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Abstract

In this paper, using a production framework in which skilled and unskilled labor are imperfect substitutes, we analyze the time paths of the efficiencies of skilled and unskilled labor and their implications for wage inequality and economic growth. We find no evidence that supports the common view that there has been an acceleration in skilled biased technical change. Indeed, after 1973 the efficiency of skilled labor grew more slowly than it had from 1961 to 1973. More interestingly, we find that after 1973 there has been a substantial decline in the efficiency of unskilled labor, implying that the decline in unskilled labor efficiency has significantly contributed to the widening in the U.S. wage structure. In a standard growth accounting framework, these findings further imply that skilled labor efficiency growth accounts for 35 to 67 percent of output growth, while changes in unskilled labor efficiency account for -31 to 2 percent of output growth, depending on exact values of the parameters of the model and the definition of skilled labor.

JEL Classification: E1, O3 and O4

Keywords: Economic Growth, Growth Accounting, Skilled (Unskilled) Labor Efficiency

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1 Introduction

Figure 1 plots the U.S. relative supply of skills vs. the skill premium, defined as (hourly) wage of skilled labor relative to that of unskilled labor, between 1961 and 2005. It shows that the relative supply of skills and the skill premium have changed dramatically. Although the relative supply of skills has increased substantially, there is no tendency for the skill premium to decline. Indeed, there has been a substantial increase in the skill premium since 1980 (Bound and Johnson (2000), Katz and Murphy (1992), and Autor et al. (2007)). This pattern underlines the common view that new technologies have been skilled biased (Bound and Johnson (2000), Katz and Murphy (1992), and Acemoglu (1998) and (2002)). Another interesting point in this figure is that the relative supply of skilled labor has increased rapidly since the late 1960s, and the skill premium has grown significantly since the early 1980s, which has led many economists to conclude that there has been an acceleration in skilled biased technical change (Autor et al. (1998) and Acemoglu (1998) and (2002)).

Naturally, one may wonder how the technologies that augment skilled and unskilled labors have evolved over this period. This is the question that we would like to address in this paper. In particular, we analyze the time paths of skilled and unskilled augmented technologies and their effects on the U.S. skill premium and economic growth during the period 1961-2005. Toward this end, we 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, we can derive the time series of the skilled and unskilled augmented technologies from the data. We then use these series to address their implications for the skilled premium and economic growth. Given that this production structure ignores some other factors that may affect the production, it is important to note that these technologies are imperfectly measured as the efficiency of labor (or labor efficiency).

Results of this paper can be summarized as follows. We find no evidence that supports

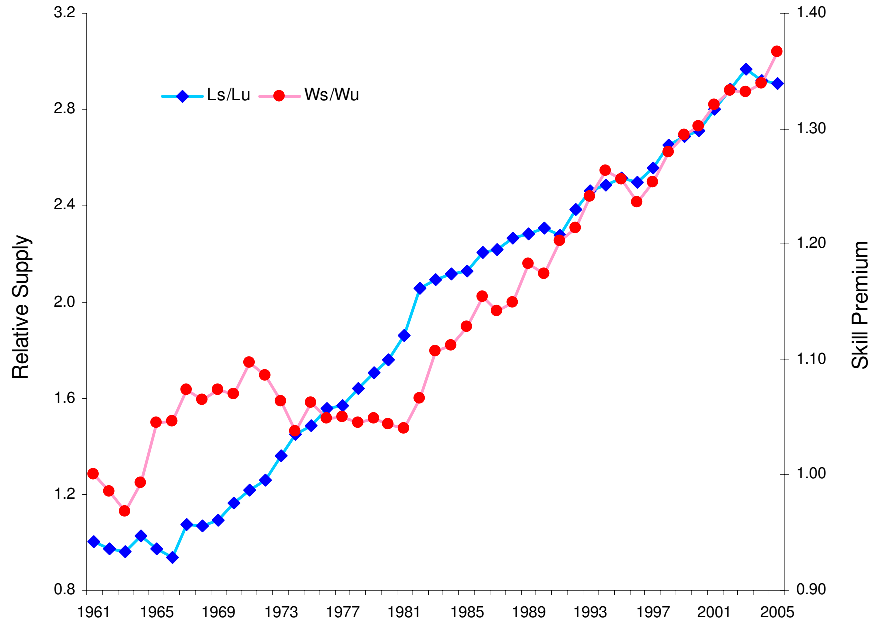


Figure 1. Relative Supply of Skills vs. Skill Premium This figure represents the U.S. relative supply of skills vs. the skill premium. Initial values are normalized to 1.

the claim that there has been an acceleration in the skilled biased technical change. Indeed, we find skilled labor efficiency grew more slowly after 1973. More interestingly, we find that beginning in the early 1970s (around 1973), there has been a substantial decline in the absolute level of the efficiency of unskilled labor. These results have interesting implications. First, they imply that the substantial widening in the U.S. wage structure has not only been driven by increases in skilled labor efficiency, but also by substantial declines in the efficiency of unskilled labor. For example, if after 1973 unskilled labor efficiency growth had slowed by the same proportion as that of skilled labor efficiency, the wage gap between skilled and unskilled workers would be about 25 to 30% lower in 2005. Second, the decline in unskilled labor augmented efficiency also has an adverse effect on output growth. Using a standard growth accounting framework, we show that skilled labor efficiency accounts for between 1.2 and 2.2 percentage points (or 35 to 67 percent) of output growth, while changes in unskilled labor efficiency accounts for between -1 and 0.05 percentage points (or -31 to

2 percent) of output growth. The total contribution of other factors to output growth is about 2 percentage points, accounting for 63 percent of growth. Thus, as in the above case, if after 1973 the growth rate of unskilled labor efficiency had slowed by the same proportion as that of skilled labor efficiency, GDP (and per capita GDP) would be about 20 to 40 percent higher in 2005. Finally, the significant decline of unskilled labor efficiency during the post 1973 period contradicts the common view that the U.S. economy has been on a balanced growth path.

