

Growth in worker quality

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Introduction and summary

Improvements in worker quality due to changes in the distribution of education and work experience are among the key determinants of the economy's potential rate of growth. The rate of such improvements is thus of substantial interest to monetary and fiscal policymakers concerned with maintaining balance between aggregate supply and demand. It also is of importance to officials charged with planning for the future of programs such as Social Security, whose projected financial condition is highly sensitive to assumptions about long-term economic growth.

In this article we provide new estimates and forecasts of the rate of improvement in worker quality. Consistent with previous research, we find that changes in the distribution of workers' education and work experience levels account for a significant portion of the growth in labor productivity. In particular, of the 2.7 percent average growth rate in labor productivity since 1965, we find that about 0.22 of a percentage point is attributable to the growth of labor quality. We also find that this contribution has fluctuated significantly over the last 35 years. For instance, as recently as the late 1980s and early 1990s, improvements in worker skill levels were adding about 0.40 percentage points per year to the growth of output. However, by the end of the 1990s, this figure had fallen to about 0.18 percentage points. Our forecasts call for a further decline to about 0.05 percentage points by 2010.

The recent figures represent the combined effects of two long-running demographic trends and a partially offsetting business-cycle effect. The two demographic trends are the continuing increase in the education levels of the labor force and the movement of workers toward experience levels associated with higher wages and productivity. A major factor in the latter trend has been the aging of the Baby Boom generation, many of whom are now in their peak earnings years.

The positive effects of demographic change are partially offset by what has recently been the relatively faster employment growth of low-education and low-experience workers, the typical pattern in a business-cycle expansion.

Our forecast of a declining growth contribution from worker quality derives from two sources. First, we expect a slight decline in the rate of educational gains. Second, and more important, as the decade progresses, a significant portion of the Baby Boom generation will move beyond the highest earnings years that most workers experience in their early 50s. Indeed, by the end of the decade, the leading edge of the Baby Boom will be at an age associated with lower than average wage rates. At the same time, the age ranges associated with maximum wages and productivity will become populated with the smaller cohorts born in the late 1960s and early 1970s. As a result, the change in experience levels will turn from a positive to a negative factor for worker quality growth.

We also examine the gap in labor quality between the employed and the pool of available workers, those who, while not working, currently report that they want a job. We find that available workers typically have predicted wages and productivity that are 15 percent to 20 percent lower than the employed. Over the course of a business cycle expansion, most potential workers with higher skill levels become employed, which tends to expand this gap. The long business cycle expansion that began in the early 1990s is particularly notable in pushing the gap in quality between the employed and the pool of available workers to nearly 23 percent, its highest level in our data.

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The compositional changes in the labor force we study can obscure the effects of changes in labor supply and labor demand on the price of an hour of constant quality labor. This may make it more difficult to evaluate macroeconomic theories that have implications for the behavior of real wages. Thus, we provide new estimates of real wage growth adjusted to a constant quality of labor hour. The resulting series is modestly more procyclical than unadjusted real wage growth measures. We also construct an unemployment rate for human capital that accounts for the fact that the loss in labor input associated with unemployment is greater when the affected worker is at a higher skill level. The resulting measure is between 0.5 and 1.0 percentage point lower than the standard civilian unemployment rate that counts all members of the labor force equally.

The importance of labor quality has been made clear by the development of human capital models, which relate productivity and wage rates to characteristics such as education and work experience. The last 35 years have seen several major shifts in the distribution of such characteristics in the labor force, most notably the increase in the share of college-educated workers and the influx of relatively inexperienced women and Baby Boomers in the 1970s. In addition, the nature of the skills learned through formal education and on-the-job training has changed, with, in particular, a tremendous increase in workers with computer skills in the 1980s and 1990s. Human capital models quantify the extent to which these transformations have caused the growth of total labor input to differ from that of raw hours worked. This difference is known as worker quality growth. It is positive when total labor input is growing faster than the raw total of hours worked.

As we show in this article, fluctuations in labor quality growth have had a significant impact on trends in output growth. Thus, by quantifying the expected future gains in labor quality, we can improve forecasts of potential output growth. In addition, quantifying past gains in labor quality is vital to producing productivity growth estimates that constitute a meaningful measure of our economy's progress. Indeed, the simple observation that accurate measurement of productivity is critically dependent on using correctly measured outputs and inputs has been the root of a long literature on growth accounting that dates back to influential work by Solow (1957), Denison (1962), and Jorgenson and Griliches (1967) and has been updated and revised by Jorgenson and his coauthors (1987, 1999, 2000) and the U.S. Department of Labor, Bureau of Labor Statistics (BLS) (1993), among others.¹ One recent prominent example is Young

(1995), who argues that input growth explains all the extraordinary output growth in East Asia in the 1970s and 1980s. This is very much in the spirit of Jorgenson and Griliches (1967) and Jorgenson, Gallup, and Fraumani (1987), who argue that proper measurement of inputs should result in estimates of total factor productivity growth that are close to zero.² By more clearly articulating the trends in worker quality, this article also contributes to improved productivity measurement.

Our measure of labor quality relies on the basic empirical implications of human capital models. Workers invest in productivity-increasing skills through formal education and on-the-job training. Moreover, in long-run competitive equilibrium, firms hire additional labor until workers' marginal productivity coincides with their wage rate. This allows us to infer the effects of worker characteristics on productivity, which are not directly observable, from their effects on predicted wages, which can be estimated from cross-sectional data. We use such wage function estimates to value additional years of education, experience, and other forms of human capital. Applying these value estimates to the changing distributions of human capital indicators yields estimates of the growth in average worker quality.

The critical assumption underlying our approach is that workers' wage rates are equal to their marginal productivity, a basic implication of the competitive model of labor markets. There are, of course, models of the labor market in which wages are not equal to marginal products. For example, if firms discriminate against women or minority groups or if unions or firms exercise market power, wage rates may differ from productivity.³ In addition, Spence (1973) argues that firms use education and other observable human capital variables as a signal of unobservable worker ability. This can lead workers to invest in education even when it provides no actual increase in productivity. Finally, implicit contract models of the type studied by Lazear (1979) suggest that in order to induce higher effort and investment in skills, firms defer a portion of workers' compensation until later in their careers. This leads to wages being below productivity early in workers' careers and above productivity in later years.

While not denying the relevance of these alternative models of the labor market in some contexts, we are nevertheless comfortable relying on the competitive model to provide at least a good first approximation to the growth in worker quality. An enormous number of empirical studies of the labor market have found competition to be a useful framework. In contrast, there is less evidence for the widespread relevance of the

alternative models. Moreover, some direct support for the link between human capital and aggregate growth emerges from recent studies using international macroeconomic data. Though some early research found little correlation between changes in human capital and output growth, studies by Heckman and Klenow (1997), Topel (2000), and Krueger and Lindahl (1999) show that macro and micro estimates of the return to education are similar once adequate account is taken of measurement error.

A bigger concern is that the available data on worker characteristics only begin to scratch the surface in explaining the determinants of wages and productivity. For instance, the productivity increase associated with a college degree must depend on the program of study, the quality of the institution, and a myriad of other factors. But typical data sources merely record whether a worker has any college degree. Similarly, the productivity increase associated with a year of work experience will vary with the nature of the work, how much time is devoted to training, and other factors. But data sources do not typically include such information. Indeed, almost all research on worker quality growth is based on *proxies* for years of work experience derived from the difference between a worker's age and their years of formal education. Unobserved differences in time out of the labor force due, for example, to raising children will lead such proxies to differ from actual experience.

The existence of unmeasured differences in worker characteristics will not greatly bias estimates of worker quality growth if the distributions of such characteristics around their means remain relatively fixed over time. In that case, changes over time in mean years of schooling and age are reasonable proxies for the overall improvement in productivity due to education and work experience. But systematic changes in unmeasured characteristics can lead to biases. For example, women tend to spend more time out of the labor force than men. So the ongoing increase in female labor force participation could lead to progressively greater overestimation of the average level of labor market experience by the usual proxy measure. In addition, some researchers suggest that the quality of education has changed systematically over time, which could cause growth in true education to differ from that suggested by increases in years of schooling. In particular, Bishop (1989) attributes a significant portion of the post-1973 slowdown in measured productivity growth to deterioration in the quality of education as evidenced by declining test scores. More recently, we suspect the greatly increased use of computers in the work place has raised the quantity of on-the-job training associated with a year of work

experience, which could also bias estimates of worker quality growth.

Other recent work on labor quality includes Ho and Jorgenson (1999) and BLS (1993). Our methodology and data differ somewhat from these papers, as we discuss in a later section. This leads to some differences in estimates of labor quality growth. However, the broad contours of our results agree reasonably well with earlier work for periods in which our results overlap. Together, our research and the earlier work show that growth in labor quality has fluctuated in important ways over time.

The quarter century after World War II was a period of especially rapid gains in worker skill levels. Indeed, Ho and Jorgenson describe the period from 1948 to 1968 as the golden age of labor quality growth. During this period, they estimate that rapid expansion of secondary and post-secondary education caused labor quality growth to average nearly 1 percent per year. As noted above, this means that changes in the composition of the labor force caused total labor input to grow nearly 1 percentage point more rapidly than total hours. However, with the flood of inexperienced Baby Boomers and female workers into the labor force in the 1970s, labor quality stagnated. Then, after 1980 as the Baby Boomers aged and educational attainment soared to new heights, labor quality accelerated again, to a growth rate of about 0.5 percent per year, about half of that seen in the 1950s and 1960s. Our estimates indicate that labor quality continued to advance in the last few years, but at a yet slower rate of only about 0.27 percentage points per year. Our forecasts call for annual growth to decline further to about 0.07 percentage points by 2010.

Given the standard assumptions of constant returns-to-scale production and cost minimization, the contribution of labor input to output growth is the product of the growth rate of labor input and labor's share in production costs. The latter figure is approximately two-thirds. Thus, our estimates for labor quality growth imply effects on real output growth of 0.18 percentage points late in the 1990s and 2000, declining to about 0.05 percentage points by 2010.⁴

In the next section of this article, we review some of the broad trends in human capital accumulation that underlie our estimates of labor quality growth. In the following two sections, we discuss our methodology and our detailed results.

Trends in human capital accumulation

Here, we document some of the broad trends in human capital accumulation that underlie estimates of worker quality growth. These are the increases in educational attainment, fluctuations in the age

distribution, and the rising fraction of female workers. We also note some other changes in the nature and composition of the work force that may affect the growth of human capital but are not usually included in analysis of labor quality.

