Educational Attainment, Unemployment, and Wage Inflation*

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We investigate the impact of rising educational attainment on wage inflation and the equilibrium (non-inflationary) rate of unemployment. Rising educational attainment may reduce wage pressures by shifting the composition of the labor force towards groups with lower equilibrium unemployment rates, or it may increase wage pressures through increased reliance on groups whose wages are relatively responsive to changes in unemployment. A measure of aggregate unemployment adjusted for changes in the age and education structure of the labor force performs well in Phillips curve estimates of the wage inflation process but does not substantially improve the ability to forecast wages or materially alter the estimates of the equilibrium unemployment rate. We also estimate models of wage inflation that are disaggregated by educational attainment and find that college-educated workers face a sharper trade-off between labor market tightness and wage growth than do other groups. We find that forecasts of wage inflation derived from the disaggregated relationships perform better than those from aggregate wage equations.

1. Introduction

The U.S. labor force has undergone significant changes during the past several decades. Compared to 30 years ago, the average worker today is older, more likely to be female, and more educated. A key question for macroeconomic forecasters and policymakers is whether and to what extent these changes have influenced the values and patterns of key aggregate measures of economic performance such as the unemployment rate and wage inflation. While considerable research has documented the importance of changing age structure and the entry of women for labor market outcomes, much less is known about the influence of educational attainment on these variables.

In this paper, we examine how changes in the educational attainment of the U.S. labor force may affect aggregate labor market outcomes and whether these effects are sufficiently large to warrant ongoing attention from researchers. Following past research that examined the effects of changes in age structure on unemployment and wage inflation, we consider two basic methods for incorporating educational attainment into models of wage inflation. Our empirical investigation begins with an adjustment to the aggregate unemployment rate based on rising educational attainment, which appears empirically valid but does not alter predictions of wage inflation obtained from aggre-

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gate Phillips curve estimates over our sample time frame (1982–2006).

We also estimate Phillips curve models of wage inflation that are disaggregated by educational attainment. We consider first whether the unemployment–wage inflation relationship differs by group and second whether accounting for these differences improves model fit and forecast performance. Our results point to important influences of educational attainment on the relationship between unemployment and wage inflation.

2. Background and Literature Review

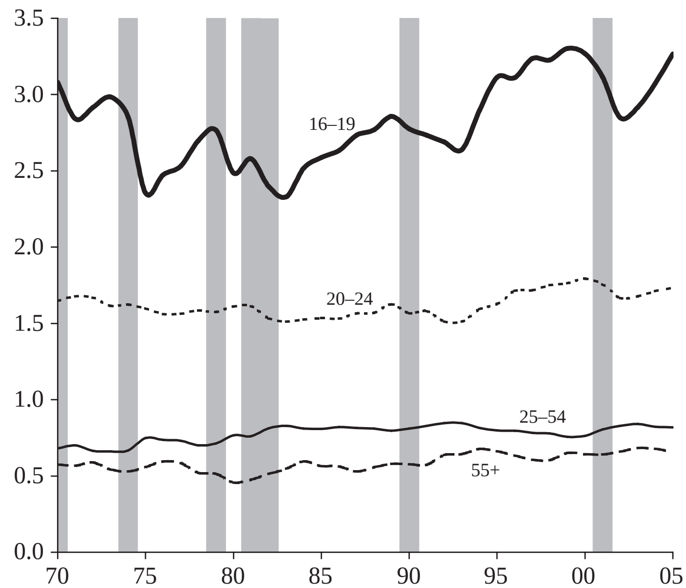
2.1. Demographic Adjustments

The idea that demographic changes can have important influences on aggregate unemployment was first highlighted in work by George Perry (1970). It is now common practice in macroeconomic analysis and modeling to adjust the aggregate unemployment rate as reported by the Bureau of Labor Statistics (BLS) for changes in the age and/or gender composition of the labor force (e.g., Brayton, Roberts, and Williams 1999, Tulip 2004). These adjustments are based on the idea that the amount of slack in the aggregate labor market depends partly on the demographic composition of the labor force, since equilibrium unemployment rates vary systematically across demographic groups.

The clearest and most empirically important example of demographic adjustment pertains to changes in labor force shares across age groups. Unemployment rates vary widely across age groups, with rates for young adults and teenagers typically running about two to three times those for prime-age workers (ages 25 to 54) (see Figure 1). As such, it is likely that shifts in the age structure of the population caused by the maturation of the baby boom generation over the past few decades have substantially influenced the aggregate unemployment rate, causing an increase in the 1960s and 1970s when young baby boomers were flooding the labor market and declines in subsequent decades as the baby boomers eased into their prime working years.

Shimer (1999) provided an extensive empirical analysis of the contribution of changing age structure to U.S. unemployment. He found that the rising share of young workers accounted for an increase in the aggregate unemployment rate of nearly 2 percentage points between 1959 and 1980 and a decline of nearly $1^1/_2$ percentage points in subsequent years. Most of this pattern is attributable to the direct impact of changing labor force shares on overall unemployment, although Shimer also identified important indirect effects of changing labor force shares on relative unemployment rates, which reinforced the direct effects. As

FIGURE 1
UNEMPLOYMENT RATES BY AGE
(RELATIVE TO AGGREGATE), 1970–2005



Note: Gray bars denote NBER recession periods.
Source: U.S. Bureau of Labor Statistics.

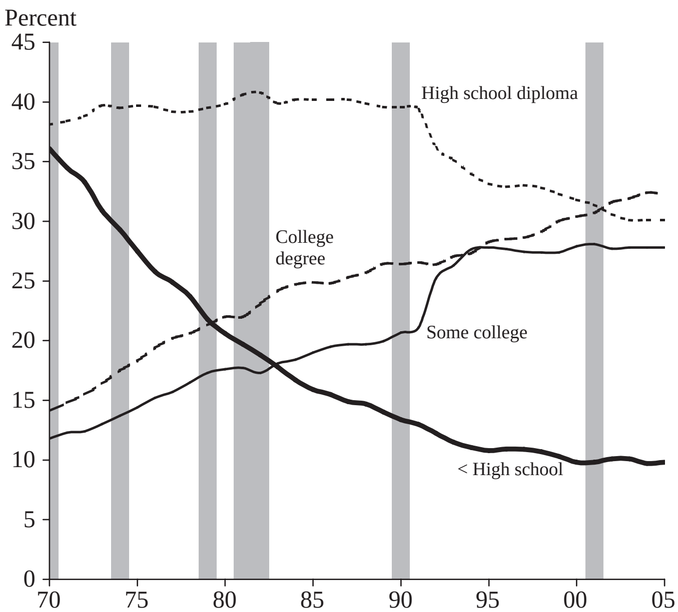
noted by Katz and Krueger (1999), however, the aging of the baby boom was important for explaining declining unemployment in the 1980s but explains little of the additional decline in the observed unemployment rate in the 1990s.

