The Outlook for Labor Quality Growth in the U.S.

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Between 1950 and 2007, labor quality in the U.S. increased nearly 0.4 percent per year, accounting for about 20 percent of growth in GDP per hour. Improvements in labor quality were largely driven by increased educational attainment of workers, the aging of the workforce, and the increased participation of women in the labor market. Going forward, contributions from each of these factors are expected to diminish. The aging of the labor force will slow, female labor force participation is levelling off, and educational attainment levels are expected to plateau. In this research project we investigate how these changes in demographic and educational trends, as well as anticipated changes in the industry and occupational composition of employment, affect the outlook for labor quality over coming decades.

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JEL-codes: J3, J11, 047.

1. Research Question

In the postwar period, growth in human capital has been an important contributor to growth in U.S. GDP per hour worked. For example, Fernald and Jones (2014) estimate that, from 1950 through 2007, increases in measured human capital, or "labor quality," accounted for about 0.4 percentage points—or about 20 percent—of the 2.0 percent annualized growth in U.S. GDP per hour. In this paper, we quantify the likely future contribution of labor quality to growth in output and labor productivity, and assess the key areas of uncertainty.

At the core of the postwar growth in labor quality are near continuous increases in the level of educational attainment of U.S. workers. Capital-skill complementarities boosted the effect of these increases by raising the productivity of highly educated workers relative to lower educated workers. Other factors also played a role. For example, the increased participation of women in the labor force and the aging of the working age population contributed to growth in the productivity of employed workers.

Looking ahead, the momentum behind each of these factors is waning. The educational attainment of newly entering cohorts of U.S. workers has fallen below that of exiting cohorts. And the rise in the returns to education has slowed. The female labor force participation rate peaked in 2000 while the aging of the working age population will slow with the retirement of the baby boomers. Combined, these changes will slow future growth in labor quality relative to the postwar experience.

Although research has discussed aspects of how these factors might change, relatively little work has quantified the implications for future U.S. labor quality growth. Aaronson and Sullivan (2002) and Jorgenson, Ho, and Samuels (2014) are the two examples we know. In part because of the limited research in the area, CBO (2014, page 110) asserts: "… researchers have examined trends in workers' skills and the effect of those trends on future economic growth; that research has not reached a clear consensus about the size of the effect."

In this paper, we seek to push towards consensus by quantifying the likely path of labor quality as well as the plausible range of outcomes. Specifically, we will investigate how ongoing changes in educational attainment, returns to education, demographics, and labor-force participation of different groups affects the outlook for labor quality. We will also examine the role of industry-occupational composition of employment, which existing literature has not generally considered.

The paper proposal includes three sections which we discuss in detail in the three subsequent sections of the proposal. In the first section we review the concept of labor quality in the context of a conventional neoclassical production function. We also provide a brief survey of different methods used to measure labor quality growth. In the second section we decompose postwar growth in labor quality measures and assess the contributions of various factors, including those mentioned above. We also discuss some of the limitations of the neoclassical assumptions used to estimate labor quality growth and provide alternative measures in which these assumptions are relaxed. Our final section combines existing predictions of demographic trends, changes in the level of educational attainment, and the evolution of the industry-occupation structure in the U.S. with predictions of their relative importance for labor quality to construct a forecast of labor quality growth over the next decade. We decompose this forecast to identify the individual factors that we anticipate to drive labor quality growth going forward.

2. Definition and different measures of labor quality growth

Definition Most measures of labor quality are based on a concept of labor quality that is derived under standard neoclassical production theory. To understand this concept, consider a neoclassical value-added production function of the form

$$Y = F(A, K, L) \tag{1}$$

Here Y is real value added, A is technology, K is the total capital input, and L is the aggregate labor input.[1]

The labor aggregate, L, is comprised of the hours of many types of workers. Let H_i be the hours worked by workers of type i. The marginal productivity per hour differs across the worker types. Labor quality is defined as the amount of aggregate labor input per hour worked. To make this definition operational within a neoclassical framework, we assume that the aggregate labor input, L, is a homogenous function of degree one in the hours worked across all n worker types. That is,

[1] The separability assumption in (1) between the labor and capital aggregates is helpful for conceptual clarity but is not actually necessary. For an alternative derivation that doesn't impose separability, see Fernald (2012). That approach simply defines labor quality, in growth rates, as the difference between growth in share-weighted hours and growth in unweighted hours. That is, it essentially uses equation (8)(13), below, to define labor quality. Nothing substantive changes.

$$L = \Lambda(\{H_i\}_{i=1}^n) \tag{2}$$

where, for all possible combinations of hours inputs $\{H_i\}_{i=1}^n$,

$$\Lambda(\{aH_i\}_{i=1}^n) = a\Lambda(\{H_i\}_{i=1}^n) \text{ for all } a \geq 0. \tag{3}$$

This homogeneity of the labor aggregator function implies that

$$L = \Lambda(\{H_i\}_{i=1}^n) = \sum_{i=1}^n \Lambda_i(\{H_i\}_{i=1}^n)H_i \tag{4}$$

where Λ_i is the partial of the labor aggregator function with respect to the hours worked by workers of type i.

