

The Outlook for U.S. Labor Quality Growth*

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Abstract

Between 1950 and 2007, labor quality growth in the U.S. contributed about 0.4 percentage point per year to growth in GDP per hour. This growth was mainly driven by increases in educational attainment and labor market experience associated with population aging. Looking ahead, the leveling off of educational attainment and the retirement of older workers will be drags on labor quality growth. How much of a drag depends on how much of the cyclical adjustment in the composition of employment towards higher skilled workers that occurred during the Great Recession will persist. Taking all of these factors into account, we forecast that labor quality growth will decline by about 0.25 percentage points a year over the next 10 years compared to the past 15 years. Should employment composition return to its pre-recession levels, the full effects of slower educational attainment growth and Baby Boom retirements would be felt, resulting in labor quality growth well below our baseline.

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1 Introduction

Growth in human capital has been a key contributor to U.S. GDP growth in the postwar period. [Fernald & Jones \(2014\)](#) estimate that increases in human capital or "labor quality" contributed 0.4 percent per year of the 2.0 percent annualized growth in U.S. GDP per hour between 1950 and 2007.

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 improving experience profile 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 and the Baby Boom generation has started to retire. Combined, these changes will slow future growth in labor quality relative to the postwar experience.

Although research has discussed how these factors might change the outlook for labor quality growth, relatively little work has quantified the implications for future U.S. labor quality growth. [Aaronson & Sullivan \(2001\)](#) and [Jorgenson *et al.*, 2014](#), are among the few examples. In part because of the limited research in the area, the [Congressional Budget Office](#) has concluded: "...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" ([2014](#), p. 100).

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 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 the industry-occupation composition of employment, which the existing literature has not generally considered.

We begin, in Section 2, by reviewing the growth-accounting definition of labor quality that we apply in this paper. Section 3 then discusses the practical challenges involved in implementing our conceptual framework and assesses alternative approaches and data sets. We conclude that a parsimonious Mincer-style regression that controls for age and education provides the most reliable estimates of how wages and productivities vary with observable characteristics. Adding occupation is justifiable, although it has only a modest effect on the estimates and introduces additional uncertainty to forecast exercises.

Section 4 examines the evolution of labor quality since 2002 through the lens of alternative model specifications and data sources. We find that all reasonable model specifications and data sets yield surprisingly similar results: labor quality grew about 0.53 percent a year between 2002 and 2013, despite markedly slower growth in educational attainment. Over this period labor quality growth was boosted by disproportionate declines in employment rates among low skilled workers, especially during and after the Great Recession.

With a framework in place, Section 5 turns to forecasts of labor quality growth over the next decade. We forecast that labor quality growth will decline by about 0.25 percentage points a year over the next 10 years. Should employment composition return to its pre-recession levels, the full effects of slower educational attainment growth and Baby Boom retirements would be felt, leading to a slowdown of labor quality growth of around 0.40 percentage point per year.

2 Definition of labor quality growth

Ever since the seminal analysis of [Jorgenson & Griliches, 1967](#), economists have recognized the central importance of human capital accumulation in accounting for economic growth. Indeed, indices of human capital or labor quality are now standard in growth-accounting studies for

many countries.¹

Most indices of labor quality are based on the conceptual framework derived under standard neoclassical production theory. To see how this works, consider a neoclassical value-added production function of the form

$$Y = F(A, K, H_1, \dots, H_n). \quad (1)$$

where output, more specifically real value added, Y , is produced by combining the n types of labor inputs with a capital input, K ; A denotes the level of technological efficiency with which the inputs are combined.²

To quantify the *effect of a shift in the distribution of hours on output growth* we need to know the contribution of each type of labor. This can be done by applying a first-order logarithmic Taylor approximation. For this approximation we define small letters as the natural logarithms of the capitalized variables. That is, y is the logarithm of output, Y . The first difference operator is denoted by Δ , such that

$$\Delta y = \ln Y_t - \ln Y_{t-1} \quad (2)$$

is the change in the logarithm of output, i.e. approximately the growth rate of output. Using this notation, the Taylor approximation reads

$$\Delta y = \frac{\partial F}{\partial A} \frac{A}{Y} \Delta a + \frac{\partial F}{\partial K} \frac{K}{Y} \Delta k + \sum_{i=1}^n \frac{\partial F}{\partial H_i} \frac{H_i}{Y} \Delta h_i. \quad (3)$$

The final term in this expression is the effect of changes in the respective labor inputs on output growth.

The next step is to distinguish between the effect of *growth in total hours* and the *change in*

¹A few notable examples include the MFP statistics [Bureau of Labor Statistics \(1993, 2015a\)](#), [EUKLEMS \(O'Mahony & Timmer, 2009\)](#), the Conference Board's Total Economy Database ([van Ark & Erumban, 2015](#)), and the Penn World Tables ([Feenstra et al., 2015](#)).

²Since we are interested in labor input, we assume that there is only one capital input. The main results generalize to the case of multiple capital inputs.

the composition of total hours. In terms of equation (3), we make this distinction by inserting a term that quantifies the effect of total hours growth. In particular, we rewrite (3) as

$$\Delta y = \frac{\partial F}{\partial A} \frac{A}{Y} \Delta a + \frac{\partial F}{\partial K} \frac{K}{Y} \Delta k + \left(\sum_{j=1}^n \frac{\partial F}{\partial H_j} \frac{H_j}{Y} \right) \left(\Delta h + \sum_{i=1}^n \frac{\frac{\partial F}{\partial H_i} H_i}{\sum_{j=1}^n \frac{\partial F}{\partial H_j} H_j} (\Delta h_i - \Delta h) \right). \quad (4)$$

This equation shows that labor contributes to output growth in two ways. The first is through growth in total hours worked, i.e. Δh . The second is due to the change in the composition of hours worked given by

$$\sum_{i=1}^n \frac{\frac{\partial F}{\partial H_i} H_i}{\sum_{j=1}^n \frac{\partial F}{\partial H_j} H_j} (\Delta h_i - \Delta h). \quad (5)$$

The change in the composition of hours worked captured in (5) amplifies or attenuates growth in total labor input relative to growth in total hours.³ This wedge between growth in labor input and growth in hours is commonly interpreted as labor quality growth.

Since in practice, the marginal products of labor, $\frac{\partial F}{\partial H_i}$ in (5) are not observed, for implementation, we assume that $\frac{\partial F}{\partial H_i}$ is proportional to the nominal hourly wage earned by workers of type i , which we denote by W_i . In addition, we assume that the proportionality constant is equal across types of labor.⁴ If this is the case then

$$\frac{\frac{\partial F}{\partial H_i} H_i}{\sum_{j=1}^n \frac{\partial F}{\partial H_j} H_j} = \frac{W_i H_i}{\sum_{j=1}^n W_j H_j}, \quad (6)$$

which is the share of total compensation that gets paid to workers of type i .

Under this assumption, labor quality growth, denoted by g_{LQ} , is the compensation-share

³If all type of labor inputs, H_i , grow at the same rate, then the composition of total hours does not change and labor quality growth is zero.

⁴The proportionality constant can include the output price level as well as a markup of price over marginal cost. This is the case under standard neoclassical assumptions where real, as in output-price deflated, wages equal marginal products as well as under more general assumptions in which there is imperfect competition in the output market or firms have monopsony power and pay wages below marginal product where the wedge is constant across types of labor.

weighted, average deviation of labor input from total hours growth by type, i.e.

$$g^{LQ} = \sum_{j=1}^n \frac{W_j H_j}{\sum_{j=1}^n W_j H_j} (\Delta h_j - \Delta h). \quad (7)$$

This is the measure of labor quality growth that we implement empirically. It is the same as the one used by Gollop *et al.* (1987) and Zoghi (2010), for example, and is also used in the Bureau of Labor Statistics (2015b) multifactor productivity (MFP) statistics.

3 Measurement of labor quality growth

To implement (7) and obtain an empirical estimate of labor quality growth requires three things:

- i **Definition of worker types:** decision regarding the specific types of workers, $i = 1, \dots, n$, the labor quality index will distinguish between.
- ii **Estimate of wage by worker type:** estimate of average hourly earnings for each worker type, W_i used to construct the share of each worker type in total compensation.
- iii **Measure of hours:** measure of hours worked by worker type, H_i , used to calculate the deviation of hours growth by worker type, Δh_i , from overall hours growth, Δh .

Measures of hours worked by individuals are available in many datasets, including the Current Population Survey’s Outgoing Rotation Groups (CPS-ORG), Current Population Survey’s Annual Social and Economic Supplement (CPS-ASEC), and American Community Survey (ACS) that we use here. So, once the worker types are defined, calculation of H_i simply involves aggregation of hours across individuals in each of the n groups.⁵ Hence, (iii) from the above list is relatively easy to fulfill.

⁵Although all three datasets have measures of hours, the exact measure varies across datasets. For the details of the hours calculation in each dataset see Appendix A.

Items (i) and (ii), are not as straightforward and we discuss the different options for dealing with them in this section. We are not the first to discuss the choice of worker types and wage measures in the context of the construction of labor quality indices. For example, see [Zoghi \(2010\)](#). Our contribution relative to that work is to introduce a framework that allows us to make tractable choices for (i) and (ii) and “test” those choices against each other using standard statistical techniques.

3.1 Criteria for choosing worker types and wage estimates

Indices of labor quality are built by dividing workers into groups based on their marginal products of labor, $\frac{\partial F}{\partial L_i}$. The decision about how many and which worker types, $i = 1, \dots, n$, to use depends on: (i) the degree to which the types capture workers with distinguishably different marginal products, and (ii) the degree to which the different worker types capture the cross-individual variation in wages.

A simple way to quantitatively assess the degree to which these criteria are met for any particular grouping is in a regression framework. To see this, consider j individuals and denote the log of their individual hourly wage by w_j . For each individual we also observe a vector \mathbf{x}_j of individual-level characteristics based on their worker type, i . Under the assumption that relative wages reflect relative marginal products, the extent to which the characteristics in the vector, \mathbf{x}_j , capture cross-individual differences in marginal products can be measured as the fraction of individual-level log-wage variation that is explained by the variables in \mathbf{x}_j . This measure is equal to the R^2 of the following standard log-wage regression

$$w_j = \mathbf{x}'_j \boldsymbol{\beta} + \varepsilon_j. \quad (8)$$

Here, $\mathbf{x}'_j \boldsymbol{\beta}$ is the part of the wage variation captured by the variables in \mathbf{x}_j .

Though simple, this specification is very general. It subsumes the case in which the elements of \mathbf{x}_j are dummy variables that span the set of worker types. In this version, every type is a

stratum made up of individuals with the characteristics, as in [Gollop *et al.* \(1987\)](#).⁶ It also includes the case where \mathbf{x}_j contains polynomial terms of variables affecting workers' marginal product. In this case (8) is a form of a [Mincer \(1974\)](#) regression. This is the model used by [Aaronson & Sullivan \(2001\)](#), among others.

Of course, in practice we do not know the true parameter vector $\boldsymbol{\beta}$ and the log-wage regression (8) is estimated using a sample of workers of finite size. This means that, at best, we can obtain an estimate $\hat{\boldsymbol{\beta}}$ of the parameter vector and that we thus infer the part of wages captured by our explanatory variables with error. To formalize this mathematically, we denote the standard deviation of the estimation error of the explained part as

$$\sigma_j = \sqrt{E \left[\left(\mathbf{x}'_j (\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \right)^2 \right]}. \quad (9)$$

Since it is important to have a reliable estimate, the smaller σ_j the better. However, for the construction of the labor quality index, we are not interested in one particular worker, j , but instead in the reliability of the relative marginal product estimate, $\mathbf{x}'_j \hat{\boldsymbol{\beta}}$, across the whole sample. To gauge the reliability of the marginal product estimate across the sample, we consider the p^{th} percentile of the standard errors, σ_j , across individuals. We denote this percentile by $\tilde{\sigma}_p$.

Based on this simple framework, we suggest two statistical criteria for determining the types of workers of distinguish and the method to use when estimating wages.

1. **R^2 of log-wage regression** This captures the share of cross-individual wage variation that is captured by our choice of worker types and specification of the log-wage equation.
2. **Percentile of Standard error, $\tilde{\sigma}_p$, of marginal product estimates** This captures how reliably we estimate the (relative) marginal product of labor across workers.

Higher R^2 's and lower $\tilde{\sigma}_p$'s are preferred.

⁶Most stratum-based studies use median rather than mean wages. Our results are not sensitive to this choice.

Importantly, there is a direct trade off between these two measures. In principle, we can obtain an $R^2 = 1$ in the estimated regression (8) by including as many variables in \mathbf{x}_j as we have observations, m . However, this would result in a regression with zero degrees of freedom and $\tilde{\sigma}_p \rightarrow \infty$. Alternatively, we can aim for a very low $\tilde{\sigma}_p$ at the expense of a R^2 .

Using these tools we can directly compare different choices of (i) worker types and (ii) wage estimates by worker type. We do so using a scatterplots that plot the R^2 and $\tilde{\sigma}_p$ for each choice that we consider. Before we construct the scatterplots, we first describe the choices of worker types and wage regressions specifications we consider.

3.2 Choices of worker types and wage regression specifications

So far, we have discussed the choices of worker types, i , and the regression specification, i.e. \mathbf{x}_j , as two distinct decisions. In practice, however, they are one and the same. This is because for the variables that are commonly considered in log wage regressions there are only a countable number of values. Consequently, for a given regression specification in terms of these variables there is only a finite number of permutations of \mathbf{x}_j across individuals. In this context, a worker type, i , corresponds to a permutation of the covariates vector \mathbf{x}_j .

With this in mind, two questions remain: (i) which variables should be included in the vector \mathbf{x}_j , and (ii) what functional form of these variables works best?

Choice of variables in wage equation

The decision regarding which variables should be included in the regression is guided by the assumption, underlying the labor quality growth derivation, that wage differentials between worker types reflect differences in relative marginal products of labor. This means that the variables we include in the wage equation should have two properties. First, they should explain a substantial part of the variation in wages across worker types. Second, the part of wage variation they explain should reflect only differences in marginal products.

Whether or not a variables has the first property is straightforward to verify statistically.

It is the second property, which variables reflect marginal product differentials, that is more controversial. This is because there are ample reasons to believe certain observable characteristics are correlated with wedges between wages and marginal products.⁷ Though such variables might improve the fit of the wage regression, (8), including them in our measure of labor quality would bias our results.

The first, and most obvious, set of variables to consider for inclusion in (8) is education and experience. Several decades of running [Mincer](#) regressions has demonstrated a robust correlation between education and potential experience (or age) and wages ([Psacharopoulos & Patrinos, 2004](#)).⁸ Although there is some controversy over the degree to which returns to education are derived from improved human capital as opposed to the signaling of unobservable worker characteristics, both perspectives tend to attribute educational wage differentials to differences in marginal product ([Weiss, 1995](#)).⁹ Overall, there is broad agreement that the correlation between wages and education or experience is driven by real productivity differentials.¹⁰

A substantial literature, summarized in [Altonji & Blank \(1999\)](#), has also pointed to a role for gender, race, and ethnicity in explaining wage differentials. Here we encounter substantial controversy as to whether, or to what degree, these wage differentials reflect differentials in productivity as opposed to discrimination. On the one hand, gender differentials may capture the fact that women are more likely to work part time or leave the labor force temporarily, which is not captured in the measures of experience available in standard datasets ([Light & Ureta, 1995](#)). And ethnic differentials may proxy for unobserved language barriers that have a

⁷See [Boeri & van Ours \(2013\)](#) for a textbook treatment of many possible sources of such wedges.