Researchers also have adjusted the aggregate unemployment rate for the rising labor force share of women (e.g., Perry 1970, Gordon 1982). However, as Shimer (1999) shows, unemployment rates for women largely converged with those for men after 1980, so that adjustments for women's changing labor force share have little impact on the aggregate unemployment rate since then. Similar reasoning applies to adjustments for race: although unemployment rates tend to be higher for blacks than for whites in the United States, relative stability in blacks' labor force share implies that adjusting for race has little impact on the aggregate unemployment rate (Shimer 1999).

2.2. Education Adjustments

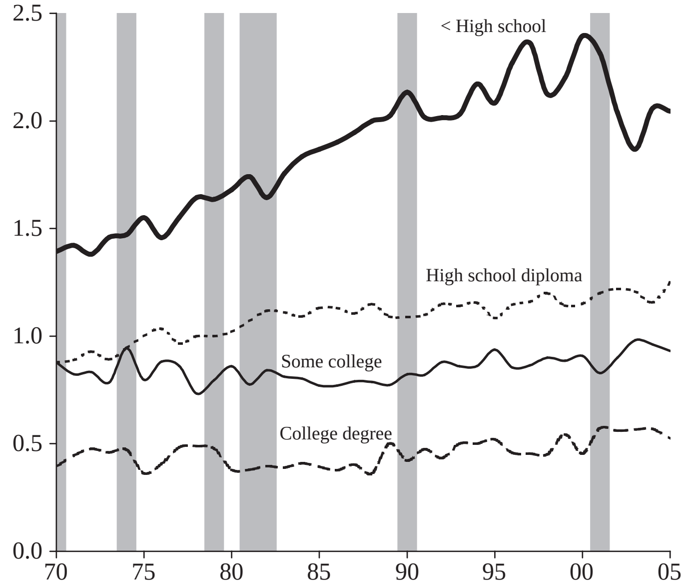
The same reasoning underlying adjustments for changes in labor force composition due to population aging could also apply to the educational composition of the labor force. The educational attainment of the labor force has increased substantially since 1970, primarily reflecting the rising

Figure 2
Labor Force Shares by Educational Attainment, 1970–2005



Note: Gray bars denote NBER recession periods.
Source: U.S. Bureau of Labor Statistics.

Figure 3
Unemployment Rates by Educational Attainment (Relative to Aggregate), 1970–2005



Note: Gray bars denote NBER recession periods.
Source: U.S. Bureau of Labor Statistics.

labor force share of individuals possessing a college degree and the declining share of individuals who lack a high school diploma (Figure 2).[1] It is possible that these trends have been important for the trend in aggregate unemployment, given the relatively low unemployment rate for college-educated individuals and high rate for those lacking a high school diploma (Figure 3). The pattern of unemployment rates by educational attainment has been largely constant since 1978, with the exception of a pronounced upward trend in the relative unemployment rate of individuals lacking a high school diploma through the year 2000 that was partly offset by a decline in their relative unemployment rate after 2000.

Despite the potential importance of rising educational attainment for aggregate unemployment, economists generally have rejected the use of educational adjustments to the aggregate unemployment rate (e.g., Summers 1986, Shimer 1999, Katz and Krueger 1999). These authors have argued that *relative* educational attainment is likely to matter more for unemployment differentials than does *absolute* educational attainment. For example, a rising share of college-educated workers increases job competition among this group and also may increase employers' unfavorable treatment of workers with less education. As such, the unemployment rates of both groups may rise, keeping overall unemployment relatively constant despite the rising labor force share of the group with lower unemployment. Alternatively, an increase in individual productivity associated with higher educational attainment may cause workers' reservation (asking) wages to rise as well, offsetting the direct effect of greater educational attainment on unemployment rates. In any case, the empirical evidence on longer-term trends suggests relatively modest effects of changes in educational attainment on unemployment: rising educational attainment has been observed over long time periods in many countries without any clearly associated reduction in average or equilibrium unemployment rates.

Despite these reservations about the impact of rising educational attainment on equilibrium unemployment, other research has discussed a possible causal link between education and unemployment. In particular, Ashenfelter and Ham (1979) and subsequent research has identified and analyzed systematic behavioral differences across workers with different levels of educational attainment. Most importantly, workers with higher education tend to exhibit

1. Thanks to Terence McMenamin from BLS for providing the data used in these figures. The discontinuous shift in the shares of individuals with high school diplomas and "some college" in 1992 is due to a change in household survey definitions.

greater job stability, which can arise due to the higher level of training embodied in such workers (Mincer 1993, Francesconi et al. 2000). This research suggests that rising educational attainment may be systematically associated with declining unemployment rates over time, thereby supporting the application of educational adjustments to the aggregate unemployment rate.

Ultimately, the validity and importance of education adjustments to the unemployment rate is an empirical issue. To understand this point, it is important first to understand how unemployment rate adjustments for changing labor force composition are formed. In general, they are constructed by calculating the aggregate unemployment rate if labor force shares for demographic or education groups are held to a base-period value. If the actual labor force share of low-unemployment groups rises subsequent to the base year, the adjusted unemployment rate will rise relative to the actual unemployment rate over time, because the adjusted rate is calculated under the counterfactual assumption that the share of low-unemployment groups does not rise.

This procedure implicitly relies on the assumption that group-specific unemployment rates do not respond to changes in group-specific labor force shares (i.e., an "exogeneity" assumption). If this assumption does not hold, the fixed-weight adjustment may overstate or understate changes in the aggregate unemployment rate associated with changing labor force shares per se. Contrary to this exogeneity assumption, past work has found systematic correlations between changes in labor force shares and unemployment rates by demographic group. For example, Shimer (1999) found a positive correlation in general between changes over time in labor force shares and unemployment rates by age group. This finding suggests a "crowding" effect, whereby competition for jobs intensifies within demographic groups that grow relative to the labor force as a whole and diminishes for groups that shrink.[2] Conversely, Shimer also uncovered a negative relationship between changes in labor force shares and unemployment rates by educational group. This suggests that an adjustment based on rising education alone is likely to overstate the direct contribution of rising educational attainment to declining unemployment rates, because the high-unemployment groups (e.g., those lacking a high school diploma) have experienced an increase in their relative unemployment rate.

