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Analyzing Skilled and Unskilled Labor Efficiencies in the US

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Analyzing Skilled and Unskilled Labor Efficiencies in the US

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Abstract

In this paper, using a production framework in which skilled and unskilled labor are imperfect substitutes, I analyze the time paths of the efficiencies of skilled and unskilled labor and their implications for economic growth and wage inequality in the US between 1950 and 2005. There are two main findings. First, I find that skilled labor efficiency has grown more slowly since the mid 1970s. Second and more interestingly, I find that beginning in the early 1970s, there has been a considerable decline in the absolute level of the efficiency of unskilled labor, implying that the decline has played a significant role in the overall productivity slowdown and the substantial widening in the U.S. wage structure.

JEL Codes: E13, J31, O30, O47, and O51

Keywords: Growth accounting, skilled (unskilled) labor efficiency, skill-biased technical change, and skill premium

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1 Introduction

This paper investigates how skilled and unskilled labor efficiencies have evolved since 1950. Toward this end, I extend the standard two-factor production function to a three-factor production function with capital, skilled labor, and unskilled labor by relaxing the assumption that the two types of labor are perfect substitutes. Assuming that markets are competitive and parameters of the model are known, I derive time series of skilled and unskilled labor efficiencies from the data.

The paper is motivated by two important facts. First, previous studies that investigate the sources of US economic growth decompose changes in output into changes in factors of production and change in overall efficiency (total factor productivity). These studies usually also assume that skilled and unskilled labor are perfect substitutes (see, e.g., Jones (2002) and Ha and Howitt (2007)). Considering a more general general production framework in which skilled and unskilled labor are imperfect substitutes and decomposing overall efficiency into skilled and unskilled efficiencies provide a better understanding of sources of the US growth. Second, there have been dramatic changes in the relative supply of skills and the skill premium, defined as the ratio of the skilled labor wage to the unskilled labor wage, in the US over the last 50 years. As shown in Figure 1, despite the rapid increase in the relative supply of skills[1] there has been a substantial increase in the skill premium over this period. Another aspect of Figure 1 is that the skill premium has trended sharply upward since the early 1980s. This pattern underlines the common view that new technologies have been skill-biased and there has been an acceleration in skill-biased technical change.[2] Naturally, one may wonder how the efficiencies of skilled and unskilled labor have changed over this period.

[1] The skilled labor class consists of college or college-plus workers and half of the workers with some college; and the unskilled labor class consists of high school dropouts, high school graduates, and half of the workers with some college. The relative supply of skills is defined as ratio of total hours worked by skilled labor to that by unskilled labor.

[2] The literature on this subject is vast. Important contributions are Bound and Johnson (1992), Katz and Murphy (1992), and Acemoglu (1998). See Aceomglu (2002) for a more comprehensive review of the literature.

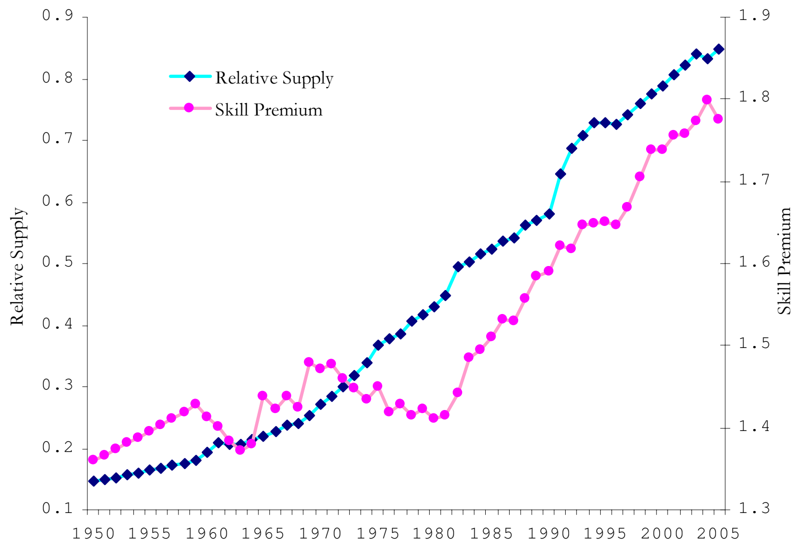


FIGURE 1. Relative Supply of Skills vs. Skill Premium

Notes: The skilled labor class consists of college or college-plus workers and half of the workers with some college; and the unskilled labor class consists of high school dropouts, high school graduates, and half of the workers with some college. The relative supply of skills is defined as ratio of total hours worked by skilled labor to that by unskilled labor.

There are two main findings of this paper. First, contrary to a priori expectations based on conventional wisdom, I find that skilled labor efficiency has grown more slowly since the mid 1970's. Second and more interestingly, I find that beginning in the early 1970s, there has been a substantial *decline* in the absolute level of the efficiency of unskilled labor. This is in sharp contrast to the period of 1950-70, during which unskilled labor efficiency was generally rising.

These results have interesting implications. First, the nonlinear path of unskilled labor efficiency contradicts the common view that the U.S. economy has been on a balanced growth path (or steady-state). Second, the decline in unskilled labor efficiency has exerted an adverse effect on output growth. For example, if after 1973 unskilled labor efficiency had remained at its level in 1973, GDP and per capita GDP would have been about 20 percent higher in 2005. Finally, these findings also suggest that the substantial widening in the U.S. wage structure has not only been driven by increases in skilled labor efficiency, but also by declines in the efficiency of unskilled labor. As in the above case, if after 1973 unskilled labor efficiency had remained at its level that prevailed in 1973, the wage gap between skilled and unskilled workers would have been about 20% narrower in 2005.

This paper is related to the accounting literature that investigates the sources of growth in the U.S. economy.[3] The paper contributes to this literature by decomposing changes in overall efficiency into changes in efficiencies of skilled and unskilled labor.[4] In backing out the actual levels of skilled and unskilled labor efficiencies from the data, this paper follows Caselli and Coleman (2006), who using a single observation from each country, study cross-country differences in skilled and unskilled labor efficiencies when skilled and unskilled labor are imperfect substitutes. This paper, on the other hand, studies the evolution of labor efficiencies in the US over time.[5] Another closely related work is an interesting paper by Jones (2002), who notes that increases in educational attainment and research intensity during the last several decades imply that the US economy is far from its balanced growth path (or steady-state). To reconcile these facts with the steady growth in output, he argues that the US economy has been on a *constant* growth path.[6] However, Jones's constant growth path argument crucially hinges on his assumption that the production function is characterized by the Cobb-Douglas form. In this paper, I show that the time path of unskilled labor efficiency is nonlinear which in turn casts doubt on the constant growth path argument.

The present study is also related to the wage inequality literature that typically addresses the determinants of the dramatic changes in the U.S. skill premium (see, Katz and Murphy

[3] See Solow (1957), Denison (1962), Jorgenson (1967) and (2005), and Jones (2002).