This paper methodologically builds on Caselli and Coleman (2006), who study cross-country differences in the aggregate production function when skilled and unskilled labor are imperfect substitutes. They find that higher-income countries use skilled labor more efficiently than lower-income countries, while they use unskilled labor relatively less efficiently. We use the same methodology to shed light on the question of how the U.S. economy has utilized skilled and unskilled labor over the last 45 years. Our analysis, however, reveals that the efficiency of unskilled labor is not monotonically declining with the increase in income levels.

This paper is related to two literatures: wage inequality and growth accounting. The studies in the wage inequality literature typically address the determinants of the dramatic changes in the U.S. skill premium (see, Katz and Murphy (1992), Krusell et al. (2000), and Autor et al. (2007), among many others). An interesting contribution to this literature is Ruiz-Arranz (2004), who uses a translog production approach to study the sources of changes in the U.S. skill premium. 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. Although her findings are similar to ours, there are still differences between the two papers. First, methodologically the two papers are different. She estimates a translog production model, and using the estimated parameters, determines the nature of technical change. In contrast, we do not estimate any model. Instead, using a few assumptions, we derive the time series of skilled and unskilled labor efficiencies from the data and our approach allows us to examine the time behavior of the efficiency series more directly and clearly than hers. For example, we find that the efficiency of unskilled labor has not always been declining. Second, our analysis also investigates the effects of changes in the efficiencies on output growth.[1]

There is now an influential literature on accounting for the sources of growth in the U.S. economy.[2] Our approach is in the same spirit as the influential work by Solow (1957).[3] The most relevant study to our work is Jones (2002), who based on a Cobb-Douglas production function, finds that total factor productivity (TFP) is the largest contributor to US output growth during the period 1950-1993. Jones also notices that increases in educational attainment and research intensity during the last several decades imply 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, along which variables also have constant growth rates. Although within the Cobb-Douglas framework the constant growth path explanation is plausible, it is not convincing when we assume skilled and unskilled labor are imperfect substitutes. In particular, our analysis reveals that the time path of the efficiency of unskilled labor does not follow a constant growth path (for a more detailed explanation, see section 3.4).

The rest of this paper is organized as follows. Section 2 introduces the production framework that underlies our analysis. Section 3 presents the quantitative analysis. In this section, we first discusses the main features of the data along with the construction of the

[1] On the other hand, she considers a four-factor production function with different elasticities of substitution between the two of types of capital and the two types of labor, whereas we do not. Extending our analysis to a more general production function with different types of capital requires calibrations of more parameters. Such an extension is left for future work.

[2] See Solow (1957), Denison (1962), Jorgenson (1967), and Jorgenson (2005). In particular, see Jorgenson (2005) for a summary of works in this literature.

[3] There are two approaches in this literature. The first one originally developed by Solow (1957) is the aggregate production function approach, which is the one that we also use in this paper. The alternative one is known as production possibility approach originally developed by Jorgenson (1966) and recently employed by Jorgenson (2005) and Jorgenson et al. (2007). Although this approach imposes less restrictions on value-added functions, it only delivers a TFP growth rate. Since we are interested in analyzing the efficiencies of skilled and unskilled labor, this second approach is not appropriate for our analysis.

key variables. Then we introduce the main results and their interpretations. Finally, we perform some sensitivity analysis and compare results to previous work. Section 4 offers some concluding remarks.

2 Modeling Production Possibility

We consider a production function with capital, different types of labor, and different types of technical progress. We assume that the production function is Cobb-Douglas over capital, and a constant elasticity of substitution (CES) function of the other inputs in the following way:

$$Y(t) = K(t)^{\alpha} \left[(A_s(t)L_s(t))^{\rho} + (A_u(t)L_u(t))^{\rho} \right]^{\frac{1-\alpha}{\rho}}, \tag{1}$$

where Y is output, K is the capital stock, and L_s (L_u) is skilled (unskilled) labor. A_s (A_u) represents skilled (unskilled) labor augmented technical change, and ρ is a time invariant production parameter. The elasticity of substitution between skilled and unskilled labors is given by $\sigma = 1/(1-\rho)$.

We assume that 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 relative supply of skills, L_s/L_u,

$$\frac{w_s}{w_u} = \left(\frac{A_s}{A_u}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{L_s}{L_u}\right)^{-\frac{1}{\sigma}}, \tag{2}$$

where w_i is the wage rate of i-type labor. This equation tells us 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 $\sigma > 1$, then an increase in A_s increases the wage gap between skilled and unskilled labor. This further implies that skilled augmented technical change is also *skilled-biased.* On the other hand, when $\sigma < 1$, an increase in A_s reduces the relative wage, which in turn implies that the skilled augmented technical change is *unskilled-biased.*

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

$$A_i = \beta_i^{\frac{\sigma}{\sigma-1}} \left(\frac{Y}{L_i}\right)\left(\frac{Y}{K}\right)^{\alpha/(1-\alpha)} \qquad \text{with} \qquad \beta_i = \frac{w_i L_i}{w_s L_s + w_u L_u}. \tag{3}$$

Thus, with the data on output, factor inputs, and factor prices, we can back out A_s and A_u from equation (3). Then A_s and A_u can be used in an accounting framework to assess their importance to income differences over time. Toward this goal, consider equation (1): taking the logarithm of both sides 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 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 $\varepsilon_{L_i} = \varepsilon_{A_i} = (1-\alpha)\beta_i$. Thus, the above equation can be rewritten as:

$$g_Y = \left(\frac{\alpha}{1-\alpha}\right) g_{K/Y} + \beta_s g_{L_s} + \beta_u g_{L_u} + \beta_s g_{A_s} + \beta_u g_{A_u}, \tag{4}$$

where the first term denotes the growth rate of K/Y.