Education

U.S. levels of formal education have expanded greatly over the last century. We can see this in figure 1, which shows the increase in high school and college graduation rates since 1870.⁵ During this period, high school graduation went from a rarity to the norm. As the figure shows, a good part of that transformation occurred during the early part of the twentieth century, a period Claudia Goldin and Lawrence Katz (Goldin 1998, Goldin and Katz, 1999a) argue was formative for American education. College attendance and graduation rates also rose rapidly during the twentieth century. Increases in college graduation rates were especially rapid after WWII with the introduction of the GI Bill and increased growth in federal funding of higher education. But even before WWII, growth in college graduation rates was impressive. Enrollment rates quadrupled between 1940 and 1970 but also tripled between 1910 and 1940. This pre-WWII expansion in education levels was unique to the U.S.; education did not expand at such rates in other countries until several decades later. These trends likely increased potential output growth in the U.S. during the early twentieth century relative to other developed nations that were slower to invest in education.

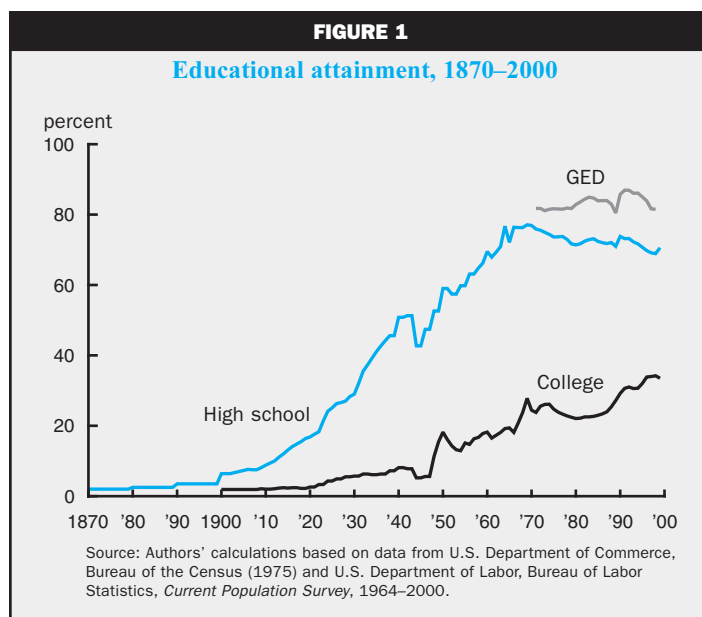
More recently, the growth in the rate of high school completion has stalled. Indeed, relative to the

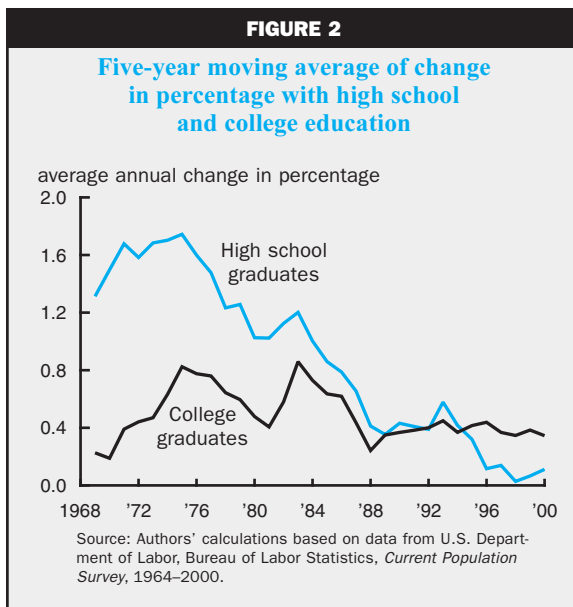
population of 17 year olds, the number of new high school diplomas granted in the late 1990s was 7 percentage points lower than it was in the early 1970s. Only when general equivalency diplomas (GEDs) are added to the totals do recent rates match earlier levels. However, Heckman and Cameron (1993) have shown that GED holders typically possess considerably less human capital than high school graduates. Thus, the recent data in figure 1 should be regarded as showing an overall deterioration in the fraction of new labor market entrants with the skills typically associated with secondary school completion.⁶

College graduation rates, however, have continued to increase, though not without some significant fluctuations. Indeed, after an especially rapid advance during the Vietnam War era, growth in new college degrees granted actually lagged the growth in 22 year olds until the mid-1980s, when it turned up again. More recently, growth accelerated in the early 1990s, and by the end of the last decade graduation rates were back to the trend line established in the post-WWII period.

Increasing graduation rates have led to a corresponding increase in the percentage of workers with high school and college education. In 1964, the beginning year for the data we use for this study, less than 58 percent of workers had completed high school or had a GED. By 2000, this figure was over 90 percent. In 1964, less than 12 percent of workers had college degrees. By 2000, more than 28 percent did. There were also healthy increases over the same period in the share of workers with at least some college education and with post-graduate education.

Though still significant, the growth in average levels of education has slowed since its high point in the early 1960s and late 1970s. This can be seen in figure 2, which plots the five-year moving average of the annual change in the percentage of workers with high school and college degrees.⁷ The figure indicates that the increase in high school graduation rates has fallen relatively steadily from around 1.7 percentage points per year at its peak in the early 1970s to only about 0.1 percentage points the last several years. Increases in college graduation rates have also declined over time, but the drop has been smaller. Between 1970 and 1975 and again between 1978 and 1983, the increase in the share of college workers peaked at a rate of about 0.8 percentage points per year. Since the mid-1980s, the advance has been relatively stable at about 0.4 percentage points per year.





Such fluctuations in the growth of average educational levels can occur for two reasons. First, younger workers entering the labor force are constantly replacing older workers reaching retirement age. The former have historically had more education. Second, some of those in the age ranges typically associated with working choose to acquire more education, often while continuing to work part or full time.

Figures 3 and 4 shed some light on the importance of new entrants replacing retiring workers for the increase in education levels. Figure 3 plots the difference in high school and college graduation rates between those near the end of their careers (55 to 59 year olds) and those near the beginning of their careers (25 to 29 year olds). As the graph shows, in the 1960s, there was a more than 30-percentage-point difference between the high school graduation rates of older and younger workers. Likewise, the expansion of college graduation rates in the 1970s led to a more than 15-percentage-point difference between the college graduation rates of older and younger workers. These large gaps between workers entering and leaving the work force were a major factor behind the rapid growth of average educational attainment during those periods. But those differences, and their resulting implications for labor quality growth, had all but disappeared by 2000. This is one of the factors underlying the slower growth in average education levels in the 1990s seen in figure 2.

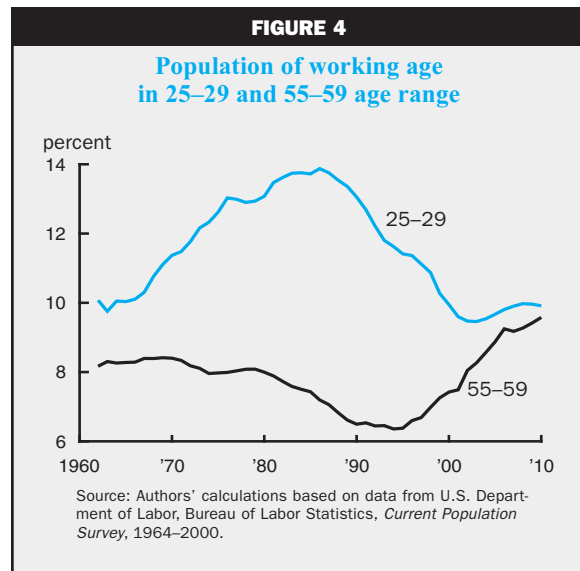
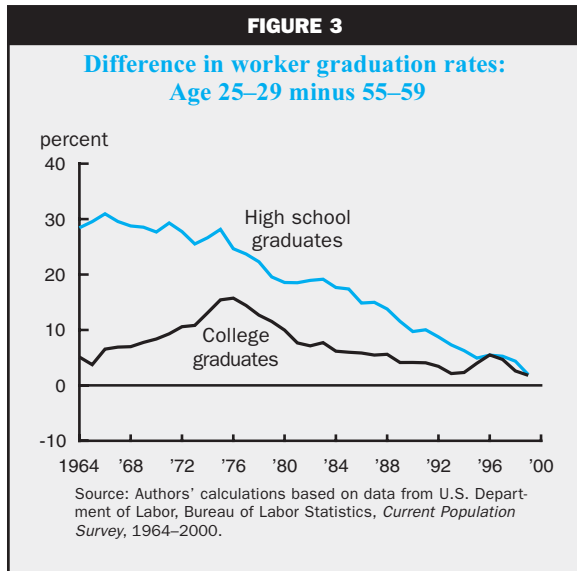
The size of cohorts entering and exiting the labor force also drives fluctuations in the growth of educational attainment. When the flow into the labor market of younger, more highly educated workers is

faster than the flow out of the labor market of older, less highly educated workers or vice versa, the average educational level increases more rapidly for a given gap in the two groups' educational attainment. These flows are, of course, largely determined by changes over time in the size of birth cohorts. Figure 4 provides an indication of how cohort sizes have varied since the mid-1960s. Specifically, the colored line shows the percentage of the working age (18–69) population made up of 25 to 29 year olds and the black line shows the percentage of 55 to 59 year olds.

The figure shows that the fraction of the working-age population accounted for by early-career workers rose from around 10 percent in the early 1960s to nearly 14 percent in the mid-1980s. A big part of that rise, which acted to increase the growth of average educational attainment, was the Baby Boom generation reaching working age. The first members of that generation reached age 25 around 1970 and its last members reached age 25 a few years after the peak in the share of early-career workers. Since the mid-1980s, the share of early-career workers has dropped to around 10.5 percent, which has contributed to the slower pace of growth in average educational attainment. Census Bureau projections call for the 25–29 share to stabilize this decade at around 10 percent.

The share of late-career workers fluctuated somewhat less, dropping from around 8 percent in the early 1960s to a minimum of about 6.5 percent in the mid-1990s, before starting to rise again. Projections are for it to continue to rise to nearly 10 percent by 2010. The increase in the size of retiring cohorts is a positive for the growth in average educational attainment, but given the currently small gap in educational attainment shown in figure 3, it is only a small positive.

Of course, many workers continue to acquire formal education until quite late in their lives. Moreover, workers with greater formal education tend to live longer and to remain more firmly attached to the labor force. Thus, even without additional school attendance, the average educational attainment of a cohort of workers can rise as the less educated workers tend to drop out of the labor force more quickly. The combined effects of additional education and the greater tendency for the less educated to drop out of the labor force induces a significant increase over time in the average educational attainment of workers from a given birth cohort. For example, figure 5 follows the cohort born between 1941 and 1945. It shows that the fraction with college degrees increased between 1970, when they were aged 25 to 29, and 2000, when they were 55 to 59. The colored line shows the proportion of the whole cohort with



college degrees, while the black line is limited to those working in the given year.

As the graph shows, the increase in the share reporting a college education has been quite significant. When this cohort was between the ages of 25 and 29 in 1970, only 16.5 percent reported having a college education. Thirty years later, the share was 25.5 percent. When we limit the samples to those who were working, the increase in the percentage was even greater, going from about 19.3 percent to about 29.3 percent. As the gap in educational attainment between younger and older workers narrows, the increasing educational attainment of middle-aged workers is becoming a bigger factor in the growth of educational levels.