Even ignoring this past evidence about indirect effects of rising educational attainment on relative unemployment rates, simply adding age and education adjustments together may be misleading due to cohort effects that attenuate or reinforce the separate effects of changing age and education. For example, since rising educational attainment is most pronounced in younger cohorts, its limiting influence on aggregate unemployment may be muted because younger workers tend to have high unemployment rates (Figure 1). By contrast, adjusting the aggregate unemployment rate based on changing shares of groups defined jointly by age and education may be more defensible than summing separate adjustments based on demographics and education. In addition to the elimination of cohort effects within educational attainment groups, a joint adjustment can exploit the higher labor market substitutability between groups defined jointly by age and education than groups defined by age or education alone. Older workers and those possessing college degrees may not be readily replaced by younger workers or those with less education, whereas it may be more possible to substitute young workers with college degrees for older workers without college degrees, for example. Such substitutability across labor market groups will limit the impact of changing labor force shares on relative unemployment rates: if a particular labor market group grows substantially, the crowding effect on that group's unemployment rate will be attenuated by the labor market spillovers to substitutable groups.

These considerations suggest that an unemployment rate series that is jointly adjusted for the changing age composition and educational attainment of the labor force may have substantial empirical validity. This validity depends on the exogeneity assumption noted earlier—i.e., that group-specific unemployment rates do not respond to changes in group-specific labor force shares. The validity of this assumption can be investigated empirically by examining the correlation between changes in group-specific unemployment rates and labor force shares for specific pairs of comparison years; under pure exogeneity, the correlation will be zero. The appendix presents the results of this analysis. Confirming Shimer's results, there is a strong positive correlation between changes in labor force shares and unemployment rates for groups defined by age and in most cases a strong negative correlation for groups defined by education.[3] However, for groups defined jointly by age and education, there is very little correlation between changes in labor force shares and changes in unemployment rates, consistent with a relatively high degree of labor market

2. This pattern forms the basis for Shimer's (1999) finding for a net effect (direct plus indirect) of changing age structure on equilibrium unemployment that exceeds the direct effect alone.

3. We use five age groups for this analysis and for the age-adjusted unemployment rate formed subsequently: 16 to 19, 20 to 24, 25 to 34, 35 to 54, and 55 and older. Our education breakdown uses the same four groups displayed in Figures 2 and 3. For the joint age/education breakdown, we use four age groups and four education groups; see the appendix for further details.

substitutability or supply responsiveness across these groups.[4] These findings suggest that an adjustment to the aggregate unemployment rate that jointly incorporates the changing age and education structure of the labor force provides a gauge of labor market tightness that is relatively consistent over time.

2.3. Adjusted Unemployment Rates

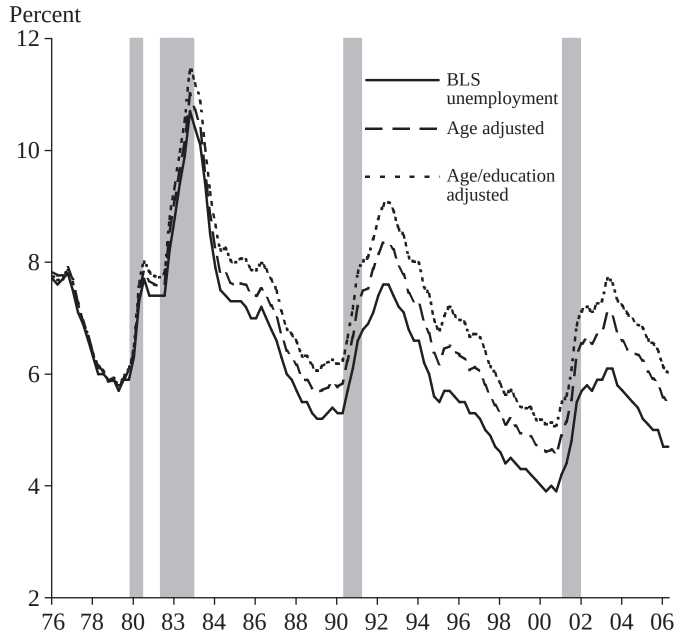
Based on the considerations described in the preceding subsection, we produce two alternative adjusted unemployment rate series for use in aggregate Phillips curve specifications: the first is adjusted for changes in labor force shares for groups defined only by age, and the second is adjusted for changes in labor force shares for groups defined jointly by age and education. These adjusted unemployment series (U^a) are formed according to the following formula:

$$U_t^a \equiv \sum_{i \in I} \omega_{i0} \times u_{it}, \tag{1}$$

where t denotes an arbitrary time period and 0 represents the base period, i represents a particular group within the entire set of groups I, and u_{it} represents the unemployment rate for group i in period t. The weighting term ω_{i0} represents the labor force share of a particular group in the base period (if the weights are set equal to labor force shares at time t, this formula produces the observed unemployment rate). Thus, the adjusted unemployment rate represents the unemployment rate if the labor force shares of a complete set of age or age and education groups had remained fixed at their base-year values.[5]

For purposes of systematic comparison and the empirical analysis in Section 3, we also use the official unemployment rate from BLS. Figure 4 displays the three aggregate unemployment rate series that we use for the period 1976 through the first quarter of 2006; in this figure, the adjusted series are normalized to equal the official series in 1978.[6] The figure shows that, as expected, the gap between the actual aggregate unemployment rate and the rate adjusted jointly for changing age and education has increased, although the pace of increase has moderated over time; the gap was 0.9 percentage point in 1989 and rose to 1.4 percentage points in 2006. Growth in the gap between the actual rate and the rate adjusted for age also slowed over time, rising from 0.5 percentage point in 1989 to 0.8 percentage point in 2006.

FIGURE 4
UNEMPLOYMENT RATES, 1976:Q1–2006:Q2



Note: Gray bars denote NBER recession periods.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

2.4. Disaggregated Estimates

While adjustments for changes in educational attainment matter substantially for measurement of the aggregate unemployment rate, such adjustments may not fully capture the labor market changes associated with rising education levels. In particular, the wage inflation process embodied in the Phillips curve may differ across worker groups defined by characteristics such as age or education; the impact of such differences will not be captured by an aggregate unemployment rate variable that is adjusted for changing educational attainment.

4. This is not an artifact of the offsetting positive and negative correlations evident for groups defined respectively by age and education; see the appendix.

5. The approach to demographically adjusted unemployment series developed by Perry (1970) and also used by Gordon (1982) is similar to the one described here but weights groups based on their total annual earnings rather than their labor force shares. Shimer (1999) showed that an age adjustment based on labor force shares is consistent with a model in which younger workers experience more unemployment due to lower job attachment, which is similar to the arguments made here about unemployment differences by educational status. Perry's earnings-based weights are more consistent with a model of wage inflation (based on the "wage push" created by shortages of workers earning different wage rates) rather than equilibrium unemployment.

6. Shimer (1999) identified 1978 as the year in which the age structure of the U.S. population was the most conducive to high unemployment rates of any year during the post-World War II period.