Equation (4) decomposes output into several components that have specific interpretations. The first term, $g_{K/Y}$, measures the contribution of capital deepening to output growth. The sum $\beta_s g_{L_s} + \beta_u g_{L_u}$ represents the total contribution of changes in labor inputs to output growth. Two finals terms, $\beta_s g_{A_s}$ and $\beta_u g_{A_u}$, measure the contributions of skilled and unskilled augmented technical change to output growth. The discrete time approximation of (4) is given by

$$\widehat{Y}_t = \frac{\alpha}{1-\alpha}\left(\widehat{K}_t - \widehat{Y}_t\right) + \bar{\beta}_{s,t}\widehat{L}_{s,t} + \bar{\beta}_{u,t}\widehat{L}_{u,t} + \bar{\beta}_{s,t}\widehat{A}_{s,t} + \bar{\beta}_{u,t}\widehat{A}_{u,t}, \tag{5}$$

where $\widehat{X}_t = \ln X_t - \ln X_{t-1}$ represents the growth rate of variable X in year t, and $\bar{\beta}_{it} = 0.5(\beta_{i,t-1} + \beta_{i,t})$. This equation will be the basis of our accounting exercise.

3 Empirical Analysis

In this section, we apply the key results presented in the previous section to investigate the effects of skilled and unskilled labor augmented TFPs on the skilled premium and economic growth in the United States between 1961 and 2005. First, however, we 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 March Current Population Surveys (CPS) from 1962 to 2006. Since wages and labor input data in the survey refer to one year earlier, our sample spans the period 1961-2005. We consider all employed people between 16 and 70 years old, excluding the self-employed workers. The appendix provides a complete description of the data sets.

Construction of the series for skilled and unskilled labor is accomplished in two steps. In the first step, following Krusell et al. (2000), we constructed more than two-hundred demographic groups and calculated their average wages using CPS sampling weights. In the second, we sort these groups into skilled and unskilled labor. We then aggregate variables across groups to obtain category-specific averages.

Following Krusell et al. (2000), in each year we divide the data into distinct labor groups characterized by age, race, sex, and years of education. Age is divided into 11 five-year groups; there are three races (white, black, and others), and two sexes. Education status, E, is divided into 4 groups: $E < 12$ (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.

This taxonomy generates a partition of the population into 264 distinct groups, and we shall denote each group by γ. Each worker is assigned to one of these groups, and for each group, we construct measures of the labor input and the labor earnings using CPS sampling weights. Total hours worked for group γ in year t is given by $\sum_{i\in\gamma} hr_{it}\mu_{it}$, where i indexes for individual, hr is annual hours worked, and μ is the CPS sample weight.[4] Similarly, the corresponding total income (from wage and salaries) is given by $\sum_{i\in\gamma} W_{it}\mu_{it}$, where W_{it} is individual i's total annual income in year t. The average hourly wage for group γ is computed as $w_{\gamma t} = \sum_{i\in\gamma} W_{it}\mu_{it} / \sum_{i\in\gamma} hr_{it}\mu_{it}$.

Crucial to our analysis is the aggregation of labor inputs into skilled and unskilled classes. Groups within a class are assumed to be perfect substitutes, and following standard practice in this literature, we use group relative wages as weights for the aggregation. The basic idea is based on the assumption that relative wages equal relative human capital. Thus labor input is human capital adjusted.[5] For each group in each year, we construct a relative wage measure by dividing each group's average hourly wage by the average hourly wage of the group which contains white males, who are between 16-20 ages, and have less than 12 years of schooling in the contemporaneous year.[6] The relative human capital index measure for each group, h_γ, is computed as the arithmetic mean of the relative wage measures in that group over 1961 to 2005.

We aggregate the set of 264 groups into skilled and unskilled classes. Following Krusell et al. (2000), we assume that everyone who has at least 16 years of schooling is skilled, and those who have not are unskilled. In robustness section, we shall consider an alternative classification in which skilled labor class consists of college or college-plus workers and half

[4]As emphasized by Lemieux (2006) and Autor et al. (2007), the March CPS data are not ideal for analyzing the hourly wage distribution since they lack a point-in-time wage measure. Hourly wages are calculated by dividing annual earnings by the product of weeks worked last year and hours worked the week before the survey. Estimates of hours worked last week from the CPS appear to be noisy and data on usual weekly hours last year are not available prior to the 1976 March CPS. For this reason, we also considered an analysis based on weekly wages. But quite interestingly, that analysis yielded very similar results to that obtained using hourly wages. Results are available upon request to the author.

[5]Labor input is usually called *efficiency-adjusted* labor, instead of human capital adjusted labor (e.g. Katz and Murphy (1992) and Autor et al. (2007)). However, in this paper *efficiency* refers to the measured values of A_s and A_u.

[6]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.

of the workers with some college; and unskilled labor class consists of high school dropouts, high school graduates, and half of the workers with some college (Card and Limeoux (2001) and Autor et al. (2007)). But results qualitatively remain mostly the same.

Let Γ_s (Γ_u) denote the set of skilled (unskilled) groups. Then the total human capital adjusted labor input in each class is given by $L_{jt} = \sum_{\gamma \in \Gamma_j} h_\gamma \ell_{\gamma t}$. Now with the data on total wages and labor inputs, the average hourly wage of j-class labor is given by $w_{jt} = \sum_{\gamma \in \Gamma_j} w_{\gamma t} \ell_{\gamma t} / L_{jt}$, as in Krusell et al. (2000). Figure 1 (in the introduction) plots the relative supply of skills and the skill premium between 1961 and 2005. The pattern presented in this figure is very similar to that in previous studies such as Katz and Murphy (1992), Krusell et al. (2000), and in particular, Autor et al. (2007) who consider a more comparable period of time (1963-2005).[7]

To construct the A_s, A_u, and A_s/A_u series, we need to know two parameters– α and σ. The parameter α measures the capital share and we set it to 1/3, which matches the U.S. historical values for this variable. The parameter σ, on the other hand, represents the elasticity of substitution between skilled and unskilled workers and there is now a large labor-economics literature focused on its estimate. The most influential study is Katz and Murphy (1992), whose estimate, based on the CPS data over the period 1963-87, is about 1.4. Autor et al. (2007) extend the period to 2005, and they find that it is about 1.6. Using a dynamic general equilibrium model, Heckman et al. (1998) estimate that it is about 1.5. Using a state-level panel data, Ciccone and Peri (2005) find that 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. Our preferred value for σ is 1.5; but we shall also report results with $\sigma = 1.75$, and $\sigma = 2$.

