquisition and locational attachment.

An increase in imports (measured as ratio to GDP) reduces demand for import competing goods and services causing some short-run unemployment. But both increased exports and increased real incomes (associated with cheaper imports) generate increases in employment, especially in the long run, counteracting and even overwhelming the sectoral unemployment effects of imports. All the signs in Table 4 are negative for the import variable but five out of eight are not significant.

The age variable is largely not significant in the short run but strongly negative and significant in the longer run. Finally the trend variable appears to be positive as the trend in unemployment was upward between 1970 and the mid eighties.

In sum the short run effects of technology, age distribution, and imports on unemployment are usually negative, but not significant in half the formulations. The negative effects are significant in the longer run. With a 5 year lag technology reduces unemployment, and there is no evidence of an opposite effect even in the short run. "Technological Unemployment" appears to be a myth.

4.3 Technology and Inflation: What happened to the unemployment trigger?

Cost reduction and product innovation are the contributions of technology to the capacity of the economy. As such these developments ought to exert downward pressure on prices. Table 5 shows the effect of technology on the inflation rate, using the same equations as in Table 4. The other factors, other than trend are expected to reduce inflation because of higher labor productivity in more mature ages and because of downward pressures on prices due to actual and potential imports. The technology effects are stronger contemporaneously, and so are the negative effects of aggregate unemployment lagged one year, here used as a cyclical index. Imports reduce the price level both in the short and longer run. The maturing labor force reduces inflation with some delay, most likely as a result of learning on the job which increases productivity. The inflation variable is the implicit GDP deflator. "Core" consumer price index yields similar results.

Declines in the unemployment rate and in the inflation rate became sizeable in the latter half decade of the 1990's According to our analysis the major factors contributing to these changes were the new NIT-technologies, the demographic changes and globalization of trade. The factors became quantitatively important in the late eighties and early nineties. In Table 6b we summarize the average effects over the 1970-1995 period of one standard deviation change in our equations on unemployment and inflation in percentage points and in standard deviation units. Table 6a lists the means and standard deviations of the variables.

The effects of a one standard deviation change in Technology, Age and Imports are different depending on the definition of technology. On average across the 4 definitions, the effect of a one standard deviation increase in technology reduces the unemployment rate by ¾ of a percent point and inflation by 0.8 of a point. One σ change in age results in a 1.25 % point decline in unemployment and 2.5 % point in inflation. One σ change in imports reduces unemployment by 1.3% points as well as 3.7 point in inflation. If the three variables moved by 1 σ each, the sum of the effects would be a 3.3% point reduction in unemployment and 5.0% point reduction in inflation in a 5-year period.

These are big effects. Actual changes prior to the late 80's were rather small. In the 5-year period 1990-1995 there was growth of 1/3, ¼ and 1/3 standard deviations in technology, age, and imports respectively. These changes predict a little over 1 percent point reduction in the unemployment rate in the 1995 to 2000 period and a similar decline in the inflation rates. The actual declines were a decline of 1.8 percentage points in the unemployment rate and of 1.5 in the inflation rate. Table 7 shows that our variables based on a 5-year lag in technology account for 56% of the actual decline in the unemployment rate, and for 71% of the actual decline in the inflation rate in the latter half of the decade of the 90's.

These estimates are based on averages across the technology variables. The range of estimates across technologies is relatively narrow. We have no basis for judging which of the technology specifications is superior, though the TFP variable is more likely to contain errors of measurement.

Dropping out TFP would raise the percent observed change predicted by the other 3 technology variables by about 5% points in unemployment (to 62%) and inflation (to 76%)

Table 7 shows that unemployment which declined by 1.8 percent points would have triggered an increase of 1.08 percent point in inflation rate had the growth of technology, the aging of the workforce, and the growth of trade stopped. The actual growth counteracted the trigger to yield a net decline in both inflation and unemployment. The future pace of these factors (and of those hidden in the residual) will determine the course of unemployment and inflation. The parameter estimates we used may not be optimal, if effects become non-linear at low levels of unemployment.

5. Summary and Conclusion

The growth and diffusion of new technologies (in information, communications, and in bio-technology) receive increasing attention in growth, productivity, and labor market studies. In the labor market the technologies appear to be skill biased, raising wages of only skilled labor in the short run, but extending the gains more widely in the longer run, when enough time is allowed for supply responses in education and training. These supply effects can eventually stop and reverse the growth of the wage gap between skilled and unskilled workers. As the data indicate, the growth of the gap in the 80's was followed by a plateau and incipient decline in the 90's.

In this paper we explore the parallel employment (unemployment) dynamics set off by skill biased shift in the demand for labor. The wage movements caused by demand shifts and supply responses ought to be reflected in employment (unemployment) changes differentiated by worker skills. And initial widening of unemployment differentials should be reversed when time is allowed for training to handle the new technologies. Studies of the supply responses have shown increases in training of workers in "high-tech" sectors, leading to reduction in turnover and in unemployment in these sectors. Empirical evidence shows the sectoral unemployment differentials in PSID micro-data cross sections covering the 1978-1993 period. The skill differentials are indeed reduced when 5-year lags are used.

While the relative unemployment effects of technology show up in cross sections in terms of sectoral differences, the picture in aggregate time series is shown in terms of worker skills measured by education. We find that following the pace of technology the ratio of unemployment rates of workers with 12 or less years of schooling to that of workers with post-secondary education first rises and about 5 years later declines. The unemployment gap moves like the wage gap but about twice as fast. This is not surprising: As with any changes in demand and supply, adjustment in hiring and retention policies are introduced rather quickly, but wage adjustments take a longer time mainly because of the delay due to the supply response in schooling.