[4] Growth in the efficiency of skilled labor is the largest contributor to output per hour growth in this decomposition, accounting for between 58 and 129 percent of growth (depending on the exact value of parameters in the model and the definition of skilled labor), while changes in the efficiency of unskilled labor accounts for between -44 and 13 percent of growth (see section 3.4).

[5] Caselli and Coleman (2006) show that higher-income countries use skilled labor more efficiently than lower-income countries, but they use unskilled labor relatively less efficiently. This paper shows that the efficiency of unskilled labor is not monotonically declining with an increase in the income level.

[6] On a constant growth path, like the balanced growth path, all variables have constant growth rates. However, unlike the balanced growth path, this situation is not supposed to continue forever.

(1992), Krusell et al. (2000), and Autor et al. (2008), among many others). These studies address the roles of different types of technical changes on the skill premium by estimating an econometric specification. In this paper, on the other hand, using a few assumptions widely accepted in the literature, I derive the time series behavior of skilled and unskilled labor efficiencies directly from the data.[7]

The rest of this paper is organized as follows. Section 2 introduces the production framework that underlies the analysis. Section 3 presents the quantitative analysis. In this section, the main features of the data along with the construction of the key variables are discussed. Then the main results and their implications are discussed. Section 4 offers some concluding remarks.

2 Modeling Production

I consider a production function with capital, different types of labor, and different types technologies. As in Caselli and Coleman (2006), total output Y_t produced at time t is given by

$$Y_t = K_t^{\alpha} \left[(A_{st} L_{st})^{\rho} + (A_{ut} L_{ut})^{\rho} \right]^{\frac{1-\alpha}{\rho}}, \tag{1}$$

where K_t is the capital stock, L_{st} is skilled labor, and L_{ut} stands for unskilled labor. A_{st} represents the efficiency of skilled labor (or skilled labor augmenting technology), while A_{ut} represents the efficiency of unskilled labor (unskilled labor augmenting technology). The parameter ρ is time-invariant and the elasticity of substitution between skilled and unskilled labor is given by $\sigma = 1/(1-\rho)$.

Factor markets are competitive so that each factor earns its marginal product. The first order conditions yield the following relationship between the skill premium, w_s/w_u, and

[7] Ruiz-Arranz (2004) extends Krusell et al. (2000) framework to study the determinants of the wage inequality in US between 1965 and 1999. Using a translog production approach, she finds that skilled labor technical innovations and the *decline* in the absolute efficiency of unskilled labor are the main factors responsible for the substantial rise in the skill premium. This study is different from mine in several aspects. Most notably, the inference in her paper is obtained from an econometric specification (with several parameters) which puts heavy demands on the limited data.

relative supply of skills, L_s/L_u,

$$\frac{w_{st}}{w_{ut}} = \left(\frac{A_{st}}{A_{ut}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{L_{st}}{L_{ut}}\right)^{-\frac{1}{\sigma}}, \tag{2}$$

where w_j is the wage rate of j-type labor. Equation (2) indicates that the relative wage, w_s/w_u, is decreasing in the relative supply of skill, L_s/L_u. The effect of A_s/A_u, however, depends on σ. If $\sigma > 1$, an increase in A_s (relative to A_u) increases the wage gap between skilled and unskilled labor. On the other hand, when $\sigma < 1$, an increase in A_s reduces the relative wage.[8]

Equations (1) and (2) can then be used to solve for A_s and A_u :

$$A_{jt} = \beta_{jt}^{\frac{\sigma}{\sigma-1}} \left(\frac{Y_t}{L_{jt}}\right) \left(\frac{Y_t}{K_t}\right)^{\alpha/(1-\alpha)} \qquad \text{with} \qquad \beta_{jt} = \frac{w_{jt}L_{jt}}{w_{st}L_{st} + w_{ut}L_{ut}}. \tag{3}$$

Thus, with the data on output, factor inputs, and factor prices, one can back out A_{st} and A_{ut} from equation (3), under the assumption that α and σ are known.

3 Quantitative Analysis

In this section, I will apply the key results presented in the previous section to investigate the effects of skilled and unskilled labor efficiencies on economic growth and the skilled premium since 1950. I start with construction of key variables used in the model.

3.1 The Data

The data on output and capital are obtained from the Bureau of Economic Analysis. The GDP and capital series are chained in 2000 chain-dollars. The key point in this exercise is the construction of the skilled and unskilled labor input and wages. The sources of labor input data are from the Census Surveys 1950 and 1960, and the March Current Population Surveys (CPSs) from 1962 to 2006. Since wages and labor input data in the survey refer

[8] If A_s and A_u are interpreted as technologies, then $\sigma > 1$ ($\sigma < 1$) implies that the skill-augmenting technical change is also *skill-biased* (*unskill-biased*).

to one year earlier, the sample spans the period 1949-2005.[9] I consider all employed people between 16 and 70 years old, excluding self-employed workers. The appendix provides a complete description of the data sets and construction of aggregate variables.

Construction of the series for skilled and unskilled labor is accomplished in two steps. First, the data in each year are divided into 72 distinct labor groups (characterized by sex, years of education, and years of experience) and their average labor inputs (measured as total hours) and hourly wages are calculated using census sampling weights.[10] In the second step, I sort these groups into skilled and unskilled labor. I assume that the skilled labor class consists of college or college-plus workers and half of the workers with some college; and the unskilled labor class consists of high school dropouts, high school graduates, and half of the workers with some college following Card and Lemieux (2001) and Autor et al. (2008). I will later consider an alternative classification scheme in which everyone who has at least 16 years of schooling is considered as skilled, and those who have fewer years of schooling are classified as unskilled (Krusell et al. (2000)); but qualitative results remain essentially the same.

Groups within a class are assumed to be perfect substitutes and, following the standard practice in this literature, I use group relative hourly wages as weights for the aggregation of labor inputs into skilled and unskilled classes. The basic idea is based on the assumption that relative wages equal relative qualities of labor.[11] Thus labor input is quality-adjusted.

To construct the A_s and A_u series, two parameters must be known– α and σ. The parameter α measures the capital share and it is set to $1/3$, which matches the U.S. historical values for this variable. The parameter σ, on the other hand, represents the elasticity of

[9]Since the Census Surveys are conducted every ten years, the data between 1950-1960 are not available. Also, there is no CPS data before 1962 and the 1963 CPS does not have education data. For intervening years, I impute each *group*'s data by log-linearly interpolating the same group's data in available neighboring surveys.

[10]Several authors, e.g. Autor et al. (2008), indicate that the March CPS data are not ideal for analyzing the hourly wage distribution since they lack a point-in-time wage measure. For this reason, I also considered an analysis based on weekly wages. However, results based on weekly wages remained mostly the same.