Baily and Tobin (1977) examined the possibility of different wage inflation processes with specific reference to teenagers vs. adults, analyzing the conditions under which policy interventions such as wage subsidies targeted at teenagers can exploit the differences in Phillips curve slopes across the two groups and lower the equilibrium unemployment rate. Their analysis relies on the generally accepted notion that teenagers and adults largely work in separate (segmented) labor markets—i.e., that in general they do not compete for the same jobs. Similar reasoning applies to groups defined by education, perhaps with greater force: a specified minimum level of educational attainment is a key requirement for many jobs, especially for college graduates.

Francesconi et al. (2000) provided a theoretical framework and empirical analysis of segmented labor markets across educational groups based on systematic differences in training costs and turnover across these groups. Their results imply that groups defined by educational attainment will face different Phillips curve relationships, implying lower equilibrium unemployment rates for more-educated groups.

The analysis of Francesconi et al. provides some support for the hypothesis that the equilibrium unemployment rate declines as educational attainment rises. By contrast, some authors have emphasized the role of technological change in recent decades, which may interact with rising educational attainment to increase overall unemployment. In particular, to the extent that the rising share of highly educated workers reflects rising skill demand associated with technological change, the flip side is stagnant demand for low-skilled workers, which may increase their unemployment rates and the aggregate equilibrium rate as well (Juhn, Murphy, and Topel 1991, Blanchard and Katz 1997, Trehan 2003).

These opposing views of the relationship between rising educational attainment and equilibrium unemployment call for an empirical assessment of the relationship between aggregate wage inflation and labor markets segmented by educational status. To this end, in addition to our aggregate Phillips curve equations, in Section 4 we estimate separate (disaggregated) Phillips curve equations by educational attainment groups and assess whether they provide improved forecasts of wage inflation compared with aggregate equations.

3. Phillips Curve Estimates and the Natural Rate

We now turn to estimates of the aggregate Phillips curve relationship between wage inflation and unemployment. For estimation purposes, we rely on a standard "wage-wage-price" Phillips curve (see, e.g., Fuhrer 1995, Gordon 1998, and Staiger, Stock, and Watson 2001), which posits that wage inflation is a function of past wage inflation and price inflation as well as a measure of labor market tightness (the unemployment rate) and a limited set of other control variables. Our intent is not to identify and estimate the "best" forecasting model for wage inflation, but rather to assess the role of incorporating measures of educational attainment in a standard Phillips curve specification. As such, we focus on a general model that we found fits the data well, without claiming that it fits better than all available alternatives. We also performed some robustness checks based on another broad model, as described below.

For our aggregate Phillips curve analysis, we regress the quarterly percentage change in wages (expressed at an annual rate) on lagged wage changes, lagged price changes, lagged values of trend productivity growth, a measure of employer contributions to social security taxes, and a measure of the unemployment rate.[7] Based on past conventions and our own specification checks, these equations include eight lags of the dependent variable with the coefficients on lags five through eight set to be equal, one lag of the sum of the four-quarter change in core personal consumption expenditure (PCE) prices and a measure of trend productivity growth, with a unity constraint imposed on the sum of the coefficients on lagged wage inflation and productivity-adjusted price inflation, a measure of employment insurance taxes, and an unemployment rate variable. We also constrained the sum of the coefficients on the lagged dependent variables to equal one; this follows standard convention and is consistent with a relatively stable rate of wage growth relative to price inflation and productivity growth over our sample time frame.

We estimate our models for two dependent variables, one measuring total compensation and the other wage compensation. Both measures come from the employment cost index (ECI) published by BLS. The total ECI series measures total compensation for private sector workers; this series includes the value of employee benefits such as health insurance but does not include nonstandard compensation components such as stock options and bonuses. The wage ECI series excludes benefits. The ECI series are "fixed weight" indices that eliminate compensation changes due to shifts in the job mix over time.[8]

7. Relative to past work such as Fuhrer (1995) and Gordon (1998), we do not include measures of supply shocks such as energy and import prices, because these are not substantively important over our sample time frame.

8. We also performed the estimation on two other BLS compensation series: compensation per hour (CPH) and average hourly earnings (AHE). The results were qualitatively and quantitatively similar to those reported below for the ECI series. Ritter (1996) provides a useful discussion of

We measure trend productivity growth using a 40-quarter moving average of quarterly productivity growth.[9] For price inflation, we use a "core" measure—the PCE deflator excluding food and energy—to minimize the influence of short-run volatility in overall price inflation that introduces noise relative to the underlying inflation trend. The sample period is 1982:Q2 through 2006:Q2; this start date is necessitated by the availability of the ECI beginning in the first quarter of 1980 and the presence of eight lags in our estimating equations.[10]

For each wage variable, we estimated three separate equations using the three different unemployment rates described in Section 2.3: the official BLS unemployment rate, the age-adjusted unemployment rate, and the unemployment rate jointly adjusted for age and education.[11] A comparison of results based on these three variables indicates the incremental impact of adjusting for changes in age structure and changes in educational attainment. The equilibrium or "non-accelerating (wage) inflation" rate of unemployment (NAIRU) is the rate of unemployment that exerts neither downward nor upward pressure on wage inflation, given expectations of price inflation. In line with the standard computation, in our framework the estimated NAIRU is equal to the negative ratio of the constant term to the coefficient on the unemployment rate (see, e.g., Staiger, Stock, and Watson 1997). Below, we transform the estimated NAIRUs based on models using each of the adjusted unemployment rates into the terms of the observed unemployment rate. As such, we estimate a constant NAIRU in models that include the official unemployment rate but a NAIRU that varies based on the gap between the adjusted and observed unemployment rate for models using the adjusted variables.

The estimates based on this equation are displayed in Table 1. The results indicate virtually no difference in fit across the three equations and no improvement from incorporating adjustments for educational attainment. The coefficient on the unemployment rate is around −0.5 to −0.75 and precisely estimated in general, achieving statistical significance at better than the 1 percent level in almost all cases. The root mean squared error (RMSE) of the residuals is lowest when the official unemployment rate is used, indicating that including this variable makes the equation fit best. The difference in fit is quite small, however. To examine the issue of relative fit in more detail, Figures 5 and 6 display residual plots (actual minus predicted rates of wage inflation) for the three unemployment rates for the ECI total and ECI wage series.[12] Consistent with the fit statistics in the table, the residual plots for the models adjusted for demographics and education generally track each other. The specification including adjustments for educational attainment fits better in the mid-1990s, a period when many models were overpredicting wage inflation. However, this advantage has unwound over the past several years, during which both models generally overpredict wage inflation.