Our empirical analysis defines several alternative measures of the pace of technology and utilizes a number of additional variables likely to affect the changes we study.

We explore two additional questions in aggregate time series: Does aggregate unemployment respond to the pace of technology like the relative unemployment? Do the factors affecting unemployment also affect inflation?

On the first question the answer is positive: the pace of technology has unclear effects on unemployment in the short run, but appears to reduce it in the longer run. In addition to technology, aging of the workforce and growth in imports reduce unemployment in the longer run. Statistically weaker effects appear for all these variables in the short run.

Using the same independent variables augmented by lagged (1 year) unemployment rate to analyze effects on the inflation rate (implicit GDP deflator) we find strong negative technology effects, and negative effects of lagged unemployment. Similar negative effects hold for maturing of the labor force and for imports. The effects are significant both in the short and long run.

The effects of technology, demography and trade are major: One standard deviation change in either reduces unemployment by close to 1% point. The inflation effects are bigger, especially when due to demography and imports.

Given the actual declines in unemployment and inflation in the latter half of the last decade and the actual increases in the three variables 5 years earlier, we find that the predicted declines in unemployment was over a half of the actual, with a 70% ratio of predicted to actual for inflation.

The equation for inflation includes the variable unemployment lagged one year. This variable has a negative sign as (Phillips) expected. The fact that the decline of this variable increases inflation is concealed by the inflation and unemployment reducing effects of the other variables. Put briefly, if the growth of technology, aging, and imports were to stop, the observed decline in unemployment would have an associated increase in inflation of over 1% point. Also, the decline in unemployment may not have materialized. The future pace of these factors will determine the course of unemployment and inflation as it did in the recent past provided the estimated parameters still hold.

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Appendix

A.1. Abbreviations of variables:

Variable Name	Description
Cross section	
P(u)	Incidence of unemployment one year before
P(s)	Incidence of separation one year before
P(u|s)	Conditional incidence of unemployment one year before
D	Duration of unemployment in weeks one year before
X	Years of experience
Ed	Years of schooling
NW	Nonwhite dummy
Mar	Married
Nat'l U	National unemployment rate
EG	Annual growth of industry employment
Union	Union membership dummy
Time Series	
u	National unemployment rate
dp	Inflation rate, GDP implicit
Wage Premium	College over high school male wage ratio
Unemployment Ratio	Unskilled unemployment rate (ed≤12) over skilled unemployment rate (ed > 12)
RDE	R&D expenditures per worker
C/W	Computer equipment per worker
C/E	Computer equipment per total equipment
TFP	Total factor productivity (Jorgenson) growth
RSG	Ratio of service sector to goods producing employment
Cap	Capacity usage in manufacturing industry
Age	Population age 25-44 over age 16-24
Imp	Import to GDP ratio

A.2 Variable definitions and sources

P(u), P(s), P(u|s), D
Construction: reported incidence of unemployment, separation, unemployment upon separation and duration of unemployment in weeks in the one-year ahead survey period. Source: PSID.

Natl' U, u
National unemployment rate. Source: Economic Report of the President 2000.

EG
Construction: Annual industry employment growth rate in percent. Source: Bureau of Labor Statistics.

Wage Premium:
Construction: Wage ratio of college educated full employed males over high school graduates wage. Source: March CPS

Unemployment Ratio:
Construction: Ratio of unemployment rates of those with ed ≤ 12 to those with post-high school education (ed > 12). Source: Report on the American Labor Force, Bureau of Labor Statistics.

Imp
Construction: Real total annual imports, ratio to GDP. Source: Economic Report of the President 2000.

dp
Annual GDP implicit inflation rate. Source: Economic Report of the President 2000.

RDE
Private and federal real research and development expenditures per worker. Source: Congressional Budget Office based on data from the National Science Foundation NSF, National Patterns of R&D Resources: 1997 Update.

C/W:
Construction: Real annual computer equipment expenditures over total employment. Source: Bureau of Economic Analysis NC-0229: Fixed and Reproducible Tangible Wealth 1925-97. Economic Report of the President 2000.

C/E:
Construction: Real annual computer equipment expenditures over total real nonresidential equipment Source: Bureau of Economic Analysis NC-0229: Fixed and Reproducible Tangible Wealth 1925-97.

TFP:
Construction: 5-year moving average of the TFP growth series. In cross section only available for 35 industries. Source: Jorgenson TFP.
RSG
Construction: Ratio of annual total employment in service sector over goods producing sector as defined in the Economic Report of the President. Source: Economic Report of the President 2000.

A.3. Independent variables in cross section

Only one technology panel is shown in Table A.1, because parameter estimates in Table A.1 are the same for technology measured by computer per worker (C/W) or total factor productivity (TFP). Also, coefficient estimates for the core variables remain unchanged in the extended equation.

The effects of these variables on turnover P(s) and on unemployment incidence are not surprising: Experience (X) and schooling (Ed) reduce turnover and race (NW) increases the incidence of unemployment, even though the turnover coefficient is weakly negative. This is because the conditional unemployment probability P(u|s) is higher for black workers. A larger proportion of blacks (compared to whites) encounters unemployment when separated, even if the proportion separated is somewhat smaller. Conditional unemployment and duration of unemployment are not significantly affected by experience.