[11]Labor input is usually called *efficiency-adjusted* labor (e.g. Katz and Murphy (1992) and Autor et al. (2008)). However, in this paper *efficiency* refers to the measured values of A_s and A_u.

substitution between skilled and unskilled workers and there is now a large labor economics literature focused on estimating its value. The most influential study is Katz and Murphy (1992), whose estimate, based on the CPSs data over the period 1963-87, is about 1.4. Autor et al. (2008) extend the period to 2005, and report that it is around 1.6. Krusell et al. (2000) find that the elasticity is about 1.7. Using state-level panel data (with an entirely different approach), Ciccone and Peri (2005) obtain the long-run elasticity of substitution between more and less educated workers to be around 1.5. Indeed, based on various econometric estimates, Autor et al. (1998) conclude that this elasticity is very unlikely to be greater than 2. Therefore, I will consider $\sigma = 1.4,\ 1.7$, and 2; and $[1.4, 1.7]$ represents the preferred range for σ.

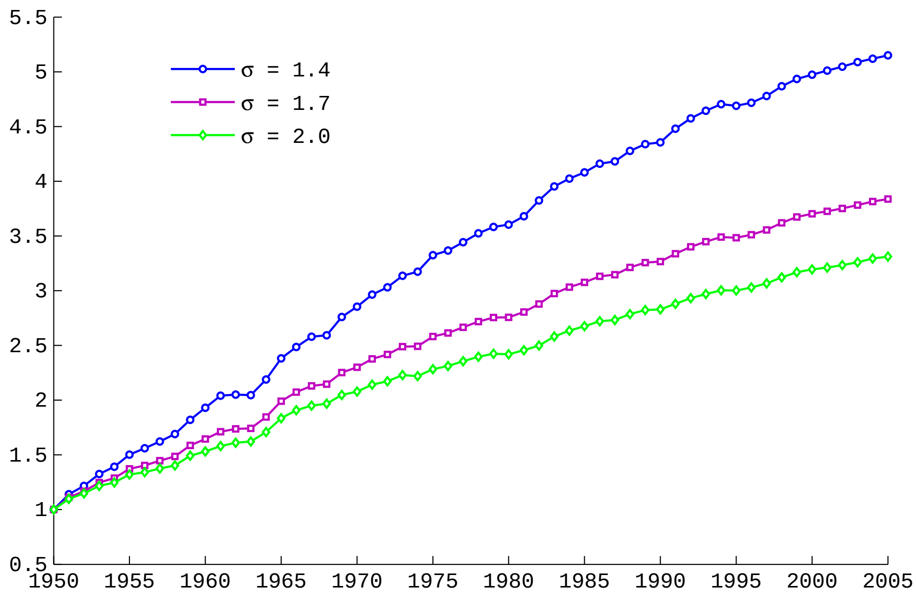
3.2 Main Results

Figures 2.a and 2.b plot the corresponding time paths of skilled and unskilled labor efficiencies, respectively. There are several interesting aspects to note in these figures. First, although there is an increase in skill premium since the early 1980s (see Figure 1), there is no acceleration in A_s. On the contrary, the plots of A_s are slightly concave around the mid 1970s, i.e. the efficiency of skilled labor has grown more slowly since the mid 1970s.[12] For example, under $\sigma = 1.4$ the average annual growth rate of A_s between 1950 and 1975 is 9.3%, while it is about 6.1% between 1975 and 2005. Table 1 represents the summary statistics for the average annual growth rates of A_s and A_u over different time periods. The results question the validity of the standard view that there has been an acceleration in skill-biased technical change. If there had been an acceleration in skill-biased technical change, why is there no signature of it as could be demonstrated by an increase in the growth rate of A_s?

Second and more interestingly, the time paths of $\ln A_u$ are highly non-linear. Although

[12] I test concavity by estimating $\ln A_{st} = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$, ($t$ is the time trend and ε_t is error term). The coefficient β_1 is positive and statistically significant, while β_2 is negative and statistically significant. Then I investigate the structural break in the data by considering the following regression: $\ln A_{st} = \beta_0 + D + \beta_1 t + \beta_2 D \times t + \varepsilon_t$, D is a dummy variable (0 for all $t \leqslant 1973$). The coefficients β_1 and β_2 were highly significant, β_2 always being negative (the results are available upon request).

a. *Time Paths of* $\ln A_s$



b. *Time Paths of* $\ln A_u$

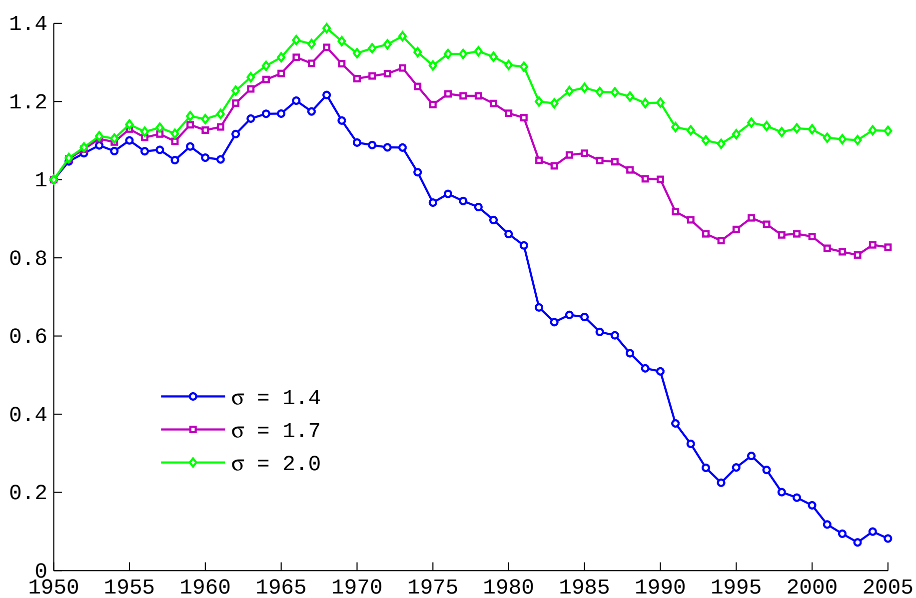


FIGURE 2. Time Series Graphs of $\ln A_s$ and $\ln A_u$

Notes: These figures represent the time paths of the efficiencies of skilled and unskilled labor under different values for substitution elasticity between skilled and unskilled labor. Initial values are normalized to 1.

TABLE 1. The Average Annual Growth Rates of A_s and A_u in US (%)

	g_{A_s}			g_{A_u}		
Period	$\sigma = 1.4$	$\sigma = 1.7$	$\sigma = 2.0$	$\sigma = 1.4$	$\sigma = 1.7$	$\sigma = 2.0$
1950-2005	7.5	5.2	4.2	-1.7	-0.0	0.2
1950-1973	9.1	6.5	5.3	0.4	1.6	1.6
1973-2005	6.4	4.2	3.4	-3.1	-1.4	-0.8

A_u has declined substantially since the early 1970s (usually after 1973), there has been no tendency for decline before this period. In fact, as Figure 2 demonstrates A_u has increased until the early 1970s. Notice that the magnitude of the decline is more significant when the elasticity of substitution is small. With $\sigma = 1.4$, the average annual growth rate of A_u between 1950 and 1973 is about 0.4%, while it is -3.1% between 1973 and 2005. If there were no decline in A_u, A_s/A_u and hence the skill-premium would grow more slowly in the post 1973 period.