Labor quality, LQ, is then defined at the amount of labor input, L, per total hours worked

$$H = \sum_{i=1}^n H_i. \tag{5}$$

Such that

$$LQ = \frac{L}{H}. \tag{6}$$

Growth rate of labor quality The above definition allows us to also define an approximation for the growth rate of labor quality. To a first approximation, the growth rate of labor quality, g_{LQ} is the difference between the growth rate of the labor input, g_L, and the growth rate of hours worked, g_H. The latter can be directly measured in the data, but the former requires another approximation.

Consider a shift in the hours inputs from $\{H_i\}_{i=1}^n$ to $\{H_i'\}_{i=1}^n$. Then, using a first-order Taylor approximation around $\{H_i\}_{i=1}^n$,[2] we can write

$$L' = \Lambda(\{H_i'\}_{i=1}^n) \approx L + \sum_{i=1}^n \Lambda_i(\{H_i\}_{i=1}^n)H_i\left(\frac{H_i'-H_i}{H_i}\right) \tag{7}$$

Using this result, we can approximate the growth rate of labor quality by a weighted average of the relative growth in hours worked by worker type. That is,

$$g_{LQ} \approx g_L - g_H = \left(\frac{L'-L}{L}\right) - \left(\frac{H'-H}{H}\right) \approx \sum_{i=1}^n \left(\frac{\Lambda_i(\{H_i\}_{i=1}^n)H_i}{L}\right)\left[\left(\frac{H_i'-H_i}{H_i}\right) - \left(\frac{H'-H}{H}\right)\right] \tag{8}$$

[2] In principle, one can also use a Taylor expansion around $\{H_i'\}_{i=1}^n$or weighted average of these expansions. This would result in slightly different index number formulas.

The problem is that this cannot be directly measured in the data. The data do contain direct measures of the growth of hours worked by worker type. However, there is no direct measure of the share of each worker type in the total labor input, i.e. of $\Lambda_i(\{H_i\}_{i=1}^n)H_i/L$.

Measuring labor quality To obtain a measure of this share we rely on standard neoclassical production theory. Optimal factor demand decisions in this framework imply that for each type of worker, i, the firm equates their wage to their marginal revenue product. That is

$$W_i = PF_2(K,L)\Lambda_i(\{H_i\}_{i=1}^n). \tag{9}$$

Here, W_i is the hourly wage rate of workers of type i, P is the output price, F_2 is the partial of the production function with respect to the labor input. This implies that

$$W_iH_i = PF_2(K,L)\Lambda_i(\{H_i\}_{i=1}^n)H_i \tag{10}$$

and aggregation of this result over all worker types yields that the total wage bill equals the marginal revenue product of the aggregate labor input, i.e.

$$\sum_{i=1}^n W_iH_i = PF_2(K,L)L \tag{11}$$

Combining the above two equations yields that the share of the labor input contributed by workers of type i equals their share in the total wage bill. That is,

$$\frac{W_iH_i}{\sum_{j=1}^n W_jH_j} = s_{i,L} = \frac{\Lambda_i(\{H_i\}_{i=1}^n)H_i}{L} \tag{12}$$

These shares can be constructed using data on wages and on hours worked by worker type. This then allows for the construction of a measure of labor quality growth using

$$g_{LQ} \approx g_L - g_H \approx \sum_{i=1}^n s_{i,L}\left[\left(\frac{H_i'-H_i}{H_i}\right) - \left(\frac{H'-H}{H}\right)\right] \tag{13}$$

Three different measurement approaches The above equation is the basis for decomposing labor quality growth into the contributions by different worker types. It requires measures of growth in hours worked for each type of worker as well as the share of total compensation earned by workers of each type.

There are three different approaches that can be taken to construct these measures. These approaches differ in the way they define worker types and in the way they measure the wages earned by each worker type.