Table A.1. Effects of independent variables other than technology PSID, Males, 1980-1993

TFP	X	X^2	Ed	NW	Mar.	Nat'l U	EG	Union
P(u)	-0.01	+0.00	-0.01	0.02	-0.03	0.01	0.01	-0.02
	(8.0)	(4.2)	(15.6)	(2.6)	(5.6)	(4.0)	n.s.	(3.1)
P(s)	-0.01	+0.00	-0.01	-0.02	-0.06	-0.00	0.01	-0.08
	(11.0)	(6.3)	(7.5)	(1.7)	(7.7)	(2.1)	n.s.	(12.0)
P(u|s)	n.s.	n.s.	-0.04	0.12	-0.03	0.04	0.15	0.11
			(8.1)	(2.9)	n.s.	(4.4)	(2.5)	(3.2)
D	n.s.	n.s.	-0.50	2.9	n.s.	1.2	-1.5	3.8
			(3.6)	(2.9)		(5.1)	n.s.	(4.9)

Note: t-statistics in parenthesis. +0.00 is < 0.005

Table 1 **Effects of Technology on Unemployment**
Males, 1980-1993, in PSID cross-section

TFP, core		**P(u)**	**P(s)**	**P(u|s)**	**D**	**C/W, core**		**P(u)**	**P(s)**	**P(u|s)**	**D**
Lags	**0**	-0.31 (2.2)	n.s.	-1.36 (2.1)	-47.2 (2.1)	**Lags**	**0**	-0.76 (4.0)	-0.86 (3.5)	n.s.	n.s.
	3	-0.38 (2.6)	neg.	n.s.	n.s.		**3**	incr.	incr.	n.s.	n.s.
	5	-0.34 (2.2)	-0.49 (2.5)	n.s.	n.s.		**5**	incr.	incr.	n.s.	n.s.
	7	-0.39 (2.4)	n.s.	n.s.	n.s.		**7**	-1.2 (3.3)	-2.2 (4.6)	n.s.	n.s.
	9	n.s.	n.s.	n.s.	n.s.		**9**	-1.4 (3.1)	-2.4 (4.1)		n.s.
TFP, ext.		**P(u)**	**P(s)**	**P(u|s)**	**D**	**C/W, ext.**		**P(u)**	**P(s)**	**P(u|s)**	**D**
	0	n.s.	n.s.	n.s.	n.s.	**Lags**	**0**	-0.58 (2.9)	-1.02 (4.1)	n.s.	n.s.
	3	-0.33 (2.3)	-0.45 (2.4)	-1.72 (2.0)	n.s.		**3**	incr.	incr.	n.s.	n.s.
	5	-0.47 (2.9)	-0.36 (1.8)	n.s.	n.s.		**5**	incr.	incr.	n.s.	n.s.
	7	-0.59 (3.5)	n.s.	n.s.	n.s.		**7**	incr.	-2.2 (4.7)	n.s.	n.s.
	9	-0.46 (2.6)	n.s.	n.s.	n.s.		**9**	-1.2 (2.6)	-2.4 (4.2)	n.s.	n.s.

Notes: t-statistics in parenthesis. n.s.= not significant. incr.= increases with length of lag.
Not shown in Table 1:
Effect on P(u|s) not significant for young workers ($X \leq 12$). For $X \geq 12$: it is -2.6 (2.5).
Effect on D n.s. for less educated ed < 12 strong for more educated (ed> 12): -101.3 (2.4) at 5-year lag
Effect on P(u) n.s. for young workers ($X \leq 12$), but –0.89 (3.9) for $X \geq 12$ at lag 3.
Effect on P(u|s) pronounced negative for less educated (ed≤ 12) and $X \geq 12$ workers: -2.9 (2.4) and –3.0 (2.4) respectively.

Table 2 Wage Differentials and Unemployment Differentials College vs. High school, 1968-1986

Variables	Wage Premium	Unemployment Ratio	
Intercept	-4.1	1.56	1.24
	(4.6)	(4.0)	(2.5)
Nat'l U Rate		0.035	0.045
		(2.3)	(3.1)
Ed_{-2}	-0.8	1.90	1.82
	(3.0)	(3.7)	(3.5)
Wage Premium		3.23	
		(2.6)	
RDE_{-3}	2.4		1.2
	(12.3)		(3.5)
RSG	0.04		
	(3.5)		
R^2	0.91	0.73	0.74

Note: t-statistics in parenthesis.
R^2 coefficient of determination

Table 3 Unemployment Ratios, 1970-1995

TFP	**Cap**	**Ed**	**RSG**	**R^2**	**TFP_{-5}**	**Cap**	**Ed**	**RSG**	**R^2**
0.23	-0.02	1.12	0.08	0.28	-14.6	-0.017	-0.065	0.04	0.52
n.s.	(1.5)	n.s.	n.s.		(3.2)	(1.8)	n.s.	n.s.	
RDE	**Cap**	**Ed**	**RSG**		**RDE_{-5}**	**Cap**	**Ed**	**RSG**	
2.0	-0.018	4.0	-0.71	0.63	-2.4	0.016	-5.0	1.15	0.67
(4.4)	(2.2)	(3.5)	(3.4)		(5.0)	(1.5)	(3.3)	(4.8)	
C/W	**Cap**	**Ed**	**RSG**		**C/W_{-5}**	**Cap**	**Ed**	**RSG**	
4.4	-0.31	1.38	-1.24	0.49	-9.6	0.031	-2.18	2.73	0.48
(2.9)	(3.0)	(1.3)	(2.6)		(2.8)	(1.5)	(1.3)	(2.8)	
C/E	**Cap**	**Ed**	**RSG**		**C/E_{-5}**	**Cap**	**Ed**	**RSG**	
12.3	-0.033	1.64	-1.4	0.65	-26.6	0.04	-2.92	3.2	0.54
(4.7)	(3.8)	(1.8)	(4.2)		(3.4)	(2.0)	(1.9)	(3.5)	