Third, the time path of A_u also contradicts the common view that the U.S. economy has been on its long-run balanced growth path. This view is based on the stylized facts that over the last 100 years, the average growth rate of per capita income has been remarkably *stable* and there are no trends in the U.S. capital output-ratio and the real interest rates (as first noticed by Kaldor (1961)). The non-linear time path of $\ln A_u$, however, suggests that the US economy has not been on a balanced growth path.

To get a better intuition about the implications of these results for the economic growth and wage inequality, I will now consider some counterfactual exercises. Obviously, if the efficiency of unskilled labor, A_u, did not have a negative growth rate since the early 1970's, the output would be higher in the subsequent years. What output level would be observed in 2005, had A_u stopped declining after 1973? Using this counterfactual value of A_u in equation (1) and with $\sigma = 1.4$, the output (and hence, per capita income) would have been about 35 percent higher in 2005. Under $\sigma = 1.7$ and $\sigma = 2.0$, the output level would have been about 14% higher and 7% higher, respectively, in comparison to the actual value in

2005.

Similarly, if A_u had stopped declining after 1973, how much lower would the skill premium be in 2005? Notice that equation (2) yields

$$g_{w_s} - g_{w_u} = \left(\frac{\sigma - 1}{\sigma}\right)(g_{A_s} - g_{A_u}) - \frac{1}{\sigma}(g_{L_s} - g_{L_u}),$$

where g_x denotes the growth rate of variable x. Thus, if g_{A_u} were 0 after 1973, the average annual growth rate of the skill premium under $\sigma = 1.4$, would have been 0.9% lower, which in turn implies that the skill premium would have been about 25% lower than the actual premium in 2005. With $\sigma = 1.7$ and $\sigma = 2.0$, the skill-premium would have been about 17% lower and 11% lower, respectively, than the actual premium in 2005.

What caused the efficiency performance of skilled and unskilled labor to change after the early/mid 1970s? Here I suggest two possible explanations for the observed performance of A_s and A_u, but a more detailed analysis of this question is left for future research. First, Greenwood and Yorukoglu (1997) argue that the slowdown in productivity after 1973 may have resulted from the information technology (IT) revolution. In particular, they argue that new ITs required a substantial period of learning by workers who would work with the technology: during this learning process, productivity was depressed as labor adapted to more powerful new technologies. Given that unskilled labor is not equipped with necessary training to use the new technologies, their productivity might even decline upon implementing them. Second, there may be a decline in the average ability level of workers in both sectors. This can happen, for example, when able people who would otherwise work in less skill-intensive jobs get more education in response to increases in the college premium, and then subsequently work in skill-intensive jobs. As a result, over time the less skill-intensive sector will be populated with less able workers. At the same time, the average ability of workers in skill-intensive jobs may also decline, if the new entrants have lower ability than the average ability of workers in skill-intensive jobs.

TABLE 2. The Average Annual Growth Rates of A_s and A_u in US (%)

	g_{A_s}			g_{A_s}		
Period	$\sigma = 1.4$	$\sigma = 1.7$	$\sigma = 2.0$	$\sigma = 1.4$	$\sigma = 1.7$	$\sigma = 2.0$
1950-2005	8.2	5.6	4.5	-0.7	0.2	0.6
1950-1973	9.7	6.9	5.7	0.9	1.6	1.8
1973-2005	6.9	4.6	3.7	-1.9	-0.7	-0.2

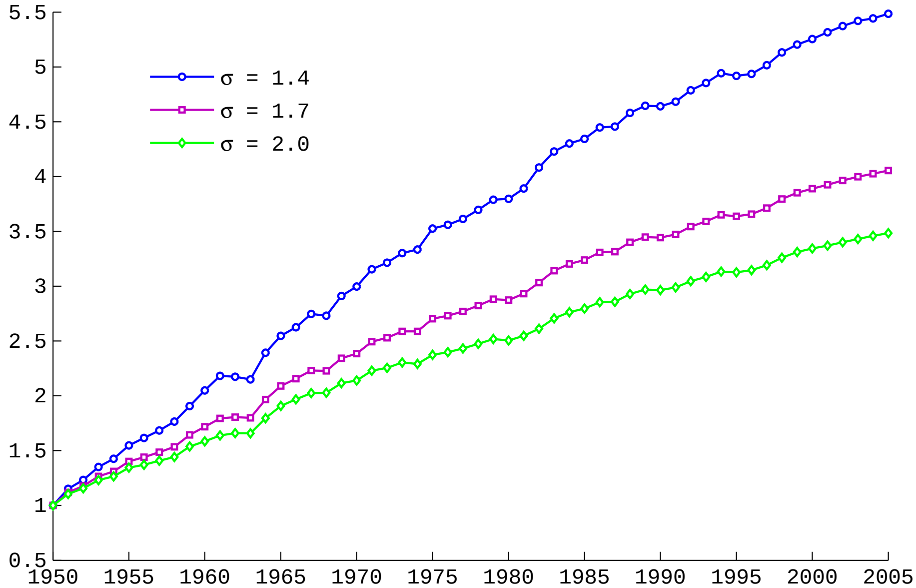
3.3 Analysis with an Alternative Classification of Labor

The analysis presented in the previous section is based on a classification in which the skilled labor class consists of college or college-plus workers. In this section, I consider an alternative classification used by Krusell et al. (2000) in which everyone who has at least 16 years of schooling (i.e., at least college degree) is considered as skilled, and those who have fewer years of schooling are unskilled.

Figures 3.a and 3.b plot the time paths of $\ln A_s$ and $\ln A_u$, respectively. These plots are similar to those in Figure 2, except that the decline in A_u is not as substantial as in Figure 3.b. Moreover, compared to the time path of A_u in Figure 2.b, A_u grew more rapidly between 1950 and 1973 (see also Table 2). For example, with $\sigma = 1.4$, the average annual growth rates of A_u over the two periods 1950-1973 and 1973-2005 are 0.9 and -1.9 percents, respectively; whereas they are 0.4 and -3.1 percents in Figure 2.b.

As in the previous section, had A_u stopped declining after 1973, how much higher would the output be in 2005? How much lower would the skill premium be in 2005? Following the same steps as in the previous section yields that (under $\sigma = 1.4$) the output and per capita income would have been about 25 percent higher in 2005. Under $\sigma = 1.7$ and $\sigma = 2.0$, however, the output level would be about 9% higher and 3% higher, respectively, in comparison to the actual value in 2005. Similarly, under $\sigma = 1.4$, the skill premium would have been about 16% lower than the actual premium in 2005. With $\sigma = 1.7$ and $\sigma = 2.0$, the skill-premium would have been about 9% lower and 4% lower, respectively,