[7] The minor differences between Figure 1 and Figure 2.A in Autor et al. (2007) stem from three facts. First, they consider only people between 18 and 64 years old. Second, their sample includes only full-time, full-year workers. Finally, as indicated above, they consider an alternative classification for skilled and unskilled workers.

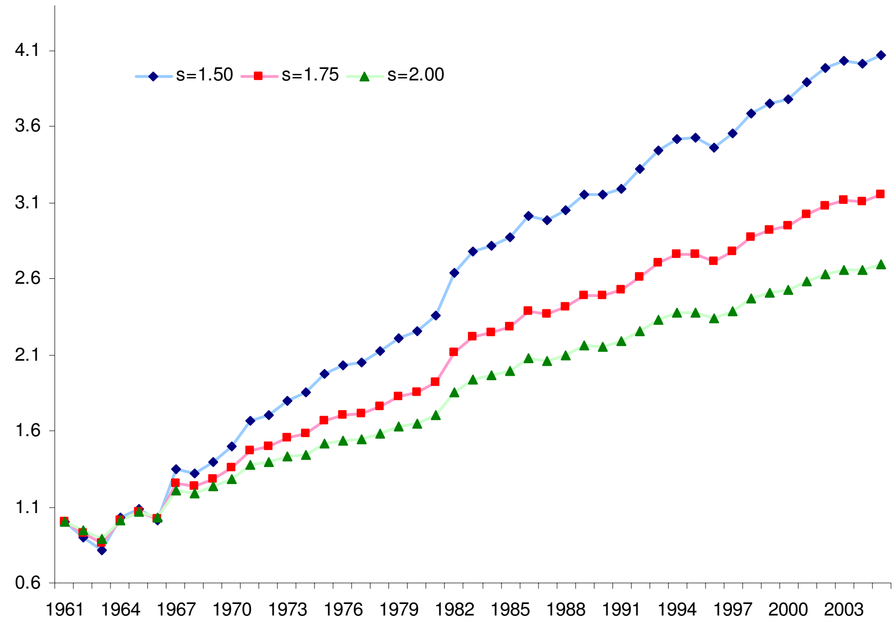


Figure 2. Time Path of $\ln A_s/A_u$. This figure represents the time path of $\ln A_s/A_u$ under different values for substitution elasticity between skilled and unskilled labor. Initial values are normalized to 1.

3.2 Main Results

Figure 2 plots time paths of log A_s/A_u based on equation (2). The growth rate of A_s/A_u has been surprisingly stable over the last 45 years: the average annual growth rate is about 7.0% for $\sigma = 1.5$, 4.9% for $\sigma = 1.75$, and 3.8% for $\sigma = 2.0$. This figure basically contradicts the common view that there has been an acceleration in skill biased technical change. A natural question arises at this point. How have A_s and A_u changed over this period? Has there really been any significant acceleration in A_s? If yes, when did it happen? What happened to A_u, when A_s accelerated?

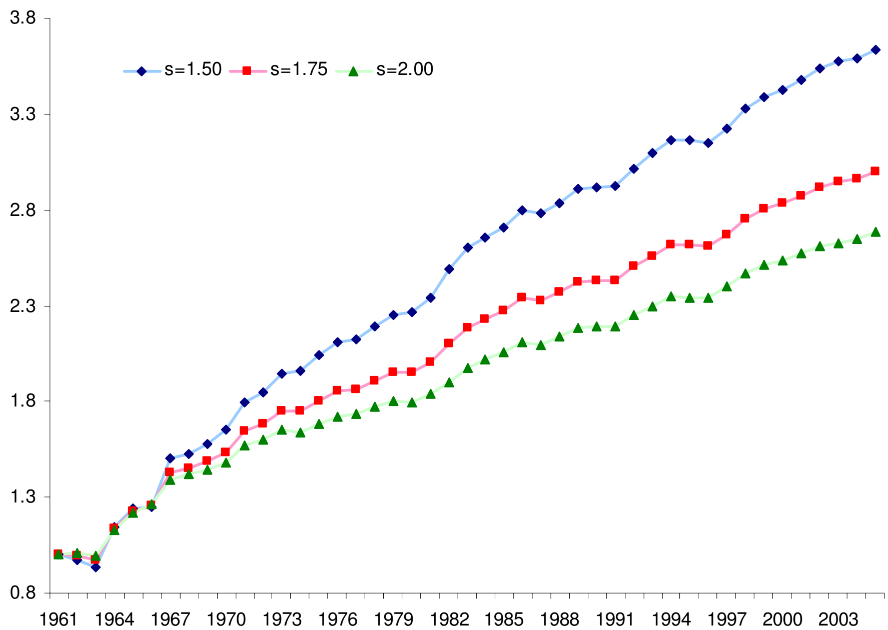
Figures 3.a and 3.b plot the corresponding log time paths of A_s and A_u, respectively. There are several interesting things to note in these figures. First, although there is an increase in skill premium since the late 1970s, we do not see any upward trend in $\ln A_s$. Indeed, if we carefully look at the figure, there is a productivity slow down beginning in the early 1970s (around 1973). For example, with $\sigma = 1.5$, the average annual growth rate of A_s between 1961 and 1973 is about 7.9%, while it is 5.3% between 1973 and 2005. This basically reinforces our above observation that there has been no accelerations in skilled-biased technical change.

Second, beginning in the early 1970s, the efficiency of unskilled labor decreased substantially and the magnitude of decline is more significant when elasticity of substitution is small. Again, with $\sigma = 1.5$, the average annual growth rate of A_u between 1961 and 1973 is about 1.2%, while it is -1.8% between 1973 and 2005. If there were no decline in A_u, A_s/A_u would grow more slowly in the post 1973 period.