Note: t-statistics in parenthesis

Table 3a Unemployment Ratios, 1970-1995

TFP	**Cap**	**Trend**	**R^2**	**TFP_{-5}**	**Cap**	**Trend**	**R^2**
3.13	-0.23	0.019	0.4	-12.7	-0.018	0.006	.56
n.s.	(1.8)	(3.3)		(2.9)	(2.0)	n.s.	
RDE	**Cap**	**Trend**		**RDE_{-5}**	**Cap**	**Trend**	
0.64	-0.017	0.006	0.44	-0.85	-0.011	0.027	0.56
n.s.	(1.7)	n.s.		(3.0)	n.s.	(5.4)	
C/E	**Cap**	**Trend**		**C/W_{-5}**	**Cap**	**Trend**	
-1.84	-0.020	0.059	0.43	-3.03	-0.011	0.072	0.61
n.s.	(2.0)	(1.8)		(3.5)	n.s.	(4.5)	
C/E	**Cap**	**Trend**		**C/E_{-5}**	**Cap**	**Trend**	
0.26	-0.02	0.015	0.39	-7.2	-0.011	0.072	0.62
n.s.	(1.9)	n.s.		(3.6)	n.s.	(n.s.)	

Note: t-statistics in parenthesis

Table 4 Factors Affecting Unemployment Rates, 1970-1995

TFP	**Age**	**Imp**	**Trend**	**R^2**	**TFP_{-5}**	**Age**	**Imp**	**Trend**	**R^2**
-46.4 (2.2)	0.15 n.s.	-49.7 (1.8)	0.13 (2.0)	0.35	n.s.	n.s.	-70.0 (2.6)	0.20 (3.4)	0.28
RDE	**Age**	**Imp**	**Trend**		**RDE_{-5}**	**Age**	**Imp**	**Trend**	
-5.6 (2.5)	0.94 n.s.	-62.6 (2.5)	0.24 (4.4)	0.37	-6.8 (4.0)	-1.6 (1.9)	-20.8 n.s.	0.25 (5.0)	0.50
C/W	**Age**	**Imp**	**Trend**		**C/W_{-5}**	**Age**	**Imp**	**Trend**	
-9.8 n.s.	-5.1 (3.1)	n.s.	n.s.	0.26	-37.8 (3.3)	-5.1 (3.1)	n.s.	0.43 (5.2)	0.44
C/E	**Age**	**Imp**	**Trend**		**C/E_{-5}**	**Age**	**Imp**	**Trend**	
-69.3 n.s.	-4.1 n.s.	-49.5 n.s.	0.56 (2.5)	0.31	-83.5 (3.2)	-4.3 (2.5)	-4.8 n.s.	0.44 (5.1)	0.44

Note: t-statistics in parenthesis

Table 5 Factors Affecting the Inflation Rates (dp), 1970-1995

TFP	**Age**	**Imp.**	**Trend**	**U_{-1}**	**R^2**	**TFP_{-5}**	**Age**	**Imp.**	**Trend**	**U_{-1}**	**R^2**
-4.9	-5.3	-89.4	-0.33	-0.31	0.83	-4.8	-5.2	-116.7	-0.43	-0.37	0.79
(2.7)	(7.8)	(3.6)	(5.3)	(2.3)		n.s.	(6.7)	(4.6)	(7.4)	(2.3)	
RDE	**Age**	**Imp.**	**Trend**	**U_{-1}**		**RDE_{-5}**	**Age**	**Imp.**	**Trend**	**U_{-1}**	
-10.7	-3.8	-106.8	0.51	-0.55	0.94	-4.9	-6.4	-92.7	0.5	-0.62	0.81
(8.6)	(8.5)	(7.8)	(5.5)	(6.6)		(2.0)	(6.9)	(3.5)	(7.8)	(3.2)	
C/W	**Age**	**Imp.**	**Trend**	**U_{-1}**		**C/W_{-5}**	**Age**	**Imp.**	**Trend**	**U_{-1}**	
-14.6	-3.2	-91.6	0.58	-0.38	0.79	17.4	-7.5	-143.8	0.31	-0.2	0.80
n.s.	(1.8)	(2.4)	(3.1)	(2.5)		n.s.	(3.4)	(4.1)	(2.5)	n.s.	
C/E	**Age**	**Imp.**	**Trend**	**U_{-1}**		**C/E_{-5}**	**Age**	**Imp.**	**Trend**	**U_{-1}**	
-142.0	2.8	-73.3	1.2	-0.45	0.87	22.8	-6.3	-131.2	0.36	-0.47	0.79
(4.5)	n.s.	(3.3)	(6.9)	(3.8)		n.s.	(3.3)	(3.9)	(2.9)	(1.9)	

Note: t-statistics in parenthesis

Table 6a Means (M) and Standard Deviations (σ) of Variables

	u	dp	TFP	RDE	C/W	C/E	Age Ratio	Import Ratio
M	6.0	4.3	0.01	1.1	0.21	0.11	1.9	0.08
σ	1.5	2.5	0.012	0.22	0.18	0.07	0.40	0.03

Table 6b Effects of one standard deviation change in independent variables on unemployment and inflation (1970-1995)

Effects measured in							Mean Effects		
	TFP	**Age**	**Imp.**	**RDE**	**Age**	**Imp.**	**Tech**	**Age**	**Imp.**
u [1]	-0.5	0	-2.1	-1.2	-0.65	-1.9	-0.76	-1.24	-1.35
σ(u) [2]	0.3	0	1.4	0.8	0.4	1.2	0.5	0.8	0.9
	C/W	**Age**	**Imp.**	**C/E**	**Age**	**Imp.**			
u [1]	-0.75	-2.6	0	-0.6	-1.7	-1.5			
σ(u) [2]	0.5	1.7	0	0.4	1.1	1.0			
	TFP	**Age**	**Imp.**	**RDE**	**Age**	**Imp.**	**Tech**	**Age**	**Imp.**
dp [1]	-0.65	-2.1	-3.5	-1.5	-2.5	-3.2	-0.8	-2.5	-3.7
σ(dp) [2]	0.25	0.8	1.4	0.6	1.0	1.3	0.32	1.0	1.6
	C/W	**Age**	**Imp.**	**C/E**	**Age**	**Imp.**			
dp [1]	0	-3.0	-4.3	-1.0	-2.5	-3.8			
σ(dp) [2]	0	1.2	1.7	0.4	1.0	1.5			

Notes: [1]Effects on unemployment are lagged and measured in percent points.
[2] Effects measured in standard deviations.