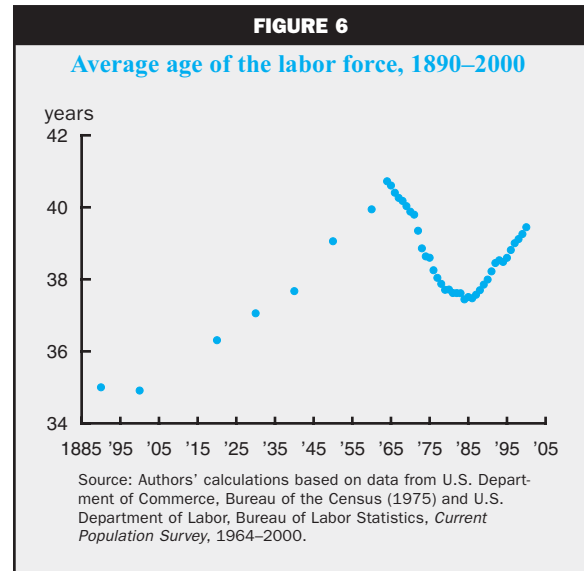
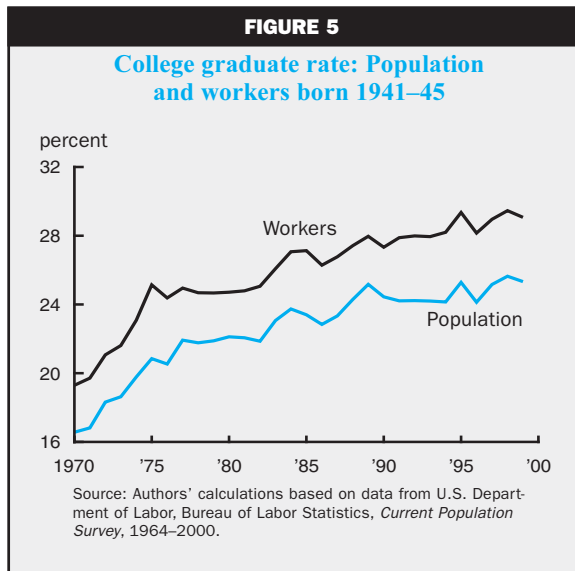
Work experience

Workers' labor market experience is a second important determinant of skill levels. Until they reach their early fifties, workers' wage rates and, thus by inference, their productivity, tend to increase with age. These increases presumably reflect skills learned over time in the labor market. As a rough indication of the trends in labor market experience, figure 6 shows the average age of workers between 1890 and 2000. Consistent with greater life expectancies and lower birth rates, the average age of workers grew from 35 at the turn of the twentieth century to over 40 at its apex in the mid-1960s. However, starting in the late 1960s, the first of the large Baby Boom cohorts entered the labor force, causing the average age to drop for the next 20 years, reaching a bottom at around 37.5 as the last of the Baby Boomers entered the labor force in the early 1980s. As we show later, this drop in experience levels partially offsets the labor quality

improvements arising from the tremendous gains in formal education during the 1970s. Since the early 1980s, the aging of the Baby Boom cohort has helped to push the average age of the working population back to about 39.5, roughly where it was in the early 1970s.

Sex composition

The final, major and easily quantifiable change in the composition of the labor force is the rise of female workers, particularly during the second half of the twentieth century. Though the gap has been narrowing in recent decades, women tend to earn lower wages than men of the same age and educational level. The competitive labor market framework that we employ in this article implies that this male–female wage gap reflects differences in productivity, rather than discrimination or some other factors.⁸ One interpretation is that the error in approximating labor market experience by age minus years of education minus six is greater for women than men, who generally spend less time not in the work force or attending school. Thus among groups with the same level of measured experience, women will tend to have less actual experience. Indeed, the wage gap between men and women is significantly smaller at low levels of experience. Under this interpretation, it is not that women are intrinsically less productive than men, but rather that they have less actual labor market experience than men of the same age and education level. Still, given their lower wage, an increasing share of women in the labor force lowers the growth of labor quality below that expected on the basis of age and education.



Beginning after WWII, the share of female workers rose from less than 25 percent to about 38 percent in 1970 to close to 47 percent by 1990, before flattening out during the last decade. Given their lower wage rates, rapid increases in the share of female workers, such as occurred in the 1950s to 1980s, tended to hold down the growth in labor quality. This negative effect on worker quality has diminished as the share of women has grown more slowly over the last decade.

Other factors

While most analyses of labor quality, including the basic estimates we present below, are based exclusively on the trends in education, age, and sex composition that we have just discussed, there are good reasons to think that other factors may also play a role. We have already noted that crude measures of years of schooling or labor market experience may fail to fully capture the accumulation of human capital when educational or work experiences differ across workers and time. One change that we wish to highlight is the increasing computerization of the workplace, which may be leading to more on-the-job investment in skills per year of labor market experience.

The 1980s and 1990s saw an explosion in the use of computer skills. Among workers age 18 to 64, roughly 25 percent used a computer in 1984. That fraction grew to 37.4 percent in 1989, 46.6 percent in 1993, and 60.5 percent in 1997.⁹ At first glance, this seems like an obvious improvement in the skill level of the work force. Krueger (1993) even attempts to quantify the rate of return to using a computer at work by estimating the gap in wages between otherwise similar workers who report that they do or do not use a computer. However, DiNardo and Pischke (1997)

argue that similar apparent rates of return are associated with using a pencil or sitting in a chair at work. In other words, computer usage may be associated with higher wages because it is correlated with unmeasured ability. On average, workers with more ability tend to have jobs that require sitting or using a computer (or pencil) at work. Therefore, the extent to which computer usage has added to labor quality is subject to a great deal of uncertainty. Thus, it would be difficult to implement a labor quality measure incorporating computer usage, even if such data were available in a general enough form. Nevertheless, the fact that there has been such a sharp increase in an important form of on-the-job training highlights the fact that simple years of labor market experience is a rather crude measure of the human capital acquired while working.

Finally, there have been a number of other trends in labor force composition that may have implications for labor quality. One is the steady increase in the minority and immigrant portions of the working population over the last 30 years. The latter is discussed extensively in work by Borjas (1999). Because minorities and immigrants tend to have lower wages than natives and whites, these trends may have had an impact on worker quality growth. A second trend is the fall in the share of married workers from around 75 percent in the mid-1960s to around 60 percent in 2000. Research on the productivity implications of marriage, and how those vary by gender, is discussed in Gray (1997). Finally, the share of those working part time has fluctuated over the years. This may have implications for productivity, since part-time workers tend to earn lower wages.¹⁰

Methodology

In this section, we discuss our methodology for summarizing the effects of the changes outlined above in an overall measure of labor quality growth.

Data

Our labor quality estimates are derived from the Bureau of Labor Statistics' *Current Population Survey* (CPS). The CPS, the source for such well-known statistics as the unemployment rate, is a monthly, nationally representative survey of approximately 50,000 households conducted by the Census Bureau. Importantly for our purposes, it collects basic demographic data, such as age, race, sex, and educational attainment, as well as data on labor market status.

Participating households are surveyed for four months, ignored for the following eight months, and then surveyed again for four more months. Those households in the fourth and eighth months of their participation are known as the outgoing rotation groups (ORGs) and are asked some additional questions that allow construction of an hourly wage measure. Moreover, the micro data from the ORGs are collected in easily accessible form. The major advantage of the ORG files is the large sample sizes (150,000 households per year) that are available. However, the data only go back to 1979, a relatively short period for examining labor quality.

Therefore, we base most of our results on the CPS data for March of each year, which are available from 1962. The advantage of the March data is that they are supplemented with additional questions about income, weeks worked, and usual hours worked per week in the previous calendar year. Using data since 1975, we can compute an hourly wage as annual earnings in the last year divided by the product of usual weekly hours and number of weeks worked in the last year. Prior to the 1976 survey, data on usual weekly hours are not available; but there are data on hours worked in the week prior to the survey that we can use to construct a wage measure. Although the March CPS files are available starting in 1962, education is missing in the 1963 survey. So we begin our analysis with the 1964 data. A disadvantage of the March data relative to the ORG files is the smaller sample sizes (50,000 households per year). However, we find that after 1980 when we can compute measures based on both data sources, the March data yield a series that, while somewhat more variable, is quite close to that based on the ORGs.

Statistical methodology

In order to compute an index of labor quality based on the trends surveyed in the last section, we

need to evaluate the impact of such variables on productivity, or on what is assumed to be the same thing, wages. We do this by estimating *linear regression models* that relate the natural logarithm (log) of workers' wage rates to their education, age, sex, and other characteristics. The estimated coefficients are the predicted effects of worker characteristics on wages and productivity. Combining the estimated regression coefficients with the micro data on education, experience, and sex yields a predicted average wage. Using the same regression coefficients to compute the predicted average wage in adjacent years isolates the portion of aggregate wage growth that is due to changes in worker characteristics, the definition of labor quality growth.

One could in principle use a single, fixed regression model to evaluate worker characteristics in all years. However, because there have been major changes over time in the valuations associated with worker characteristics, we choose to allow the regression coefficients to vary over time. Moreover, to compute our index, we adopt a chain-weighting procedure that bases the growth in the index from one year to the next on the geometric average of the growth rates in worker quality obtained using regression coefficients in the two years.

In more detail, the first step in the construction of our index is to estimate for each year regression models for the log wage of the form

$$\log W_{it} = S_{it}\alpha_t + \sum_{j=1}^4 E_{it}^j\beta_{jt} + \sum_{j=1}^4 F_{it}E_{it}^j\gamma_{jt} + F_{it}\phi_t + X_{it}\delta_t + \varepsilon_{it},$$

where $\log W_{it}$ is the log hourly wage of worker i in year t , S_{it} is a vector of education variables, E_{it}^j is estimated labor market experience raised to the j th power, F_{it} is an indicator variable that takes the value one if the worker is female, and X_{it} is a vector of other background variables that might affect wages, including, race, marital status, and whether the worker is employed part time.¹¹ We also include an interaction between the quartic polynomial in experience and the female indicator to allow for different rates of return to experience between genders. We do this because, as we discussed in the last section, the only available measure of work experience is potential (maximum) experience, computed as age minus years in school minus six. Since women have more career interruptions than men, they also have larger deviations between actual and potential experience. The interaction terms account for this difference by allowing a different rate of return to potential experience across genders.

In each year in our sample, we classify individuals into five education categories: less than high school, high school graduate, some college, college graduate, and post-graduate. However, a complication arises because a 1992 redesign of the CPS changed the educational attainment question from one on the number of years of education to one on type of degree completed. This change caused a significant break in the fractions of our sample in the five education categories. We employed two methods for dealing with this problem. First, we followed the method described in Jaeger (1997) for optimally matching CPS education questions pre- and post-1992. Second, for the construction of 1991 to 1992 labor quality growth rates, we collapsed the responses into three more easily comparable categories: less than high school, high school graduates (including some college), and college graduates (including post-graduates). We then use these three categories to compute labor quality growth for 1991 to 1992 and the five categories for all other years.