Table 1
Phillips curve Models by Alternative Measures of Unemployment, 1982:Q2–2006:Q2

	Employment cost index, total compensation	Employment cost index, wages
Official BLS unemployment		
rate coefficient	−0.55 (0.12)	−0.76 (0.14)
RMSE	0.861	0.818
Mean NAIRU	5.32	5.52
Age-adjusted unemployment		
rate coefficient	−0.55 (0.13)	−0.72 (0.15)
RMSE	0.868	0.832
Mean NAIRU	5.38	5.56
Age/education-adjusted unemployment		
rate coefficient	−0.51 (0.13)	−0.63 (0.14)
RMSE	0.876	0.849
Mean NAIRU	5.41	5.58

Note: See text for complete specification. Coefficient standard errors are in parentheses. Each NAIRU is expressed in terms of the official BLS unemployment rate.

Despite the minimal difference in fit across the equations using different unemployment rates, the NAIRUs implied by the official and adjusted series are noticeably different. Notably, the NAIRU obtained from the equations including adjustments for educational attainment fluctuate more over time than the one based on the simple demographic adjustment. The time-series patterns in the NAIRUs are displayed in Figures 7 and 8, which parallel

the differences between these series; for additional information, see the technical materials that accompany the relevant BLS data releases.

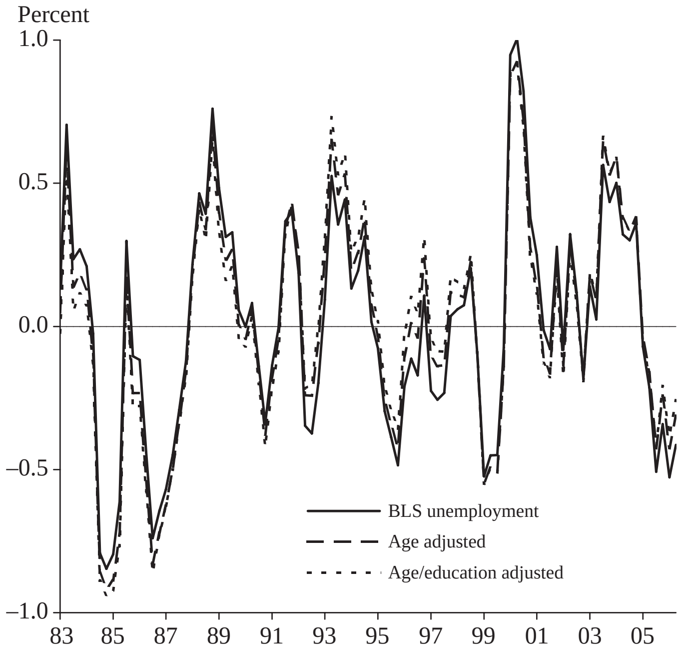
9. We use the moving average specification rather than sample mean productivity because past results suggest that accounting for the increase in trend productivity growth in the 1990s is important for the stability of estimated Phillips curves in samples that include this period (e.g., Staiger, Stock, and Watson 2001).

10. We performed similar analyses over the longer sample periods enabled by the AHE and CPH variables, without any substantive change in our results.

11. We use the contemporaneous value of the unemployment rate, which provides a better fit than any combination of lagged values in our primary specification.

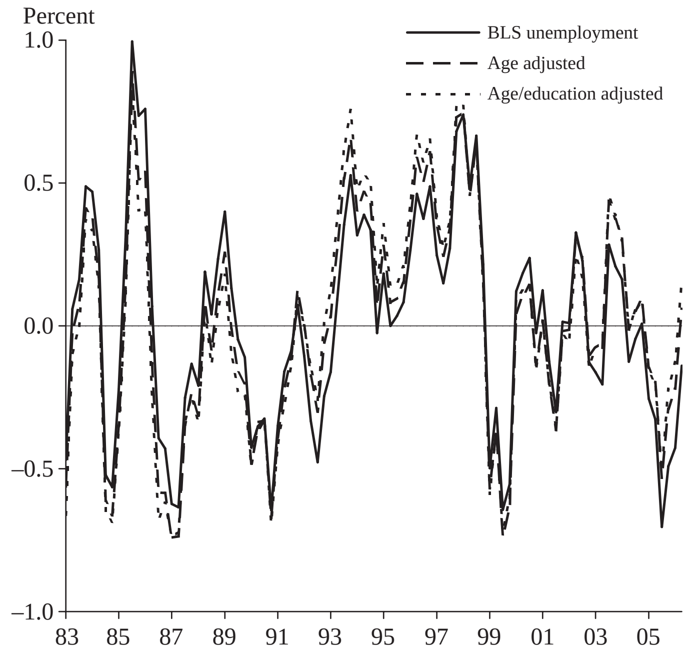
12. There is weak evidence of upward trends in the residuals in these models, which is slightly more pronounced in the models that use the unemployment rate adjusted for changing age and education. However, this tendency towards trended residuals is not a specific feature of that variable; see the discussion of our alternative specification below.

FIGURE 5
RESIDUALS, ECI TOTAL MODEL, 1983:Q1–2006:Q2



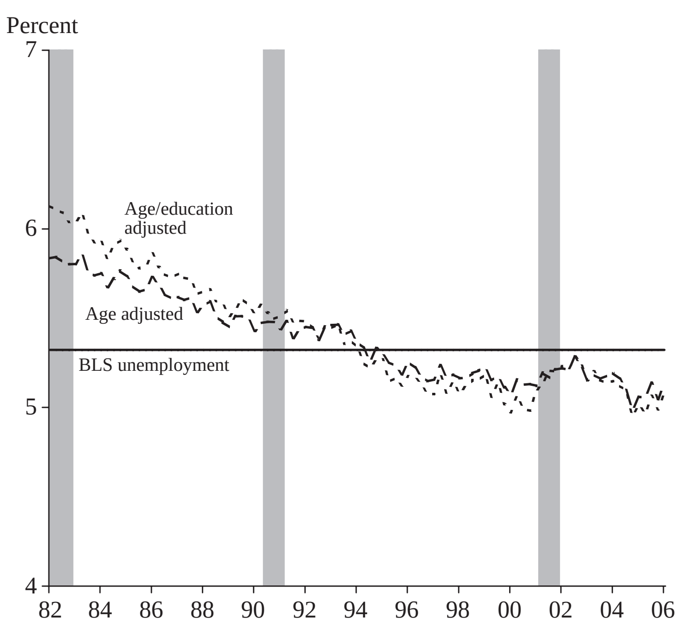
Note: Residuals are expressed as four-quarter moving averages.