Table 7 Actual and Predicted Change in Unemployment and Inflation

Period		**Tech**	**Age**	**Imp.**	**Δ u $_{t-1}$**	**Sum**	**Actual Decline**	**% Predicted / Actual**
90-94	Obs. change in σ units	1/3	1/4	1/3	6/5			
95-99	Predicted change in *u*	-0.25	-0.31	-0.45		-1.01	-1.8	**56%**
95-99	Predicted change in *dp*	-0.27	-0.60	-1.28	1.08	-1.07	-1.50	**71%**

Figure 1 **Relative Wage: 1965-1998**
Source: Current Population Survey (CPS)

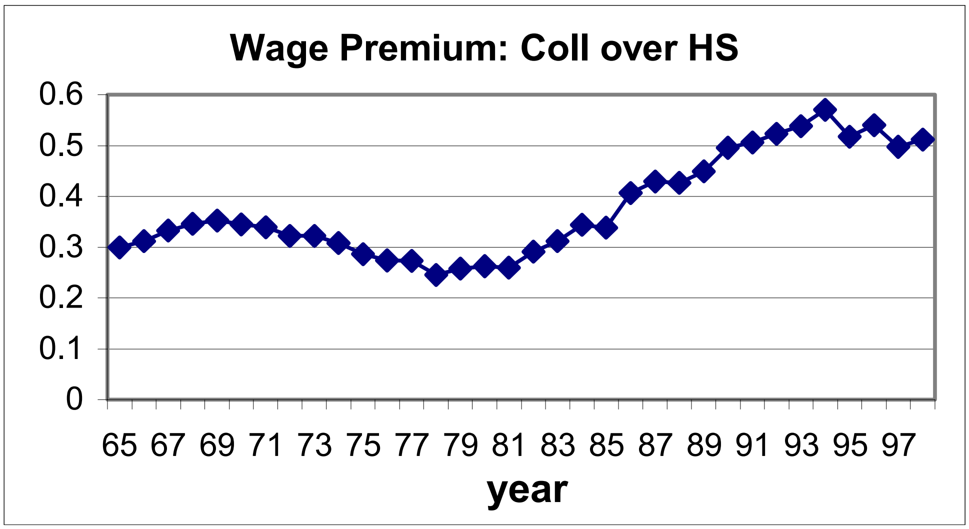


Figure 2 **Unemployment Ratio 1970-1995**
Source: Report on the American Labor Force, BLS

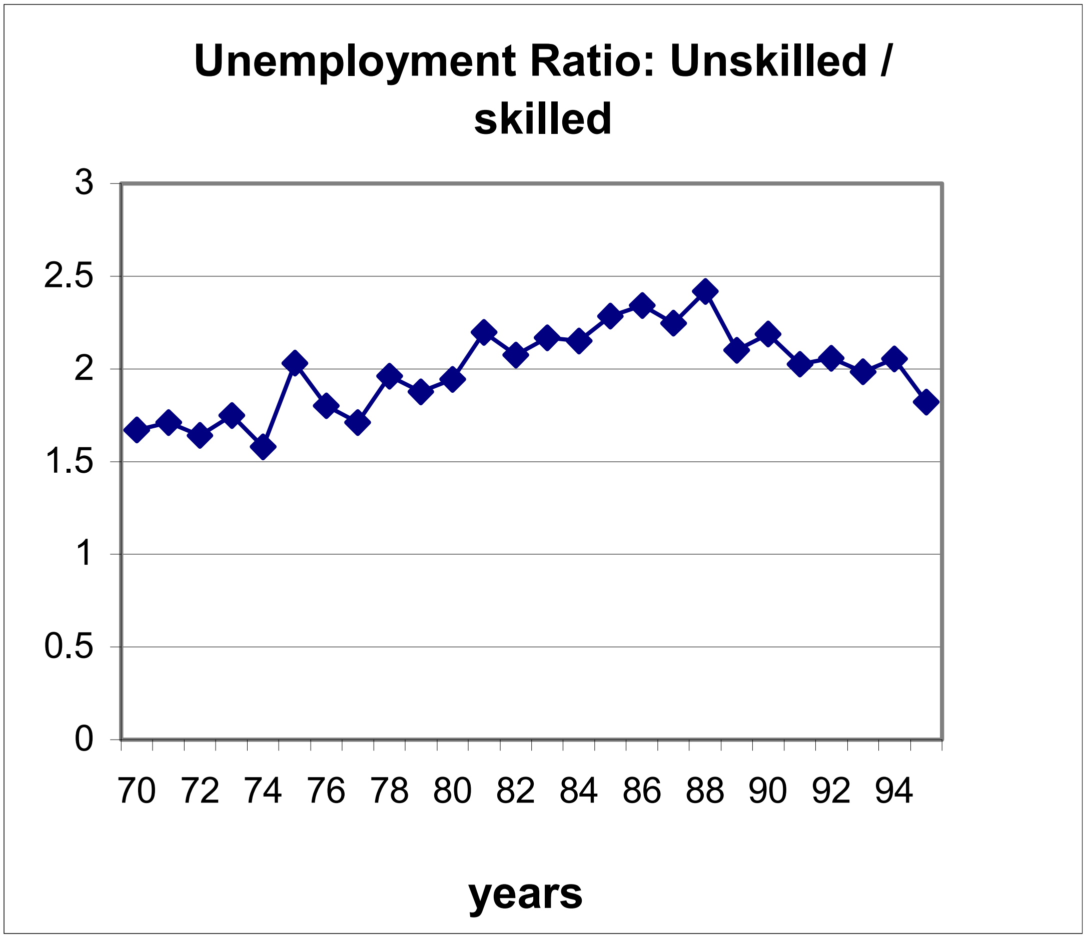
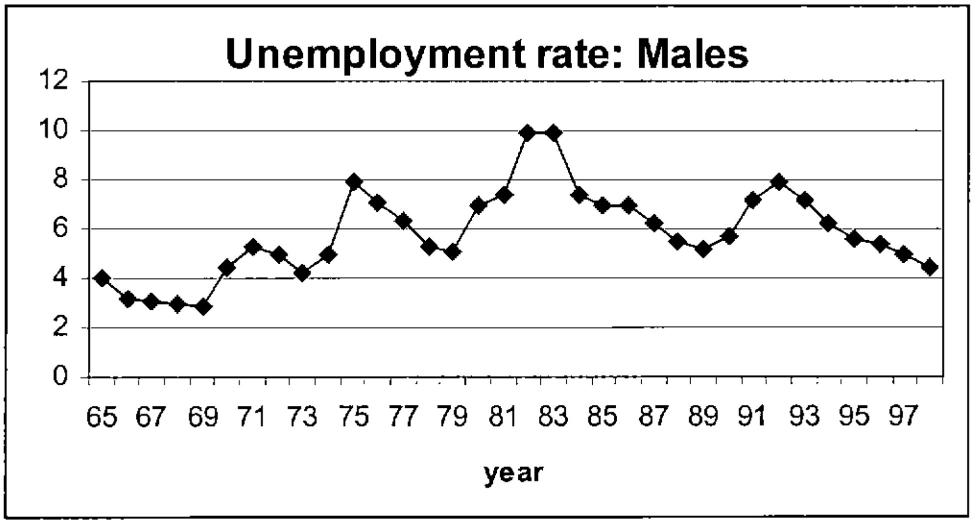