Third, time paths of A_u also contradict the common view that the U.S. economy has been on its long-run balanced growth path. This common 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-monotonic time path of A_u, however, suggests that the US economy has not been on a balanced growth path. This conclusion is in line with Jones (2002), who notices that rising educational attainment and research intensity during the last several decades implies that the U.S. economy is far from its balanced growth path.

What caused the efficiency performance of skilled and unskilled labor to deteriorate after 1973? Clearly accelerated skill-biased technology explanation is not convincing. In an interesting article, titled 1974, 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. This argument has two important implications which are also, to some extent, consistent with the pattern presented in Figure 3. First, the new technologies would adversely affect both skilled and unskilled labor productivity. Given that unskilled labor is not equipped with necessary training to

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



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

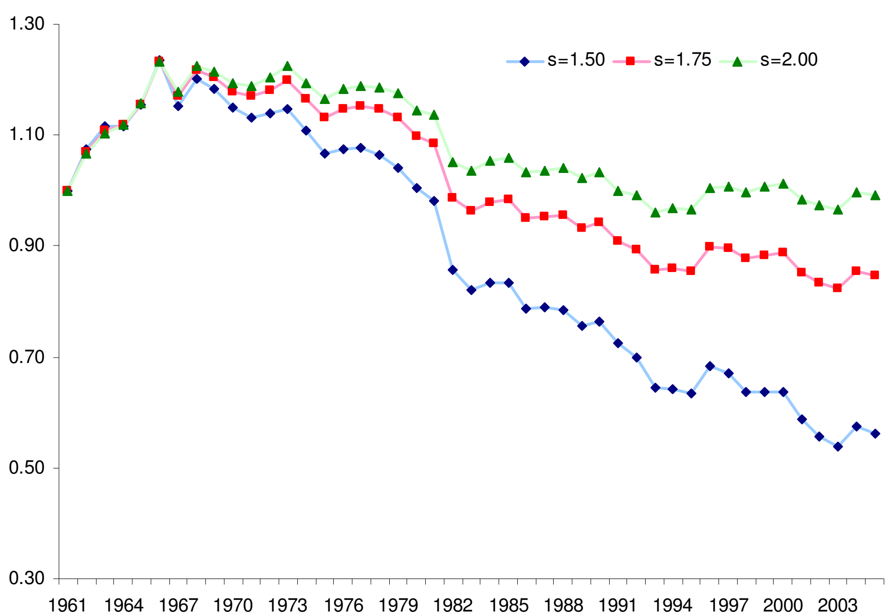


Figure 3. Time Paths of $\ln A_s$ **and** $\ln A_u$.These figures represent the time paths of the efficiencies of skilled and unskilled labor under different values for substitution elasticity between skilled and unskilled labor. Initial values are normalized to 1.

use the new technologies, their productivity might even decline upon implementing them. Second, over the time when workers are used to working with the new technologies, we should see a productivity surge. Indeed, in the late 1990s, skilled labor productivity grew relatively more rapidly than it had for the preceding 20 years. But it is still puzzling that there has been no surge in the efficiency of unskilled labor.

Before turning to the growth accounting exercise, it will be interesting to investigate implications of the above trends for the skill premium. Towards this end, we reconsider equation (2). Taking the logarithm of both sides, differentiating with respect to time, and rearranging the terms 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.

Obviously, if the efficiency of unskilled labor, A_u, had a positive growth rate between 1973 and 2005, the gap between skilled and unskilled labor wage rates would be lower. Now we would like to address the following question: instead of declining so rapidly after 1973, if A_u had grown more slowly, as that of A_s, how much lower would the skill premium be in 2005? We note that under $\sigma = 1.5$, the average growth rate of A_s after 1973 is about 33% lower than that in 1961-73 period. If A_u growth declined by the same proportion, its annual growth rate would be 0.8% (instead of -1.8%) during the period 1973-2005. In this case, the average annual growth rate of the skill premium, $g_{w_s} - g_{w_u}$, would be 0.27% lower, which in turn implies that the skill premium would be about 25% lower in 2005. Following the same steps under $\sigma = 1.75$ and $\sigma = 2.0$, we find similar results, i.e. the skill premium would be about 25% lower in 2005.[8]

We now turn to our accounting exercises. Table 1 reports the growth accounting exercise based on equation (5). According to this table, the contribution of factor inputs to output

[8]With $\sigma = 1.75$ ($\sigma = 2.0$), the average growth rate of A_u during 1961-1973 is about 1.66% (1.88%), while it is about -1.10%(-0.73%) between 1973 and 2005. The average growth rates of A_s, on the other hand, are 6.3% (5.5%) during 1961-73, and 3.9% (3.2%) during 1973-2005.

Table 1: Accounting For US Growth, 1961-2005

		Contribution of				
		Capital	Skilled	Unskilled	S-Labor	U-Labor
Elasticity	Output	Intensity	Labor	Labor	Efficiency	Efficiency
σ	$\hat{Y}$	$\frac{\alpha}{1-\alpha}(\hat{K}-\hat{Y})$	$\bar{\beta}_s\hat{L}_s$	$\bar{\beta}_u\hat{L}_u$	$\bar{\beta}_s\hat{A}_s$	$\bar{\beta}_u\hat{A}_u$
1.50	0.033	-0.001	0.012	0.010	0.018	-0.006
	(100)	(-4)	(36)	(31)	(55)	(-18)
1.75	0.033	-0.001	0.012	0.010	0.015	-0.002
	(100)	(-4)	(36)	(31)	(41)	(-5)
2.00	0.033	-0.001	0.012	0.010	0.012	0.000
	(100)	(-4)	(36)	(31)	(35)	(2)

Notes: This table reports the growth accounting decomposition based on equation (5). The specifications are sorted according to the value for σ. Numbers in parentheses represent relative contributions in percentage. S-Labor (U-Labor) efficiency represent the efficiency of skilled (unskilled) labor.

growth is about 63 percent. The remaining 37 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 one of the largest contributors to output growth in this decomposition, accounting for between 35 to 55 percent of output growth, depending on exact value of the elasticity of substitution σ. Second, changes in the efficiency of unskilled labor accounts for between 2 to -18 percent of output growth, depending on the exact value of σ.