FIGURE 6
RESIDUALS, ECI WAGE MODEL, 1983:Q1–2006:Q2



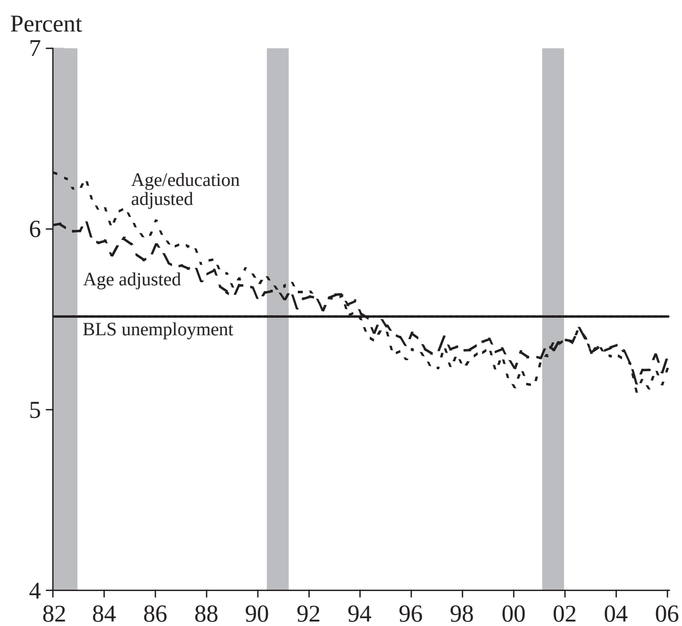
Note: Residuals are expressed as four-quarter moving averages.

FIGURE 7
NAIRUS, ECI TOTAL MODEL, 1982:Q1–2006:Q2



Note: Gray bars indicate NBER recession periods.

FIGURE 8
NAIRUS, ECI WAGE MODEL, 1982:Q1–2006:Q2



Note: Gray bars indicate NBER recession periods.

the residual plots in Figures 5 and 6. Although the equations are specified to yield time-invariant NAIRUs, the NAIRUs in the figures are expressed in terms of the observed unemployment rate and as such reflect the movement over time in the gaps between the adjusted and actual unemployment rates. The NAIRUs obtained from equations using the official unemployment rate series vary from 5.3 to 5.5 percent. By contrast, the NAIRU series obtained using the adjusted unemployment rates generally drop from just over 6 percent at the start of our sample time frame down to about 5 to $5^1/_4$ percent at the end. These NAIRUs implied by the adjusted unemployment rates are generally within or near the range of commonly used estimates. For example, in its economic analyses and projections, the U.S. Congressional Budget Office (CBO) has assumed that the NAIRU has equaled 5.0 percent since the third quarter of 2000, down from a peak of about $6^1/_4$ percent in the late 1970s (U.S. CBO 2007). The NAIRU series implied by the unemployment series adjusted for age and that adjusted jointly for age and education differ little, suggesting that accounting for education makes little difference for estimates of the relationship between labor market tightness and wage inflation.

The NAIRU obtained from the model with educational attainment exhibits greater variability due to the cyclical sensitivity of labor force shares for groups defined by age and educational attainment. Further investigation of this variability shows that in economic downturns the secular decline in the labor force share of less-educated workers accelerates for some demographic groups, as they disproportionately exit the labor force. In economic expansions, the pattern reverses, offsetting the secular decline and resulting in little change in labor force shares for these groups. In the late 1990s, this general pattern changed, as the entry of less-educated workers picked up substantially. The pickup likely reflects the unusually tight labor market conditions of those years and institutional factors such as welfare reform, elimination of Supplemental Security Income for immigrants, and changes in eligibility rules for disability benefits. These developments reduced the gap between the unemployment rate adjusted for educational attainment and the unemployment rate adjusted for demographics alone. More generally, the relatively low level of the NAIRU incorporating educational attainment explains why this model does a slightly better job predicting wage inflation in the mid-1990s than the other unemployment series.

The substantially lower NAIRUs obtained when using the adjusted unemployment rates versus the observed rate may seem surprising. For example, by early 2006 the NAIRUs implied by the adjusted rates were about four-tenths of a point lower than the NAIRU obtained using the official rate, suggesting that the rate of wage growth implied by the models relying on the adjusted unemployment rates should be lower than that obtained using the official rate. The residual plots in Figures 5 and 6 show that this is indeed the case, with generally higher residual values evident in recent years for the models using the adjusted series. However, the difference in residuals is quite small in general, because the estimated coefficients on the unemployment rate translate into variation in the rate of wage inflation that is smaller than the gap between the observed unemployment rate and the NAIRU. In early 2006, the four-tenths of a point spread in the NAIRUs implies a spread of about two-tenths of a point in the predicted rates of wage growth, which is approximately the spread evident in the residuals.

For comparison, we also estimated these models using the alternative specification of Staiger, Stock, and Watson (2001; SSW). This specification has a less-complicated lag structure (four lags of the dependent variable) and is more restrictive with respect to the relationship between growth in wages, productivity, and prices than our primary model (i.e., it is estimated in terms of growth in unit labor costs). As in our primary model, we imposed the restriction that the lags on the dependent variable sum to one. Relative to the results discussed above, the residuals show less tendency to trend in the SSW specification, and the residual trend is especially limited for the unemployment series that is adjusted jointly for age and education. This model fit best with two lags of the unemployment rate replacing the contemporaneous values used in our primary specification. However, the overall fit generally is poorer in this alternative specification than in our primary specification, except for the runs that use compensation per hour as the dependent variable. Beyond these differences in fit, our primary finding that adjusting for education makes little difference for predicted wage inflation is maintained. However, this alternative specification produces noticeably lower NAIRUs than our primary specification, with implied NAIRUs based on the adjusted series generally in the range of 4.5 to 5.0 percent in recent years.

Overall, the results from our aggregate analyses suggest that the inclusion of an educational adjustment does not improve forecasts of wage inflation obtained from aggregate Phillips curve estimates. Indeed, incorporating education causes the fit to deteriorate slightly, and the NAIRU implied by the series adjusted jointly for age and education differs little from that implied by the series adjusted only for age.

4. Disaggregated Estimates

As discussed in Section 2.4, the influence of rising educational attainment on wage inflation may not be fully captured by an adjustment to the aggregate unemployment rate, due to segmentation across labor markets and corresponding differences in the wage inflation process across groups defined by educational attainment. Such differences and their implication for forecasts of wage inflation can be more fully investigated in a disaggregated framework. To explore further the information provided by the labor market outcomes for different education groups, we turn to Phillips curve models that are disaggregated by educational attainment.