Figure 3 **Unemployment Rates of Males**
Source: ERP 2000



ERP –Economic Report of the President

Figure 4 **GDP- inflation rate**
Source: ERP 2000

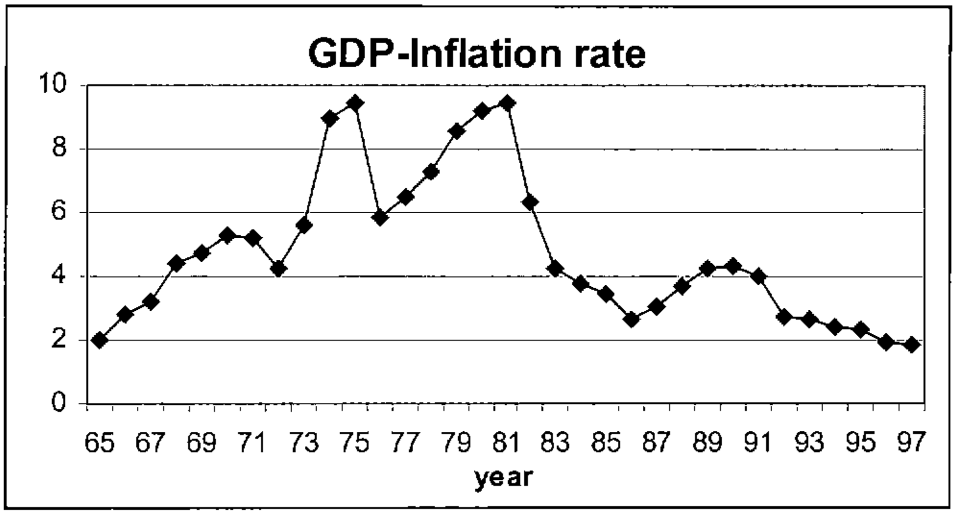
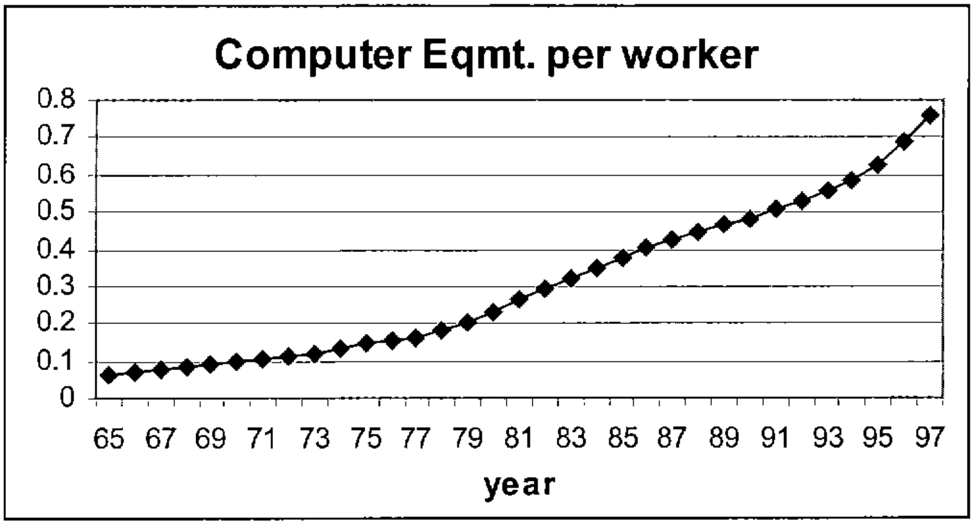