a. *Time Paths of* $\ln A_s$



b. *Time Paths of* $\ln A_u$

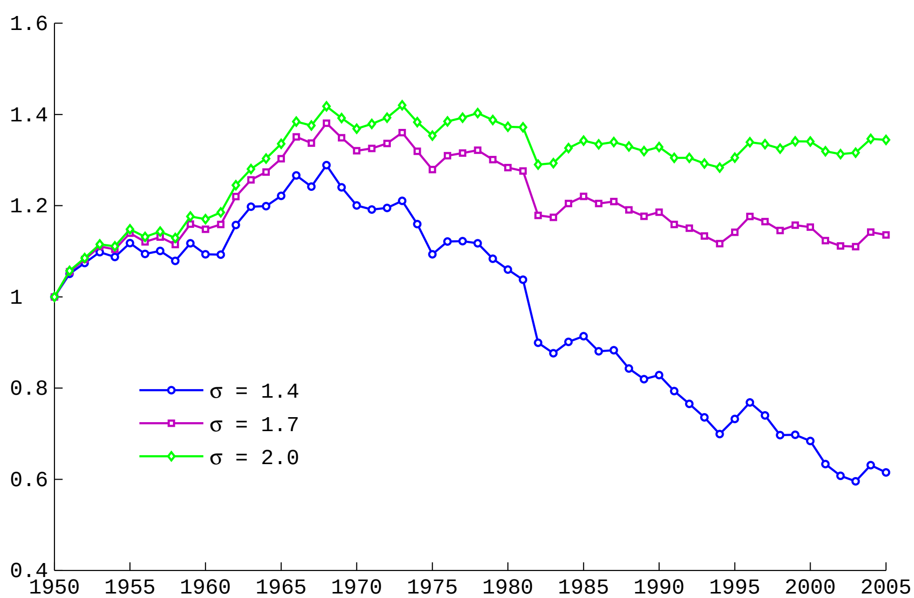


FIGURE 3. Time Series Graphs of $\ln A_s$ and $\ln A_u$

Notes: These figures represent the time paths of the efficiencies of skilled and unskilled labor under different values for substitution elasticity between skilled and unskilled labor. Everyone who has at least 16 years of schooling is skilled, otherwise they are considered as unskilled. Initial values are normalized to 1.

than the actual premium in 2005.

3.4 Accounting for Sources of U.S. Growth

Having A_s and A_u, one can easily implement a growth accounting exercise to assess their importance to output growth. Taking the logarithm of both sides in equation (1) and differentiating with respect to time yields

$$g_Y = \varepsilon_K g_K + \varepsilon_{L_s} g_{L_s} + \varepsilon_{L_u} g_{L_u} + \varepsilon_{A_s} g_{A_s} + \varepsilon_{A_u} g_{A_u},$$

where, as before, g_x represents the growth rate of variable x and $\varepsilon_x = (\partial Y/\partial x)(x/Y)$ is the elasticity of x with respect to output, Y. It is easy to show that $\varepsilon_K = \alpha$ and $\varepsilon_{L_{jt}} = \varepsilon_{A_{jt}} = (1-\alpha)\beta_{jt}$. Furthermore, from section 3.1, it is known that the labor input is quality-adjusted: $L_{jt} = q_{jt}N_{jt}$, where q_{jt} represents the quality index of j-type labor, and N_{jt} is the total hours worked by the corresponding individuals. Let N_t denote the total labor hours worked (i.e., $N_t = N_{st} + N_{ut}$), then the above equation yields:

$$g_y = \left(\frac{\alpha}{1-\alpha}\right) g_{K/Y} + \beta_s g_{q_s} + \beta_u g_{q_u} + \beta_s g_{n_s} + \beta_u g_{n_u} + \beta_s g_{A_s} + \beta_u g_{A_u}, \tag{4}$$

where $y \equiv Y/N$ and $n_j = N_j/N$. The first term denotes the growth rate of K/Y. The motivation for considering changes in the capital-output ratio rather than changes in capital is to assign the long-run effects of changes in capital and technology entirely to these variables (see, for example, Jones (2002)). However, this presentation cannot completely isolate the effects of technical changes on the contributions of labors to output growth. For example, a change in A_s changes β_s, which in turn affects the contribution of skilled labor to output growth. Therefore, the results of the corresponding accounting exercises should be taken with a grain of salt.

Equation (4) decomposes output into several components that have specific interpretations. The first term, $g_{K/Y}$, measures the contribution of capital deepening to labor productivity (output per hour) growth. The terms $\beta_s g_{q_s}$ and $\beta_u g_{q_u}$ represent the contributions of changes in the quality of skilled and unskilled labor, respectively, to the output growth, while $\beta_s g_{n_s}$ and $\beta_u g_{n_u}$ represent the effects of labor reallocations into two different classes. The finals terms, $\beta_s g_{A_s}$ and $\beta_u g_{A_u}$, measure the contributions of skilled and unskilled augmenting efficiency changes to labor productivity growth. The discrete time approximation of (4) is given by

$$\hat{y}_t = \frac{\alpha}{1-\alpha}\widehat{\left(\frac{K}{Y}\right)}_t + \bar{\beta}_{st}\hat{q}_{st} + \bar{\beta}_{ut}\hat{q}_{ut} + \bar{\beta}_{st}\hat{n}_{st} + \bar{\beta}_{ut}\hat{n}_{ut} + \bar{\beta}_{st}\hat{A}_{st} + \bar{\beta}_{ut}\hat{A}_{ut}, \tag{5}$$

where $\widehat{x}_t = \ln x_t - \ln x_{t-1}$ represents the growth rate of variable x in year t and $\bar{\beta}_{jt} = 0.5(\beta_{j,t-1} + \beta_{j,t})$.

Tables 3.a reports the growth accounting exercise based on the above equation. The contribution of factor inputs to labor productivity growth is about 15 percent. The remaining 85 percent of growth is attributed to changes in efficiencies. This effect itself is the sum of two components. First, growth in the efficiency of skilled labor is the largest contributor to productivity growth in this decomposition, accounting for between 72 and 129 percent of output growth, depending on the exact value of the elasticity of substitution, σ. Second, changes in the efficiency of unskilled labor accounts for between -44 and 13 percent of growth, again depending on the exact value of σ.

Table 3.b reports the accounting exercise over the two subperiods, 1950-73 and 1973-2005. For the sake of brevity, I only present results under $\sigma = 1.7$. Results based on different elasticity of substitutions are qualitatively similar (and they are available upon request). Consistent with the trends in Figures 2.a and 2.b, contribution of A_u to output growth is substantially negative over the post-1973 period. During this period, contributions of factor inputs increase by 18 percentage points compared to the pre-1973 period.