⁸Some of the recent Mincer regression literature has suggested that there are important differences in the education-experience return profiles between cohorts ([Lemieux, 2006](#); [Heckman *et al.*, 2008](#)). We allow for such cohort effects in that we estimate wage regressions on annual cross-sectional data. Thus, in our analysis cohort and age effects are indistinguishable. This is appropriate for our application, because we are only interested in making robust wage predictions and not in isolating specific returns.

⁹Outside of developing countries there has been little empirical research that even asks the question of whether educational wage differentials might reflect something other than productivity, and the research in developing countries has generally concluded that the differentials are consistent with differences in productivity ([Jones, 2001](#); [Hellerstein & Neumark, 1995](#)).

¹⁰Broad as the agreement is, it is not entirely universal: incomplete labor contracts, labor market segmentation, or cultural factors could potentially drive a wedge between wage premia associated with education and experience and differentials in marginal product ([Blaug, 1985](#)).

real impact on productivity (Hellerstein & Neumark, 2008).¹¹ Yet, there is also a substantial literature documenting the existence of labor market discrimination, particularly on the basis of race and ethnicity, in both hiring and wages (Bertrand & Mullainathan, 2003; Pager *et al.*, 2009; Hellerstein *et al.*, 2002; Oaxaca & Ransom, 1994).

Finally, there is also a body of literature suggesting that there are inter-industry wage differentials that persist even after controlling for education and experience (Dickens & Katz, 1987; Krueger & Summers, 1988).¹² Once again, such differentials could originate from genuine differences in productivity (the matching of a worker to a particular job may reflect differences in social skills (Deming, 2015)) or from non-productivity related features of an industry (such as compensation for the risk of harm on the job (Olson, 1981)). Interestingly, although similar arguments could apply to occupational differences, there has been little research that considers whether there are persistent inter-occupation wage differentials independent of educational and experience prerequisites. Though not the main purpose of our analysis, our estimates of (8) partially fill this void by including occupation in our analysis.

Thus, the observables we focus on are age, education, gender, race, industry, and occupation. We are aware that there are many other variables that could be interpreted as reflecting differences in marginal product of labor across workers. Examples include marital status, rural-urban location, or family structure. However, given the limited evidence that these variables are of first-order importance in explaining cross-individual variation in wages, we omit them from our analysis.

There is also a wide range of potentially influential unobservable characteristics (such as entrepreneurial talent (Silva, 2007), cognitive and non-cognitive abilities (Heckman *et al.*, 2006), and physical attractiveness (Hamermesh & Biddle, 1994)).¹³ Although it would be ideal to include measurements of, or proxies for, these characteristics in our analysis, that is

¹¹See Skrentny (2013) and Lang (2015) for a discussion of the theoretical and empirical evidence on race and worker productivity.

¹²Gibbons *et al.* (2005), however, suggest that sectoral wage differentials can be accounted for by allowing for sector-specific returns to skill.

¹³These characteristics are unobservable in the sense that they are not measured as part of the standard datasets (ACS, CPS-ASEC, and CPS-ORG) that we use for our analysis.

not possible in the datasets available.

Choice of functional form

With the set of variables to include in \mathbf{x}_j in hand, that last thing to consider is the specific functional form imposed on these variables. For example, is the traditional [Mincer](#) regression, with a constant, linear years of education, and a quadratic polynomial in experience, the appropriate functional form or should dummies for high school graduation and college graduation be included to account for sheepskin effects ([Hungerford & Solon, 1987](#))? Are education and experience additively separable, or is there a nonlinear interaction between the two? These questions have been investigated quite carefully for the traditional Mincer regression variables of education and experience ([Lemieux, 2006](#)), but less attention has been paid to the other four.

Given this uncertainty around the appropriate functional form, one approach is to allow for the maximum flexibility in the log-wage regression, (8). To do this, one would treat each possible combination of values of the included variables as a worker type. This boils down to running a fully non-parametric regression in which \mathbf{x}_j is a vector with separate dummies for each worker type. The fitted log wage, $\mathbf{x}_i' \hat{\boldsymbol{\beta}}$, for each worker type in that case is the average log wage for workers with that combination of values for the included variables. This approach, though flexible, results in a significant loss of degrees of freedom.

For example, if we only consider age and education, restrict the population under consideration to 16-64 year olds, and distinguish 16 educational categories (as is the case with most standard U.S. micro datasets), then this regression has 768 estimated parameters corresponding to the 768 possible permutations of age and education in the data. In practice many of these worker types will contain very few observations in the data. For those worker types for which there is only one observation the standard error of the estimated mean log wage is infinite, i.e. $\sigma_i = \infty$.

Though such a non-parametric regression might result in a very good fit, the heterogeneity in marginal products of labor across worker types will be estimated with a high degree of

uncertainty.

Stratum-based methodologies, which have been used extensively in prior growth accounting exercises that account for labor quality (Gollop & Jorgenson, 1983; Gollop *et al.*, 1987; Ho & Jorgenson, 1999; Jorgenson *et al.*, 2014), are a form of this type of dummy regression. Stratum-based studies define worker types by partitioning the population by observable characteristics, with the mean wage of each part being interpreted as the wage for workers of that type.

In practice, in order not to run into the curse of dimensionality described above, stratum-based studies do not treat each value of a variable as distinct. Instead, they group different values of the variables together. For example, the 16 educational categories are often collapsed into less-than-high-school, high-school, some college, and college categories. Using a less granular partition regains some degrees of freedom but with a loss of some flexibility in the functional form. How granular a partition can be used largely depends on the sample size of the dataset used.

In the context of the regression framework that we use here, this grouping of values imposes multidimensional step functions on the data. Thus, although the most granular partitions result in a non-parametric regression that will have an R^2 that is at least as high as any other regression specification, the partitions used in practice actually impose a restrictive functional form that does not necessarily fit the data better than alternative model specifications.

Concerns about the step functions imposed by partitioned dummy regressions have led some researchers to hew more closely to the Mincer regression literature (Aaronson & Sullivan, 2001; Bureau of Labor Statistics, 1993). These specifications focus on education and experience as the fundamental drivers of human capital, marginal product, and wages.¹⁴ These regressions generally include education (either as a polynomial in years of education or as a set of dummies indicating levels of educational attainment) and a polynomial in experience.

In addition to the baseline education and experience variables, these human capital specifications often include some interaction between gender and experience to account for womens higher rate of part-time work and temporary withdrawal from the labor force (either as an

¹⁴As commonly done, we define experience as the difference between age and years of education (plus six).

interaction between gender and experience or by estimating the regression on men and women separately). In some cases (Aaronson & Sullivan, 2001; Bureau of Labor Statistics, 1993, 2015a,b) they also include control variables like part-time status, marital status, veteran’s status, race, and rural location. These variables are not included to capture differences in marginal products across workers but instead to reduce omitted variables bias in the education and experience coefficients.

Comparison of specifications

Between the question of which variables to include and what functional form to impose, the task of selecting a preferred regression specification for a labor quality measure is quite daunting. Even in the narrowed down set of variables we consider, age, education, gender, race, industry, and occupation, there are several options on how to group their values. For each of the six variables we use, Table 1 lists how many different classifications we consider for our comparison of model specifications. In the last four columns of each row, the table lists how many groups are defined for each classification. For example, for age we consider two classifications: one that splits the individuals up into 9 age groups and another into 13 age groups. The number of permutations across the different classifications of variables is 192. This includes one classification for each of the variables. Once one allows for dropping variables, then the possible number of stratum specifications increases to 1,799. The most detailed one, which includes the most granular classification for all variables, consists of 8,486,400 worker types.¹⁵

As noted, we apply the statistical tools R^2 and $\tilde{\sigma}_p$ as two clear criteria on which we can base our model specification decision. For our application we use the adjusted R^2 , i.e. \bar{R}^2 , as it penalizes for overfitting the data. We consider the 80th percentile of the standard errors of the estimated relative marginal product of labor across workers, i.e. we use $\tilde{\sigma}_{80}$ as our measure of the reliability of the imputed wages.¹⁶

¹⁵To put the amount of potential overfitting in perspective, this most granular definition of strata means that, on average, there are less than 20 workers per worker type in the U.S., since civilian employment has never exceeded 150 million

¹⁶In principle, the choice of p for the percentile is arbitrary. However, qualitatively all results that we emphasize in this section hold for choices of $p > 75$. The reason we do not use the mean is that, in the case

We complete our analysis using three different datasets. Our results are qualitatively very similar across datasets. For the sake of brevity, we present results obtained using the ACS, since this is the dataset with the largest sample size.¹⁷

Figure 1 illustrates the tradeoff between the goodness-of-fit, \bar{R}^2 , and the precision of the wage imputation, $\tilde{\sigma}_{80}$. Panel 1a shows the scatter plot in $(\tilde{\sigma}_{80}, \bar{R}^2)$ space for all 1799 stratum-based model specifications from Table 1. This panel shows how increasing the \hat{R}^2 of the model specification comes at the cost of the precision with which the relative marginal products are imputed, i.e. an increase in $\tilde{\sigma}_{80}$. Because a higher \hat{R}^2 and lower $\tilde{\sigma}_{80}$ are preferred, we are focusing on specifications that move us to the upper-left in the plotted $(\tilde{\sigma}_{80}, \bar{R}^2)$ space.

Panel 1b shows the same 1799 points as panel 1a with two sets of points highlighted. The red crosses are the 192 stratum specifications that include all six variables we consider just at different levels of granularity. These points are the ones where $\tilde{\sigma}_{80}$ is high, compared to \bar{R}^2 , and thus correspond to specifications that overfit the data. At the other end of the cloud of points are the ones highlighted as red circles. These are the specifications that do not include age and education. The blue points are specifications that include age and education but not all other variables. When we compare the red circles with the blue points we find that, among the blue points, there are several specifications that have a substantially higher \bar{R}^2 and not much higher levels of $\tilde{\sigma}_{80}$.

We find that adding occupational dummies to the stratum definitions that already condition on age and education, yields the greatest improvement in fit and a relatively small decline in the precision of the imputed wages. This can be seen from panel 1c, which highlights the specifications that add only occupations as green dots. As can be seen from the figure, adding occupation adds about 0.1 to the \bar{R}^2 but increases $\tilde{\sigma}_{80}$ only slightly. In contrast, adding industry alone, depicted by the red squares, does not improve the fit as much as adding occupation and results in lower precision with which the wages are imputed. Adding both industry and occupation results in values of $\tilde{\sigma}_{80}$ well above 0.5. This means that for more than

of the stratum-based methods, $\sigma_j = \infty$ for all worker types with one observation. This would also make the sample mean of the σ_j 's go to ∞ .

¹⁷See Appendix B for results based on CPS-ORG and CPS-ASEC data.

20 percent of the strata log wages are imputed with a standard error of more than 0.5 (65 percent).

Panel 1d adds gender and race/ethnicity to the stratum definitions that include education and age. Race/ethnicity only slightly increases the fit at the cost of a substantial reduction in the precision of the marginal product imputation. Gender does increase the fit substantially. The question is what part of the variation in wages that is captured by gender reflects marginal product differentials. In our analysis, the in- or exclusion of gender does not have a large effect on our estimates of labor quality growth. As such, we exclude gender from our specifications in the rest of this paper.

In addition to the stratum-based model specifications, we also consider *Mincer*-type regressions. In particular, the *baseline Mincer* specification on which we settled includes a quadratic polynomial in experience and 5 education dummies.¹⁸ Because our stratum-based analysis suggests that occupation is an important determinant of wages, we also consider a *baseline-plus-occupation* specification which adds 51 occupation dummies.¹⁹

Figure 2 compares the regression-based fit and precision of imputed wages for the *baseline* and *baseline-plus-occupation* specifications with the stratum-based specifications. The lower cross in the figure shows the point for the baseline specification and the lower blue dots are the stratum-based points that only include age and education.²⁰ Because the *Mincer*-type regression is more parsimonious than the semi-parametric regressions, it results in more precisely imputed marginal product levels across workers, i.e. it has a smaller $\tilde{\sigma}_p$. Moreover, the quartic polynomial in experience captures more of the variations in wages across workers than the piecewise linear specifications implied by the stratum-based methods. Consequently the regression results in a higher \bar{R}^2 . Thus, the flexibility of the semi-parametric specification that Zoghi (2010) emphasizes when she proposes to use stratum-based medians as estimates of

¹⁸A similar *Mincer* specification, with the addition of several control variables, was also used by Aaronson & Sullivan (2001),

¹⁹We focus on this parsimonious *baseline* specification in the main text and illustrate that our main qualitative results are unaltered when additional covariates are included as controls in Appendix B.

²⁰Note that because experience is a linear combination of age and education, these specifications contain the same covariates.

wages,²¹ is outperformed by the quartic polynomial in experience that we use here. As a result, the [Mincer](#)-regression based way of imputing wages dominates the stratum-based methods in terms of both model-selection criteria.

This is not only true for the *baseline* regression specification. It is also true for the one that includes occupational dummies. In Figure 2 the upper cross corresponds to the *baseline-plus-occupations* regression and the upper cloud of blue dots to the corresponding stratum-based regressions that include age, education, and occupation. Again, the [Mincer](#)-regression-based specification outperforms the stratum-based ones.

This evidence shows that our *baseline* and *baseline-plus-occupation* specifications perform well in terms of our two model-selection criteria.

3.3 Index formula

Given the choice of the vector \mathbf{x}_j and the period-by-period estimates of the parameter vector $\hat{\boldsymbol{\beta}}_t$, based on (8), the final choice to be made for the calculation of the labor quality index is the index formula.

In line with the log-linear approximation of (4), the index formula that is used for most labor quality index calculations is of the Translog form and estimates labor quality growth as the compensation-share weighted average of log changes in hours across worker types.²² That is,

$$\hat{g}_t^{LQ} = \sum_{i=1}^n \left(\frac{s_{i,t} + s_{i,t-1}}{2} \right) (\Delta h_i - \Delta h), \text{ where } \hat{W}_t(\mathbf{x}_i) = \exp(\mathbf{x}_i' \hat{\boldsymbol{\beta}}_t) \quad (10)$$

$$\text{and } s_{i,t} = \frac{\hat{W}_t(\mathbf{x}_i) H_{i,t}}{\sum_{s=1}^n \hat{W}_t(\mathbf{x}_s) H_{s,t}}. \quad (11)$$

This translog index formula is preferred over many others because it is a superlative index

²¹The regression framework we use here results in the conditional mean for a stratum to be the imputed wage. In unreported results we redid our analysis with the conditional median as the wage estimate and obtained the same results compared to the [Mincer](#) specifications.

²²The compensation share is generally averaged across the two periods between which the growth rate is calculated.

(Diewert, 1978) that is exact for a general second-order approximation of the production function.

In the case of labor quality growth calculations, implementation of the Translog formula is complicated by the fact that in some cases the number of hours worked by a worker type, i is zero. In that case Δh_i can not be calculated and such worker types are dropped from the calculations. Though dropping these worker types is a reasonable option, because their compensation share is, presumably, small, one can also use another superlative price index formula that does not suffer from this problem.