The next step of the calculation is to compute weighted averages of predicted wages for workers in the CPS based on coefficients for education (α_i), experience (β_{jt}), female–male differential in value of experience (γ_{jt}), and female (ϕ_i) estimated from alternative years of data

$$\hat{W}_{it}^s = \exp \left(S_{it} \alpha_s + \sum_{j=1}^4 E_{it}^j \beta_{js} + \sum_{j=1}^4 F_{it} E_{it}^j \gamma_{js} + F_{it} \phi_s \right),$$

where the s superscript on \hat{W}_{it}^s denotes that the predicted wage is computed using coefficients estimated from year s data. The weights given to different individuals vary for two reasons. First, the CPS is a probability sample in which different individuals have different probabilities of being sampled. In order to form consistent estimates of population quantities, the Census Bureau provides weights that undo the probability sampling in expectation. Using these weights would allow us to consistently estimate the average predicted wage for all workers in a given year. However, our interest is not in the average worker, but rather in the average hour worked. Those who work more hours are, therefore, more important for this average than those who work fewer hours. Thus, we base our weights on the product of the usual CPS weight and hours worked by the individual. That is, the averages of the \hat{W}_{it}^s are based on $\tilde{w}_{it} = w_{it} h_{it} / \sum w_{it} h_{it}$ for person i in year t , where w_{it} is the usual CPS weight and h_{it} is the number of hours worked.

Finally, for each year t , we identify growth in average labor quality with the growth in average predicted wages relative to year $t-1$ using a common

set of rates of return to value human capital characteristics in the two years. We compute such growth using rates of return estimated using year $t-1$ data,

$$dQ_t^0 = \sum_i \tilde{w}_{it} \hat{W}_{it}^{t-1} / \sum_i \tilde{w}_{it-1} \hat{W}_{it-1}^{t-1},$$

and using year t data,

$$dQ_t^1 = \sum_i \tilde{w}_{it} \hat{W}_{it}^t / \sum_i \tilde{w}_{it-1} \hat{W}_{it-1}^t.$$

Both of these ratios are estimates of the growth in average wages that is attributable to improved worker quality; they differ from one only because of changes from $t-1$ to t in the distribution of education, experience, and sex. Since it is arbitrary whether we use rates of return based on estimates from year t or $t-1$, we emulate the strategy of a Fisher ideal index by taking the geometric average of the results based on year t and $t-1$ regression coefficients. Thus, the final estimate of worker quality growth in year t can be expressed as

$$dQ_t = \left(dQ_t^0 \times dQ_t^1 \right)^{1/2}.$$

An overall index can be formed by “chaining” together the above growth rates from an arbitrary base level in some year. Relative to an index based on a single, fixed vector of rates of return, the advantage of the above is that it allows for varying rates of return.

Alternative measures of labor quality

Our method of measuring labor quality differs to some extent from that used by earlier researchers. BLS (1993) provides a detailed account of its methodology, along with those of Jorgenson et al. (1987) and Denison (1985). Below, we briefly describe the BLS (1993) methods and those of Ho and Jorgenson (1999), an updated version of Jorgenson et al.

Ho and Jorgenson split the working population into 168 possible cells, partitioned by sex, age ranges, education, and self-employment status. They then compute changes in hours worked and compensation per hour for each cell. In addition to using data from the decennial *Census of Population* and the CPS, their measures of compensation include imputations of the value of nonwage compensation that they derive from the National Income and Product Accounts. In this framework, the growth in total labor input is a Tornqvist index or weighted average of the change in log hours in the various cells, where the weights are given by the average share of total compensation attributable to the cell in the two years. The growth in their labor quality index is defined as the difference

between this total labor input growth and the growth in raw labor hours worked.

Ho and Jorgenson's disaggregation of workers into many cells allows for substantial flexibility in measuring the distribution of labor services across "types" of workers. However, their method assumes that all workers in a given cell have equal levels of human capital, which our regression analysis shows not to be the case. At the same time, mean wages must be estimated based on some relatively small samples. Thus, we prefer our approach, which in a sense allows for a separate cell for each individual worker in the CPS, but derives wage estimates from a standard wage regression. This provides the maximum possible flexibility, while keeping the number of estimated parameters relatively low. Since fringe benefits and the value of social insurance make up a significant fraction of total labor compensation, we are sympathetic to Ho and Jorgenson's attempts to account for them in their wage measures. However, splitting measures of total nonwage compensation obtained at high levels of aggregation between different classes of workers based on factors such as age and education is inherently arbitrary. The fundamental problem is that none of the sources of data on wages by demographic characteristics contain information on the value of nonwage compensation. Thus, we find it most sensible to stick to wage and salary compensation for which there is solid data.

The methodology developed by the BLS (1993) uses a combination of a regression approach to estimating the effect of worker characteristics on wages that is similar to ours and a Tornqvist index computed on a number of discrete worker cells based on characteristics that resembles Ho and Jorgenson's methodology. Relative to Ho and Jorgenson, the major difference is that rather than estimating average wage rates for a large number of cells, the BLS estimates cell means using a regression model. This eliminates the problem of cell means based on small numbers of observations, but the use of a constant growth rate for all workers in a cell still represents what we think is an unnecessary constraint relative to our less restrictive analysis.

A potential strength of the BLS methodology is its use of a special data set containing records from the 1973 CPS matched to Social Security Administration work history files. This allows the BLS to compute actual work experience for this group of workers. Moreover, based on a regression model estimated using this sample of 25,000 workers, the BLS imputes actual experience for workers in all time periods.

The BLS's imputation of actual work experience data addresses one of the most serious shortcomings of CPS data for measuring labor quality. However,

patterns of labor force participation change over time, so it is not clear that those imputations are particularly helpful for data separated significantly in time from 1973. Moreover, such imputations may do little other than to provide an interpretation of why certain variables affect wages. For instance, if marital status affects the level of actual experience relative to potential experience, then marital status may be useful for predicting wages even if wages in reality only depend on education and actual work experience. Consistent with this possibility, the BLS approach forces the dependence of wages on such factors to be through their effect on experience. However, it is also possible that factors such as marital status have a direct effect on wages in addition to any effect on work experience. In such cases, the alternative results discussed below, in which we include such variables in the calculation of the quality index, may better capture their effects on worker quality growth.

Differences in methodology may not be particularly critical to estimates of labor quality. Where samples overlap, our results are broadly similar to those of Ho and Jorgenson (1999) and the BLS (1993). However, as we discuss below, our estimated series appear to be somewhat less variable and to align in a more reasonable way with the business cycle.

Forecasting labor quality growth

In this article, we also provide *forecasts* of labor quality growth for the rest of this decade. These are necessarily somewhat speculative, relying on the extrapolation of certain trends in population, educational attainment and labor force participation. We do not attempt to forecast changes in the regression coefficients used to value education and experience. We simply rely on the coefficients estimated in the last year of our actual data. These are applied to simulated populations of workers defined by age, education, race, and sex.

In constructing these simulated populations for the rest of this decade, we start with the "middle" population projections made by the U.S. Census Bureau. These show the likely number of U.S. residents by one-year age group, sex, race, and Hispanic ethnicity. We combine this information with a statistical model predicting educational attainment on the basis of such characteristics to obtain a simulated population broken down by educational levels as well. That is, each cell of the Census's projected population is divided into separate cells corresponding to different levels of education. The breakdown of the population into these sub cells is determined by the statistical model to be described below. The final step in the construction of our simulated population is to project what fraction of

the people in these simulated populations will be in the labor force. We do this also on the basis of a statistical model. We then use the 1999 regression coefficients relating wages to worker characteristics to compute the growth in predicted wages due to the changing distribution of age, education, and sex among the labor force participants in the simulated populations.

Given that the Census Bureau has good information on the population of individuals not yet of working age as well as birth rates, they are in a good position to forecast the growth and changing composition of the working-age population over the next decade.¹² These translate fairly straightforwardly into projections for the component of labor quality based on labor market experience.

Given that the average age of workers is projected to rise over the decade by about a year and a half to a little over 42 years, one might expect the contribution of work experience to boost labor quality growth over the decade. However, the contribution of labor market experience to worker quality growth depends on the whole distribution of experience levels, and as the decade progresses, the large Baby Boom cohorts move beyond their peak earnings years, which actually contributes to slowing labor quality growth.

The forces underlying our projections of the effect of experience on worker quality are illustrated for men in figure 7.¹³ The upper panels of the figure show the change in the proportion of people of a particular age. The leading edge of the Baby Boom stands out in the graphs. In 2001, the cohort born in 1947, which was much larger than that born in 1946 is 54 years old. Thus the first panel of the figure, which covers the change from 2000 to 2001, has a large spike at age 55. Birth cohorts continued to grow until the early 1960s. Thus, in the first panel there are generally positive changes in the proportion of the population aged 40 to 52. Of course, the sum over all ages of the changes in the proportion of the population accounted for by each age is zero, so there are always ages that are declining in their share of population. For instance, in the case of the panel corresponding to the 2000 to 2001 transition, most of the ages between 25 and 40 have decreasing shares of the population.

The top panel graphs in figure 7 also show the relative wage rate associated with each age. These are obtained from a log wage regression like those described above, except that the quartic in experience was replaced with a quartic in age. The coefficients of the quartic are used to compute wages for each age level. The plots show the percentage difference between this predicted wage and the overall mean wage based on the base year's distribution of ages. Thus,

if the value shown for a given age is 0.1, that age is associated with wages that are 10 percent above average. The graph shows that male workers generally earn higher than average wages between their mid-thirties and late fifties. The peak age for wages is in the early fifties.