- **Stratum-based methods** define worker types as strata (or cells) based on worker characteristics. For example, in Jorgenson et al. (1987) as well as BLS (2014) these cells are combinations of industry-gender-age-education groups. Wages, W_i are measured as average (or median) wage for workers within this stratum.

- **Regression-based methods** do not take a stance on defining worker types in terms of specific cells. These methods use Mincer-type regressions to predict a worker's wage based on a vector of worker characteristics, $\boldsymbol{x}_i$. The number of worker types is thus effectively the number of workers for which there is data and the wage is set to the predicted wage, i.e. $W_i = \widehat{W}(\boldsymbol{x}_i)$, that is implied by the wage regression. This method was pioneered by Aaronson and Sullivan (2002) and is currently applied in the quarterly total factor productivity estimates published by Fernald (2012) and FRBSF (2014). We discuss those estimates below.

- **Individual-based methods** exploit the availability of data for individual wages, W_i, and hours worked, H_i and H_i', in longitudinally linked microdata. If the sample of individuals is representative of the population of workers, then these data can be used to estimate (13) directly. Currently, no such estimate of labor quality growth is implemented. But, given the right data set, it is straightforward to do.

Which measurement approach is feasible and most appropriate depends on the data available for the analysis.

For our paper we will analyze four commonly used datasets that each allow for the construction of measures of labor quality growth. Table 1 lists the four data sources that we are planning on using as well as which of the LQ growth measurement methodologies are feasible with these data. As can be seen from the table, our analysis would yield eight different measures of labor quality growth. Figure 1 shows the two measures that are currently included in the Fernald/FRBSF total factor productivity release.

We propose to calculate these eight different measures for two reasons. First of all, this allows us to consider how robust the main facts about labor quality growth are to differences in methodology

and data sources. Secondly, the different data sources contain information about different factors that potentially affect labor quality. For example, the CPS contains detailed data on demographics but only provides coarse data on industry and occupation categories. The Occupational Employment Statistics provide much greater detail on the industry-occupation composition of the workforce but has no data on demographics. Finally, the American Community Survey contains a large sample of individuals and has some more detail on, for example, educational attainment. Thus calculating these different LQ indices allows us to focus on different factors across data sets.

3. Decomposing past labor quality growth

To understand how changes in demographics, educational attainment, and the industry-occupation composition going forward will affect the growth of labor quality, it is important to first analyze how these factors affected labor quality growth in the past. For this we use the indices of labor quality that we will construct.

So far, we have implemented the regression-based method; these estimates are part of the Fernald (2012) (and Federal Reserve Bank of San Francisco (2014) growth-accounting dataset). Table 2 shows that the contribution of labor quality to GDP growth has been relatively stable over the postwar period. The estimate in the table multiplies labor-quality growth by labor's share of income. It is useful to compare the 0.25 percentage point of labor quality growth with the contribution of Total Factor Productivity (TFP) growth, which is defined as output growth less share-weighted capital, hours, and labor quality. TFP growth in the table is thus already net of labor quality changes and, in the postwar period, accounted for about 1.25 percentage points of business-sector output growth a year.

For understanding the sources of growth, it is thus important to account for the composition of the labor force. For example, many estimates of TFP growth do not explicitly consider labor quality and would include that ¼ percentage point in their estimates of technology. This includes the CBO (2014) and many macro papers in the DSGE literature. A corollary is that, if labor quality is expected to contribute less in the future, it would correspondingly change these estimates of measured TFP growth, even with no change in the underlying technology process.

Factors that account for labor quality growth

We focus on which factors contributed importantly to labor quality growth over the past decades. A preliminary analysis, based on CPS-strata-based results, suggests that the main driver of labor quality growth has been educational attainment and that the experience effect due to the aging of the labor force and the drag induced by the entry of women in the labor force cancel each other out.

We will expand on these preliminary results and also analyze other factors that drive labor quality growth that cannot be examined with the CPS, but can be considered using the ACS or OES. For example, Altonji et al. (2012) have used the ACS to estimate returns to different college majors, see Figure 2. So, using the ACS we can consider the effect of the composition of college graduates across majors on labor quality.

Wedges between wages and marginal products of labor

The neoclassical framework applied to estimate labor quality growth relies on the identifying assumption that relative wages reflect relative productivity differentials. Of course, there are many other potential reasons for relative wage differentials. For example, as we pointed out above the entry of women into the labor force has been a drag on labor quality growth because the neoclassical framework applied interprets the Gender Wage Gap, discussed in for example Blau and Kahn (2007), as reflecting relative productivity differentials between men and women.