Figure 5 **Computer Equipment per worker**
Sources: BEA and ERP 2000



BEA –Bureau of Economic Analysis

Figure 6 **Computer Equipment per total nonresident Equipment**
Source: BEA

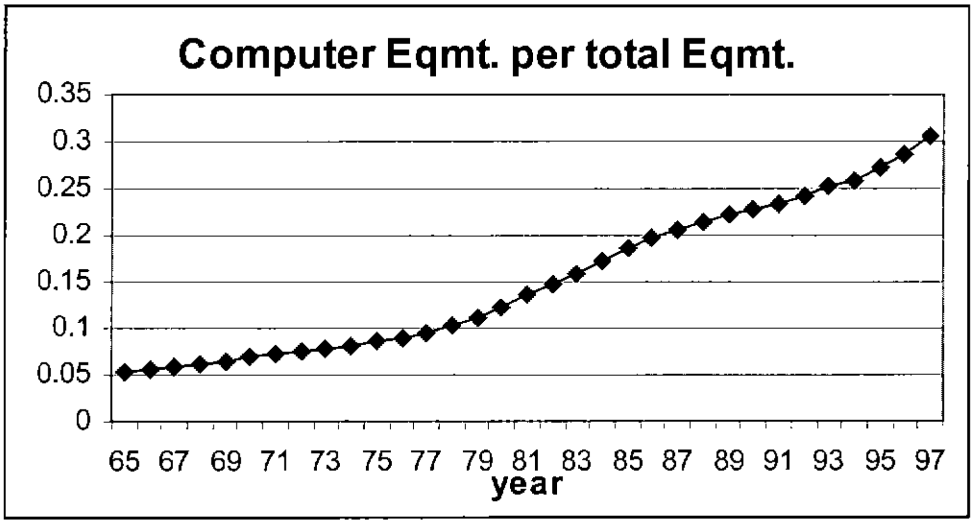


Figure 7 **TFP – 5 year moving average**
Source: Jorgenson et al.