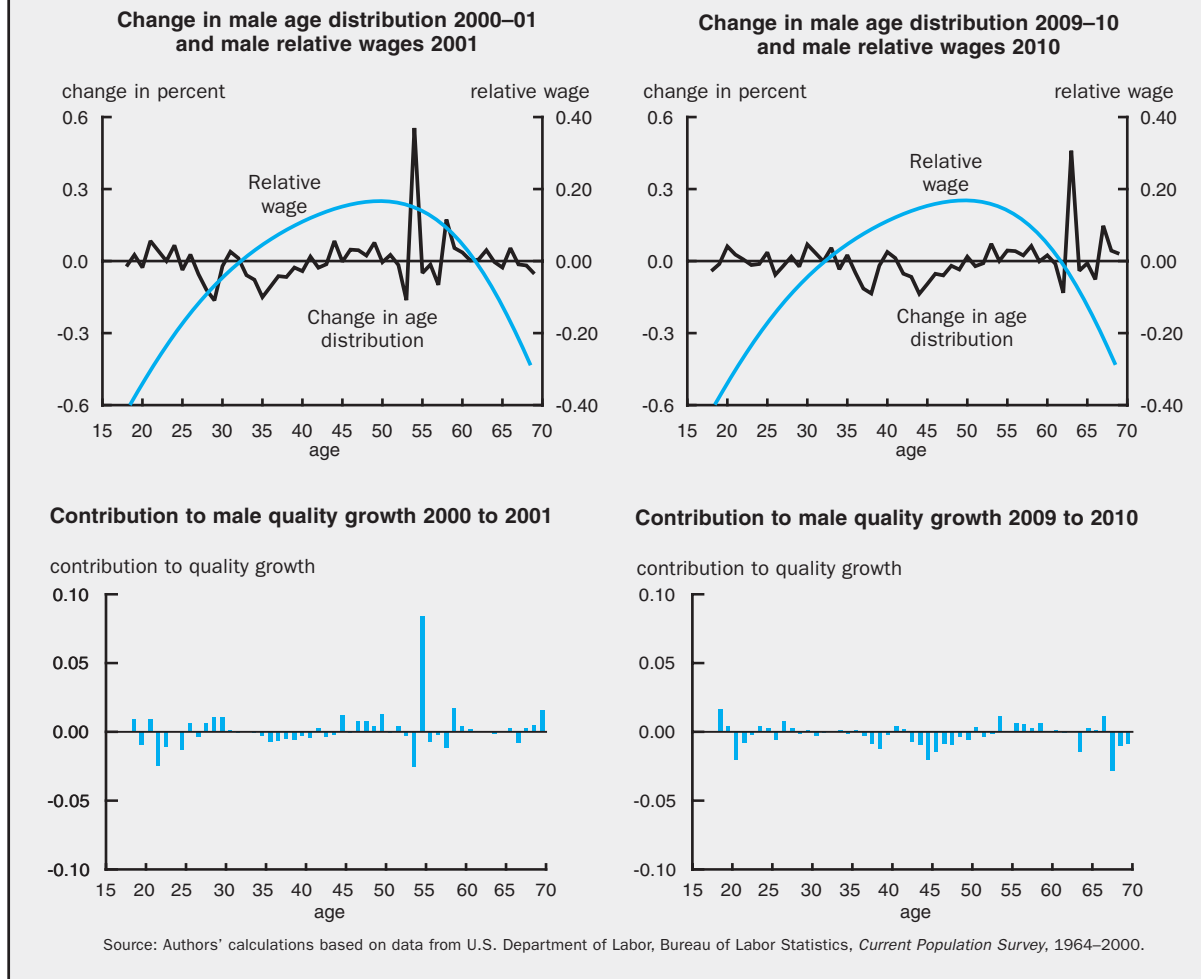
The contribution to worker quality will be greatest when there is a positive correlation between the change in the proportion at the age and the relative wage deviation. That is, quality grows fastest when there are large increases in the proportion of workers at the age levels associated with high relative wages and large decreases in the proportion of workers at ages associated with low relative wages. The bottom panels in figure 7 show the product of the change in the proportion at the age and the relative wage associated with the age. The overall contribution of the changing age distribution to worker quality is approximately the sum of those products.

For the 2000 to 2001 transition, the positive products in the bottom panel substantially outweigh the negatives, leading to a positive contribution to worker quality growth from the changing age distribution. A big part of that contribution comes from the effects of the leading edge of the Baby Boom. The age group (55 year olds) associated with the big increase in proportion of the labor force is one that also has a high relative wage. This implies a sizable positive contribution to labor quality growth.

The panels on the right in figure 7 show what happens by the end of the decade. In 2010, the oldest Baby Boomers will actually be at an age (63) associated with below-average wages. This, combined with the movement of the smaller birth–death generation into the peak earnings years, swings the overall labor quality growth contribution of the age distribution to negative territory.

Forecasting the effects of changes in education requires making additional forecasts of educational attainment and labor force participation. We make these forecasts based on statistical models estimated using the ORG files for the years 1992 to 1999. The detailed methodology is described in box 1.

The approximate effects of our educational projections on labor quality growth are shown in figure 8. This figure has the same layout as figure 7, except that instead of showing the impact of changes in the age distribution, it shows the impact of changes in the educational distribution. The top panels show the projected change in the fraction of the population with each of the five educational levels and the relative wage rate associated with those levels. The contribution to labor quality growth is the product of the change in

FIGURE 7**Effects of experience on male worker quality**

proportion with the relative wage and is shown in the bottom panels. The sum of these contributions approximates the contribution of increasing education to worker quality.

Figure 8 shows that between 2000 and 2001, the shares of workers with less than a high school education and exactly a high school education were both falling. In contrast, the shares with some college, a college degree, and post-graduate education were all rising. Figure 8 also shows the relative wage rates associated with the different levels of education. These range from negative 45 percent for high school dropouts to positive 85 percent for those with post-graduate education. Clearly, there is a strong positive correlation between relative wages and growth in population share. This positive correlation is reflected in the mainly positive contribution estimates shown in the bottom left panel. The sum of these contributions is substantially positive.

Figure 8 also shows that the effects of education on worker quality will change only slightly by 2010. Our predictions indicate that the rate at which the share of high school dropouts is shrinking will decline by about half from 0.29 percentage points to 0.14 percentage points, and that there will be a similar sized decline in the rate at which the some college group is growing. Given the large negative relative wage of dropouts, the former effect has a bigger impact on labor quality growth. Thus, as the decade progresses, we predict a slightly smaller increase in labor quality growth from improving educational attainment.

Results

Worker quality

Figure 9 displays our estimate of 1964 to 2000 labor quality growth for the working population based on trends in the educational, experience, and sex

BOX 1

Forecasting trends in educational attainment and labor force participation

This section describes the statistical models that we use to forecast trends in educational attainment and labor force participation in order to forecast the growth of labor quality. We begin by forecasting educational attainment as a function of age, birth year, sex and race. We then forecast labor force participation on the basis of those variables and educational attainment.

Let $p_{it}^j = \text{Prob}[y_{it} = j] \ j = 1, \dots, 5$ be the probability that the i th worker in year t has educational level j , where $j=1$ is less than high school and $j = 5$ is more than college and let

$q_{it}^j = \text{Prob}[y_{it} \geq j | y_{it} \geq j-1] \ j = 2, \dots, 5$ be the probability that the worker reaches at least level j given that he reached level $j = 1$. We fit statistical models to predict the q_{it}^j and then recover the p_{it}^j from

$p_{it}^j = \prod_{k=2}^j q_{it}^k (1 - q_{it}^{j+1})$. Specifically, the q_{it}^j are predicted on the basis of logistic regression models of the form

$$\log \frac{q_{it}^j}{1 - q_{it}^j} = \sum_a D_{it}^a \alpha_{ja} + \sum_b D_{it}^b \beta_{jb} + x_{it} \gamma_j,$$

where the D_{it}^a and D_{it}^b are indicator variables for the person being age a and born in year b , respectively, and x_{it} is a vector of additional control variables. Models for q_{it}^j are estimated using all those in the ORG files from 1992 to 1999 that had education of at least level $j - 1$ and met an age requirement of 18 for the high school, 19 for the some college, 22 for the college, and 26 for the post-graduate models.

The idea behind this model is that there is a typical lifetime pattern of the probability of completing another level of schooling. For instance, the probability of completing high school or the equivalent rises very rapidly up to age 20, then increases only slowly with age. According to the model, cohorts born in different years follow the same basic time pattern, but at a uniformly higher or lower level in terms of the log odds. Models for high school, some college, and college are estimated separately for the eight sex by race combinations without any additional controls (x_{it} variables). Samples of nonwhite workers with college degrees become somewhat small, however. So

models for post-graduate education are estimated separately for men and women with race indicators included as controls. For each population cell defined by age, birth year, sex and race, the estimated model is used to predict the fraction in each year with each of the five levels of educational attainment.

Our estimation samples yield birth year coefficients (β_{jb}) corresponding to birth years for which there are individuals in the appropriate age range in the ORG files. But as the projection period progresses, we also need cohort coefficients for workers born too soon to be in the ORG files. For instance, no one born in 1990 is included in our ORG files. Thus we have no data from which to estimate the tendency for that cohort to complete different educational levels. However, by 2010, many such individuals will be in the labor force. For each race and sex combination, we forecast these additional cohort coefficients on the basis of a linear regression on year of birth using the last 15 coefficients up to, but not including, the last one estimated. (The last one estimated is based on only one year of data and thus, especially for minority races, small sample sizes.) This admittedly ad hoc procedure extrapolates recent trends in educational attainment. We chose 15 years because most of those trends appeared fairly close to constant over that period. Results are not sensitive to extrapolating based on the last 10 or last 20 birth year coefficients.

The above procedure yields forecasts of the distribution of age, sex, and educational attainment. These can be used to obtain forecasts of labor quality for the whole population. However, to obtain forecasts of labor quality for workers only, we also need to forecast labor force participation. We do that using a model with the same form as above, except that educational attainment becomes an additional control variable. As with educational attainment, cohort coefficients for birth years too late to yield workers in our data sets are forecast from a linear regression on birth year using the last 15 coefficients up to, but not including, the last one estimated. For each year out to 2010, this procedure yields a forecast of the population of cells defined by age, race, sex, educational attainment, and labor force participation. Thus, we can construct a forecast for labor quality in those years.

distributions of workers. The black line uses the CPS March supplements. The colored line uses the ORG files. As we mentioned earlier, the ORG begins in 1979 (so growth rates begin in 1980). As the ORG-based measure is based on three times more data, the year-to-year variability of ORG-based labor quality growth is lower.¹⁴ However, the general trends are very similar;