Our specification for the disaggregated analysis is a simplified version of our aggregate Phillips curve specification described in the previous section. For each of the four educational attainment groups identified earlier, we estimate separate wage-price Phillips curve equations based on annual data.[13] In these models, annual wage inflation for each group is regressed on overall price inflation (current and lagged) and the group-specific unemployment rate. The wage inflation term is defined as the annual percentage change in average hourly earnings; these series are obtained from the Employment Policy Institute (EPI) and are based on their tabulations from the monthly files from the Current Population Survey (CPS).[14] Price inflation is defined as the 12-month percent change in the core consumer price index for all urban consumers (CPI-U), which excludes food and energy prices. Our specification checks indicate that the best fit is obtained when we include the contemporaneous value of price inflation and its first lag. Unemployment rates and labor force shares by educational attainment are tabulated from the monthly CPS files. Our sample period is 1983–2006; values for 2006 are based on the average of the first two quarters.

Our disaggregated analysis involves two parts. First, for each group, we estimate the simplified model and test for the equality of the coefficients on the unemployment rate across equations. The equations are estimated using the technique of "seemingly unrelated regression" (SUR), which accounts for arbitrary correlation across the error terms in the separate group equations (Zellner 1962). In the second part of our examination, we aggregate the results (weighted by labor force shares) and compare them with the estimates from an aggregate model using the same data and specification.

Consistent with theories of labor market segmentation by educational attainment, the results of our disaggregated analysis indicate sizeable differences in the estimated slope of the Phillips curves by educational attainment (Table 2, top panel, four-group model). The sensitivity of wages to the group-specific unemployment rate is higher for individuals at the college degree level than for other workers. The results of the chi-squared test displayed in the table show that these differences in the slopes of the Phillips curves across education groups are significant at about the 5-percent level, suggesting that the aggregate Phillips curve model is misspecified and that the disaggregated specification provides added information for predicting aggregate wage growth. Our robustness checks include estimating a two-group model that combines individuals possessing less than a four-year college degree into a single group (see the bottom panel of Table 2)—to focus on demand shifts toward college-educated workers over our sample frame (see e.g. Lemieux 2006)—and using wage shares in place of labor force shares to aggregate the results (see the standard error of the regression (SER) for wage weights listed in both panels of Table 2). Neither of these changes makes a qualitative difference to our findings. However, the chi-squared test does not reject equality of the unemployment rate coefficients at conventional significance levels in the two-group model, suggesting that the four-group model is preferred.

Turning to comparisons of the aggregate and the fully disaggregated models, Table 2 and Figure 9 provide quantitative and visual evidence on the added information obtained through disaggregation. The last row of the table (both panels) reports the SER for the aggregate and disaggregated models. The SER values are noticeably lower for the four-group disaggregation (using either labor force weights or wage weights for aggregation) than for the aggregate equation, indicating that the disaggregated equations provide more precise in-sample forecasts of overall wage inflation. Figure 9 plots the time series of the residuals in the two models. While these plots generally track each other, the superior fit of the disaggregated model is reflected in the more limited residual spikes in the early and late 1990s. This pattern suggests that the disaggregated approach does a better job of capturing increases in the rate of wage inflation when the labor market tightens (i.e., the disaggregated model shows less tendency to underpredict the pace of wage growth during these periods).

Finally, as in the aggregate analysis, it is useful to consider how accounting for education affects estimates of the NAIRU. Consistent with the notion that there are barriers across labor markets defined by educational attainment, we

13. Compared with the quarterly frequency used for the aggregate analyses in the preceding section, the annual data used for the disaggregated analyses yield more reliable estimates of average hourly earnings by educational attainment. In addition, reliance on a simplified Phillips curve model allows us to sidestep complex issues such as estimating trend productivity growth by educational attainment; this specification is similar to the specification of the aggregate Phillips curve used by Blanchard and Katz (1997).

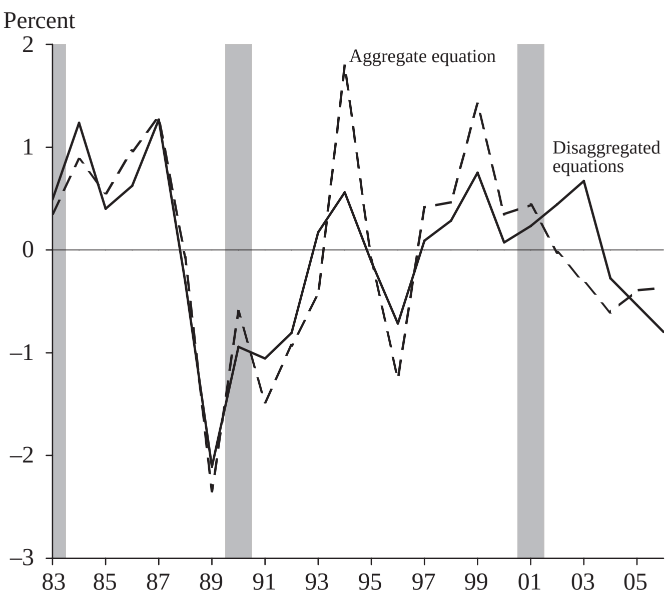
14. The data files and a detailed description can be found at www.epinet.org. These data have been used by other researchers doing similar analysis, e.g., Katz and Krueger (1999).

TABLE 2
PHILLIPS CURVE MODELS, FULLY DISAGGREGATED BY EDUCATION: ANNUAL DATA, 1983–2006

		Educational attainment of wage earner (SUR)			
		Four educational groups			
Independent variable	Aggregate equation	Less than high school diploma	High school diploma	Some college	College degree or more
Unemployment rate	–0.91 (0.21)	–0.73 (0.14)	–0.94 (0.11)	–1.24 (0.20)	–1.71 (0.47)
Constant	4.93 (1.08)	8.13 (1.70)	5.55 (0.71)	5.70 (0.92)	5.12 (1.21)
RMSE	0.835	1.203	0.744	0.832	1.150
		Test of cross-equation equality on unemployment rate coefficients			
		$\chi^2(3) = 7.68$			
		Prob $> \chi^2 = 0.0530$			
Standard error of the regression (SER)	0.915	SER (labor force weights)	0.752		
		SER (wage weights)	0.818		
		Two educational groups			
		Less than college degree		College degree or more	
Unemployment rate		–0.83 (0.14)		–1.43 (0.59)	
Constant		5.05 (0.92)		4.41 (1.51)	
RMSE		0.732		1.147	
		Test of cross-equation equality on unemployment rate coefficients			
		$\chi^2(1) = 1.13$			
		Prob $> \chi^2 = 0.2870$			
		SER (labor force weights)	0.724		
		SER (wage weights)	0.935		

Note: Coefficient standard errors in parentheses. Disaggregated results based on SUR framework (see text).