As in the above case, what output level would we observe in 2005, if the growth rate of A_u had declined by the same proportion as that of A_s after 1973? From the above analysis, we know that under $\sigma = 1.5$ such slow down would imply a 0.82 percent average annual growth rate for A_u. Using this counterfactual time trend in equation (1) implies that the output would be about 38 percent higher in 2005. Under $\sigma = 1.75$ and $\sigma = 2.0$, however, the output level would be about 29 (25) percent higher in 2005.

3.3 Analysis with Different Definition of Skilled Labor

Analysis presented in the previous section is based on a college-completed definition of skilled. In this section, we consider an alternative classification used by Card and Limeoux (2001), Autor et al. (2007), and others in which 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.

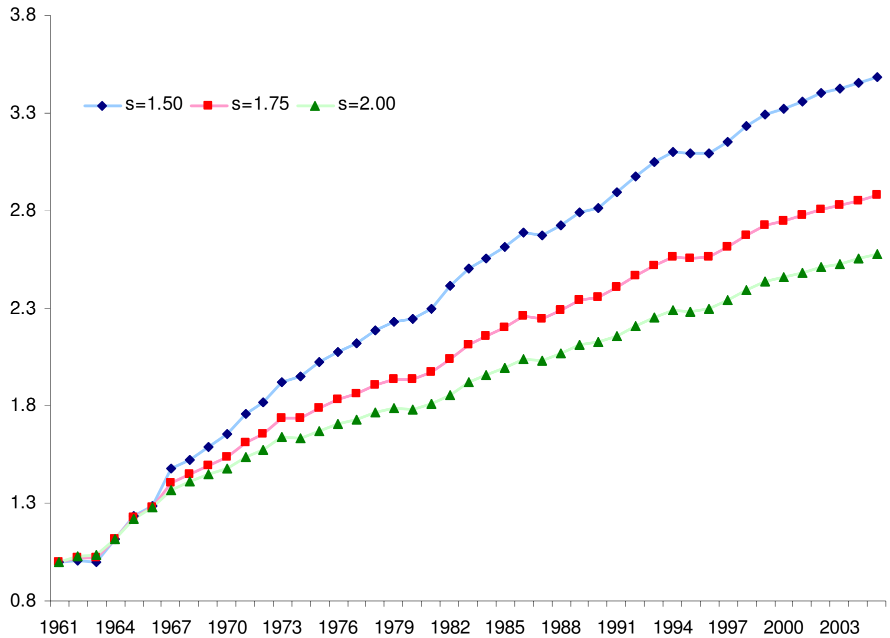
Figures 4.a and 4.b plot the time paths of $\ln A_s$ and $\ln A_u$, respectively.[9] These plots are very similar to that in Figure 3, except decline in A_u is more significant in Figure 4.b. Moreover, compared to time path of A_u in Figure 3.b, A_u grows more slowly between 1961 and 1973. For example, with $\sigma = 1.5$ the average annual growth rates of A_u over two periods (1961-1973 and 1973-2005) are 0.7 and -2.9 percents, respectively; whereas they were 1.2 and -1.8 percents in Figure 3.b.

Table 2 reports the growth accounting exercise. Contribution of factor inputs to output growth is about 2 percentage points; while the remaining 1.3 percentage of contribution to out growth is attributed to changes in efficiencies. Growth in the efficiency of skilled labor is usually the largest contributor to output growth in this decomposition, accounting for between 43 to 67 percent of output growth, depending on the exact value of the elasticity of substitution σ. Note that although the contribution of each factor to output growth is different than that in Table 1, the relative contribution of factor inputs vs. total efficiency is the same as in Table 1: factor inputs account for about 63 percent of output growth.

We can also perform similar counterfactual exercises as we did in the previous section. We want to address the question of how much the skill premium and output would be different in 2005, if the efficiency of unskilled labor, A_u, had grown more slowly, as that of the efficiency of skilled labor, in the post 1973 period. We find that the skill premium

[9] For the sake of brevity, we don't report counterparts of Figures 1 and 2. The overall pattern is very similar and they are available upon request.

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



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

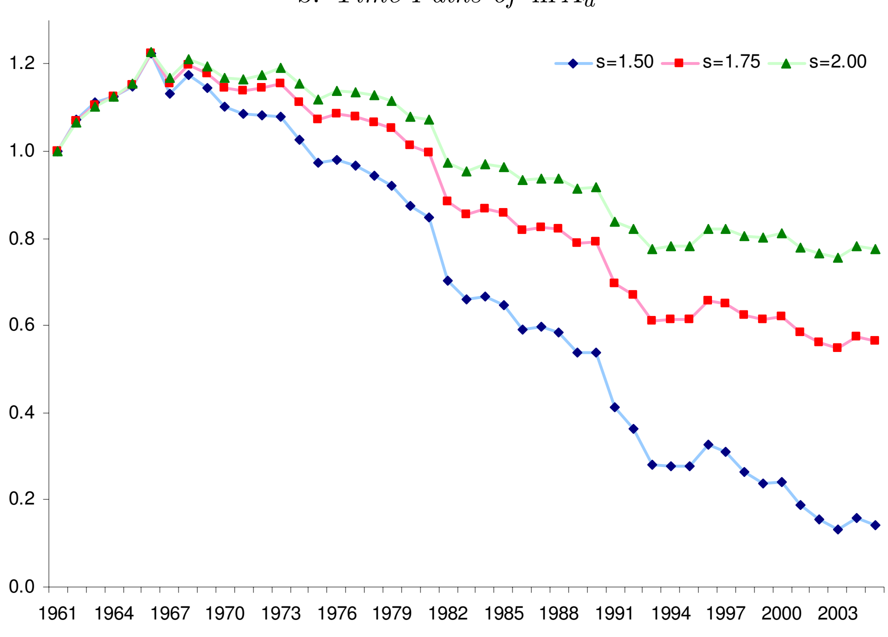


Figure 4. Time Paths of $\ln A_s$ **and** $\ln A_u$.These figures represent the time paths of skilled and unskilled labor efficiencies based on a different definition of skilled. Initial values are normalized to 1.