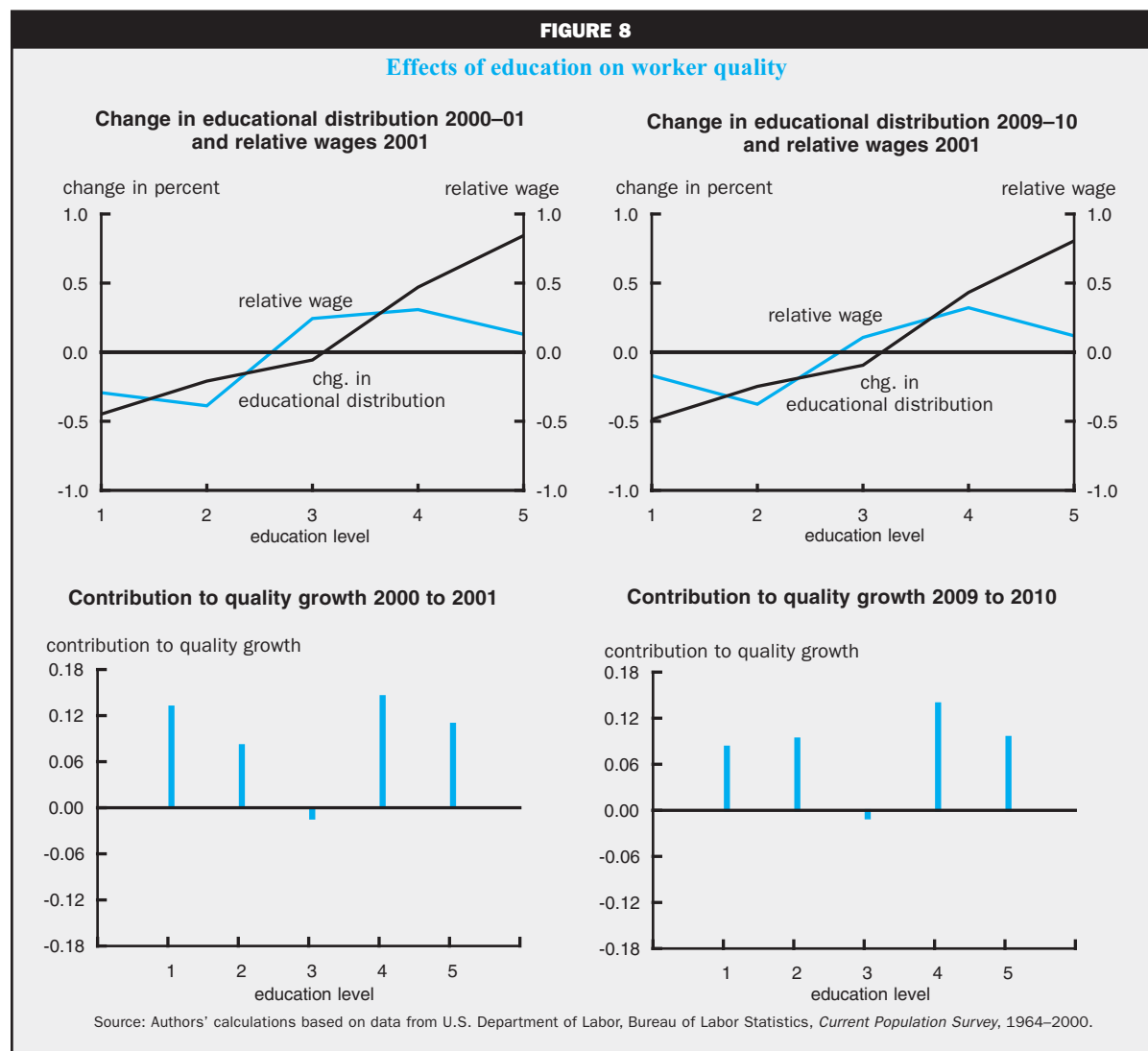
from 1980 to 2000, labor quality grew 0.50 percent per year according to the ORG and 0.43 percent per year according to the March supplements. Furthermore, since 1990, the ORG and March growth rates are also similar—0.48 percent and 0.42 percent per year, respectively. Therefore, the use of one data set over another has little effect on any of our inferences.

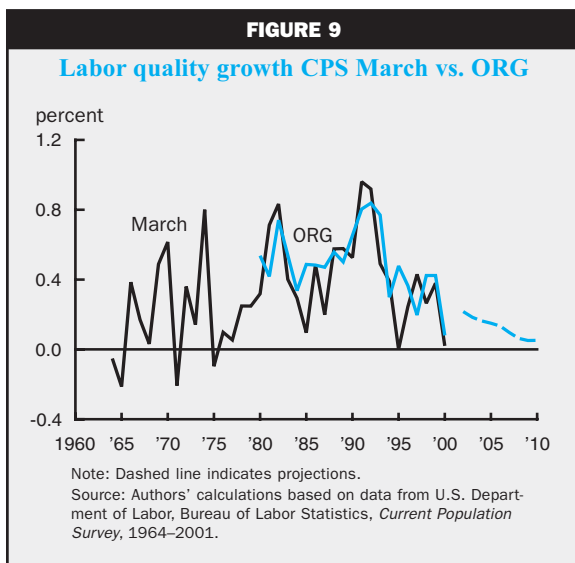
There are several notable features of figure 9. First, labor quality is somewhat countercyclical; peaks in the data occur near the trough of recessions in November 1970, March 1975, November 1982, and March 1991. This is consistent with firms reacting to economic downturns by first dismissing low-quality workers, resulting in an increase in the aggregate quality of the working population (but not the full population). As hiring heats up during expansions, workers of lower productivity find employment more readily and labor quality drops. Typically, toward the end of expansions, we might expect to see labor quality growth slow even further, as the pool of available human capital is drained. This seems to have happened somewhat in the 1990s but not during the 1980s expansion.

The extraordinary increase in educational attainment during the 1970s and 1980s offset any cyclical effect from the declining pool of high human capital.

This brings us to the second notable feature of the data: the deceleration, acceleration, and deceleration of labor quality over the last three decades. During the late 1960s and 1970s, labor quality grew by approximately 0.2 percent per year. This coincides with the beginning of the post-1973 productivity slowdown, which lasted for two decades.¹⁵ But the slowdown in labor quality did not last long. Beginning in the early 1980s, the U.S. experienced a sizable acceleration in labor quality growth, rising to 0.4 percent per year from 1979 to 1987 and close to 0.6 percent per year from 1988 to 1995. Since 1995, labor quality has decelerated to 0.27 percent per year, although there was a mild upturn (0.36 percent per year) from 1997 to 1999, including a 0.38 percent rate of growth in 1999. In 2000, labor quality growth fell to 0.

Figure 9 also shows our projections of labor quality growth. As described above, these are based





on projections of the labor force. Thus, they are free from any variation due to changes in the level of unemployment. As can be seen, they decline smoothly as the decade progresses. By 2010, they are down to only 0.07 percent, much below the average of the previous 35 years.

Figure 10 decomposes the growth of overall labor quality into contributions due to education, experience, and gender. The overall trends in education and experience that we saw in figures 2 to 5 are readily apparent. The improvement in education attainment in the 1970s and 1980s was the sole positive contributor to labor quality growth, adding 0.54 percent per year to labor quality growth between 1965 and 1985. The slowdown in education, particularly the lack of further progress in reducing the fraction of high school dropouts, resulted in a decelerating education component of labor quality growth of 0.30 percent per year after 1985 and 0.18 percent per year after 1995.¹⁶ The modest increase from 1997 to 1999 is the main contributor to the pickup in overall labor quality observed in that period.

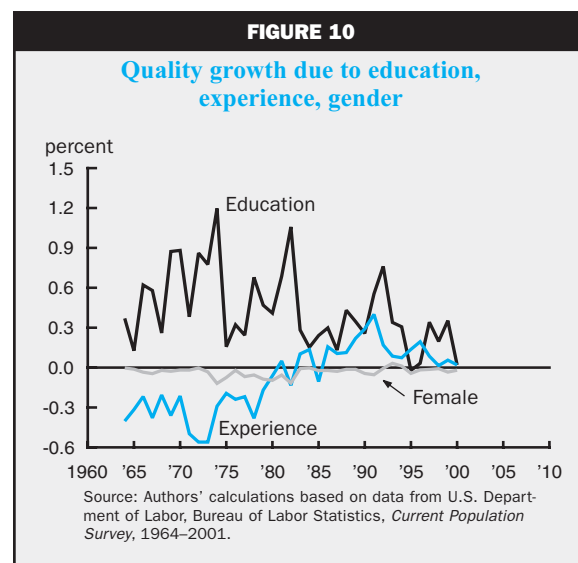
Offsetting the big increases in education during the 1970s and 1980s was the drop in work experience resulting from the entry of the Baby Boomers. This cut 0.34 percentage points per year off labor quality growth from 1965 to 1980. However, as those workers moved into age ranges associated with higher relative earnings after 1980, the contribution of labor market experience averaged a positive 0.09 percentage points per year.

The increase in female labor force participation has little overall impact on our labor quality growth estimates, cutting only about 0.03 percentage points per year over the full period. This small effect is

partly due to a somewhat arbitrary accounting choice. That is, we include the effects of the female–experience interactions in the contribution attributable to experience. This means that the only wage gap between men and women that goes into the calculation of the female contribution is that corresponding to zero years of experience. Since the male–female wage gap is relatively minor for new labor market entrants, the corresponding implications for worker quality are also minor. Given our preferred interpretation of the wage gap, our accounting convention seems appealing. However, some might argue to include the interactions of the female and experience terms in the female category. Doing so would make the contribution of the female component of the index substantially more negative. The contribution of the experience component would be correspondingly more positive.

The forecasts of the individual components show that the forecast decline in quality growth over this decade is largely due to the contribution of experience becoming negative by mid-decade. The forces underlying this projection were discussed in detail in the last section. The positive contribution to growth from increasing education levels is also forecast to decline slightly. Given our definition of the female contribution, it is unimportant to the projections.

Figure 11 provides an indication of how our results change with the inclusion of an expanded list of human capital variables available in the CPS. These are race, gender–race, marital status, gender–marital status, and full-time work status. As we discussed, on the one hand, there are reasons why such variables might affect workers' productivity or be correlated with unmeasured variables that affect productivity, and, thus,



ought to be included in a measure of worker quality. On the other hand, it is possible that the correlation of such variables with wages may be due to labor market discrimination or other reasons unrelated to productivity, in which case they ought not to be included in a measure of labor quality. While the patterns look quite similar, growth in the expanded labor quality index is lower, particularly in the late 1970s and early 1980s. This suggests that more work might be warranted to investigate the source of correlation between these variables and wages.

The detailed reasons for the growth in the extended index being below the one based only on education, experience, and sex are shown in figure 12. Race has evidently had little impact and, since 1976, the same is true for full-time/part-time status. But steady drops in marriage rates have consistently been a drag on the extended measure of labor quality growth.

Table 1 presents growth rates in labor quality by gender, industry, and region. For comparison, the top row presents overall trends. The results are split into business cycle periods with the first column presenting the average growth rate over the full 35-year period.

Rows 2 and 3 stratify the sample by sex. Since 1965, female labor quality has grown faster than male labor quality by 0.15 percent per year.¹⁷ There has been a remarkably stable 0.13 percentage point per year difference in growth rates between the two sexes for most of the sample—except the 1980s, when the difference expanded to 0.26 percent per year.