Though we will not strive to resolve what part of this gap is due to such productivity differentials and what part might be due to other factors, we will construct alternative measures in which we set this wage gap to zero. We also plan on doing this for some other variables, like race, and for inter-industry wage differentials. Doing so allows us to get an upper-bound estimate of how much deviations from the neoclassical assumptions might affect measures of labor quality growth.

4. Predicting labor quality growth going forward

Once we have identified the factors that have driven labor quality growth in the past, we construct an outlook for labor quality growth in the coming decades.

Projecting the composition of the workforce and predicting wages for different workers

Constructing an outlook for labor quality growth involves combining two different estimates. The first is a projection of the composition of the U.S. work force over the next decades. For this we will rely on the BLS' Employment projections. The second is to forecast relative wage growth of workers of different types.

To illustrate how hard the latter is, consider Figure **3**. The figure shows the returns to different types of education relative to high school based on 12-month rolling Mincer regressions in the CPS. Quantifying how an anticipated change in the educational composition of the workforce affects future labor quality requires forecasting the, highly non-linear, paths of these returns to education.

We will introduce a formal framework for combining the two different estimates in this part of the paper. This framework will differ by methodology and data set.

The outlook for U.S. labor quality growth going forward

Here we will present the resulting estimates of labor quality growth going forward and discuss which projected developments are most important for this outlook and how they differ from the factors that have driven labor quality growth in the past.

Comparison with previous forecasts of labor quality growth?

It will be hard to produce standard errors around our forecast. However, we can compare our labor quality growth forecast with one produced in the past and discuss how well the past forecast has turned out to be and why. This is what we will do in the final part of our analysis in which we compare our forecast with the one produced by Aaronson and Sullivan (2002) over a decade ago. Aaronson and Sullivan's forecast turned out to be too pessimistic and we will analyze why and whether there are any reasons to believe our outlook might have predictable forecast errors that one can take into account based on the experience of Aaronson and Sullivan (2002).

In addition, we can quantify some of the key uncertainties about projections for the future. For example, we will consider the effects on labor quality growth of differential labor force participation rates, particularly at older ages, of more educated versus less educated workers.

5. Conclusions

The proposed paper serves three purposes. First, it will provide a survey of the literature on the measurement of labor quality growth and discuss the different methods considered and how they are applicable depending on the data source. Second, it will produce an analysis of what drove labor quality growth in the past. Finally, it will offer a forecast of labor quality growth and discuss how this forecast might be affected by different long-run demographic, educational, and technological trends.

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Table 1. LQ growth measures and data sources.

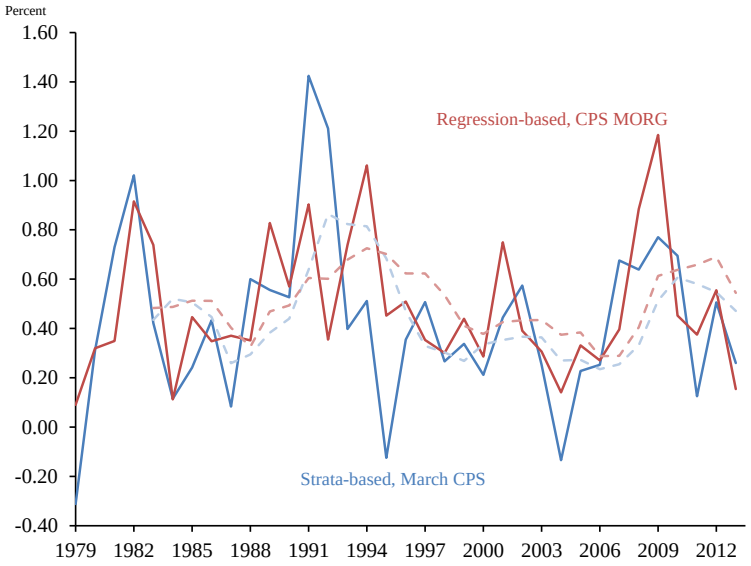
Data source	Method/measure		
	Stratum-based	Regression-based	Individual-based
1. CPS March Supplement	✓	✓	
2. CPS Monthly Outgoing Rotation Groups	✓	✓	✓
3. American Community Survey	✓	✓	
4. Occupational Employment Statistics	✓		

Table 2. Average annual contributions of labor quality and TFP to output growth

Period	Labor Quality	TFP (excl. labor quality)
1947-2014	0.25	1.28
1948-1969	0.23	1.97
1970-1994	0.23	0.81
1995-2014	0.29	1.08