This is what we do in this paper. In particular, we follow Aaronson & Sullivan (2001) and use a Fisher Ideal index formula of the form

$$\hat{g}_t^{LQ} = \left\{ \frac{H_{t-1}}{H_t} \right\} \left\{ \frac{\sum_i \hat{W}_t(\mathbf{x}_i) H_{i,t}}{\sum_i \hat{W}_t(\mathbf{x}_i) H_{i,t-1}} \right\}^{\frac{1}{2}} \left\{ \frac{\sum_i \hat{W}_{t-1}(\mathbf{x}_i) H_{i,t}}{\sum_i \hat{W}_{t-1}(\mathbf{x}_i) H_{i,t-1}} \right\}^{\frac{1}{2}} - 1. \quad (12)$$

This formula allows us to include all worker types, i , in our calculations even if $H_{i,t} = 0$ or $H_{i,t-1} = 0$.²³²⁴

²³For our benchmark specification, the problem of zeros does not occur, and the Translog and Fisher are virtually identical. It can make a little more difference in cases with extremely large numbers of cells, where there are more zeros.

²⁴Note that exponentiating the predicted log-wage would not normally be sufficient to get a predicted wage in levels because

$$E[w_j] = E[\exp(\mathbf{x}_j\beta + \epsilon_j)] = E[\exp(\mathbf{x}_j\beta) + (\epsilon_j)] = \exp(\mathbf{x}_j\beta) \cdot E[\exp(\epsilon_j)]$$

and $E[\exp(\epsilon_j)]$ is not 1. It is, however, a constant if the residuals are assumed to be independently and identically distributed. So if $\hat{W}_i = \exp(\mathbf{x}_j\beta)$ and $c = E[\exp(\epsilon_j)]$, then plugging the predictions into the share of the wage bill calculation from (7) gives

$$\frac{W_i H_i}{\sum_{j=1}^n W_j H_j} \equiv \frac{c \hat{W}_i H_i}{\sum_{j=1}^n c \hat{W}_j H_j} = \frac{c \hat{W}_i H_i}{c \sum_{j=1}^n \hat{W}_j H_j} = \frac{\hat{W}_i H_i}{\sum_{j=1}^n \hat{W}_j H_j}.$$

Therefore we need not make any adjustments to the predictions, nor do we need to impose an assumption on the distribution of the residuals beyond the standard assumption that they are IID.

4 Historical labor quality growth

Before we consider the forecast of labor quality growth, we first examine its behavior over the past 15 years. This is useful for two reasons. First, by comparing historical results for different specifications and datasets, we can assess how sensitive the labor quality growth estimates are to the different choices discussed in Section 3. Second, and most importantly, concerns about plateauing educational attainment and the retirement of experienced older workers were expressed that are being discussed today were also concerns in the early 2000's. Our historical analysis shows that, contrary to these concerns, labor quality growth barely slowed over the past 15 years. This realization of labor quality growth owes much to a reduction in the employment rates of less productive individuals, especially during and after the Great Recession. We will return to this point in the forecast section.

4.1 Comparison across methods and datasets

As we discussed in Section 3, we construct our benchmark labor quality index using ACS data based on our *baseline Mincer* specification. The index for labor quality obtained from this specification is plotted as the blue line, labeled *Regression - age and education*, in Figure 3a.

From 2002 through 2013 the cumulative growth in the index was 5.96 percent, which is 0.53 annually. As the figure shows, labor quality growth has been far from constant at this average during our sample period. Its standard deviation across years is 0.39. From 2002 to 2006 labor quality by this measure grew relatively slowly, about 0.37 percent per year. Subsequently, during the Great Recession from 2008-2010 labor quality growth logged in at 0.94 percent a year. Since then it has come down to 0.36 percent.

In Section 3 we showed how our *baseline* specification outperformed many others in terms of goodness of fit of the log-wage regression as well as the precision of imputed wages. In terms of labor quality growth our baseline specification yields an estimate that is very close to those obtained using other specifications that include age and education. This can also be seen in Figure 3a. As the figure plots, the stratum- and regression-based methods give

very similar estimates of the labor quality index when both age and education are included in the vector \mathbf{x}_i . Moreover, the index constructed does not change very much when we use the *baseline-plus-occupation* specification instead of the *baseline* specification.

Among the series plotted in Figure 3a there are two clear outliers that exhibit much less cumulative labor quality growth. The first of them is the stratum-specification that includes all variables. Such a specification results in large errors in imputed wages which reduces the correlation between hours growth and wages that drives labor quality growth. As a result, the overfitted specification yields much less labor quality growth than our *baseline* model. The other outlier series is the version that excludes age and education entirely (the underfit stratum). That series is flat, confirming that age and education are what drives the series.

Excluding the two outlier series, the cross-specification mean of average annual growth rates of labor quality is equal to the average annual labor quality growth rate implied by our *baseline* index, namely 0.53 annually. The cross-specification standard deviation in these average annual rates is 0.03. Besides very similar mean growth rates, all these indices also show a very similar qualitative pattern over the sample period: Slow growth from 2002-2006, an acceleration during the Great Recession, and a subsequent slowdown in 2011 and 2012.

The results in Figure 3a are reminiscent of Zoghi (2010)²⁵ in that she suggests that estimated average annual labor quality growth rates are fairly robust to the choice of model specification. This robustness of estimated average annual labor quality growth rates also translates across datasets.

This can be seen from Figure 3b. It plots the *baseline* and *baseline-plus-occupation* results for the three datasets that we consider in this paper, i.e. for ACS, CPS-ASEC, and CPS-ORG. The six indices plotted look remarkably similar.²⁶ In terms of their summary statistics, the mean average annual labor quality growth rate across series in the figure is 0.49 percent with a standard deviation of 0.03.

²⁵See Zoghi (2010) Table 12.2, page 478.

²⁶The only exception is the ACS-based indices in 2005-2006. In this year the sample size of the ACS was expanded from 1 to 3 million respondents, which appears to have resulted in a sample with a slightly lower level of labor quality than before.

Together, these results suggest that the pattern of labor quality growth from 2002 through 2013 we find using our *baseline* case is not the result of the particular specification or dataset chosen. Indeed, we find this pattern for all reasonable model specifications and across all data sets. Overall, we conclude that from 2002-2013 labor quality has grown around 0.5 percent a year. This is about the same as the average of 0.4 to 0.5 percent labor quality growth between 1992 and 2002 ([Bureau of Labor Statistics, 2015a](#); [Fernald, 2015](#)).

4.2 Counterfactuals to identify the sources of growth

The fact that we find no substantial deceleration in labor quality growth since 2002 is surprising, especially given the slow growth of educational attainment and the beginning of retirement among the oldest baby boomers, during the period. Our analysis shows that as these adverse demographic and educational trends were pulling down labor quality growth, a disproportionate decline in the employment-to-population (EPOP) ratio of lower quality worker types was pushing it up. To illustrate this, we calculate three counterfactual historical indices, which are plotted in [Figure 4](#).

These counterfactuals take advantage of the fact that hours worked by workers of type i , i.e. H_i , are the product of (i) average hours worked per year by workers of this type, η_i , (ii) the EPOP of these workers, E_i , and (iii) the population of these workers, P_i . That is,

$$H_i = \eta_i E_i P_i. \quad (13)$$

Using this expression, we can create different counterfactuals by holding one of the three factors, i.e. η_i , E_i , and P_i , fixed at its 2002 level.

[Figure 4](#) shows our baseline estimate, labeled *observed index*, as well as the three counterfactual indices. As can be seen from the figure, changes in average hours worked across worker types have had very little impact on labor quality growth. In contrast, if the composition of the population would not have changed since 2002 then labor quality growth would have been about a third lower. This is because removing population changes eliminates the continued

accumulation of experience of the baby boom generation from the calculations.

The most striking of the three counterfactuals, however, is the one for the EPOP ratio. From Figure 4 it is clear that if EPOP ratios by worker type had remained at their 2002 levels labor quality growth would have been half of what we observed over the past decade. Notably, the wedge between the observed index and the counterfactual with constant EPOP ratios increased most rapidly during the Great Recession. This wedge is consistent with the extensively documented composition effect of recessions on real wages. Many studies, including those by [Bils \(1985\)](#) and [Solon *et al.* \(1994\)](#), find that the incidence of unemployment is more cyclical among low-wage workers. In growth-accounting terms, this cyclical composition effect means that labor quality has a countercyclical component ([Ferraro, 2014](#)). Our labor quality index captures the fact that EPOP ratios among lower quality worker types are more cyclical. And our counterfactual shows that the disproportionate decline in employment rates among less-skilled workers led to a recession-driven increase in labor quality growth.

An important question for any forecast of labor quality growth is to what extent these movements in EPOP ratios by worker types are transitory or permanent. Since a large part of the decline in these EPOP ratios is reflective of declines in labor force participation rates, this is largely a question of what fraction of recent movements in labor force participation is structural versus cyclical.

If labor force participation rebounds substantially, as [Congressional Budget Office \(2015\)](#) projects, this will put downward pressure on labor quality growth over our forecast horizon. However, if, as [Aaronson *et al.* \(2014\)](#) suggest, the bulk of the movements in participation rates across groups since 2007 have been structural, then our labor quality index would be unaffected. In that case there would be no downward pressure on labor quality growth coming from changes in labor force participation by skill.

This finding highlights an important lesson from our analysis. We should not be misled by the positive sound of “*increases* in labor quality” due to composition effects. Generally, labor quality is discussed assuming a path of total hours. But these composition effects refer to increases in labor quality due to a decline in hours (or slowdown in hours growth). From

(4) we know that what matters for output growth is the growth rate of the total labor input, which is hours growth plus labor quality growth. Hence, if labor quality grows as a result of a selection effect among workers when total hours decline, then this is neither necessarily good news for growth of the overall labor input nor for output growth.

5 Forecasting labor quality growth

So far we have focused on historical labor quality growth. In this section we consider the outlook for labor quality growth going forward. We do so in three steps. In the first step we review the variables required for any forecast of labor quality growth. We then discuss the reliability of projections of these variables. In the second step we examine the historical performance of the forecast for 2002-2013. This allows us to assess projection errors and see which components have contributed most to historical forecast errors. Finally, we present our outlook for U.S. labor quality going forward and discuss risks to this forecast in the context of the historical forecast error experience.

5.1 Components of labor quality projections

Equation (12) is a highly non-linear function of the parameter vector β_t and the hours worked by worker types, H_i . Therefore, an optimal forecast of labor quality growth would be based on the joint distribution of the future log-wage regression coefficients and future hours worked by all worker types, i . Unfortunately, we have no information about this joint distribution. Thus, constructing such an optimal forecast is not feasible.

Instead, we forecast labor quality growth by evaluating (12) in our projections of the log-wage parameter vector, β , and the hours worked by worker type, H_i . In particular, we denote the h period ahead projections of the log-wage parameter vector as $\hat{\beta}_{t+h}$ and of hours worked by worker type i as $\hat{H}_{i,t+h}$. For our baseline forecast, we set the projected log-wage parameters equal to the estimated parameter vector for the last year for which we have data, i.e. $\hat{\beta}_{t+h} = \hat{\beta}_t$.

For the construction of our projections of the hours worked by worker type, $\hat{H}_{i,t+h}$, we

again split hours into the three factors from equation (13), namely (i) average hours, $\hat{\eta}_{i,t+h}$, (ii) the EPOP rate, $\hat{E}_{i,t+h}$, and (iii) population, $\hat{P}_{i,t+h}$.

Historically, there is not much difference between the hours-based and employment-based indices. This can be seen from Figure 5 which plots the observed index, based on hours worked as the measure of the labor input, versus an index based on employment as the labor input. The latter index is equivalent to the assumption that average hours worked are the same across all worker types, i.e. $\eta_{i,t} = \eta_t$ for all i . If we do not account for the heterogeneity in average hours worked across worker types, then we obtain average annual labor quality growth of 0.61 percent (employment-based), about a tenth of a percentage point higher than the 0.52 we obtain using the hours-based index.²⁷

With this in mind, we construct our forecast abstracting from cross-worker-type heterogeneity in average hours worked. That is $\hat{\eta}_{i,t+h} = \eta_{t+h}$. Our projections of the EPOP ratios, $\hat{E}_{i,t+h}$, and population levels by age and education, \hat{P}_i we use a method similar to that applied by Aaronson & Sullivan (2001). Because we do not take into account hours heterogeneity across worker types in our forecast, we use the 0.61 percent observed average annual growth of labor quality for the employment based index in Figure 5 as our baseline comparison number when we compare the observed index with forecasts.

Details of our projection method are provided in subsection A.2 of Appendix A. We summarize the intuition here. Following Aaronson & Sullivan (2001) we start off with the Census' population projections by age, gender, and race. Because our *baseline* specification contains age and education, we need population projections for all age and education combinations. We obtain these by running a multinomial Logit model that estimates the probability distribution of the 5 education levels that we distinguish for an individual based on age, cohort, gender, and race for all the years in our sample. We use these estimated probabilities to construct population projections by age and education, i.e. to construct $\hat{P}_{i,t+h}$, across worker types.

Finally, to project the fraction of the population of worker types that is employed, i.e. the

²⁷This difference between the hours-worked-based and employment-based indices is smaller in the CPS-ORG and CPS-ASEC data than in the ACS (See Appendix B).

type-specific epop ratio $\hat{E}_{i,t+h}$, we estimate the probability that an individual is employed as a function of age, cohort, education, using Logit models that vary by gender and race for all the years in our sample.

Using these estimates for the three factors in equation (13), we construct

$$\hat{H}_{i,t+h} = \hat{\eta}_{i,t+h} \hat{E}_{i,t+h} \hat{P}_{i,t+h}. \quad (14)$$

as our projected level of hours worked by workers of type i . For the interpretation of our forecast it is important to realize that the equations for educational attainment and EPOP ratios on which this projection is based, are estimated over all years in our samples. Therefore, changes in educational attainment and EPOP ratios across age, gender, race, and cohorts since the end of the sample period, will affect the accuracy of the forecast.

Thus far, we have focused on our *baseline* specification and have not discussed how we extend it to cover the *baseline-plus-occupation* specification. Such an extension would require forecasting population and EPOP ratios by age, education, and occupation. This turns out to result in very imprecise forecasts. The best way to understand this is to realize that projections of employment (population times EPOP ratios) by occupation alone already have large forecast errors. To see this, consider Figure 6. It plots the Bureau of Labor Statistics' actual versus projected growth in employment between 1996-2006 by 6-digit SOC codes. Because forecasting employment growth by occupation results in such large forecast errors, we limit ourselves to our *baseline* specification for our forecast.

5.2 Historical forecast and sources of forecast errors

Before we apply our forecast method to quantify the outlook for labor quality going forward, we consider how the method would have performed if we used it to predict labor quality growth in 2002. The results are shown in Figure 7.²⁸

²⁸Because the first ACS data were released in 2002, we cannot use ACS data for the estimation of the EPOP and educational attainment models. Instead, we estimate these models using 1992-1997 data from the CPS-ORG for this historical forecast.

The top and bottom lines in Panel 7a are the actual observed employment-based index, which came in at 0.61 percent average annual labor quality growth, and the 2002 forecast of the index, which was for 0.19 percent average annual labor quality growth. The figure shows that if we had applied our forecast method for labor quality growth in 2002 we would have substantially underestimated future labor quality growth. This result is not specific to our method or data. The forecast by Aaronson & Sullivan (2001) also came in well below the actual observed labor quality growth over the past decade.