Table 4.a and 4.b present results based on the college-completion definition of skilled labor. Compared to those results in Tables 3.a and 3.b, the contribution of each component is usually different. For example, while according to Table 3.a unskilled labor (in)efficiency contributes -44 to 13 percent to labor productivity growth, its contribution is about -20 to 27 percent in Table 4.a. Although the contributions of subcomponents are different, the

TABLE 3.a. Accounting For US Growth, 1950-2005 (%)

Elasticity	Output per Hour	Contribution from: Capital	Quality of Labor		Relocation of Labor		Efficiency	
σ	$\hat{y}$	$0.5\widehat{\left(\frac{K}{Y}\right)}$	$\bar{\beta}_s\hat{q}_s$	$\bar{\beta}_u\hat{q}_u$	$\bar{\beta}_s\hat{n}_s$	$\bar{\beta}_u\hat{n}_u$	$\bar{\beta}_s\hat{A}_s$	$\bar{\beta}_u\hat{A}_u$
1.4	2.0	-0.1	0.0	0.1	0.8	-0.5	2.6	-0.9
	(100)	(-4)	(0)	(5)	(40)	(-26)	(129)	(-44)
1.7	2.0	-0.1	0.0	0.1	0.8	-0.5	1.7	-0.1
	(100)	(-4)	(0)	(5)	(40)	(-26)	(87)	(-2)
2.0	2.0	-0.1	0.0	0.1	0.8	-0.5	1.4	0.3
	(100)	(-4)	(0)	(5)	(40)	(-26)	(72)	(13)

TABLE 3.b. Accounting Exercise with $\sigma = 1.7$ (%)

Period	Output per Hour	Contribution from: Capital	Quality of Labor		Relocation of Labor		Efficiency	
	$\hat{y}$	$0.5\widehat{\left(\frac{K}{Y}\right)}$	$\bar{\beta}_s\hat{q}_s$	$\bar{\beta}_u\hat{q}_u$	$\bar{\beta}_s\hat{n}_s$	$\bar{\beta}_u\hat{n}_u$	$\bar{\beta}_s\hat{A}_s$	$\bar{\beta}_u\hat{A}_u$
1950-1973	2.6	-0.1	0.0	0.1	0.7	-0.5	1.5	1.0
	(100)	(-4)	(-2)	(3)	(26)	(-17)	(56)	(37)
1973-2005	1.5	-0.1	0.0	0.1	0.9	-0.6	1.9	-0.8
	(100)	(-5)	(2)	(7)	(59)	(-39)	(127)	(-51)

Notes: This table reports the growth accounting decomposition based on equation (5). Numbers in parentheses represent relative contributions in percentage.

total contribution of factor inputs, and hence, labor efficiencies, remains almost the same.

It is interesting to compare these results to those in Jones (2002) who studies the sources of US economic growth from 1950 to 1993. Jones uses the following Cobb-Douglas specification for the aggregate production function

$$Y_t = K_t^{\alpha}(A_t H_t)^{1-\alpha}, \tag{6}$$

where A_t is the total factor productivity (TFP) and H_t is the total amount of human capital employed to produce output, i.e. $H_t = h_t N_t$. Human capital per person, h_t, is given by $h_t = e^{\phi E_t}$, where E_t is the average years of schooling that each person has, and ϕ is the

TABLE 4.a. Accounting For US Growth, 1950–2005 (%) under Different Classification of Labor

Elasticity	Output per Hour	Contribution from Capital	Quality of Labor		Relocation of Labor		Efficiency	
σ	$\hat{y}$	$0.5\widehat{\left(\frac{K}{Y}\right)}$	$\bar{\beta}_s\hat{q}_s$	$\bar{\beta}_u\hat{q}_u$	$\bar{\beta}_s\hat{n}_s$	$\bar{\beta}_u\hat{n}_u$	$\bar{\beta}_s\hat{A}_s$	$\bar{\beta}_u\hat{A}_u$
1.4	2.0	-0.1	0.0	0.1	0.6	-0.4	2.1	-0.4
	(100)	(-4)	(0)	(7)	(30)	(-19)	(105)	(-20)
1.7	2.0	-0.1	0.0	0.1	0.6	-0.4	1.4	0.3
	(100)	(-4)	(0)	(7)	(30)	(-19)	(72)	(13)
2.0	2.0	-0.1	0.0	0.1	0.6	-0.4	1.1	0.5
	(100)	(-4)	(0)	(7)	(30)	(-19)	(58)	(27)

TABLE 4.b. Accounting Exercise with $\sigma = 1.7$ (%)

	Output per Hour	Contribution from Capital	Quality of Labor		Relocation of Labor		Efficiency	
Period	$\hat{y}$	$0.5\widehat{\left(\frac{K}{Y}\right)}$	$\bar{\beta}_s\hat{q}_s$	$\bar{\beta}_u\hat{q}_u$	$\bar{\beta}_s\hat{n}_s$	$\bar{\beta}_u\hat{n}_u$	$\bar{\beta}_s\hat{A}_s$	$\bar{\beta}_u\hat{A}_u$
1950-1973	2.6	-0.1	0.0	0.1	0.5	-0.3	1.1	1.3
	(100)	(-4)	(-1)	(3)	(20)	(-13)	(44)	(50)
1973-2005	1.5	-0.1	0.0	0.2	0.7	-0.4	1.6	-0.4
	(100)	(-5)	(1)	(10)	(44)	(-27)	(105)	(-28)

Notes: This table reports the growth accounting decomposition based on equation (5). Numbers in parentheses represent relative contributions in percentage. Everyone who has at least college degree is skilled, and otherwise they are considered as unskilled.

return to schooling estimated in a Mincerian wage regression (see Mincer (1974)).[13] Based on the estimates in Bils and Klenow (2000), Jones assumes that the return to schooling is

[13] In constructing the quality-adjusted labor input, I followed the standard approach used in the labor economics literature that group relative hourly wages as weights for the aggregation of labor inputs. The main advantage of this approach over the one used by Jones (2002) is that it not only capture differences from schooling, but also from sex and experience status. Having said that, as a robustness check I also constructed skilled and unskilled labor inputs as $L_{jt} = h_{jt}N_{jt}$, where h_{jt} is the average human capital per person in class j. However, analysis based on this alternative approach yielded very similar results to those reported in Figures 2 and 3, and Tables 3 and 4.

TABLE 5. Accounting For US Growth, 1950–2005 (%)
with Cobb-Douglas Specification

Output per Hour	Contribution from Physical Capital	Human Capital	Total Factor Productivity
$\hat{y}$	$0.5\widehat{\left(\frac{K}{Y}\right)}$	$\hat{h}$	$\hat{A}$
2.0	-0.1	0.4	1.7
(100)	(-4)	(20)	(85)

7 percent, i.e. $\phi = 0.07$. Given these, the above production function yields

$$\hat{y}_t = \frac{\alpha}{1-\alpha}\widehat{\left(\frac{K}{Y}\right)}_t + \hat{h}_t + \hat{A}_t, \tag{7}$$

where, as before, $\hat{x}_t$ represents the growth rate of variable x in year t.[14]

By decomposing output per hour according to equation (7), Jones finds that the contribution of factor inputs to growth is about 27 percent. Of this about 32 percent stems from the rise in educational attainment, i.e. increase from human capital. The total factor productivity (TFP) growth, on the other hand, accounts for 73 percent labor productivity growth. I extend Jones's analysis to 2005 and Table 5 reports results from the corresponding accounting exercise. The human capital component, associated with the rise in educational attainment, contributed 0.4 percentage points to output per hour growth, accounting for 20 percent of growth.[15] Compared to Jones's original results, the contribution of human capital to growth is about 0.2 percentage points lower, and this mainly stems from the way that the average years of schooling are calculated in the two papers.[16]

[14]In Jones's specification, people work either in production or in the R&D sector; as a result, there is an additional term in (7) which captures the changes stemming from the relocation of labor to production. However, as shown by Jones, this term has a negligible effect on growth, since less than 1 percent of the U.S. labor force works as a researcher.