Table 2: Accounting For US Growth, 1961-2005

		Contribution of				
		Capital	Skilled	Unskilled	S-Labor	U-Labor
Elasticity	Output	Intensity	Labor	Labor	Efficiency	Efficiency
σ	$\hat{Y}$	$\frac{\alpha}{1-\alpha}(\hat{K}-\hat{Y})$	$\bar{\beta}_s\hat{L}_s$	$\bar{\beta}_u\hat{L}_u$	$\bar{\beta}_s\hat{A}_s$	$\bar{\beta}_u\hat{A}_u$
1.50	0.033	-0.001	0.016	0.006	0.022	-0.010
	(100)	(-4)	(48)	(19)	(67)	(-31)
1.75	0.033	-0.001	0.016	0.006	0.017	-0.005
	(100)	(-4)	(48)	(19)	(55)	(-15)
2.00	0.033	-0.001	0.016	0.006	0.014	-0.002
	(100)	(-4)	(48)	(19)	(43)	(-6)

Notes: This table reports the growth accounting decomposition based on equation (5). The specifications are sorted according to the value for σ. Numbers in parentheses represent relative contributions in percentage. S-Labor (U-Labor) efficiency represent the efficiency of skilled (unskilled) labor.

would be about 30 percent lower in 2005, while GDP (and per capita GDP) would be 23 to 38 percent higher in 2005.

3.4 Comparison to Cobb-Douglas Specification

In this section we consider a Cobb-Douglas production function in which skilled and unskilled labor are perfect substitutes:

$$Y(t) = K(t)^{\alpha}(A(t)L(t))^{1-\alpha},$$

where A denotes the TFP and L is the labor input ($L(t) = L_s(t) + L_u(t)$). Like in the previous sections, the labor input is measured in efficiency units, i.e. $L(t) = h(t)N(t)$, where h is the average human capital index and N is the total raw labor measured in hours. The Cobb-Douglas production function has been widely used in the growth accounting literature and has recently been used by Jones (2002) to assess the sources of economic growth in the U.S. economy.

Table 3: Accounting For US Growth, 1961-2005

		Contribution of			
Output	Output per Hour	Capital Intensity	Human Capital	Labor Hours	TFP
$\hat{Y}$	$\hat{y}$	$\frac{\alpha}{1-\alpha}(\hat{K}-\hat{Y})$	$\hat{h}$	$\hat{N}$	$\hat{A}$
3.30		-0.001	0.003	0.019	0.012
(100)		(-4)	(10)	(58)	(36)
	0.014	-0.001	0.003		0.012
	(100)	(-9)	(24)		(85)

Notes: This table reports the growth accounting decomposition based on equations (6.a) and (6.b). Numbers in parentheses represent relative contributions in percentage.

The corresponding growth accounting equation is now given by

$$\hat{Y} = \frac{\alpha}{1-\alpha}\left(\hat{K} - \hat{Y}\right) + \hat{h} + \hat{N} + \hat{A}, \tag{6.a}$$

where $\hat{X}$ represents the average growth rate of variable X between 1961 and 2005. By subtracting $\hat{N}$ from both sides, this equation can further be written as

$$\hat{y} = \frac{\alpha}{1-\alpha}\left(\hat{K} - \hat{Y}\right) + \hat{h} + \hat{A}, \tag{6.b}$$

where $\hat{y} = \hat{Y} - \hat{N}$ denotes average growth rate of output per hour. This form is useful when we compare our results to that in Jones (2002).

Table 3 represents the accounting results based on equations (6.a) and (6.b). The total contribution of factor inputs to output growth is about 2.1 percentage points, accounting for about 64 percent of output growth. The remaining 36 percent contribution comes from TFP growth. From this perspective, the Cobb-Douglas specification delivers the same results as that obtained under the CES specification. However, there are two problems with the Cobb-Douglas approach. First, it assumes that skilled and unskilled labors are perfectly substitutable, i.e. the elasticity of substitution between skilled and unskilled workers is infinity. However, as we emphasized before, the empirical labor literature documents that it is around 1.5, well below infinity. Second, this approach does not allow us to separate the contribution of skilled and unskilled labor inputs and the corresponding efficiencies to output growth.

Results in the last two rows of Table 3 are different from those in Table 2 in Jones (2002) and this stems from the differences in time periods analyzed in both periods, construction of variables, and data sources on labor inputs.[10] Furthermore, Jones considers human capital based on years of schooling, whereas we construct human capital index based on relative wages. Jones finds that the contribution of human capital to the growth of output per hour is about 30 percent and the remaining 70 percent of growth is attributed to a rise in TFP. Although this distribution is different than that in Table 3, both papers find that growth in total efficiency is the single largest contributor to growth in this decomposition.

Jones (2002) uses an endogenous growth model to show that more than 80 percent of the growth in the US from 1950 to 1993 is attributed to the transitional dynamics associated with educational attainment and the stock of ideas. Using the same steps, we can show that this conclusion remains mostly the same in our sample too. Thus, as Jones notices, this contradicts the conventional wisdom that the U.S. economy is on a balanced growth path. To reconcile this with stable growth in output per hour, Jones proposes the constant growth path hypothesis in which all growth rates are constant.[11] In particular, he assumes that the capital stock, K, and the stock of ideas, A (measured by TFP), grow at constant rates. Although there is a slowdown in the growth of A after 1973, assuming that K and A grow at constant rates are not implausible as a first approximation and our data also

[10]For example, Jones finds that average growth rate of output per hour is 2 percent between 1950 and 1993, and ours is considerably lower than that. The main reason for this difference is the growth in labor input in both studies. Jones assumes a constant year of 50 weeks. In our sample, however, we find a significant variation in the number of weeks worked across groups and the average annual growth rate of the average number of weeks is about 0.2 percent over the sample period. Furthermore, in our sample the average weekly hours remain mostly constant, whereas in Jones' data it declines about 0.3 percent each year. The average weekly hours data in Jones (2002) represents the average hours of production workers for total private industry from the Bureau of Labor Statistics.