Panel 7a of the figure also shows that the historical forecast errors were due to deviations in the projected variables rather than changes in the regression parameters. The line labeled “2002 betas; observed demographics” in the figure shows that if we reconstruct the forecast keeping the wage-regression parameters fixed at $\hat{\beta}_{2002}$ and use the actual observed demographics, i.e. $H_{i,t}$, we obtain a projection that is much closer to the actual index than the forecast index. Oppositely, if we construct a forecast with the observed, rather than predicted, log-wage regression parameters and the projected demographics, $\hat{H}_{i,t+h}$, we obtain a series that is very close to the forecasted index. Thus, time-variation in the log-wage regression parameters drives only a small part of the forecast errors.

The other thing to take away from Panel 7a is that the bulk of the forecast errors accumulate during the Great Recession. In other words, deviations in demographics, $H_{i,t}$, from their projections, $\hat{H}_{i,t}$, in the Great Recession account for most of the forecast error. Panel 7b shows which components of these demographic projections account for these forecast errors.

The lines labeled “All observed” and “All projected” are the observed and forecasted indices (from Panel 7a) respectively. The line labeled “Observed age & education; proj employment” depicts an alternative index that is based on all observed components of the demographics, except for the EPOP ratios for which we use their projections. The difference between this line and the “All observed” index isolates the effect of projection errors in EPOP ratios across worker types. As can be seen from the figure, these errors account for about one-third of the cumulative forecast error in labor quality growth and are especially important after the onset of the Great Recession in 2008. From the line “Observed age; proj education & employment”

it can be seen that projection errors in educational attainment account for approximately another one-third of the forecast error in labor quality growth. The rest is due to inaccuracies in Census' population forecasts.

Contrary to the part of the forecast error due to errors in the EPOP projections, the parts due to miscues in the population and education forecasts accumulate relatively smoothly over time. This suggests that about a third of the historical forecast error is due to unanticipated cyclical movements in the EPOP ratios across worker types during the Great Recession and that the other parts are due to errors in projections of more longer-run trends in the labor market.

5.3 Current forecast and risk assessment

These longer-run trends, of course, will likely continue beyond the end of our sample in 2013. For this reason we present not only our outlook for labor quality growth from 2015 through 2025 obtained using the projection method described above. We also calculate alternative forecasts that take into account two risks. First, there might be a *substantial positive cyclical factor in labor quality in 2013* that built up due to the composition effect during the Great Recession. Second, our projection method might miss some longer-run trends happening in the labor market.

First we present our baseline forecast for the three datasets that we consider. Figure 8 shows these forecasts for the ACS, CPS-ORG, and CPS-ASEC. These data sets result in forecasts of average annual labor quality growth from 2015-2025 of 0.36, 0.29, and 0.05, respectively.²⁹ All three projections are for relatively constant labor quality growth over the next decade that is substantially lower than the 0.61 percent we observed for 2002 through 2013 period.

In particular, our ACS-based results point to about a quarter percentage point decline in labor quality growth over the next 10 years compared to the 2002-2013 period. With a labor share of about 60 percent, such a quarter percentage point decline would shave about 0.15

²⁹The low forecast that we obtain using CPS-ASEC seems largely due to the extrapolated cohort parameters, which are unreliably estimated due to the small sample size of the dataset.

percentage point off trend output growth over the next decade compared to the past 15 years.

We are not the first to forecast a slowdown in labor quality growth. [Aaronson & Sullivan \(2001\)](#) did so a decade ago and our own historical forecast from the previous subsection is in line with their analysis. However, their forecast did not materialize. As we illustrated, this was in large part because of the upswing in labor quality partly induced by the Great Recession and to a lesser extent to do with a mis-assessment of underlying longer-run trends in the labor market.

To assess how sensitive our projections are to our baseline assumptions regarding the future path of labor force participation we compute a set of alternative forecasts based on different assumptions and scenarios.

Our scenarios are constructed to show the sensitivity of our baseline results to alternative assumptions regarding the future paths of educational attainment and EPOP ratios. The results obtained under these scenarios are listed in [Table 2](#). Rows 2-4 of the table correspond to three alternative scenarios about future educational attainment. Columns II-IV are about future EPOP ratios.

As can be seen by comparing the rows of the table, the difference in labor quality growth forecasts across plausible future paths of educational attainment is small, less than 0.1 percentage points. So, our results are not very sensitive to our assumptions about education. In contrast, comparing forecasts across EPOP assumptions shows substantial differences in projected labor quality growth. If EPOP rates revert back to pre-recession *levels*, column (*III*), then labor quality growth over the next decade will be considerably slower than our baseline. If, instead, pre-recession EPOP *trends* that tilt the composition of the labor force towards higher-skilled workers continue, column (*II*), then labor quality growth is likely to come in above its historical average over the next decade.

6 Conclusion

Between 1950 and 2007, labor quality growth in the U.S. contributed about 0.4 percentage point per year to growth in GDP per hour. Recent trends in educational attainment and retirement of the most experienced part of the workforce point towards a slowdown in labor quality growth going forward.

We construct a forecast of labor quality growth for 2015 - 2025. This forecast is based on a preferred specification that we select in the context of a new model selection framework that encompasses the two most commonly used methods to impute marginal product differentials across workers; stratum-based and regression-based wage models.

We find that a parsimonious [Mincer](#)-regression-based model performs well historically and yields historical labor quality growth estimates that are very similar to those obtained using alternative specifications.

Forecasting labor quality does not only involve forecasting wage differentials between worker types but also the distribution of hours (or employment) across worker types. It turns out that, historically, this has been the major source of error in labor quality projections.

In part this is due to the fact that business cycle fluctuations, like the Great Recession, result in unforeseen movements in labor quality. For example, during the Great Recession employment-to-population ratios for lower-wage workers declined more than for higher-wage ones. This resulted in a cyclical upswing in labor quality that was not accounted for in historical forecasts for the past decade. Whether this upswing retreats or becomes a more persistent feature of the labor market poses an important risk to any forecast of labor quality.

Our current forecast of labor quality growth for the next decade suggests that it will slow by about a quarter percentage point a year. This forecast, however, is subject to substantial uncertainty that is mainly related to the future path of participation rates across worker types. We quantify its sensitivity by recalculating forecasts based on alternative assumptions about future participation and education.

These sensitivity analyses show that the forecast is relatively robust across the range of

reasonable assumptions about future educational attainment. However, it varies substantially across plausible paths of future participation. Under these paths we project labor quality growth to be between 0.16, if we return to pre-crisis EPOP ratios, and 0.66 pre-recession EPOP *trends* that tilt the composition of the labor force towards higher-skilled workers continue.

These findings highlight an important aspect of the discussion of labor quality going forward. Labor quality is often discussed without much thought to total hours. However, our alternative scenarios highlight the importance of taking into account that they are jointly determined. In particular, if low-skilled workers continue to exit the labor force, then this will boost labor quality growth at the expense of total hours growth. On the other hand, a substantial reentry of these workers would depress labor quality growth but increase hours growth. Since output growth is a function of the sum of hours and labor quality growth, the overall effect on output growth of such a trend is ambiguous but presumably positive.

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A Data details

A.1 ACS, CPS-ASEC, and CPS-ORG

To verify the robustness of our results, we calculate them for commonly used U.S. datasets that each allow for the construction of measures of labor quality growth. The first is the ACS, which is a smaller, annual version of the decennial census and collects a relatively narrow range of demographic and socioeconomic data on a sample of about 1 percent of the population (approximately 3 million individuals) each year.³⁰ The second, CPS-ORG, consists of the the outgoing rotation groups from the Current Population Survey. This is the quarter of CPS respondents that are asked about their earnings and income in any given month. This results in an annual sample of about 135,000 individuals. The final dataset, CPS-ASEC, is the Annual Social and Economic Supplement to the Current Population Survey, also known as the March supplement. It contains annual earnings and income data from the full March CPS sample (70,000 individuals).

Though based on different samples and sampling methods, each of the datasets allows for the construction of similar hourly wages, as well as the six variables of education, age, sex, race/ethnicity, industry, and occupation, that are our main focus.

For each dataset we construct the *sample* of workers to cover those in the civilian noninstitutional population ages 16+ that are employed in the private business sector (specifically, excluding anyone with self-employment or government employment earnings) and have positive earnings and hours. The sample period is 2002-2013, because that is the period for which we have a consistent set of occupation and industry crosswalks and data from all three datasets.³¹

We define *wages* as hourly wages. Because of differences in reference period and questions asked this necessitates slightly different constructions of wages in each dataset. In the CPS-

³⁰The sample of the ACS has been expanded twice and has only been a 1 percent sample of the population since 2006. In its first year, 2000, the sample was just under 400,000 individuals and between 2001 and 2005 the sample was slightly over 1 million

³¹ In principle, the CPS-ASEC is available from 1962 on and the CPS-ORG from 1979 on if industry and occupation are omitted or approximate crosswalks are used. The ACS is available from 2000 on without any need for adjustments.

ORG we use the hourly wage constructed in the National Bureau of Economic Researchs CPS Labor Extracts (Feenberg & Roth, 2007). For the CPS-ASEC and ACS we define hourly wages as total annual earnings divided by the product of usual hours worked per week and weeks worked per year.³² All wages are deflated into real 2005 dollars and exclude self-employment, self-owned business, and farm income.

A.2 Projections of educational attainment and employment

The Census Bureau provides projections of the age, gender and race/ethnicity distribution of the population, but to forecast labor quality we need to further break these cells down by educational attainment and employment rates. To do so we follow a methodology similar to that used by Aaronson & Sullivan (2001)—our primary adjustments are that we use five race/ethnicity categories instead of four and we define employment more narrowly as being employed exclusively in the private business sector to match the sample selection stated in Section A.1. Given that the methodology is substantively unchanged, this section is largely a restatement of Box 1 from (Aaronson & Sullivan, 2001, p. 65).

Let $p_{it}^j = P[y_{it} = j]$ for $j = 1, \dots, 5$ be the probability that individual i in year t has educational attainment j , where the five levels of attainment are less than high school, high school graduate (including GEDs), some college (including associates degree holders), college graduates (Bachelor’s), and post-graduates, and let $q_{it}^j = P[y_{it} \geq j | y_{it} \geq j - 1]$ for $j = 2, \dots, 5$ be the probability of attaining education j given that the individual has completed the “prerequisite” education (e.g. for $j = 4$ this is the probability of an individual having completed college given

³²In 2008 the ACS switched from collecting weeks worked as a continuous to a categorical value (13 weeks or less, 14-26 weeks, 27-39 weeks, 40-47 weeks, 48 or 49 weeks, and 50-52 weeks). Prior to 2008 the distribution of weeks worked within those ranges was remarkably stable over time, so we imputed a continuous value of weeks worked using the pre-2008 mean of people reporting weeks worked within a given range. We also tested using a more complex regression model on demographic characteristics to impute weeks worked but found that it gave little more variation or precision in predicted weeks worked than using the pre-2008 mean. The same approach is used by the BLS for pre-1975 data, which has the same issue (Bureau of Labor Statistics, 1993, p. 77).

that they have completed some college). We predict \hat{q}_{it}^j using a logistic regression of the form

$$\log \frac{q_{it}^j}{1 - q_{it}^j} = \sum_a D_{it}^a \alpha_{ja} + \sum_b D_{it}^b \beta_{jb} + \mathbf{x}_{it} \gamma_j, \quad (15)$$

$$\text{and } \hat{q}_{ab}^j = \frac{\exp(\alpha_{ja} + \beta_{jb})}{1 + \exp(\alpha_{ja} + \beta_{jb})} \quad (16)$$

where D_{it}^a and D_{it}^b are dummies for being age a and born in year b , and x_{it} is a vector of control variables. From \hat{q}_{ab}^j it is possible to calculate $\hat{p}_{ab}^j = \prod_{k=2}^j \hat{q}_{ab}^k (1 - \hat{q}_{ab}^{j+1})$, which can be interpreted as the predicted share of people born in year b with education j at age a or, since age, year, and birth year are perfectly collinear, the predicted share of people of age a with education j in year $b+a$. The models for education level j are estimated on the sample of people with at least $j - 1$ education and who are above an education-level specific age threshold.³³ To avoid cyclical biases from the Great Recession the projections for the forecasts in Section 5 are estimated on the 2002 to 2007 data for whichever dataset is used in the forecast. For the projections for the forecast error decomposition exercises in Section 5 the models are estimated on the CPS-ORGs from 1992 through 1999.³⁴

The idea behind these models is that educational attainment follows some sort of lifecycle pattern, with the probability of completing a certain level of education increasing rapidly for people under 30 and then more gradually for those who are older. This lifecycle pattern is assumed to be the same for different cohorts, but cohorts born in different years are allowed to have uniformly higher or lower log-odds of completing a given level of education. For high school, some college, and college levels of education the model is estimated separately for each of ten gender-race-ethnicity combinations without any control variables (\mathbf{x}_{it}). For post-graduates some of the gender-race-ethnicity samples become quite small, so the model is estimated separately for men and women with race/ethnicity dummies included as con-

³³The thresholds are 18 for high school, 19 for some college, 22 for college, and 26 for post-graduate.

³⁴Ideally this would have been estimated on ACS data to ensure consistency between these projection models and the log-wage regression. However, in order to distinguish age and cohort effects the projection model must be estimated on multiple years of data. Since there is no pre-2000 data for the ACS, this forces us to rely on another dataset to construct the education and employment projections.

trols. The estimated model is then used to predict the fraction of individuals with each level of educational attainment based on the Census Bureau projections of the age, gender, and race/ethnicity distribution of the population.

The projection model is only able to estimate birth year coefficients (β_{jb}) for birth years that are observed in the sample. However, some birth years that are too young to be observed in the sample will be old enough to be in sample by later years of the projections — a child born in 2000 is too young to be in any of our current samples, but by 2025 they will be 25 years old and of critical importance to our forecasts. Therefore we define these unobserved cohort coefficients by a linear extrapolation using the last 15 birth year coefficients (not including the most recent).³⁵ In effect, this approach extrapolates recent trends in educational attainment into the future.³⁶

This process yields projections of the population distribution of age and educational attainment, the key variables for our baseline [Mincer](#) specification. However, to construct our forecast of labor quality we must also project the EPOP rates for these worker types. Our EPOP projection model is identical to the educational attainment projection model, except educational attainment is added as a control variable. Rather than using the standard BLS definition of employment we define employment as being employed exclusively in the private business sector — this makes our definition consistent with the sample selection used to construct our labor quality measures.

A.3 Alternative educational attainment and employment scenarios

The Fisher Ideal index does not have the circularity property, so the labor quality growth calculated from comparing a target year to a base year is not necessarily the same as the growth calculated from cumulated year-over-year changes. However, this is not true for the labor quality growth forecasts because our assumption that the log-wage regression coefficients

³⁵The most recent coefficient is omitted because it is based on just one year of observations, making the sample size quite small.

³⁶The results are not sensitive to changing the extrapolation window to 10 or 20 birth year coefficients.

are constant over time means that the Fisher Ideal index collapses into the Laspeyres index, which does have the circularity property. This allows us to construct alternative forecast scenarios based on assumptions about the education and employment distribution in the target year alone, without having to make assumptions about the path of educational attainment or EPOP between now and then. Therefore our alternative forecast scenarios discussed in 5 are based on the Census Bureau age projections for the year 2025 and the education and employment assumptions described below. The empirical labor force in 2013 is used as the baseline and scenarios are calculated using ACS data.