[15]Results based on the average quality, q_t, instead of human capital, h_t, are almost identical to those in Table 5.

[16]The average years of schooling in this paper are constructed from the census and CPSs data using the corresponding survey weights, while Jones's calculations are based on the simple average of the educational attainment data provided by U.S. Census Bureau. The approach taken in this paper is more reliable than Jones's approach for two reasons. First, it uses a more sophisticated and accurate weighting scheme than the simple average. Second, the education data provided by the Census Bureau report years of school completed

The TFP contribution to growth in output per hour is remarkably similar to the total contributions of efficiencies reported in Tables 3 and 4. Thus, in addressing the importance of factor inputs vs. efficiency, the Cobb-Douglas specification does a good job.[17] However, there are two main problems with the Cobb-Douglas specification. First, it assumes that skilled and unskilled labor are perfectly substitutable, i.e. the elasticity of substitution between skilled and unskilled workers is infinity. The empirical labor literature, on the other hand, documents that it is around 1.5, well below infinity. Second, this approach is completely silent about the contributions of subcomponents to productivity growth. It does not, for example, separate the contribution of skilled and unskilled labor efficiencies to growth. The analysis in this paper reveals that the components A_s and A_u shows disparate trends.

Jones (2002) also notices that there has been a substantial increase in research intensity during the last several decades. Combined with the rise in educational attainment, this implies that the U.S. economy is far from its balanced growth path. To reconcile these facts with the steady growth in output per hour worked, he argues that the U.S. economy has been on a *constant* growth path (CGP), on which, like the balanced growth path (BGP), all variables have constant growth rates. However, unlike the BGP, "it is not required to be a situation that can continue forever" (Jones (2002)). In Jones's framework, the CGP requires that variables K, h, and A must grow at constant rates. The CGP is a reasonable description for these variables, at least as a first approximation. However, behavior of A_u, obtained in this paper, makes it clear that a CGP model may not be a good approximation for the long-run economic growth either.[18]

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by *all* people 25 years and over, as opposed to the average years of schooling for the U.S. workers. When these facts are taken into account, it is seen that human capital accumulation has grown more slowly over the last two decades, a fact also observed by Ha and Howitt (2007).

[17]This conclusion holds even if one considers a slightly more general form of equation (6): $Y_t = A_t^\theta K_t^\alpha (L_{st}^{\beta_{st}} L_{ut}^{\beta_{ut}})^{1-\alpha}$, where β_{jt} is defined in equation (3). This production structure has the similar problems to the one above. First, in this specification, the elasticity of substitution between the two different types of labor is one, which is less than what the empirical studies have found. Second, like (6), this production function does not differentiate skilled and unskilled labor efficiencies.

[18]The variable q_u also does not follow a CGP. However, because its contribution is small, this pattern is

4 Conclusion

The relative supply of skilled labor has increased rapidly since the late 1960s, and the skill premium has increased sharply since 1980. It has been argued that this pattern is a result of the acceleration of skill-biased technical change. In this paper, using a production framework in which skilled and unskilled labor are imperfect substitutes, I analyze the time paths of skilled and unskilled labor efficiencies and investigate their implications for the economic growth and wage inequality in the US over the last half-century.

I document a slowdown in the growth rate of skilled labor efficiency since the mid 1970s, and a substantial decline in the absolute level of the efficiency of unskilled labor since the early 1970s. These patterns imply that (i) the decline in unskilled labor efficiency also has an adverse effect on labor productivity growth; (ii) the dramatic rise in the U.S. skill premium over the last two decades has not only been driven by increases in the skilled labor efficiency, but also by considerable declines in unskilled labor efficiency.

Data Appendix

The data on the labor supply and income are from the March Current Population Surveys (CPSs) for years between 1963 and 2006, Census IPUMS 1 percent extracts for years 1950 and 1960. Unfortunately, the data on employment benefits are not available. Thus, calculations of β_{jt} are based on the total income from wages and salaries. In this way, it is implicitly assumed that the fractions of total compensation paid as employer benefits to skilled and unskilled workers are the same.[19]

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not important in the analysis.

[19]However, the Bureau of Labor Statistics reports employer benefits according to different occupational groups between 1986 and 2007 (http://www.bls.gov/ncs/ect/home.htm#tables). The percentage of total compensation paid to white-collar (blue-collar) workers has remained mostly stable around 27 (32) percent over this period, suggesting that the differences from employment benefits have negligible impacts on the results. I would like to thank Julie B. Cullen for bringing this data source to my attention.

Processing of March CPS Data

The March CPS is obtained from Unicon Research Corporation. The main advantage of using the data from Unicon is that Unicon has cleaned up all of the problems in the raw CPS files provided by the Census Bureau and recoded variables so that the surveys became more comparable across years. Construction of the series for aggregate variables are accomplished in five steps:

Step 1: In each year, the data on employed people between 16 and 70 years old are divided into 72 groups characterized by sex, education, and experience.[20] Education status, E, is divided into 4 categories: $E < 12$ (no high school diploma), $E = 12$ (high school graduate), $13 \leq E \leq 15$ (some college), and $E \geq 16$ (college graduate or more) to depict years of schooling.[21] Potential experience is calculated as Min{age–years of schooling–7, age–17} following Katz and Murphy (1992), and experience status is divided into 9 categories (0–4, 5–9,$\cdots$, 35–39, 40+). Using the CPS sample weights, the fraction of total labor for each group in each year is calculated. These fractions are then multiplied by the annual employment data from the BEA to obtain the number of workers in each group.[22] Let $N_{\gamma t}$ represents the total number of workers in group γ in year t.

Step 2: Self-employed workers and workers with imputed earnings are excluded.[23] Two

[20]This taxonomy is the same as in Autor et al. (2008). When aggregating labor inputs, Autor et al. divide potential experience status into finer groups than I do. However, in that case several groups remained empty. To be more consistent across all groups, I consider a higher level of aggregation. In the previous version of this paper, I imputed the data for an empty group by assigning the mean of a more aggregated group (following Autor et al. (2008)), but such approach yielded very similar results.

[21]Commencing in 1992, the Bureau of the Census changed the emphasis of its educational attainment question from years of education to degree receipt. To obtain a comparable educational-attainment data across years, the classification proposed by Jaeger (1997) is followed. Specifically, high school dropouts are those with fewer than 12 years of schooling; high school graduates are those with either 12 years of education and/or a high school diploma; some college are those attending some college or holding an associate's degree; and college plus are those with a bachelor's degree or higher.

[22]The annual employment numbers reported by the BEA are usually close to the number of workers obtained from the CPSs. In some years, however, the total employment data obtained from the CPSs fluctuate substantially from the adjacent years. Therefore, individual cells are adjusted according to the BEA employment data.