FIGURE 9
RESIDUALS, DISAGGREGATED AND AGGREGATE PHILLIPS CURVES (FOUR GROUPS, 1983–2006)

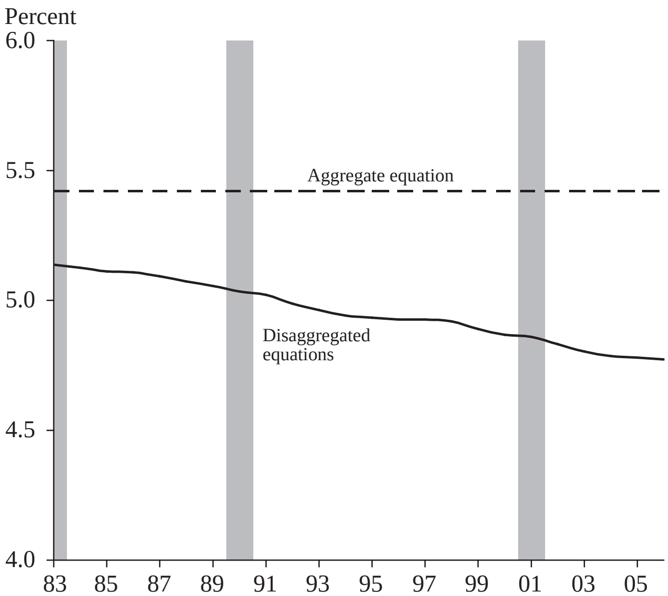


Note: Disaggregated results from SUR model, aggregated by labor force shares. Gray bars indicate NBER recession dates.

find sizeable differences in the NAIRUs estimated for each group. Based on the model presented in Table 2 we find a NAIRU of about 3 percent for college-educated workers compared with a NAIRU of about 11 percent for workers lacking a high school diploma. By contrast, the NAIRU obtained from the aggregate equation is 5.4 percent, which hides considerable variation in equilibrium labor market conditions across groups.

Moreover, it is possible to combine the group-specific NAIRUs to produce an aggregate NAIRU based on the disaggregated results (again using labor force weights for aggregation). As displayed in Figure 10, the overall NAIRU obtained from the disaggregated equations is below the aggregate NAIRU over our entire sample frame and falling over time. This pattern arises because the disaggregate equations more accurately capture the overall sensitivity of wages to the unemployment rate than does the aggregate equation. This can be seen in Table 2, where the coefficients on the group-specific unemployment rates in the four-group model in general are larger in absolute value than the corresponding coefficient from the aggregate equation (with the sole exception of the equation for individuals lacking a high school diploma). This higher sensitivity of group-specific wages to the unemployment rate is consistent with labor market segmentation by educational

Figure 10
NAIRUs, Disaggregated and Aggregate Phillips Curves (Four Groups, 1983–2006)



Note: Disaggregated results from SUR model, aggregated by labor force shares. Gray bars indicate NBER recession dates.

attainment, and it is critical for the better in-sample predictions obtained using the disaggregated framework.

5. Conclusions

We find that incorporating an educational adjustment into the aggregate unemployment rate does not improve the fit of a standard Phillips curve specification, despite the finding that rising educational attainment has reduced equilibrium aggregate unemployment over the past three decades. The limited impact of an aggregate educational adjustment arises due to the limited sensitivity of wage inflation to differences in the unemployment rate in standard Phillips curve models.

On the other hand, we find that disaggregating the Phillips curve estimates by educational group improves the in-sample predictions of wage inflation. Underlying this improvement in fit are significant differences in the slopes of the group-specific Phillips curves. These results suggest that our understanding of the dynamics of unemployment and wage inflation may be improved through consideration of the role of educational attainment, particularly in the context of disaggregated analyses. Additional investigation with expanded data and more elaborate models seems warranted, along with analysis of out-of-sample forecast accuracy.

Appendix

Validating Adjustments to Aggregate Unemployment

Simple demographic adjustments to the aggregate unemployment rate are formulated by calculating what the aggregate unemployment rate would be if labor force shares for demographic groups remained fixed at a base period value. A similar procedure can be applied to groups defined jointly by demographic characteristics and educational attainment.

In the paper, we focus on two adjusted unemployment rate series:

(1) the unemployment rate adjusted for age. The adjustment is based on the labor force shares in 1978 of five groups defined by age: 16 to 19, 20 to 24, 25 to 34, 35 to 54, and 55 and older.

(2) the unemployment rate adjusted jointly for age and education. The adjustment is based on the 1978 labor force shares of groups defined by the interaction of age groups and education groups. The age groups used are the same as in (1), but with ages 25 to 34 and 35 to 54 combined. The education groups consist of individuals without a high school diploma, those with a high school diploma, those with some college experience, and those with a college degree or more. This four-by-four breakdown produces 16 groups defined by their age range and educational attainment. To account for age limitations on the distribution of educational attainment and consequent sparse cells, individuals aged 16 to 19 who report educational attainment of "some college" or a college degree are included in the "high school graduate" group, yielding a total of 14 groups.

The adjustment procedure relies in part on the assumption that group-specific unemployment rates do not respond to changes in group-specific labor force shares (i.e., an "exogeneity" assumption; see Shimer 1999). If this assumption does not hold, the fixed-weight adjustment may overstate or understate changes in the aggregate unemployment rate associated with changing labor force shares per se. The exogeneity assumption can be investigated empirically by examining the correlation between changes in group-specific unemployment rates and labor force shares for specific pairs of comparison years; under pure exogeneity, the correlation will be zero. As shown in Table A1, this correlation in general is substantially smaller (in absolute value) for groups defined jointly by age and education than for groups defined separately by age and education, indicating that the joint breakdown by age and education fulfills the exogeneity condition better than do separate breakdowns by age and education.[15] This finding is not a

15. These calculations are based on annual averages of the underlying non-seasonally adjusted quarterly series. The criteria used to choose the

TABLE A1
CORRELATIONS BETWEEN CHANGES IN GROUP SHARES AND UNEMPLOYMENT RATES

	Group definition		
Years	Age	Education	Age/education
1979–2005	0.609	−0.454	−0.243
1979–2000	0.483	−0.147	0.073
1989–2005	−0.013	0.061	−0.023
1989–2000	0.467	0.602	0.193
1982–2003	0.614	0.791	0.399

mechanical artifact of the generally offsetting positive and negative correlations for groups defined separately by age and education: for changes between 1989 and 2000, the correlations are positive for age and education groups but substantially smaller for groups defined jointly by age and education.

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year pairs displayed included similar points on the business cycle, similar unemployment rates, years that fall within or near our sample time frame, and use of the most recent full year of data, 2005. Shimer (1999) defined and used a "pseudo-correlation" that produces only slightly different results than the simple correlation used here.

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