Education scenarios All three education scenarios assume that the educational distribution for those over 30 will stay the same as they age. For example, the educational attainment of 52 year olds in 2025 is assumed to be the same as that of 40 year olds in 2013 (the most recent year in our data). Although non-traditional educational attainment, differential mortality rates, and immigration make it unlikely that this assumption strictly holds, those forces are marginal enough that they are unlikely to cause substantial deviations. Where the scenarios differ is in their assumptions on the educational attainment of 1) people 30 and under in 2025 (the “young group”), and 2) the educational attainment of people under 30 in 2013 that will be over 30 in 2025 (31-42 year olds in 2025; the “middle group”). The educational attainment of the *young group*, which was in middle school or below during the Great Recession and thus unlikely to have been driven by cyclical factors — their educational attainment can be thought of as representing what we think is a “normal” level. Unlike the young group, those in the middle group were making critical education decisions (such as whether to drop out of high school or college and whether to enroll in college or grad school) during the Great Recession and its aftermath. Therefore, if “educational sheltering” has been a strong force during and after the Great Recession, as posited by [Barrow & Davis \(2012\)](#), [Sherk \(2013\)](#), and [Johnson \(2013\)](#), then their attainment may deviate from the norm.

Revert to pre-crisis educational plateau The first education scenario assumes that the educational attainment of young people reverts to its pre-crisis levels. This reflects the possibility that the uptick in enrollment and graduation rates over the past several years is simply a tem-

porary cyclical effect of the Great Recession. For the young group, this scenario assumes they will have the same distribution of educational attainment as people of the same age in 2007.³⁷ For those in the middle age group, whose attainment may have been increased by “educational sheltering” effects, this scenario assumes that they will either have the educational attainment of someone that age in 2007 or their current educational attainment, whichever is higher. That is, they will have at least the educational attainment that would have been expected of them before the recession, and they may have a little more if the recession encouraged them to stay in school. Specifically, let \hat{q}_a^j be the probability of someone with age a having at least education j in 2007, let \tilde{q}_{a-12}^j be the probability of someone that will be age a in 2025 having at least education j in 2013, and let $q_a^j = \max(\hat{q}_a^j, \tilde{q}_{a-12}^j)$. Then for this scenario the share of people of age $a = 31, \dots, 42$ with education j will be $p_a^j = q_a^j - q_a^{j+1}$.

Persist at 2013 educational plateau The second scenario assumes that the educational attainment of young people persists at its 2013 rate, reflecting the possibility that there was a step increase in educational attainment over the past several years but that attainment has once again reached a plateau. This scenario assumes that people in the young group will have the same distribution of educational attainment as someone of the same age in 2013. For the middle group we have to account for the fact that the increase in educational attainment was gradual and had not fully propagated through for those over 30 but people under 30 will often go on to further education, meaning that there is no clear baseline group. To get a baseline for this group we calculate the probability q^j in 2013 of completing at least education j for the five year age group that are young enough to have experienced a sheltering effect but old enough that we would expect them to have completed that level of education already.³⁸ For this scenario we define the expected educational attainment distribution of the middle group as $p^j = q^j - q^{j+1}$.

³⁷Recent research suggests that the housing boom depressed educational attainment by providing good job opportunities to low skill workers, in which case the educational attainment patterns from the boom years would be unusually low [Charles et al. \(2015\)](#). That would suggest that this may be a particularly pessimistic implementation of this “cyclical uptick” hypothesis. However, we believe this is still a useful scenario to consider as it provides a plausible worst-case scenario for education trends.

³⁸For high school we use 19-23, for some college we use 23-27, for college we use 25-29, and for post-graduate we use 30-34. Less than high school is the residual category.

Extrapolate 2007-2013 trends in education The final scenario assumes that the uptick in educational attainment over the past several years represents a resumed upward trend in education attainment rather than a temporary cyclical boost or a one-off step increase. Age-specific time trends in educational attainment are estimated from logistic regressions of the form

$$\log \frac{q_{it}^j}{1 - q_{it}^j} = \sum_a [year \cdot D_{it}^a \beta_a + D_{it}^a \gamma_a]. \quad (17)$$

As in Section A.2, these logits are estimated on the population of people with education $j - 1$ or higher, and they are estimated on 2007-2013 data. Let q_a^{2013} be the probability that a person of age a had education j or higher in 2013. Then this scenario assumes that the probability of having at least education j at age a in 2025 is the probability of having education j in 2013 plus the age-specific time trend — that is, they have probability $q_a^j = \text{invlogit} [\text{logit} (q_a^{2013}) + 12 \cdot \beta_a]$ of having at least education j at age a in 2025. As in the other cases, we then recover the share of people with education j at age a in 2025 as $p_a^j = q_a^j - q_a^{j+1}$.

Employment scenarios The employment scenarios are much more straightforward to construct because there is little to no need to keep track of the stock of employment — the fact that 85 percent of 29 year old college graduates were employed in 2013 does not impose particularly binding constraints on our assumptions about the EPOP rate of 41 year old college graduates in 2025. Therefore, our two baseline employment scenarios simply assume that the EPOP rates for specific age-education groups in 2025 will be the same as in some other base year. For the *revert to pre-crisis EPOPs* scenario we assume that the probability of a person of age a with education j being employed in 2025 is the same as it would have been in 2007.³⁹ This scenario corresponds to the view that the entire decline in EPOP rates for specific age-education groups is cyclical.⁴⁰ The second employment scenario is the inverse

³⁹As with the first education scenario, this may be an extreme assumption on what the pre-crisis norm was — if the housing boom boosted EPOP rates to abnormal levels, then this scenario overstates the baseline EPOP rates. Similar to the education case, we believe this remains a useful scenario to consider as it illustrates a sort of best-case scenario for employment rates.

⁴⁰This still allows for a demographically (or educationally) driven structural decline in the aggregate employment-to-population ratio. What it does not allow for is a structural decline (or increase) in EPOP for specific age-education groups. For example, it does not allow for a structural decline in students working part-time, or a structural increase in older people staying employed past the traditional retirement age.

of this and assumes that the entire change in the EPOP rates of specific age-education groups is structural and will *persist at 2013 EPOPs*.⁴¹

Extrapolated 2002-2007 structural trends in EPOPs The final scenario extrapolates certain pre-crisis trends in employment patterns out to 2025. In particular, it extrapolates the declining EPOP rates of young people (with heterogeneity across education groups), the increasing EPOP rates of older people (particularly the more educated), and the widening gap between the EPOP rates of more and less educated working age people [Dennett & Modestino \(2013\)](#); [Burtless \(2013\)](#); [Aaronson et al. \(2014\)](#). Given that we have pre-selected the trends that are extrapolated, this scenario can be accused of cherry-picking. We do not deny that vulnerability, and we do not intend this scenario to be understood as a probable outcome. Again, these scenarios are primarily intended to illustrate the mechanics of labor quality growth and what factors are most critical to the setting expectations about future labor quality growth in the U.S., as well as to impose certain bounds on plausible forecasts of labor quality growth.

To implement the third employment scenario we follow an approach similar to that in the education trends scenario above. To extract age and education-specific time trends in employment we run the following logistic regression on the sample of 16-24 and 55-69 year olds over the 2002-2007 period

$$\log \frac{p_{it}}{1 - p_{it}} = \sum_a \sum_j [year \cdot D_{it}^a \cdot D_{it}^j \beta_{aj} + D_{it}^a \cdot D_{it}^j \gamma_{aj}] . \quad (18)$$

and to extract education-specific time trends in employment among prime age workers we run the following logistic regression on 25-54 year olds over the same period

$$\log \frac{p_{it}}{1 - p_{it}} = \sum_j [year \cdot D_{it}^j \beta_j + D_{it}^j \gamma_j] . \quad (19)$$

where p_{it} is the probability of individual i being employed in year t , D_{it}^a is an indicator for

⁴¹This scenario may be too pessimistic in that the labor market has clearly continued to improve since 2013. Once more recent ACS data becomes available we will revise this scenario to reflect the most recent year of data available. However, this once again provides a sort of outlier case with unusually low EPOP rates.

being age a , and D_{it}^j is an indicator for having education j . Let p_{aj}^{2007} be the probability that a person of age a with education j was employed in 2007. Then this employment trends scenario assumes that the probability of a person of age a and education j being employed in 2025 is the probability of being employed in 2007 plus the relevant age- and education-specific time trend. For 16-24 and 55-69 year olds this is $p_{aj} = \text{invlogit} [\text{logit} (p_{aj}^{2007}) + 18 \cdot \beta_{aj}]$ and for 25-54 year olds it is $p_{aj} = \text{invlogit} [\text{logit} (p_{aj}^{2007}) + 18 \cdot \beta_j]$.⁴²

B Robustness checks

In this section of the appendix we present additional results that illustrate that our qualitative results are unchanged when we change some of the underlying assumptions, specifications, and across datasets.

B.1 Adding control variables to the baseline Mincer regression

Throughout the main text we limited ourselves to parsimonious baseline [Mincer](#) regression. However, prior implementations of such specifications have included control variables to ensure that only productivity-induced wage differentials are reflected in the estimated wages ([Aaronson & Sullivan, 2001](#); [Bureau of Labor Statistics, 1993](#)). Here we consider the robustness of our results to including standard control variables, such as part-time status, marital status, veterans status, race, and geographic location.

As discussed in subsection , it is critical that the variables included in the labor quality specification (\mathbf{x}_j) be 1) correlated with wages, and 2) that the correlation is driven by differentials in the marginal product of labor. A desirable property of a regression-based framework like (8) is that it allows for the inclusion of control variables, \mathbf{z}_j , that may be correlated with both individual wages, w_j , and the variables meant to quantify marginal product differentials,

⁴²For people 70 and over there is no time-trend added in and their EPOP rate in 2025 is assumed to be the same as it was in 2007.

\mathbf{x}_j . The resulting generalized regression framework is

$$w_j = \mathbf{x}'_j \boldsymbol{\beta} + \mathbf{z}'_j \boldsymbol{\gamma} + \varepsilon_j. \quad (20)$$

Because we attribute only the part of wage variations explained by the variables in \mathbf{x}_j to marginal product differentials, we impute the log marginal product of a worker as $\mathbf{x}'_j \hat{\boldsymbol{\beta}}$. The inclusion of these control variables does not alter our definitions of σ_j and $\tilde{\sigma}_p$. They continue to be based on \mathbf{x}_j and $\hat{\boldsymbol{\beta}}$.

What is less clear is the appropriate measure of fit when considering a regression with controls. Consider, for example, a set of controls \mathbf{z} that predict wages ($\boldsymbol{\gamma} \neq \mathbf{0}$) but for which the correlation between any element x of \mathbf{x} and any element z of \mathbf{z} is zero ($\text{corr}(x, z) = 0$). In this case the regression \bar{R}^2 will increase, making the specification appear more appealing than the version without \mathbf{z} despite the fact that substantive components of the regression, \mathbf{x} and $\hat{\boldsymbol{\beta}}$, remain unchanged.⁴³ An alternative approach would be to consider the partial R-squared with respect to \mathbf{x} , \bar{r}_x^2 . However, then maximizing \bar{r}_x^2 is not necessarily desirable. For example, if the association between a control variable z and the core variables \mathbf{x} has the same sign as the association between z and wages w , then the \bar{r}_x^2 will decline in the regression with z . But the \bar{r}_x^2 declined precisely because z had been a source of omitted variable bias and we are now controlling for that.

Ultimately, the selection of \mathbf{z} operates on an orthogonal basis from the selection of \mathbf{x} in a *properly controlled regression*. As discussed in subsection , the desirability of higher \bar{R}^2 is entirely conditional on the assumption that $\hat{W}_j \equiv \exp(\mathbf{x}'_j \boldsymbol{\beta}) = c \cdot W$ — if any omitted variable bias is loaded onto $\boldsymbol{\beta}$ then this assumption is violated. In principle, this means that one should optimize \mathbf{z} for each separate specification of \mathbf{x} , at which point we can compare the \bar{r}_x^2 of the controlled regressions as is done in subsection .

Rather than undertaking this highly multidimensional and daunting task, we consider whether it is likely to be of first-order importance to any of our results. Specifically, we

⁴³The standard errors will also slightly increase because of the loss of degrees of freedom.

consider the impact of including two standard sets of controls in our *baseline* Mincer and *baseline+occupation* specifications. The first set of controls is a set of indicators for part-time employment, marriage, and race, which are the controls included in the specification used by Aaronson & Sullivan (2001).⁴⁴ The second set of controls is similar Bureau of Labor Statistics (1993) and includes indicators for part-time employment, veteran status, and which Census division the individual lives in.⁴⁵

Figure B.1a, which is comparable to Figure 2, plots the adjusted R-squared (\bar{R}^2) against the 80th percentile standard error of the predictions ($\tilde{\sigma}_{80}$). This shows that, as expected, the inclusion of the additional variables increases both \bar{R}^2 and $\tilde{\sigma}_{80}$. The Aaronson & Sullivan (2001) controls improve the fit slightly more and increase imprecision slightly less than the Bureau of Labor Statistics (1993) controls. However, as can be seen in Figure B.1b, there is almost no change in the partial R-squared with respect to \mathbf{x} , suggesting that either the control variables are not a significant source of omitted variable bias or that the biases they induce balance out on average. This suggests that the impact of including these control variables on measured labor quality growth is likely to be quite limited. This is confirmed in Figure B.1c, which plots the resulting labor quality indices. The indices with the Bureau of Labor Statistics (1993) controls are virtually indistinguishable from their uncontrolled counterparts, while the Aaronson & Sullivan (2001) controls appear to exert a modest negative drag on labor quality, on the order of a couple hundredths of a percentage point per year. These results suggest to us that control variables are not of first-order importance in measuring or forecasting labor quality growth.

B.2 Additional results for CPS-ORG and CPS-ASEC

The majority of the results presented in the main text were produced using data from the ACS, but it is possible to conduct the same exercises using both the CPS-ORG and CPS-ASEC. In

⁴⁴We use five race/ethnicity indicators where they used four race indicators—we distinguish Hispanics from non-Hispanic whites, blacks, Asians, and other.

⁴⁵The Bureau of Labor Statistics (1993) specification also includes indicators for whether the individual is in a central city or balance of a SMSA/CBSA or in a rural area, which we omit.

this section we evaluate the robustness of key results from the main text in these alternative data sources. All of the qualitative results hold up, with some minor differences in magnitude.

Figures B.2a and B.2b plot the adjusted R-squared (\bar{R}^2) against the 80th percentile standard error ($\tilde{\sigma}_{80}$) of the same specifications considered in Section 3 and Figure 2 for the CPS-ORG and CPS-ASEC, respectively. As we note in the main text, the large sample size of the ACS is relatively favorable to stratum-based specifications: with the CPS datasets, which are more than an order of magnitude smaller, the standard errors are an order of magnitude higher. In fact, the CPS-ASEC is small enough that for some of the more granular specifications more than 20 percent of the observations are in single-observation cells with infinite standard errors, leaving $\tilde{\sigma}_{80}$ undefined.⁴⁶ However, the tradeoff between fit and precision is still clearly visible, the age and education or age, education and occupation specifications strike a reasonable balance between fit and precision, and the *baseline* and *baseline+occupation* Mincer specifications dominate the stratum-based specifications. In short, the results are entirely consistent with our findings from the ACS.