Productivity analysts have been concerned with explaining differences in productivity growth across industries and regions. Our results show that some of those differences reflect differences in the growth

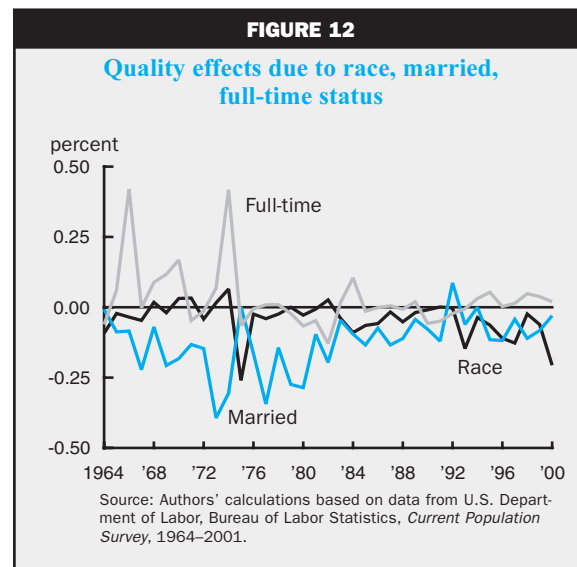
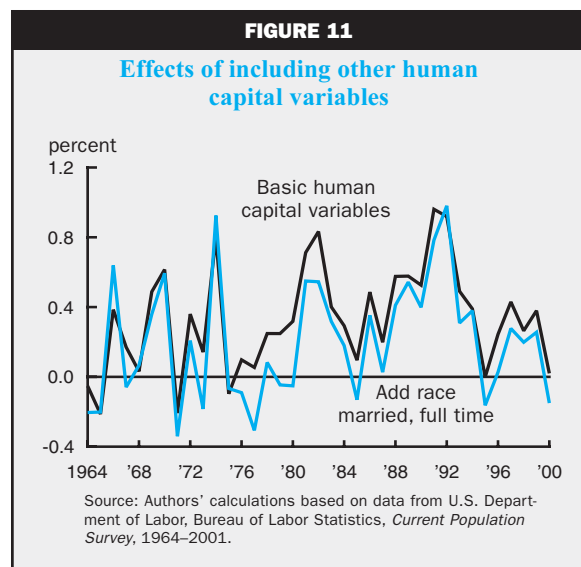
rates of labor quality. Table 1 shows that labor quality has grown fastest in agriculture, durable and nondurable manufacturing, and transportation, communication, and public utilities (TCPU) over the last 35 years. Lagging industries include retail trade and construction. All industries follow the general overall trend of lower growth in the late 1960s and 1970s, followed by accelerating growth during the 1980s and early 1990s. However, some—for example, nondurable manufacturing and construction—experience more variable labor quality growth, while others—for example, services and government—grow more steadily. Over the last five years, labor quality growth has been particularly strong in durable manufacturing and weakest in mining, agriculture, construction, and services.

Finally, labor quality in the south (East South Central and South Atlantic) and east (Mid Atlantic and New England) has grown quickly since 1965, while the west (Mountain and Pacific) has lagged behind. Since 1995, the midwestern region has experienced the fastest labor quality growth and the western region the slowest.

Labor quality growth of nonworkers

The results above provide evidence on labor quality growth of the working population. However, in light of the rise in employment-to-population ratios over the last five years and the ensuing concern about the size of the pool of available workers, we are also interested in evaluating quality growth trends among those who are available and interested in jobs, but not currently at work. Therefore, in this section, we report results for the quality of the potential work force.

Figure 13 presents one view of this. The colored line represents the labor quality growth of workers



| TABLE 1 | | | | | | |
|---|---------|---------|---------|---------|---------|---------|
| Labor quality growth, by gender, industry, and region | | | | | | |
| | 1964–00 | 1964–71 | 1972–77 | 1978–86 | 1987–94 | 1995–00 |
| All workers | 0.33 | 0.15 | 0.23 | 0.40 | 0.58 | 0.22 |
| Men | 0.40 | 0.23 | 0.36 | 0.49 | 0.59 | 0.25 |
| Women | 0.55 | 0.37 | 0.49 | 0.75 | 0.72 | 0.30 |
| Construction | 0.21 | 0.12 | 0.07 | 0.27 | 0.46 | 0.06 |
| Durables | 0.43 | 0.12 | 0.24 | 0.61 | 0.52 | 0.63 |
| Nondurables | 0.46 | 0.27 | 0.16 | 0.60 | 0.83 | 0.30 |
| TCPU | 0.39 | 0.03 | 0.40 | 0.63 | 0.61 | 0.19 |
| Wholesale trade | 0.31 | 0.28 | 0.21 | 0.07 | 0.58 | 0.43 |
| Retail trade | 0.11 | -0.10 | -0.13 | 0.18 | 0.41 | 0.15 |
| Services | 0.32 | 0.20 | 0.44 | 0.44 | 0.42 | 0.06 |
| FIRE | 0.34 | 0.27 | 0.16 | 0.30 | 0.76 | 0.13 |
| Government | 0.34 | 0.03 | 0.38 | 0.48 | 0.39 | 0.44 |
| Agriculture | 0.45 | 0.25 | 0.77 | 0.27 | 1.01 | -0.06 |
| Mining | 0.41 | 0.46 | -0.45 | 0.94 | 0.90 | -0.37 |
| New England | 0.37 | 0.21 | 0.33 | 0.36 | 0.74 | 0.07 |
| Mid Atlantic | 0.39 | 0.26 | 0.34 | 0.39 | 0.64 | 0.21 |
| East North Central | 0.34 | 0.11 | 0.06 | 0.32 | 0.54 | 0.52 |
| West North Central | 0.36 | -0.11 | 0.31 | 0.37 | 0.53 | 0.48 |
| South Atlantic | 0.46 | 0.39 | 0.51 | 0.49 | 0.65 | 0.17 |
| East South Central | 0.53 | 0.60 | 0.38 | 0.43 | 0.79 | 0.47 |
| West South Central | 0.36 | 0.18 | 0.35 | 0.56 | 0.45 | 0.05 |
| Mountain | 0.19 | 0.37 | -0.34 | 0.46 | 0.34 | 0.00 |
| Pacific | 0.20 | -0.09 | 0.07 | 0.29 | 0.52 | -0.01 |

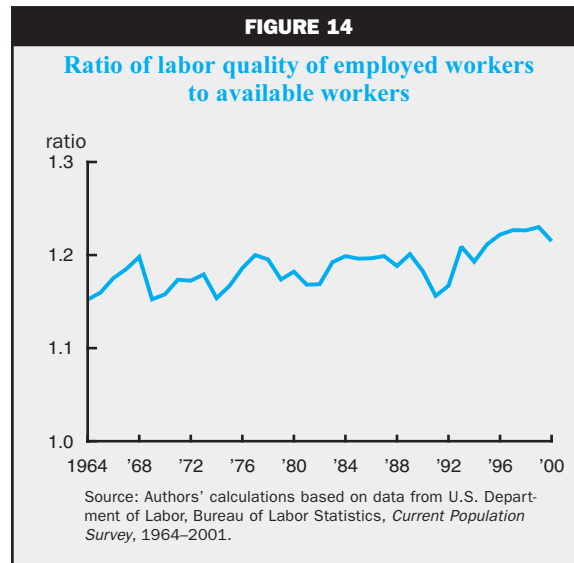
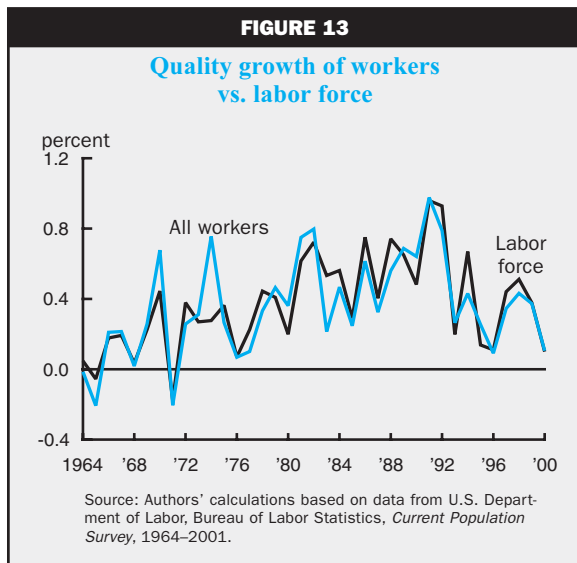
Notes: TCPU is transportation, communication, and public utility. FIRE is financial, insurance, and real estate.
Source: Authors' calculations based on data from U.S. Department of Labor, Bureau of Labor Statistics, *Current Population Survey*, 1964–2001.

and the black line represents labor quality growth of the entire labor force. The latter includes workers plus those who are unemployed (that is, searching for work).¹⁸ Not surprisingly, the graphs line up quite well since most of the labor force is employed. The most important differences arise during recessions when hoarding of higher-skilled workers leads to a more rapid increase in the labor quality of the working than the unemployed.

A more comprehensive view of the quality of available workers is presented in figure 14. Here, we link two groups together—those unemployed (searching) and those not in the labor force (not searching) but who want a job—and refer to them as the group of available workers.¹⁹ Figure 14 reports the ratio of the labor quality of workers to the labor quality of available workers.²⁰ For example, if the ratio is 1.18, it implies that the labor quality of the employed is 18 percent higher, on average, than the quality of the average available worker. If the ratio increases, the quality of workers is growing faster than the quality of available workers. If the ratio decreases, the quality of available workers is growing faster than the quality of workers.

From 1965 to the early 1990s, the labor quality ratio remained roughly flat, bouncing between 1.15 (during recessions) and 1.20 (at the end of expansions).²¹ However, in the last five years, the labor quality of workers has risen steadily faster than the quality of available workers. By 2000, an average employed worker had 21.5 percent higher human capital than an average available worker; this is just off the highest that this ratio has been over the 35-year sample period which was reached in 1999. The jump in the last five years is due to relative changes in both education and work experience between the two groups. Among the employed, high school and college graduation rates have increased by 0.5 percentage points and 1.7 percentage points, respectively, since 1995, but, among available workers, high school graduation rates have dropped by 0.5 percentage points and college graduation rates have increased by only 0.7 percentage points. Furthermore, the average age of a worker has increased by 0.9 years, but the average age of an available worker has dropped by 0.8 years.

Moreover, it seems likely that the ratio of labor qualities shown in figure 14 underestimates the true ratio. As we have noted, the reported information on



education and age barely begins to summarize the differences between workers' skill levels. There are many differences in the quality of education, actual labor market experience, and the like that are unmeasured in the CPS. It seems likely that those in the pool of available workers would also have a worse distribution of such characteristics. This would lead to the ratios in figure 14 being underestimated. Somewhat more speculatively, the business-cycle-related swings in the quality ratio may also be underestimated.

Related measures

In addition to being an input into forecasts of long-run output growth and improved measures of productivity, such as in Basu, Fernald, and Shapiro (2000), our labor quality measures can also be used to adjust measures of wage growth to better reveal fluctuations in the price of a raw hour of labor and to provide a more comprehensive measure of the extent of unemployed labor resources.

Fluctuations in standard measures of aggregate wage growth confound the effects of changes in the price of a constant unit of labor with changes in worker quality. In particular, some portion of the increase in measured wage rates reflects changes in the distribution of education and work experience rather than actual changes in the price of a constant unit of labor services. Using our measure of labor quality growth, however, it is straightforward to adjust measures of aggregate wage growth to reveal fluctuations in the true price of labor services. Such a measure could help to clarify the nature of business cycles. For instance, simple equilibrium business cycle models can only account for the relatively substantial fluctuations in hours worked if the real wage is significantly procyclical.