[11]The constant growth path is different from balanced growth path in that it is not required that the economy will stay on this path forever.

support this.[12]

Following the same steps in Jones (2002), it can be shown that accounting results based on the constant growth path hypothesis delivers similar results that in Table 3, confirming that the constant growth path hypothesis is a reasonable approximation. One may worry whether this hypothesis is applicable when we consider an alternative production function. Our analysis in previous sections shows that this approach does not work under the CES production function. In particular, the time path of A_u is far from a constant growth path.

4 Concluding Remarks

Beginning in the late 1960s, the relative supply of skilled labor has increased more rapidly than before, and the skilled wage premium has increased sharply since 1980. Many economists argue that this pattern is resulted from the acceleration of skilled biased technical change. In this paper, using a production framework in which skilled and unskilled labor are imperfect substitutes, we analyze the time paths of skilled and unskilled labor augmneted efficiencies and investigate their implications for wage inequality and economic growth.

We find a slowdown in skilled labor augmented efficiency growth after 1973, and a substantial decline in the absolute level of the efficiency of unskilled labor since then. These basically imply that 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 substantial declines in unskilled labor efficiency. Using these in a growth accounting exercise implies that skilled labor augmented efficiencies growth accounts for 38 to 72 percent of output growth, while the unskilled labor TFP growth accounts for -33 to 2 percent of output growth. The total contribution of other factors to output growth is about 2 percentage points, accounting for 60 percent of growth.

There are two main directions that the present work can be extended. First, extending the analysis to a panel of countries will be an interesting exercise. As indicated in the in-

[12] The growth rate of K has been remarkably constant at 3.1 percent and its constancy can be discerned from the negligible contribution of K/Y to output growth.

troduction, Caselli and Coleman (2006) find that higher-income countries use skilled labor more efficiently than lower-income countries, while they use unskilled labor relatively less efficiently. We, on the other hand, find that the efficiency of unskilled labor is not monotonically declining with an increase in income levels. These findings suggest that extending this work to a panel of countries can uncover several interesting facts about direction of technical changes across countries.

Supply and wage dynamics at sectoral level have been quite dramatic. For example, Autor and Dorn (2007) show that employment in low-skill service jobs expanded persistently and rapidly between 1980 and 2005, with modest gains in real wages. This contradicts the general trends of employment and earnings of low-skill workers in other sectors in US. Reshef (2007), on the other hand, shows that in the growing skill intensive services sector technical progress has been unskilled biased; while in the unskilled intensive goods sector, technical progress has been skilled biased. Thus, extending the current analysis to a more disaggregated level will shed more light on how different sectors in US have utilized skilled and unskilled labor.

A Data Appendix

Data on output and capital is obtained from the Bureau of Economic Analysis and they are measured in 2000-chained prices. The sources of labor input data are from the March Current Population Surveys (CPS), covering 1962 to 2006, which are obtained from Unicon Research Corporation. The main advantage of using the CPS data from Unicon is that Unicon has cleaned up the all problems in the raw CPS files provided by Census Bureau and recoded variables so that the surveys became more comparable across years. It also provides extensive documentation about variables, which are especially useful in construction of more aggregated variables.

We consider all employed people between 16 and 70 years old, excluding self-employed workers. 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, family earnings allocation flags (1966-1975) and individual earnings allocation flags (1976 onward) are used.

Two adjustments for topcoded earnings are also made. First, following Autor et al. (2007) 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.[13] Earnings are deflated using the Personal Consumption Expenditure (PCE) deflator from BEA. Earnings of below $112 per week (in 2000 dollars) are dropped, following Autor et al. (2007).

As indicated in the main text, in each year we divide the data into 264 groups characterized by age, race, sex, and years of education. Commencing in 1992, the Bureau of the Census changed emphasis of its educational attainment question from years of education to degree receipt. To obtain a comparable educational-attainment data across years, we follow the classification proposed by Jaeger (1997). Specifically, we define high school dropouts as those with fewer than 12 years of schooling; high school graduates as those with either 12 years of education and/or a high school diploma; some college as those attending some college or holding an associate's degree; and college plus as those with a bachelor's degree or higher.

Weekly wages are formed by dividing annual incomes by imputed measures of weeks worked during the previous year. We use an imputed measure of worked since the exact number of weeks worked is not available in the CPS prior to 1976. Following Card and Lemieux (2001), we assign 10 for 1-13 weeks category, 22 for 14-26 weeks category, 35 for 27-39 weeks category, 45 for 40-47 weeks category, 48.5 for 48-49 weeks category, 52 for 50-52 weeks category.

[13]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.

Similarly, 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. We use hours worked last week since the data on hours worked last year are not available in the CPS prior to 1976. In computing the group labor hour, we also consider the those workers who reported zero hours worked last week. We assume that their weekly supply of hours is equal to that of the average worker with nonzero hours worked belonging to the same group. In all such calculations we use CPS weights.

Some individuals reported zero incomes. We also consider all such individuals by imputing their wages from the data as follows. We divide the data into 40 groups characterized by sex, education, and experience, where we define years of potential experience as $Min\{age - \text{years of schooling} - 7, age - 17\}$ (Katz and Murphy (1992)). Log weekly wages are regressed in each year separately by sex on the dummy variables for educational categories, 3 region dummies, black and other race dummies, and a quartic experience as in Autor et al. (2007). We use estimated wages for those who reported zero income.

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