Figures B.3a and B.3b plot the 2002-2013 labor quality indices presented in Section 4 and Figure 3 for the CPS-ORG and CPS-ASEC, respectively. Once again the results are quite similar to those found in the ACS. The overfit specification (which includes all six variables considered in Section 3) and the underfit specification (which includes all variables except age and education) both show very little labor quality growth over the 2000s. In the case of the CPS-ASEC the overfit and underfit specifications are quite noisy, with implausible jumps and changes in direction.

All of the age and education specifications (with or without occupation) and the *baseline* and *baseline+occupation* Mincer specifications, by contrast, are clustered together and quite similar to the ACS results in Figure 3a, although the CPS-ORG specifications show about 0.5 percent less cumulative labor quality growth by 2013. The CPS-ORG results are also slightly more closely clustered than those for the other two datasets. This may be because hourly

⁴⁶We substitute the highest observed percentile standard error, which is the source of the vertical lines in the upper right region of the figure.

wages are measured directly in the CPS-ORG, whereas in the CPS-ASEC and ACS hourly wages are noisily derived from annual earnings divided by the product of usual weekly hours and weeks worked per year.

One notable difference is that ACS indices show an unexpected decline in labor quality between 2005 and 2006, while the CPS-based indices do not. This appears to be a data artifact induced by the tripling of the ACS sample size in 2006. A similar jump occurs when we calculate labor quality growth between 2000 and 2001 in the ACS (not reported), and there also appears to be a slight tick in the 2012-2013 period for the ASEC, which saw a sample size change in 2013. Why changing sample size can induce these sharp adjustments in labor quality is somewhat unclear and bears more careful investigation.

Figures [B.4a](#) and [B.4b](#) plot the 2002-2013 counterfactual labor quality indices presented in Section 4 and Figure 4 for the CPS-ORG and CPS-ASEC, respectively. The results are qualitatively the same in the CPS datasets as in the ACS, with changes in average hours worked contributing relatively little to labor quality growth while changes in population demographics and demographic-specific EPOP rates both contributing significantly. However, there are two quantitative differences.

First, average hours appear to matter less in the CPS datasets. This is likely due to the fact that the ACS uses a categorical measure weeks worked after 2008, which induces additional noise in the measurement of average hours relative to the other two datasets. This is consistent with the fact that hours only make a significant difference after 2008. The relative unimportance of hours further strengthens our conviction that projecting average hours is not critical to a labor quality forecast and that attempts to do so are likely to introduce as much forecast error as they address.

Second, whereas for the ACS the evolution of EPOP rates induced more labor quality growth than changing demographics (compare the yellow line to the red), in the two CPS datasets the contributions of employment and demographics are almost equal. Additionally, the contribution of EPOP rates, reflected in the yellow lines, is more obviously cyclical for the two CPS datasets — it is virtually flat before and after the Great Recession, with a substantial

step increase during the Great Recession. The ACS, by contrast, shows significant labor quality growth from EPOP rates even before the Great Recession, with the Great Recession simply accelerating the trend.

These observations have important implications for which of the scenarios presented in Section 5 and Table 2 one finds most compelling. If one believes the CPS datasets more accurately reflect the role of the employment margin in driving labor quality growth, then the two plateau scenarios appear most compelling: they suggest that the U.S. experienced an unusual upskilling of employment during the Great Recession that will either persist or unwind, while offering little evidence of a pre-Great Recession upskilling trend in employment. If, on the other hand, one believes that the ACS data more accurately reflects the contribution of employment composition to labor quality then there appears to have been a significant pre-Great Recession structural trend, suggesting that the labor quality growth from employment composition is unlikely to fully unwind and may even continue to drive a significant portion of labor quality growth going forward.

Table 1: Different levels of granularity of classification of variables

Variable	Number of classifications	Groups per classification			
		(I)	(II)	(III)	(IV)
1. Gender	1	2	-	-	-
2. Age	2	9	13	-	-
3. Education	4	4	5	7	16
4. Race/ethnicity	4	2	3	5	8
5. Industry	2	12	50	-	-
6. Occupation	3	10	22	51	-

Note: Total number of possible stratum specifications (including omission of one or more variables) is 1,799. Most granular definition includes 8,486,400 strata.

Table 2: Alternative scenarios for labor quality growth forecast

	EPOP ratio			
	Trend		Level	
	Extrapolated '02-'07 cohort effects (baseline) (I)	Extrapolated '02-'07 trends in EPOP (II)	Revert to pre-crisis EPOPs (III)	Persist at 2013 EPOPs (IV)
1. Extrapolated '02-'07 cohort effects (baseline)	0.36	-	-	-
2. Extrapolate 2007-2013 trends in education	-	0.66	0.26	0.49
3. Revert to pre-crisis educational attainment	-	0.57	0.16	0.42
4. Persist at 2013 educational attainment	-	0.62	0.22	0.47

Note: Reported are average annual growth rates for 2015-2025.

Row scenarios: (2) Uptick in educational attainment since Great Recession reflects a permanent acceleration in educational attainment of those 30 and younger. (3) Uptick since 2008 is fully cyclical and educational attainment reverts to its 2008 level. (4) Uptick in educational attainment since Great Recession reflects a step increase educational attainment of those 30 and younger.

Column scenarios: (II) Pre-Great-Recession ('02-'07) trends in EPOP continue. (III) EPOP ratios in 2025 have reverted to their 2007 levels. (IV) EPOP ratios will remain at their 2013 levels.

More details about these scenarios can be found in section A.3.

Figure 1: Trade off between fraction of wage variation captured and precision of imputed wages.

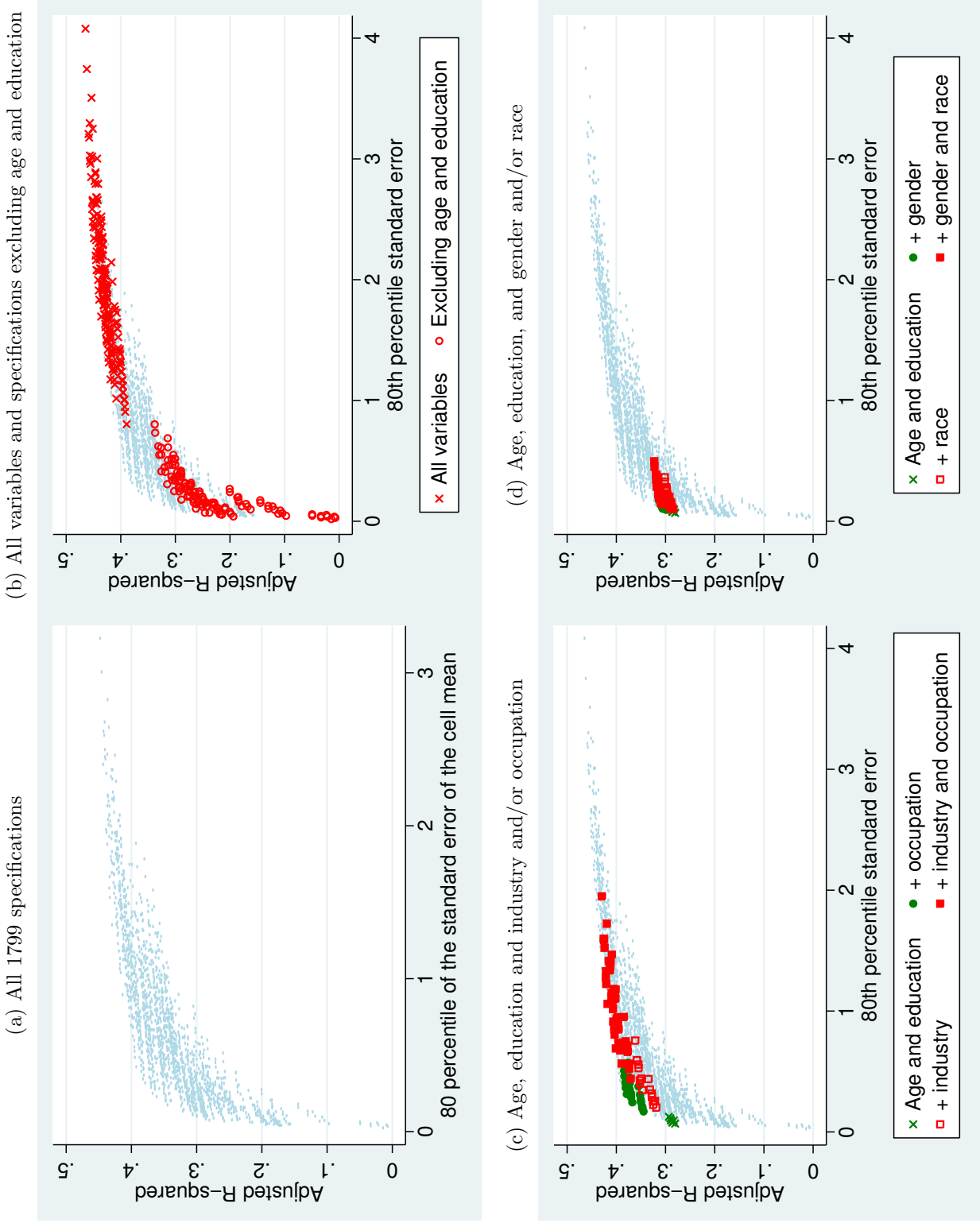


Figure 2: Regression-based fit and precision compared to stratum-based specifications.

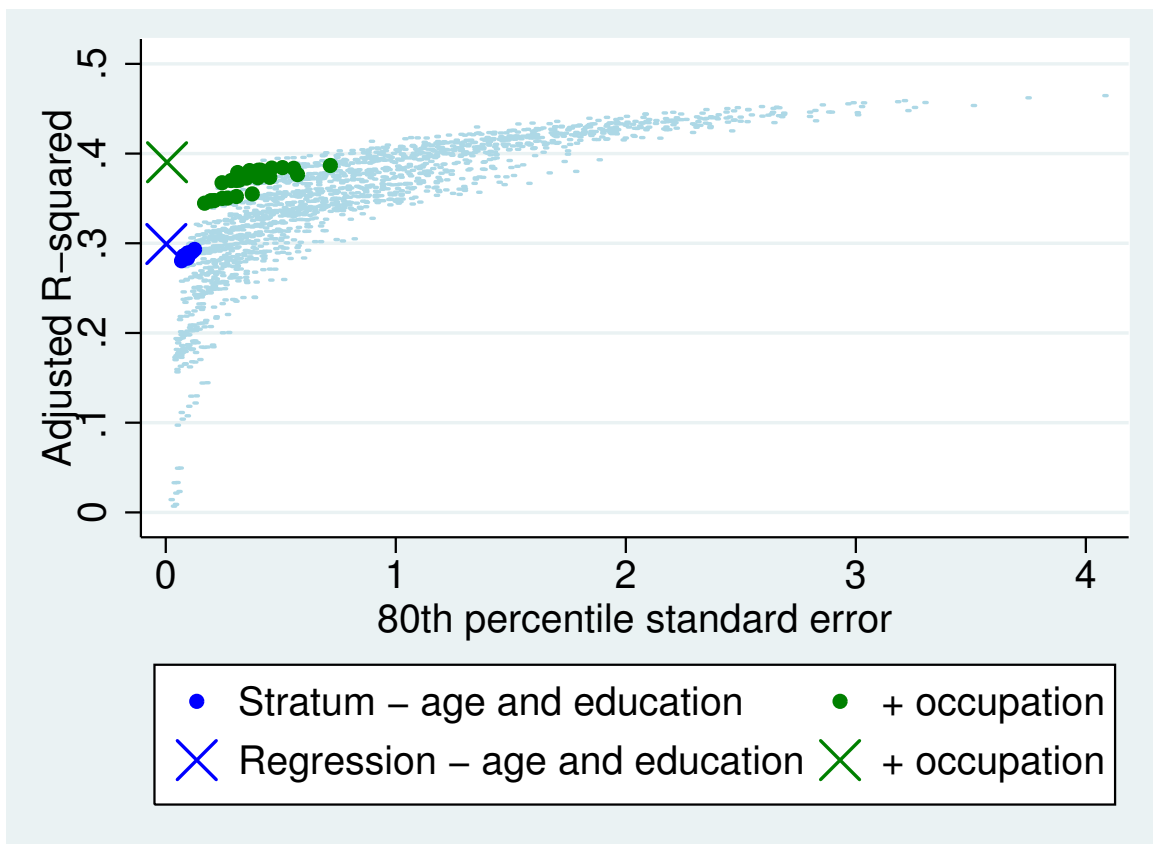
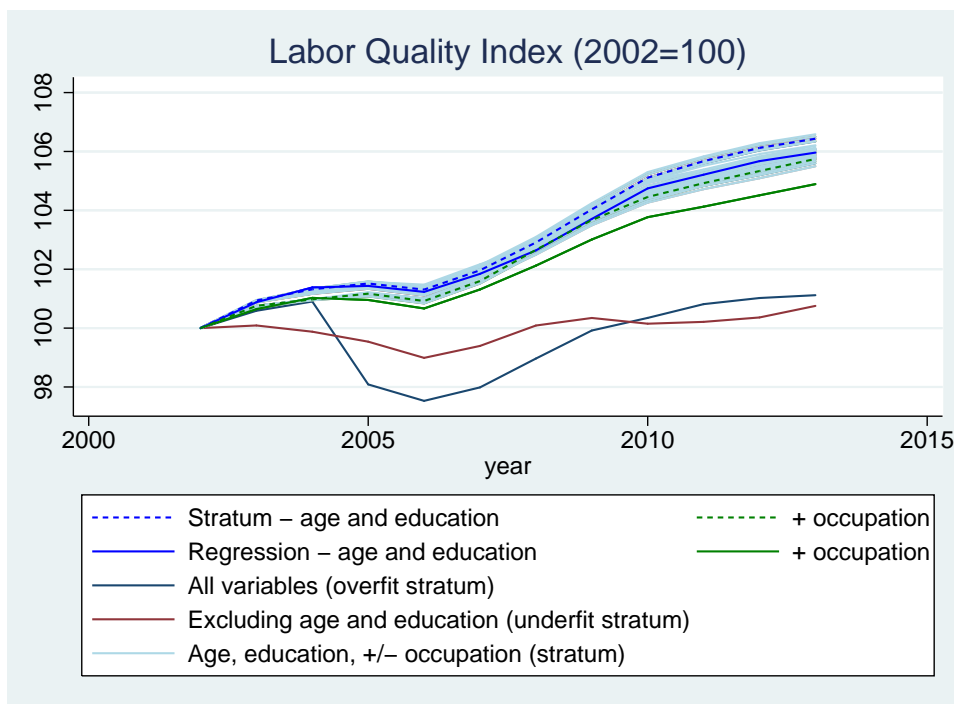


Figure 3: Comparison of results across specifications and datasets: 2002-2013.