One measure of the price of raw labor is shown in figure 15. The black line is just the standard growth rate in real hourly compensation in the business sector.²² The colored line is our adjusted measure obtained by subtracting our measure of labor quality growth. As we have noted already, on average, labor quality grew by roughly 0.33 percent per year over the last 35 years. However, the cyclical nature of labor quality adjusted differences in compensation growth occur in or near recessions. For example, in March 1992, real hourly compensation growth increased 2.0 percent, but 0.9 percent of this gain was due to improvements in the quality of the labor force. Therefore, the price of raw labor increased only 1.1 percent over the previous March. Over the last four years, real hourly compensation has grown about 2.2 percent; the labor quality adjusted growth rate is 1.9 percent. Thus, adjusting for labor quality growth does make real wage growth appear somewhat more procyclical.

The adjustments to the price of labor reported in figure 15, while noticeable, do not greatly increase the extent to which real wages appear to be procyclical. Thus, they do not greatly change the evidence on the plausibility of simple equilibrium business cycle models. However, as noted above, it is possible that our results, which rely only on a few observable worker characteristics, underestimate the effects of worker quality in masking procyclical wage growth. For instance, Solon et al. (1994) find a larger compositional effect using longitudinal data that control for changes in unobserved worker differences.

Our labor quality growth measures can also help to clarify the cost of unemployed labor resources.

Because workers differ significantly in their levels of human capital, the standard unemployment rate, which counts every member of the labor force equally, does not fully capture variation in the level of unutilized labor resources. In particular, there is a greater loss of output when high-productivity workers are unemployed than when low-productivity workers are unemployed. Figure 16 shows an alternative measure of unemployed human capital based on our labor quality estimates that does allow for differences in worker productivity. This is estimated by computing the unemployment rate of the March CPS labor force, weighted by our gauge of labor quality.

The colored line in figure 16 shows our quality-adjusted unemployment rate. In general, accounting for human capital accumulation reduces the unemployment rate by 0.5 to 1.0 percentage points. Most recently (March 2001), the CPS unemployment rate drops from 4.4 percent to 3.6 percent, after labor quality adjustments are included. These figures indicate that because higher skilled workers are less likely to be unemployed, the standard unemployment measure overestimates the fraction of human capital that is not being utilized.

Conclusion

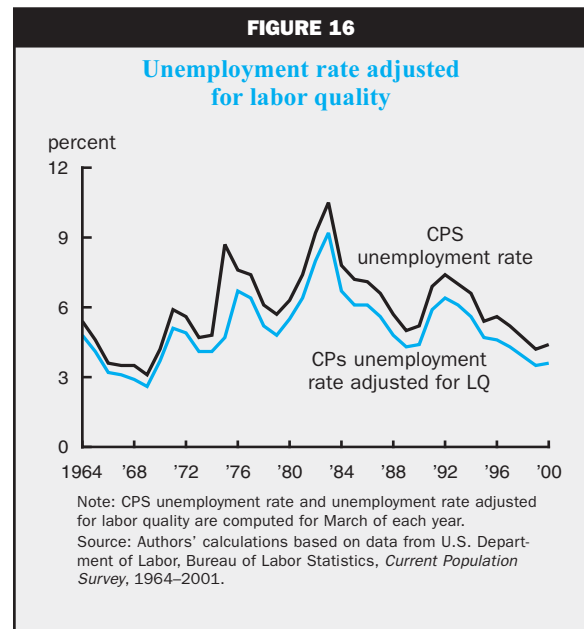
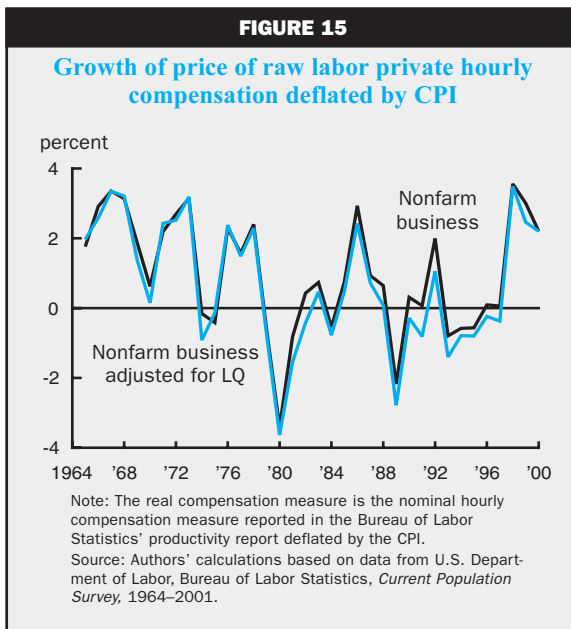
As we have seen, the characteristics of the labor force have changed significantly over the last 35 years, with educational levels improving at varying rates and typical labor market experience levels first falling then rising. Using the cross-sectional relationship between these characteristics and wage rates

allows us to infer that the pace of improvement in worker quality has varied over time from a low of around 0.15 percent per year between 1964 and 1971 to a peak of around 0.58 percent per year between 1987 and 1994. In the period since 1995, we find that worker quality improvement had slowed to about 0.27 percent per year. Largely because the Baby Boom generation will be moving beyond their peak earnings years, we forecast that worker quality improvement will slow further over the remainder of this decade to a rate of about 0.07 percent per year.

In addition to such long-run variation in the pace of worker quality improvement, we observe shorter-run fluctuations associated with the business cycle. In particular, average worker quality improvement tends to be especially rapid during downturns, as those with lower predicted wages are more likely to become unemployed or leave the labor force. Conversely, as more and more workers are drawn into the labor force over the course of a long expansion, there is a tendency for worker quality growth to slow.

A related finding is that the gap in predicted quality between the employed and the pool of available workers widens over the course of an expansion. That pattern was particularly pronounced over the course of the long expansion that began in the early 1990s, with the gap between the average predicted wage rate for workers and that for the pool of available workers reaching an all-time high of 23 percent in 1999.

Correcting for variation over time in average worker quality implies a modestly more procyclical pattern to real wage growth. It also shows that



depending on the state of the business cycle, the rate of unemployment of total human capital is between 0.5 and 1.0 percentage points lower than the standard civilian unemployment rate that counts all members of the labor force equally.

Finally, while our current findings provide substantial insight into the determinants of long-term productivity growth, it should be recognized that the measures of worker characteristics on which our work is based are quite crude. Levels of formal schooling and years of potential labor market experience only

begin to scratch the surface in predicting productivity and wage rates. While we find that including in our analysis additional characteristics such as race, marital status, and part-time status led to only modest changes in our conclusions, even these characteristics likely fail to capture the full range of human capital determinants that may be evolving in ways significant for productivity growth. Extending the analysis to other data sources that contain a richer characterization of the determinants of workers' wages may be a priority for future research.

NOTES

¹A recent innovation has been the use of longitudinal firm-level data to measure not only the factors that underlie productivity growth but also the extraordinary amount of heterogeneity and persistence in productivity growth across manufacturing firms. See Bartelsman and Doms (2000) and Hulten (2000) for recent surveys.

²Topel (2000) criticizes this line of research for, among other reasons, the difficult measurement issues involved, including the complexity of distinguishing capital and labor returns in a simple Cobb–Douglas framework and the limitations of human capital measures.

³See Altonji and Blank (2000) for a review of the labor market discrimination literature and Lewis (1986) for a review of the union literature.

⁴That is, two-thirds of labor quality growth rates of 0.27 percentage points and 0.07 percentage points equals approximately 0.18 percentage points and 0.05 percentage points of output growth.

⁵New high school and college graduates are compared to, respectively, the population of 17 year olds and 23 year olds. These figures were obtained from the National Center for Education Statistics website at <http://nces.ed.gov/> and the U.S. Department of Commerce, Bureau of the Census (1975).

⁶Unfortunately, the data we use to construct our measures of labor quality do not distinguish between high school graduates and GED holders. Given the more rapid growth in the latter, this may imply some overestimation of the rate of quality improvement.

⁷Because of the lack of strict comparability between the 1991 and 1992 figures, this change is left out of the moving averages. For the five years effected, the average is based on only four years of data.

⁸See Altonji and Blank (2000) for a review of the literature.

⁹These are computed from the October supplements of the *Current Population Survey*.

¹⁰See Aaronson and French (2001).

¹¹All of the results in this paper are very robust to some common differences with other papers, including controlling for state of residence, using age instead of potential experience, and eliminating government, self-employed, and private household workers from the sample.

¹²Of course, changes in immigration policy could make a significant difference to that composition.

¹³The forces determining the contribution of work experience to labor quality for women are very similar.

¹⁴The standard deviation of the 1980 to 2000 annual growth rates is 0.27 for the March data and 0.16 for the ORG data. Our March estimates are actually slightly less variable than those of Ho and Jorgenson. For comparable years in our samples (1965 to 1995), the standard deviation of Ho and Jorgenson's annual measure is 0.37 percent versus 0.31 percent for ours. We use the quality series reported in table B2 of Ho and Jorgenson.

¹⁵Bishop (1989) argues that a drop in labor quality, as measured by test scores, explains much of the productivity slowdown during the 1970s.

¹⁶As we noted earlier, growth in educational attainment of older workers has been particularly strong in the last decade. The labor quality of workers aged 50 to 59 increased by 0.72 percent per year during 1996 to 2000. By comparison, over the same period, labor quality of workers in their thirties grew 0.28 percent per year, and labor quality of workers in their forties fell by 0.22 percent per year.

¹⁷Note that labor quality growth for both men and women is higher than for workers overall. This reflects the negative effects on overall quality growth of a growing fraction of female workers.

¹⁸Because unemployed workers have no hours worked, our labor quality measure is weighted by CPS population weights only. For comparison purposes, the colored line also is weighted by CPS population weights.

¹⁹Prior to 1976, the CPS does not ask about wanting a job. Therefore, we include the unemployed from 1964–75 and the unemployed plus those not in the labor force who are available for work from 1976 to the present.

²⁰The ratio is computed as $\frac{\sum_{\text{workers}} \hat{W}_i^0 / \sum_{\text{available}} \hat{W}_i^0}{\sum_{\text{workers}} w_i h_i / \sum_{\text{available}} w_i h_i}$ where the numerator is weighted by $w_i h_i / \sum_{\text{workers}} w_i h_i$ and the denominator is weighted by $w_i h_i / \sum_{\text{available}} w_i h_i$.

²¹Educational attainment gains were fairly similar across groups between 1964 and 1995. The rate of high school graduation of employed workers grew from 58 percent to 90 percent, a gain of 32 percentage points, and from 41 percent to 75 percent among available workers, a gain of 34 percentage points. Likewise, college graduation rates grew from 12 percent to 26 percent among the employed and 3 percent to 11 percent among available workers. The average age of each group dropped by about two years.

²²The real compensation measure is the nominal hourly compensation measure reported in the BLS productivity report deflated by the CPI. The adjusted growth rate subtracts the growth in worker quality.

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