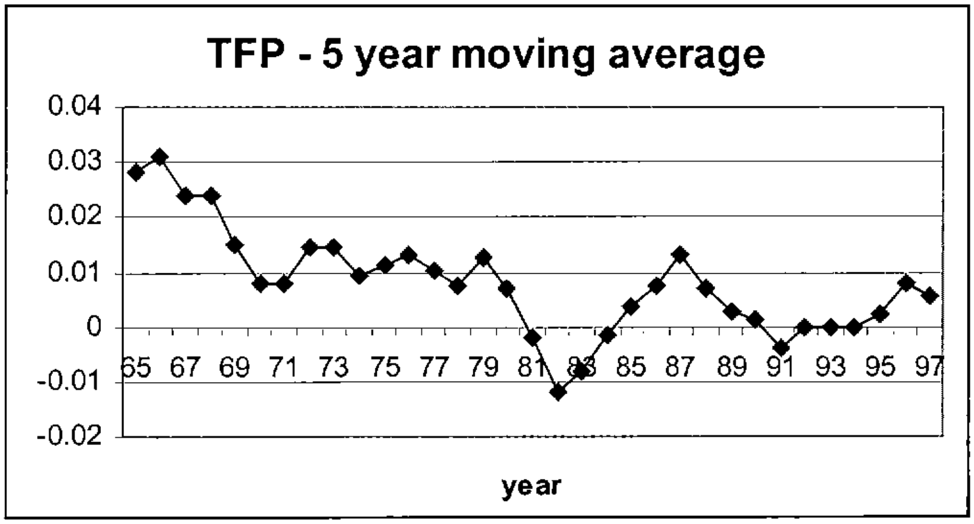


Figure 8 **R&D expenditure per worker**
Sources: NSF, BLS, and ERP 2000

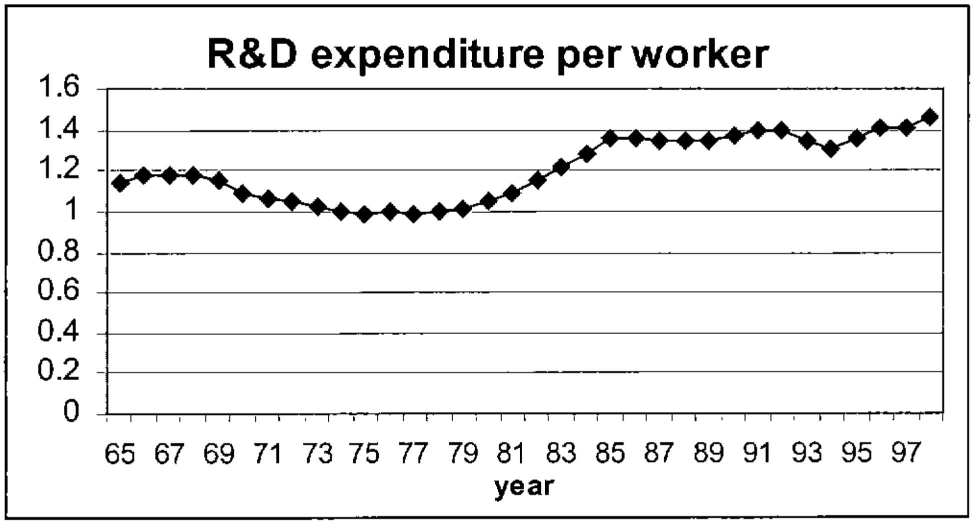


Figure 9 **Age Distribution of US Working Age Population**
Source: ERP 2000

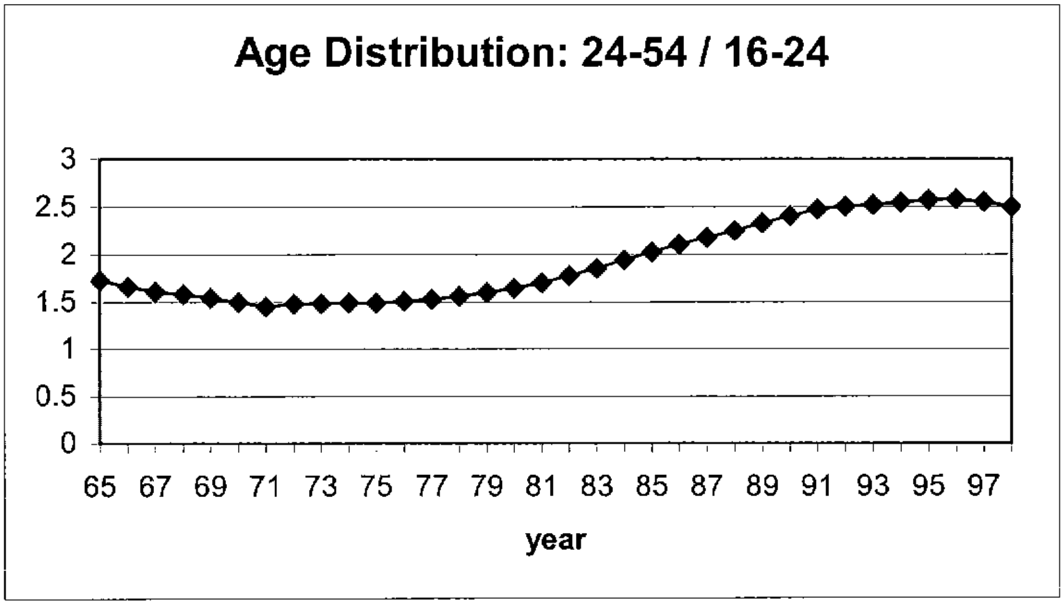


Figure 10 **Real Import to GDP Ratio**
Source: ERP 2000

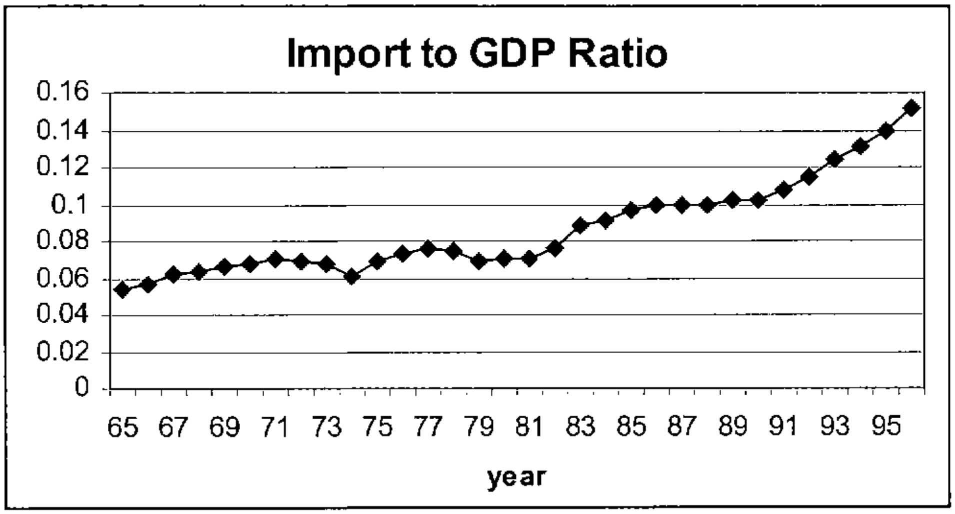


Figure 11 Average years of schooling
Source: CPS

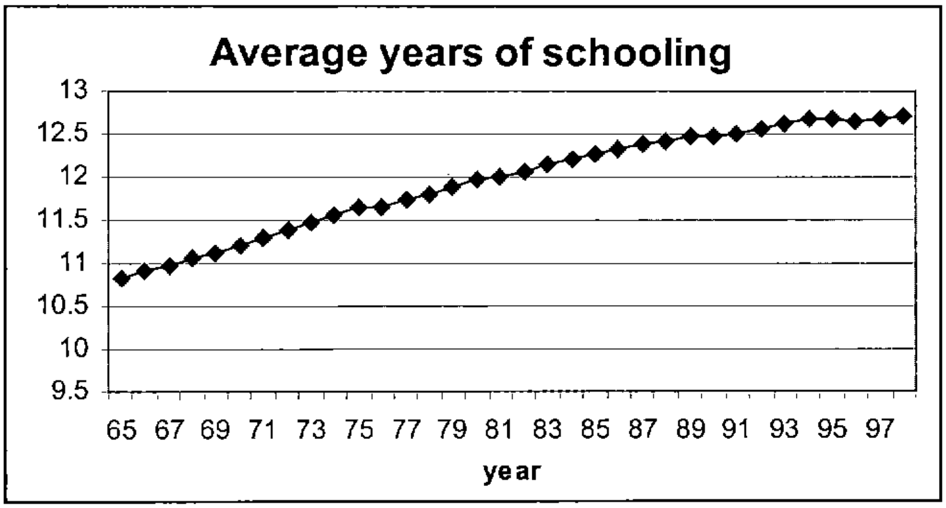


Figure 12 Employment: Service to Goods Producing Industries
Source: ERP 2000