(a) Different specifications using ACS data



(b) ACS, CPS-ASEC, and CPS-ORG

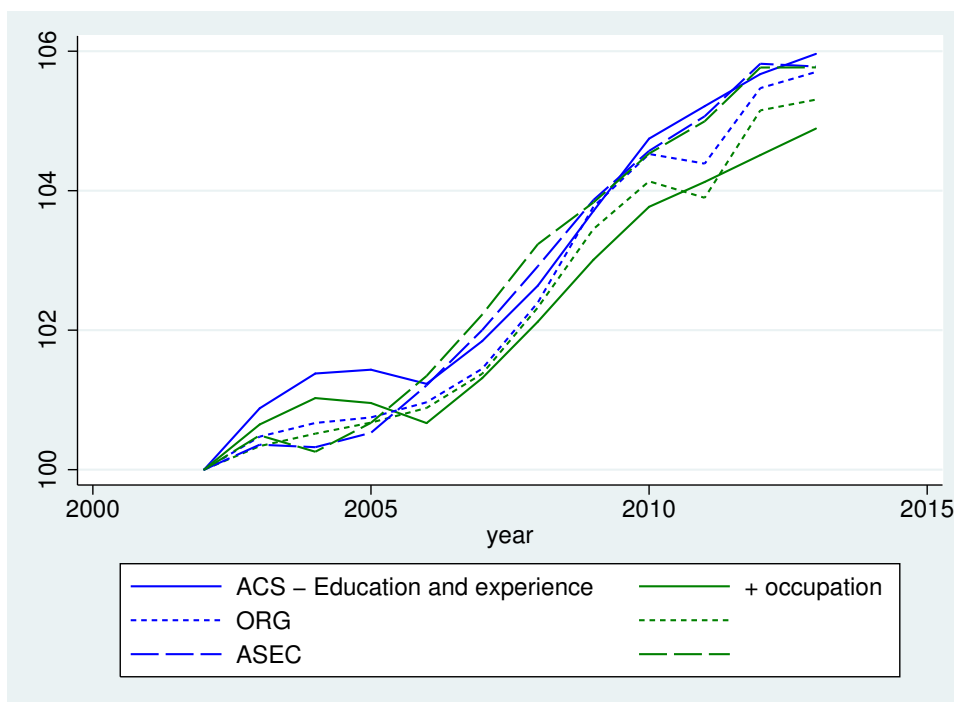


Figure 4: Counterfactual indices for 2002 baseyear hours, employment, and population.

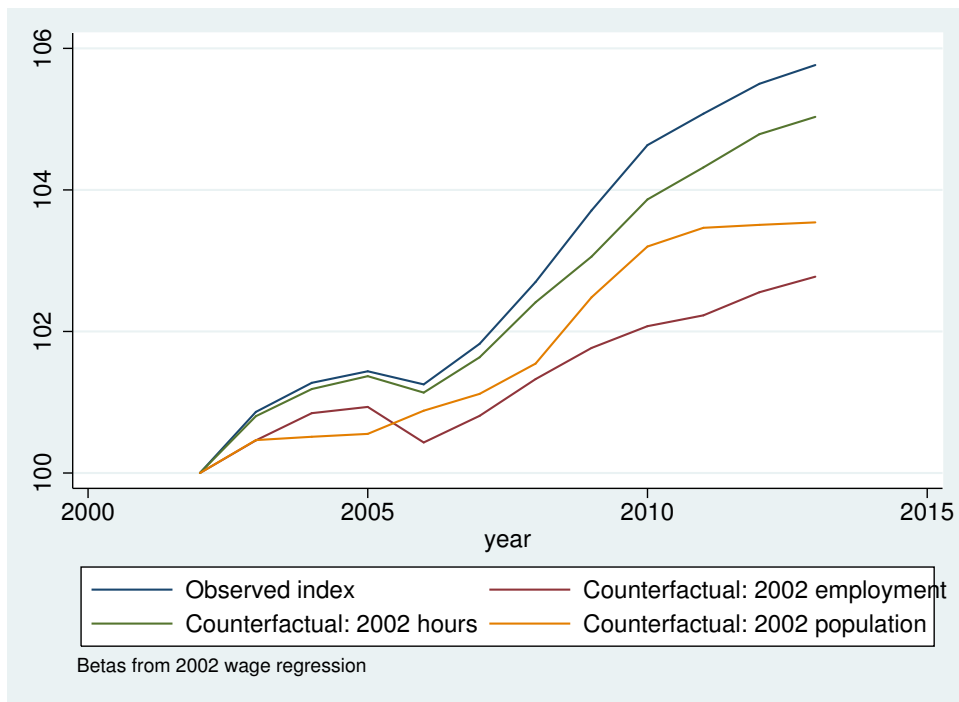
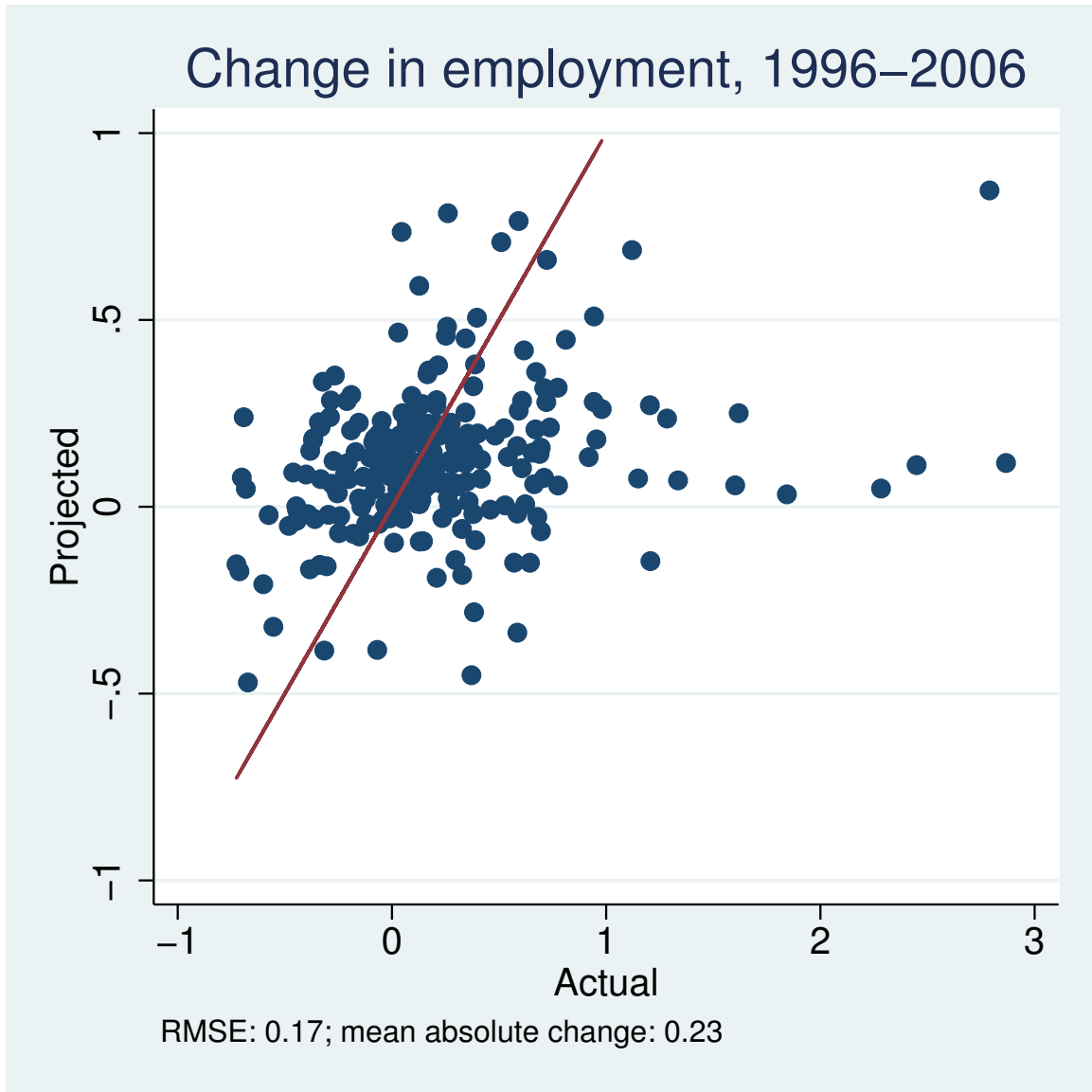


Figure 5: Hours- versus employment-based historical labor quality indices.



Note: Employment-based indices ignore variation in average hours worked, $\eta_{i,t}$, across worker types.

Figure 6: Actual and projected employment growth by occupation (6-digit SOC).

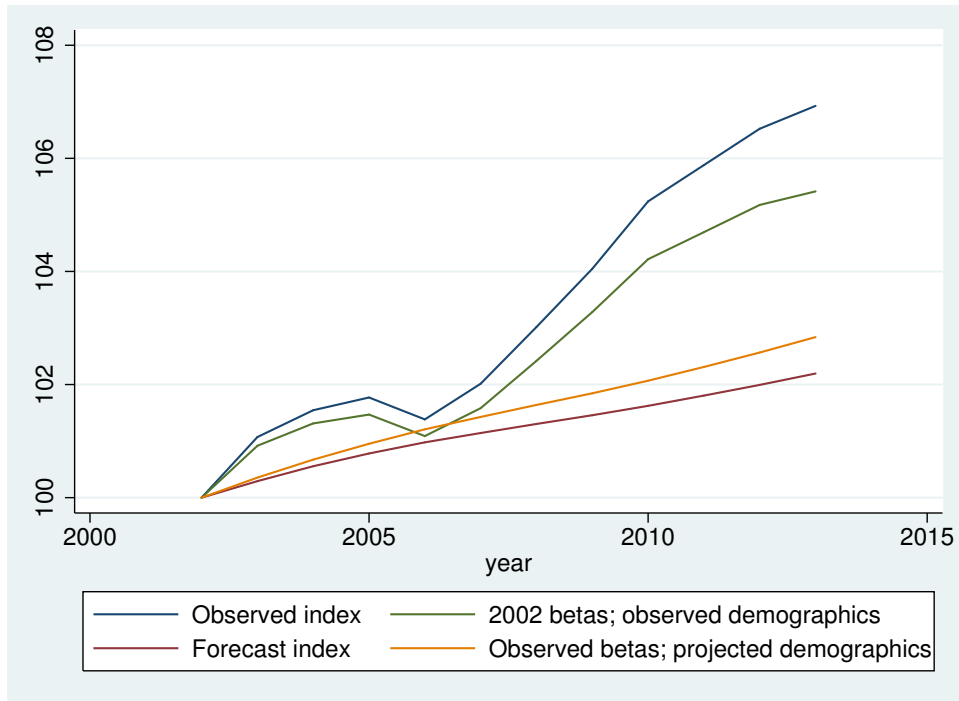


Note: plotted are actual and projected average annual percent changes in employment by 6-digit SOC occupation.

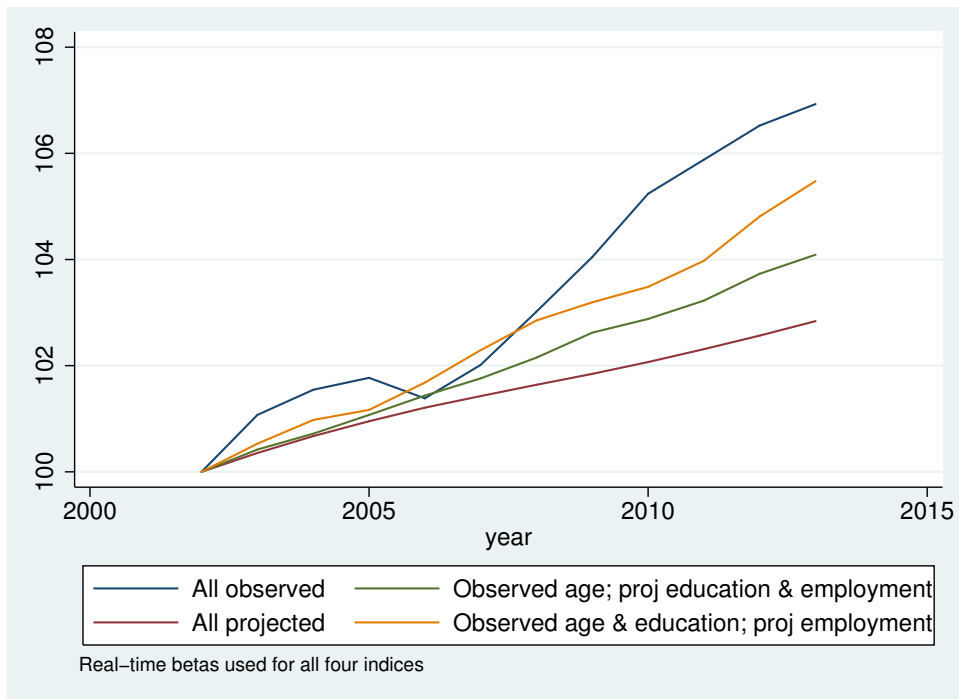
Source: [Wyatt \(2010\)](#).

Figure 7: Decomposition of forecast errors from 2002-2013.

(a) Projected hours distribution of \mathbf{x}_i and projected β_t

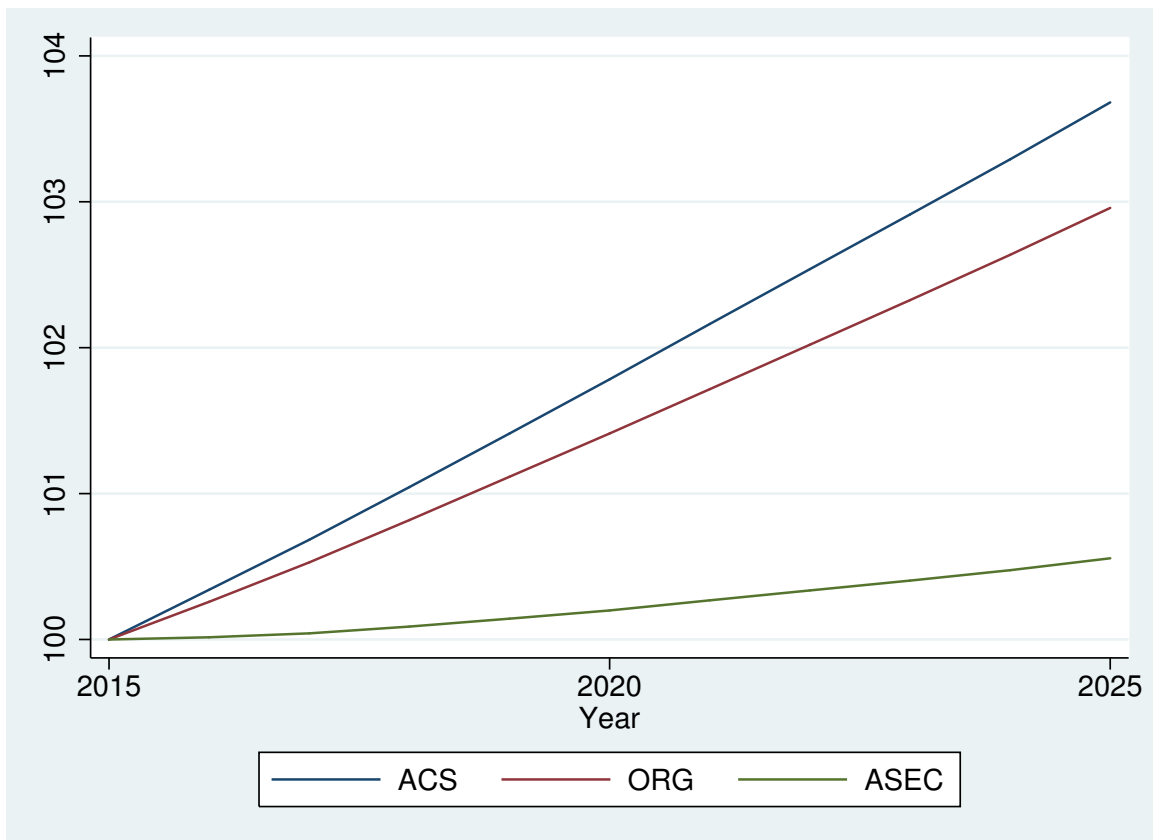


(b) Projected EPOP ratios and education rates for observed β s



Note: EPOP and educational attainment models used to construct historical forecasts based on 1992-1997 CPS-ORG data. *Forecast index* in panel (a) is based on extrapolated cohort effects holding β s constant at their 2002 values. *Observed betas* in panel (a) is the same as *All projected* in panel (b).