[23]The sample does not include allocated earnings observations due to the fact that the imputation procedures changed between 1975 and 1976. To exclude imputed wages, following Autor et al. (2008), family

adjustments for topcoded earnings are also made. First, following Autor et al. (2008) income of workers with top coded earnings are imputed by multiplying the annual topcode amount by 1.5. Second, starting in 1996, topcoded earnings values are assigned the mean of all topcoded earners. In these cases, we simply reassign the topcoded values to all observations and again multiply by 1.5.[24] Earnings are deflated using the Personal Consumption Expenditure (PCE) deflator from the BEA.

Step 3: Hourly wages are formed by dividing annual incomes by imputed measures of hours worked during the previous year. Imputed hours are formed by multiplying *imputed* weeks by hours worked last week. An imputed measure of weeks worked is used since the exact number of weeks worked is not available in the CPS prior to 1976. Following Katz and Murphy (1992), the sample for 1976-2005 is divided into groups defined by the weeks worked brackets used in the earlier surveys and sex. The means of weeks worked for these groups from the 1976-2005 surveys are used as estimates of weeks worked for individuals in the corresponding groups.[25]

Hours worked last week are used, since the data on hours worked last year are not available in the CPS prior to 1976. In computing the group labor hour, first the individuals are sorted into part-time and full-time status using the census part-time, full-time flag. Full-time is defined as those who work at least 35 hours per week. Then, in each group, for full-time workers who reported less than 35 hours per week, it is assumed that their weekly supply of hours is equal to that of the average full-time worker belonging to the same group. The same method is used to calculate the weekly supply of hours by part-time workers who reported either zero hours or worked more than 35 during the last week.[26] In all such

earnings allocation flags (1966-1975) and individual earnings allocation flags (1976 onward) are used.

[24]Unassigned topcoded values are available in the surveys. For example, for the secondary earning value, the topcoded maximum is set at 99,999 from 1988 to 1995, falls to 25,000 for 1996 through 2002, and rises to 35,000 in 2003 through 2006.

[25]To be consistent over time, unlike Katz and Murphy (1992) who use the estimated weeks only for the earlier surveys, estimated weeks are used in all years. Imputations based on the 72-group classification yielded similar estimates.

[26]The part-time workers constitute relatively small fraction of employed labor force, less than 20% of the

calculations CPSs weights are used. Following Autor et al. (2008), the full-time workers with real hourly wage below \$2.6 (which roughly corresponds \$112 per week) are dropped. Similarly, the bottom 1 percent of hourly wages of part-time workers are also dropped. In each year, the maximum hourly wage of part-time workers is also limited to the maximum annual income of full-time workers divided by 1,750 (35 hours per week and 50 weeks per year). This correction prevents part-time workers from having a higher feasible hourly wage than full-time workers (see Autor et al. (2008)). These adjustments are made to reduce possible measurement errors stemming from the imputed weeks/hours, but the results are not sensitive to such corrections. The average annual hours of each group is then adjusted by a fixed factor so that the average annual hours worked per person is the same as that reported by the BEA.[27]

Step 4: Let W_{it} and ℓ_{it} represent individual i's annual income and total labor input in year t, respectively. The corresponding hourly wage rate, w_{it}, is given by $w_{it} = W_{it}/\ell_{it}.$. For the group γ, the average labor input and the average wage rate are then computed as

$$\ell_{\gamma t} = \frac{\sum_{i \in \gamma} \ell_{it} \mu_{it}}{\sum_{i \in \gamma} \mu_{it}}, \qquad w_{\gamma t} = \frac{\sum_{i \in \gamma} w_{it} \mu_{it}}{\sum_{i \in \gamma} \mu_{it}},$$

where μ_{it} is individual i's CPS sampling weight.

Total annual income of group γ in year t, $W_{\gamma t}$, is then given by $W_{\gamma t} = w_{\gamma t} \ell_{\gamma t} N_{\gamma t}$, where $N_{\gamma t}$ is the total number of people in group γ. Thus, the total compensation paid to the skilled workers, W_{st}, is given by $W_{st} = \sum_{\gamma \in \Gamma_s} W_{\gamma t}$, where Γ_s denotes the set of skilled groups. Similarly, the total compensation paid to the unskilled workers, W_{ut}, is given by $W_{ut} = \sum_{\gamma \in \Gamma_u} W_{\gamma t}$.

sample.

[27]The BEA also reports total hours worked from 1947 to 2006. Using the employment data, it is easy to derive the average annual hours worked by each person. Compared to these data, the average annual hours data obtained from the CPSs show some deviations. To correct these deviations, I multiplied each group average hour by the ratio of the BEA average annual hours per worker to that obtained from the CPS data. Notice that such an adjustment does not affect relative wages and relative labor supplies, and hence, does not affect their time trends. Analysis without such an adjustment yields similar results to those reported in the text.

Step 5: The aggregation of labor inputs into skilled and unskilled classes is achieved as follows. Groups within a class are assumed to be perfect substitutes, and as indicated in the main text, group relative wages are used as weights for the aggregation. For each group in each year, a relative wage measure is constructed by dividing each group's average hourly wage by the average hourly wage of the group which contains white males who have less than 12 years of schooling and less than 5 years of experience in the contemporaneous year.[28] The relative quality index measure for each group, q_γ, is computed as the arithmetic mean of the relative wage measures in that group over 1950 to 2005. Then the total quality-adjusted labor input in each class is given by

$$L_{jt} = \sum_{\gamma \in \Gamma_j} q_\gamma \ell_{\gamma t} N_{\gamma t}, \qquad j = s, u.$$

The corresponding *quality-adjusted* average wage rate for each class is calculated as $w_{jt} = W_{jt}/L_{jt}$, as in Krusell et al. (2000).

Processing of Census Data

The Census IPUMS surveys are available at www.ipums.org. The processing of census data is very similar to that of the CPS; the data on employed people (who are currently employed) between 16 and 70 years old are divided into 72 groups characterized by sex, education, and experience. Following Autor et al. (2008), (i) individuals who are self-employed, (ii) worked in unpaid family work, and (iii) who did not live in correctional institutions, mental institutions, or other non-institutional group quarters are excluded from the sample. Top-coded earnings are multiplied by 1.5 and the earning numbers are deflated using the PCE.

Imputed weeks from the previous section are used. For the 1960 sample, an imputed measure of hours worked last week is used since the *exact* number of hours worked is not available in that year. To impute hours, the census sample for 1950 is divided into groups defined by the hours worked brackets used in the 1960 survey and sex. The means of

[28] This choice of the base group is innocuous. For example, Katz and Murphy (1992) index each group's wage to the wages for a fixed bundle of workers.

hours worked for these groups in the 1950 survey are used as estimates of hours worked for individuals in the corresponding groups.

Imputed hours are formed by multiplying imputed weeks by hours worked last week. Unfortunately, there is no worker type flag to distinguish who is a full-time worker. As a result, all observations with real hourly earnings below $2 dollar are dropped. The maximum hourly wage of part-time workers is limited to the maximum annual income of workers divided by 1,750 (35 hours per week and 50 weeks per year), following Autor et al. (2008).

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