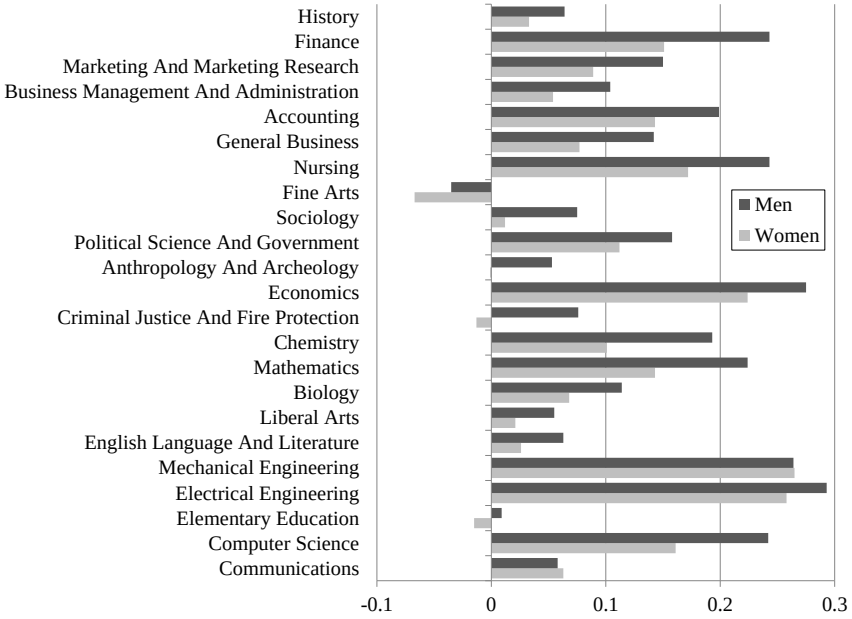
Note: Average annual percentage point contribution to growth rate of U.S. business-sector output. TFP is net of the contribution of labor-quality improvements.
Source: Fernald (2012) and FRBSF (2014)

Figure 1. Comparison of two measures of labor quality growth.



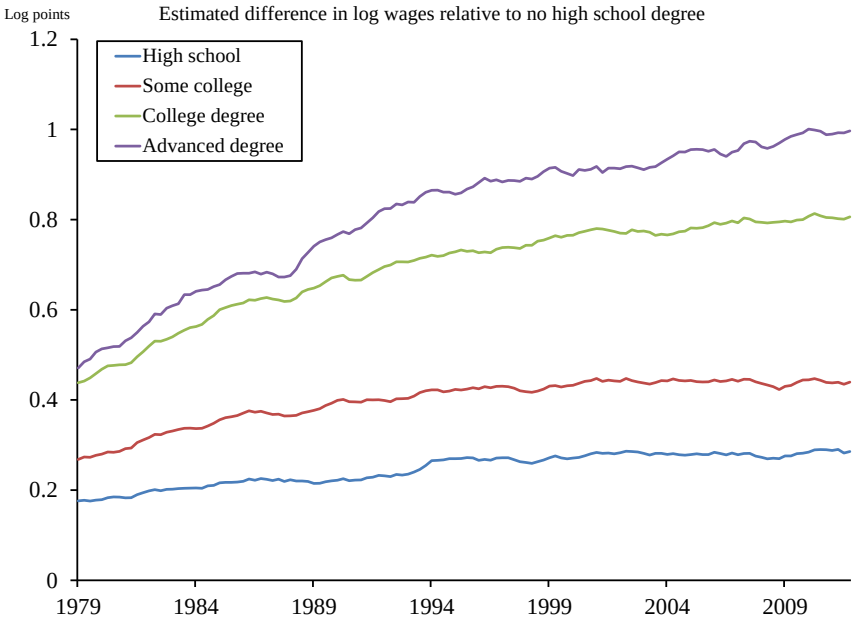
Note: Annual growth rate of labor quality growth. Strata-based measure using March CPS data taken from Bureau of Labor Statistics (2014). Regression-based measure taken from FRBSF (2014) and is based on Aaronson and Sullivan (2002). Dashed lines are the five-year moving averages of the corresponding annual time series.

Figure 2. Returns to 23 most popular college majors compared to general education.



Source: Altonji et al. (2012) based on American Community Survey data.
Note: Reported are log wage coefficients from Mincer Regression that includes occupation fixed effects.

Figure 3. Time path of estimated returns to different levels of education.



Source: 12-month rolling Mincer Regressions. Current Population Survey