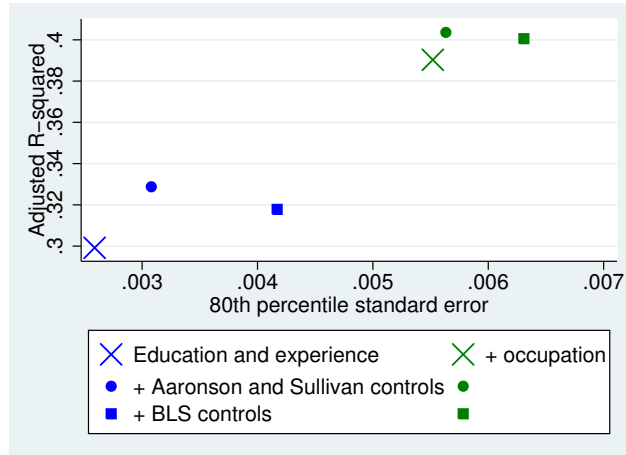
Figure 8: Forecast of labor quality growth for ACS, CPS-ORG, CPS-ASEC: 2015 - 2025.



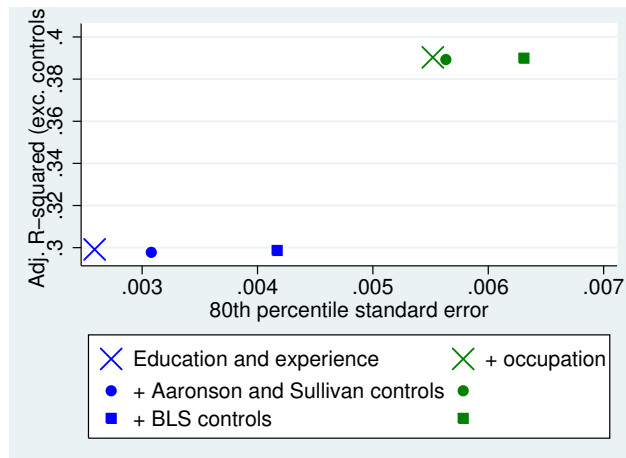
Note: Forecasts based on extrapolated cohort effects from 2002-2007.

Figure B.1: Impact of including controls in Mincer specifications.

(a) Fit of both core and control variables



(b) Fit of the core variables only



(c) Labor quality indices, with and without controls

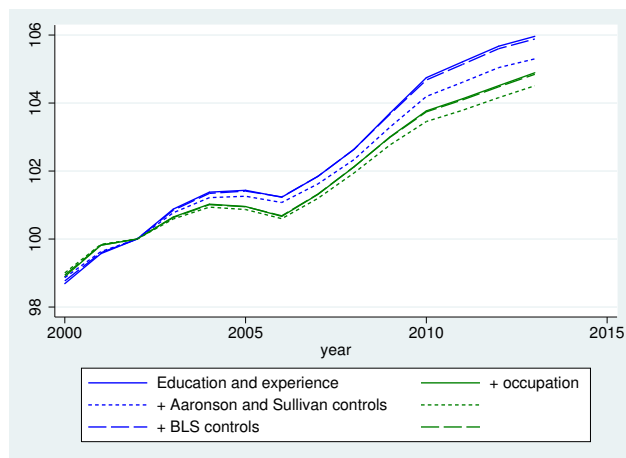
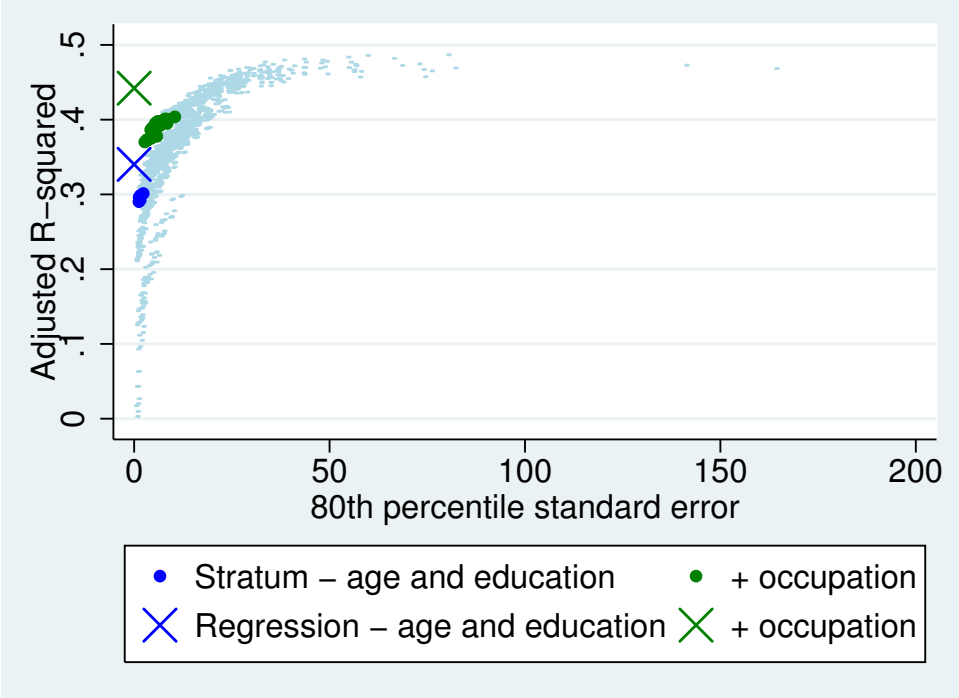


Figure B.2: Regression-based fit and precision compared to stratum-based specifications—CPS datasets.

(a) CPS-ORG



(b) CPS-ASEC

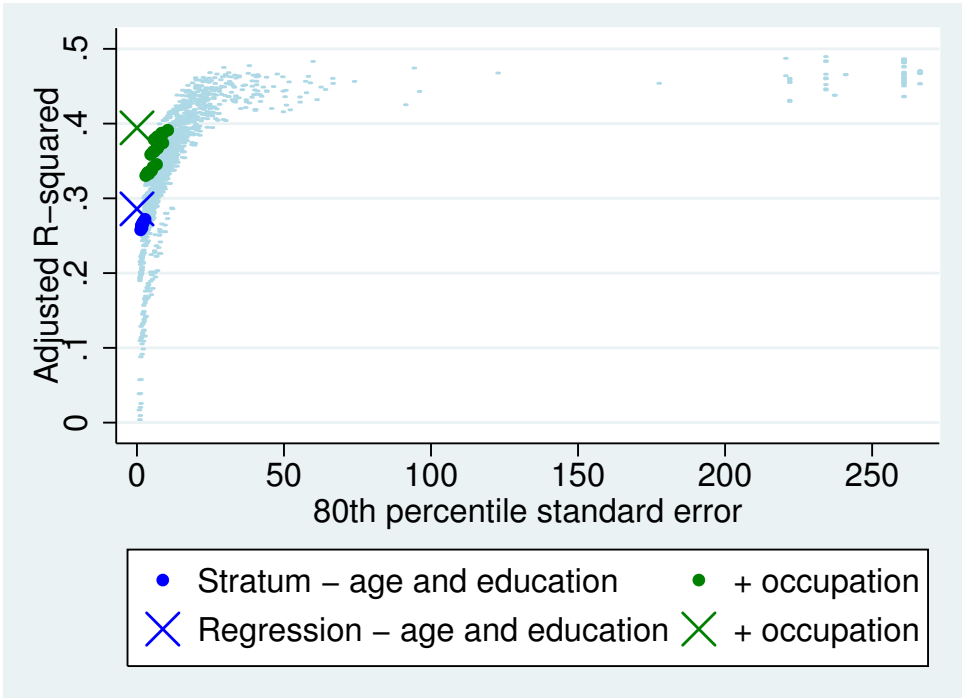
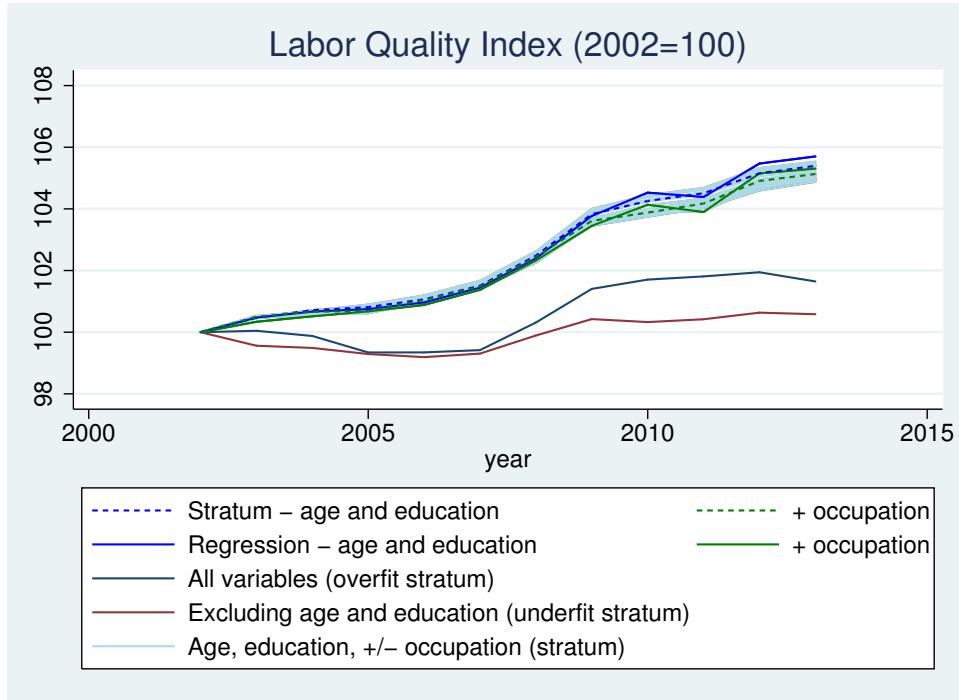


Figure B.3: Comparison of results across specifications: 2002-2013—CPS datasets.

(a) CPS-ORG



(b) CPS-ASEC

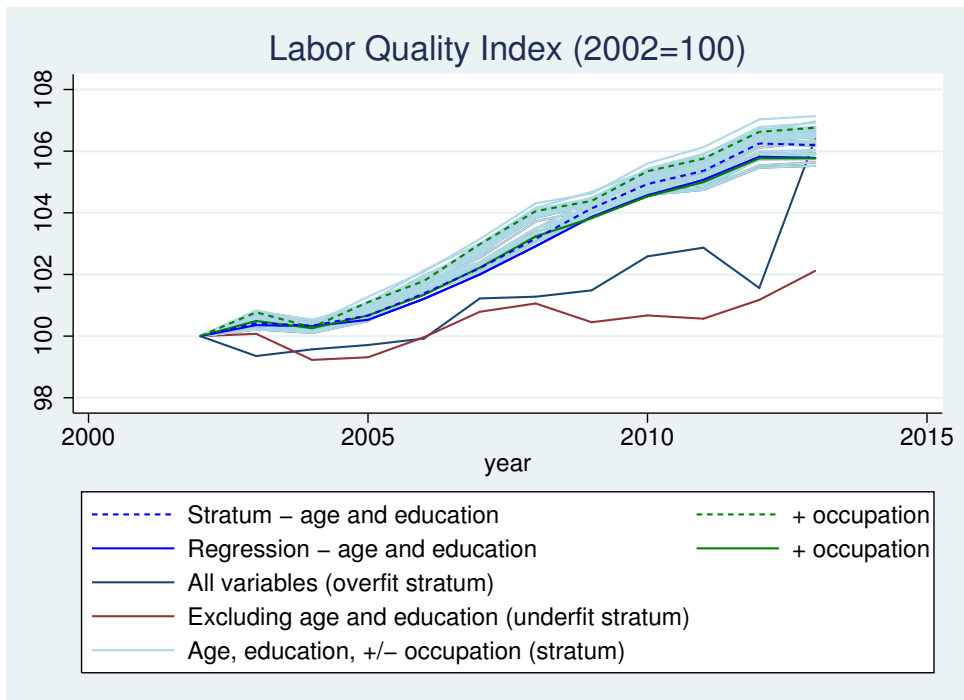
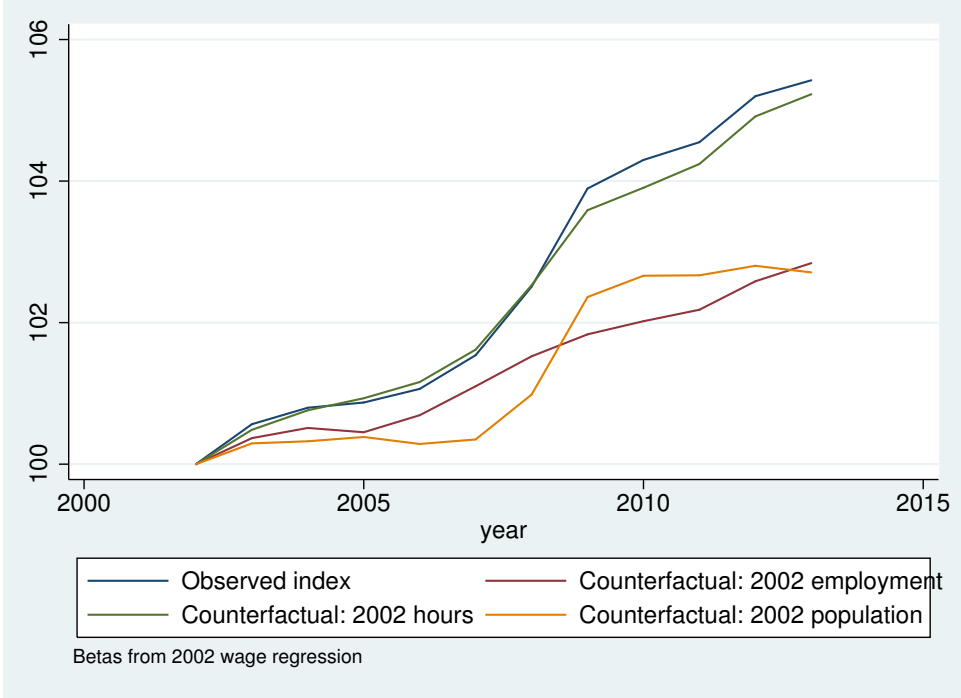


Figure B.4: Counterfactual indices for 2002 baseyear hours, employment, and population—CPS datasets.

(a) CPS-ORG



(b) CPS-ASEC

